Publication Bias in Estimating the Social Cost of Carbon

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Declaration of Authorship

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Prague, July 31, 2014

Signature
Acknowledgments

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Abstract

In this thesis we used the meta-regression analysis to estimate the damages caused by a currently emitted ton of carbon. This effect is also called the social cost of carbon. The uniqueness of this work is that it is the first meta-analysis on this matter which takes publication bias into account. By using proven methods, we identified strong publication bias in estimating the social cost of carbon. The value of the social cost of carbon beyond publication bias is according to our results 0.706 USD/tC. Our estimate is significantly lower than estimates which do not take publication bias into account. This means that, in this instance, publication bias very significantly contributes to the overestimation of this effect. This overestimation consequently biases the perception of the true impact of an emitted ton of carbon. This results in an ineffective global climate policy.

JEL Classification        F12, F21, F23, H25, H71, H87

Keywords                  meta-analysis, publication bias, social cost of carbon, carbon

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Abstrakt

V této praci jsme využili metodu meta-regresní analýzy k odhadnutí škod, které jedna v současné době emitovaná tuna uhlíku způsobí. Tento efekt je také pojmenován jako sociální náklady uhlíku. Jedinečnost této práce spočívá v tom, že jako první meta-analýza na toto téma bere v potaz publikační selektivitu. S využitím ověřených metod jsme identifikovali silnou publikační selektivitu při odhadování sociálních nákladů uhlíku. Hodnota sociálních nákladů uhlíku očišťená o publikační selektivitu je dle našich výsledků 0,706 USD/tC. Náš odhad je výrazně nižší oproti odhadům, které v potaz publikační selektivitu neberou. To znamená, že v tomto případě publikační selektivita velmi výrazně přispívá k nadhodnocení odhadů tohoto efektu. Toto nadhodnocení následně zkresluje vnímání skutečného vlivu vypuštěné emise uhlíku a dává tak prostor neefektivní globální klimatické politice.

Klasifikace JEL
- F12, F21, F23, H25, H71, H87

Klíčová slova
- meta-analýza, publikační vliv, sociální náklady uhlíku, uhlík

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## Acronyms

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<th>Description</th>
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<tbody>
<tr>
<td>FAT</td>
<td>Funnel Asymmetry Test</td>
</tr>
<tr>
<td>GHG</td>
<td>GreenHouse Gases</td>
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<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
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<tr>
<td>SCC</td>
<td>Social Cost of Carbon</td>
</tr>
<tr>
<td>ME</td>
<td>Mixed-Effect</td>
</tr>
<tr>
<td>MRA</td>
<td>Meta-Regression Analysis</td>
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<tr>
<td>OLS</td>
<td>Ordinary Least Squares</td>
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<td>SE</td>
<td>Standard Error</td>
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<td>WLS</td>
<td>Weighted Least Squares</td>
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<tr>
<td>PRTP</td>
<td>Pure Rate of Time Preference</td>
</tr>
<tr>
<td>PR</td>
<td>Peer-Reviewed</td>
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<tr>
<td>EW</td>
<td>Equity Weighing</td>
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Bachelor Thesis Proposal

Author  Šimon Hofman
Supervisor  PhDr. Tomáš Havránek, Ph.D.
Proposed topic  Publication Bias in Estimating the Social Cost of Carbon

Topic characteristics  In recent decades, the impact of human behaviour on the quality of the environment increased dramatically. For this reason, it should be the responsibility of new generations to examine this effect. Gases released into the atmosphere today will have a major impact on climate change even more than a hundred years from now. One of the most prominent among these gases is carbon. Quantifying damages caused by a ton of carbon is very important for the effective adjustment of climate policy. For this reason, many studies trying to estimate this effect have emerged. Because many impacts of increased carbon atmospheric concentrations have serious uncertainties and many factors are arbitrary, individual estimates vary greatly. The objective of this thesis will be to apply meta-regression analysis in order to estimate the effect of the social cost of carbon. This thesis is going to be the first among SCC meta-analyses which takes publication selectivity into account.

Hypotheses  Is there any significant effect of carbon emission? Does SCC literature suffer from publication selection bias?

Methodology  We will apply meta-regression analysis. Before performing the meta-regression analysis, we are going to use graphical methods to illustrate the problem. In subsequent meta-regression analysis, we will probably use a mixed-effects multilevel model.
Outline

1. Introduction
2. Social Cost of Carbon
3. Methodology Description
4. Literature Review and Data
5. Meta-Regression Analysis
6. Conclusion

Core bibliography

Chapter 1

Introduction

“A reliable estimate of the social cost of carbon provides government with an explicit shadow price of carbon that helps to minimise policy inconsistencies.” (Guo et al. 2006)

The social cost of carbon (SCC) is a concept that enables us to perform thorough cost-benefit analysis when pursuing climate change policy. Obtaining a reasonable estimate of the SCC effect is crucial both for policy makers and researchers. There are many SCC studies that can help them make the best decisions. Their adoption of a policy regulation or their decision to accept a hypothesis impacts all of us.

In recent decades, numerous researchers have attempted to come up with an estimate of this effect. Despite the considerable effort that was put into this challenge, they were not able to develop transparent approach to SCC estimation. Many steps of the SCC estimation process have major uncertainties, which results in substantial arbitrariness when choosing the functions and parameters. Taking this into account, it is not surprising that the estimates vary considerably.

The main contribution of this thesis is an examination of the presence of a possible publication bias in the SCC estimation process. It is our understanding that this thesis is a pioneering work on this topic. None of the previous meta-analyses concerning SCC examined whether the process of SCC estimation had some degree of publication bias. We applied sophisticated meta-analytic models to detect this phenomenon. One of them is the mixed-effects multilevel model.

Before performing the meta-analysis, it was necessary to pull together all of
1. Introduction

the studies estimating the SCC. Tol (2008) provided a summary of all studies estimating SCC published in 2006 or before. We extended this summary by including studies that were published after 2006.

To detect possible publication bias, we made use of the relationship between each SCC estimate and its standard error. Because standard errors are not usually reported together with estimates in this scientific area, we had to compute them. In order to do this, we accepted several assumptions that were previously applied for the same purpose.

The dataset used in this thesis includes 84 estimates from 37 studies. The estimates collected range from 1.5 to 815 USD/tC. Some of the estimates and even whole studies had to be excluded from our dataset. We only took this action when we could not use any of our methods to compute the estimates’ standard errors.

We used rigorously chosen models to examine the publication bias. Our results confirm the hypothesis that publication bias is present in SCC empirical literature. For this reason, we followed with estimation of the true effect of SCC beyond the publication bias. The value of SCC beyond the publication bias is 0.706 USD/tC. This number is surprisingly low and represents only a negligible fraction of the simple mean of collected estimates (142.4 USD/tC).

We structured our thesis into six chapters. Chapter 2 provides readers with fundamental information regarding the SCC. It also describes the reasoning behind integrated assessment models, which are used for SCC estimation. In Chapter 3 we introduce all of the theoretical concepts that we intend to use in our work. It includes formulas for computation of standard errors as well as econometric models. Chapter 4 provides a summary of the results of the previously published literature on this topic. All of the results obtained are presented in Chapter 5. Chapter 6 has the conclusion for the whole thesis.
Chapter 2

Social cost of carbon

2.1 Definition of the social cost of carbon

“This concept (SCC) represents the economic cost caused by an additional ton of carbon dioxide emissions or its equivalent.” (Nordhaus 2011)

Social cost of carbon (SCC) is one of the factors that determine the costs and benefits of greenhouse gas (GHG) emissions. Increased level of GHG emissions fuels climate changes which consequently impact our planet. To capture most of these impacts is very difficult; and it is even more difficult to estimate their size.

