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BACHELOR THESIS

Publication Bias in Measuring Anthropogenic Climate Change

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Declaration of Authorship

I declare, that I compiled this thesis independently, using only the listed resources and literature.

Furthermore, I have written this thesis only for purpose of acquiring the bachelor‘s degree at IES FSV UK.

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Prague, May 14, 2014

Dominika Rečková

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Abstract

People around the world are interested in climate changes. Especially the impact of human being on climate changes plays an important role in the policy discussion about environment. One of the measures of anthropogenic climate change is climate sensitivity. The main aim of this thesis is to apply meta-analysis methodology on relationship between human activity and climate change. Until now, tens to hundreds of studies have been written on this topic, but only few report the estimate of climate sensitivity. Despite majority of the studies refer to recognizable influence of human activity on the climate change, the results of individual studies do not correspond in absolute values perfectly. Until now only one meta-analysis concerns publication bias in literature covering climate change, it uses vote-counting and detects publication selectivity efforts. But no meta-regression analysis was published on this topic yet.

The thesis investigates if the results of studies reporting climate sensitivity are influenced with the effort to publish only positive and significant estimates. It applies effective statistic instrument, meta-regression analysis, that allows systematic evaluation of an inconsistent sample of estimates. This method was applied on the data set consisting of 48 estimates coming from 16 studies. Results detects strong upward publication selectivity. Besides the meta-analysis find out that the true effect of climate sensitivity corrected for publication bias oscillates between 1.4 and 2.3 °C.

JEL Classification C42, Q53, Q54

Keywords Meta-analysis, Publication bias, Climate change, Climate sensitivity, CO_2

Abstrakt

O klimatické změny se zajímají lidé po celém světě. Zejména vliv člověka na klimatické změny hraje důležitou roli při rozhodování o politice vůči životnímu prostředí. Jedním z měřítek klimatické změny způsobené člověkem je klimitická citlivost (climate sensitivity). Cílem této práce je aplikovat metodu meta-regresní analýzy na vztahu mezi lidskou činností a klimatickou změnou. Doposud byly napsány desítky až stovky studií zabývajících se vlivem lidské činnosti na klimatickou změnu, ale jen málo z nich reportuje odhad klimatické citlivosti. Navzdory tomu, že většina studií poukazuje na znatelný vliv lidské činnosti na globální oteplování, výsledky jednotlivých studií se co do absolutní hodnoty značně liší. Doposud se publikačním vychýlením literatury o kliamatických změnách zabývala jen jedna studie, která používá metodu sčítání hlasů (vote-counting) a odhalila snahu o publikování jen vybraných výsledků. Ale žádná meta-regresní analýza na toto téma pulikována zatím nebyla.

Tato práce zkoumá, zda jsou výsledky studií reportujících klimatickou citlivost ovlivněny snahou o publikování pouze pozitivních a statisticky signifikantních odhadů. K tomu používá efektivního statistického nástroje, meta-regresní analýzu, která umožňuje systematicky zhodnotit různorodou skupinu odhadů. Pomocí této metody bylo na základě 48 odhadů z 16 studií zjištěno, že odhady klimatické citlivosti jsou silně nadhodnocené v důsledku publikační selektivity. Mimo to meta-analýza odhalila, že pravdivý odhad klimatické citlivosti očištěný o publikační vychýlení se pohybuje mezi 1,4 a 2,3 °C.

JEL klasifikace	C42, Q53, Q54
Klíčová slova	Meta-analýza, Publikační selektivita, Klimatická změna, Citlivost klimatu, CO_2

Rozsah práce

Počet znaků: 65.975
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Abbreviations

CS	Climate Sensitivity
FAT	Funnel Asymmetry Test
FE	Fixed-Effect
GHG	GreenHouse Gases
GLS	Generalized Least Squares
IPCC	Intergovernmental Panel on Climate Change
LR	Likelihood Ratio
ME	Mixed-Effect
MLE	Maximum Likelihood Estimation
MRA	Meta-Regression Analysis
OLS	Ordinary Least Squares
SCC	Social Cost of Carbon
SE	Standard Error
WLS	Weighted Least Squares

Bachelor Thesis Proposal

Author	Dominika Rečková
Supervisor	PhDr. Tomáš Havránek, Ph.D.
Proposed topic	Publication Bias in Measuring Anthropogenic Climate Change

Topic characteristics The main aim of this thesis is to investigate relationship between human activity and climate change. People around the world are interested in climate changes. Especially the impact of human being on climate changes plays an important role in the policy discussion about environment. One of the measures of anthropogenic climate change is climate sensitivity. Until now, tens to hundreds of studies have been written on this topic, but only few report the estimate of climate sensitivity. Despite majority of the studies refer to recognizable influence of human activity on the climate change, the results of individual studies do not correspond in absolute values perfectly. Until now only one meta-analysis concerns publication bias in literature covering climate change, it uses vote-counting and detects publication selectivity efforts. I will provide quantitative survey of literature reporting climate sensitivity.

Hypotheses and research questions Is there any anthropogenic climate change at all? Do researchers publish preferably significant outcomes?

Methodology I am going to apply effective statistic instrument, commonly called a meta-regression analysis. Meta-analysis allows systematic evaluation of an inconsistent sample of estimates. I will not end with the standard vote-counting method but I will also employ advanced meta-analysis methodology. I will apply robust and pseudo-panel meta-regression.

Outline

1. Itroduction
2. Climate Sensitivity and Publication Bias
3. Description of Meta-Regression
4. Description of Data
5. Meta-Regression
6. Discussion of Results
7. Conclusions

Core bibliography

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Author Supervisor

Chapter 1

Introduction

"*An overwhelming majority of climate scientists agree that global warming is happening and that human activity is the primary cause.*" (of Concerned Scientists [2013])

On that account hundreds of researchers make an effort to estimate the influence of human being on the climatic changes. The problematic is, however, complicated and results uncertain. This thesis concerns estimates of equilibrium climate sensitivity, often simply termed the climate sensitivity, that is basically the measure of climatic response on double increase of CO_2 concentrations. (Solomon *et al.* 2007). The uncertainty in this research field surfaces also in the low number of studies that provide estimate of climate sensitivity instead of only likely range of climate sensitivity. Last (fifth) report of Intergovernmental Panel on Climate Change (IPCC) predicts climate sensitivity likely ranges from 1.5 to 4.5 with high confidence and extremely unlikely is lower than 1 again with high confidence. (Stocker 2013). Nevertheless IPCC does not report exact estimate of climate sensitivity. Therefore I apply a useful tool, meta-regression analysis (MRA), for summary and quantification of the reported estimates of climate sensitivity. Researchers report diverse results across the studies, however the estimate of climate sensitivity most frequent oscillates around 3.

The main objective of this thesis is to find out based on collected data sample whether the reported estimates of climate sensitivity suffer publication bias, since no such analysis was until now published that I know of. I collected 48 estimates of climate sensitivity from 16 studies ranging from 0.7 to 10.4 with the mean estimate 3.27. The analysis based on that reported estimates should not be correlated with their standard errors. Graphical tests expose if such relationship is present indicating publication selection bias at first glance. Further I provide broader analysis by employing OLS regression of the climate sensitivity estimates on their standard errors. The estimates with lower standard error are closer to the true value of climate sensitivity while the estimates with larger standard error get dispersed which makes this regression heteroscedastic. Therefore the regression is weighted by the degree of this heteroscedasticity, standard errors of the reported estimates, and WLS, FE, and mixed-effect multilevel regressions are applied. The thesis also checks for the asymmetry of distribution of the CS estimates which could cause the false impression of publication bias. It performs the analysis on subsets of median and mean estimates of CS separately. Besides this thesis estimates the true effect of climate sensitivity corrected for publication bias.

The thesis is organized as follows: Chapter 2 introduces the problematic of climate sensitivity and publication bias generally. Chapter 3 explains the meta-analysis methodology and the used models. Chapter 4 summarizes the literature published on this topic and describes the collected data set of climate sensitivity. Chapter 5 provides the results of the meta-analysis. Chapter 6 states conclusions and the summary of main contribution of this thesis is presented in the Chapter 7.

Chapter 2

Climate sensitivity and publication bias

This chapter develops the problematic of climate sensitivity. It introduces the method used in this thesis, meta-analysis. Lastly it presents possible sources of publication bias selectivity.

2.1 Equilibrium climate sensitivity

"*The climate sensitivity is the equilibrium response of global surface temperature to a doubling of equivalent CO_2 concentration.*" (Houghton *et al.* 2001)

This is common definition of equilibrium climate sensitivity but some differ a bit. Another one defines equilibrium climate sensitivity as: "*the response in global-mean near-surface temperature to a doubling of atmospheric CO_2 concentrations from preindustrial levels*" (Klocke *et al.* 2011). The discrepancies in the definition of climate sensitivity could damage the meta-analysis. Therefore I focused by the sampling of estimates on what exactly is predicted. Not all studies provides the definition of climate sensitivity, but lot of them state the definition as a change from pre-industrial levels. The character of data used in collected studies indicates that both given definitions state the same and all collected estimates are therefore commensurate. Furthermore if researchers would predict the climate sensitivity from certain level of CO_2 concentrations other than pre-industrial, they would have to state from which level they compute it.

