Estimates of the social cost of carbon have increased over time

Richard S.J. Tol

1Department of Economics, Jubilee Building, University of Sussex, Falmer, BN1 9SL, United Kingdom, r.tol@sussex.ac.uk
2Institute for Environmental Studies, Vrije Universiteit, Amsterdam, The Netherlands
3Department of Spatial Economics, Vrije Universiteit, Amsterdam, The Netherlands
4Tinbergen Institute, Amsterdam, The Netherlands
5CESifo, Munich, Germany
6Payne Institute for Public Policy, Colorado School of Mines, Golden, CO, USA

August 4, 2022

Abstract

A meta-analysis of published estimates shows that the social cost of carbon has increased as knowledge about climate change accumulates. Correcting for inflation and emission year and controlling for the discount rate, kernel density decomposition reveals a non-stationary distribution. In the last 10 years, estimates of the social cost of carbon have increased from $33/tC to $146/tC for a high discount rate and from $446/tC to $1925/tC for a low discount rate. Actual carbon prices are almost everywhere below its estimated value and should therefore go up.

Significance statement

Greenhouse gas emissions should be taxed at the social cost of carbon. Many estimates have been published, ranging from -$1,000/tC to +$110,000,000/tC. I use kernel density estimation to reflect the large and asymmetric uncertainty, and kernel decomposition to test for changes over time. Correcting for inflation and emission year, and controlling for the discount rate, I show that estimates of the social cost of carbon have increased over time—estimates have more than quadrupled over the last 10 years. This justifies a tightening of climate policy.
Main

The social cost of carbon is a key indicator of the seriousness of climate change. Have its estimates changed over time? Should we raise our ambitions to reduce greenhouse gas emissions? Have we learned since the first estimate was published in 1982[1]? There is broad agreement among scholars that greenhouse gas emissions should be taxed, but the uncertainty about the optimal level of that tax is very large. I estimate the probability distribution of published estimates of the social cost of carbon and how it changes over time. I develop and apply a non-parametric test for the stationarity of this, and apply a range of other statistical tests, to show that we have. An upwards trend can be discerned. Climate policy should be intensified.

The social cost of carbon is the damage done, at the margin, by emitting more carbon dioxide into the atmosphere. If evaluated along the optimal emissions trajectory, the social cost of carbon equals the Pigou tax[2, 3] that internalizes the externality and restores the economy to its Pareto optimum[4] where no one can be made better off without making someone else worse off. The social cost of carbon is then the optimal carbon price. It informs the desired intensity of climate policy.

Some have argued[5, 6] that the debate on optimal climate policy is over since the Paris Agreement has set targets for international climate policy. Analysis should focus on the cheapest way of meeting these targets, and emissions should be priced based on the shadow price of carbon, which is the scarcity value of the carbon budget.[5] The shadow price is different from the social cost of carbon, and their growth rates are different too. However, the first stock-take of the commitments under the Paris Agreement[7] reveals that few countries plan to do what is needed to meet the agreed targets. The debate over the ultimate target of international climate policy, and so the debate on the social cost of carbon, is not over. Indeed, President Biden reinstated (and renamed) the Interagency Working Group on the Social Cost of Greenhouse Gases to reassess the appropriate carbon price.[8]

There is a large literature on the social cost of carbon spanning four decades[1, 9]. The social cost of carbon depends on many things, including the total economic impact of climate change, potential tipping points, the scenarios for population, economy and emissions, changes in vulnerability and relative prices with development, the rate of degradation of carbon dioxide from the atmosphere, the rate and level of global warming, the discount rate, the distribution of impacts and inequity aversion, and the uncertainties about impacts and risk aversion. The estimates used here—5,905 estimates in 207 papers, published before 2022—make different assumptions about all these matters.

These are estimates of the social cost of carbon for carbon dioxide emitted in the recent past. The carbon tax should increase over time (until climate change has been mitigated to the point that its marginal impacts start to fall[10]). 94 papers estimate how fast, showing estimates of the social cost of carbon at two or more points in time, for a total of 1,974 estimates of the growth rate of the social cost of carbon.
I apply meta-analysis to these estimates. Meta-analysis is not the only way to make the social cost of carbon more transparent. Sensitivity analysis[11] and model comparison[12] are insightful too. Decomposition of model updates[13, 14] helps to understand the evolution of estimates, but only within the confines of a single model. Closed-form equations [15, 16] give an exact relationship between input parameters and the social cost of carbon, but require rather restrictive and unrealistic assumptions. Only meta-analysis can show how the entire literature has evolved over time.

Figure 1 shows the mean and standard deviation of estimates of the social cost of carbon by year of publication. Estimates are shown with and without standardization. The social cost of carbon is expressed in 2010 US dollars per metric tonne of carbon, for emissions in the year 2010. The literature uses nominal dollars and a variety of emission years. See Figure S9. Particularly, later studies report the social cost of carbon in later dollars for later emission years. Average inflation was 2.9% over the period. The social cost of carbon grows by some 2.2% per year; this is the average across the 94 studies that estimate its growth rate; see Figure S7. Without correcting for emission year and inflation, the apparent trend in the social cost of carbon equals 5.1% per year. After correction, some of the early estimates are the highest. Between 1993 and 2008, estimates went up and down without a discernible trend in either direction. Since 2009 or so, there appears to be an increase in the social cost of carbon, and three of the last four years stand out. An earlier meta-analysis finds that the social cost of carbon has not increased over time[17] but a more recent one finds that it has[18]. The mean for 2021 is higher than all but two other years; paired t-tests shows the 2021 mean is statistically significantly higher than all but four other years.

Figure 1 shows that the range of estimates is large and has remained large over the years, perhaps even grown recently. An assessment of the literature of the social cost of carbon should reflect that uncertainty, not just the first and second moment, but the entire probability distribution. Figure 1 is incomplete. In this paper, I use bespoke kernel methods to reflect the true uncertainties—including the uncertainties about parameter values, model structure, future scenarios, and ethics.

The uncertainty about the social cost of carbon is right-skewed, [19] because the uncertainty about climate sensitivity is,[20] because impact functions are non-linear,[21] and because of risk aversion.[22] This asymmetry is lost by adding and subtracting the standard error from the mean, as is done in Figure 1. The uncertainty about the social cost of carbon is thick- or even fat-tailed.[23] There is considerably more probability mass outside the Gaussian confidence bounds. The above t-tests are overconfident. If the distribution of the social cost of carbon is right-skewed and fat-tailed, then recent estimates may well be within the historical range.

Kernel densities are a flexible alternative to parametric distribution functions[24]. Kernel densities have been used to visualize the uncertainty about the social cost of carbon.[25] I here add many more observations, and decompose that uncertainty into discrete components, particularly publication periods,
testing whether the components differ from one another. Simple kernel regression is helpful for specifying the relationship between two variables.[26] Kernel quantile regression can be used to show this relationship across the distribution.[27] However, these methods are not suitable if the explanatory variable is categorical—as is the case for assumed discount rates, authors, or recorded years of publication. The method proposed here, kernel density decomposition, works for categorical data, shows both central tendency and spread, and does not make assumptions about functional form or the shape of the probability distribution. This method, while uncommon, is therefore best suited for the problem at hand.

Kernel density decomposition offer a valid basis for statistical tests. In order to test for changes over time, I split the sample into six periods, demarcated by important events in the publication history of the social cost of carbon. These key events are the Second Assessment Report of the Intergovernmental Panel on Climate Change[28], the Third Assessment Report of the IPCC[29], the Stern Review[30], the Obama update of the social cost of carbon[31], and the 2018 Nobel Memorial Prize in Economic Sciences.[32]

The kernel density is estimated with bespoke kernel functions, reflecting the deep and asymmetric uncertainty of the social cost of carbon. The data are weighted for quality—age, computational method, scenario, peer-review, validity, novelty—but the results are largely robust to these weights. Furthermore, implausibly high estimates are censored or, in the appendix, winsorized. The decomposition of the kernel density is based on the fact that the weighted sum of probability densities is a probability density.[33] The statistical test is that for the equality of proportions[34], adjusted for finite sample size. Applied to different publication periods, this is a test for the stationarity of the distribution[35] of the social cost of carbon. See Methods for the details, the Supplementary Information for sensitivity analyses.

Figure 2 (bottom panel) shows the kernel density of the social cost of carbon and its the decomposition by publication period. The kernel density has the same shape as the histogram in Figure 2 (top panel): There is a little probability mass below zero, a pronounced mode, and a thick right tail. Compared to the histogram, the kernel density is smooth and spread wider. This is also seen in Table 1: Kernel mean and standard deviation are larger than their empirical counterparts because (1) I use the mode rather than the mean as the central estimate and (2) I assume a right-skewed kernel function.

Earlier studies exclude negative estimates, and the kernel density decomposition shows a fatter right tail for recent years. Table S5 confirms this. It shows the contributions of estimates of the social cost of carbon published in a particular period to the overall kernel density and its quintiles. The null hypothesis that the quintile shares are the same as the overall shares is rejected; \(\chi^2_{20} = 12.77\) is larger than the critical value at 1%.

This analysis only considers time. Figure S10 shows that the discount rate used to estimate the social cost of carbon has varied over time. Particularly, the once popular pure rate of time preference of 3.0% has been largely replaced by 1.5%. This would increase estimates of the social cost of carbon. Table 1 and
Figure S16 confirm this. Of course, economists using a different discount rate does not mean that the discount rate itself has changed.[36]

Table 2 therefore repeats the analysis for the four pure rates of time preference for which there are observations in every time period: 0%, 1%, 2% and 3% (see Table S1). Conditional on the pure rate of time preference, the Equality of Proportions test finds statistically significant differences between the publication periods, except for the lowest discount rate. The Kolmogorov-Smirnov test finds differences at a finer resolution but not for quintiles (see Table S10). Note that these tests does not reveal how things have changed, only that they have.

Five more analyses are included in the Supplementary Material. These analyses assume normality of error terms, avoiding the asymmetry and thick tail that are a feature of the social cost of carbon but make upward trends harder to detect. The first additional analysis is a weighted linear regression of the social cost of carbon on the pure rate of time preference, which shows a highly significant coefficient, and the year of publication, which is insignificant; either result is independent of the weights used. See Table S15. In a second analysis, the pure rate of time preference is dropped. The time trend is still insignificant. In the third analysis, the linear time trend is replaced by a flexible time trend. Again, the effect of publication year is insignificant regardless of weights. See Figure S15. Fourthly, quantile regression is used. The pure rate of time preference is significant for almost all quantiles and weights; the year of publication for almost none. However, the social cost of carbon appears to increase over time if estimates are weighted for quality and attention is restricted to the central parts of the distribution. See Table S15. Fifthly, the pure rate of time preference is dropped again. A trend appears in the 30th percentile, and in the median and 90th percentile if quality weights are used. All together, the upward trend in Figure 1 is partly because analysts have used lower discount rates but also because higher-quality studies have become more pessimistic about climate change.

Earlier claims of an increase in the social cost of carbon[14, 37–39] are confirmed. There is an apparent upward trend because estimates are reported for later years, because of price inflation, and because later analyses tend to use lower discount rates. Correcting for these factors and properly accounting for the asymmetric, heavy-tailed uncertainty, there is indeed a statistically significant time trend in published estimates of the social cost of carbon.

Table 3 shows how much estimates of the social cost of carbon have changed. Between earlier periods, estimates went up and down. In the last 10 years, however, there has been a steady increase. For a pure rate of time preference of 3%, 2% or 0%, the estimates more than quadrupled in 2018-2022 compared to 2007-2013. For all estimates, the increase is smaller while estimates decrease for a 1% PRTP. Overall, however, economists have become more pessimistic about climate change and its impacts.

Research continuously refines our knowledge and updates our estimates, sometimes upwards, sometimes downwards. There are still many things left to research[40] and things that have been studied but are not yet reflected in
our estimates of the social cost of carbon.[41, 42] Researchers will continue to disagree on how best to express the ethical dimensions of the social cost of carbon. Moreover, the social cost of carbon reflects the impact of future climate change and the future will remain uncertain.

The implication of the meta-analysis presented here is that the literature on the social cost of carbon does justify an upward revision of carbon prices and emission reduction targets. Furthermore, the literature, summarized in Table 1, suggests that, in most of the world, the price of carbon is too low. This is partly because other kinds of climate policies suppress the price of emission permits or reduce the need for a carbon tax. Almost 80% of greenhouse gas emissions is not priced at all.[43]. Only the EU ETS, now with permit prices around $250/tC, is in the ballpark of published estimates of the social cost of carbon.[44] There is often a gap between the announced emissions targets and the policies supposed to achieve the targets.[7] Besides raising the social cost of carbon, the recommended carbon price, policy makers should focus on raising the actual price of carbon.

| PRTP | empirical | kernel |
|------|-----------|--------|
| 3%   | 43        | 81     |
|      | (54)      | (79)   |
| 2%   | 238       | 663    |
|      | (492)     | (641)  |
| 1%   | 155       | 420    |
|      | (318)     | (502)  |
| 0%   | 407       | 841    |
|      | (539)     | (806)  |
| all  | 179       | 509    |
|      | (382)     | (560)  |

Table 1: Empirical and kernel average (standard deviation) of estimates of the social cost of carbon ($/tC) by pure rate of time preference (PRTP).

| Test statistic | p-value | 10% | 5% | 1% |
|----------------|---------|-----|----|----|
| All            | 11.82   | 0.92| 5.83| 6.86|9.51|
| PRTP = 0%      | 1.05    | 1.00| 3.23| 4.02|5.47|
| PRTP = 1%      | 7.88    | 0.99| 3.68| 4.85|6.47|
| PRTP = 2%      | 15.07   | 0.77| 3.21| 4.08|6.15|
| PRTP = 3%      | 14.59   | 0.80| 2.12| 3.24|5.21|

Table 2: Test for the equality of quintiles between selected publication periods and the whole record, for the whole sample and for selected pure rates of time preference. The third column shows the p-value of the asymptotic $\chi^2_{20}$ test, the next three columns bootstrapped critical values.
Table 3: The kernel mean of social cost of carbon ($/tC) by publication period and pure rate of time preference (PRTP). Estimates are quality weighted and censored.

| PRTP | 1982-1995 | 1996-2001 | 2002-2006 | 2007-2013 | 2014-2017 | 2018-2022 |
|------|-----------|-----------|-----------|-----------|-----------|-----------|
| any  | 847       | 408       | 277       | 328       | 373       | 683       |
| 3%   | 26        | 129       | 36        | 33        | 64        | 146       |
| 2%   | 44        | 60        | 74        | 195       | 257       | 1315      |
| 1%   | 686       | 118       | 110       | 450       | 264       | 340       |
| 0%   | 573       | 1097      | 639       | 446       | 979       | 1925      |

Figure 1: Average social cost of carbon by publication year. Orange diamonds are as reported, blue dots are corrected for inflation and year of emission. Error bars are plus and minus the standard deviation of the published estimates. Estimates are quality weighted and censored.
Figure 2: Histogram of the social cost of carbon. Results are quality-weighted and censored (top panel). Composite kernel density of the social cost of carbon and its composition by publication period (bottom panel).
Methods

Kernel density decomposition

A kernel density is defined as

\[ f(x) = \frac{1}{nh} \sum_{i=1}^{n} K \left( \frac{x - x_i}{h} \right) \]  \hspace{1cm} (1)

where \( x_i \) are a series of observations, \( h \) is the bandwidth, and \( K \) is the kernel function. The kernel function is conventionally assumed to be a (i) non-negative (ii) symmetric function that (iii) integrates to one, with (iv) zero mean and (v) finite variance.[24] That is, any standardized symmetric probability density function can serve as a kernel function. The Normal density is a common choice.

