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Abstract

We examine potential selective reporting in the literature on the social cost of carbon (SCC) by conducting a meta-analysis of 809 estimates of the SCC reported in 101 studies. Our results indicate that estimates for which the 95% confidence interval includes zero are less likely to be reported than estimates excluding negative values of the SCC, which creates an upward bias in the literature. The evidence for selective reporting is stronger for studies published in peer-reviewed journals than for unpublished papers. We show that the findings are not driven by the asymmetry of confidence intervals surrounding the SCC and are robust to controlling for various characteristics of study design and to alternative definitions of confidence intervals. Our estimates of the mean reported SCC corrected for the selective reporting bias are imprecise and range between 0 and 130 USD per ton of carbon in 2010 prices for emission year 2015.

Keywords: Social cost of carbon, climate policy, integrated assessment models, meta-analysis, selective reporting, publication bias

JEL Codes: C83, Q54

*An online appendix with data and code is available at `meta-analysis.cz/scc`. Corresponding author: Zuzana Irsova, `irsova@berkeley.edu` or `zuzana.irsova@ies-prague.org`. Zuzana Irsova acknowledges support from the Grant Agency of Charles University in Prague (grant #558713); Tomas Havranek acknowledges support from the Czech Science Foundation (grant #P402/11/0948). The research leading to these results has received funding from the People Programme (Marie Curie Actions) of the European Union's Seventh Framework Programme FP7/2007-2013 under REA grant agreement number 609642. We thank Richard Tol for sending us his data set and are grateful to Jan Babecky, Jiri Schwarz, Diana Zigraiova, and seminar participants at Charles University for their helpful comments. The views expressed here are ours and not necessarily those of our employers.

1 Introduction

A key parameter for the formulation of climate policy is the social cost of carbon emissions. If the social cost of carbon was pinned down precisely, policy makers could use the parameter to set the optimal carbon tax. For this reason, dozens of researchers using different families of models have estimated the SCC—but their findings and the resulting policy implications vary greatly. Several previous studies have offered quantitative surveys of the literature (Tol, 2005b, 2008, 2011, 2013b), focusing especially on the characteristics of study design that may influence the reported estimates, but no study has discussed nor tested for the potential selective reporting bias in the estimates of the social cost of carbon.

Selective reporting is the tendency of editors, referees, or authors themselves to prefer empirical estimates that are conclusive, have a particular sign supported by theory or intuition, or both. Also called the file-drawer problem or publication bias (we prefer the term selective reporting because the bias can be present in unpublished studies as well), it has been discussed in literature surveys since Rosenthal (1979). The problem of selective reporting is widely recognized in medical research, where many of the best journals now require prior registration of clinical trials as a necessary condition for any potential submission of results (Krakovsky, 2004). In a similar vein, the American Economic Association has agreed to establish a registry of randomized controlled experiments to counter selective reporting (Siegfried, 2012, p. 648).

Doucouliagos & Stanley (2013) conduct a large survey of meta-analyses (quantitative literature surveys) in economics and conclude that most fields suffer from selective reporting, which exaggerates the magnitude of the mean reported effect, and thus biases our inference from the literature. A recent survey among the members of the European Economic Association, Necker (2014), reveals that a third of economists in Europe admit that they have engaged in presenting empirical findings selectively so they confirm their arguments and in searching for control variables until they get a desired result. A meta-analysis by Havranek *et al.* (2012) indicates that 40% of the estimates of the price elasticity of gasoline demand end up hidden in researchers' file drawers because of an unintuitive sign or statistical insignificance; this selective reporting exaggerates the mean reported price elasticity twofold.

Several studies examine selective reporting in the context of climate change research. The problem is widely discussed in phenology (Both *et al.*, 2004; Gienapp *et al.*, 2007; Menzel *et al.*, 2006), and the evidence suggests that while selective reporting is a minor issue in multi-species studies, positive results from single-species studies are reported more often than neutral results (Parmesan, 2007). Maclean & Wilson (2011) conduct a meta-analysis of the relation between climate change and extinction risk and find mixed results concerning selective reporting, with evidence for the bias among estimates of extinction risk, but no bias among estimates of high extinction risk. Michaels (2008) examines 166 papers on climate change published in Science and Nature and argues that there is substantial evidence for selective reporting. Swanson (2013) indicates that many of the current model simulations of climate change are inconsistent with the observed changes in air temperature and the frequency of monthly temperature extremes, which might be due to selective reporting. In contrast, Darling & Côté (2008) investigate the relationship between climate change and biodiversity loss and find no evidence of selective reporting, and Massad & Dyer (2010) find no signs of selective reporting in the literature on the effects of climate change on plant-herbivore interactions.

Another motivation for the examination of potential selective reporting is the controversy concerning the scientific consensus on anthropological climate change between John Cook and colleagues on one side and Richard Tol on the other. Cook *et al.* (2013) collect almost 12,000 abstracts from peer-reviewed studies and conclude that 97% of those support the argument that climate change is human-made. Tol (2014) disagrees and has reservations to the way how Cook *et al.* (2013) select papers for their survey. Cook *et al.* (2014), in turn, disagree with the response of Tol (2014) and point out several alleged mistakes in Tol's arguments. From our perspective the main problem of the Cook *et al.* (2014) survey is that it does not mention nor correct for potential selective reporting. Given how widespread the file-drawer problem is in many fields, the fact that 97% studies report positive results does not necessarily translate into a 97% consensus of the scientific community that climate change is human-made. Because our prior about the sign of the relation between human activity and climate change is so strong, researchers may be less inclined to report neutral than large positive estimates of the relationship. It is perhaps a case in point that before being accepted by Energy Policy, Tol's comment was rejected by Environmental Research Letters, the outlet where Cook *et al.* (2013) was published.[1]

[1] As Richard Tol describes on his website: http://richardtol.blogspot.com/2013/06/draft-comment-on-97-consensus-paper.html.

In contrast to most subjects of meta-analysis in economics, the social cost of carbon is not estimated in a regression network. Rather, the SCC is a result of a complex calibration exercise, and the uncertainty surrounding the estimates is usually determined via Monte Carlo simulations. Therefore by definition the literature lacks the usual suspects when it comes to potential selective reporting: specification search across models with different control variables, choice of the estimation technique, and the selection of the data sample. On the other hand, the authors have the liberty to choose among many possible values of the parameters that enter the computation and influence both the estimated magnitude of the SCC and the associated uncertainty. In a critical review of integrated assessment models, Pindyck (2013, p. 863) argues that "these models can be used to obtain almost any result one desires." Despite the difficulty in computing the SCC, we believe it is worth trying to pin down this crucial parameter. Testing for the potential selective reporting bias represents a part of this effort.

The remainder of the paper is structured as follows. Section 2 briefly discusses how the authors derive estimates of the social cost of carbon. Section 3 describes how we collect data for the meta-analysis. Section 4 explains the methods used in economics for the detection of selective reporting and addresses the specifics of their application in the case of the social cost of carbon. Section 5 presents the results of meta-regression analysis based on the tests of funnel asymmetry. Section 6 concludes the paper. A list of studies included in the meta-analysis and summary statistics of regression variables are reported in the Appendix.

2 Estimating the Social Cost of Carbon

The purpose of this section is to outline the intuition behind the estimation of the SCC and discuss the results of the related literature, not to provide a detailed overview of estimation methodology. For the latter we refer the reader to Pindyck (2013) and Greenstone *et al.* (2013).

The first estimate of the shadow price of carbon emissions dates back to Nordhaus (1982). In the early 1990s William Nordhaus developed the first predecessor of the current generation of models, Nordhaus (1991), which he applied to the US economy. Later, Nordhaus extrapolated his country-level estimates of welfare effects to a global estimate, which has become the norm in the literature. Several researchers followed this approach (for example, Ayres & Walter, 1991), but it was not before Fankhauser (1994) that an uncertainty component was introduced into the analysis. In the following years the literature differentiated further and more distinct models were introduced: among others, Tol (1995), Nordhaus & Yang (1996), and Plambeck & Hope (1996).

The workhorse tool for the estimation of the SCC are the so-called integrated assessment models. In simple terms, an integrated assessment model puts the expected climate effects of carbon emissions into the framework of economic growth theory. The social cost of carbon is then calculated as the difference between the present and future GDP influenced by damages resulting from carbon emissions, discounted back to the present time. The three most commonly used models are DICE [Dynamic Integrated Climate and Economy] developed by William Nordhaus (Nordhaus, 2008), PAGE [Policy Analysis of the Greenhouse Effect] developed by Chris Hope (Hope, 2008b), and FUND [Climate Framework for Uncertainty, Negotiation, and Distribution] developed by Richard Tol (Tol, 2002a,b). Each model specifies how climate impacts result in economic damages in a different way (for more details on the differences in methodology see, for example, NRC, 2009; IWG, 2010, 2013).