The problematic of climate change is, however, more complicated, since CO_2 concentrations are not the only aspect influencing the temperature change. According to Edwards *et al.* (2007) the size of forested area, ice melting, cloudiness, frequency of extreme events or change in land cover and other aspects can affect the global temperature. Some of these aspects can warm as well as cool the atmosphere, for instance clouds: low, white clouds reflect solar radiation back to space which cools the atmosphere while high, dark clouds have exactly opposite effect. Besides the prediction remains still uncertain due to the imperfect knowledge of: ocean uptake of CO_2, the terrestrial carbon cycle, and primarily the sensitivity of climate system to the change.

Edwards *et al.* (2007) also quotes techniques of estimation climate sensitivity: to infer it directly from observations, to compare model simulations to observations, and to weight predictions of climate sensitivity from several different models. Predictions of climate sensitivities that I collected were estimated only through the comparison or weighing technique.

2.2 Meta-analysis and publication bias

Meta-analysis is an econometric tool used across the scientific areas (health sciences, psychology, education, marketing and social sciences) for summary and quantification of results. (Nelson & Kennedy 2009). The method bases on collection of studies that contain certain statistic. The first step of meta-analysis is to choose the right statistic that best fits to the examined problem and is reported in published papers with its standard error or a statistic from which the standard error can be computed. (Stanley 2001). This could be a problem in measuring anthropogenic climate change as even scientists are not sure which statistic is the best fitted. First of all I choose net anthropogenic radiative forcing. That is defined as: "...a measure of the influence that a factor has in altering the balance of incoming and outgoing energy in the Earth-atmosphere system and is an index of the importance of the factor as a potential climate change mechanism." (Solomon *et al.* 2007). But only few papers on this topic were published and therefore I prefer climate sensitivity as the summary statistic.

Meta-analysis could uncover aspects influencing the examined effect (statistic) and is also commonly used for detection of publication bias. In the second case models analyse the relationship of reported estimates and their standard errors, in the absence of publication bias they should not be correlated. Common assumption is that regression parameter is approximately normally distributed, the ratios of the regression estimates to their standard errors are assumed to have a t-distribution. More detailed description of the methodology will be given in Chapter 3. Neither all written studies could be published, nor all sent to an editor. Reasons could be different. Since 1956 there is a discussion about selectivity bias as "the editor of the Journal of Abnormal Social Psychology indicated that negative studies were less likely to be published in his journal". (Thornton & Lee 2000)

The publication bias arises from various motivations of different people. The efforts could come from the scientist as well as from the editor of journal that want to publish only attractive or reliable results. Their motivation to bias the results or just publish the selected results are similar: first the selection of significant estimates (type II bias in the terminology of Stanley (2005)), second the selection of estimates with intuitive magnitude (type I bias). Publishing only selected results is called “file drawer problem”. (Rosenthal 1979). Although the selection of significant estimates is more benign (Stanley 2005), it still causes publication bias which avoids an accurate overview of corresponding problematic. (De Long & Lang 1992)

Chapter 3

Theory

This chapter describes the methodology of meta-analysis. First I construct standard errors of the collected climate sensitivity estimates. Further I provide broader analysis by employing OLS, WLS and mixed-effect multilevel regressions. I check for the asymmetry of distribution of the CS estimates which could cause the false impression of publication bias, I also perform the analysis on subsets of median and mean estimates of CS separately. Lastly I try to correct for the publication bias and estimate the true effect of climate sensitivity.

3.1 Method of calculation standard error of the estimates

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

$$SE_{up} = \frac{up - est}{z} \tag{3.1}$$

where *SEup* denotes the standard error, *up* represents the upper bound of confidence interval, *est* is the estimate of climate sensitivity and z is the corresponding value for the magnitude of confidence intervals. In most of the studies 90 % confidence intervals are reported that imply z equals to 1.645, one study reports only 66 % confidence intervals for that I use z equals to 0.955. Because the estimates are in most cases asymmetrically distributed I compute two values of the standard error depending on which bound I use to calculation.

$$SE_{low} = \frac{est - low}{z} \tag{3.2}$$

where SE_{low} denotes the standard error, *low* represents the lower bound of confidence interval. The assumption of normality is the best choice even if it would be inaccurate. Law *et al.* (1994, pg. 427) mention that 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, pg. 252) notices that "the failure of normality assumption, unless extreme, bears only marginally on the validity of the conclusions drawn". Therefore I consider the standard normal distribution of estimates of climate sensitivity will be a good approximation. For assurance I check if the possible relationship between the estimates and their standard errors is not caused only though huge asymmetry in the distribution by the ratio of standard errors constructed from "below" and from "above". Overview of the calculated standard errors is summarized in table A.4 in Annexes.

3.2 Meta-analysis methodology

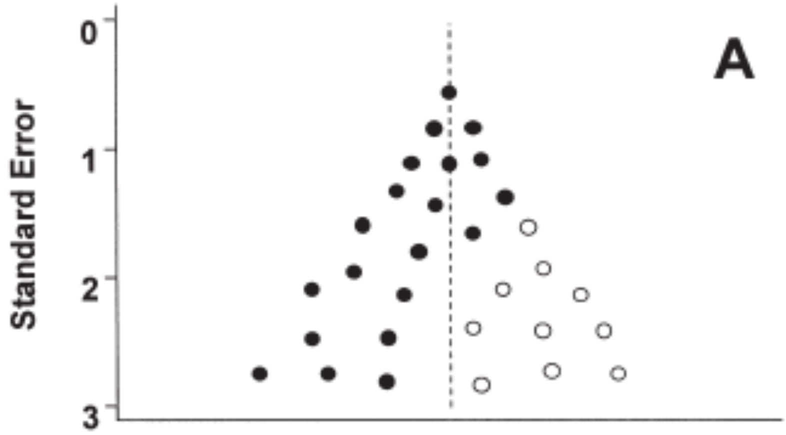
Simple methods for detecting publication bias are graphical tests. Probably the most common is so-called funnel plot. (Sterne *et al.* 2001; Stanley 2005). The name comes from the shape of the diagram. It depicts the estimated climate sensitivity on horizontal axis while the vertical axis measures the estimates precision, the inverse of the standard error. Without any bias the diagram should look like an inverse funnel. The estimates should be symmetrical around the values with the highest precision and the imprecise estimates present, although infrequent and more dispersed as is it at Figure 3.1, since all estimates have the same chance of being reported. (Havranek 2013).

Nevertheless, formal test for publication bias, often called the funnel asymmetry test or FAT, is described as the relation between the reported estimates and their standard errors (Murphy *et al.* 2004):

$$cs_i = c_0 + \beta_0 \cdot Se(cs_i) + \beta_1 \cdot mea + u_i, \quad u_i|Se(cs_i)\ N(0, \delta^2), \tag{3.3}$$

where cs_i denotes the estimate of climate sensitivity, c_0 is the average climate sensitivity, $Se(cs_i)$ is the standard error of cs_i, β_0 measures the magnitude of publication bias, *mea* is a dummy variable that equals 1 if the estimate of CS is mean, thus β_1 corrects for the differences between mean and median estimates, and u_i is a disturbance term. In the absence of publication bias the estimates are randomly

Figure 3.1: Hypothetical funnel plot in the absence of publication bias



Source: Sterne *et al.* (2000). *Notes:* Inverted y axes of standard error denotes the same as y axes of precision. On the x axes are the effect sizes, climate sensitivities. This is an example of funnel plot in the absence of publication bias. If the open circles would be missing, the bias would be present.

distributed around the true mean climate sensitivity, c_0. If some estimates, however, fall into "file drawer" as they are insignificant or just have too low magnitudes, the reported estimates will be correlated with their standard errors and β_0 will be positive. As the estimates with a low standard error lie close to the mean climate sensitivity. The bigger the standard error, the more dispersed estimates get, and some get very small, some get large. Therefore if researchers omit the estimates low in magnitude but keep the large imprecise ones, the correlation between cs_i and $Se(cs_i)$ arises. Then a significant estimate of β_0 provides formal evidence for publication bias and funnel asymmetry.

Nevertheless, estimates coming from one study are likely to be dependent. Therefore I employ study level clusters to avoid within study heterogeneity. For the same reason I apply also fixed effect model specified as follows:

$$cs_{ij} = c_0 + \beta_0 \cdot Se(cs_{ij}) + \beta_1 \cdot mea + \xi_{ij}, \quad \xi_{ij}|Se(cs_{ij})\ N(0, \delta^2), \tag{3.4}$$

where i and j denote estimate and study subscripts, and other variables remain the same as in equation (3.3). Besides too large asymmetry in the distribution of climate sensitivity estimates could cause the correlation between the estimates and their standard errors. For that reasons I specify following two models with robust standard errors:

$$cs_{ij} = c_0 + \beta_0 \cdot Se(cs_{ij}) + \beta_1 \cdot mea + \beta_2 \cdot Se_{lowup}(cs_{ij}) + \xi_{ij}, \quad \xi_{ij}|Se(cs_{ij})\ N(0,\delta^2), \tag{3.5}$$

where $Se_{lowup}(cs_{ij})$ is defined as: $\frac{Se(cs_{ij})}{Se_{up}(cs_{ij})}$ and detects the magnitude of asymmetry in the distribution of estimates. If β_2 is statistically significant the correlation between climate sensitivity estimates and their standard errors do not have to signal the publication selection bias. On the other hand if we can not reject the null hypothesis $H_0 : \beta_2 = 0$ we have the evidence that it is not the asymmetrical distribution what cause the relationship between the climate sensitivity estimates and their standard errors.

$$cs_{ij} = c_0 + \beta_0 \cdot Se(cs_{ij}) + \beta_1 \cdot mea + \beta_3 \cdot inter(cs_{ij}) + \xi_{ij}, \quad \xi_{ij}|Se(cs_{ij})\ N(0,\delta^2), \tag{3.6}$$

where $inter(cs_{ij})$ is defined as: $Se(cs_{ij}) \cdot \frac{Se(cs_{ij})}{Se_{up}(cs_{ij})}$ and detects the magnitude of asymmetry in the distribution of estimates. The idea behind this variable is the same as in previous case. If β_3 is statistically significant the correlation between climate sensitivity estimates and their standard errors do not have to signal the publication selection bias. On the other hand if we can not reject the null hypothesis $H_0 : \beta_3 = 0$ we have the evidence that it is not the asymmetrical distribution what cause the relationship between the climate sensitivity estimates and their standard errors.