To describe the complexity of this issue, Newbold et al. (2010) defines the SCC in the following way: “The SCC represents the present value of the marginal social damages of increased GHG emissions in a particular year—including the impacts of global warming on agricultural productivity and human health, loss of property and infrastructure to sea level rise and extreme weather events, diminished biodiversity and ecosystem services, etc.?and therefore it also represents the marginal social benefits of emissions reductions.”

To estimate these impacts of climate changes (e.g. global warming on agriculture), researchers need to include many parameters into their calculations. Unfortunately, there are many uncertainties that surround values of these parameters and function forms (Ingham & Ulph 2003). Consequently, these uncertainties result in disagreements over the value of SCC between the opponents and the proponents of strict climate policy.
2.2 Usage

In recent decades, we have been witnesses of rapidly increasing impacts that human behaviour has on our planet. This brings new challenges to the society. Our society needs to evaluate some of the possible impacts their current actions cause.

As we suggested in the previous section, SCC value is commonly used in decision making. Policy makers need to consider this number in cost-benefit analyses of regulatory measures. These purposes, which the SCC serves, could be divided into two. The first one is most commonly known and used - to assess new projects and potential regulatory measures. Simply to evaluate concrete short-term actions. The other one and far more abstract is the use for setting the whole environment, which is important for a longer time period.

2.3 Introduction to SCC estimation

2.3.1 Methods of SCC estimation

There are two approaches to estimate the SCC. The first one is the CBA (cost-benefit analysis) approach and the other one is the MC (marginal cost) approach.

To define both methods accurately, we follow Clarkson et al. (2002). The CBA approach is based on the computation of the optimum level of emissions in the atmosphere. This optimum level represents the amount of emissions at which the marginal cost of reducing one emission is equal to the benefit of reducing this emission. To attain this optimum level of emissions, a tax set to a certain level is needed. This tax is the social cost of carbon. In contrast, the MC approach tries to compute the disparity between the potential future damages if one additional emission was not emitted and if it was. Both of these approaches have its problems and have substantial uncertainties.

2.3.2 Integrated assessment models

When we want to compare different climate policies, we often use integrated assessment models (IAMs). These models aim to capture the complicated relationships that the whole process of estimation has. They need to formulate the implications between increased levels of GHG emissions and their subsequent impacts on our planet and welfare. There are many models used to compute the
2. Social cost of carbon

According to Warren et al. (2006), the most commonly employed are the following: DICE, its regional form RICE, MERGE, PAGE and FUND. In all of these models, damages are represented as a percentage loss of GDP. Showing small differences between these models is not the purpose of this paper, but the reader can find a detailed introduction and comparisons in Warren et al. (2006).

2.4 Intuitive understanding of IAMs

Instead of describing different features of each model mentioned in the previous paragraph, we would like to explain the intuition behind all of these models. What do these models have to cover and why do the results of most of the estimations performed vary so much?

In this paragraph, we would like to briefly describe the relationships that IAMs have to cover. As mentioned by Pindyck (2013), we can divide the tasks into three steps. Firstly, it should quantify the relationship between released $CO_2$ emissions and the resulting $CO_2$ concentrations that subsequently accumulate in the atmosphere. Secondly, these $CO_2$ concentrations have an influence on temperature changes for instance. IAM should express this numerically as well. Finally, IAMs have to account for harmful effects on welfare (represented in % of GDP or consumption per capita) that impacts of these temperature increases cause.

To give a reader more detailed perspective, we would like to discuss the topic of climate policy analysis. For this purpose we describe in greater detail what these analyses need to contain in greater detail. In the following paragraph, we again gathered information from Pindyck (2013), who provides a good summary on these relationships.

The proposed analyses have to estimate the quantity of $CO_2$ emissions or its equivalents emitted into the air. To do this, each analysis has to predict the growth of GDP (and the quantity of tons of emissions emitted per one dollar of GDP). Following the preceding step, it has to forecast the future concentrations of these emissions. Another point, which each of these analyses has to contain, is the prediction of the effect that previously computed concentrations will have on temperature rise, sea level rise and other impacts on our planet. The most disputable step comes with the prediction of how these changes affect our welfare, i.e. effects on our GDP or consumption per capita. Also, it has to mention the costs of reducing these emissions and premises about the discount
2. Social cost of carbon

rates and others. Discount rates are especially important since they determine how we discount the damages that are imposed on future generations.

There are many uncertainties that every model needs to cope with in its own way. Some choices of functions and parameter values are completely up to the person performing the research. Our aim is to describe the intuition behind the whole estimation process and identify its weak spots. To dig deeper into the subject matter, we would like to explain some of the features or assumptions that were identified as drivers of heterogeneity among the estimates produced by previous studies. We use these study characteristics in our following meta-analysis and discuss its possible links with greater publication bias. We employ the multivariate meta-regression for the purpose of discovering what arbitrary points may be misused and may cause a bias. We would like to introduce these characteristics and give a reader some perspective on their possible influence on final result.

We are going to introduce the most important assumptions (i.e. the magnitude of a discount rate and potential application of equity weighting). Every person conducting research has to accept some view on these assumptions. In addition, we are also going to explain the key functions and parameters which are incorporated into every model. As we suggested earlier, the greatest uncertainties come with one of the final steps of the process (i.e. determining the climate change impacts on our welfare).

To introduce the decision making process, we will present these attributes that are necessary to incorporate while describing the process of SCC estimation. We will divide the description of the process into two parts.

The first part of description will be devoted to the climate sensitivity and the damage function. These elements are necessary to install into the model. Researchers need to do so in order to estimate the effects of carbon concentrations and potential impacts that these effects have. To obtain a final estimate of SCC, researcher has to go through the second part and try to estimate the consequences these impacts have on human welfare.

More specifically, the second part contains the introduction of two assumptions and the social welfare function. All those three parts need to integrated into the model. Assumptions we describe in detail are equity weighting and the choice of discount rate. The second part is tied with greatest uncertainties and therefore presents some potential for possible publication bias.
2. Social cost of carbon

2.4.1 Estimating potential impacts

The first part contains two steps of SCC estimation process. Firstly, it is dedicated to the introduction of elements crucial for the assessment of how the \( CO_2 \) concentrations translate into temperature rise and other effects. Secondly, it introduces which impacts these effects consequently cause.

**Climate sensitivity**

Climate sensitivity is part of every model. The objective of climate sensitivity is to capture a possible increase in temperature caused by doubling the \( CO_2 \) concentrations in the atmosphere. We would like to stress that the role of climate sensitivity is to express the pace of global warming. (Ackerman & Stanton 2012). Many sensitivity analyses have been performed in order to estimate this parameter. Intergovernmental Panel on Climate Change (IPCC) stated that there is 66% probability that the climate sensitivity is between 1.5 and 4.5 degrees Celsius. There is a serious uncertainty regarding this parameter. In the DICE model, it is the only parameter tied with uncertainty, in the PAGE and FUND there are more of them. To discuss the topic of uncertainty regarding this parameter, we have to stress that there are many climate feedbacks (water vapour, sea ice and clouds) that have not been recorded or calculated by the researchers yet.

