Energy Economics 83 (2019) 555–566

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

A social cost of carbon for (almost) every country

Richard S.J. Tol*

Department of Economics, University of Sussex, Falmer, United Kingdom
Institute for Environmental Studies, Vrije Universiteit, Amsterdam, The Netherlands
Department of Spatial Economics, Vrije Universiteit, Amsterdam, The Netherlands
Tinbergen Institute, Amsterdam, The Netherlands
CESifo, Munich, Germany
Payne Institute for Earth Resources, Colorado School of Mines, Golden, CO, USA

ARTICLE INFO

Article history:
Received 7 January 2019
Received in revised form 7 June 2019
Accepted 3 July 2019
Available online 16 July 2019

JEL classification:
Q54

Keywords:
Climate change
Pigou tax
Climate policy
Non-cooperation
Social cost of carbon

ABSTRACT

This paper uses imputed national climate change impact functions to estimate national social costs of carbon, which are largest in poor countries with large populations. The national social costs of carbon of faster growing economies are less sensitive to the pure rate of time preference and more sensitive to the rate of risk aversion. The pattern of national social costs of carbon is not sensitive to the assumed impact function, climate sensitivity, and scenario, although the global social cost of carbon is. Income convergence raises the national social costs of carbon of poorer countries, and lowers them for richer countries. Both global and national social costs of carbon are most sensitive to the income elasticity of climate change impacts, a parameter about which we know little.

1. Introduction

The social cost of carbon is the incremental impact of emitting an additional tonne of carbon dioxide, or the benefit of slightly reducing emissions. When evaluated along an optimal emissions trajectory, it is the Pigou (1920) tax—the carbon tax needed to restore efficiency. Greenhouse gases mix uniformly in the atmosphere. Emissions are *global* externalities. The social cost of carbon is the tax a global planner would impose. National planners may disagree. This paper therefore presents estimates of the social cost of carbon *for every nation*.

There have been a number of reviews of the social cost of carbon (Guivarch et al., 2016; Metcalf and Stock, 2017; Pindyck, 2017a,b; Pizer et al., 2014; Revesz et al., 2017) and its application (Greenstone et al., 2013; Hahn and Ritz, 2015; Heyes et al., 2013; Rose, 2012; Sunstein, 2014), as well as meta-analyses (Havranek et al., 2015; Tol, 2005, 2009, 2011, 2013, 2018; Wang et al., 2018). These papers focus on the global social cost of carbon (see Cai and Lontzek, 2019; Nordhaus, 1982, and many other papers published in between), and largely ignore the regional composition. That is exactly what this paper is about.

The models used to estimate the global social cost of carbon, and the studies on which they are calibrated, often have regional or even national estimates. The national social costs of carbon are rarely spelled out, and hardly ever discussed. That is perhaps as it should be: Carbon dioxide is a global externality after all (Gayer and Viscusi, 2016). However, besides the academic interest in knowing the regional composition of the social cost of carbon, the Trump Administration has decided that its climate impacts on the rest of the world are irrelevant for US policy while the *Nationally Determined* Intended Contributions of the Paris Agreement also suggest that climate policy is a non-cooperative game, in which cross-border externalities are ignored.

This is the second paper to estimate the social cost of carbon per country. Ricke et al. (2018) base their estimates on the work by Burke et al. (2015) and Dell et al. (2012), who regress economic growth on temperature (see also Burke et al., 2018; Lemoine and Kapnick, 2015; Pretis et al., 2018). Weather is, from an economic perspective, random. The impact of weather is arguably identified. However, the impact of a weather shock is not the same as the impact of climate change (Dell et al., 2014). Climate is what you expect, weather is what you get. Adaptation to weather shocks is therefore

* Jubilee Building, BN1 9SL, United Kingdom.
E-mail address: r.tol@sussex.ac.uk.
URL: http://www.ae-info.org/ae/Member/Tol_Richard.

https://doi.org/10.1016/j.eneco.2019.07.006
0140-9883/

limited to immediate responses—put up an umbrella when it rains, close the flood doors when it pours. Adaptation to climate change extends to changes in the capital stock—buy an umbrella, invest in flood gates—as well as adjusted expectations and re-directed technological progress. In other words, weather studies estimate the short-run elasticity, whereas the interest is in the long-run elasticity. See Deryugina and Hsiang (2017) and Lemoine (2018) for the, rather strict, conditions under which weather variability is informative about climate change.