Conventions are just that. As long as the kernel function is non-negative (the assumption of non-negativity is relaxed for bias reduction,[45]) and integrates to one, an appropriately weighted sum of kernel functions is non-negative and integrates to one—such a sum is a probability density function.[33, 46, 47]

The kernel density is thus defined as the sum of probabilities; see Equation (1). It is a vote-counting procedure[48] where the votes are uncertain. This interpretation fits the nature of the data. Estimates of the social cost of carbon are not “data” in the conventional sense of the word, nor can integrated assessment models be seen as “data generating processes”. Besides, I use the population of estimates rather than a sample. There is therefore no Frequentist interpretation of the proposed method. There is no Bayesian interpretation either. While we might take the kernel function to express degrees of belief, a Bayesian procedure would take the first estimates[1] as prior and later estimates as likelihoods, multiplying rather than adding probability densities. Because some of the estimates are mutually exclusive with other estimates, a Bayesian interpretation is problematic. In this interpretation, dependence between studies and estimates are not an issue: The repetition of a previous estimate raises confidence in that estimate.

A kernel density can also be seen as a mixture density.[49, 50]. This reinterpretation opens a route to decomposition. We can construct the kernel density of any subset of \( x_i \). The weighted sum of the kernel densities of all subsets is a kernel density.

With the right weights and bandwidths, the weighted sum of the kernel densities of subsets of the data is identical to the kernel density of the whole data set. To see this, partition the observations into \( m \) subsets of length \( m_j \) with \( \sum_j m_j = n \), as \( x_1, x_2, \ldots, x_{m_1}, x_{m_1+1}, \ldots, x_{m_1+m_2}, x_{m_1+m_2+1}, \ldots, x_n \). Then

\[ f(x) = \sum_{j=1}^{m} \frac{m_j}{n} \frac{1}{m_j h} \sum_{i=\sum_{k=1}^{j-1} m_k+1}^{\sum_{k=1}^{j} m_k} K \left( \frac{x - x_i}{h} \right) =: \sum_{j=1}^{m} \frac{m_j}{n} f_j(x) \]  \hspace{1cm} (2)
In the middle expression, the inner sum is a sum of kernel functions. The sum is over a subsample of the data. The outer sum is over all subsamples. As the weights and bandwidths are the same, the resulting kernel density is identical to Equation (1). Moreover, as shown by the right-most expression, each of the components \( f_j \) of the composite kernel density \( f \) is itself a kernel density. This is the kernel density for a subsample of the data.

Kernel decomposition works with any set of weights that add to one, and with any kernel function or bandwidth for the subsets:

\[
f(x) = \sum_{j=1}^{m} \frac{w_j}{m_j h_j} \sum_{i=\lfloor \sum_{k=1}^{j-1} m_k \rfloor + 1}^{\lfloor \sum_{k=1}^{j} m_k \rfloor} K_j \left( \frac{x - x_i}{h_j} \right) =: \sum_{j=1}^{m} w_j f_j(x; h_j) \tag{3}
\]

In this case, the composite kernel density is not the same as the kernel density fitted to the complete data set. It is hard to argue for different kernel functions \( K_j \) for different subsets of the data, but different subsets of the data would have different spreads and hence bandwidths \( h_j \). I do not do this here, instead use the same bandwidth for every subsample.

**Inference**

Equation (3) holds that the kernel density \( f(x) \) is composed of \( m \) kernel densities \( f_j(x) \) with weight \( m_j/n \). For each interval \( \bar{x} < x < \bar{x} \), I test whether the shares of the component densities equal its weight, using the Equality of Proportions test[34] but using the bootstrapped distribution rather than the asymptotic \( \chi^2 \) distribution proposed by Pearson. Suppose, for example, that a component density makes up 17% of the overall density. Then, the null hypothesis is that the left-tail, central part and right-tail of the component density also make up 17% of the left-tail, central part and right-tail of the overall density.

Let intervals correspond to \( p \) percentiles of the composite distribution. The test statistic is

\[
\chi^2_{(m-1)(p-1)} = \frac{n}{p} \sum_{k=0}^{p} \sum_{j=1}^{m} \left( \int_{P_{k+1}}^{P_k} f_j(x)dx - \frac{m_j}{m} \right)^2 \tag{4}
\]

The test only works if there are two components or more, \( m \geq 2 \). If not, there would be nothing to compare. The distribution needs to be split in two quantiles or more, \( p \geq 2 \), because each component density adds up to its weight \( m_j/n \) by construction. Again, there would be nothing to compare with fewer than two quantiles.

**References**

1. Nordhaus, W. D. How Fast Should We Graze the Global Commons? *American Economic Review* **72**, 242–246 (1982).
2. Pigou, A. *The Economics of Welfare* (Macmillan, London, 1920).

3. Bator, F. M. The Anatomy of Market Failure. *The Quarterly Journal of Economics* **72**, 351–379. [https://doi.org/10.2307/1882231](https://doi.org/10.2307/1882231) (1958).

4. Pareto, V. *Manuale di economia politica con una introduzione alla scienza sociale* (Società Editrice Libraria, Milan, 1906).

5. Kaufman, N., Barron, A., Krawczyk, W., Marsters, P. & McJeon, H. A near-term to net zero alternative to the social cost of carbon for setting carbon prices. *Nature Climate Change* **10**, 1010–1014 (2020).

6. Stern, N. & Stiglitz, J. E. *The Social Cost of Carbon, Risk, Distribution, Market Failures: An Alternative Approach* Working Paper 28472 (National Bureau of Economic Research, Feb. 2021). [http://www.nber.org/papers/w28472](http://www.nber.org/papers/w28472).

7. UNFCCC. *NDC Synthesis Report* tech. rep. (United Nations Framework Convention on Climate Change Secretariat, Feb. 2021). [https://unfccc.int/process-and-meetings/the-paris-agreement/nationally-determined-contributions-ndcs/nationally-determined-contributions-ndcs/ndc-synthesis-report](https://unfccc.int/process-and-meetings/the-paris-agreement/nationally-determined-contributions-ndcs/nationally-determined-contributions-ndcs/ndc-synthesis-report).

8. J.R. Biden. *Executive Order on Protecting Public Health and the Environment and Restoring Science to Tackle the Climate Crisis* tech. rep. (White House, Jan. 2021). [https://www.whitehouse.gov/briefing-room/presidential-actions/2021/01/20/executive-order-protecting-public-health-and-environment-and-restoring-science-to-tackle-climate-crisis/](https://www.whitehouse.gov/briefing-room/presidential-actions/2021/01/20/executive-order-protecting-public-health-and-environment-and-restoring-science-to-tackle-climate-crisis/).

9. Taconet, N., Guivarch, C. & Pottier, A. Social Cost of Carbon Under Stochastic Tipping Points. *Environmental & Resource Economics*. [https://link.springer.com/article/10.1007/s10640-021-00549-x](https://link.springer.com/article/10.1007/s10640-021-00549-x) (forthcoming).

10. van der Ploeg, F. & Withagen, C. Growth, Renewables, And The Optimal Carbon Tax. *International Economic Review* **55**, 283–311 (2014).

11. Anthoff, D. & Tol, R. J. The uncertainty about the social cost of carbon: A decomposition analysis using FUND. *Climatic Change* **117**, 515–530 (2013).

12. Diaz, D. & Moore, F. Quantifying the economic risks of climate change. *Nature Climate Change* **7**, 774–782 (2017).

13. Nordhaus, W. D. Evolution of modeling of the economics of global warming: changes in the DICE model, 1992–2017. *Climatic Change* **148**, 623–640 (2018).

14. Hänsel, M. *et al.* Climate economics support for the UN climate targets. *Nature Climate Change* **10**, 781–789 (2020).

15. Golosov, M., Hassler, J., Krusell, P. & Tsyvinski, A. Optimal Taxes on Fossil Fuel in General Equilibrium. *Econometrica* **82**, 41–88 (2014).
16. Van Den Bremer, T. & Van Der Ploeg, F. The risk-adjusted carbon price. *American Economic Review* **111**, 2782–2810 (2021).

17. Havranek, T., Irsova, Z., Janda, K. & Zilberman, D. Selective reporting and the social cost of carbon. *Energy Economics* **51**, 394–406 (2015).

18. Wang, P., Deng, X., Zhou, H. & Yu, S. Estimates of the social cost of carbon: A review based on meta-analysis. *Journal of Cleaner Production* **209**, 1494–1507. [http://www.sciencedirect.com/science/article/pii/S0959652618334589](http://www.sciencedirect.com/science/article/pii/S0959652618334589) (2019).

19. Tol, R. S. J. The marginal costs of greenhouse gas emissions. *Energy Journal* **20**, 61–81 (1999).

20. Roe, G. H. & Baker, M. B. Why Is Climate Sensitivity So Unpredictable? *Science* **318**, 629–632. [https://science.sciencemag.org/content/318/5850/629](https://science.sciencemag.org/content/318/5850/629) (2007).

21. Nordhaus, W. D. An Optimal Transition Path for Controlling Greenhouse Gases. *Science* **258**, 1315–1319 (1992).

22. Anthoff, D., Tol, R. S. J. & Yohe, G. W. Risk aversion, time preference, and the social cost of carbon. *Environmental Research Letters* **4**, 024002 (2009).

23. Weitzman, M. L. On Modeling and Interpreting the Economics of Catastrophic Climate Change. *The Review of Economics and Statistics* **91**, 1–19 (2009).

24. Takezawa, K. *Introduction to Nonparametric Regression* (John Wiley and Sons, Hoboken, 2005).

25. Tol, R. S. J. The Economic Impacts of Climate Change. *Review of Environmental Economics and Policy* **12**, 4–25. [https://doi.org/10.1093/reep/rex027](https://doi.org/10.1093/reep/rex027) (Jan. 2018).

26. Altman, N. An introduction to kernel and nearest-neighbor nonparametric regression. *American Statistician* **46**, 175–185 (1992).

27. Yu, K. & Jones, M. Local linear quantile regression. *Journal of the American Statistical Association* **93**, 228–237 (1998).

28. Pearce, D. W. *et al.* in *Climate Change 1995: Economic and Social Dimensions – Contribution of Working Group III to the Second Assessment Report of the Intergovernmental Panel on Climate Change* (eds Bruce, J. P., Lee, H. & Haïtes, E. F.) 179–224 (Cambridge University Press, Cambridge, 1996).

29. Smith, J. B. *et al.* in *Climate Change 2001: Impacts, Adaptation, and Vulnerability* (eds McCarthy, J. J., Canziani, O. F., Leary, N. A., Dokken, D. J. & White, K. S.) 913–967 (Press Syndicate of the University of Cambridge, Cambridge, UK, 2001).

30. Stern, N. H. *et al.* *Stern Review: The Economics of Climate Change* (HM Treasury, London, 2006).
31. Interagency Working Group on the Social Cost of Carbon. Technical support document: Technical update of the social cost of carbon for regulatory impact analysis under Executive Order 12866 Report (United States Government, 2013).

32. Nordhaus, W. Climate Change: The Ultimate Challenge for Economics. *American Economic Review* 109, 1991–2014. [https://www.aeaweb.org/articles?id=10.1257/aer.109.6.1991](https://www.aeaweb.org/articles?id=10.1257/aer.109.6.1991) (June 2019).

33. Quetelet, A. Lettres à S. A. R. le Duc Régnant de Saxe-Cobourget Gotha, sur la théorie des probabilités, appliquée aux sciences morales et politiques (Hayez, Brussels, 1846).

34. Pearson, K. On the criterion that a given system of deviations from the probable in the case of a correlated system of variables is such that it can be reasonably supposed to have arisen from random sampling. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science* 50, 157–175. [https://doi.org/10.1080/14786440009463897](https://doi.org/10.1080/14786440009463897) (1900).

35. Andrews, I. & Kasy, M. Identification of and Correction for Publication Bias. *American Economic Review* 109, 2766–94. [https://www.aeaweb.org/articles?id=10.1257/aer.20180310](https://www.aeaweb.org/articles?id=10.1257/aer.20180310) (Aug. 2019).

36. Drupp, M. A., Freeman, M. C., Groom, B. & Nesje, F. Discounting Disentangled. *American Economic Journal: Economic Policy* 10, 109–34. [https://www.aeaweb.org/articles?id=10.1257/pol.20160240](https://www.aeaweb.org/articles?id=10.1257/pol.20160240) (Nov. 2018).

37. Van Den Bergh, J. & Botzen, W. A lower bound to the social cost of CO₂ emissions. *Nature Climate Change* 4, 253–258 (2014).