The mapping of carbon emissions to economic costs is associated with significant uncertainties. The authors must rely on trends and scenarios taken from other sources, which involves simplification of complex processes. The authors must make assumptions about the level of current and future emissions (under different scenarios), about how these emissions translate into atmospheric gas concentrations (resulting from current, past, and future emissions), how these concentrations translate into warming (climate sensitivity), and how the warming translates into economic damages (projections of technological change, social utility assumptions, and damage functions). A major source of uncertainty is linked to the discount rate in monetary valuations. The resulting SCC is either a best-guess value of the calibration provided by the researcher or a mean/median value with a probability distribution, usually constructed using a Monte Carlo simulation. The reported values of the SCC vary widely.

Several attempts have been made to synthesize the published information on the optimal carbon tax. The IPCC (1995) literature review reports the range of best guesses from existing studies published until 1995: for carbon emitted in 1995, the range of estimates covers 5–125 USD/tC (in 1990 prices). In IPCC (2007), the values for 2005 emissions are extracted from about 100 estimates and range from −11 USD/tC to 348 USD/tC with an average value of

44 USD/tC (in 2005 prices). Both studies find the net damage costs of climate change to be significant and increasing over time. The IPCC emphasizes that these intervals do not represent the full range of uncertainty.[2]

The first comprehensive meta-analysis on the topic, Tol (2005b), collects 103 estimates from 28 different studies. Combining all the estimates into a composite probability density function, Tol (2005b) finds a median estimate of 14 and mean of 93, not exceeding 350 with a 95% probability. The estimates are driven by the choice of the discount rate and equity weights; Tol (2005b) also finds that the largest estimates with substantial uncertainty come from studies not published in peer-reviewed journals. In an update of the meta-analysis, Tol (2008) confirms his previous findings using 211 estimates collected from 47 studies; moreover, he identifies a downward trend in the reported SCC. Using the Fisher-Tippett fat-tailed distribution for the probability density function, for emission year 1995 discounted to 1995 he estimates the median SCC at 74 and the mean at 127, not exceeding 453 with a probability of 95%.

In another update, Tol (2011) performs a meta-regression analysis of 311 estimates of the social cost of carbon. He estimates a global mean SCC to be 177 (in 2010 USD and for 2010 emission year), median to be 116 with a standard deviation of 293, not exceeding 669 USD/tC with a 95% probability. A lower discount rate leads to a higher social cost of carbon, and peer-reviewed estimates and estimates from newer studies seem to be less pessimistic. In the most recent survey, Tol (2013b) adds another 277 estimates from 14 studies to the meta-analysis and gets a mean estimate of 196 and a median of 135 with a standard deviation of 322.

3 The SCC Data Set

The first step of any meta-analysis is the collection of results from primary studies that report estimates of the effect in question. We take the advantage of the previous meta-analyses of the literature estimating the social cost of carbon and start with the data set provided by Richard Tol. The data set covers studies published until mid-2012 and includes 79 papers. Additionally we search in Google Scholar for new studies published in 2012 and later; the search query is available in the online appendix. We identify 22 new studies, bringing the total number of papers included in the meta-analysis to 101, listed in the Appendix. Most studies

[2] The fifth assessment report, IPCC (2014), refers to the updated meta-analyses by Richard Tol.

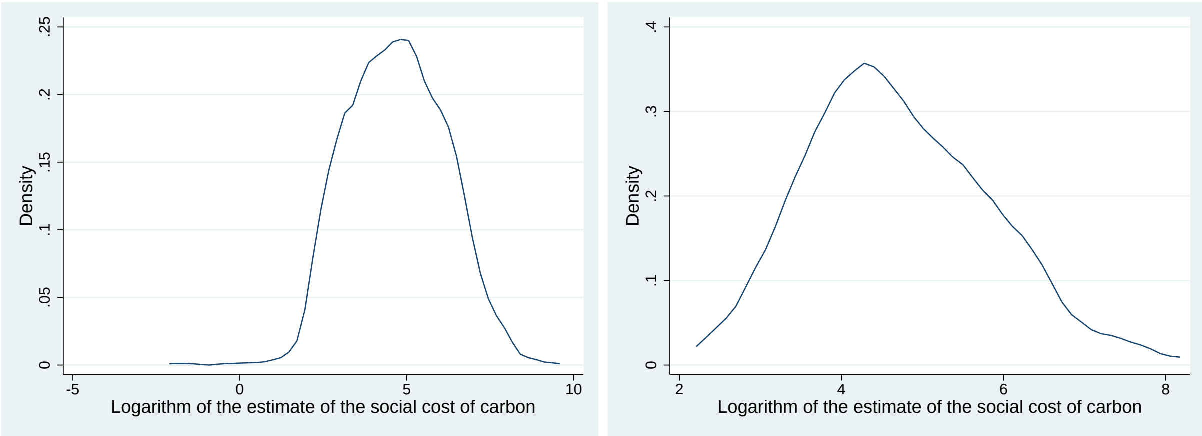
report multiple estimates of the social cost of carbon; for example, with different assumptions concerning the pure rate of time preference or different economic scenarios. We collect all of the estimates, which yields 809 observations. To put these numbers into perspective, we refer to the recent survey of meta-analyses in economics, Doucouliagos & Stanley (2013), who note that the largest meta-analysis conducted so far uses 1,460 estimates from 124 studies.

Aside from collecting additional studies, we also make adjustments in the original data set provided by Tol. Some studies available as mimeographs at the time when Tol collected the data have been published since 2012, and for these studies we checked the reported results and, if needed, changed the coding of the data accordingly. We also collect additional variables that may help explain the heterogeneity in the estimates of the social cost of carbon. Because the estimates of the SCC are reported for different emission years and evaluated in nominal US dollars, we have to recompute them to a common metric. We choose 2010 as the price year and 2015 as the emission year; for the normalization of the emission year we assume a constant growth of the SCC of 3.11% per year, the mean growth of the estimated real SCC between emission years in our data set (more details are available in the online appendix). Some studies report the SCC as the cost of emission of a molecule of carbon dioxide, while others refer to the cost of emission of an atom of carbon. We recompute the estimates so that they relate to the cost per metric ton of carbon.

We add the last study to our data set on August 1, 2014. At that time all studies taken together had obtained almost 17 thousand citations in Google Scholar (or almost 1,700 on average per year), which shows the scientific impact of the literature estimating the SCC. The first estimate was reported in 1982, but the median study in our data set comes from 2008: more and more studies on the topic are reported each year. Out of the 101 studies in our sample, 63 are published in peer-reviewed journals; the remaining 38 studies are book chapters, government reports, mimeographs, and other publications for which peer review is not guaranteed. We include the latter group of studies as well, partly following the advice of Tom Stanley to "better err on the side of inclusion in meta-analysis" (Stanley, 2001, p. 135) and partly because we are interested in any potential differences in selective reporting between published and unpublished studies. Our approach to data collection and analysis is consistent with the Meta-Analysis of Economics Research Reporting Guidelines (Stanley *et al.*, 2013).

Figure 1: Kernel density plots

(a) All estimates (b) Study-level medians



Notes: Because the smallest estimate in our data set is −12.8, we add 13 to all estimates of the social cost of carbon before taking logs.

Figure 1 shows the distribution of the estimates of the social cost of carbon in our data set. Because the distribution is skewed to the right (the mean estimate is 290, the median is 99), we choose the logarithmic scale for the depiction of the data set. To be able to take the log of all estimates, we add 13 to the observations (the smallest estimate is −12.8). Panel A of Figure 1 shows the distribution for all estimates; Panel B shows the distribution of study-level medians reported in studies: both distributions are approximately log-normal, which is corroborated by the skewness and kurtosis test of normality, although the distribution of medians is slightly skewed to the right even after taking logs. The mean and median of study-level median estimates are smaller than those of all estimates (201 vs. 290 and 82 vs. 99, respectively), which suggests that studies which obtain larger SCC in general report more estimates.

Figure 2 depicts the box plot of the estimates of the SCC reported in individual studies. Even with the logarithmic scale, the figure shows substantial heterogeneity across studies. It follows that it is important to control for the methodology of the SCC computation employed in the study and to cluster standard errors in the resulting regressions at the study level, because estimates reported within individual studies are unlikely to be independent. All variables that we collect for this meta-analysis are summarized and explained in Table 1; the table corresponds to the entire data set of 809 observations. Summary statistics for the two additional data sets (study medians and estimates with reported uncertainty) are shown in the Appendix.