Ricke et al. (2018) find little difference between the social cost carbon based on the impact functions of Burke et al. (2015) and Dell et al. (2012). However, Burke's impact estimates are much higher than Dell's. There are three reasons for Ricke's remarkable result. Firstly, Dell finds that rich countries are not affected by weather shocks. In the base specification, Burke makes no such differentiation; in an alternative specification, the impact of weather shocks is lower in richer countries, but not zero. Ricke initially put the threshold between rich and poor at $20,715 per person per year, referring to this as the "median income" in 1980. Using the same data source, the World Bank, I find that the country-weighted median was $1566/p/yr, the population-weighted median $275/p/yr in 1980. Ricke's inexplicably high threshold overestimates the impact according to Dell. Kate Ricke (personal communication, 2019) has acknowledged this mistake, and a correction has been published: The original estimates were adjusted downwards. Secondly, Burke argues that the growth effect depends on the level of the temperature,[1] whereas Dell argues it depends on the change in temperature. This implies that, in a scenario without climate change, Burke would see different growth rates in hot and cold countries, but Dell would not. Ricke does not recalibrate the growth scenarios when switching from Burke to Dell. Thirdly, Burke and Dell estimate their impact functions on past weather, which is stochastic. Ricke uses GCM output, but removes the annual variability. This does not matter for the Dell impact function, which is linear, but it does for the quadratic impact function of Burke. Let's assume that the annual temperature is normally distributed $T_t \sim \mathcal{N}(\mu_t, \sigma^2)$. If the impact function is $I_t = \alpha \Delta T_t$ (Dell's) then $\mathbb{E} I_t = \alpha \Delta \mu_t$. Setting $\sigma = 0$ is immaterial for the estimate of the expected impact. However, if $I_t = \beta T_t + \gamma T_t^2$ (Burke's) then $\mathbb{E} I_t = \beta \mu_t + \gamma(\sigma^2 + \mu_t^2)$. Setting $\sigma = 0$—that is, removing the stochasticity—underestimates the expected impact. Within each run of their Monte Carlo analysis, Ricke estimates the mode rather than the mean. Incongruously, Ricke's central estimate is the average mode. I did not replicate Ricke's estimates with these three errors corrected, so I do not know which of the three explains most of the lack of divergence between Burke and Dell.

Ricke et al. (2018) further assume that climate change affects economic growth, rather than the level of economic activity (Fankhauser and Tol, 2005; Piontek et al., 2018). This is known to substantially increase estimates of the social cost of carbon (Dietz and Stern, 2015; Moore and Diaz, 2015; Moyer et al., 2014). The empirical evidence suggests that the growth effect of weather is small (Letta and Tol, 2018). Newell et al. use cross-validation tests to show that weather shocks affect the level of economic activity, rather than its growth rate.

[1] The econometrics of Burke et al. (2015) do not stand up to scrutiny. They regress the difference of the log of per capita income, a stationary variable, on temperature, a non-stationary variable, and year dummies. As a non-stationary variable cannot explain a stationary one, Burke's year dummies must have *de facto* detrended temperature. This is indeed the case, as confirmed by their replication package. To the best of my knowledge, the statistical properties of regressing a stationary variable on a cointegrating vector are not known. However, that cointegration vector is measured with error. Errors-in-variables induce bias, of unknown sign in non-linear models (Griliches and Ringstad, 1970). Burke's unusual procedure works fine in-sample, but goes off the rails out-of-sample (Newell et al.) as the year dummies cannot be predicted.

Therefore, this paper is based on estimates of the impact of *climate change*, rather than *weather shocks*, on the *level* of economic activity, rather than on the *growth rate* of the economy. It follows from the above discussion that the estimates here are very different from, and arguably much better than those by Ricke et al. (2018).

The paper proceeds as follows. Section 2 discusses the total impact of climate change. Section 3 defines the social cost of carbon, and details its calculation. Section 4 presents the estimates of the national social costs of carbon. Section 5 concludes.

2. The total impact of climate change

Fig. 1 shows the 27 published estimates of the total economic impact of climate change. See also Howard and Sterner (2017) and Nordhaus and Moffat (2017). The change in the global annual mean surface air temperature since pre-industrial times is on the horizontal axis as an indicator for the extent of climate change. The welfare equivalent income change is on the horizontal one. A global warming of 2.5° would make the average person feel as if she had lost 1.3% of her income.