Specification (3.3) obvious suffers from heteroscedasticity, since the explanatory variable, $Se(cs_i)$, is a sample estimate of standard error deviation of the response variable, cs_i. For that reason meta-analysts rather use weighted least squares (Stanley (2005); Stanley *et al.* (2008)):

$$\frac{cs_{ij}}{Se(cs_{ij})} = t_{ij} = c_0 \cdot 1/Se(cs_{ij}) + \beta_1 \cdot \frac{mea}{Se(cs_{ij})} + \beta_0 + \xi_{ij}, \quad \xi_{ij}|Se(cs_{ij})\ N(0,\delta^2), \tag{3.7}$$

where i and j denote estimate and study subscripts, t_{ij} correspond to the t-statistic of climate sensitivity estimates from the primary studies, other characteristics remain the same as in equation (3.3) but the interpretation is now different, since we employ the precision term, $1/Se(cs_i)$, instead of the $Se(cs_i)$. The intercept and slope coefficients are reversed from equation (3.3) and precision becomes the key variable in this meta-analysis. As Stanley *et al.* (2008) and many other meta-analysts argue the significance of coefficient c_0 may correspond to significance of authentic effect of climate sensitivity beyond the publication bias. Testing $H_0 : \beta_0 = 0$ is then effective in detection of publication bias.

The dependency of estimates coming from one study originates probably in the use of various data sets or specific explanatory variables for estimation across the studies. This produces between-study heterogeneity. To cope with this problem meta-analysts often apply the mixed-effects multilevel model (Doucouliagos & Stanley 2009), which allows for unobserved between-study heterogeneity. I use the model specified by Havranek & Irsova (2011) as follows:

$$t_{ij} = c_0 \cdot 1/Se(cs_{ij}) + \beta_1 \cdot \frac{mea}{Se(cs_{ij})} + \beta_0 + \zeta_j + \epsilon_{ij}, \quad \zeta_i | Se(cs_i j)\ N(0,\psi), \epsilon_{ij} | Se(cs_i j), \zeta_j\ N(0,\theta) \tag{3.8}$$

The new model divides the overall error term ξ_{ij} into study-level random effects ζ_j and estimate-level disturbances ϵ_{ij}. Because the model assumes both components of the error term to be independent, we can calculate the overall error variance as follows: Var $\xi_{ij} = \psi + \theta$, where ψ explains the between-study variance (that is, between-study heterogeneity) and θ describes the within-study variance. If ψ would be zero, the simple ordinary least squares (OLS) model would be equally suitable as the mixed-effect multilevel estimator. I will employ the likelihood-ratio test (LR) to consider witch one estimator to use.

As already Havranek *et al.* (2012) mentioned, the mixed-effect multilevel model resembles to the random effect commonly used in panel data-econometrics. Nevertheless, the mixed-effect multilevel model approaches hierarchical ordering of the data. The symbolic behind mixed-effect originates in the presence of fixed effect c_0 as well as random part ζ_j. Thus multilevel framework is more appropriate in meta-analysis as it considers the imbalances in the data set. It uses maximum likelihood estimator (MLE) instead of generalized least squares (GLS) and allows for multiple random effects (author-, study-, or country- level). Thus the mixed-effect multilevel is more flexible. According to Havranek *et al.* (2012) because the data in meta-analysis are oft unbalanced, it is difficult to competently test for exogeneity assumptions behind the mixed-effect multilevel model. But as Nelson & Kennedy (2009) notices until the violation of exogeneity assumptions is huge the damage caused by the mixed effects does not prevail the benefit from them. I will control for the violation though comparison with OLS, clustered at study level. Huge differences between estimates from OLS and mixed effects would imply the violation of exogeneity assumptions.

3.2.1 Robustness checks

So far I supposed that all differences in the estimates are caused by sampling the error and publication bias. But in reality also other factors can bring the differences. Individual studies use distinct methods for calculation and various data sets, which may themselves lead to systematically different results. Although I do not concentrate to explain all sources of heterogeneity[1] in the estimates I try to find out whether some aspects of primary studies can influence the differences of outcomes between individual estimates (that is, the publication bias). I obtain 13 variables reflecting the characteristics of the data, design of the analysis and publication characteristics. I follow the methodology of Stanley *et al.* (2008), who adds these variables interacted with the standard errors of the effect (climate sensitivity in this case) to regression (3.3). After weighting by the standard error and adding study-level random effects we get this specification:

$$t_{ij} = c_0 \cdot 1/Se(cs_{ij}) + \beta_1 \cdot \frac{mea}{Se(cs_{ij})} + \sum(\alpha_l \cdot z_l) + \beta_0 + \xi_{ij}, \tag{3.9}$$

where **Z** is a vector of l descriptive variables, and other variables have the same properties as in specification (3.7). To be able to choose the variables that most affect the publication bias, I apply stepwise regression. It is a useful tool that based on significance level of the variables intuitively builds models in a sequential fashion. (Lum & Wong 2003). Either forward stepwise regression begins with empty model and adds the variables or backward stepwise regression begins with full model and removes the variables (see Draper & Smith (1981) for details). Table 3.1 summarizes all 10 out of 13 variables I take into account. I choose only characteristics that appear by at least 10 estimates of CS (that is, more or less the fifth of all collected estimates). I use WLS regression with study-level clustering according to Havranek *et al.* (2012) for the stepwise procedure. My criterion for adding variable is 0.05 t-test p-value and for removing 0.1 t-test p-value. The specification after both forward and backward stepwise regression yields:

$$t_{ij} = c_0 \cdot 1/Se(cs_{ij}) + \beta_1 \cdot \frac{mea}{Se(cs_{ij})} + \alpha_1 \cdot ice + \alpha_2 \cdot cloud + \beta_0 + \xi_{ij}, \tag{3.10}$$

where *ice* is a dummy variable that equals one if the primary study uses data for the ice surface to estimate the particular climate sensitivity and zero otherwise, *cloud* is a dummy variable that equals one if the primary study employs data for the cloud feedback and zero otherwise, and other variables have the same properties as in specification (3.7).

[1] Since the studies do not provide exact information about all characteristics used to the estimation of climate sensitivity, I do not have enough inputs to explain all sources of heterogeneity. Therefore I use only accessible data to uncover the influence on publication bias and to check the robustness of results.

Table 3.1: **List of explanatory variables for WLS regression**

Variable	Description	
puby	Publication year	
model	Number of model used in primary study	
cit	Number of citations of the primary study	
	List of dummy variables	Occurrence in studies
mea	Mean estimate of CS	25
asa	Anthropogenic sulfate aerosol	17
solar	Solar irradiation	32
cloud	Cloud feedback	15
ozon	Ozon forcing	29
volcan	Volcanic forcing	10
ice	Ice sheet	10

Notes: I choose only characteristics (variables) that appear by at least 10 estimates of CS (that is, more or less the fifth of all collected estimates).

Nevertheless, my sample of estimates of climate sensitivity contains two[2] different types: mean and median estimates. Therefore I try to verify if the results of the meta-analysis model will be similar also on the subsets. I apply specifications (3.7) and (3.8) on the subset of median estimates and then on the subset of mean estimates. While previous analysis contains all mean estimates, it does not contain some median estimates since some studies report both mean and median estimates and in such a case only mean estimates are included. On that account I specify following models:

$$\frac{mean_{ij}}{Se(cs_{ij})} = p_{ij} = c_0 \cdot 1/Se(cs_{ij}) + \beta_0 + \xi_{ij}, \tag{3.11}$$

$$\frac{median_{ij}}{Se(cs_{ij})} = r_{ij} = c_0 \cdot 1/Se(cs_{ij}) + \beta_0 + \xi_{ij}, \tag{3.12}$$

where $mean_{ij}$ represents the mean estimates of climate sensitivity, $median_{ij}$ represents the median estimates of climate sensitivity, and other characteristics remain the same as in equation (3.7).

$$p_{ij} = c_0 \cdot 1/Se(cs_{ij}) + \beta_0 + \zeta_j + \epsilon_{ij}, \tag{3.13}$$

$$r_{ij} = c_0 \cdot 1/Se(cs_{ij}) + \beta_0 + \zeta_j + \epsilon_{ij}, \tag{3.14}$$

where p_{ij} and r_{ij} are defined as in equations (3.11) and (3.12), and other characteristics are the same as in the regression (3.8). To control for the differences in

[2]It contains also mod and best estimates but only six estimates together, therefore I ignore it.

publication bias by mean and other estimates in the whole sample I specify following model according to Stanley *et al.* (2008):

$$t_{ij} = c_0 \cdot 1/Se(cs_{ij}) + \beta_1 \cdot mea + \beta_2 \cdot Se(cs_{ij}) + \beta_0 + \zeta_j + \epsilon_{ij}, \tag{3.15}$$

where mea demonstrates the divergence in publication bias instead of differences between magnitudes of climate sensitivity estimates ($mea/Se(cs_{ij})$), all characteristic remain the same as in (3.8).