As we suggested in the previous paragraph, according to estimations performed by Intergovernmental Panel on Climate Change (IPCC), there is a high probability that the climate sensitivity parameter stays below 5 degrees Celsius. There is a serious concern, however, that it is much higher.

**Damage function**

Hanemann (2008) defines the damage function as follows: “the impact assessment involves the use of damage functions, which express physical or environmental outcomes as a function of changes in climate variables.”

Mostly, damage functions express a relationship between a change in temperature and a change in GDP or consumption (in %). This change in GDP or consumption can be expressed as regional as well as global, depending on the choice of researcher. This area of evaluating effects of climate changes on our welfare has not been investigated to a greater extent yet. It is not surprising that this part of estimation is a cause of much greater disagreement than the climate change investigation. (Hanemann 2008) Difficult evaluation of
potential impacts on welfare, however, does not change the fact that disputes over the appropriateness of damage functions are a serious issue. The choice of the damage function is completely arbitrary. This makes it a subject of many concerns, given how substantial effect different damage functions have on final SCC estimates. 

To illustrate how some of the functions express the relationship between temperature rise and e.g. loss in GDP, we can borrow a function from FUND 1.6, which is defined in the following form (Clarkson et al. 2002):

\[ D_t = \alpha_t + \beta_t \Delta T^2 + \rho_t D_{t-1}, \]

where \( D_t \) is the regional damage in year \( t \), \( \Delta T \) represents the change in temperature in the same year and \( \alpha_t, \beta_t \) and \( \rho_t \) are parameters that vary through time.

As we mentioned earlier, the selection of damage function is arbitrary. This does not change the fact, however, that disputes over the relationship between temperatures and damages still prevail. This relationship is expressed as the exponent of \( \Delta T \) in the equation. The shape of the damage function affects the results to a very large extent. In DICE/RICE and MERGE models the relationship between change in temperature and resulting damages is quadratic. In contrast, in PAGE model the relationship is between linear and cubic determined by the probability function. (Warren et al. 2006) According to Nordhaus (1992) the exponent is 2; some researchers ran more alternative scenarios with changes in the damage function exponent (Cline 1992); some even included uncertainty into the damage function itself. (Kopp et al. 2012).

For some of the models, a certain increase in temperature is considered to be beneficial (FUND). For other ones the damages come even from the first degrees of warming (DICE).

2.4.2 Estimating effects on welfare

Discount rate

"Whose preferences should count? Over what time period?" (Pearce et al. 2003)

The choice of a discount rate is particularly important because the damage caused by a ton of carbon emitted now will cause damages throughout more than the next hundred years. This is the reason why a researcher has to accept some assumptions regarding the valuation of future damages caused today. The
discount rate serves this purpose. It helps us to quantify the present costs of damages which will affect future generations.

If we put lower value on future damages (i.e. we discount back with higher discount rate 5%), the resulting estimate is going to be significantly lower than if we do it the other way round (i.e. we discount with lower discount rate 1%). Tol (2008) confirms in his meta-analysis that a lower discount rate implies a higher estimate.

According to Arrow et al. (1996) there are two approaches to determine the value of SCC. The first one is a descriptive approach; this approach tries to preserve as many economic resources as possible for our descendants. Therefore it logically produces rather high discount rates that do not evoke the need for spending a lot of money on avoiding the damages. The second one is prescriptive approach. This prescriptive approach is more complex and therefore requires introduction of new parameters.

The prescriptive approach uses the pure rate of time preference ($PRTP$), growth rate of per capita consumption ($g$) and negative of income elasticity of marginal utility ($\theta$). Also, we should note that the discount rate used to discount changes in the future consumption is called the social rate of time preference. (Clarkson et al. 2002). So the whole equation is structured as follows:

$$SRTP = PRTP + \theta g$$

The pure rate of time preference ($PRTP$) part of the equation in this case expresses the extent to which a person values the future damages. The second part of the equation ($\theta g$) represents the fact that consumers will earn more in the future, which translates to lower marginal benefit from additional dollar received. (Arrow et al. 1996). Thanks to the second part of the equation, the $SRTP$ is endogenous variable which varies through time. The researcher needs to choose $PRTP$, which is the reason for many disputes. These disputes come from simple assumption that the pure rate of time preference is different in the countries with higher or lower standard of living. As noted above, choosing discount rate constant in time is not suitable. (Clarkson et al. 2002).

**Equity weighting**

Another important assumption which author of analyses estimating SCC has to accept is the assumption regarding an aggregate valuation of impacts caused
by carbon emissions. Different regions are characterized by different average incomes. Today, income differences are substantial among many geographical regions on our planet. How to quantify the utilities from abatement of carbon emissions for someone who is poor and for someone who is rich? Equity weighting tackles this issue for market as well as non-market impacts.

As we suggested in the previous paragraph, there are many impacts that cannot be easily quantified using existing price tags. These non-market impacts are expressed by the willingness to pay (WTP) function, which expresses how much a person is willing to pay to lower the potential risk. Different and far more simple case are these impacts which we can express by market valuations. In contrast, these are called market impacts.

Equity weighting captures the differences in marginal utility of different individuals regarding market as well as non-market impacts. These differences arise from the assumption that the relationship between rising income and utility is depicted by the concave function. This means that the higher the income of an individual, the lower his utility from gaining additional dollar.

We can simply conclude that regions with incomes that are on average lower than the global average are given weight which is greater than 1. This means that the lower the income, the greater the weight put on the region. Because general view is that most damages have impact on people with low income, the equity weighting inclusion should principally increase estimates of SCC.

For some purposes, however, the general consensus is that equity weighting should not be included into estimation. This is the case of individual regional projects evaluation. So it should not be included when producing estimate which is eventually going to be used in the regional or national policy. (Clarkson et al. 2002).

**Social welfare function**

We can divide the models into utility-based and output-based (Nordhaus 2011). In the output-based models, it is necessary to use utility function. In the utility-based models, we have to evaluate output or consumption with the social welfare function.

To value the damages in the consumption lost, we pick a simple social welfare function from Pindyck (2013) and describe the intuition behind the equation.

$$ W = \frac{1}{1-\eta} \int_0^\infty C_t^{1-\eta} e^{-\delta t} dt $$
where: \( \eta \) is index of relative risk aversion. This number reflects the extent to which people value what they have. \( \delta \) is the rate of time preference, which reflects the individual’s priorities through the time. \( \varepsilon_0 \) is not that important for our purposes. It only reflects that the we incorporate the expectation of consumption, not the given consumption as might be the case in most of the other examples. To sum this paragraph, Pindyck (2013) uses rate of time preference as well as risk aversion which may be considered the most deterministic factors for computation of climate change effects on human welfare.