2.1. Methods

Impacts were estimated using a variety of methods. Most studies use the enumerative method to estimate the direct cost (Berz; d'Arge, 1979; Fankhauser, 1995; Hope, 2006; Nordhaus, 1982, 1991, 1994b, 2008; Nordhaus and Boyer, 2000; Nordhaus and Yang, 1996; Plambeck and Hope, 1996; Tol, 1995, 2002), a poor approximation of the change in welfare. Other studies shock a computable general equilibrium model (Bosello et al., 2012; Roson and van der Mensbrugghe, 2012), using a proper welfare measuring and including interactions between countries and sectors, but limiting the analysis to what is in the national accounts. Other estimates are based on regressions of economic indicators on climate (Mendelsohn et al., 2000, Nordhaus, 2006, Maddison, 2003, Rehdanz and Maddison, 2005, Maddison and Rehdanz, 2011, Mendelsohn et al., 2000). These studies use actual (rather than modelled) behaviour, but assumed that a relationship observed over space holds over time. Nordhaus (1994a) elicited the views of *supposed* experts.

2.2. Combining estimates

Besides the primary estimates, Fig. 1 also shows a curve—the impact of climate change as a function of global warming since pre-industrial times. Seven alternative impact functions, suggested in the literature, were fitted to the data shown in Fig. 1. See Table 1. Assuming normality of the residuals, the loglikelihood was computed for each model. The curve shown is the Bayesian average of the seven models. A piecewise linear model is the best fit to the data, and the average curve indeed looks like that. The near-linearity of the impact function is driven by the two moderate estimates for high warming.

As show in Table 1, most analysts argue that the impact of climate change is non-linear, and intuition indeed suggests that 4° warming is more than twice as bad as 2° warming. Section 4.9 finds that the piecewise linear function is particularly sensitive to the details of calibration and imputation, while Section 4.4 finds that the spatial pattern for the piecewise linear function is similar to that for the parabolic function. I will therefore use the latter as the default choice.

Only 7 of the 27 estimates have a reported standard deviation, or an upper and lower bound. I imputed upper and lower bounds from twice the reported standard deviations. I assume that the upper and lower bounds are linear functions of the temperature, with slopes 0.92%GDP/° and 2.33%GDP/° on the cold and hot side, respectively. This is roughly a 90% confidence interval.

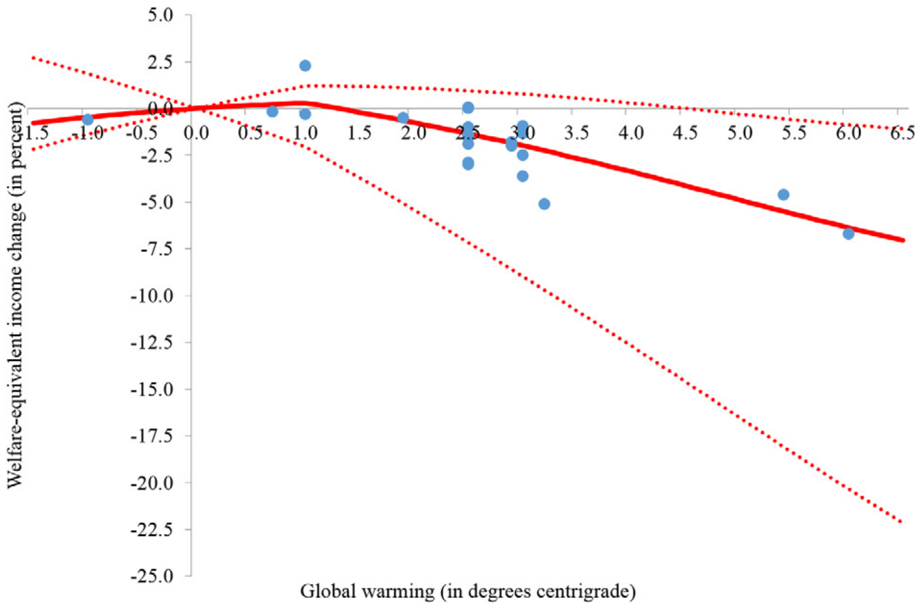

Fig. 1. The global total annual impact of climate change.

2.3. Results

Fig. 1 contains many messages, but these are based on only 27 estimates. The 11 estimates for 2.5° show that researchers disagree on the sign of the net impact but agree on the order of magnitude. A century of climate change may be about as bad as losing a year of economic growth.