38. Base the social cost of carbon on the science. *Nature* 541, 260 (2017).

39. Wagner, G. Recalculate the social cost of carbon. *Nature Climate Change* 11, 293–294 (2021).

40. Burke, M. *et al.* Opportunities for advances in climate change economics. *Science* 352, 292–293 (2016).

41. NAS. Valuing climate damages: Updating estimation of the social cost of carbon dioxide 1–262 (National Academies of Sciences, Engineering, and Medicine, Washington, D.C., 2017).

42. Wagner, G. *et al.* Eight priorities for calculating the social cost of carbon. *Nature* 590, 548–550 (2021).

43. WorldBank. *Carbon Pricing Dashboard* tech. rep. (International Bank for Reconstruction, Development, and the International Development Association, Sept. 2021). [https://carbonpricingsdashboard.worldbank.org/](https://carbonpricingsdashboard.worldbank.org/).

44. ICAP. *Allowance Price Explorer* tech. rep. (International Carbon Action Partnership, Apr. 2021). [https://icapcarbonaction.com/en/ets-prices](https://icapcarbonaction.com/en/ets-prices).
45. Jones, M. & Signorini, D. A comparison of higher-order bias kernel density estimators. *Journal of the American Statistical Association* **92**, 1063–1073 (1997).

46. Quetelet, A. Sur quelques propriétés curieuses que présentent les résultats d’une série d’observations, faites dans la vue de déterminer une constante, lorsque les chances de rencontrer des écarts en plus et en moins sont égales et indépendantes les unes des autres. *Bulletins de l’Académie royale des sciences, des lettres et des beaux-arts de Belgique* **19** (2), 303–317 (1852).

47. Pearson, K. III. Contributions to the mathematical theory of evolution. *Philosophical Transactions of the Royal Society of London. (A.)* **185**, 71–110. https://royalsocietypublishing.org/doi/abs/10.1098/rsta.1894.0003 (1894).

48. Laplace, P.-S. *Essai philosophique sur les probabilités* (Ve Courcier, Paris, 1814).

49. Makov, U. in *International Encyclopedia of the Social & Behavioral Sciences* (eds Smelser, N. J. & Baltes, P. B.) 9910–9915 (Pergamon, Oxford, 2001). ISBN: 978-0-08-043076-8.

50. McLachlan, G. & Peel, D. *Finite Mixture Models* (John Wiley and Sons, Hoboken, 2001).
Supplementary materials: Data and methods

Papers used in the meta-analysis

The database draws on earlier meta-analyses of the social cost of carbon,[1–6] extended with recent papers that were found using search engines and a review of the publication records of active researchers. 207 papers were used.[7–212] The record is close to complete for papers published before 2022.

Most of the papers report results in tabular format. Some only show results in graphs, but most authors emailed the underlying data upon request; if not, the Matlab routine grabit[213] was used to digitize the graphs.

The meta-analysis uses the estimate of the social cost of carbon, the year of emission, the year of the nominal dollar, the year of publication, the author, weights, censoring, and the pure rate of time preference. These data, plus some not used here, can be found on GitHub.

Other factors are known to also affect the social cost of carbon, notably the scenario used, the damage function assumed, and the curvature of the utility function. However, reporting is haphazard and the relationship with the social cost of carbon is complicated. I therefore omit these factors.

Descriptive statistics

Table S1 shows the number of estimates per publication period and discount rate, and the number of papers per period. Three papers are counted double because they present comparative results of two different models. There is an upward trend in the number of papers per period, and in the number of estimates per paper.

Table S2 shows the mean and standard deviation of the estimates of the social cost of carbon by publication period and year. The range of estimates has grown very wide in recent years.

Figure 2 (top panel) shows the histogram of the published estimates of the social cost of carbon, using quality weights and censoring (see below). Some estimates are negative, a social benefit of carbon, but the vast majority is positive. The mode lies between 0 and $50/tC, but there is a long right tail. The 95th percentile is $800/tC.

Bandwidth and kernel function

The choice of kernel function and bandwidth is key to any kernel density estimate, as illustrated in Figure S1. If kernel density estimation is interpreted as vote-counting, kernel and bandwidth should be chosen to reflect the nature of the data, shown in Figure 2 (top panel). In this case, the uncertainty about the social cost of carbon is large and right-skewed. Furthermore, the social cost of carbon is, most researchers argue, a cost and not a benefit.

A conventional choice would be to use a Normal kernel function, with a bandwidth according to the Silverman rule[214], that is, 1.06 times the sample
standard deviation divided by the fifth root of the number of observations. Figure S1 reveals two problems with this approach: The right tail of the resulting kernel density is thin, and a large probability mass is assigned to negative social costs of carbon. See Table S3. If the bandwidth instead equals the sample standard deviation to reflect the wide uncertainty, the right tail appropriately thickens but the probability of a Pigou subsidy on greenhouse gas emissions increases too.

In order to reflect the skew in the data, I transform the observations. As the social cost of carbon can be both positive and negative, I use the inverse hyperbolic sine. I assume a Normal kernel density with the transformed observation as its mean, mode and median and the sample standard deviation. In the dollar-per-tonne-of-carbon space, this is an arcsinh-normal kernel or Johnson’s SU distribution.[215] As shown in Table S3, this has two effects: The left tail, represented by the probability of a negative social cost of carbon, thins too much and right tail, represented by the chance of a social cost of carbon in excess of the Leviathan tax, thickens too much. The expected social cost of carbon escalates.

With conventional approaches less than satisfactory, unconventional ones should be tried. Many of the published estimates of the social cost of carbon are based on an impact function that excludes benefits of climate change. Climate change can only do damage and additional carbon dioxide can only be bad. Honouring that, I assign a knotted Normal kernel function to these observations. As the kernel function is asymmetric, centralization needs to be carefully considered—is $x_i$ in Equation (1) the mean, median or mode of $K$? I prefer to use the mode as its central tendency, in line with the interpretation of kernel density estimation as vote-counting (see above). With these assumptions, Figure S1 shows that the probability of a negative social cost of carbon falls. The studies that report the possibility of a negative social cost of carbon nonetheless argue in favour of a positive one. A symmetric Normal kernel does not reflect that. I therefore replace it with a Gumbel kernel:

$$f(x) = \frac{1}{\beta} \exp \left( -\frac{x - \mu}{\beta} - \exp \left( -\frac{x - \mu}{\beta} \right) \right)$$  \hspace{1cm} (S1)

The Gumbel distribution is defined on the real line but right-skewed. Again, I use the mode $\mu$ as its central tendency. This thickens the right tail and thins the left tail.

A knotted Normal kernel is not only peculiar near zero but it also has a thin tail. I therefore replace it with a Weibull kernel:

$$f(x) = \frac{\kappa}{\lambda} \left( \frac{x}{\lambda} \right)^{\kappa - 1} \exp \left( -\left( \frac{x}{\lambda} \right)^{\kappa} \right)$$  \hspace{1cm} (S2)

The Weibull is defined on the positive real line, $f(x)$ is near zero if $x$ is near zero, and right-skewed. I use the mode $\lambda (\kappa - 1/\kappa)^{1/\kappa}$ as its central tendency. The right tail of the kernel distribution thickens again.

The bottom line of Table S3 shows the Mean Integrated Square Error, the sum of the squared difference between the empirical frequency and modelled
probability, weighted by the empirical frequency. The Normal kernel function with the Silverman bandwidth performs best on this criterion, by construction. However, I give preference to the considerations above and use the Weibull-Gumbel kernel distribution as the default. The large probability of a carbon subsidy weighs particularly heavy against the Normal/Silverman kernel density.

The preferred mix of Weibull and Gumbel kernel functions leads to a kernel density that is discontinuous at zero. This is because the 1911 estimates from 42 studies that allow for climate change benefits are qualitative different from the estimates and studies that do not. The final kernel density is therefore a mixture of a density on the real line and a density on the positive real line. The discontinuity at zero follows inevitably.

The Matlab code can be found on GitHub.

Weights

The social cost of carbon is an estimate of the willingness to pay to reduce carbon dioxide emissions. Willingness to pay is limited by ability to pay. Papers that report a willingness to pay that exceeds income forgot to impose a key budget constraint. 282 out of 5,791 estimates violate this, from 11 papers (with one paper [212] having 232 disqualified estimates). No paper was completely excluded. If the estimated social cost of carbon were levied as a carbon tax, tax revenue would exceed total income. This is not possible: There would be no private income left. Those estimates, exceeding $7,609/tC (the global average carbon intensity in 2010), are excluded.

Another 1,186 estimates (from 37 papers) are so large that, if levied as a carbon tax, the public sector would grow beyond its global average of 15% in 2010, even if all other taxes would be abolished. Estimates in excess of this Leviathan tax [216], $1,141/tC, are discounted. The discount is linear, varying between 0 for $1,141/tC and 1 for $7,609/tC. At most half of the estimates from a single paper [175] were so discounted. Without these discounts, very large estimates of the social cost of carbon dominate the analysis; cf. Table S2.

The estimates of the social cost of carbon are weighted in four different ways. First, all estimates are treated equally. This is graph “no weights” in Figure S2. While some papers present a single estimate of the social cost of carbon, other papers show many, up to 1,229 variants [212]. This emphasizes studies that ran many sensitivity analyses, which became easier as computers got faster. Therefore, secondly, estimates are weighted such that the total weight per paper equals one. This is “paper weights” in Figure S2. Within each paper, estimates that are favoured by the authors are given higher weight. Favoured estimates are highlighted in the abstract and conclusions, and they are used as the starting point in robustness checks. Estimates that are shown in order to demonstrate that the new model can replicate earlier work are not favoured. I gave double weight to favoured estimates, noting that estimates can be doubly or triply favoured. Some papers report their favoured estimates multiple times, in which case no weights were applied. Authors weights are scaled to add to one. This is “author weights” in Figure S2.
Different experts have cast different numbers of votes. I count one paper as one vote. One can also argue that it should be one vote per expert, or that papers should be weighted by citations, journal prestige, or author pedigree. Composite kernel densities naturally allow for this, but it is a dangerous route to travel in this case. Older papers are cited more than younger papers; journal rankings are hard enough within disciplines, harder still between disciplines; and prestige, reputation and pedigree often reflect old glory rather than current wits.

Instead, I use a set of weights that reflect the quality of the paper. Over 95% of the estimates are peer-reviewed; these score 1; the rest score 0. Almost 95% use an emission scenario; these score 1; papers based on arbitrary emissions score 0 as do papers assuming a steady state. Almost 99% of estimates estimate the social cost of carbon as a true marginal or a small increment; these score 1; papers with ropy mathematics (e.g. no apparent mathematical model) score 0 as do papers reporting an average rather than a marginal. Over 68% of estimates assume that vulnerability to climate change is constant; these score 0; papers that recognize that the impacts of climate change vary with development score 1. Only 3% of estimates is based on new estimates of the total impact of climate change; these score 1; the rest score 0. These scores are added. This is “quality weights” in Figure S2.

Figure S2 shows the impact of the weights. The censoring of large estimates, in excess of the Leviathan tax or even in excess of income, has the largest effect. The maximum estimate in the data is $107,260,751/tC. Not even Jeff Bezos could afford to pay such a carbon tax. Including estimates like these, the kernel bandwidth becomes so large that the kernel density becomes almost uniform.

Winsorizing the data has a similar effect. Replacing estimates in excess of $7,609/tC by $7,482/tC, the largest estimate below the threshold, leads to a large kernel bandwidth and an almost uniform kernel density.

The censored data reveal an articulated probability density function. The unweighted estimates have the fattest tail; that is, papers that are more pessimistic about climate change present more estimates of the social cost of carbon. Giving every paper, rather than every estimate, a unit weight thins the right tail. Discounting estimates that their own authors discount further thins the tail. This result is mechanical, as the convention in sensitivity analysis is to show both high and low alternatives to the central assumptions. Quality weights thin the tail further still. More credible studies are less pessimistic.

**Inference**

The statistic used to test the null hypothesis that the kernel distribution is equal to its components is given in Equation (4). This test statistic was proposed by Karl Pearson.[217] It is the normalized sum of squared deviations of the observed numbers from the expected numbers. The distribution of this statistic is asymptotically $\chi^2$ and, for tables greater than $2 \times 2$, relies on a series of approximations. The distinctly non-normal distribution of the social cost of carbon, the weights used, and the kernel distribution further decelerate convergence. The
power of the asymptotic test is low as a result. I therefore bootstrap the test statistics, using a 1,000 random draws (with replacement) from the set of reported social costs of carbon and randomly splitting the sample into 5 (discount rate, author) or 6 (period) groups.

Figure S3 contrasts the bootstrapped cumulative density function of Pearson’s test statistic and its asymptotic counterpart for the publication periods, the sample split of interest. The asymptotic test is severely underpowered, not rejected the null hypothesis when it should in almost all cases.

Uncertainty about uncertainty

The kernel density describes the uncertainty about the social cost of carbon. The kernel density is an estimate and as such uncertain. Above and below, I ignore the uncertainty about the uncertainty. Figure S4 shows the 95% confidence interval around the Weibull-Gumbel kernel distribution of Figure S1, using quality weights as in Figure S2. This confidence interval is based on a bootstrap of 1,000 replications of the published estimates (without reweighing).

The shape of the kernel distribution is well-defined. The key uncertainty is about the weight of the tail relative to the central part of the distribution. Ignoring the uncertainty about the uncertainty makes it more likely to detect patterns. The bootstrap test discussed above therefore includes the meta-uncertainty.

Publication bias

Publication bias in the literature on the social cost of carbon has been reported [218]. Standard tests for publication bias are designed for statistical analyses, particularly test for a reluctance to publish insignificant results. The reported “publication bias” thus reflects that few studies report negative estimates of the social cost of carbon. Indeed, in the original DICE model [14], the social cost of carbon is positive by construction (see above). Many later papers follow in Nordhaus’ footsteps. The reported publication bias is perhaps better interpreted as confirmation bias: Researchers adopted Nordhaus’ assumption that climate change cannot have positive impacts.