2.4.3 What is missing in IAMs?

There are still substantial gaps in our knowledge and evaluation of potential risks when estimating SCC. Watkiss & Downing (2008) even identified some of the impacts that are not incorporated in most of the studies. Among the market impacts, we can name e.g. possible risks of weather related catastrophes like increased risks of floods, storms, droughts as well as loss of land. Among the non-market ones we can name e.g. irreversible losses and ecosystem changes.
Chapter 3

Theory applied

3.1 Computing standard errors

3.1.1 Estimates with confidence intervals

Reporting standard errors is usually not part of SCC research. Therefore we have to compute standard errors using different methods. The first method is to compute them from reported confidence intervals. To perform this action, we adjust formulas from Ramachandran & Tsokos (2009) to compute the standard error of ith estimate $SE_i$:

We know that the UpperBound of the confidence interval can be formulated as follows:

$$UpperBound = \bar{X} + z_{\alpha/2} \frac{\sigma}{\sqrt{n}}$$  \hspace{1cm} (3.1)

where $\sigma$ is a standard deviation and $\bar{X}$ is our estimate. We also know that:

$$SE = \frac{\sigma}{\sqrt{n}}$$  \hspace{1cm} (3.2)

so the (3.1) can be rewritten as follows:

$$SE_{up} = \frac{UpperBound - estimate}{z_{\alpha/2}}$$  \hspace{1cm} (3.3)

We follow the same process when computing the SE from the lower bound of the confidence interval. We know that the LowerBound of the confidence
interval can be formulated as follows:

\[ \text{LowerBound} = \bar{X} - z_{\alpha/2} \frac{\sigma}{\sqrt{n}}, \]  

(3.4)

which can be rewritten as:

\[ SE_{\text{low}} = \frac{\text{estimate} - \text{LowerBound}}{z_{\alpha/2}} \]  

(3.5)

To obtain the standard error of each estimate, we average both of these errors. After averaging both errors we get:

\[ SE_i = \frac{SE_{\text{low}} + SE_{\text{up}}}{2}, \]  

(3.6)

which can also be for the ith estimate rewritten as follows:

\[ SE_i = \frac{\text{UpperBound}_i - \text{LowerBound}_i}{2z_{\alpha/2}}, \]  

(3.7)

where \( \text{UpperBound}_i \) represents the upper bound of the confidence interval belonging to ith estimate; and \( \text{Lowerbound}_i \) represents the lower bound of the confidence interval belonging to ith estimate. In all of our studies reporting estimates with confidence intervals, at least one of reported intervals was always the 90% confidence interval. Therefore, we choose 90% confidence intervals to work with. After checking the statistic tables we know that we have to use \( z \)-statistic with value 1.645.

### 3.1.2 Estimates without confidence intervals

The second method is used when we obtain studies with multiple estimates where none of them is reported with the confidence interval. In these situations, we assume the distribution of estimates obtained from a single study to be normal. We compute the simple mean of reported estimates. We assume that reported estimates is a sample drawn from normal distribution. This assumption is commonly used in economics. We then compute standard error to this mean. We can describe the whole process using formulas from Ramachandran & Tsokos (2009): We compute the mean of the estimates obtained from one particular study by the following formula:

\[ \bar{x} = \frac{x_i}{n}, \]  

(3.8)
From Ramachandran & Tsokos (2009) we know that the standard error to this mean is defined as follows:

\[ SE_{\bar{x}} = \frac{\sigma}{\sqrt{n}}, \]  

(3.9)

where

\[ \sigma = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2} \]  

(3.10)

When we (3.9) and (3.10), so the reduced form equation is:

\[ SE_{\bar{x}} = \frac{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2}}{n}, \]  

(3.11)

This means that when we employ this method, we obtain only one estimate from each study. This estimate is the computed mean of the originally collected estimates. Then we obtain the standard error to the mean estimate using (3.11) and the normality assumption.

### 3.2 Meta-analysis methodology

The most important reason for the execution of any empirical research project is its result. The interpretation of this result is of great importance if the research aims to capture the true effect well. Over the course of time, more and more research projects examining one particular effect emerged. These research projects generated results that were in most cases different one from another. These situations were followed by attempts aiming to find a coherent method when summarizing those sets of results. This summary is crucial for decision making in many areas. It provides a message for policy makers as well as researchers. These people need to look at the subject from a justifiable perspective when making assumptions and decisions. For a very long period of time, researchers struggled to deliver these cumulative summaries.

After some time, researchers came up with a suggestion to tackle this problem. The first solution to this issue was a selection of some of the so called experts in each particular field. This expert had to read all the extensive literature on some particular subject and then formulate a conclusive summary by himself. This solution turned out to be only temporary because of its major drawbacks. It was criticized for its lack of objectivity; the whole conclusion was determined by only one person. Another issue was the durability of these summaries. They became outdated as soon as new literature on that topic
emerged. This obsolete summary could also be an inappropriate starting point for subsequent projects.

Consequently, researchers developed a quantitative tool to help themselves not only quantitatively summarize studies on particular topics. It also helped them discover the drivers behind the heterogeneity of these different study results. This quantitative tool is called meta-analysis and is extensively used in various scientific fields. More specifically, meta-analysis is most prevalent in medicine and psychology. Also, meta-analysis was firstly introduced to the social sciences by Glass (1976). The major drawbacks of previously employed methods were eventually sorted out. Some might argue, however, that subjectivity still prevails. This holds because researchers determine the method they are using when collecting studies.

3.2.1 Publication selection bias

According to ?: “One of the main criticisms about the technique (meta-analysis) is that it is prone to publication and other forms of selection biases.”

To define publication selection bias precisely, we can borrow the citation from Stanley & Doucouliagos (2007): “publication bias means that a non-random sample of the estimates remain unpublished and unreported; hence, the pool of research available is a biased representation of the population of estimates.”

To elaborate the topic, publication selection stems from the pool of research results which does not represent the whole population of results well. A reader can find some studies that thoroughly investigate that economic meta-analysis is very frequently tied with examination of publication selection, e.g. Stanley (2005). There are two types of publication selection that appear in the empirical literature.

The first type of publication selection occurs when researchers prefer to publish results that are in accordance with the theory. This type of preference in publishing estimates of certain effects may have very serious consequences in over- or underestimation of the true effect. One of the most alarming examples of this phenomenon has been a radical overestimation of the water price elasticity, discovered by Stanley (2005). One of the recent examples is the overestimation in the price elasticity of gasoline demand, discovered by Havranek
This type of publication selection can be graphically assessed by the funnel plot.

Second type of publication selection occurs when researchers prefer to publish significant results, irrespective of the sign of the effect. This is the case when a researcher runs the specification search until she finds the estimate large enough to exceed its standard error in such a way that estimate becomes significant. This may also result in eventual over- or underestimation of the true effect. Recent example of this type of selection is e.g. Havranek et al. (2012). A reader can find an elegant graphical method suitable for the assessment of this type of publication selection in galbraith plot.

To detect publication bias and obtain the true value of the effect beyond the publication selection bias we need regression tests. For this purpose, we are going to introduce FAT-PET for detection of publication bias. We also use mixed-effects multilevel model, because it is more appropriate; some of our primary studies are from the same author and some of them produce more results. To take this into account, we have to differentiate the between-study and within-study heterogeneity. To correct for publication bias in mixed-effects multilevel model and to obtain the true effect beyond publication bias, we perform Heckman meta-regression. Heckman meta-regression was firstly introduced in Stanley & Doucouliagos (2007).

### 3.2.2 Graphical approaches to assess publication bias

Firstly, we use the Epanechnikov kernel density to see the distribution function of collected estimates in the graph. If it is asymmetrical and estimates are not randomly scattered around the true effect, it may mean that some type of publication selection is present. We have to reiterate, this method is not sophisticated enough to give us any proof of publication selection. For this reason, we have to continue with other methods and models.