Initial warming may be net positive, while further warming would lead to net damages. The *incremental* impacts turn negative around 1.1° global warming, a point we may have reached already.

The uncertainty is rather large, and probably an underestimate of the true uncertainty, as experts tend to be overconfident and as the 27 estimates were derived by a group of researchers who know each other and each other's work well. The uncertainty is right-skewed. Negative surprises are more likely than positive surprises of similar magnitude. In that light, the above conclusion needs to be rephrased: A century of climate change is no worse than losing a decade of economic growth.

2.4. Distribution of impacts

Thirteen of the twenty-two studies referred to above include estimates of the regional impacts of climate change—see Appendix A—or, in the studies involving David Maddison, national impact estimates. Regressing the estimated regional impact for 2.5° warming on per capita income and average annual temperature, with dummies for the studies, I find that

$$I_c \propto 1.68(0.80)\ln y_c - 0.45(0.14)T_c \qquad (1)$$

where I_c is the impact in country c (in %GDP), y_c is its average income (in 2010 market exchange dollars per person per year), and T_c is the average annual temperature (in degrees Celsius). Hotter countries have more negative impacts. Richer countries have more positive impacts. Eq. (1) does not capture the special vulnerability of delta and island nations. I use this equation to impute national impacts, making sure that the regional or global totals match those in the original estimates.

Fig. 1 shows the world average impact for 27 studies. Fig. 2 shows results for individual countries for 2.5° warming. Countries are ranked from low to high per capita income and low to high temperature. In Fig. 1, the world total impact is roughly zero. In Fig. 2, the majority of countries show a negative impact. However, the world economy is concentrated in a few, rich countries. The world average in Fig. 1 counts dollars, rather than countries, let alone people.

Fig. 2 suggests that poorer countries are more vulnerable to climate change than are richer countries. There are a few exceptions to this—such as Mongolia, which is poor but so cold that warming would bring benefits, and Singapore, which is rich but a low-lying

Table 1
Alternative models of the total impact of climate change.

Name	Function	Weight	SCC
Golosov	$-4.16 \cdot 10^{-175}\left(e^{e^T} - e\right)$	0.0%	\$0.00/tC
Ploeg	$-0.02\,(e^T - 1)$	0.0%	\$3.87/tC
Hope	$-0.71T$	0.2%	\$28.10/tC
Nordhaus	$-0.19T^2$	8.7%	\$22.59/tC
Tol (parabolic)	$-0.12T - 0.16T^2$	10.2%	\$24.02/tC
Weitzman (7)	$-0.21T^2 - 5.79 \cdot 10^{-6}T^7$	13.6%	\$25.77/tC
Weitzman (6)	$-0.22T^2 - 3.71 \cdot 10^{-5}T^6$	14.2%	\$25.65/tC
Tol (piecewise linear)	$0.74TI_{T<1.01} + (2.17 - 1.41T)I_{T\geq 1.01}$	53.2%	\$145.26/tC