The last check will be the specifications (3.7) and (3.8) with the use of upper limit of confidence intervals instead of the lower limit. As upward bias is expected the upper tail of confidence intervals is mostly not well constrained, the use of lower tail of confidence intervals for constructing the standard error is more appropriate. This will help however, to check if the new precision term will be significant. In such a case the result of publication bias will be robust.

3.2.2 Correction of publication bias

So far only significance of the true effect of climate sensitivity was tested. To examine the magnitude of the authentic effect beyond publication selection bias I follow Havranek *et al.* (2012) and apply so called Heckman meta-regression. This method is based on nonlinear relationship between the estimates and their standard errors. (Stanley & Doucouliagos 2007). The specification bases on equation (3.8) and takes into account heteroscedasticity and between-study heterogeneity, it assumes quadratic relationship between standard errors and publication bias:

$$t_{ij} = c_0 \cdot 1/Se(cs_{ij}) + \beta_1 \cdot \frac{mea}{Se(cs_{ij})} + \beta_2 \cdot Se(cs_{ij}) + \beta_0 + \zeta_j + \epsilon_{ij}, \tag{3.16}$$

where c_0 measures the magnitude of the average climate sensitivity corrected for publication bias.

Chapter 4

Literature review and data set description

Following chapters apply meta-analysis on literature reporting climate sensitivity. The main aim of the meta-analysis is to uncover if the literature suffer publication selectivity bias. All needed calculations and charts are made in statistical program STATA.

4.1 Literature review

The main contribution of this thesis lies in summary of published studies with reported estimate of climate sensitivity. To the extend that I know no published analysis discusses or documents publication bias in climate change literature. Except Michaels (2008) that analyses 116 publications of two specialised magazines *Science* and *Nature* which forecast climate change. He found bias towards "worse" results. But the analysis of Michaels (2008) only categorises statements about climate change into thee groups: "better" , "worse" , "neutral" , and does not deal with any exact estimates of climate change. The reason is maybe the estimates of climate change including climate sensitivity rarely occur in the scientific literature. For instance the fifth assessment report of Intergovernmental Panel on Climate Change (IPCC) predicts only climate sensitivity likely ranges from 1.5 to 4.5 with high confidence and extremely unlikely is lower than 1 again with high confidence. (Stocker 2013). For comparison the third assessment report of IPCC estimates climate sensitivity "*likely*" ranges between 2 and 4.5 and is "*very unlikely*" less than 1.5. (Pachauri & Reisinger 2007). Andronova & Schlesinger (2001) disagrees with the third report of IPCC and argues climate sensitivity lies with 54 % likelihood outside IPCC range. He finds 90 % confidence interval for CS is 1 to 9.3.

Estimates differ across studies and it has various reasons. Masters (2013) notes a robust relationship between the modeled rate of heat uptake in the global oceans and the modeled climate sensitivity. It signals that researchers could have options how to influence their results. I apply common tool, meta-regression analysis, for detection of publication bis in the literature about climate sensitivity. The first step of MRA is to choose the right statistic that best fit to the examined problem and is reported in published papers with its standard error or a statistic from which the standard error can be computed. (Stanley 2001)

4.2 Data set collection and description

I search in Web of Knowledge and Google Scholar for studies that estimate the climate sensitivity. I am restricted only to studies written in English and freely available at least at Charles University. Furthermore to be able to use modern meta-analysis methods I have to include only estimates with reported standard error or a statistic from which the standard error can be computed. I collect all the estimates from the papers and also codify 13 variables reflecting the context in which researchers obtain the estimates of climate sensitivities including the information about the character of the estimate. The literature provides more types of climate sensitivity estimates. For the analysis, I use only one type of estimate from each study in this preference order: mean, median, mod, best estimate. I add the last study to the data set on March 3, 2014, and terminate the search. The oldest study was published in 2001, and the most recent ones in 2013.

Table 4.1: **List of primary studies used**

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

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

Although some meta-analysts argue for using estimates from all available studies in order to avoid publication bias. I decide to not use estimates from unpublished papers as the magnitude of any bias caused by failure to include unpublished papers has never been well quantified. (Thornton & Lee 2000). Moreover collecting estimates only from studies published in peer reviewed journals serves as simple guaranty of quality and avoids multiple including of the same results. By that I try to prevent comparison of "apples with oranges" - pooling primary studies of varying quality. (Nelson & Kennedy 2009). Additionally collecting of all unpublished papers without biasing the sample by non-random selection of studies would be beyond my strength due to time constrain.

A total of 15 published papers and one dissertation from Switzerland provide 49 estimates of the climate sensitivity. Nevertheless, I decide to exclude one estimate or it would bias the meta-analysis. It comes from a study with more estimates computed with different models and even the study does not explain how it is possible to have the value of estimate infinity. All 16 included papers are listed in Table 4.1. The estimates of climate sensitivity range from 0.7 to 10.4 with the average estimate 3.27. Full summary statistics of the estimates are reported in Table 4.2 and Table 4.3 lists and describes the dummy variables.

Table 4.2: **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
Mod 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 t-statistic	48	4.316	1.86	2.043	11.475
low (confidence interval)	48	1.689	0.596	0.3	2.9
up (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
Num. of citations of study	48	124.646	186.317	2	918
Num. of models in study	48	9.417	21.576	1	128

Notes: 11 studies report both mean and median estimate of climate sensitivity. In such a case only mean estimate are included in the data set of this meta-analysis (that means, variable Climate sensitivity contains 17 median estimates) except for the specification (3.10) where all collected median estimates are used. Similarly variable climate sensitivity contain only 4 best estimates. The t-statistics are computed in following way: $cs_i/Se(cs_i)$ with the use of constructed standard error of CS estimate from the lower limit of reported confidence intervals. The search for primary studies was terminated on March 3, 2014.

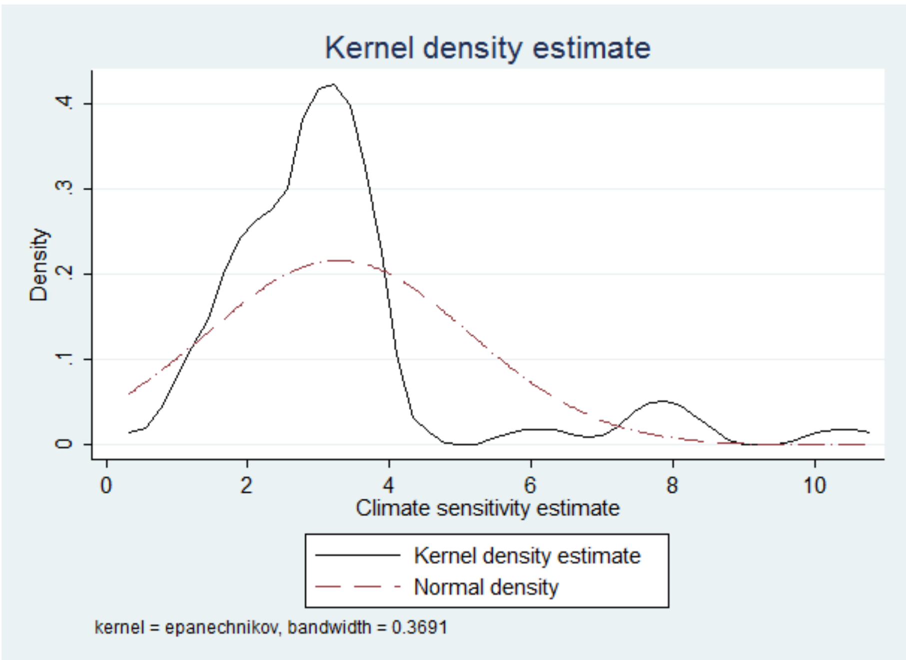
Figure 4.1 depicts the kernel density of the estimated climate sensitivity with the use of the Epanechnikov kernel. (Samiuddin & El-Sayyad 1990). It indicates the distribution is skewed. The right-hand-side tails of the distribution is much longer than the left-hand-side. In meta-analysis a common assumption is that in the absence of bias the estimates are standard normal distributed around a hypothetical true effect. (Stanley 2001). Figure 4.1 depicts the normal density as the long-dash dot line for comparison.

Table 4.3: **The 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 ice sheet	10
mo	The sudy uses models for generating data	19
mea	The estimate of CS is mean	25
medi	The estimate of CS is median	28

Notes: 11 studies report both mean and median estimate of climate sensitivity. In such a case only mean estimate are included in the data set of this meta-analysis (that means, the data set contains 17 median estimates) except for the specification (3.10) where all collected median estimates are used. The search for primary studies was terminated on March 3, 2014.

Figure 4.1: The kernel density of climate sensitivity estimates



Source: author's computations.