To assess publication bias in the empirical literature, we can employ either graphical tests or regression tests. From the graphical tests we have chosen the funnel plot and the galbraith graph; these are among the ones that are mostly used for this purpose in the recent empirical literature. (Havranek et al. 2012; Stanley 2005).
Funnel plot

Funnel plot is one of the most used techniques for examination of publication bias. As noted by Terrin et al. (2005): “researchers are becoming more aware of the potential for publication and related biases. Many have turned to the funnel plot, a simple graphic technique for detecting these biases.”

To construct the funnel plot we plot the estimates of a particular effect against the precision of every one of them. (Egger & Smith 1995) This precision can be expressed in many ways, e.g. inverted standard error of each particular estimate, number of observations or even the square root of observations. (Stanley 2005). We use the inverted standard error of each estimate.

According to the theory, funnel plot should widen with decreasing precision of estimates. To give a reader some insight into this we should note that it is so because estimates occurring further from the true effect should be the less precise ones. This is the reason for its name; the shape of the funnel plot should resemble an inverted funnel. To get an idea of whether the 1st type of publication bias might be present the researcher should focus on the symmetry of the funnel plot. If the funnel plot is symmetrical, the effects are randomly spread out around the true effect.

If the symmetry is not obvious then the study is probably affected by publication selectivity. On the other hand, if the funnel plot is symmetrical, i.e. it is not cut off at one side, etc., it probably does not enjoy a significant level of publication selection bias. From the shape of the funnel we can even detect potential type of publication selection. If the funnel plot is concave and very wide, the 2nd type of publication selection (significant estimates preferred) is probably present. We are going to further examine this type of selection bias in the following galbraith graph.

According to Terrin et al. (2005), authors should be more cautious when interpreting the funnel plots, because the shape of the funnel plot may be influenced by a chance.

Galbraith graph

Another graphical method is the galbraith graph. This graph is especially useful for detection of the second type of publication selection; this type of publication selection means that significant results are preferred. This graph can be created by plotting the precision of the estimate against its t-statistic. The intuition
behind this plot is that it aims to depict the probability of reporting significant result.

For this purpose, we initiate the general t-statistic. This general t-statistic can be described by the following formula: \( \frac{|\text{effect}_i - TE|}{SE_i} \); where TE is the true effect. This means that if the true effect is zero, the t-statistic should not exceed the level of \( \pm 1.96 \) in more than 5% of times. If it happens, we can become suspicious about the presence of the second type of publication bias. According to Stanley (2005), the galbraith graph is basically the funnel plot turned 90 degrees and purified of heteroskedasticity.

3.2.3 Regression tests

**FAT-PET**

FAT publication selectivity test is based on the assumption that author of some particular study tries to specify model in such a way that she obtains significant estimates of examined effect. This behaviour gains momentum in those situations where the author needs to obtain effect that is so big it offsets its standard error. Following this logic we can conclude that publication selectivity can be detected when we observe ceteris paribus dependence between magnitude of some particular estimate and the magnitude of its standard error (i.e. its inverted precision). This relationship can be described by the following model:

\[
\text{scc}_i = \beta + \beta_0 SE(scc_i) + u_i |SE(scc_i) N(0,\delta^2) \quad (3.12)
\]

In this equation, the true effect is represented by \( \beta \) and publication bias is represented by \( \beta_0 \). To test for publication bias we test the following hypothesis \( H_0 : \beta_0 = 0 \).

Unfortunately, because of some characteristics of our data we have to further specify the model differently. Our primary studies use different data, observations, etc., so the variances of estimates are most likely not the same. For this reason residuals suffer from heteroskedasticity. (Stanley & Jarrell 1989).
This is important for our analysis; obviously the standard errors are skewed. To remedy this problem, we have to specify the model differently and use weighted least squares, i.e. divide the (3.12) by its standard error:

\[
\frac{scc_i}{Se(scc_i)} = t_i = \beta \frac{1}{Se(scc_i)} + \beta_0 + \xi_i \xi_i|Se(scc_i) \sim N(0, \delta^2) (3.13)
\]

In this equation, we again test the hypothesis of possible presence of publication bias by the hypothesis \( H_0 : \beta_0 = 0 \). If we can reject this hypothesis, the publication bias is present. Testing this hypothesis is called the FAT test. We also test the hypothesis that \( H_1 : \beta = 0 \); if we cannot reject this hypothesis, the examined effect (i.e. SCC in USD/tC) is not significant. This part of testing is called the PET test.

By adjustment to weighted least squares we get the t-statistic. As it is obvious from its definition, t-statistic is standardized which makes effects comparable among themselves. Unfortunately, we have to tackle other issues regarding the structure of the data. This will be further introduced by the mixed-effects multilevel model.

**Mixed-effects multilevel model**

Because we obtained more than one estimate from most of the studies and some of the studies are from the same author, we have to account for strong correlation between some of the estimates. If we used model from specification (3.13), the results would be skewed. This particular problem is often solved by using the mixed effect multilevel models. (Nelson & Kennedy (2009); Havranek et al. (2012)). This mixed effect multilevel model is appropriate because it takes the between-study heterogeneity into account. (Havranek et al. 2012). This is our specification of mixed-effects multilevel model:

\[
t_{ij} = \beta \frac{1}{Se(scc_{ij})} + \beta_0 + \zeta_i + \epsilon_{ij} \zeta_i|Se(scc_{ij}) \sim N(0, \psi) \epsilon_{ij}|Se(scc_{ij}) \zeta_j \sim N(0, \theta) (3.14)
\]
Mixed-effects multilevel model is similar to random effects model in panel data. This model is called mixed-effects because it contains both random as well as fixed part. Fixed part is represented by $\beta$ and the random part is represented by $\zeta_j$. The error term is in this specification divided into two parts. The first one $\zeta_j$ represents the disturbances on the study level and $e_{ij}$ represents the disturbance on the estimate level. We can break the variance into two parts: $\text{Var}(\xi_{ij}) = \psi + \theta$. The first part is between-study variance ($\psi$) and the second one is within-study variance ($\theta$). It is important to note that if we observe that between-study variance is close to zero, benefit of using the mixed-effects multilevel model instead of the previous one is very small.

We also need to perform a robustness check. OLS regression model with clustered standard errors will serve us for this purpose. If we observe large disparities between the OLS and mixed-effects multilevel model, the assumption of exogeneity might be violated. (Havranek et al. 2012)

**Heckman meta-regression**

Now after getting the glimpse of how we can estimate the magnitude and significance of publication bias, we need some specification to examine the true magnitude of the SCC effect beyond publication bias. For this purpose we use the Heckman meta-regression model. I followed Stanley & Doucouliagos (2007) for this purpose.

$$t_{ij} = \beta \frac{1}{SE(scc_{ij})} + \beta_0 SE + \zeta_j + e_{ij} \cdot \zeta_j | SE(scc_{ij}) \cdot N(0, \psi) \cdot e_{ij} | SE(scc_{ij}) \cdot N(0, \theta) \tag{3.15}$$

This model is crucial for our meta-analysis. It provides us with the value of SCC that is beyond the detected bias. Values beyond publication bias can vary substantially and could discover that some perceptions about the magnitudes of certain effects are biased.