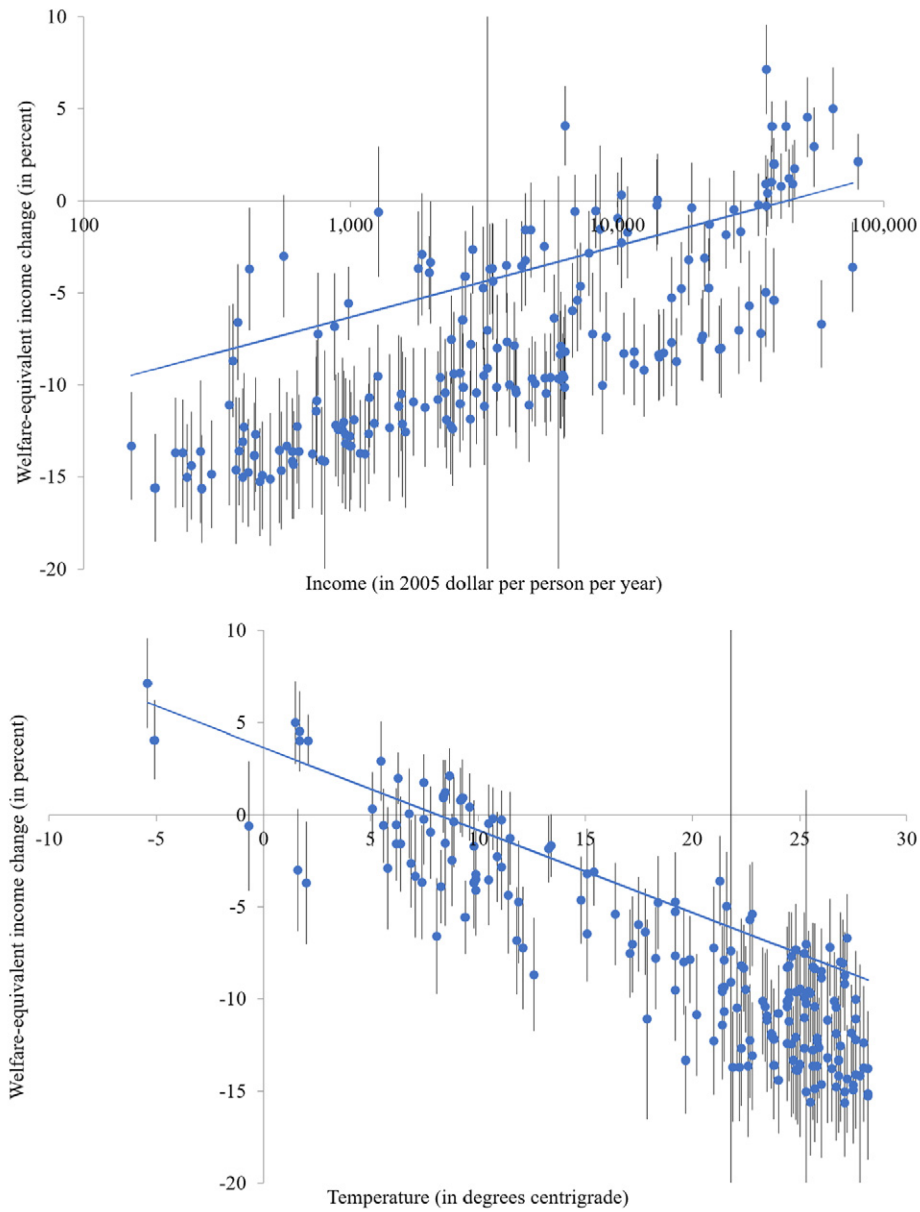

Fig. 2. The economic impact of climate change for a 2.5° warming for all countries as a function of their 2005 income (top panel) and temperature (bottom panel).

island on the equator—but by and large the negative impacts of climate change are concentrated in the developing economies.

There are three reasons for this. Poorer countries are more exposed, having a larger share of their economic activities in agriculture. Poorer countries tend to be in hotter places, so that ecosystems are closer to their biophysical upper limits, and so that there are no analogues for human behaviour and technology. Poorer countries also typically have a limited *adaptive capacity* (Adger, 2006; Yohe and Tol, 2002).

3. The social cost of carbon

3.1. Definition

The social cost of carbon is defined as the monetary value of the first partial derivative of global, net present welfare to current carbon dioxide emissions. It is sometimes calculated as a true marginal along a welfare-optimizing emissions trajectory, and so equals the Pigou (1920) tax on carbon dioxide. More often, the social cost of carbon is approximated as a normalized increment along an arbitrary emissions path. Essentially, you compute the impacts of climate change for a particular scenario; you slightly increase emissions in 2018 and compute the slightly different impacts; you take the difference between the two series of future impacts; discount them back to today; and normalize the net present value of the difference with the change in emissions.

Formally, if the utility function CRRA and inequity aversion zero,

$$SCC_c = \left(\frac{P_{c,0}}{C_{c,0}}\right)^{\eta} \frac{\partial}{\partial E_0} \sum_t \frac{1}{(1+\rho)^t} \frac{P_{c,t}}{1-\eta} \left(\frac{C_{c,t}}{P_{c,t}}\right)^{1-\eta} \tag{2}$$

where *SCC* is the social cost of carbon at time 0, E_0 denote emissions, $P_{c,t}$ population in country c at time t, and $C_{c,t}$ consumption; ρ is a parameter, the pure rate of time preference, and η is the rate of relative risk aversion.

Carbon dioxide stays in the atmosphere for a long time, and the climate is a dynamic system. Therefore, an additional tonne of carbon dioxide emitted today will have a long-lasting impact, that needs to be discounted to today. This is the summation. Utility is discounted at rate ρ, consumption at rate $\rho + g_P + \eta g_C$, where g_P is the growth rate of the population and g_C is the growth rate of consumption. The first partial derivative is welfare to emissions. The social cost of carbon is expressed in dollar per tonne of carbon. The first element in Eq. (2) normalizes the marginal impact on net present utility with the marginal utility of consumption at the time of emission.