Earlier tests for publication bias[219] are inapplicable: Estimates of the social costs of carbon are not published as a statistical result. These papers cannot have been selected on a p-value.

A recently proposed test for publication bias[220] is more general and can be applied to non-statistical results. The null hypothesis is that earlier and later studies are drawn from the same distribution. If not, later studies are influenced by earlier results—a sign of publication bias. The test used here is similar in spirit—does the distribution change over time?—but the interpretation is about the knowledge base rather than the publication practice. It is not possible to disentangle changes in knowledge from changes in publication practice.
Supplementary materials: Results

To tax or not to tax

The social cost of carbon can be estimated along an arbitrary emissions scenario or along the optimal emissions scenario. In the latter case, the social cost of carbon equals the carbon tax imposed. That carbon tax is the Pigou tax. The majority of estimates, 4155, are for the Pigou tax. The other 1750 estimates are for arbitrary emissions. As a carbon tax would reduce emissions, the Pigou tax should be lower. It is, but not significantly so. The empirical means are $192(23)/tC and $158(19)/tC. The difference is $36/tC with a standard error of $30/tC.

Figure S5 shows the empirical cumulative distribution functions. Taxing greenhouse gas emissions takes away some of the heavy right tail of the distribution of the social cost of carbon, but the difference is not that large.

The growth rate of the social cost of carbon

Different studies report the social cost of carbon for different years of emission. Estimates are standardized to emissions in the year 2010, assuming that the social cost of carbon grows by some 2.2% per year. That is, estimates for 2000, say, are multiplied by $1.022^{10}$ and estimates for 2020 are divided by the same factor.

In the analyses above and below, this correction factor is the same for all studies and for all estimates. This is for comparability and consistency. Alternatively, I use the growth rate associated with that particular estimate, if available, and impute the average growth rate, if not. Figure S6 shows the cumulative distribution function for the two alternatives. There is hardly any difference.

Figure S7 shows the composite kernel density of the growth rate of the social cost of carbon, decomposed for the pure rate of time preference; 2.2% is the mean of this distribution. The density is symmetric for a 3.0% utility discount rate. However, for discount rates of 1.5% and 2.0%, little probability mass is added to the left tail, and a lot to the right tail.

Table S4 shows the shares by quintile of the kernel density. The same pattern is seen as in the graph, and Pearson’s test rejects the null hypothesis that the component densities are equal to the composite one; $\chi^2_{24} = 3.50$; the critical value for 1% is 2.41. The growth rate of the social cost of carbon differs between discount rates.

However, many estimates of growth rate of the social cost of carbon use a different pure rate of time preference or a different form of discounting altogether. This is the “other” in Figure S7. The same is true for the estimates of the social cost of carbon itself; see Figure S16. A discount-rate-specific growth rate would introduce further assumptions to impute growth rates. I avoid that complexity and assume the same growth rate for all estimates.

The core analysis assumes that the social cost of carbon grows by 2.2%
per year, the average of the published estimates of the growth rate. Figure S8 shows the quality-weighted and censored means per publication year for two alternative assumptions: The average plus or minus the standard deviation of the published estimates. If the growth rate of the social cost of carbon is 3.2% per year, then older estimates, normalized to 2010 as the year of emission, are higher and younger estimates are lower. The reverse happens when the growth rate is assumed to be 1.2% per year. That is, if a faster (slower) growth rate is assumed, an upward trend will be harder (easier) to detect.

This result is paradoxical. The social cost of carbon is a measure of the current seriousness of climate change. The growth rate of the social cost of carbon is a measure of the future seriousness of climate change. The faster the growth of the social cost of carbon, the more serious climate change, but the harder it is to detect an upward trend in the social cost of carbon.

**Time and discount**

Table S5 and Figure 2 (bottom panel) show that the distribution of the social cost of carbon has significantly changed over time. Figure S10, however, reveals that the pure rate of time preference used to estimate the social cost of carbon has changed over time. Notably, a 1.5% pure rate of time preference was first used in 2011 and became the dominant choice in later years. It could be that the increase in the social cost of carbon is because analysts prefer to use a lower discount rate.

I therefore redo the decomposition per period for four alternative pure rates of time preference, 0%, 1%, 2%, and 3%, which have been used throughout the period. Tables S6, S7, S8 and S9 and Figures S11, S12, S13 and S14 show the detailed results, Table 2 the summary. The null hypothesis that the six periods show the same probability density function for the social cost of carbon cannot be rejected for a 0% pure rate of time preference—the uncertainty is so large that any signal is swamped—but for larger discount rates, differences between periods are statistically significant.

**Alternative non-parametric tests**

Pearson’s equality of proportions test is designed to compare the distributions of subsamples to the distribution of the whole sample. Alternatively, the subsample distributions can be scaled up to sum to one, and tests for the equality of distributions can be applied. However, for most of these tests, critical values are tabulated for specific null hypotheses only. These tests can be used to check whether the subsample distribution is, say, Normal but not whether it conforms to the whole-sample kernel distribution. The Kolmogorov-Smirnov test is the exception: Its test statistic converges to a known distribution, independent of the null hypothesis.[221] I did not use the standard tabulations[222], instead computed the p-values.[223] Pearson’s Equality of Proportions test considers the difference between entire distributions. The Kolmogorov-Smirnov test, on the other hand, consider the maximum deviation between distributions.
Table S10 shows the results. The null hypothesis that the quintiles of the subperiod distributions are equal to the quintiles of the distribution of the whole period, cannot be rejected. The equality of proportions test was applied to quintiles too. The two statistical tests disagree (although the asymptotic Kolmogorov-Smirnov test agrees with the asymptotic Pearson test).

The null hypothesis cannot be rejected for deciles and ventiles either. However, the null hypothesis is rejected for the third period if quinquagintiles are considered. For centiles, the null hypothesis is rejected for the first, second and fourth periods, but not for the other periods. That is, the subperiod distributions are indistinguishable at a crude resolution but differences appear at a finer scale.

Tables S11 to S14 repeat the analysis, splitting the sample by discount rate and time period. Rejections of the null hypothesis are common, also for deciles and ventiles, and more so for lower discount rates. However, Table S1 reveals that cell-sizes can be small, down to five estimates. With so few observations, confidence in the estimated kernel densities is low. Nonetheless, the more discerning Kolmogorov-Smirnov test points to changes over time that the asymptotic Pearson test cannot detect. The results of the Kolmogorov-Smirnov test are in line with the bootstrap Pearson test.

**Parametric tests**

Table S15 shows the results for the weighted linear regression, based on the conventional assumptions of linearity and normality, of the social cost of carbon on the pure rate of time preference and the year of publication, using paper, author and quality weights. The time trend is not statistically significant from zero.

I repeat the analysis using year fixed effects rather than a linear time trend. Figure S15 shows the estimated time dummies, measuring the deviation from 1982. The dummies do not show a trend.

Table S15 also shows the results of quantile regressions, for quintiles as above. The time trend is insignificant for paper and author weights. Using quality weights, the time trend is positive and significant at the 5% level for the three lower quintiles. That is, lower estimates of the social cost of carbon are gradually disappearing from the higher-quality literature.

**Discount rate**

The social cost of carbon is the net prevent value of the additional future damages done by emitting slightly more carbon dioxide. The assumed discount rate is obviously important in its calculation.

Figure S16 decomposes the kernel density of the social cost of carbon into its components by pure rate of time preference used. “Other” refers to a range of numbers and methods, including constant consumption rates, various forms of declining discount rates, and Epstein-Zin preferences. As one would expect, the lower discount rates contribute more to the right tail of the distribution.

S8
Table S16 shows the contributions of estimates of the social cost of carbon using a particular pure rate of time preference to the overall kernel density (denoted “null”) as well as to the five quintiles of that density (denoted Q1-5). The null hypothesis that all shares are equal is firmly rejected; $\chi^2_{24} = 50.69$; the 1% critical value is 4.79.

This result justifies splitting the sample by discount rate.

**Author**

I also test whether different researchers reach different conclusions, one test of the impact of subjective judgements on estimates of the social cost of carbon.

The decomposition of the kernel density by author opens another interpretation of kernel densities: Vote-counting.[224] Different experts have published different estimates of the social cost of carbon. These can be seen as votes for a particular Pigou tax. But as the experts are uncertain, they have voted for a central value and a spread. The kernel function is a vote, the kernel density adds those votes. Note the difference with Bayesian updating, which multiplies rather than adds probabilities.

I split the sample into estimates by those who have published ten papers or more (i.e., Christopher W. Hope, William D. Nordhaus, Frederick van der Ploeg, Richard S.J. Tol) and others.

Figure S17 decomposes the kernel density by author. Of the named authors, estimates by van der Ploeg are the narrowest, Tol contributes most to the left tail, and Hope to the right tail.

Table S17 shows the contributions of estimates of the social cost of carbon published by a particular author to the overall kernel density and its quintiles. There are patterns in figure and table, and the null hypothesis that the quintile shares are indistinguishable from the overall shares can be rejected; $\chi^2_{16} = 20.42$; the 1% critical value is 3.67.

This result notwithstanding, I do not split the sample by period, discount rate, and author because cell sizes would be too small.

|            | 1982-1995 | 1996-2001 | 2002-2006 | 2007-2013 | 2014-2017 | 2018-2021 | total |
|------------|-----------|-----------|-----------|-----------|-----------|-----------|-------|
| 3.0%       | 33        | 27        | 39        | 108       | 24        | 106       | 337   |
| 2.0%       | 5         | 7         | 14        | 7         | 139       | 313       | 485   |
| 1.5%       | 0         | 0         | 0         | 38        | 216       | 1705      | 1959  |
| 1.0%       | 8         | 16        | 28        | 100       | 190       | 448       | 790   |
| 0.1%       | 0         | 4         | 1         | 21        | 69        | 143       | 238   |
| 0.0%       | 68        | 5         | 33        | 43        | 124       | 262       | 535   |
| other      | 12        | 25        | 26        | 317       | 287       | 894       | 1561  |
| # estimates| 126       | 84        | 141       | 634       | 1049      | 3871      | 5905  |
| # papers   | 19        | 18        | 23        | 51        | 52        | 44        | 207   |

Table S1: Number of papers on the social cost of carbon by publication period and the number of estimates by period and pure rate of time preference.
### Table S2: Average (standard deviation) of estimates of the social cost of carbon ($/tC) by publication period and pure rate of time preference. Estimates are uncensored and unweighted.

| Pure Rate of Time Preference | 1982-1995 | 1996-2001 | 2002-2006 | 2007-2013 | 2014-2017 | 2018-2021 | All |
|-----------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----|
| 3.0%                        | 25 (15)   | 73 (98)   | 27 (26)   | 25 (16)   | 53 (27)   | 126 (50)  | 45  |
| 2.0%                        | 46 (23)   | 64 (32)   | 70 (48)   | 136 (125) | 170 (137) | 953 (1185)| 221 |
| 1.5%                        |           |           |           |           |           |           |     |
| 1.0%                        |           |           |           |           |           |           |     |
| 0.1%                        |           |           |           |           |           |           |     |
| 0.0%                        |           |           |           |           |           |           |     |
| Other                       | 1226 (2097) | 538 (763) | 131 (123) | 146 (183) | 175 (325) | 22916 (1225350) | 5053 |
| All                         | 481 (1212) | 252 (504) | 160 (345) | 157 (387) | 629 (6554) | 12849 (736271) | 3106 |

Table S2: Average (standard deviation) of estimates of the social cost of carbon ($/tC) by publication period and pure rate of time preference. Estimates are uncensored and unweighted.

| Pure Rate of Time Preference | Normal | Silverman | Johnson SU | Normal | Silverman | Johnson SU | Normal | Gumbel | Normal | Gumbel | Observed |
|-----------------------------|--------|-----------|------------|--------|-----------|------------|--------|--------|--------|--------|----------|
| Average                     | 179    | 225       | 1083       | 2453   | 361       | 4376       | 509    | 179    |
| $P(\text{SCC} < 0)$         | 0.1882 | 0.3373    | 0.0000     | 0.0007 | 0.0911    | 0.0860     | 0.0151 |
| $P(\text{SCC} > 1186)$      | 0.0234 | 0.0607    | 0.0588     | 0.0674 | 0.0563    | 0.0572     | 0.0000 |
| MISE                        | 0.0396 | 0.0607    | 0.0588     | 0.0674 | 0.0563    | 0.0572     | 0.0000 |

Table S3: Key characteristics of alternative kernel densities and the data: Mean social cost of carbon ($/tC), probability of a social benefit of carbon, probability that the social cost of carbon exceeds the Leviathan tax, and Mean Integrated Squared Error (MISE).

| Pure Rate of Time Preference | 3.0 | 2.0 | 1.5 | 1.0 | 0.1 | 0.0 | Other |
|-----------------------------|-----|-----|-----|-----|-----|-----|-------|
| Q1                          | 0.0464 | 0.0014 | 0.0181 | 0.0293 | 0.0068 | 0.0202 | 0.0751 |
| Q2                          | 0.0407 | 0.0083 | 0.0383 | 0.0299 | 0.0096 | 0.0070 | 0.0644 |
| Q3                          | 0.0252 | 0.0107 | 0.0593 | 0.0208 | 0.0059 | 0.0239 | 0.0566 |
| Q4                          | 0.0234 | 0.0098 | 0.0771 | 0.0208 | 0.0090 | 0.0089 | 0.0507 |
| Q5                          | 0.0204 | 0.0154 | 0.0708 | 0.0270 | 0.0118 | 0.0066 | 0.0505 |
| Null                        | 0.0312 | 0.0091 | 0.0527 | 0.0256 | 0.0086 | 0.0133 | 0.0595 |

Table S4: Observed and hypothesized contribution to the kernel density of the growth rate of the social cost of carbon by quintile and pure rate of time preference.
Table S5: Observed and hypothesized contribution to the kernel density of the social cost of carbon by quintile and publication period.