Figure 2: Estimates of the social cost of carbon vary

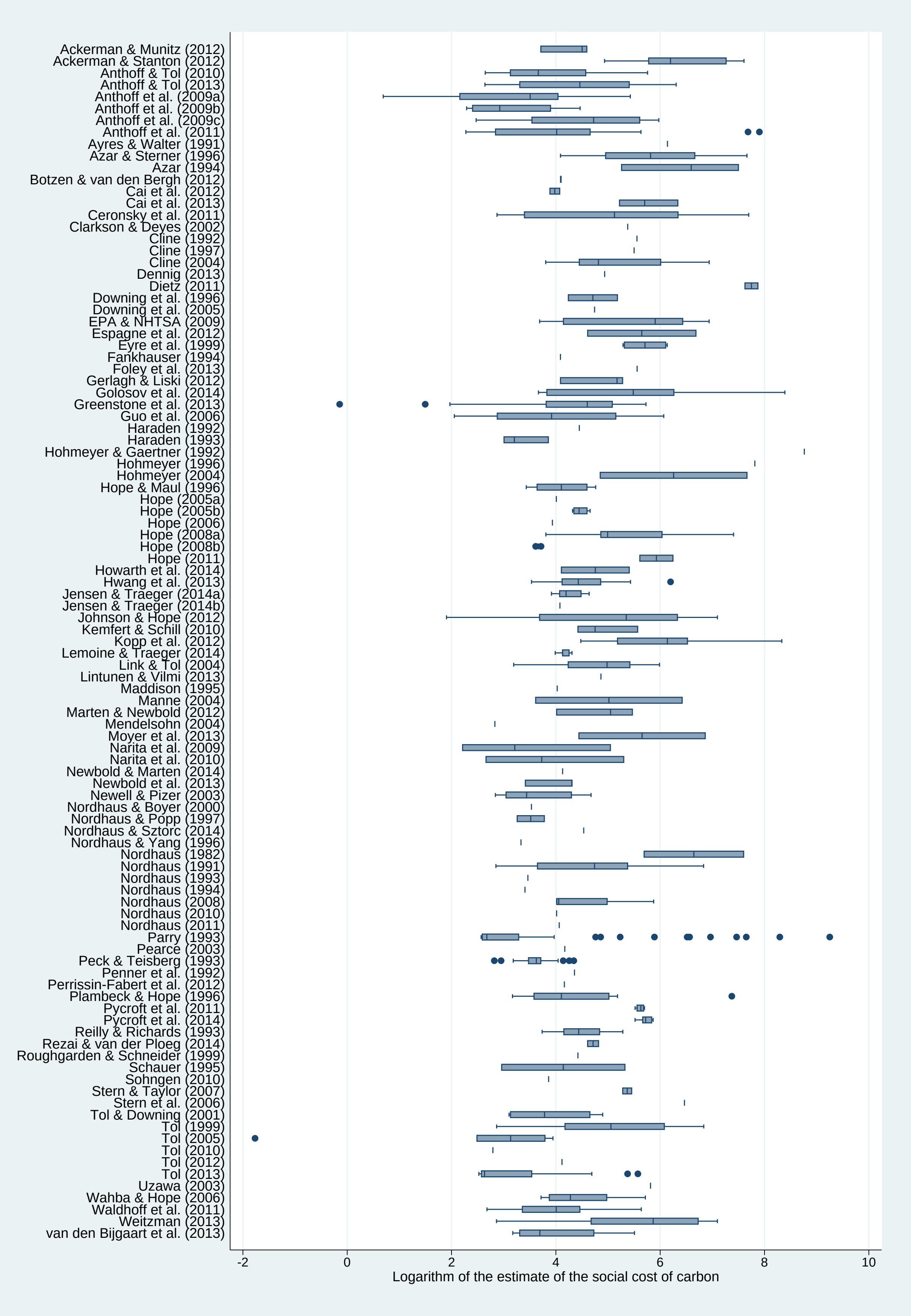


Table 1: Description and summary statistics of regression variables

Variable	Description	Obs.	Mean	Std. dev.
SCC	The reported estimate of the social cost of carbon in USD per ton of carbon (normalized to 2015 emission year in 2010 dollars).	809	290	635
Standard error	The approximate standard error of the estimate computed from the reported lower bound of the confidence interval.	267	162	235
Upper SE	The approximate standard error of the estimate computed from the reported upper bound.	267	1182	1921
Reviewed	= 1 if the study was published in a peer-reviewed outlet.	809	0.80	0.40
Publication year	The year of publication of the study (base: 1982).	809	24.7	7.46
Mean estimate	= 1 if the reported SCC estimate is the mean of the distribution.	809	0.23	0.42
Median estimate	= 1 if the reported SCC estimate is the median of the distribution.	809	0.21	0.41
Marginal costs	= 1 if the study estimates marginal damage costs (damage from an additional ton of carbon emitted) rather than average costs (the total impact divided by the total emissions of carbon).	809	0.96	0.20
Dynamic impacts	= 1 if the study examines dynamic impacts of climate change or uses a dynamic model of vulnerability.	809	0.40	0.49
Scenarios	= 1 if the study uses climate and economic scenarios that are internally consistent. A few studies use arbitrary assumptions about climate change.	809	0.82	0.39
FUND	= 1 if the authors use the FUND model or derive their model from FUND.	809	0.40	0.49
DICE or RICE	= 1 if the authors use the DICE/RICE model or derive their model from DICE/RICE.	809	0.46	0.50
PAGE	= 1 if the authors use the PAGE model or derive their model from PAGE.	809	0.19	0.39
PRTP	The pure rate of time preference assumed in the estimation.	633	1.23	1.57
Equity weights	= 1 if equity weighting is applied.	809	0.18	0.38
Pigovian tax	= 1 if the estimate is computed along a trajectory of emissions in which the marginal costs of emission reduction equal the SCC, then the estimate corresponds to a Pigovian tax.	809	0.29	0.45
Citations	= The logarithm of the number of Google Scholar citations of the study.	809	3.54	1.30
Journal rank	= SciMago journal rank based on the impact factor extracted from Scopus.	809	1.32	2.33

Notes: Data are collected from studies estimating the social cost of carbon. The data set is available at `meta-analysis.cz/scc`.

The construction of the approximate standard errors for the estimates of the social cost of carbon (the second and third item in Table 1) will be described in detail in the following two sections. We can only approximate standard errors for estimates for which the authors of primary studies report a measure of uncertainty, usually a confidence interval. Only 267 out of 809 estimates in our data set are reported together with a measure of uncertainty. These estimates are on average much larger than the rest of the data: the mean estimate with uncertainty is 411 (in contrast with 290 when all estimates are considered) and the median is

241 (in contrast with 99). In other words, authors who provide a probabilistic distribution of estimates tend to report much larger median values of the SCC than authors who only report their best-guess estimates.

We include a dummy variable to take into account whether the study in which the estimate is reported is published in a peer-reviewed journal. We also control for the year of publication of the study: perhaps novel methods of estimating the SCC bring systematically different results, and the literature converges to a consensus value. We include dummy variables for the case when the reported estimate corresponds to the median and mean of the distribution; the base category corresponds to best-guess estimates. Some studies estimate average costs rather than marginal damage costs, and we control for this aspect of methodology as well. We include dummy variables for studies that examine dynamic impacts of climate change and studies that use internally consistent climate and economic scenarios to simulate the evolution of emissions.

Three families of integrated assessment models are predominant in the estimation of the social cost of carbon: the FUND, PAGE, and DICE (RICE) models; most author teams also use consistently the same family of models. We include three dummy variables to distinguish between these approaches. Some estimates are constructed as weighted averages of several model approaches, and a few studies use models independent of the main three families. An important feature in estimating the SCC is the assumed discount rate, especially the rate of pure rate of time preference—we control for the value assumed in the computation, but some authors do not report it; we only have data on the pure rate of time preference for 633 estimates. Next, some studies employ equity weights in the computation, and we control for this aspect of methodology. We also include a dummy variable that equals one if the estimate corresponds to the optimal abatement path and can be interpreted as the Pigovian tax on carbon emissions. Finally, we control for the number of Google Scholar citations of the study and the SciMago journal rank of the outlet (the SciMago journal rank based on Scopus citations is available for more journals in our sample than the Thompson Reuters impact factor and the RePEc impact factor): perhaps these study characteristics capture aspects of quality not covered by the methodology variables introduced above.