3.2. Model

I wrote Matlab code to combine the impact models in Table 1 with the SRES (Nakicenovic and Swart, 2000) and SSP (Riahi et al., 2017) scenarios of population, income and emissions, the Maier-Reimer and Hasselmann (1987) carbon cycle model and the Schneider and Thompson (1981) climate model. Readers are free to download, run, manipulate and share the code.

3.3. Impacts of climate change

Eq. (1) is used to impute national impact estimates from global and regional estimates. These are benchmark estimates. In the default model, I combine the calibrated *global* impact function with the estimated income elasticity in Eq. (1) to impute national impact functions. As robustness checks, I use both income and temperature to impute national impact functions; and I use the imputed national impacts to calibrated national impact functions. As shown below, these alternative procedures do not yield plausible results, as the available evidence is overinterpreted.

3.4. Scenarios

The scenarios are build following the Kaya identity: population, per capita income, energy intensity of the economy, and carbon intensity of energy supply. The national scenarios extrapolate observed trends (see below) and are rescaled to match the four core SRES scenarios and the five SSP baseline scenarios, as defined by the model averages from the IIASA database.

The national population growth rate is the weighted average of the latest observed growth rate and the growth rate of the SRES and SSP scenarios. The weight placed on the observations is near one in the first scenario year, and falls linearly to almost zero in the final scenario year. The size of the global population then does not match the SRES and SSP scenarios. Therefore, each national population is scaled, by the same factor, to make sure the scenarios are aligned.

Economic output follows a Cobb-Douglas production function, with a output elasticity of 0.8 with respect to labour. The labour force is assumed proportional to population size. The capital stock depreciates at 10% per year. The savings rate is 20%. Total factor productivity grows by 5.9% per year minus 0.0048 times the natural logarithm of per capita income. These numbers follow from regressing the change in total factor productivity on per capita income, both taken from the Penn World Tables. Total factor productivity growth is capped from below at 1%. This implies income convergence. The size of the global economy then does not match the SRES and SSP scenarios. Therefore, each national economy is scaled, by the same factor, to make sure the scenarios are aligned.

The energy intensity of the economy and the carbon intensity of the energy sector follow from a log-log regression of intensity on per capita income, with an income elasticity of −0.39 for energy intensity and an income elasticity of −0.32 for carbon intensity. National energy use and carbon dioxide emissions are scaled so that the global totals match the SRES and SSP scenarios.

3.5. Uncertainties v sensitivities

There are a number of key parameters and assumptions in the model, including the scenario, the climate sensitivity, the impact function, the discount rate, the income elasticity, and the imputation method. Below, I vary these one at a time and discuss the effect on the global social cost of carbon and its spatial pattern.

Instead, I could have used an uncertainty analysis. However, that sits awkwardly with methodological choices, such as the imputation method, and ethical decisions, such as the pure rate of time preference. Furthermore, some parameters, such as the climate sensitivity, have a reasonably well-defined probability density function while other parameters, such as the scenario used, do not. Besides, an uncertainty analysis with many dimensions is not particularly informative unless accompanied by a decomposition of the output uncertainty into its constituent parts, the input uncertainties. Such a decomposition shows the sensitivity of the output to the inputs—which can also be shown, but without having to make assumptions about the uncertainties, with a sensitivity analysis.

4. Results

4.1. Base

The base case uses the parabolic impact function, the SSP2 scenario, a pure rate of time preference of 1%, and a rate of risk aversion of 1. The global social cost of carbon is \$24.02/tC. As the assumed impact function is strictly negative, the social cost of carbon is strictly positive. All national social costs of carbon are therefore a fraction of the global social cost. Bigger countries have a larger national cost. The national social cost of carbon is \$5.74/tC for India, \$3.07/tC for China, \$1.17/tC for Ethiopia, \$1.13/tC for Bangladesh, \$1.05/tC for Pakistan, \$0.85/tC for Indonesia, \$0.33/tC for the EU, and \$0.15/tC for the USA. These eight countries[2] together make up 56% of the global social cost of carbon.

Fig. 3 plots the national social cost of carbon per capita against per capita income in 2015. The line is regular and smooth. A per capita social cost is a meaningless indicator, but Fig. 3 reveals that population size and per capita income explain almost all variation in the social cost of carbon between countries.