|        | 1982-1995 | 1996-2001 | 2002-2006 | 2007-2013 | 2014-2017 | 2018-2021 |
|--------|-----------|-----------|-----------|-----------|-----------|-----------|
| Q1     | 0.0078    | 0.0199    | 0.0328    | 0.0814    | 0.0565    | 0.0284    |
| Q2     | 0.0116    | 0.0237    | 0.0270    | 0.0638    | 0.0703    | 0.0297    |
| Q3     | 0.0125    | 0.0224    | 0.0225    | 0.0580    | 0.0606    | 0.0324    |
| Q4     | 0.0150    | 0.0203    | 0.0170    | 0.0469    | 0.0467    | 0.0367    |
| Q5     | 0.0303    | 0.0176    | 0.0092    | 0.0247    | 0.0236    | 0.0507    |
| Null   | 0.0154    | 0.0208    | 0.0217    | 0.0550    | 0.0515    | 0.0356    |

Table S6: Observed and hypothesized contribution to the kernel density of the social cost of carbon by quintile and publication period, for a pure rate of time preference of 0%.

|        | 1982-1995 | 1996-2001 | 2002-2006 | 2007-2013 | 2014-2017 | 2018-2021 |
|--------|-----------|-----------|-----------|-----------|-----------|-----------|
| Q1     | 0.0268    | 0.0014    | 0.0835    | 0.1003    | 0.0092    | 0.0047    |
| Q2     | 0.0360    | 0.0050    | 0.0720    | 0.0987    | 0.0217    | 0.0025    |
| Q3     | 0.0291    | 0.0089    | 0.0711    | 0.0668    | 0.0272    | 0.0032    |
| Q4     | 0.0232    | 0.0157    | 0.0660    | 0.0334    | 0.0326    | 0.0045    |
| Q5     | 0.0147    | 0.0237    | 0.0644    | 0.0108    | 0.0267    | 0.0162    |
| Null   | 0.0260    | 0.0109    | 0.0714    | 0.0620    | 0.0235    | 0.0062    |

Table S7: Observed and hypothesized contribution to the kernel density of the social cost of carbon by quintile and publication period, for a pure rate of time preference of 1%.

|        | 1982-1995 | 1996-2001 | 2002-2006 | 2007-2013 | 2014-2017 | 2018-2021 |
|--------|-----------|-----------|-----------|-----------|-----------|-----------|
| Q1     | 0.1507    | 0.2579    | 0.2119    | 0.0205    | 0.0769    | 0.0114    |
| Q2     | 0.0000    | 0.0095    | 0.0177    | 0.0167    | 0.0837    | 0.0102    |
| Q3     | 0.0000    | 0.0000    | 0.0000    | 0.0080    | 0.0399    | 0.0140    |
| Q4     | 0.0000    | 0.0000    | 0.0000    | 0.0004    | 0.0042    | 0.0214    |
| Q5     | 0.0000    | 0.0000    | 0.0000    | 0.0009    | 0.0099    | 0.0442    |
| Null   | 0.0301    | 0.0535    | 0.0459    | 0.0091    | 0.0411    | 0.0202    |

Table S8: Observed and hypothesized contribution to the kernel density of the social cost of carbon by quintile and publication period, for a pure rate of time preference of 2%.
Table S9: Observed and hypothesized contribution to the kernel density of the social cost of carbon by quintile and publication period, for a pure rate of time preference of 3%.

| Quintile | 1982-1995 | 1996-2001 | 2002-2006 | 2007-2013 | 2014-2017 | 2018-2021 |
|----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Q1       | 0.0535    | 0.0199    | 0.0597    | 0.1145    | 0.0057    | 0.0031    |
| Q2       | 0.0736    | 0.0268    | 0.0749    | 0.1648    | 0.0129    | 0.0032    |
| Q3       | 0.0187    | 0.0280    | 0.0505    | 0.0613    | 0.0206    | 0.0057    |
| Q4       | 0.0006    | 0.0348    | 0.0173    | 0.0088    | 0.0156    | 0.0112    |
| Q5       | 0.0000    | 0.0842    | 0.0027    | 0.0010    | 0.0010    | 0.0255    |
| Null     | 0.0293    | 0.0387    | 0.0410    | 0.0701    | 0.0112    | 0.0097    |

Table S10: p-values of Kolmogorov-Smirnov test statistic for the equality of the distributions of the period subsample and the whole sample (rows) for different discretizations of the distribution (columns).

| Period     | 5   | 10  | 20  | 50  | 100 |
|------------|-----|-----|-----|-----|-----|
| 1982-1995  | 0.9991 | 0.9321 | 0.5992 | 0.1039 | 0.0055 |
| 1996-2001  | 0.9903 | 0.8160 | 0.3937 | 0.0350 | 0.0006 |
| 2002-2006  | 1.0000 | 1.0000 | 0.9967 | 0.8032 | 0.3779 |
| 2007-2013  | 0.9999 | 0.9807 | 0.7726 | 0.2218 | 0.0244 |
| 2014-2017  | 1.0000 | 1.0000 | 0.9999 | 0.9488 | 0.6398 |
| 2018-2021  | 1.0000 | 1.0000 | 1.0000 | 0.9808 | 0.7708 |

Table S11: p-values of Kolmogorov-Smirnov test statistic for the equality of the distributions of the social cost of carbon for the period subsample and the whole sample (rows) for different discretizations of the distribution (columns), for a 0% pure rate of time preference.

| Period     | 5   | 10  | 20  | 50  | 100 |
|------------|-----|-----|-----|-----|-----|
| 1982-1995  | 1.0000 | 0.9780 | 0.8312 | 0.2106 | 0.0164 |
| 1996-2001  | 0.1191 | 0.0064 | 0.0000 | 0.0000 | 0.0000 |
| 2002-2006  | 0.9867 | 0.7959 | 0.3724 | 0.0301 | 0.0005 |
| 2007-2013  | 1.0000 | 0.9998 | 0.9697 | 0.5846 | 0.1781 |
| 2014-2017  | 1.0000 | 0.9780 | 0.7602 | 0.1907 | 0.0152 |
| 2018-2021  | 1.0000 | 1.0000 | 0.9924 | 0.7203 | 0.2647 |

S12
|                | 5    | 10   | 20   | 50   | 100  |
|----------------|------|------|------|------|------|
| 1982-1995      | 0.0149 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| 1996-2001      | 0.5564 | 0.1260 | 0.0073 | 0.0000 | 0.0000 |
| 2002-2006      | 0.9992 | 0.9364 | 0.6062 | 0.1072 | 0.0058 |
| 2007-2013      | 0.6657 | 0.1964 | 0.0185 | 0.0000 | 0.0000 |
| 2014-2017      | 0.7592 | 0.2932 | 0.0426 | 0.0001 | 0.0000 |
| 2018-2021      | 1.0000 | 0.9920 | 0.8394 | 0.2905 | 0.0428 |

Table S12: p-values of Kolmogorov-Smirnov test statistic for the equality of the distributions of the social cost of carbon for the period subsample and the whole sample (rows) for different discretizations of the distribution (columns), for a 1% pure rate of time preference.

|                | 5    | 10   | 20   | 50   | 100  |
|----------------|------|------|------|------|------|
| 1982-1995      | 0.6039 | 0.2070 | 0.0194 | 0.0000 | 0.0000 |
| 1996-2001      | 0.6617 | 0.2386 | 0.0273 | 0.0000 | 0.0000 |
| 2002-2006      | 1.0000 | 0.9780 | 0.7708 | 0.2106 | 0.0174 |
| 2007-2013      | 0.9003 | 0.4477 | 0.0941 | 0.0009 | 0.0000 |
| 2014-2017      | 1.0000 | 0.9780 | 0.7633 | 0.2074 | 0.0174 |
| 2018-2021      | 1.0000 | 1.0000 | 1.0000 | 0.9999 | 0.9770 |

Table S13: p-values of Kolmogorov-Smirnov test statistic for the equality of the distributions of the social cost of carbon for the period subsample and the whole sample (rows) for different discretizations of the distribution (columns), for a 2% pure rate of time preference.

|                | 5    | 10   | 20   | 50   | 100  |
|----------------|------|------|------|------|------|
| 1982-1995      | 1.0000 | 1.0000 | 0.9984 | 0.8127 | 0.3586 |
| 1996-2001      | 0.9973 | 0.9020 | 0.5364 | 0.0781 | 0.0030 |
| 2002-2006      | 0.9605 | 0.6855 | 0.2544 | 0.0117 | 0.0001 |
| 2007-2013      | 1.0000 | 0.9966 | 0.9627 | 0.5522 | 0.1610 |
| 2014-2017      | 0.9993 | 0.9464 | 0.6450 | 0.1282 | 0.0081 |
| 2018-2021      | 1.0000 | 1.0000 | 0.9893 | 0.7067 | 0.2755 |

Table S14: p-values of Kolmogorov-Smirnov test statistic for the equality of the distributions of the social cost of carbon for the period subsample and the whole sample (rows) for different discretizations of the distribution (columns), for a 3% pure rate of time preference.
| weight  | %ile | PRTP  | year    | year only |
|--------|------|-------|---------|-----------|
| paper  |      |       |         |           |
| 0.1    | -131*** (27) | -6.56* (3.49) | -3.18 (3.36) |
| 0.3    | -15.5** (6.5) | 0.487 (0.891) | 1.31** (0.55) |
| 0.5    | -37.1*** (10.4) | 0.117 (1.440) | 1.53 (1.54) |
| 0.7    | -71.9** (33.4) | -0.108 (4.616) | 0.311 (4.091) |
| 0.9    | -131 (120) | -5.78 (16.50) | -0.303 (13.131) |
| author |      |       |         |           |
| 0.1    | -135*** (26) | -6.29* (3.36) | -3.24 (3.21) |
| 0.3    | -15.2** (6.4) | 0.610 (0.852) | 1.35** (0.53) |
| 0.5    | -35.8*** (9.3) | 0.358 (1.246) | 1.60 (1.31) |
| 0.7    | -69.7** (30.5) | -0.102 (4.046) | 0.625 (3.754) |
| 0.9    | -150 (116) | -2.76 (15.50) | -0.311 (10.179) |
| quality|      |       |         |           |
| 0.1    | -104*** (16) | -2.70 (2.02) | 0.03 (1.86) |
| 0.3    | -11.6*** (2.05) | 0.911*** (0.271) | 1.39*** (0.17) |
| 0.5    | -33.1*** (3.8) | 0.705 (0.508) | 2.08*** (0.52) |
| 0.7    | -61.1*** (11.5) | 0.200 (1.520) | 1.56 (1.35) |
| 0.9    | -137*** (31) | 0.935 (4.101) | 3.25 (2.66) |

Table S15: Results of weighted least squares and weighted quantile regression of the social cost of carbon on the pure rate of time preference and the publication year (middle columns) or publication year only (right columns). Standard errors are reported in brackets. Coefficients marked with ***, ** or * are statistically significant at the 1%, 5% or 10% level, respectively. The top row has results for the mean regression, the next five rows for the quantile regression for the indicated percentile.

| Q1 | 0.1389 | 0.0068 | 0.0376 | 0.0413 | 0.0053 | 0.0076 | 0.0526 |
| Q2 | 0.0559 | 0.0250 | 0.0437 | 0.0231 | 0.0524 | 0.0483 |
| Q3 | 0.0082 | 0.0002 | 0.0437 | 0.0231 | 0.0524 | 0.0483 |
| Q4 | 0.0096 | 0.0232 | 0.0437 | 0.0231 | 0.0524 | 0.0483 |
| Q5 | 0.0390 | 0.0101 | 0.0389 | 0.0321 | 0.0700 | 0.0102 | 0.0625 |

Table S16: Observed and hypothesized contribution to the kernel density of the social cost of carbon by quintile and pure rate of time preference.
Table S17: Observed and hypothesized contribution to the kernel density of the social cost of carbon by quintile and author.

| Quintile | Hope | Nordhaus | Ploeg | Tol | Other |
|----------|------|----------|-------|-----|-------|
| Q1       | 0.0185 | 0.0270  | 0.0205 | 0.0740 | 0.0882 |
| Q2       | 0.0234 | 0.0261  | 0.0276 | 0.0405 | 0.1063 |
| Q3       | 0.0212 | 0.0036  | 0.0247 | 0.0297 | 0.1120 |
| Q4       | 0.0185 | 0.0000  | 0.0216 | 0.0163 | 0.1201 |
| Q5       | 0.0094 | 0.0000  | 0.0176 | 0.0048 | 0.1485 |
| Null     | 0.0182 | 0.0114  | 0.0224 | 0.0331 | 0.1150 |

Figure S1: Kernel density of the social cost of carbon for alternative kernel functions and bandwidths.
Figure S2: Kernel density of the social cost of carbon for alternative weights.
Figure S3: The bootstrapped cumulative distribution function of Pearson’s test statistic and its asymptotic p-value.
Figure S4: The 95% confidence interval of the kernel density of the social cost of carbon.
Figure S5: The empirical cumulative distribution function of the social cost of carbon if estimates are (a) along an arbitrary emission scenario and (b) along the optimal emission scenario.
Figure S6: The empirical cumulative distribution function of the social cost of carbon (a) if all estimates are normalized to 2010 with the average growth rather and (b) if estimates are normalized to 2010 with their specific growth rate, if available, or the average growth rate, if not.
Figure S7: Composite kernel density of the growth rate of the social cost of carbon and its composition by discount rate.
Figure S8: Average social cost of carbon by publication year, corrected for inflation and year of emission, for alternative growth rates of the social cost of carbon: Blue dots use the average of published growth rates, red triangles (green squares) the average plus (minus) the standard deviation. Estimates are quality weighted and censored.
Figure S9: Year of emission and year of nominal dollar by year of publication. Estimates are weighted such that every published paper counts equally.
Figure S10: The pure rate of time preference used to estimate the social cost of carbon by publication period. Estimates are weighted such that every published paper counts equally.
Figure S11: Composite kernel density of the social cost of carbon and its composition by publication period, for a pure rate of time preference of 0%.
Figure S12: Composite kernel density of the social cost of carbon and its composition by publication period, for a pure rate of time preference of 1%.
Figure S13: Composite kernel density of the social cost of carbon and its composition by publication period, for a pure rate of time preference of 2%.
Figure S14: Composite kernel density of the social cost of carbon and its composition by publication period, for a pure rate of time preference of 3%.
Figure S15: Year fixed-effects from a regression of the social cost of carbon on the pure rate of time preference, using quality weights. Base year is 1982; error bars denote the 67% confidence interval.
Figure S16: Composite kernel density of the social cost of carbon and its composition by the pure rate of time preference.
Figure S17: Composite kernel density of the social cost of carbon and its composition by author.
Additional references

1. Tol, R. S. J. The marginal damage costs of carbon dioxide emissions: an assessment of the uncertainties. *Energy Policy* **33**, 2064–2074. issn: 0301-4215 (2005).