Chapter 5

Results

The publication selectivity bias appears in all executed tests. First the asymmetric funnel plots signal selectivity efforts. OLS, WLS, fixed-effect, and mixed-effect multilevel regressions then provide formal test since all give significant estimates of publication bias, β_0. Also the specific variable regression confirms the robustness of the meta-analysis conclusions. Lastly, correction of the publication bias estimates the true effect of climate sensitivity is 1.74.

5.1 Graphical tests of publication bias

Figure 5.1 depicts funnel plot for the estimate of climate sensitivity using the standard error constructed with the lower tail of confidence interval and Figure 5.3 the same using the construction with upper tail. The funnels are heavily asymmetrical: the left-hand side of the funnels is almost completely missing, hence we have a good reason to believe that publication selection bias in this literature is strong.

At Figure 5.1 doted lines pick out climate sensitivity with the magnitude 1 and 2 while the dashed line represents precision 2 (that is, standard error 0.5), with increasing precision the estimates converge to climate sensitivity 1. Figure 5.2 excludes the one most precise as well as the lowest estimate of climate sensitivity to depict the funnel in more detail with the same lines as in Figure 5.1. Figure 5.2 shows most estimates between 2 and 4 with quite low precision between 0.6 and 2, since the most precise estimates differs in magnitude: one of them predicts climate sensitivity around 3.5 while four of them predict it between 1 and 2. Although the magnitude of climate sensitivity estimates varies, Figure 5.2 clearly displays the relationship between the estimates and their precision: almost holds the highest precision the lowest estimate of climate sensitivity. In the absence of publication bias these figures should look like an inverted funnel, while Figure 5.1 and Figure 5.2 depicts only the right-hand side of the inverted funnel and left-hand side is completely missing indicating the efforts to publication selectivity bias.

Figure 5.3 represents a check if the situation is similar with the use of standard error constructed from the CS estimates upper bound of confidence interval. Figure 5.3 again signals publication bias since the left-hand side of the inverted funnel is missing. The relationship between the estimates and their standard errors is, however, not so straightforward at Figure 5.3 as in previous figures. At Figure 5.3 estimates with very low precision (lower than 1, that means standard error higher than 1) converge with increasing precision to the value of climate sensitivity 4. Nevertheless, high precision estimates range around climate sensitivity 2 and increase with decreasing precision. Besides at Figure 5.3 there are six estimates missing, since one value of the reported upper limit of confidence interval is also missing and the collected sample includes five values infinity of the upper limit and therefore standard error can not be calculated. The limit of infinity alone assumes that the estimate is more and more imprecise going to infinity. It gives the evidence that the upper tail of the estimates' confidence interval is not well constrained[1]. For that reason and because the upward publication bias is expected, further analysis employs only the lower tail. Meta-analysis literature argues that the funnel plot explains both of the sources of publication bias, selection of significant estimates and selection of expected magnitude or sign, although the explanation is oft poor.

Figure 4.1 depicts the density of estimated climate sensitivity using Epanechnikov kernel. Again in the absence of publication bias the distribution should be symmetrical, which is not the case of Figure 4.1. Left-hand side of the graph is completely missing and also the shape of the solid line representing the kernel density of climate sensitivity estimates does not correspond to the normal density pictured as the long-dash dot line.

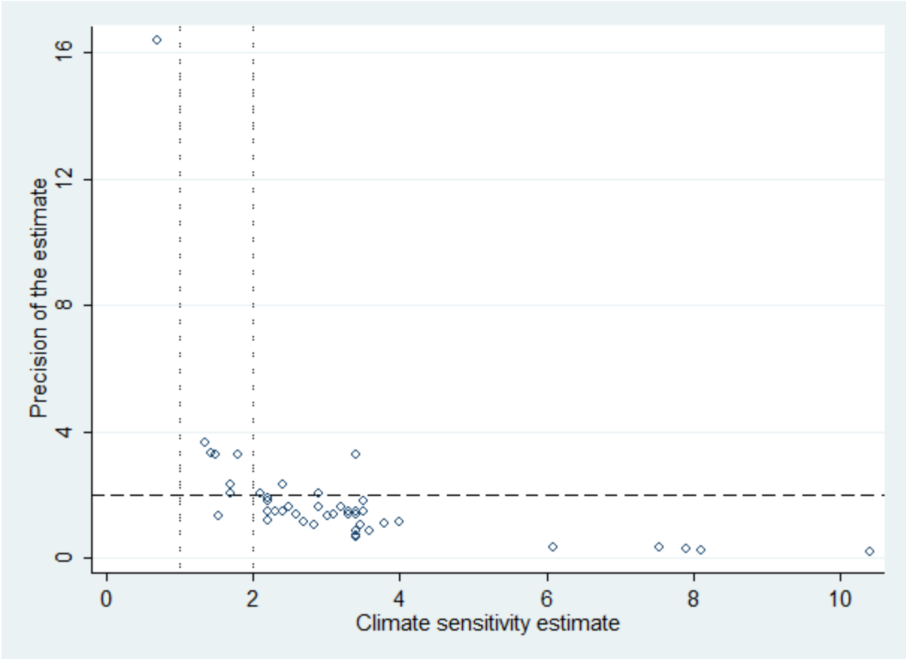
All figures indicate publication bias selectivity. Nevertheless asymmetry in the funnel plots can be also caused by other factors than just publication bias like data irregularities or heterogeneity in the data set. (Sterne *et al.* 2000). Therefore further analysis is needed.

5.2 Econometric tests of publication bias

Let us proceed to the formal test of publication bias, described by regression (3.3). It is often called the funnel asymmetry test or FAT since it follows directly from the funnel plot. Though regression (3.3) only depends on the standards errors, according to many meta-analysis literature (for instance,Duval & Tweedie (2000)) it still captures both sources of publication bias: first the selection of significant estimates (type II bias in the terminology of Stanley (2005)), second the selection of estimates with intuitive magnitude (type I bias). Although the suitability of funnel plots to

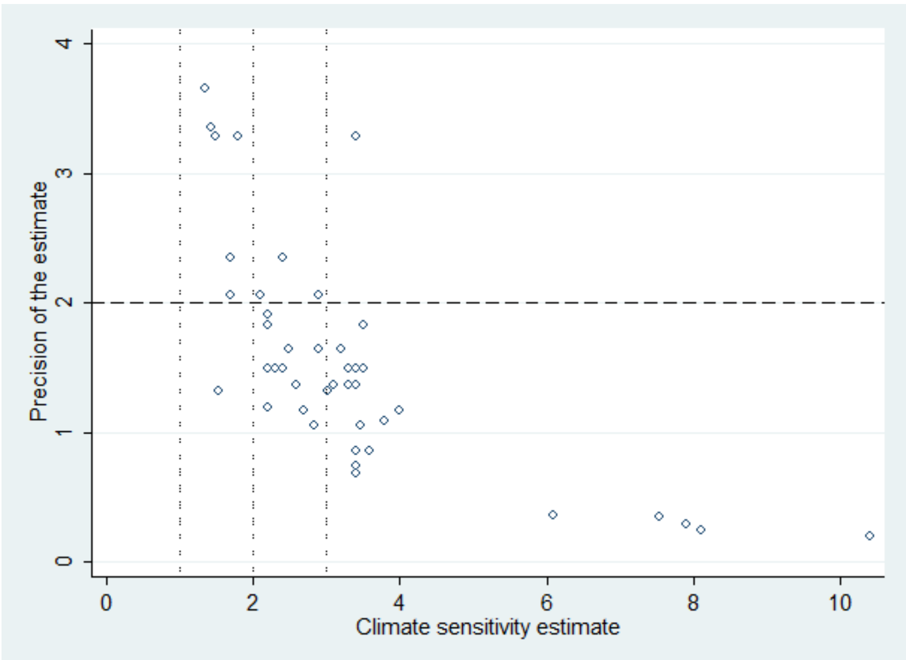
[1] Sterne *et al.* (2000) describes the contrary convergences as a signal of overestimation of treatment effects with lower methodological quality.

Figure 5.1: Funnel plot of the estimated climate sensitivities with the use of Se_{low}



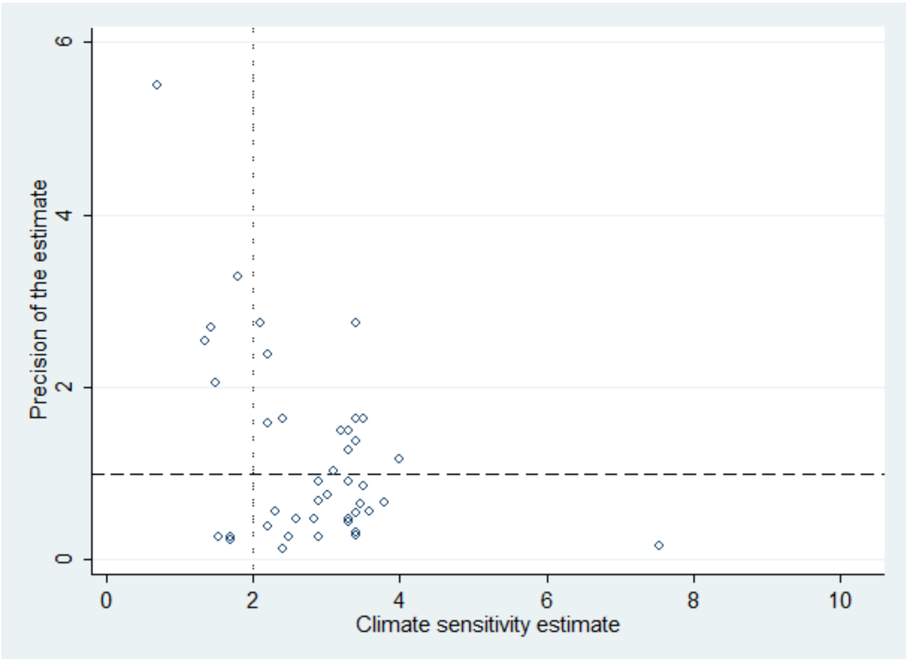
Source: author's computations. *Notes:* In the absence of publication bias, the funnel plot should be symmetrical around the most precise estimates of climate sensitivities. This funnel is asymmetrical, which suggests publication bias, since the negative and very low positive estimates are not reported, even though there should be at least few of them because of the law of chance.