Table 2 compares the estimates of the regional social cost of carbon to those reported by Nordhaus (2017). The key differences are that, because of the high income elasticity, rich regions (including fast-growing China) contribute much less to the global social cost of carbon and poor regions much more. If the income elasticity is set to zero, the regional pattern is more like that in other studies.

4.2. Discount rates

In the base specification, the pure rate of time preference is 1% per year and the rate of risk aversion is 1. The global social cost of carbon is \$24.02/tC. This increases to \$29.91/tC for a 0.1% pure rate of time preference and falls to \$11.65/tC for 5%. As has been seen in numerous previous papers, the social cost of carbon is highly sensitive to the pure rate of time preference.

The Ramsey (1928) Rule has that the consumption discount rate equals the pure rate of time preference plus the rate of risk aversion times the growth rate of consumption: $r = \rho + \eta g$. This implies that the pure rate of time preference is more (less) important for countries that grow more slowly (faster).

Because the per capita incomes as constructed strictly converge, this can be illustrated with the richest and poorest country in the sample. The global social cost of carbon is 2.57 times as big for a 0.1%

[2] Climate policy is a matter for the European Union rather than its Member States.

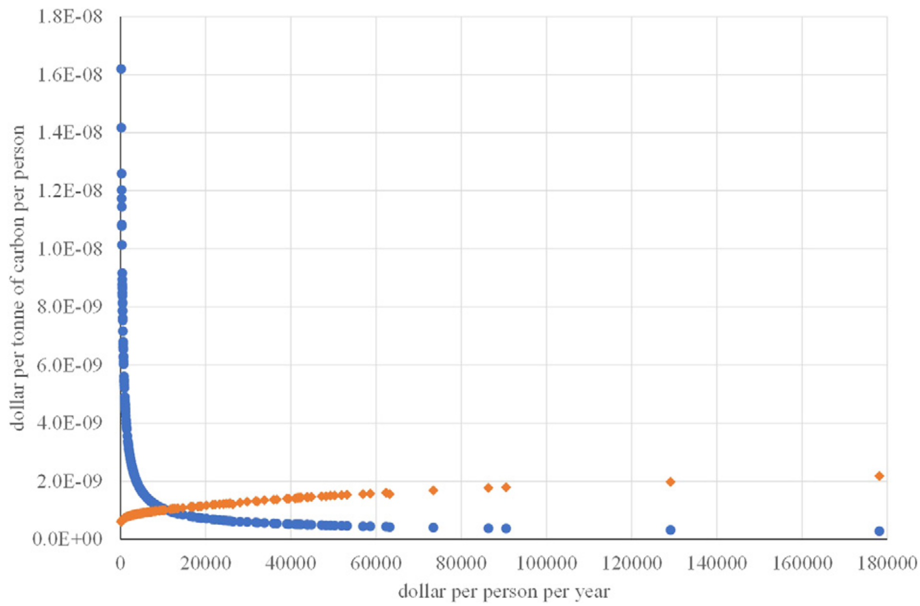

Fig. 3. The per capita social cost of carbon plotted against per capita income for an income semi-elasticity of −1.68 (blue dots) and −0.88 (orange triangles).

pure rate of time preference than for a 5% one; for Luxembourg, this ratio is 3.47; for Afghanistan, it is 2.56. This highlights that the global social cost of carbon is dominated by poor countries. Fig. 4 illustrates this. The social cost of carbon of faster growing economies are less sensitive to the pure rate of time preference.

The Ramsey Rule also implies that faster (slower) growing economies are more (less) sensitive to the assumed rate of risk aversion. If the rate of risk aversion is 0.5, rather than 1.0, the global social cost of carbon rises to \$38.67/tC; for a rate of risk aversion of 2.5, it is \$9.01/tC. The ratio is 4.31. This suggests that the social cost of carbon is more sensitive to the rate of risk aversion than to the pure rate of time preference, but it is hard to compare like with like for two poorly constrained parameters.

For Afghanistan, the poorest and assumedly fastest growing country, the ratio is 4.30; for Luxembourg, the richest and assumedly slowest growing country, the ratio is 4.13. Portugal is the most sensitive country, with a ratio of 4.67. Fig. 4 illustrates that there is a U-shaped relationship between the sensitivity of the national social cost of carbon to the rate of risk aversion and the assumed growth rate of the economy. The reason for this is as follows. If a country grows faster, it discounts the future harder, and this is more pronounced as the utility function is more curved. This explains the upward slope for countries with an average income above \$20,000 per person per year in 2015. However, countries that grow faster also become less vulnerable to climate change more quickly, and their impacts are concentrated in the nearer future. The discount rate therefore becomes less important. This effect dominates for countries with an income below \$20,000. It explains the downward slope.