2. Tol, R. S. J. The Economic Effects of Climate Change. *Journal of Economic Perspectives* **23**, 29–51. https://www.aeaweb.org/articles?id=10.1257/jep.23.2.29 (June 2009).

3. Tol, R. S. J. The Economic Impact of Climate Change. *Perspektiven der Wirtschaftspolitik* **11**, 13–37. https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1468-2516.2010.00326.x (2010).

4. Tol, R. S. J. The Social Cost of Carbon. *Annual Review of Resource Economics* **3**, 419–443. https://doi.org/10.1146/annurev-resource-083110-120028 (2011).

5. Tol, R. S. J. Targets for global climate policy: An overview. *Journal of Economic Dynamics and Control* **37**, 911–928. issn: 0165-1889. https://www.sciencedirect.com/science/article/pii/S0165188913000092 (2013).

6. Tol, R. S. J. The Economic Impacts of Climate Change. *Review of Environmental Economics and Policy* **12**, 4–25. https://doi.org/10.1093/reep/rex027 (Jan. 2018).

7. Nordhaus, W. D. How Fast Should We Graze the Global Commons? *American Economic Review* **72**, 242–246 (1982).

8. Ayres, R. & Walter, J. The greenhouse effect: Damages, costs and abatement. *Environmental & Resource Economics* **1**, 237–270 (1991).

9. Nordhaus, W. D. To Slow or Not to Slow: The Economics of the Greenhouse Effect. *Economic Journal* **101**, 920–937 (1991).

10. Nordhaus, W. D. A sketch of the economics of the greenhouse effect. *American Economic Review* **81**, 146–150 (1991).

11. Cline, W. *Optimal Carbon Emissions over Time: Experiments with the Nordhaus DICE Model* Working Paper (Institute for International Economics, Washington, D.C., 1992).

12. Haraden, J. An improved shadow price for CO2. *Energy* **17**, 419–426 (1992).

13. Holmeyer, O. & Gaertner, M. *The costs of climate change—a rough estimate of orders of magnitude* Working Paper (Fraunhofer-Institut für Systemtechnik und Innovationsforschung, Karlsruhe, 1992).

14. Nordhaus, W. D. An Optimal Transition Path for Controlling Greenhouse Gases. *Science* **258**, 1315–1319 (1992).

15. Penner, S., Haraden, J. & Mates, S. Long-term global energy supplies with acceptable environmental impacts. *Energy* **17**, 883–899 (1992).
16. Haraden, J. An updated shadow price for CO2. *Energy* 18, 303–307 (1993).

17. Nordhaus, W. D. Rolling the ‘DICE’: An Optimal Transition Path for Controlling Greenhouse Gases. *Resource and Energy Economics* 15, 27–50 (1993).

18. Parry, I. Some estimates of the insurance value against climate change from reducing greenhouse gas emissions. *Resource and Energy Economics* 15, 99–115 (1993).

19. Peck, S. & Teisberg, T. CO2 emissions control. Comparing policy instruments. *Energy Policy* 21, 222–230 (1993).

20. Reilly, J. & Richards, K. Climate change damage and the trace gas index issue. *Environmental & Resource Economics* 3, 41–61 (1993).

21. Azar, C. The Marginal Cost of CO2 Emissions. *Energy* 19, 1255–1261 (1994).

22. Fankhauser, S. Social costs of greenhouse gas emissions: An expected value approach. *Energy Journal* 15, 158–184 (1994).

23. Nordhaus, W. *Managing the Global Commons: The Economics of Climate Change* (MIT Press, Cambridge MA, 1994).

24. Maddison, D. A cost-benefit analysis of slowing climate change. *Energy Policy* 23, 337–346 (1995).

25. Schauer, M. Estimation of the greenhouse gas externality with uncertainty. *Environmental & Resource Economics* 5, 71–82 (1995).

26. Azar, C. & Sterner, T. Discounting and distributional considerations in the context of global warming. *Ecological Economics* 19, 169–184 (1996).

27. Downing, T., Eyre, N., Greener, R. & Blackwell, D. *Projected Costs of Climate Change for Two Reference Scenarios and Fossil Fuel Cycles* Working Paper (Environmental Change Unit, University of Oxford, Oxford, 1996).

28. Hohmeyer, O. in *Social Costs and Sustainability - Valuation and Implementation in the Energy and Transport Sector* (eds Hohmeyer, O., Ottinger, R. & K. Rennings) 61–83 (Springer, Berlin, 1996).

29. Hope, C. & Maul, P. Valuing the impact of CO2 emissions. *Energy Policy* 24, 211–219 (1996).

30. Nordhaus, W. & Yang, Z. A Regional Dynamic General-Equilibrium Model of Alternative Climate-Change Strategies. *American Economic Review* 86, 741–765 (1996).

31. Plambeck, E. & Hope, C. PAGE95: An updated valuation of the impacts of global warming. *Energy Policy* 24, 783–793 (1996).

32. Cline, W. in *Environment, Energy, and Economy* (eds Kaya, Y. & Yokobori, K.) (United Nations University Press, Tokyo, 1997).
33. Nordhaus, W. & Popp, D. What is the value of scientific knowledge? An application to global warming using the PRICE model. *Energy Journal* **18**, 1–28 (1997).

34. Howarth, R. B. An Overlapping Generations Model of Climate-Economy Interactions. *Scandinavian Journal of Economics* **100**, 575–591 (Sept. 1998).

35. Eyre, N., Downing, T., Hoekstra, R., Rennings, K. & Tol, R. J. in *Externalsities of Energy, Vol.7: Metholodogy and 1998 Update* (eds Holland, M., Berry, J. & Forster, D.) (Office for Official Publications of the European Communities, Luxembourg, 1999).

36. Roughgarden, T. & Schneider, S. Climate change policy: Quantifying uncertainties for damages and optimal carbon taxes. *Energy Policy* **27**, 415–429 (1999).

37. Tol, R. S. J. The marginal costs of greenhouse gas emissions. *Energy Journal* **20**, 61–81 (1999).

38. Nordhaus, W. & Boyer, J. *Warming the World: Economic Models of Global Warming* (MIT Press, Cambridge MA, 2000).

39. Tol, R. J. & Downing, T. *The Marginal Damage Costs of Climate Changing Gases* Working Paper D00/08 (Institute for Environmental Studies, Vrije Universiteit, Amsterdam, 2000).

40. Kelly, D. & Kolstad, C. Malthus and climate change: Betting on a stable population. *Journal of Environmental Economics and Management* **41**, 135–161 (2001).

41. Clarkson, R. & Deyes, K. *Estimating the Social Cost of Carbon Emissions* Working Paper (Government Economic Service, HM Treasury, London, 2002).

42. Mendelsohn, R. *The Social Costs of Carbon: An unfolding value* Paper Prepared for the Social Cost of Carbon Conference London UK July 7, 2003 (School of Forestry and Environmental Studies, Yale University, New Haven, 2003).

43. Newell, R. & Pizer, W. Discounting the distant future: How much do uncertain rates increase valuations? *Journal of Environmental Economics and Management* **46**, 52–71 (2003).

44. Pearce, D. The social cost of carbon and its policy implications. *Oxford Review of Economic Policy* **19**, 362–384 (2003).

45. Tol, R. J. Is the uncertainty about climate change too large for expected cost-benefit analysis? *Climatic Change* **56**, 265–289 (2003).

46. Uzawa, H. *Economic theory and global warming* (Cambridge University Press, Cambridge, 2003).

47. Cline, W. *Meeting the Challenge of Global Warming* Copenhagen Consensus Challenge Paper (National Environmental Assessment Institute, Copenhagen, 2004).
48. Hohmeyer, O. in Externe Kosten in der Stromerzeugung (ed Ziesing, H.-J.) 11–24 (VWEW Energieverlag, Frankfurt, 2004).
49. Link, P. M. & Tol, R. S. J. Possible economic impacts of a shutdown of the thermohaline circulation: An application of FUND. Portuguese Economic Journal 3, 99–114 (2004).
50. Manne, A. S. in Global Crises, Global Solutions (ed Lomborg, B.) (Cambridge University Press, Cambridge, 2004).
51. Mendelsohn, R. O. in Global Crises, Global Solutions (ed Lomborg, B.) (Cambridge University Press, Cambridge, 2004).
52. Newell, R. & Pizer, W. Uncertain discount rates in climate policy analysis. Energy Policy 32, 519–529 (2004).
53. Ceronsky, M., Anthoff, D., Hepburn, C. & Tol, R. S. J. Checking The Price Tag On Catastrophe: The Social Cost Of Carbon Under Non-Linear Climate Response Working Paper FNU-87 (Research unit Sustainability and Global Change, Hamburg University, Aug. 2005).
54. Downing, T. et al. Social Cost of Carbon: A Closer Look at Uncertainty tech. rep. (Department of Environment, Food and Rural Affairs, London, 2005).
55. Hope, C. The climate change benefits of reducing methane emissions. Climatic Change 68, 21–39 (2005).
56. Hope, C. Exchange Rates and the Social Cost of Carbon Working Paper WP05/2005 (Judge Institute of Management, Cambridge University, 2005).
57. Tol, R. S. J. Emission abatement versus development as strategies to reduce vulnerability to climate change: an application of FUND. Environment and Development Economics 10, 615–629 (2005).
58. Guo, J., Hepburn, C., Tol, R. J. & Anthoff, D. Discounting and the social cost of carbon: A closer look at uncertainty. Environmental Science and Policy 9, 205–216 (2006).
59. Hope, C. The marginal impacts of CO₂, CH₄ and SF₆ emissions. Climate Policy 6, 537–544 (2006).
60. Hope, C. The social cost of carbon: What does it actually depend on? Climate Policy 6, 565–572 (2006).
61. Hope, C. The Marginal Impact of CO₂ from PAGE2002: An Integrated Assessment Model Incorporating the IPCC’s Five Reasons for Concern. Integrated Assessment 6, 19–56 (2006).
62. Stern, N. H. et al. Stern Review: The Economics of Climate Change (HM Treasury, London, 2006).
63. Wahba, M. & Hope, C. The marginal impact of carbon dioxide under two scenarios of future emissions. Energy Policy 34, 3305–3316 (2006).
64. Nordhaus, W. D. A Review of the Stern Review on the Economics of Climate Change. *Journal of Economic Literature* **45**, 686–702 (2007).

65. Nordhaus, W. D. To Tax or Not to Tax: Alternative Approaches to Slowing Global Warming. *Review of Environmental Economics and Policy* **1**, 26–44. [https://doi.org/10.1093/reep/rem008](https://doi.org/10.1093/reep/rem008) (2007).

66. Nordhaus, W. Critical assumptions in the stern review on climate change. *Science* **317**, 201–202 (2007).

67. Stern, N. & Taylor, C. Climate change: Risk, ethics, and the Stern Review. *Science* **317**, 203–204 (2007).

68. Hope, C. W. Discount rates, equity weights and the social cost of carbon. *Energy Economics* **30**, 1011–1019 (2008).

69. Hope, C. W. Optimal Carbon Emissions and the Social Cost of Carbon over Time under Uncertainty. *Integrated Assessment Journal* **8**, 107–122 (2008).

70. Nordhaus, W. & Boyer, J. A Question of Balance—Weighing the Options on Global Warming Policies (Yale University Press, New Haven CT, 2008).

71. Anthoff, D., Hepburn, C. & Tol, R. J. Equity weighting and the marginal damage costs of climate change. *Ecological Economics* **68**, 836–849 (2009).

72. Anthoff, D., Tol, R. S. J. & Yohe, G. W. Risk aversion, time preference, and the social cost of carbon. *Environmental Research Letters* **4**, 024002 (2009).

73. Anthoff, D., Tol, R. S. J. & Yohe, G. W. Discounting for Climate Change. *Economics - The Open-Access, Open-Assessment E-Journal* **3**, 1–22 (2009).

74. EPA & NHTSA. Proposed Rulemaking to Establish Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Efficiency Standards. *Federal Register* **74**, 49454–49789 (2009).

75. Narita, D., Tol, R. J. & Anthoff, D. Damage costs of climate change through intensification of tropical cyclone activities: An application of FUND. *Climate Research* **39**, 87–97 (2009).

76. Anthoff, D. & Tol, R. J. On international equity weights and national decision making on climate change. *Journal of Environmental Economics and Management* **60**, 14–20 (2010).

77. Interagency Working Group on the Social Cost of Carbon. *Technical Support Document: Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866* Report (United States Government, 2010).

78. Kemfert, C. & Schill, W.-P. in *Smart Solutions to Climate Change* (ed Lomborg, B.) (Cambridge University Press, Cambridge, 2010).

79. Narita, D., Tol, R. J. & Anthoff, D. International climate policy and regional welfare weights. *Environmental Science and Policy* **13**, 713–720 (2010).
80. Narita, D., Tol, R. J. & Anthoff, D. Economic costs of extratropical storms under climate change: An application of FUND. *Journal of Environmental Planning and Management* **53**, 371–384 (2010).

81. Newbold, S., Griffiths, C., Moore, C., Wolverton, A. & Kopits, E. *The Social Cost of Carbon Made Simple* Working Paper 2010-07 (National Center for Environmental Economics, Environmental Protection Agency, Washington, D.C., 2010).

82. Nordhaus, W. D. Economic aspects of global warming in a post-Copenhagen environment. *Proceedings of the National Academy of Sciences* **107**, 11721–11726. [https://www.pnas.org/content/107/26/11721](https://www.pnas.org/content/107/26/11721) (2010).