In the next step we examine how method and publication characteristics are correlated with the reported estimates of the SCC. The first two columns of Table 2 report the results of a

Table 2: Explaining the heterogeneity in the SCC estimates

	SCC		log SCC	
	All estimates	PRTP	All estimates	PRTP
Reviewed	-187.1***	-149.2*	-0.741***	-0.574**
	(65.34)	(78.37)	(0.225)	(0.253)
Publication year	-4.877	-4.004	0.0212	0.0241
	(6.595)	(7.129)	(0.0177)	(0.0246)
Mean estimate	138.8***	256.7***	0.439**	0.914***
	(52.64)	(65.96)	(0.182)	(0.227)
Median estimate	316.4***	243.0***	1.366***	1.185***
	(76.60)	(72.92)	(0.252)	(0.306)
Marginal costs	-331.7	-380.7	-1.204***	-1.179***
	(272.0)	(287.2)	(0.387)	(0.414)
Dynamic impacts	-213.1***	-330.0**	-0.482*	-0.946**
	(78.70)	(152.5)	(0.272)	(0.429)
Scenarios	140.5	199.8	0.745***	0.676*
	(124.3)	(148.2)	(0.235)	(0.357)
FUND	45.66	33.65	-0.270	-0.202
	(99.22)	(140.0)	(0.295)	(0.393)
DICE or RICE	75.01	-70.24	0.240	-0.531
	(56.30)	(84.98)	(0.160)	(0.340)
PAGE	-173.2**	-304.9**	-0.147	-0.679*
	(76.14)	(145.7)	(0.199)	(0.353)
Equity weights	31.31	73.26	0.392*	0.554**
	(52.89)	(71.41)	(0.202)	(0.262)
Pigovian tax	-85.01	-46.26	-0.226	0.137
	(81.76)	(72.78)	(0.253)	(0.295)
Citations	-20.58	-24.49	0.0568	0.116
	(29.55)	(32.32)	(0.0775)	(0.0790)
Journal rank	36.43***	26.02*	0.102***	0.0107
	(8.943)	(13.98)	(0.0270)	(0.0402)
PRTP		-112.7***		-0.425***
		(22.64)		(0.0913)
Constant	774.6**	999.1**	4.800***	5.384***
	(366.4)	(431.6)	(0.633)	(0.695)
Observations	809	633	809	633

Notes: The table presents the results of regression $SCC_{ij} = \alpha + \beta \cdot X_{ij} + u_{ij}$, where SCC_{ij} is the i-th estimate of the social cost of carbon reported in the j-th study and X is a vector of the estimate's characteristics. In the last two columns we use the logarithm of the estimates of SCC as the dependent variable; because the smallest estimate in our data set is -12.8, we add 13 to all estimates of the social cost of carbon before taking logs. Estimated by OLS; standard errors are clustered at the study level and shown in parentheses. PRTP = only estimates for which the authors report the pure rate of time preference used in the computation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

regression of the estimates on the estimates' characteristics; the third and fourth column use a logarithm of the estimate of the SCC on the left-hand side of the regression. In all cases we cluster standard errors at the study level to take into account within-study correlation in SCC estimates. The results suggest that studies published in peer-reviewed journals report, on average, substantially smaller estimates of the social cost of carbon. This evidence is consistent with previous research (Tol, 2011), and can be interpreted in two ways. The first potential interpretation, suggested by Tol (2011), puts forward that many large estimates of the SCC that we observe in the literature are not verified by the peer-review process, and thus may be of questionable quality. The second possible interpretation, in line with the topic of this paper, would suggest that the peer-review process results in a selective reporting bias in favor of more conservative estimates of the SCC. We will examine this issue in detail in the next two sections.

Table 2 also shows that the year of publication is not systematically related to the magnitude of the reported SCC. (We also experimented with several specifications that were nonlinear in the year of publication, but obtained no statistically significant results.) In contrast, Tol (2011) finds that newer studies tend to report smaller estimates of the SCC. Our results are different because we include new studies published between 2012 and 2014; these studies often report large estimates of the SCC as they try to incorporate potential catastrophic outcomes of climate change. Next, we find that authors who report uncertainty associated with their central estimates (usually confidence intervals around mean or median expected SCC values) tend to report larger SCC. The evidence on the importance of estimating marginal instead of average costs is mixed: we only find significant results in the case of log-level regressions, which suggest that estimating average costs exaggerates the reported SCC. Authors investigating dynamic impacts of climate change report, on average, smaller estimates of the SCC.

Studies employing internally consistent economic and climate scenarios tend to report larger estimates of the SCC, but the effect is only statistically significant in the log-level specifications of the regression. There is also some evidence that authors employing a variant of the PAGE model report, ceteris paribus, smaller estimates of the SCC than other studies, but the effect is not statistically significant at the 5% level in all specifications. The log-level regressions suggest that using equity weights results in larger reported SCC. In contrast, it does not seem to be important for the magnitude of the estimated SCC whether the estimate is consistent with the optimal abatement path and thus represents a Pigovian tax. Similarly the number of citations of the study is not systematically related to the reported results. The ranking of the journal, on the other hand, is correlated with the estimated SCC: studies published in better journals tend to report larger estimates. Finally, as expected, a larger assumed pure rate of time preference leads to smaller estimates of the SCC.

4 Detecting Selective Reporting

In this section we overview the tools that are available for the examination of selective reporting in economics. Three methods are commonly used to detect potential selective reporting bias in the literature: Hedges' model, the funnel plot, and meta-regression analysis. Concerning the first method, Hedges (1992) introduces a model of selective reporting which assumes that the probability of reporting of estimates is determined by their statistical significance. The probability of reporting only changes when a psychologically important p-value is reached: in economics these threshold values are commonly assumed to be 0.01, 0.05, and 0.1. When no reporting bias is present, all estimates, significant and insignificant at conventional levels, should have the same probability of being published. The augmented model developed by Ashenfelter *et al.* (1999) allows for heterogeneity in the estimates of the underlying effect. The augmented log-likelihood function is (Ashenfelter *et al.*, 1999, p. 468):

$$L = c + \sum_{i=1}^{n} \log w_i(X_i, \omega) - \frac{1}{2}\sum_{i=1}^{n}\Big(\frac{X_i - \mathbf{Z}_i\Delta}{\eta_i}\Big)^2 - \sum_{i=1}^{n}\log(\eta_i) - \sum_{i=1}^{n}\log\Big[\sum_{j=1}^{4}\omega_j B_{ij}(\mathbf{Z}_i\Delta, \sigma)\Big], \quad (1)$$

where $X_i \sim N(\Delta, \eta_i)$ would be the estimates of the social cost of carbon. The parameter Δ is the average underlying SCC, and $\eta_i = \sigma_i^2 + \sigma^2$, where σ_i are the reported standard errors of the estimates and σ measures heterogeneity in the estimates. The probability of reporting is determined by the weight function $w(X_i)$. In this model $w(X_i)$ is a step function associated with the p-values of the estimates. Meta-analysts usually choose four steps reflecting different levels of conventional statistical significance of the estimates: p-value < 0.01, $0.01 <$ p-value < 0.05, $0.05 <$ p-value < 0.1, and p-value > 0.1. $B_{ij}(\Delta, \sigma)$ represents the probability that an estimate X_i will be assigned weight ω_i. For the first step, p-value < 0.01, ω is normalized to 1 and the author evaluates whether the remaining three weights differ from this value. Z_i is a vector of the characteristics of estimate X_i. In the absence of selective reporting the meta-analyst is not able to reject the hypothesis $\omega_2 = \omega_3 = \omega_4 = 1$; that is, estimates with different levels of statistical significance have the some probability of being reported.

The second method of detecting selective reporting is a visual examination of the so-called funnel plot (Egger *et al.*, 1997). The funnel plot is a scatter plot of the estimated coefficients (in our case the reported estimates of the social cost of carbon) on the horizontal axis and their precision (the inverse of standard error) on the vertical axis. The most precise estimates are close to the top of the funnel and are tightly distributed. As precision decreases, the dispersion of estimates increases, which yields the shape of an inverted funnel with a sharp tip on the top and a wide base on the bottom. In the absence of selective reporting the funnel should be symmetrical: all imprecise observations have the same probability of being reported. Even if the true effect is positive, due to the laws of chance we should observe some negative estimates with low precision (as well as large estimates with low precision). If, in contrast, some estimates (for example, the negative ones) are systematically omitted, the funnel becomes asymmetrical.

The third method used to investigate potential selective reporting is closely related to the funnel plot, but uses meta-regression analysis to statistically examine the degree of funnel asymmetry. When selective reporting is not present in the literature the estimates of the SCC should be randomly distributed around the true mean estimate of the social cost of carbon, SCC_0. But if authors discard some estimates because they are statistically insignificant or have a sign that is inconsistent with the theory or the mainstream prior, the reported estimates of the SCC will be correlated with their standard errors (Card & Krueger, 1995):

$$SCC_i = SCC_0 + \beta_0 \cdot Se(SCC_i) + u_i, \tag{2}$$

where SCC_i is the estimate of the social cost of carbon, SCC_0 denotes the average underlying value of the social cost of carbon, $Se(SCC_i)$ denotes the standard error of SCC_i, β_0 measures the magnitude of selective reporting, and u_i is an error term. Specification (2) can be thought of as a test of the asymmetry of the funnel plot: the regression follows from rotating the axes of the plot and inverting the values on the new horizontal axis. A statistically significant estimate of β_0 provides formal evidence for funnel asymmetry, and thus for selective reporting. Note that β_0 close to 2 is consistent with a situation when only positive and statistically significant

SCC estimates (that is, the estimates for which the corresponding 95% confidence intervals exclude zero) are selected for reporting and other estimates are hidden in file drawers. Since specification (2) is heteroscedastic (the dispersion of the dependent variable increases when the values of the independent variable increase), in practice meta-analysts often estimate it by weighted least squares with precision taken as the weight (Stanley, 2005):

$$SCC_i/Se(SCC_i) = t_i = SCC_0 \cdot 1/Se(SCC_i) + \beta_0 + \xi_i. \tag{3}$$

Because studies usually report more estimates of the SCC, it is important to take into account that estimates reported in one study are likely to be correlated. A way how to address this issue is to employ the so-called mixed-effects multilevel model (Doucouliagos & Stanley, 2009), which assumes unobserved between-study heterogeneity. We specify the mixed-effects model following Havranek & Irsova (2011) and Havranek *et al.* (2012):

$$t_{ij} = e_0 \cdot 1/Se(SCC_{ij}) + \beta_0 + \zeta_j + \epsilon_{ij}, \tag{4}$$

where i and j denote estimate and study subscripts and t_i denotes the approximate t-statistic. The overall error term (ξ_{ij}) now breaks down into study-level random effects (ζ_j) and estimate-level disturbances (ϵ_{ij}).