Figure 5.2: More detailed funnel plot of the estimated CS



Source: author's computations. *Notes:* This figure excludes the most precise one estimate from the data set and blows up Figure 5.1.

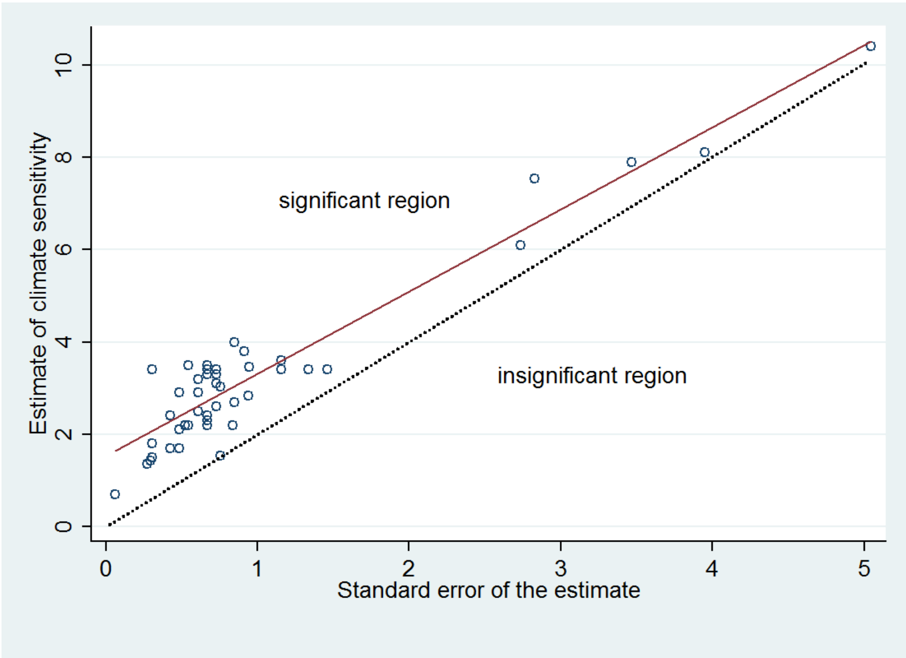
Figure 5.3: Funnel plot of the estimated climate sensitivities with the use of Se_{up}



Source: author's computations. *Notes:* In the absence of publication bias, the funnel plot should be symmetrical around the most precise estimates of climate sensitivities. This funnel is asymmetrical, which suggests publication bias, since the negative and very low positive estimates are not reported, even though there should be at least few of them because of the law of chance.

detect both sources of publication bias should be discussed as the literature explains it in detail seldom. (Havranek *et al.* 2012).

Figure 5.4: Visualization of the funnel asymmetry test



Source: author's computations. *Notes:* The dotted line denotes the combinations of the estimates of climate sensitivities and their standard errors for which the t statistics equals two. The solid line denotes a linear fit of the points - that is, regression (3.3); its positive slope suggests publication bias.

Figure 5.4 visualizes the regression relationship (3.3) between estimates and their standard errors. (Compared with the funnel plot, the axes are switched and the values on the new horizontal axis are inverted.) In the absence of publication bias the regression (3.3) would yield no significant slope coefficient β_0 as the estimates should be randomly distributed around the true mean climate sensitivity c_0. Moreover Figure 5.4 would picture isosceles triangle with the most precise estimates on the tip. At Figure 5.4 the tip will estimate 1.69 the predicted true climate sensitivity. First, let us assume that only enough high estimates, without dependency of their statistical significance, were reported. In such a case the triangle would lose its lower part. Regression (3.3) would yield a positive slope coefficient, evidence of publication bias. Second, let us suppose that researchers omit to report estimates insignificant at 5% level, irrespective of the estimates magnitude. In such a case the imaginary triangle would lose its middle part. Boundary of significance at 5% level dotted line at Figure 5.4 isolates the significant part from the insignificant one as it represents the t-statistics 2 (since the estimates from primary studies are only positive, the figure does not picture the t-statistic -2). In the case of type II bias researchers do not report estimates with |t| <2. Regression (3.3) would predict again positive slope coefficient indicating publication bias.

The steep positive slope of the regression line at Figure 5.4 signifies the presence of strong upward publication bias. The source of it is identified in both types of bias. Missing values in the right-hand lower corner of the imaginary isosceles triangle make evidence for publication bias type I, since only 5 out of 48 estimates are lower than 1.69. The low number of estimates with high standard errors (higher than 2) shows the presence of type II bias. At Figure 5.4 should be according to the law of chance more estimates lower than 1.69, the tip of the hypothetical triangle, including the insignificant ones. In the problematic of climate sensitivity negative estimates rarely occur. Still it is possible to estimate negative climate sensitivity and there should be at least few negative insignificant estimates and definitely more low positive estimates of climate sensitivity.

To sum up the solid line at Figure 5.4 shows a linear fit based on regression (3.3) and its positive slope indicates strong publication bias. Assuming the standard error being close to zero the regression calculates average estimate of the climate sensitivity. In other words if the precision would be infinite, the hypothetical estimate of climate sensitivity would be shown at Figure 5.4 as intercept of the solid line with the vertical axis (climate sensitivity 1.69 at Figure 5.4). Table 5.1 shows the results of regression (3.3) compared to regression (3.3) with robust standard errors clustered at study level. Both specifications detect publication bias since the coefficient of the standard error is significant even at 1% level.

Table 5.1: **Test of publication bias through OLS regression**

Response variable: Estimate of CS	OLS	Clustered OLS
Se (Evidence of publication bias)	1.817***	1.817***
	(0.088)	(0.065)
Constant (Average true effect of CS)	1.692***	1.692***
	(0.138)	(0.177)
mea (Correction for mean estimates)	-0.365**	-0.365*
	(0.171)	(0.203)
Observations	48	48
R^2	0.906	0.906

Notes: Standard errors are shown in parentheses and for second OLS clustered at the study level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

Nevertheless, because of heteroscedasticity and between-study heterogeneity regression (3.3) is not commonly estimated itself. Moreover too large asymmetry in the distribution of climate sensitivity estimates could cause the correlation between

Table 5.2: **Test of asymetric dirstribution of CS estimates**

Response variable: Estimate of CS	Model-Share of SE	Model-Interaction term
Se	2.131***	1.713***
	(0.153)	(0.351)
inter		0.848
		(0.587)
Se_{low}/Se_{up}	0.538	
	(0.344)	
mea	-0.389*	-0.395**
	(0.182)	(0.178)
Constant	1.18***	1.451***
	(0.285)	(0.203)
Observations	42	42
R^2	0.741	0.741

Notes: Standard errors, clustered at the study level for OLS, are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level. Interaction term ($inter = Se(cs_{ij}) \cdot \frac{Se(cs_{ij})}{Se_{up}(cs_{ij})}$) and the share of SE detect the magnitude of asymmetry in the distribution of estimates.

the estimates and their standard errors. Table 5.2 summarizes the results based on specifications (3.5) and (3.6) which control for the magnitude of the asymmetric distribution. As β_0 is not significant at 14% level, we have a good reason to believe that the relationship between climate sensitivity estimates and their standard errors stems with the publication bias. WLS regression (3.7) corrects for the heteroscedasticity, fixed effect (FE) (3.4) for within study heterogeneity, and the mixed-effect multilevel (ME) (3.8) for the between- and within-study heterogeneity. We can see in the Table 5.3 results of OLS and ME regressions are consistent. This serves as a robustness check of the mixed-effect multilevel regression, since testing of exogeneity assumptions behind this model is difficult because of high degree of unbalancedness of the data. As the differences between mixed-effect multilevel and clustered OLS regression are negligible the exogeneity assumption behind the mixed-effects model are not seriously violated. Likelihood-ratio tests reject the null hypothesis about absence of between-study heterogeneity, that suggests the OLS is misspecified, and mixed-effects model is more reliable.

Table 5.4 compares the results of all mentioned specifications WLS, FE, and mixed-effect multilevel using the standard error based on (3.1) constructed using the upper limit of confidence interval of the estimated climate sensitivities. The result should verify the robustness of my analysis with the standard error based on (3.2) constructed using the lower tail of confidence interval of the estimated CS. Both

Table 5.3: **Test of publication bias**

Response variable: t-statistic	ME	Clustered OLS	Clustered FE
Constant (publication bias)	2.192***	2.577***	2.043***
	(0.328)	(0.178)	(0.08)
1/SE	1.689***	1.425***	2.15***
	(0.188)	(0.3)	(0.085)
mea/SE	-1.105***	-0.832***	-1.573***
	(0.186)	(0.274)	(0.077)
Observations	48	48	48
R^2		0.707	0.637
Likelihood-ratio test (χ^2)	8.82***		

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

regressions give significant coefficient of publication bias at least at 1% level. The magnitude of the bias is: 0.84 in the case of WLS, 0.78 in the case of mixed-effect multilevel, and 0.88 in the fixed effect regression. I will explain later why significant publication bias around |2| signals publication selectivity efforts. Therefore I have a good reason to believe that the choice of Se_{low} for implementing in the meta-analysis does not damage its results.