83. Solngen, B. in *Smart Solutions to Climate Change* (ed Lomborg, B.) (Cambridge University Press, Cambridge, 2010).

84. Tol, R. J. in *Smart Solutions to Climate Change* (ed Lomborg, B.) (Cambridge University Press, Cambridge, 2010).

85. Anthoff, D., Rose, S. K., Tol, R. S. J. & Waldhof, S. *The Time Evolution of the Social Cost of Carbon: An Application of FUND* Working Paper WP405 (Economic and Social Research Institute, Dublin, 2011).

86. Anthoff, D. & Tol, R. S. J. *The uncertainty about the social cost of carbon: A decomposition analysis using FUND* Working Paper WP404 (Economic and Social Research Institute, Dublin, 2011).

87. Ceronsky, M., Anthoff, D., Hepburn, C. & Tol, R. S. J. *Checking the Price Tag on Catastrophe: The Social Cost of Carbon Under Non-linear Climate Response* Working Paper WP392 (Economic and Social Research Institute, Dublin, June 2011).

88. Hope, C. W. The Social Cost of CO₂ from the PAGE09 Model. *Economics—The Open-Access, Open-Assessment E-Journal* **39**, 1–32 (2011).

89. Marten, A. L. Transient temperature response modeling in IAMs: The effects of over simplification on the SCC. *Economics—The Open-Access, Open-Assessment E-Journal* **5**, 1–42 (2011).

90. Nordhaus, W. The economics of tail events with an application to climate change. *Review of Environmental Economics and Policy* **5**, 240–257 (2011).

91. Pycroft, J., Vergano, L., Hope, C., Paci, D. & Ciscar, J. C. A tale of tails: Uncertainty and the social cost of carbon dioxide. *Economics - The Open-Access, Open-Assessment E-Journal* **5**, 1–29 (2011).

92. Waldhof, S., Anthoff, D., Rose, S. K. & Tol, R. S. J. *The marginal damage costs of different greenhouse gases: An application of FUND* Working Paper WP380 (Economic and Social Research Institute, Dublin, 2011).

93. Ackerman, F. & Munitz, C. Climate damages in the FUND model: A disaggregated analysis. *Ecological Economics* **77**, 219–224 (2012).
94. Ackerman, F. & Stanton, E. Climate risks and carbon prices: Revising the social cost of carbon. *Economics—The Open-Access, Open-Assessment E-Journal* 6 (2012).

95. Botzen, W. J. W. & van den Bergh, J. C. J. M. How sensitive is Nordhaus to Weitzman? Climate policy in DICE with an alternative damage function. *Economics Letters* 117, 372–374 (2012).

96. Cai, Y., Judd, K. & Lontzek, T. Open science is necessary. *Nature Climate Change* 2, 299 (2012).

97. Johnson, L. & Hope, C. The social cost of carbon in U.S. regulatory impact analyses: An introduction and critique. *Journal of Environmental Studies and Sciences* 2, 205–221 (2012).

98. Kopp, R. E., Golub, A., Keohane, N. O. & Onda, C. The influence of the specification of climate change damages on the social cost of carbon. *Economics—The Open-Access, Open-Assessment E-Journal* 6, 1–40 (2012).

99. Marten, A. & Newbold, S. Estimating the social cost of non-CO$_2$ GHG emissions: Methane and nitrous oxide. *Energy Policy* 51, 957–972 (2012).

100. Perrissin Fabert, B., Dumas, P. & Hourcade, J.-C. *What Social Cost of Carbon? A Mapping of the Climate Debate* Working Paper 2012.34 (Fondazione Eni Enrico Mattei, May 2012).

101. Van der Ploeg, F., Rezai, A. & Withagen, C. *Economic Growth and the Social Cost of Carbon: Additive versus Multiplicative Damages* OxCarre Working Papers 093 (Oxford Centre for the Analysis of Resource Rich Economies, University of Oxford, Sept. 2012). [https://ideas.repec.org/p/oxf/oxcrwp/093.html](https://ideas.repec.org/p/oxf/oxcrwp/093.html).

102. Rezai, A., Foley, D. & Taylor, L. Global warming and economic externalities. *Economic Theory* 49, 329–351 (2012).

103. Ackerman, F., Stanton, E. & Bueno, R. Epstein-Zin Utility in DICE: Is Risk Aversion Irrelevant to Climate Policy? *Environmental & Resource Economics* 56, 73–84 (2013).

104. Anthoff, D. & Tol, R. J. The uncertainty about the social cost of carbon: A decomposition analysis using FUND. *Climatic Change* 117, 515–530 (2013).

105. Foley, D., Rezai, A. & Taylor, L. The social cost of carbon emissions: Seven propositions. *Economics Letters* 121, 90–97 (2013).

106. Hope, C. W. Critical issues for the calculation of the social cost of CO2: Why the estimates from PAGE09 are higher than those from PAGE2002. *Climatic Change* 117, 531–543 (2013).

107. Hope, C. W. & Hope, M. The social cost of CO2 in a low-growth world. *Nature Climate Change* 3, 722–724 (2013).
108. Interagency Working Group on the Social Cost of Carbon. *Technical support document: Technical update of the social cost of carbon for regulatory impact analysis under Executive Order 12866 Report* (United States Government, 2013).

109. Marten, A. *et al.* Improving the assessment and valuation of climate change impacts for policy and regulatory analysis. *Climatic Change* **117**, 433–438 (2013).

110. Newbold, S. C., Griffiths, C., Moore, C., Wolverton, A. & Kopits, E. A Rapid Assessment Model For Understanding The Social Cost Of Carbon. *Climate Change Economics (CCE)* **4**, 1–40 (2013).

111. Nordhaus, W. D. in *Handbook of Computable General Equilibrium Modelling* (eds Peter, B. D. & Dale, W. J.) 1069–1131 (Elsevier, Amsterdam, 2013).

112. Van der Ploeg, F. & de Zeeuw, A. *Climate Tipping And Economic Growth: Precautionary Capital And The Price Of Carbon* OxCarre Working Papers 118 (Oxford Centre for the Analysis of Resource Rich Economies, University of Oxford, July 2013). [https://ideas.repec.org/p/oxf/oxcrwp/118.html](https://ideas.repec.org/p/oxf/oxcrwp/118.html).

113. Tol, R. S. J. Climate policy with Bentham–Rawls preferences. *Economics Letters* **118**, 424–428 (2013).

114. Weitzman, M. Tail-hedge discounting and the social cost of carbon. *Journal of Economic Literature* **51**, 873–882 (2013).

115. Crost, B. & Traeger, C. Optimal CO2 mitigation under damage risk valuation. *Nature Climate Change* **4**, 631–636 (2014).

116. Golosov, M., Hassler, J., Krusell, P. & Tsyvinski, A. Optimal Taxes on Fossil Fuel in General Equilibrium. *Econometrica* **82**, 41–88 (2014).

117. Heal, G. M. & Millner, A. Agreeing to disagree on climate policy. *Proceedings of the National Academy of Sciences* **111**, 3695–3698. [https://www.pnas.org/content/111/10/3695](https://www.pnas.org/content/111/10/3695) (2014).

118. Howarth, R., Gerst, M. & Borsuk, M. Risk mitigation and the social cost of carbon. *Global Environmental Change* **24**, 123–131 (2014).

119. Jensen, S. & Traeger, C. Optimal climate change mitigation under long-term growth uncertainty: Stochastic integrated assessment and analytic findings. *European Economic Review* **69**, 104–125 (2014).

120. Lemoine, D. & Traeger, C. Watch your step: Optimal policy in a tipping climate. *American Economic Journal: Economic Policy* **6**, 137–166 (2014).

121. Marten, A. L. The Role Of Scenario Uncertainty In Estimating The Benefits Of Carbon Mitigation. *Climate Change Economics* **5**, 1–29 (2014).

122. Moyer, E., Woolley, M., Matteson, N., Glotter, M. & Weisbach, D. Climate impacts on economic growth as drivers of uncertainty in the social cost of carbon. *Journal of Legal Studies* **43**, 401–425 (2014).
123. Newbold, S. & Marten, A. The value of information for integrated assessment models of climate change. *Journal of Environmental Economics and Management* **68**, 111–123 (2014).

124. Nordhaus, W. Estimates of the Social Cost of Carbon: Concepts and Results from the DICE-2013R Model and Alternative Approaches. *Journal of the Association of Environmental and Resource Economists* **1** (2014).

125. van der Ploeg, F. & Withagen, C. Growth, Renewables, And The Optimal Carbon Tax. *International Economic Review* **55**, 283–311 (2014).

126. De Zeeuw, A. J. & van der Ploeg, F. *Climate Tipping and Economic Growth: Precautionary Saving and the Social Cost of Carbon* CEPR Discussion Papers 9982 (C.E.P.R. Discussion Papers, May 2014). [https://ideas.repec.org/p/cpr/ceprdp/9982.html](https://ideas.repec.org/p/cpr/ceprdp/9982.html).

127. Pycroft, J., Vergano, L. & Hope, C. The economic impact of extreme sea-level rise: Ice sheet vulnerability and the social cost of carbon dioxide. *Global Environmental Change* **24**, 99–107 (2014).

128. Waldhoff, S., Anthoff, D., Rose, S. K. & Tol, R. S. J. The marginal damage costs of different greenhouse gases: An application of FUND. *Economics - The Open-Access, Open-Assessment E-Journal* **8**, 1–33 (2014).

129. Cai, Y., Judd, K., Lenton, T., Lontzek, T. & Narita, D. Environmental tipping points significantly affect the cost-benefit assessment of climate policies. *Proceedings of the National Academy of Sciences of the United States of America* **112**, 4606–4611 (2015).

130. Dennig, F., Budolfson, M., Fleurbaey, M., Siebert, A. & Socolow, R. Inequality, climate impacts on the future poor, and carbon prices. *Proceedings of the National Academy of Sciences of the United States of America* **112**, 15827–15832 (2015).

131. Dietz, S. & Stern, N. Endogenous growth, convexity of damage and climate risk: How Nordhaus’ framework supports deep cuts in carbon emissions. *Economic Journal* **125**, 574–620 (2015).

132. Freeman, M. & Groom, B. Positively gamma discounting: Combining the opinions of experts on the social discount rate. *Economic Journal* **125**, 1015–1024 (2015).

133. Freeman, M., Groom, B., Panopoulou, E. & Pantelidis, T. Declining discount rates and the Fisher Effect: Inflated past, discounted future? *Journal of Environmental Economics and Management* **73**, 32–49 (2015).

134. Hatase, K. & Managi, S. Increase in carbon prices: analysis of energy-economy modeling. *Environmental Economics and Policy Studies* **17**, 241–262 (2015).

135. Lemoine, D. *The Climate Risk Premium* Working Paper 15-01 (Department of Economics, University of Arizona, 2015).
136. Lontzek, T., Cai, Y., Judd, K. & Lenton, T. Stochastic integrated assessment of climate tipping points indicates the need for strict climate policy. *Nature Climate Change* **5**, 441–444 (2015).

137. Marten, A., Kopits, E., Griffiths, C., Newbold, S. & Wolverton, A. Incremental CH4 and N2O mitigation benefits consistent with the US Government’s SC-CO2 estimates. *Climate Policy* **15**, 272–298 (2015).

138. Moore, F. & Diaz, D. Temperature impacts on economic growth warrant stringent mitigation policy. *Nature Climate Change* **5**, 127–131 (2015).

139. Nordhaus, W. D. Climate Clubs: Overcoming Free-Riding in International Climate Policy. *American Economic Review* **105**, 1339–70. http://www.aeaweb.org/articles?id=10.1257/aer.15000001 (Apr. 2015).

140. van der Ploeg, F. Untapped fossil fuel and the green paradox: a classroom calibration of the optimal carbon tax. *Environmental Economics and Policy Studies* **17**, 185–210 (2015).

141. Pottier, A., Espagne, E., Perrissin Fabert, B. & Dumas, P. The Comparative Impact of Integrated Assessment Models’ Structures on Optimal Mitigation Policies. *Environmental Modeling and Assessment* **20**, 453–473 (2015).

142. Rezai, A. & van der Ploeg, F. Robustness of a simple rule for the social cost of carbon. *Economics Letters* **132**, 48–55 (2015).

143. Shindell, D. The social cost of atmospheric release. *Climatic Change* **130**, 313–326 (2015).

144. Ackerman, F. & Munitz, C. A critique of climate damage modeling: Carbon fertilization, adaptation, and the limits of FUND. *Energy Research and Social Science* **12**, 62–67 (2016).

145. Van den Bijgaart, I., Gerlagh, R. & Liski, M. A simple formula for the social cost of carbon. *Journal of Environmental Economics and Management* **77**, 75–94 (2016).

146. Cai, Y., Lenton, T. & Lontzek, T. Risk of multiple interacting tipping points should encourage rapid CO2 emission reduction. *Nature Climate Change* **6**, 520–525 (2016).

147. Freeman, M. & Groom, B. How certain are we about the certainty-equivalent long term social discount rate? *Journal of Environmental Economics and Management* **79**, 152–168 (2016).

148. Lemoine, D. & Traeger, C. Economics of tipping the climate dominoes. *Nature Climate Change* **6**, 514–519 (2016).

149. van der Ploeg, F. & Zeeuw, A. Non-cooperative and Cooperative Responses to Climate Catastrophes in the Global Economy: A North–South Perspective. *Environmental & Resource Economics* **65**, 519–540 (2016).
150. Rezai, A. & der Ploeg, F. V. Intergenerational Inequality Aversion, Growth, and the Role of Damages: Occam’s Rule for the Global Carbon Tax. *Journal of the Association of Environmental and Resource Economists* 3, 493–522 (2016).

151. Adler, M. *et al.* Priority for the worse-off and the social cost of carbon. *Nature Climate Change* 7, 443–449 (2017).

152. Budolfson, M., Dennig, F., Fleurbaey, M., Siebert, A. & Socolow, R. H. The comparative importance for optimal climate policy of discounting, inequalities and catastrophes. *Climatic Change* 145, 481–494. https://doi.org/10.1007/s10584-017-2094-x (2017).