The mixed-effects multilevel model is similar to the random-effects model used in panel-data econometrics, but the terminology follows hierarchical data modeling. For the purposes of meta-analysis the multilevel framework is more suitable because it takes into account the unbalancedness of the data (the restricted maximum likelihood estimator is used instead of generalized least squares) and allows for nesting multiple random effects. The problem of the mixed-effects model is that it assumes no correlation between study-level random effects and the independent variables. This assumption is rarely tenable in practice, and we thus prefer to run the the fixed-effects model and cluster standard errors at the study level.

The three methods of detecting selective reporting introduced above are designed for regression estimates of the parameter in question and require that the ratio of the point estimate to the standard error be t-distributed. In contrast, estimates of the social cost of carbon are based on calibration and assumptions concerning the uncertainty about parameters entering the computation. For most estimates of the SCC the authors do not report confidence intervals, and even if they do, we cannot assume the ratio of the point estimate to the standard error to have a t-distribution because of the asymmetries in uncertainty surrounding the SCC (especially catastrophic events). In particular, Hedges' method assumes that authors decide on which estimates to report depending on whether the estimates surpass a certain threshold of the p-value, which is unlikely to be the driving factor of selective reporting in the literature on the SCC. In contrast, we believe that we can use the intuition behind the two methods based on the analysis of funnel plot asymmetry.

To be able to employ the methods based on the funnel plot, we need to compute the approximate standard errors of the estimates. Few authors report the standard errors directly, and only 267 out of 809 estimates are reported together with a measure of uncertainty from which confidence intervals can be computed (usually 95% confidence intervals). The confidence intervals of the estimates of the SCC are typically asymmetrical, which means that for the approximation of the standard error we have to choose whether we will use the lower or upper bound of the confidence interval. We choose the lower bound, because we assume that any potential selective reporting in the literature will be associated with the sign of the estimate and the authors' confidence that the true SCC is nonzero. We also examine whether the asymmetry of the confidence intervals reported by the authors affects our results concerning potential selective reporting in the literature.

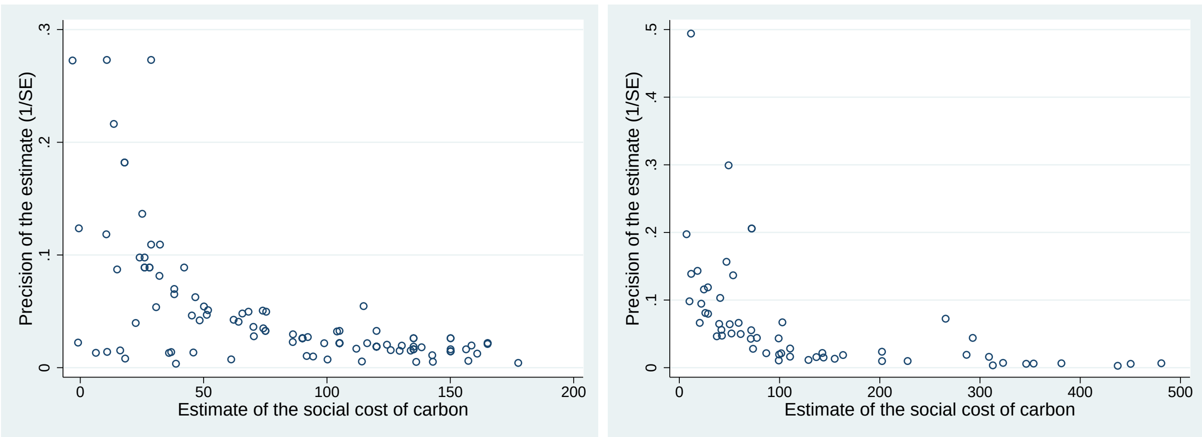
Because for most estimates of the SCC the authors do not report confidence intervals or other measures of uncertainty, we also choose an alternative approach for the computation of approximate standard errors. From each study we take the median estimate of the SCC and then construct the standard error as the difference between the 50^{th} and the 16^{th} percentile of the distribution of estimates. (We only use studies that report multiple estimates of the SCC.) The standard errors are computed under the simplifying assumption that estimates in each study are normally distributed. Most studies produce an asymmetric distribution of estimates, but we are interested in quantifying the confidence of the authors that their estimate of the social cost of carbon is different from zero, which is analogous to statistical significance for classical regression estimates used in economic meta-analyses. We expect that selective reporting in the literature would manifest itself as a tendency to report less uncertainty (a smaller approximate standard error computed from the lower bound of the confidence interval or the distribution of estimates in a study) for smaller estimates of the SCC in the absolute value.

5 Meta-Regression Results

Figure 3 reports two funnel plots for the literature estimating the social cost of carbon: the funnel in panel A corresponds to estimates for which the authors report a measure of uncertainty, the funnel in panel B corresponds to study-level medians computed from all observations reported in the study. Both scatter plots resemble a right-hand part of an inverted funnel; the left-hand part is missing: few negative estimates of the social cost of carbon are reported. The funnels are clearly asymmetrical, with smaller estimates being typically more precise—that is, reporting less uncertainty in the downward direction. Large point estimates of the SCC are usually associated with a lot of uncertainty and do not exclude the possibility of small positive SCC. It is remarkable that the funnels have a similar shape even though the method of computing approximate standard errors differs a lot for the two cases.

Figure 3: Funnel plots show signs of selective reporting

(a) Estimates with uncertainty (b) Study-level medians



Notes: In the absence of selective reporting the funnel should be symmetrical around the most precise estimates of the social cost of carbon. Precision is the inverse of the approximate standard error computed from the lower bound of the reported confidence interval (or from the distribution of estimates in the study in the case of study-level medians). Outliers are excluded from the figure but included in all statistical tests.

Panel A of Table 3 shows the results of funnel asymmetry tests for the sample of estimates with uncertainty; in all specifications we cluster standard errors at the study level. In the first column we run a simple OLS regression of point estimates of the SCC on the approximate standard errors. The slope coefficient in the regression is positive and statistically significant, which corroborates our intuition based on funnel plots: larger estimates of the SCC are associated with larger downward uncertainty, and vice versa. The estimated slope coefficient equals approximately 1.7, which corresponds to "substantial" selective reporting bias according to the classification by Doucouliagos & Stanley (2013). We have noted that the slope coefficient close to 2 would be consistent with a situation when researchers systematically omitted estimates for which the 95% confidence interval included zero.

The constant in the regression can be interpreted as the mean estimate of the SCC when uncertainty about the SCC approaches zero (that is, corrected for any potential selective reporting), and is large and statistically significant in this specification, though smaller than the simple mean of all estimates. In the second column we add study-level fixed effects; in this way we filter out all study-specific characteristics that may influence the reported estimates. The result concerning the extent of selective reporting is similar to the previous case, but the estimate of the underlying SCC is now statistically insignificant at conventional levels.