**Multivariate meta-regression**

Meta-analysis does not only help us with the detection of the publication bias or potential correction for it. It can also enable us to discover what drives the heterogeneity among the estimates from different studies. Firstly, we have to select the variables that have some potential to influence the magnitude of estimated effect. To choose these variables, we have to be very familiar with
the theoretical background of selected research topic. Because not always are the characteristics of the studies in comprehensive tables, we need to be very careful when reading the studies and collect the characteristics we need. We tried to select some of the criteria, i.e. type of IAM used or the type of damage function. Unfortunately, none of these proved to be a good choice, since the models chosen were still updated and new and new potential impacts were taken into account while some of the others omitted. For this reason, we eventually stucked to the variables that are by an extensive SCC review (Clarkson et al. 2002) detected as the most influential ones. Variables that we are going to present in the following paragraph are proved to be the source of heterogeneity Tol (2008) and we are going to examine whether some of them are associated with publication bias.

The first chosen variable is equity weighting represented by the variable $ew$. Equity weighting is believed to have a positive impact on estimated effect.

Another one is the year of publication. As Tol (2008) points out: “splitting the sample by publication date, shows that the estimates of the SCC published before AR2 were larger than the estimates of the SCC published between AR2 and AR3, which in turn were larger than the estimates published since.” We use the variable $aft$ for this purpose. This dummy variable assigns 1 to estimates published in year 1996 or later.

Also, it is logical from the theory that estimates with lower discount rates generally tend to be higher. Differences in discount rates are tackled as the differences in the pure rate of time preference $prtp$. We divide this variable into three dummy variables; dummy variable $prtp3$ assigns value 1 to those estimates, where $prtp$ of 3% was used. $Prtp1$ and $prtp0$ assign the values to estimates following the same logic; $prtp1$ for estimates with 1% of PRTP and $prtp0$ for estimates with 0% PRTP. This relationship between discount rate and pure rate of time preference is described by Chapter 2 in greater detail.

Also, we have chosen variables $Tol$ and $Hope$. These would help us to detect whether there is some relationship between the magnitude of estimated effect and the fact that author of the estimate is the person which engages in this topic extensively and has very deep knowledge.

As the last dummy variable we selected the $pr$ variable to detect whether the results from peer-reviewed studies vary from the ones that are not peer-reviewed.

The regression we use for this purpose is specified the following way:
\[ t_{ij} = \beta_0 \frac{1}{s(e(scc_{ij}))} + \alpha_1ew + \alpha_2 aft + \alpha_3 prtp3 + \alpha_4 prtp1 + \alpha_5 prtp0 + \alpha_6 Tol + \alpha_7 Hope + \alpha_8 pr + \zeta_j + e_{ij} \] (3.16)

Testing for significance of selected dummy variables will give us a good perspective on which of them are affiliated with publication bias.

### 3.3 MRA application on SCC

Stanley & Jarrell (1989) define MRA as follows: “meta-regression analysis (MRA) is the regression analysis of regression analyses.”

It is important to emphasize that choosing MRA as a technique to integrate studies estimating SCC results is, to a certain extent, an experimental approach. Standard MRA methods are built on the results from regression analyses. Estimates of SCC are, unfortunately, not obtained by performing regression analysis.

The effects of SCC are estimated by the use of multiple simulations. This is because there are many aspects of climate change that are clouded with uncertainty. This uncertainty plays the same role as standard error in regression estimates. Some aspects of uncertainty in SCC effect estimation were introduced in Chapter 2. These uncertain aspects of the process are given a probabilistic distribution and multiple simulations are performed to most precisely estimate the effect and provide a probabilistic distribution.

These distributions are often asymmetrical. This happens because even the remote possibility of a catastrophic outcome means a substantial increase in the estimated effect. In other words, there are much greater impacts on the effect when a pessimistic scenario gains momentum compared to the positive one. This makes the confidence intervals asymmetrical, which could also distort the results of the meta-regression analysis. It makes sense to compute standard error from the lower bound of the confidence interval because the zero bound is psychologically important and therefore could be tied to publication selectivity.

The value of this topic, however, far outweighs previously mentioned liabilities. The uniqueness of this work is what makes it very intriguing. At least
two reviews or meta-analyses were published about SCC, all of them written by Tol. None of them, however, examines publication bias. To extend our research, we searched for meta-analyses examining publication bias in the climate change research. We were only able to one empirical paper, Michaels (2008). According to our results, we can conclude that publication bias has rarely been applied in this area of research. This is despite the fact that publication bias might cause serious overestimation or underestimation of the researched effect, Stanley (2005).
Chapter 4

Literature review and data

4.1 Literature review

4.1.1 Publication bias in climate change literature

By the elaboration of this thesis we tried to contribute to the current research by gathering all studies estimating SCC effect. Then we try to examine possible publication bias in SCC literature. We tried to search for any work that aimed to examine publication bias in SCC literature before, but we could not find any. Therefore we believe that this is the first work trying to examine this phenomenon in such an important area, which is what makes this thesis so interesting. Even when we search for studies examining publication bias in the whole climate change literature, we could find only one in Michaels (2008). Why is it so? The reason might be that there is still very little research in the whole area of climate change. To devote substantial amount of time into the research in this area is difficult. Examining the value of SCC specifically is currently not in interest of big industrial organisations. For this reason, researchers have a difficult time when seeking funding for their work in this area.

4.1.2 Performed meta-analyses on SCC

Regarding the SCC, we found two meta-analyses on the social cost of carbon. Tol (2008; 2005). As we pointed out earlier, none of them takes the publication bias into account. The SCC estimates vary because huge uncertainties are involved. Depending on how we deal with the uncertainty, the final estimates vary a lot. According to Tol (2005), under the standard assumptions regarding
equity weighting and discount rate, the SCC should not exceed 50 USD/tC. This very well summarizes results obtained from these meta-analyses. In coherence with the statement paraphrased in the previous statement, Tol (2008) points out that estimate 314 USD/tC reported by the Stern review is an outlier.

4.2 Data collection and summary

4.2.1 Data collection

We searched in Google Scholar, EconLit and SCOPUS databases and tried to find as many studies estimating SCC as possible. We found an extensive summary of studies published in 2006 or before collected by Tol (2008). This summary helped us to identify a lot of studies. We obviously tried to find studies estimating SCC conducted from 2007 to 2014 and we found 9 of them. There are reasons why collected estimates vary so much. Researchers might readjust their models and choose these parameters to alter the result. For this reason, we are suspicious that some parameters might be tied with publication bias. When studying the topic thoroughly, we identified some arbitrary parameters of this kind and also other characteristics of studies that have influence on the SCC estimate. Therefore impact of these study characteristics on heterogeneity of estimates is indisputable. For this reason, we are also suspicious that these parameters might be tied with publication bias. When we found the studies, we also collected these variables linked with estimates. We provide a detailed description behind the selection of these study characteristics in Chapter 3. In the following Table 4.1 we present the distribution of studies according to their characteristics.