The suitability of using the estimate of climate sensitivity as mix of mean and median estimates should not be overlooked. The effect of mod and best estimate can be neglected since there are only six such estimates in the collected sample. Some studies report both median and mean estimates which creates a good subset for testing. These two new samples contain all mean estimates that are also in the original data set but contain 11 median estimates extra. Table 5.5 summarizes all the results showing that there are quit huge differences between the magnitude of bias depending on whether mean or median estimate of climate sensitivity is used. The likelihood-ratio test does not reject the null hypothesis in the model with median, which suggest the mixed-effect multilevel has no benefit over OLS regression (that means, no between-study heterogeneity is present). But LR test rejects this hypothesis in the specification with mean estimates suggesting the mixed-effect multilevel is more appropriate. The reason why only model with median estimates suffer between-study heterogeneity is probably because it contains estimates from 11 studies since the model with mean values contains estimates from only half of them,

Table 5.4: **Test of publication bias using Se_{up}**

Response variable: t-statistic	Mixed-effects	Clustered OLS	Fixed effect
Constant (publication bias)	0.78***	0.844***	0.882***
	(0.245)	(0.201)	(0.206)
$1/SE_{up}$	2.227***	2.388***	2.327***
	(0.192)	(0.336)	(0.275)
mea/SE_{up}	-0.59***	-1.216**	-0.645***
	(0.083)	(0.421)	(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-effect multilevel brings the same benefit as OLS). ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

from 6 studies. Concentrating OLS regression by mean estimation and multilevel by median estimation, the constants are in both cases significant at least at 1% level, which indicate publication bias. The magnitudes differ, the bias in studies reporting mean estimates is more than twice the bias in studies reporting the median value.

Table 5.5: **Test of publication bias on subsets**

	Mixed-effects multilevel		Clustered OLS	
Response variable: t-statistic	mean	median	mean	median
Constant (publication bias)	4.154***	1.847***	4.154***	1.813**
	(1.068)	(0.537)	(0.828)	(0.616)
1/SE	0.564**	1.596***	0.564***	1.663**
	(0.288)	(0.273)	(0.061)	(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-effect multilevel brings the same benefit as OLS). *** and ** denote statistical significance at the 1% and 5% level.

Nevertheless, the whole sample provides more reliable results, since it contains 48 estimates of climate sensitivity, which means the sample is almost two times larger than each of the individual subsets. Although it does not include the 11 median estimates, it adds instead of it the mean values and 6 estimates more from another studies. Moreover all specifications correct for the differences between the mean and other estimates through the *mea* variable. Its' negative sign indicates that the mean estimates should be on average lower than the median estimates (or, except OLS models, they have on average higher standard errors which decreases their t-statistics and makes them less precise). This corresponds to the data: the averages of mean and median estimates differ slightly (3.42, 3.21, respectively) and the averages of their standard errors differ more (1.16, 0.79, respectively) and that is why median estimates have on average higher t-statistic than mean estimates. Therefore I add interaction term between the standard error and *mea* into equation (3.3) to distinguish whether the differences of mean and median estimates implicate rather variance in publication bias or in the magnitude of climate sensitivity. (Stanley *et al.* 2008). The first row in Table 5.6 refers to specification(3.3) and points the added interact term statistically insignificant. The interact term is, however, high correlated with the variable standard error of climate sensitivity and both together they are significant. After weighing by the standard errors of CS (that means the interact term changes to *mea*) the "interact" term becomes statistically significant at least at 5 % level in all models (WLS, fixed effect, mixed-effect). It's sign is in all cases negative, which decreases the magnitude of publication bias of the studies using mean estimate. But the results are not consistent with the analysis on the subsets, where the selectivity efforts in studies using mean estimates of climate sensitivity seems to be higher. To sum up there is no solid evidence to believe the magnitude of publication bias varies between mean and median estimates.

Table 5.6: **Test of differences in publication bias between mean and median estimates**

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

Notes: ME denotes mixed-effects multilevel, OLS ordinary least square, and FE fixed effect regression. Standard errors are shown in parentheses and clustered at the study level. ***, **, 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 of publication bias. Although

Table 5.7: **Multivariate meta-regression**

Response variable: t-statistic	Mixed-effects	Clustered OLS	Fixed effect
Constant (publication bias)	1.929***	2.352***	1.764***
	(0.344)	(0.179)	(0.119)
1/SE	1.74***	1.476***	2.255***
	(0.187)	(0.309)	(0.099)
mea/SE	-1.152***	-0.873***	-1.676***
	(0.184)	(0.276)	(0.089)
Ice	0.901**	0.844***	0.941***
	(0.452)	(0.186)	(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-effect multilevel brings the same benefit as OLS). ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

it is not the main aim of this thesis, Table 5.7 summarizes results of specification Equation 3.10 showing possible aspects that influence the publication bias. With the stepwise regression out of 14 variables only mea, ice, and cloud were chosen as possible drivers. Nevertheless, the fixed-effect model omits cloud because of colinearity. Therefore the final model contains only one extra variable compared to the previous specifications. Results again signal serious publication selectivity efforts and estimate the true climate sensitivity in the range 1.47 - 2.26. It serves as a robustness check of the analysis, since the results do not differ. The selectivity efforts seem to be higher in 10 studies using data about ice surface (it increases β_0 by approximately 0.9), but some studies do not report all characteristics used to estimation of climate sensitivity and therefore we can not take this result as a rule.

As expected after creating the funnel plots, the meta-regression identifies upward publication selection bias, significant at least at 1% level for all applied models. In all specifications the intensity of publication bias, β_0, oscillates between 1.8 and 3. Such magnitude of publication bias signals serious selection efforts. Doucouliagos & Stanley (2011) determines significant FAT higher than 2 in absolute value as “severe” selectivity: if the true climate sensitivity was zero and only statistical significant estimates of climate sensitivity were reported, the estimated coefficient of publication bias will be approximately 2 as the most common critical value of t-statistic. Publication bias in this literature is hence strong enough to produce much higher significant average estimate of climate sensitivity than it is in reality. Table 5.3 also shows that the estimate of true effect after correcting for publication bias fluctuates between 1.4 and 2.3 at least at 1% significance level in all specifications. But to estimate the true average climate sensitivity precisely I employ according to Stanley & Doucouliagos (2007) and Moreno *et al.* (2009) the Heckman meta-regression specified in equation (3.16). Table 5.8 summarizes the results and likelihood-ratio test suggests again that at least at 1% significance level the mixed-effect multilevel regression is more suitable. The models provide similar estimates of the true climate sensitivity: 1.3 (WLS), 1.6 (ME), and 2.1 (FE).

After correcting for publication bias the best estimate assumes the mean of climate sensitivity equals 1.6 with a 95% confidence interval (1.246, 1.989). This is one half of the simple uncorrected average, 3.27: publication bias contains the estimate of true CS approximately two times. Out of the 48 collected estimates 5 are smaller or equal to the average true effect, the lowest one reaches 0.7. That means almost half of the estimates of climate sensitivity may be put into the "file drawer".

Since the preferred mixed-effects model also adjust for heteroscedasticity and other factors applying WLS or study-level random effects, the comparison with a simple average may not be straightforward. (Havranek *et al.* 2012). Using the mixed-effects model on the unchanged original data set the estimate of uncorrected average yields 3.274 with the 95 % confidence interval (2.752, 3.797). That is as close as possible to the simple average (3.274). It suggests that the used specification characteristics of the meta-regression does not imply the differences between simple averages and the corrected estimates. All results of this meta-analysis provide a strong evidence of publication bias and the estimated true effects also do not significantly differ. Table 5.9 compares the estimated true sensitivities across the model specifications. The estimates of the true CS range between 1.4 and 2.3 in the extreme cases and the average equals 1.74. That is very close to the preferred mixed-effect model estimate, 1.6, and therefore there is a good reason to believe that the result is robust.

Table 5.8: **Test of true climate sensitivity beyond publication bias**

Response variable: t-statistic	ME	Clustered OLS	Clustered FE
1/SE (true CS)	1.617***	1.276***	2.087***
	(0.19)	(0.316)	(0.086)
mea/SE	-1.074***	-0.732**	-1.55***
	(0.183)	(0.286)	(0.079)
SE	-0.234*	-0.316***	-0.226***
	(0.132)	(0.086)	(0.017)
Constant (bias)	2.5***	3.054***	2.353***
	(0.369)	(0.232)	(0.068)
Observations	48	48	48
Likelihood-ratio test (χ^2)	8***		
R^2		0.728	0.647

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

Table 5.9: **List of true effects of climate sensitivity**

Specification model:	True climate sensitivity
OLS	1.692***
	(0.138)
clustered OLS	1.692***
	0.177
clustered WLS	1.425***
	(0.3)
clustered WLS with dummy variables	1.476***
	(0.309)
clustered WLS: correction of publication bias	1.276***
	(0.316)
mixed-effects	1.689***
	(0.188)
mixed-effects with dummy variables	1.74***
	(0.187)
mixed-effects: correction of publication bias	1.617***
	(0.19)
fixed-effects	2.15***
	(0.085)
fixed-effects with dummy variables	2.255***
	(0.099)
fixed-effects: correction of publication bias	2.087***
	(0.086)

Notes: Standard errors are shown in parentheses and clustered at the study level. *** denotes statistical significance at the 1% level.