Table 3: Funnel asymmetry tests, estimates with uncertainty

Panel A	OLS	FE	Precision	Study	ME
Standard error	1.705**	1.889**	2.467***	1.213**	1.819***
	(0.630)	(0.762)	(0.480)	(0.527)	(0.0825)
Constant	134.1**	104.2	10.27	63.14	-18.69
	(58.16)	(123.9)	(7.361)	(40.12)	(48.43)
Observations	267	267	267	267	267
Panel B	OLS	FE	Precision	Study	ME
Standard error	1.662**	1.907**	2.451***	0.780	1.835***
	(0.663)	(0.779)	(0.538)	(0.548)	(0.0843)
Upper SE	0.0246	-0.0109	0.00283	0.222	-0.00788
	(0.0254)	(0.00676)	(0.0107)	(0.143)	(0.0100)
Constant	112.0**	114.1	9.555	45.29	-17.78
	(50.00)	(118.6)	(6.133)	(29.63)	(48.81)
Observations	267	267	267	267	267

Notes: Panel A presents the results of regression $SCC_{ij} = SCC_0 + \beta \cdot SE(SCC_{ij}) + u_{ij}$, where SCC_{ij} is the i-th estimate of the social cost of carbon reported in the j-th study and $SE(SCC_{ij})$ is the corresponding approximate standard error computed from the lower bound of the reported confidence interval. Panel B presents the results of regression $SCC_{ij} = SCC_0 + \beta \cdot SE(SCC_{ij}) + \gamma \cdot SE^{up}(SCC_{ij}) + u_{ij}$, where $SE^{up}(SCC_{ij})$ is the corresponding approximate standard error computed from the upper bound of the reported confidence interval. The standard errors of regression parameters are clustered at the study level and shown in parentheses. FE = study level fixed effects. Precision = weighted by the inverse of the standard error. Study = weighted by the inverse of the number of estimates reported per study. ME = study-level mixed effects. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

In the next specification we weight estimates by their precision—the inverse of the approximate standard error. This weighted-least-squares specification has two benefits, for which it has commonly been used in meta-analysis: see, for example, Stanley (2005). First, it corrects for heteroskedasticity in the baseline regression, where the independent variable (the standard error of the estimate of the SCC) is a measure of dispersion of the dependent variable (the magnitude of the estimate of the SCC). Second, by definition it gives more weight to more precise results, which further alleviates the effects of selective reporting. The results are similar to the previous specification, but the coefficient associated with selective reporting is even larger—2.5, which corresponds to "severe" selective reporting based on the guidelines by Doucouliagos & Stanley (2013)—and statistically significant at the 1% level.

In the fourth column we use weighted least squares again, but instead of precision the weight is now the inverse of the number of estimates reported in each study. In unweighted regressions, studies that report many estimates get overrepresented and influence the results more heavily than studies with few reported estimates. Weighting by the inverse of the number of estimates reported per study seems natural because it gives each study approximately the same influence on the results. Compared to the baseline OLS regression, this specification yields smaller estimates of both the selective reporting parameter and the underlying mean SCC. The coefficient representing selective reporting is still statistically significant at the 5% level, and its extent would still be classified as substantial. In contrast, the coefficient that captures the mean effect corrected for the selective reporting bias is not statistically significant at conventional levels.

Finally we also employ the mixed-effects multilevel model and report the results in the last column of panel A in Table 3 . The mixed-effects model allows for random differences in the extent of the underlying SCC across studies and also gives each study approximately the same weight. The results corroborate the evidence reported in the previous columns concerning statistically significant and substantial selective reporting. The estimate of the underlying value of the social cost of carbon is once again statistically insignificant, and here even negative.

In panel B of Table 3 we examine whether our results concerning selective reporting are influenced by the asymmetry of confidence intervals that the authors report for their estimates of the social cost of carbon. The asymmetry of confidence intervals reported in individual studies is not an issue per se: many applications of meta-analysis quote the central limit theorem, which would imply that estimates should be symmetrically distributed in the absence of selective reporting even if the individual distributions were skewed. The problem is that the crucial assumption of the central limit theorem, independence of individual studies and estimates, is unlikely to hold in this case.

To see whether asymmetry drives our results, we need to include an interaction term of the approximate standard error computed based on the lower bound of the confidence interval and the ratio of the standard error computed from the upper bound and from the lower bound. This means that we can simply add an independent variable that captures the approximate standard error computed based on the upper bound ($SE \cdot SE^{up}/SE = SE^{up}$), and Table 3 shows that it is statistically insignificant in all cases. All other results are qualitatively similar to the baseline regression, except for the specification where we use the inverse of the number of estimates reported per study as the weight—the coefficient corresponding to selective reporting loses statistical significance. In general, however, the results show that the evidence for selective reporting identified in the previous regressions is not substantially affected by the asymmetry of individual confidence intervals.

Table 4: Funnel asymmetry tests, study-level medians

	OLS	Precision	OLS	Precision
Standard error	1.506***	1.936***	1.502***	1.958***
	(0.372)	(0.307)	(0.413)	(0.307)
Upper SE			0.00387	-0.0295***
			(0.0496)	(0.00540)
Constant	61.07***	21.06***	60.53***	26.01***
	(16.47)	(5.957)	(15.28)	(6.069)
Observations	68	68	68	68

Notes: Columns 1 and 2 present the results of regression $SCC_j = SCC_0 + \beta \cdot SE(SCC_j) + u_j$, where SCC_j is the median estimate of the social cost of carbon reported in the j-th study and $SE(SCC_j)$ is the corresponding approximate standard error computed from the distribution of estimates in the study. Columns 3 and 4 present the results of regression $SCC_j = SCC_0 + \beta \cdot SE(SCC_j) + \gamma \cdot SE^{up}(SCC_j) + u_j$, where $SE^{up}(SCC_j)$ is the corresponding approximate standard error computed from the 84$^{\text{th}}$ percentile of the distribution of estimates in the study. The standard errors of regression parameters are robust to heteroskedasticity and shown in parentheses. Precision = weighted by the inverse of the standard error. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

In Table 4 we repeat the previous exercise for study-level median estimates. In this setting, however, we have to omit the fixed-effects model, the mixed-effects model, and the weighted-least-squares regression with the inverse of the number of observations reported per study taken as the weight. Therefore we only report two sets of results, an OLS regression and a specification where estimates are weighted by their precision; both are run for the baseline relation between the estimates of the SCC and their standard errors and for the extended specification that includes the interaction of the standard error and the ratio of the upper and lower standard error (which simplifies to the upper standard error). The results concerning selective reporting are consistent with the evidence reported in Table 3: we obtain estimates of the selective reporting bias that are both statistically significant at the 5% and "substantial" according to the classification by Doucouliagos & Stanley (2013). In contrast to Table 3, however, we find consistently significant estimates of the mean SCC corrected for selective reporting: approximately between 20 and 60.

In Table 5 and Table 6 we examine whether our estimates of the magnitude of the selective reporting bias in the literature change when we control for additional aspects of estimates and studies. Table 5 focuses on the estimates for which the authors report a measure of uncertainty. In this setting we cannot use the fixed-effects specification, because some of the explanatory variables have the same value for all estimates reported in one study, so the variables would be perfectly correlated with individual study dummies. Note also that it makes little sense to interpret the constant in this regression; it still represents the mean value of the SCC corrected for selective reporting, but it is conditional on the values of all the other independent variables included in the regression. It is important that the estimates of the coefficient capturing selective reporting are consistent with the evidence reported in the previous tables: the estimates are statistically significant at the 5% level and lie in the range 1.2–2.3. The same findings hold in Table 6, where we use study-level medians and construct medians for the independent variables that are not defined at the study level.

In Table 7 we investigate whether publication characteristics are associated with selective reporting. To this end we use the baseline specification of the funnel asymmetry test and include interactions of the standard error and the number of citations, a dummy variable that equals one if the study is published in a peer-reviewed journal, and ranking of the journal. The results are consistent both for the sub-sample of estimates with uncertainty and for median estimates taken from individual studies: studies published in peer-reviewed journals tend to suffer more from selective reporting than unpublished papers. The number of citations and journal rank, in contrast, do not systematically influence the magnitude of the selective reporting bias.

Table 5: Controlling for heterogeneity, estimates with uncertainty

	OLS	PRTP	Precision	Study	ME
Standard error	1.800***	1.899**	2.344***	1.227***	1.800***
	(0.628)	(0.731)	(0.534)	(0.439)	(0.0806)
Reviewed	195.6	193.2	48.76	-52.38	195.6*
	(123.8)	(135.1)	(42.35)	(125.5)	(111.2)
Publication year	-12.16	-15.47	-2.430	12.09	-12.16
	(18.66)	(20.65)	(2.341)	(13.23)	(8.480)
Mean estimate	350.1**	-373.3	33.29	-24.50	350.1**
	(157.0)	(309.8)	(31.73)	(131.4)	(137.3)
Median estimate	288.9*	-153.5	46.00*	-24.53	288.9**
	(145.8)	(238.8)	(26.16)	(105.1)	(131.2)
Marginal costs	-823.3*	-1041.4**	-64.37	-123.6	-823.3**
	(476.7)	(476.4)	(82.34)	(228.1)	(357.1)
Dynamic impacts	-303.7	-41.23	-101.7	-162.0	-303.7**
	(189.0)	(220.5)	(91.32)	(130.1)	(150.3)
Scenarios	411.7*	296.2***	31.09	387.2	411.7***
	(231.8)	(93.62)	(32.69)	(247.5)	(121.2)
FUND	202.8	753.3***	49.34	-1.745	202.8
	(144.7)	(209.3)	(95.21)	(138.2)	(160.7)
DICE or RICE	40.25	785.3*	-33.27	-112.8	40.25
	(114.9)	(402.9)	(30.39)	(123.6)	(99.38)
PAGE	-13.54	879.8**	-38.93	59.47	-13.54
	(100.4)	(399.9)	(28.10)	(77.51)	(83.10)
Equity weights	118.4	-50.70	17.53	-24.11	118.4
	(127.0)	(105.5)	(14.33)	(94.67)	(78.02)
Pigovian tax	213.2	-18.85	42.28	30.85	213.2**
	(148.6)	(61.46)	(36.31)	(100.5)	(95.60)
Citations	2.556	-65.95	-4.060	59.93	2.556
	(53.01)	(66.05)	(13.17)	(52.61)	(35.18)
Journal rank	-21.89	-6.780	-10.89	50.11	-21.89
	(50.63)	(67.52)	(10.81)	(70.51)	(45.80)
PRTP		-47.21			
		(35.44)			
Constant	255.3	868.6	79.47	-611.6	255.3
	(701.8)	(722.9)	(117.9)	(577.8)	(460.7)
Observations	267	217	267	267	267