Table 4.1: Distribution of studies according to their characteristics

<table>
<thead>
<tr>
<th>Attribute</th>
<th>PR</th>
<th>EW</th>
<th>PRTP=0</th>
<th>PRTP=1</th>
<th>PRTP=3</th>
<th>Tol</th>
<th>Hope</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>62</td>
<td>36</td>
<td>1</td>
<td>12</td>
<td>34</td>
<td>4</td>
<td>7</td>
<td>71</td>
</tr>
<tr>
<td>No</td>
<td>22</td>
<td>43</td>
<td>83</td>
<td>72</td>
<td>50</td>
<td>80</td>
<td>77</td>
<td>13</td>
</tr>
<tr>
<td>Unspec.</td>
<td>0</td>
<td>5</td>
<td>33</td>
<td>33</td>
<td>33</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Source: author's computations.
4.2.2 Data summary

The oldest study that we used is from 1992 and the most recent one is from 2013. We used also studies that were not peer-reviewed, to make subsequent examination of publication bias as transparent as possible. There is relatively large number of estimates which do not use equity weighting. Most of estimates which do not use equity weighting were collected in studies published long time ago. Another interesting fact is that we collected only a few estimates from Tol. This is a consequence of our need to compute standard errors of estimates. Estimates from Tol did not usually provide a useful statistic to compute standard error, so we had to create simple mean of estimates from a particular study. Only this mean was included into our dataset as an estimate, which resulted in significant loss of estimates from this author.

Following the methods to obtain standard errors mentioned in previous paragraphs and concluded in Chapter 3, we collected 84 estimateds from 37 studies in total. It is important to stress that we would have much more estimates of SCC at disposal if we did not need standard error to each estimate. Summary statistics are provided in section Summary statistics from Chapter 5.
Chapter 5

Results

5.1 Summary statistics

We used a total of 84 SCC estimates. Some of them are computed means of estimates from one study. We had to compute means where we did not have any other possible options to compute standard errors of reported estimates. Summary statistics for all of the estimates that we eventually used are presented in Table 5.1. Collected estimates of SCC range from 1.5 to 815 USD/tC. The mean estimate is 142.4 USD/tC. The simple mean of our estimates is greater than those in previously reported meta-analysis. Tol (2008). In the following analysis we are going to examine the effect of publication bias. If the publication bias is present, then we should not put much weight on the computed mean of estimates. In this case, the computed mean would significantly overvalue the true effect.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs.</th>
<th>Mean</th>
<th>Median</th>
<th>Std. dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCC</td>
<td>84</td>
<td>142.3981</td>
<td>59</td>
<td>172.730</td>
<td>1.5</td>
<td>815</td>
</tr>
</tbody>
</table>

5.2 Graphical methods

5.2.1 Kernel density of estimated effects

Figure 5.1 depicts the density function of reported SCC estimates. Specifically, this type of function is the Epanechnikov kernel version. It is very apparent that
the shape of this distribution is very far from the shape of a standard normal
distribution. The density of estimates in the right-hand part of the graph is
much higher than in the left-hand part. This makes the density function very
asymmetrical. This happens because very few negative estimates are reported.
By constrast, estimates that are positive are published very frequently. A
considerable portion of the positive ones are those that are very far from zero
effect. This makes the right tail of the distribution much fatter than its left
tail. For this reason, we can conclude that there might exist some unknown
force (other than sampling error) that influences the final published figure of
the estimated effect.

5.2.2 Funnel plot

Figure 5.2 depicts the funnel plot. A detailed description of the funnel plot can
be found in Chapter 3. As we can see when we look at the axes, every estimate
is plotted against its precision (i.e. inverted standard error in our case) in
this graph. To explain the situation clearly for the reader, two curves marking
the significance level on both sides are plotted. When there is no publication
bias, the points in the graph should resemble an inverted funnel. The results
shown in Figure 5.2 do not hold to this assumption. As we can see, estimates
with the greatest precision (i.e. lowest standard error) are positive, but rather
small in magnitude. Even more essential for our futher analysis, however, are
the missing points in the left-hand part of the graph. Negative estimates are not consistent with the theory, which might be the reason why there are none. Although we can not be sure what drives this phenomenon until we further examine this situation by the regression test, there is a reasonable suspicion for publication bias. There is also evidence that the vast majority of the reported estimates is insignificant. We can also examine this by plotting the galbraith graph.

5.2.3 Galbraith graph

We know that if the second type of publication bias is not present, the probability of reporting estimate with t-statistic over 1.96 or under -1.96 should be 5%. It is very clear from the Figure 5.3 that this is not the case in our sample. This bound is represented by the red line in Figure 5.3. The percentage of estimates with a higher t-statistic is much higher. Therefore we have a good reason to believe that second type of publication selection is present in our sample.

5.3 Econometric methods

5.3.1 FAT-PET test

In Table 5.2, we performed a simple OLS regression formulated in specification (3.12) for testing publication bias. This version of the FAT-PET test is the
simplest one and does not take into account heteroskedasticity and between-study heterogeneity. We also performed OLS version of this model with robust standard errors clustered at the study level. We observe that the explanatory variable SE, which captures the publication bias, is significant even at the 1% level for both of the models. In addition, the average true effect of SCC is 42.377 USD/tC and is also significant even at the 1% level.

Table 5.2: Test for publication bias - simple OLS

<table>
<thead>
<tr>
<th>Response variable:</th>
<th>OLS</th>
<th>OLS (clustered)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate of SCC SE (publication bias)</td>
<td>0.886***</td>
<td>0.886***</td>
</tr>
<tr>
<td></td>
<td>(0.070)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Intercept (average true effect of SCC)</td>
<td>42.377***</td>
<td>42.377***</td>
</tr>
<tr>
<td></td>
<td>(13.518)</td>
<td>(12.705)</td>
</tr>
<tr>
<td>Observations</td>
<td>84</td>
<td>84</td>
</tr>
</tbody>
</table>

Source: author’s computations.

We continue with the weighted least squared version of the FAT-PET test. This version of the model takes into account the heteroscedasticity. As we can see in Table 5.3 in the column called OLS (clustered), the results confirm our hypothesis about the possible presence of publication bias. The presence of publication bias can be detected by the significance of the intercept. The p-value of the intercept is p < 0.01, which means that the intercept is significant.
even at the 1% level. For this reason, we can conclude that the publication bias is present according to this model. The model, however, is not preferential in our analysis because it gives too much weight to studies which report multiple estimates. When we look at the coefficient of the precision variable, we see that the examined effect (SCC) is not significant at any level of significance. We can see that the examined SCC is not statistically different from zero.

### 5.3.2 Mixed-effects multilevel model

To take the between-study heterogeneity into account, we employed a preferred mixed-effects multilevel model. This model is described by specification (3.14) in the third chapter. In our case, we put much more stress on the results from the mixed-effects multilevel model than the OLS model. This stems from the characteristics of the data. Some of the studies that we collected are from the same author, and some of them provide multiple results. For this reason, the estimates can be correlated and it is much better to examine them by the mixed-effects multilevel model. We used two different types of estimation. The first one is when the estimates are distributed by the authors. The other one is distributed by the studies. As a robustness check, we also perform OLS with robust standard errors clustered at the study level. We need to do this because if the coefficients of the ME and OLS models were significantly different, the exogeneity assumption might be violated. As we observe, there is no reason to believe that this assumption is violated.

<table>
<thead>
<tr>
<th>Response variable:</th>
<th>OLS (clustered)</th>
<th>ME1</th>
<th>ME2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept (publication bias)</td>
<td>2.065***</td>
<td>2.064***</td>
<td>2.064***</td>
</tr>
<tr>
<td>1/SE (average true effect of SCC)</td>
<td>1.024***</td>
<td>1.024</td>
<td>1.024</td>
</tr>
<tr>
<td>Observations</td>
<td>84</td>
<td>84</td>
<td>84</td>
</tr>
</tbody>
</table>

*Source: author’s computations. ME1 - mixed-effects multilevel model by authors; ME2 - mixed-effects multilevel model by studies*

We again detect a strong publication bias. The intercept is significant even at the 1% level of significance for our WLS version which takes heteroskedasticity into account.
5. Results

As we can see, the coefficients for both ways of sorting estimates into groups (both by authors and studies) are estimated with similar coefficients. This means that we probably do not have many studies from the same authors. This makes the results from model selecting groups of estimates by authors very similar to the model where the groups are selected by studies.