153. Dayaratna, K., McKitrick, R. & Kreutzer, D. Empirically-constrained climate sensitivity and the social cost of carbon. *Climate Change Economics* (2017).

154. Golub, A. & Brody, M. Uncertainty, climate change, and irreversible environmental effects: application of real options to environmental benefit-cost analysis. *Journal of Environmental Studies and Sciences* 7, 519–526 (2017).

155. Hafeez, S., Weller, S. & M. Kellett, C. Impact of Climate Model Parametric Uncertainty in an MPC Implementation of the DICE Integrated Assessment Model. *IFAC-PapersOnLine* 50, 959–965 (2017).

156. Moore, F., Baldos, U., Hertel, T. & Diaz, D. New science of climate change impacts on agriculture implies higher social cost of carbon. *Nature Communications* 8 (2017).

157. Nordhaus, W. Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences of the United States of America* 114, 1518–1523 (2017).

158. Pindyck, R. Coase Lecture—Taxes, Targets and the Social Cost of Carbon. *Economica* 84, 345–364 (2017).

159. Van der Ploeg, F. & Rezai, A. Cumulative emissions, unburnable fossil fuel, and the optimal carbon tax. *Technological Forecasting and Social Change* 116, 216–222 (2017).

160. Rezai, A. & van der Ploeg, F. Climate policies under climate model uncertainty: Max-min and min-max regret. *Energy Economics* 68, 4–16 (2017).

161. Rezai, A. & van der Ploeg, F. Second-Best Renewable Subsidies to Decarbonize the Economy: Commitment and the Green Paradox. *Environmental & Resource Economics* 66, 409–434 (2017).

162. Rezai, A. & Van Der Ploeg, F. Abandoning Fossil Fuel: How Fast and How Much. *Manchester School* 85, 16–44 (2017).

163. Rose, S., Diaz, D. & Blanford, G. Understanding the social cost of carbon: A model diagnostic and inter-comparison study. *Climate Change Economics* 8 (2017).
164. Scovronick, N. et al. Impact of population growth and population ethics on climate change mitigation policy. *Proceedings of the National Academy of Sciences of the United States of America* **114**, 12338–12343 (2017).

165. Shindell, D., Fuglestvedt, J. & Collins, W. The social cost of methane: Theory and applications. *Faraday Discussions* **200**, 429–451 (2017).

166. Barrage, L. Be careful what you calibrate for: Social discounting in general equilibrium. *Journal of Public Economics* **160**, 33–49. [http://www.sciencedirect.com/science/article/pii/S0047272718300380](http://www.sciencedirect.com/science/article/pii/S0047272718300380) (2018).

167. Ekholm, T. Climatic Cost-benefit Analysis Under Uncertainty and Learning on Climate Sensitivity and Damages. *Ecological Economics* **154**, 99–106 (2018).

168. Faulwasser, T., Nydestedt, R., Kellett, C. & Weller, S. Towards a FAIR-DICE IAM: Combining DICE and FAIR Models. *IFAC-PapersOnLine* **51**, 126–131 (2018).

169. Guivarch, C. & Pottier, A. Climate Damage on Production or on Growth: What Impact on the Social Cost of Carbon? *Environmental Modeling and Assessment* **23**, 117–130 (2018).

170. Hänsel, M. & Quaas, M. Intertemporal Distribution, Sufficiency, and the Social Cost of Carbon. *Ecological Economics* **146**, 520–535 (2018).

171. Kotchen, M. Which social cost of carbon? A theoretical perspective. *Journal of the Association of Environmental and Resource Economists* **5**, 673–694 (2018).

172. Nordhaus, W. Projections and uncertainties about climate change in an era of minimal climate policies. *American Economic Journal: Economic Policy* **10**, 333–360 (2018).

173. Nordhaus, W. D. Evolution of modeling of the economics of global warming: changes in the DICE model, 1992–2017. *Climatic Change* **148**, 623–640 (2018).

174. Van der Ploeg, F. & de Zeeuw, A. Climate Tipping and Economic Growth: Precautionary Capital and the Price of Carbon. *Journal of the European Economic Association* **16**, 1577–1617. [https://doi.org/10.1093/jeea/jvx036](https://doi.org/10.1093/jeea/jvx036) (2017).

175. Quiggin, J. The importance of ‘extremely unlikely’ events: tail risk and the costs of climate change. *Australian Journal of Agricultural and Resource Economics* **62**, 4–20 (2018).

176. Ricke, K., Drouet, L., Caldeira, K. & Tavoni, M. Country-level social cost of carbon. *Nature Climate Change* **8**, 895–900 (2018).

177. Yang, P. et al. Social cost of carbon under shared socioeconomic pathways. *Global Environmental Change* **53**, 225–232 (2018).

178. Zhen, Z., Tian, L. & Ye, Q. *A simple estimate for the social cost of carbon* in. **152** (2018), 768–773.
179. Anthoff, D. & Emmerling, J. Inequality and the social cost of carbon. *Journal of the Association of Environmental and Resource Economists* **6**, 243–273 (2019).
180. Barrage, L. Optimal Dynamic Carbon Taxes in a Climate–Economy Model with Distortionary Fiscal Policy. *The Review of Economic Studies* **87**, 1–39. [https://doi.org/10.1093/restud/rdz055](https://doi.org/10.1093/restud/rdz055) (2019).
181. Budolfson, M. *et al.* Optimal Climate Policy and the Future of World Economic Development. *World Bank Economic Review* **33**, 21–40 (2019).
182. Bretschger, L. & Pattakou, A. As Bad as it Gets: How Climate Damage Functions Affect Growth and the Social Cost of Carbon. *Environmental and Resource Economics* **72**, 5–26 (2019).
183. Cai, Y. & Lontzek, T. The social cost of carbon with economic and climate risks. *Journal of Political Economy* **127**, 2684–2734 (2019).
184. Daniel, K. D., Litterman, R. B. & Wagner, G. Declining CO₂ price paths. *Proceedings of the National Academy of Sciences* **116**, 20886–20891. [https://www.pnas.org/content/116/42/20886](https://www.pnas.org/content/116/42/20886) (2019).
185. Jaakkola, N. & van der Ploeg, F. Non-cooperative and cooperative climate policies with anticipated breakthrough technology. *Journal of Environmental Economics and Management* **97**, 42–66 (2019).
186. Nordhaus, W. Climate Change: The Ultimate Challenge for Economics. *American Economic Review* **109**, 1991–2014. [https://www.aeaweb.org/articles?id=10.1257/aer.109.6.1991](https://www.aeaweb.org/articles?id=10.1257/aer.109.6.1991) (June 2019).
187. Nordhaus, W. Economics of the disintegration of the Greenland ice sheet. *Proceedings of the National Academy of Sciences of the United States of America* **116**, 12261–12269 (2019).
188. Pindyck, R. The social cost of carbon revisited. *Journal of Environmental Economics and Management* **94**, 140–160 (2019).
189. van der Ploeg, F. & Rezai, A. Simple Rules for Climate Policy and Integrated Assessment. *Environmental & Resource Economics* **72**, 77–108 (2019).
190. Van der Ploeg, F. & Rezai, A. The agnostic’s response to climate deniers: Price carbon! *European Economic Review* **111**, 70–84 (2019).
191. Tol, R. S. J. A social cost of carbon for (almost) every country. *Energy Economics* **83**, 555–566 (2019).
192. Zhen, Z. & Tian, L. The impact of climate damage function on the social cost of carbon and economic growth rate. *Mitigation and Adaptation Strategies for Global Change* (2019).
193. Bastien-Olvera, B. & Moore, F. Use and non-use value of nature and the social cost of carbon. *Nature Sustainability* (2020).
194. Dayaratna, K., McKitrick, R. & Michaels, P. Climate sensitivity, agricultural productivity and the social cost of carbon in FUND. *Environmental Economics and Policy Studies* (2020).
195. Gschnaller, S. The albedo loss from the melting of the Greenland ice sheet and the social cost of carbon. *Climatic Change* **163**, 2201–2231 (2020).

196. Hänsel, M. *et al.* Climate economics support for the UN climate targets. *Nature Climate Change* **10**, 781–789 (2020).

197. Howard, P. & Sylvan, D. Wisdom of the experts: Using survey responses to address positive and normative uncertainties in climate-economic models. *Climatic Change* **162**, 213–232 (2020).

198. Kalkuhl, M. & Wenz, L. The impact of climate conditions on economic production. Evidence from a global panel of regions. *Journal of Environmental Economics and Management* **103**, 102360. [http://www.sciencedirect.com/science/article/pii/S0095069620300838](http://www.sciencedirect.com/science/article/pii/S0095069620300838) (2020).

199. Naeini, M., Leibowicz, B. & Bickel, J. Can you trust a model whose output keeps changing? Interpreting changes in the social cost of carbon produced by the DICE model. *Environment Systems and Decisions* **40**, 301–320 (2020).

200. Okullo, S. J. Determining the Social Cost of Carbon: Under Damage and Climate Sensitivity Uncertainty. *Environmental & Resource Economics* **75**, 79–103 (2020).

201. Scovronick, N., Ferranna, M., Dennig, F. & Budolfson, M. Valuing health impacts in climate policy: Ethical issues and economic challenges. *Health Affairs* **39**, 2105–2112 (2020).

202. Zhen, Z. & Tian, L. The impact of climate damage function on the social cost of carbon and economic growth rate. *Mitigation and Adaptation Strategies for Global Change* **25**, 1287–1304 (2020).

203. Van Den Bremer, T. & Van Der Ploeg, F. The risk-adjusted carbon price. *American Economic Review* **111**, 2782–2810 (2021).

204. Coleman, T., Dumont, N., Li, W., Liu, W. & Rubtsov, A. Optimal Pricing of Climate Risk. *Computational Economics* (2021).

205. Dietz, S., Rising, J., Stoerk, T. & Wagner, G. Economic impacts of tipping points in the climate system. *Proceedings of the National Academy of Sciences of the United States of America* **118** (2021).

206. Drupp, M. A. & Hänsel, M. C. Relative Prices and Climate Policy: How the Scarcity of Nonmarket Goods Drives Policy Evaluation. *American Economic Journal: Economic Policy* **13**, 168–201. [https://www.aeaweb.org/articles?id=10.1257/pol.20180760](https://www.aeaweb.org/articles?id=10.1257/pol.20180760) (Feb. 2021).

207. Hambel, C., Kraft, H. & Schwartz, E. Optimal carbon abatement in a stochastic equilibrium model with climate change. *European Economic Review* **132**, 103642. [https://www.sciencedirect.com/science/article/pii/S0014292120302725](https://www.sciencedirect.com/science/article/pii/S0014292120302725) (2021).

208. Hambel, C., Kraft, H. & Schwartz, E. The social cost of carbon in a non-cooperative world. *Journal of International Economics* **131** (2021).
209. Kikstra, J. et al. The social cost of carbon dioxide under climate-economy feedbacks and temperature variability. *Environmental Research Letters* **16** (2021).

210. Kotlikoff, L., Kubler, F., Polbin, A., Sachs, J. & Scheidegger, S. Making Carbon Taxation A Generational Win Win. *International Economic Review* **62**, 3–46 (2021).

211. Lupi, V. & Marsiglio, S. Population growth and climate change: A dynamic integrated climate-economy-demography model. *Ecological Economics* **184**, 107011. [https://www.sciencedirect.com/science/article/pii/S0921800921000690](https://www.sciencedirect.com/science/article/pii/S0921800921000690) (2021).

212. Taconet, N., Guivarch, C. & Pottier, A. Social Cost of Carbon Under Stochastic Tipping Points. *Environmental & Resource Economics*. [https://link.springer.com/article/10.1007/s10640-021-00549-x](https://link.springer.com/article/10.1007/s10640-021-00549-x) (forthcoming).

213. *GRABIT* version 1.0.0.1. 2005. [https://www.mathworks.com/matlabcentral/fileexchange/7173-grabit](https://www.mathworks.com/matlabcentral/fileexchange/7173-grabit).

214. Silverman, B. W. *Density Estimation for Statistics and Data Analysis* (Chapman & Hall, London, 1986).

215. Johnson, N. L. Systems of Frequency Curves Generated by Methods of Translation. *Biometrika* **36**, 149–176. [http://www.jstor.org/stable/2332539](http://www.jstor.org/stable/2332539) (1949).

216. Tol, R. S. J. Leviathan carbon taxes in the short run. *Climatic Change* **114**, 409–415 (2012).

217. Pearson, K. On the criterion that a given system of deviations from the probable in the case of a correlated system of variables is such that it can be reasonably supposed to have arisen from random sampling. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science* **50**, 157–175. [https://doi.org/10.1080/14786440009463897](https://doi.org/10.1080/14786440009463897) (1900).

218. Havranek, T., Irsova, Z., Janda, K. & Zilberman, D. Selective reporting and the social cost of carbon. *Energy Economics* **51**, 394–406 (2015).

219. Begg, C. B. & Mazumdar, M. Operating Characteristics of a Rank Correlation Test for Publication Bias. *Biometrics* **50**, 1088–1101. [http://www.jstor.org/stable/2533446](http://www.jstor.org/stable/2533446) (1994).

220. Andrews, I. & Kasy, M. Identification of and Correction for Publication Bias. *American Economic Review* **109**, 2766–94. [https://www.aeaweb.org/articles?id=10.1257/aer.20180310](https://www.aeaweb.org/articles?id=10.1257/aer.20180310) (Aug. 2019).

221. Kolmogorov, A. Sulla determinazione empirica di una legge di distribuzione. *Giornale dell’Istituto Italiano degli Attuari* **4**, 83–91 (1933).

222. Smirnov, N. Table for Estimating the Goodness of Fit of Empirical Distributions. *The Annals of Mathematical Statistics* **19**, 279–281 (1948).
223. Iglin, S. *Kolmogorov Distribution Functions* version 1.0.0.0. 2004. [https://www.mathworks.com/matlabcentral/fileexchange/4369-kolmogorov-distribution-functions](https://www.mathworks.com/matlabcentral/fileexchange/4369-kolmogorov-distribution-functions).

224. Laplace, P.-S. *Essai philosophique sur les probabilités* (V° Courcier, Paris, 1814).