Notes: The table presents the results of regression $SCC_{ij} = SCC_0 + \beta \cdot SE(SCC_{ij}) + \delta \cdot X_{ij} + u_{ij}$, where SCC_{ij} is the i-th estimate of the social cost of carbon reported in the j-th study, $SE(SCC_{ij})$ is the corresponding approximate standard error computed from the lower bound of the reported confidence interval, and X is a vector of the estimate's characteristics. Standard errors are clustered at the study level and shown in parentheses. OLS = an ordinary least squares regression using all estimates. PRTP = only estimates for which the authors report the pure rate of time preference used in the computation. Precision = weighted by the inverse of the standard error. Study = weighted by the inverse of the number of estimates reported per study. ME = study-level mixed effects. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

Table 6: Controlling for heterogeneity, study-level medians

	All estimates		PRTP	
	OLS	Precision	OLS	Precision
Standard error	1.589***	1.851***	1.654***	1.851***
	(0.425)	(0.375)	(0.495)	(0.446)
Reviewed	81.20	-16.86	93.95	-24.14**
	(83.47)	(13.09)	(71.90)	(9.920)
Publication year	10.73	0.764	11.98	1.031
	(7.146)	(0.607)	(9.059)	(0.742)
Mean estimate	16.47	-22.67	4.793	-9.382
	(28.62)	(21.41)	(56.41)	(19.02)
Median estimate	27.90	48.09	84.64*	3.734
	(38.79)	(46.46)	(49.34)	(26.10)
Marginal costs	-133.3	-26.95*	-160.0	-6.354
	(86.94)	(14.95)	(124.3)	(12.76)
Dynamic impacts	17.84	9.220	-58.19	-18.98
	(46.98)	(23.39)	(85.12)	(24.30)
Scenarios	6.820	28.19*	-62.67	-2.849
	(33.18)	(16.14)	(61.30)	(14.83)
FUND	-68.63	-27.48	104.7	6.847
	(56.58)	(31.29)	(75.86)	(23.96)
DICE or RICE	-45.27	29.69**	-7.099	10.32
	(66.20)	(14.09)	(67.90)	(14.38)
PAGE	136.4	44.90*	251.8	26.45
	(98.68)	(26.30)	(229.1)	(28.57)
Equity weights	-23.66	29.96	-64.86	13.23
	(82.51)	(19.56)	(116.8)	(16.38)
Pigovian tax	7.854	-13.88	54.04	-0.107
	(32.06)	(15.28)	(48.21)	(16.74)
Citations	34.00	-1.969	47.56	0.835
	(25.44)	(3.763)	(35.67)	(2.428)
Journal rank	-10.61	6.241*	-22.29	3.532
	(12.20)	(3.638)	(14.59)	(3.488)
PRTP			-23.29	4.893
			(34.28)	(8.478)
Constant	-256.9	7.316	-273.3	3.199
	(283.6)	(21.95)	(364.5)	(25.15)
Observations	68	68	53	53

Notes: The table presents the results of regression $SCC_j = SCC_0 + \beta \cdot SE(SCC_j) + \delta \cdot X_j + u_j$, where SCC_j is the median estimate of the social cost of carbon reported in the j-th study, $SE(SCC_j)$ the corresponding approximate standard error computed from distribution of estimates in the study, and X is a vector of the estimate's characteristics. Standard errors are robust to heteroskedasticity and shown in parentheses. PRTP = only estimates for which the authors report the pure rate of time preference used in the computation. Precision = weighted by the inverse of the standard error. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

The finding that selective reporting is associated more with published studies than unpublished manuscripts could indicate that self-censorship is not the only source of selection in the literature on the social cost of carbon. The results are consistent with a situation when journal editors or referees prefer estimates of the SCC that are conclusive; that is, the estimates for which the approximate 95% confidence interval excludes zero. Nevertheless, the same pattern would be achieved through self-censorship if the authors believed that editors and referees preferred conclusive estimates and, therefore, selected such estimates for submission to journals.

Table 7: What drives selective reporting?

	Estimates with uncertainty			Study-level medians	
	OLS	Precision	ME	OLS	Precision
Standard error	0.793*	0.650	0.891***	1.342***	1.692***
	(0.427)	(0.536)	(0.178)	(0.204)	(0.426)
SE · Reviewed	3.409***	2.548***	3.593***	2.581***	1.386**
	(0.862)	(0.645)	(0.252)	(0.833)	(0.555)
SE · Citations	-0.494	-0.127	-0.548***	-0.130	-0.0990
	(0.300)	(0.248)	(0.109)	(0.110)	(0.133)
SE · Journal rank	-0.368	-0.453*	-0.297***	-0.269**	-0.0974
	(0.248)	(0.250)	(0.0860)	(0.118)	(0.0590)
Constant	44.92**	12.48**	-15.34	31.15	19.29***
	(21.25)	(5.814)	(37.13)	(19.68)	(5.997)
Observations	267	267	267	68	68

Notes: Columns 1–3 present the results of regression $SCC_{ij} = SCC_0 + \beta \cdot SE(SCC_{ij}) + \epsilon \cdot X_{ij} \cdot SE(SCC_{ij}) + u_{ij}$, where SCC_{ij} is the i-th estimate of the social cost of carbon reported in the j-th study, $SE(SCC_{ij})$ is the corresponding approximate standard error computed from the lower bound of the reported confidence interval, and X is a vector of the estimate's characteristics. Columns 4 and 5 present the results of regression $SCC_j = SCC_0 + \beta \cdot SE(SCC_j) + \epsilon \cdot X_j \cdot SE(SCC_j) + u_j$, where SCC_j is the median estimate of the social cost of carbon reported in the j-th study, $SE(SCC_j)$ is the corresponding approximate standard error computed from the distribution of estimates in the study, and X is a vector of the estimate's characteristics. The standard errors of regression coefficients are clustered at the study level (or robust to heteroskedasticity in columns 4 and 5) and shown in parentheses. Precision = weighted by the inverse of the standard error. ME = study-level mixed effects. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

6 Concluding Remarks

In this paper we conduct a meta-analysis of the literature estimating the social cost of carbon. We examine 809 estimates of the SCC reported in 101 primary studies. We employ meta-regression methods commonly used in economics and other fields to detect potential selective reporting in the literature. Our results suggest that, on average, the authors of primary studies tend to report preferentially estimates for which the 95% confidence interval excludes zero, which creates an upward bias in the literature. In other words, we observe that small estimates of the SCC are associated with less uncertainty (expressed as the approximate standard error used to compute the lower bound of the confidence interval) than large estimates. The finding suggests that some small estimates with large uncertainty—that is, not ruling out negative values of the SCC—might be selectively omitted from the literature. Our results also indicate that selective reporting tends to be stronger in studies published in peer-reviewed journals than in unpublished manuscripts.

Three qualifications are in order. First, we do not suggest that selective reporting in the literature on the social cost of carbon is intentional; in contrast, we believe that, as in many other fields of economics, it reflects the implicit urge to produce interesting results that are useful for policy-making: results that, in this case, help save the planet. There is an overwhelming consensus that the social costs of carbon are positive, so perhaps it makes sense to disregard estimates that are inconsistent with this view, because they probably arise from model misspecification or other estimation shortcomings. The problem is that while unintuitively small estimates are easy to recognize because of the natural lower limit of zero, there exists no obvious upper limit for the SCC. If researchers omit many small estimates but report most of the large ones (which might also be due to random misspecifications), the literature gets on average skewed toward larger estimates.

Second, we use meta-analysis methods that are designed for the synthesis of regression estimates. The estimates of the social cost of carbon are not regression-based, but mostly produced by calibrations and Monte Carlo simulations. When the authors report confidence intervals for their estimates, we argue we can use the same intuition which underlies the classical meta-analysis methods for the detection of selection reporting. Nevertheless, the large asymmetry in uncertainty about the SCC—in particular, uncertainty about potential high-impact catastrophic events triggered by climate change—leads to asymmetrical confidence intervals reported in many studies, which may, in turn, influence our estimates of the selective reporting bias. While the classical meta-analysis methods assume a symmetrical distribution of estimates, we find no evidence that the asymmetry would drive the results in our case.