We also use the model from specification (3.15) to detect the true effect of SCC beyond publication bias. This model is called Heckman meta-regression and is introduced in Clarkson et al. (2002) in greater detail. Results from the Heckman meta-regression are presented in Table 5.4:

Table 5.4: Heckman meta-regression - SCC beyond publication bias

<table>
<thead>
<tr>
<th>Response variable:</th>
<th>OLS (clustered)</th>
<th>ME1</th>
<th>ME2</th>
</tr>
</thead>
<tbody>
<tr>
<td>t-statistic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1/SE (average true effect of SCC)</td>
<td>0.706**</td>
<td>0.706**</td>
<td>0.706**</td>
</tr>
<tr>
<td></td>
<td>(0.295)</td>
<td>(1.006)</td>
<td>(1.006)</td>
</tr>
<tr>
<td>SE</td>
<td>-0.004***</td>
<td>-0.004***</td>
<td>-0.004***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Intercept</td>
<td>2.533***</td>
<td>2.533***</td>
<td>2.533***</td>
</tr>
<tr>
<td></td>
<td>(0.469)</td>
<td>(0.486)</td>
<td>(0.486)</td>
</tr>
<tr>
<td>Observations</td>
<td>84</td>
<td>84</td>
<td>84</td>
</tr>
</tbody>
</table>

Source: author’s computations. ME1 - mixed-effects multilevel model by authors; ME2 - mixed-effects multilevel model by studies.

As we pointed out before, the results are very similar. The magnitude of the true estimated effect (SCC/tC) beyond publication bias is 0.706 USD/tC.

5.3.3 Multivariate meta-regression

As we explained in the third chapter, we tried to select some variables that were in previously published reviews (Clarkson et al. 2002) mentioned as important for the magnitude of the estimated effect. Other possible variables are the employment of equity weighting, whether the study was peer-reviewed, the discount rate used, the publication year (before or after 1996), and if the author is Tol or Hope. When there were more authors to one study, we worked with the data as if the author was the first one named. We tried to examine whether some of these variables are affiliated with more publication bias than the other ones.

We can see that some of the variables really are associated with more bias than others. These are PRTP at 1% as well as PRTP at 0%. Also equity
Table 5.5: Multivariate meta-regression

<table>
<thead>
<tr>
<th>Response variable:</th>
<th>ME1</th>
<th>ME2</th>
</tr>
</thead>
<tbody>
<tr>
<td>t-statistic</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1/SE</td>
<td>0.970</td>
<td>0.970</td>
</tr>
<tr>
<td></td>
<td>(1.029)</td>
<td>(1.029)</td>
</tr>
<tr>
<td>pr</td>
<td>0.192</td>
<td>0.192</td>
</tr>
<tr>
<td></td>
<td>(1.010)</td>
<td>(1.010)</td>
</tr>
<tr>
<td>prtp3</td>
<td>-0.315</td>
<td>-0.315</td>
</tr>
<tr>
<td></td>
<td>(1.014)</td>
<td>(1.014)</td>
</tr>
<tr>
<td>prtp1</td>
<td>3.251**</td>
<td>3.251**</td>
</tr>
<tr>
<td></td>
<td>(1.272)</td>
<td>(1.272)</td>
</tr>
<tr>
<td>prtp0</td>
<td>14.134***</td>
<td>14.134***</td>
</tr>
<tr>
<td></td>
<td>(3.529)</td>
<td>(3.529)</td>
</tr>
<tr>
<td>ew</td>
<td>-2.114**</td>
<td>-2.114**</td>
</tr>
<tr>
<td></td>
<td>(1.022)</td>
<td>(1.022)</td>
</tr>
<tr>
<td>aft</td>
<td>0.707</td>
<td>0.707</td>
</tr>
<tr>
<td></td>
<td>(1.273)</td>
<td>(1.273)</td>
</tr>
<tr>
<td>Tol</td>
<td>-2.476</td>
<td>-2.476</td>
</tr>
<tr>
<td></td>
<td>(3.506)</td>
<td>(3.506)</td>
</tr>
<tr>
<td>Hope</td>
<td>-0.291</td>
<td>0.291</td>
</tr>
<tr>
<td></td>
<td>(1.801)</td>
<td>(1.801)</td>
</tr>
<tr>
<td>Intercept</td>
<td>1.719</td>
<td>1.719</td>
</tr>
<tr>
<td></td>
<td>(1.543)</td>
<td>(1.543)</td>
</tr>
<tr>
<td>Observations</td>
<td>61</td>
<td>61</td>
</tr>
</tbody>
</table>

Source: author’s computations. Standard errors in parentheses. ME1 - mixed-effects multilevel model by authors; ME2 - mixed-effects multilevel model by studies.
weighting is affiliated with more publication bias. These results are to a large extent consistent with the intuition. Because these assumptions are arbitrary to a large extent, researchers use them to alter their results. They choose these assumptions so that they obtain significant estimates or estimates that are in accordance with the economic theory.
Chapter 6

Conclusion

The main contribution of our thesis was collecting studies estimating SCC and selecting estimates with obtainable standard errors. In order to do this, we extended the dataset provided by R.S.J. Tol. Then we had to go through the studies and rigorously collect essential information for our analysis.

We collected studies that estimated SCC and performed one of the first meta-analyses on the SCC. Unlike other SCC meta-analyses performed previously, our analysis took publication bias into account. After the computation of standard errors, we selected 84 estimates from 37 studies, which were applicable for conducting the meta-analysis. The simple mean of the selected estimates is 142.4 USD/tC. We then employed graphical and regression tests to detect publication bias. We introduced several models to test for publication bias. Some of them served as a robustness check for the most sophisticated one of them: the mixed-effects multilevel model. All of the regression tests identified strong publication bias in the collected empirical literature.

After the detection of publication bias, we discovered SCC value beyond this bias. According to the mixed-effects multilevel model, which accounts for between-study heterogeneity, the value of SCC beyond publication bias is 0.706 USD/tC. This value is significantly lower than the simple mean of the sample. When we compared this result with the estimates published in the empirical literature, our estimate beyond publication bias represents only a fraction of these estimates. Our result indicates that there is very serious overestimation when assessing this effect. Even if the general perception of the price of SCC was one tenth of the mean of the reported estimates, it would still mean that SCC is perceived as much more serious effect than it should be.

We acknowledge that our dataset is different from the dataset used by Tol,
but 28 out of the 37 studies were the same ones that he used for his meta-
analysis. Tol (2008). Previous meta-analyses discovered some characteristics of
studies that have an influence on the heterogeneity of individual SCC estimates.
We also employed multivariate meta-regression analysis to find out which of the
characteristics represented as dummy variables are associated with publication
bias more than others. We found out that equity weighting had a significantly
negative effect on publication bias. This means that equity weighting is tied
with less publication bias. On the contrary, the choice of low (i.e. 0% or 1%)
pure rate of time preference is tied with more publication bias.
Bibliography