Chapter 6

Discussion

The objective of this thesis is to uncover if climate scientists publish their results with a clear conscience, or if the reported estimates of climate sensitivity are for some reasons biased. This thesis provides meta-regression analysis of climate sensitivity though 48 estimates from 16 studies ranging from 0.7 to 10.4 with the mean estimate 3.27.

The analysis yields interesting results. Although the estimates of climate sensitivity should not be correlated with their standard errors, 14 models indicate the opposite. Publication bias is present in the literature of climate sensitivity at least at 5 % significance level. Unfortunately the analysis can not precisely identify the reasons of such bias. The selectivity efforts to publish only significant or preferred magnitude estimates can have researchers as well as editors of journals that the studies print.

In the sample I collected, researchers report the estimates of climate sensitivity in the form of mean, median, mod or best estimate (best means according to their decision without the information if the estimate is mean, median or anything else). Even their decision of what they will report is fundamental. Mean or median estimates are reported most common and only 11 studies state both of them. Table A.1 presents that on average mean estimates reach higher values than median estimates in the collected sample. At the same time the magnitude of median estimates reported in studies together with mean estimates are on average lower than median estimates reported alone. This suggests researchers maybe tend to report higher estimates because of their magnitude or in order to achieve higher significance, since the higher the t-statistic the higher significance level and t-statistic is computed as a fraction of the estimate divided by their standard error[1].

Both mixed-effect and WLS models (on mean and median subsets) indicate serious publication bias. By the mean estimates β_0 reaches 4 at least at 1 % significance level and by median estimates of climate sensitivity publication bias (β_0) is 2 at least

[1] In one model all the estimates have the same standard error.

at 5 % significance level. If the true climate sensitivity was zero and only statistical significant estimates of climate sensitivity were reported, the estimated coefficient of publication bias will be approximately 2 as the most common critical value of t-statistic. (Doucouliagos & Stanley 2011). LR test shows that between-study heterogeneity is in the subset of median estimates. The definitions of median as middle value and mean as average possibly explain it, since median could vary across different samples with the same mean. The mean and median subsets of CS estimates are of similar magnitude, 25 coming from 6 studies and 28 coming from 11 studies, respectively. Samples of such magnitude should provide already significant results. This analysis signals stronger selectivity efforts in the studies reporting mean estimate of climate sensitivity than in studies reporting median estimates. Nevertheless the analysis of the whole sample does not confirm such efforts (results in Table 5.6), to the contrary it indicates stronger publication bias by median estimates. Even mean estimates still suffer serious selectivity efforts (β_0 oscillates between 1.72 and 2.71 based on the method of calculation), Table A.3 in annexes summarizes all results.

The publication selectivity bias in this literature is substantial, since its intensity in the full data set, β_0, is around 2 and in the models corrected for heteroscedasticity and heterogeneity it approaches 4. This means that the literature could produce even two times higher significant estimates of climate sensitivity than the true effect is in reality. What consequences could it have? Predictions of climate change caused by human influence the policy debate within most nations. Current environmental policy across many nations concerns decreasing greenhouse gas (GHG) emissions, especially CO_2, for instance EU targets decreasing GHG emissions until 2020 by 20 % compared to 1990. (EU [2014]). Government of United States of America has formed special institute investigating the social cost of carbon (SCC). They estimate the social cost of carbon as an economic value of small emission increase, that is a dollar value interpreting benefit for small emission reduction. (EPA [2013]). SCC analysis the benefit of employment a policy decreasing CO_2, and can be understood as amount of money spent due to extreme weather on agriculture, human health etc. linked to climate change for small increase of CO_2 emissions. This is exactly what climate sensitivity represents. It is possible that policy targets would be different if researchers would report lower climate sensitivities. Lower estimate of climate sensitivity would imply lower estimate of social cost of carbon, which influences the budget spent on decreasing carbon dioxide in the atmosphere. These money could be utilized in other area of environmental protection.

Chapter 7

Conclusion

The main aim of this thesis was to find out based on collected data sample whether the reported estimates of climate sensitivity suffer publication bias. The thesis provides analysis of 48 collected estimates of climate sensitivity from 16 studies ranging from 0.7 to 10.4 with the mean estimate 3.27. The analysis bases on relationship between reported estimates and their standard errors. In the absence of publication bias they should not be correlated. I apply the mixed-effect multi-level meta-regression and the results confirm: publication bias in this literature is strong. When I correct for the bias, the estimated true effect of climate sensitivity yields approximately one half of the simple mean of all estimates in the collected sample of literature. If the simple mean reflects the climate scientists impression about the magnitude of climate sensitivity, the impression exaggerates the true climate sensitivity two times.

The main contribution of this thesis is the first quantitative survey of journals estimating climate sensitivity and one of the first survey of literature concerning climate change. I found only one meta-analysis with similar investigation. Michaels (2008) focuses on publication bias in journals *Science* and *Nature* covering global warming. He collected larger sample, 116 articles, but his analysis does not take into account any exact measure of global warming and therefore does not use any econometric model. Michaels (2008) classifies the articles according to “worse”, “better”, and “neutral” prediction of warming and compares the quantity in each bin (so called vote-counting meta-analysis). From that he comes to the conclusion that the literature is biased.

This thesis samples estimates of climate sensitivity that are mean, median, mod or best estimates, but the majority are mean or medians. The model with 28 median estimates of CS opposite to the model on with 25 mean estimates of CS indicates publication bias on the subset of medians is one time stronger than on the subset of means. Both subsets and the whole data set suffer upward publication bias selectivity. This interpretation is not straightforward, however. The definition of median allowing to the estimate to be lower as well as higher than mean estimate causes the analysis of all estimates together signals stronger publication bias by median estimates. Whether the magnitude of publication bias differ between mean and median estimates or not, the estimated climate sensitivity corrected for publication bias is approximately 1.6 accounting for one estimate from each collected measurement (in this preference order: mean, median, mod, best estimate). Though meta-regression analysis is generally considered as statistically efficient tool, the estimate of corrected climate sensitivity is a reference value. It averages across many methods, primary data sets, factors influencing CS and if there would be another aspect influencing all studies, also this MRA will be biased. The level of uncertainty in the prediction of climate sensitivity is high and huge amount of factors influence it. I tried to check for as many aspect as I could, but sometimes it is not possible to take them all into account. Still publication selectivity in this literature is substantial, which might have impact on policy decisions.

Concerning future research, authors interested in differences between studies coming from various countries may collect more estimates and focus on this aspect. Although researchers work sometimes in international groups which complicates it. Broader analysis of the heterogeneity between the estimates of climate sensitivity due to their different characteristic would enhance the research. Definitely larger sample could be collected, since I believe more estimates of climate sensitivity were reported, it was only too tricky to find them (many studies discuss climate sensitivity without reporting the estimate and their standard errors or similar statistic). Using the methodology described in this thesis on larger sample would provide even stronger conclusions.

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Appendix A

Additional tables

Table A.1: **Summary statistics of collected estimates of climate sensitivity**

Variable	Observations	Mean	Std. dev.	Min	Max
Median estimates of CS used in variable Climate sensitivity	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
Mod 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: Variable Climate sensitivity contains estimates included in the data set for the meta-analysis. 11 studies report both mean and median estimate of climate sensitivity. In such a case only mean estimate are included in the data set (that means, variable Climate sensitivity contains 17 median estimates) except for the specification (3.10) where all collected median estimates are used. Similarly variable Climate sensitivity contain only 4 best estimates. The search for primary studies was terminated on March 3, 2014.

Table A.2: **Summary statistics of standard errors**

Standard error of:	Observations	Mean	Std. dev.	Min	Max
Median estimates of CS used in variable Climate sensitivity	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
Mod 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: Variable Climate sensitivity contains estimates included in the data set for the meta-analysis. 11 studies report both mean and median estimate of climate sensitivity. In such a case only mean estimate are included in the data set (that means, variable Climate sensitivity contains 17 median estimates) except for the specification (3.10) where all collected median estimates are used. Similarly variable Climate sensitivity contain only 4 best estimates. The search for primary studies was terminated on March 3, 2014.

Table A.3: **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***	3.668***	4.829***
	(0.331)	(0.365)	(0.103)
1/SE	0.614***	0.618***	0.596***
	(0.064)	(0.08)	(0.047)
mea	-1.152**	-0.962**	-3.114***
	(0.46)	(0.373)	(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 square, and FE fixed effect regression. Null hypothesis for the likelihood-ratio test H_0: no between-study heterogeneity (that is mixed-effect multilevel brings the same benefit as OLS). *** and ** denote statistical significance at the 1% and 5% level.

Table A.4: **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

Appendix B

Details about collected studies

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

Lindzen & Choi (2011) reports two confidence intervals for one estimate of climate sensitivity. I would have to include this estimate two times if I would calculate with both intervals. In order to keep the data as consistent as possible I use only the 90 % confidence interval of the estimate for constructing standard error (studies in the collected data set report most the 90 % confidence interval).