Third, our results concerning selective reporting are based on a sub-sample of all available estimates of the social cost of carbon. Only about a third of the estimates are reported with a measure of uncertainty from which approximate standard errors can be computed. As an alternative, we also explore the distribution of estimates reported in studies (even if no measures of uncertainty are reported for the individual estimates), but for this exercise we can only use studies that report multiple estimates of the SCC. Both approaches produce remarkably similar results concerning the magnitude of selective reporting in the literature, but yield different estimates of the SCC corrected for the selective reporting bias: the values vary in the range 0–130 USD per ton of carbon in 2010 prices for emission year 2015. The range corresponds to the mean of median SCC values obtained by individual models or studies, not a confidence interval for the "true" SCC: especially the upper bound is difficult to pin down because of the potential catastrophic outcomes of climate change, whose probability is difficult to quantify.

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Appendix: Included Studies and Summary Statistics

Table 8: List of studies used in the meta-analysis

Ackerman & Munitz (2012)	Haraden (1993)	Nordhaus (1994)
Ackerman & Stanton (2012)	Hohmeyer & Gaertner (1992)	Nordhaus & Yang (1996)
Anthoff *et al.* (2009a)	Hohmeyer (1996)	Nordhaus & Popp (1997)
Anthoff *et al.* (2009b)	Hohmeyer (2004)	Nordhaus & Boyer (2000)
Anthoff *et al.* (2009c)	Hope & Maul (1996)	Nordhaus (2008)
Anthoff & Tol (2010)	Hope (2005a)	Nordhaus (2010)
Anthoff *et al.* (2011)	Hope (2005b)	Nordhaus (2011)
Anthoff & Tol (2013)	Hope (2006)	Nordhaus & Sztorc (2014)
Ayres & Walter (1991)	Hope (2008a)	Parry (1993)
Azar (1994)	Hope (2008b)	Pearce (2003)
Azar & Sterner (1996)	Hope (2011)	Peck & Teisberg (1993)
van den Bijgaart *et al.* (2013)	Howarth *et al.* (2014)	Penner *et al.* (1992)
Botzen & van den Bergh (2012)	Hwang *et al.* (2013)	Perrissin-Fabert *et al.* (2012)
Cai *et al.* (2012)	Jensen & Traeger (2014a)	Plambeck & Hope (1996)
Cai *et al.* (2013)	Jensen & Traeger (2014b)	Pycroft *et al.* (2011)
Ceronsky *et al.* (2011)	Johnson & Hope (2012)	Pycroft *et al.* (2014)
Clarkson & Deyes (2002)	Kemfert & Schill (2010)	Reilly & Richards (1993)
Cline (1992)	Kopp *et al.* (2012)	Rezai & van der Ploeg (2014)
Cline (1997)	Lemoine & Traeger (2014)	Roughgarden & Schneider (1999)
Cline (2004)	Link & Tol (2004)	Schauer (1995)
Dennig (2013)	Lintunen & Vilmi (2013)	Sohngen (2010)
Dietz (2011)	Maddison (1995)	Stern *et al.* (2006)
Downing *et al.* (1996)	Manne (2004)	Stern & Taylor (2007)
Downing *et al.* (2005)	Marten & Newbold (2012)	Tol (1999)
EPA & NHTSA (2009)	Mendelsohn (2004)	Tol & Downing (2001)
Espagne *et al.* (2012)	Moyer *et al.* (2013)	Tol (2005a)
Eyre *et al.* (1999)	Narita *et al.* (2009)	Tol (2010)
Fankhauser (1994)	Narita *et al.* (2010)	Tol (2012)
Foley *et al.* (2013)	Newbold *et al.* (2013)	Tol (2013a)
Gerlagh & Liski (2012)	Newbold & Marten (2014)	Uzawa (2003)
Golosov *et al.* (2014)	Newell & Pizer (2003)	Wahba & Hope (2006)
Greenstone *et al.* (2013)	Nordhaus (1982)	Waldhoff *et al.* (2011)
Guo *et al.* (2006)	Nordhaus (1991)	Weitzman (2013)
Haraden (1992)	Nordhaus (1993)	

Notes: The last study was added on August 1, 2014.

Table 9: Summary statistics, estimates with standard errors

Variable	Description	Obs.	Mean	Std. dev.
SCC	The reported estimate of the social cost of carbon in USD per ton of carbon (normalized to 2015 emission year in 2010 dollars).	267	411	521
Standard error	The approximate standard error of the estimate computed from the reported lower bound of the confidence interval.	267	162	235
Upper SE	The approximate standard error of the estimate computed from the reported upper bound.	267	1182	1921
Reviewed	= 1 if the study was published in a peer-reviewed outlet.	267	0.94	0.24
Publication year	The year of publication of the study (base: 1982).	267	27.9	4.88
Mean estimate	= 1 if the reported SCC estimate is the mean of the distribution.	267	0.30	0.46
Median estimate	= 1 if the reported SCC estimate is the median of the distribution.	267	0.64	0.48
Marginal costs	= 1 if the study estimates marginal damage costs (damage from an additional ton of carbon emitted) rather than average costs (the total impact divided by the total emissions of carbon).	267	1.00	0.06
Dynamic impacts	= 1 if the study examines dynamic impacts of climate change or uses a dynamic model of vulnerability.	267	0.12	0.32
Scenarios	= 1 if the study uses climate and economic scenarios that are internally consistent. A few studies use arbitrary assumptions about climate change.	267	0.96	0.19
FUND	= 1 if the authors use the FUND model or derive their model from FUND.	267	0.13	0.34
DICE or RICE	= 1 if the authors use the DICE/RICE model or derive their model from DICE/RICE.	267	0.69	0.46
PAGE	= 1 if the authors use the PAGE model or derive their model from PAGE.	267	0.32	0.47
PRTP	The pure rate of time preference assumed in the estimation.	217	1.12	1.54
Equity weights	= 1 if equity weighting is applied.	267	0.15	0.36
Pigovian tax	= 1 if the estimate is computed along a trajectory of emissions in which the marginal costs of emission reduction equal the SCC, then the estimate corresponds to a Pigovian tax.	267	0.57	0.50
Citations	= The logarithm of the number of Google Scholar citations of the study.	267	3.25	0.92
Journal rank	= SciMago journal rank based on the impact factor extracted from Scopus.	267	0.48	0.86

Notes: Data are collected from studies estimating the social cost of carbon. The data set is available at `meta-analysis.cz/scc`.

Table 10: Summary statistics, study-level medians

Variable	Description	Obs.	Mean	Std. dev.
SCC	The reported estimate of the social cost of carbon in USD per ton of carbon (normalized to 2015 emission year in 2010 dollars).	68	201	344
Standard error	The approximate standard error of the estimate computed from the reported lower bound of the confidence interval.	68	93	184
Upper SE	The approximate standard error of the estimate computed from the reported upper bound.	68	237	327
Reviewed	= 1 if the study was published in a peer-reviewed outlet.	68	0.72	0.45
Publication year	The year of publication of the study (base: 1982).	68	24.5	7.49
Mean estimate	= 1 if the reported SCC estimate is the mean of the distribution.	68	0.30	0.46
Median estimate	= 1 if the reported SCC estimate is the median of the distribution.	68	0.09	0.29
Marginal costs	= 1 if the study estimates marginal damage costs (damage from an additional ton of carbon emitted) rather than average costs (the total impact divided by the total emissions of carbon).	68	0.91	0.29
Dynamic impacts	= 1 if the study examines dynamic impacts of climate change or uses a dynamic model of vulnerability.	68	0.37	0.49
Scenarios	= 1 if the study uses climate and economic scenarios that are internally consistent. A few studies use arbitrary assumptions about climate change.	68	0.76	0.43
FUND	= 1 if the authors use the FUND model or derive their model from FUND.	68	0.31	0.47
DICE or RICE	= 1 if the authors use the DICE/RICE model or derive their model from DICE/RICE.	68	0.29	0.46
PAGE	= 1 if the authors use the PAGE model or derive their model from PAGE.	68	0.24	0.43
PRTP	The pure rate of time preference assumed in the estimation.	53	1.44	1.01
Equity weights	= 1 if equity weighting is applied.	68	0.19	0.39
Pigovian tax	= 1 if the estimate is computed along a trajectory of emissions in which the marginal costs of emission reduction equal the SCC, then the estimate corresponds to a Pigovian tax.	68	0.20	0.40
Citations	= The logarithm of the number of Google Scholar citations of the study.	68	3.35	1.49
Journal rank	= SciMago journal rank based on the impact factor extracted from Scopus.	68	1.62	2.74

Notes: Data are collected from studies estimating the social cost of carbon. The data set is available at `meta-analysis.cz/scc`.