4.3. Constant discount rate

The US government uses a constant consumption discount rate (IAWGSCC, 2013), against the advice of experts (Arrow et al., 2013, 2014). A constant discount rate is inconsistent with theory, and invariant between scenarios. It is also invariant between countries, unless the international capital market is perfect (which it is not). This in turn means that a constant discount rate introduces an implicit penalty or premium on the impact in particular countries.

Fig. 5 illustrates this. It shows the ratio of the national social cost of carbon for a pure rate of time preference of 1% per year to the national social cost of carbon for a constant discount rate of 4.9%.

Table 2
Alternative estimates of the regional distribution of the social cost of carbon.
Source: Nordhaus (2017) except rightmost columns.

	RICE	FUND	PAGE	PNAS	This study	
					−1.68	0
USA	10	17	7	15	0.6	26.1
EU	12	24	9	15	1.4	27.3
Japan	2	3	na	3	0.3	8.8
Russia	1	10	na	3	0.8	1.7
Eurasia	1	na	na	5	2.4	0.7
China	16	8	11	21	12.8	7.6
India	12	5	22	9	23.9	2.5
Middle East	10	na	na	7	2.6	4.0
Africa	11	6	26	3	30.4	2.6
Latin America	7	na	11	6	4.3	6.8
Other high income	4	na	na	3	0.4	9.0
Other	12	−28	−16	8	20.2	2.7

Regional contributions are given in percentages. Two sets of results are shown for this study, one with the default income elasticity of impacts (−1.68) and one with a zero income elasticity.

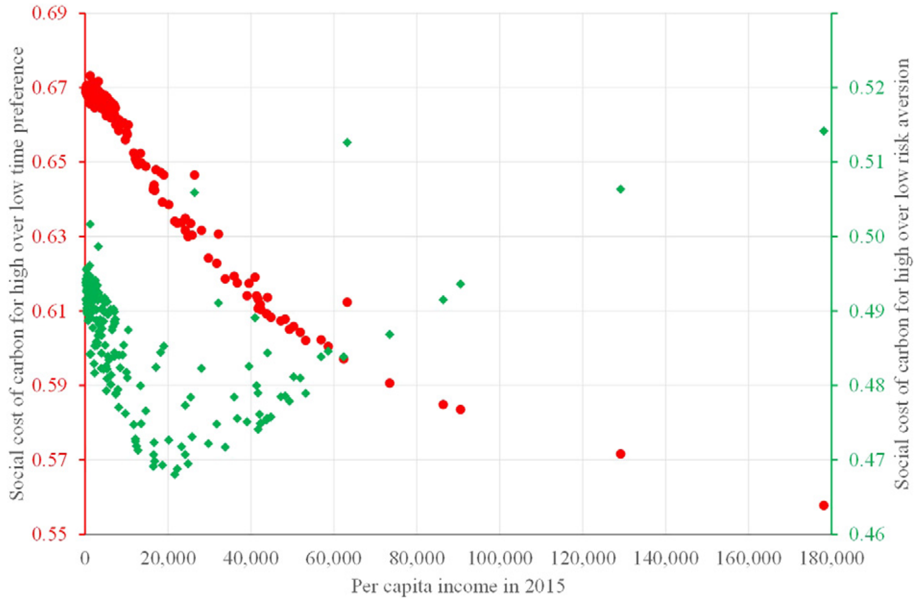

Fig. 4. The ratio of the social cost of carbon for a 1% pure rate of time preference to a 3% rate (red dots, left axis) and for a risk aversion of 2 over the social cost of carbon for a risk aversion of 1 as a function of per capita income in 2015 (green diamonds, right axis).

For both nominator and denominator, I assume the parabolic impact model and scenario SSP2. The constant discount rate equals 4.9% so that the US social cost of carbon equals \$0.15/tC, as above. Fig. 5 plots this ratio against the assumed economic growth rate. A constant discount rate overemphasizes (underemphasizes) the impact of climate change in fast-growing (slow-growing) countries.

Fig. 6 shows the national social cost of carbon estimates. Only the 30 countries with largest social cost of carbon are included. The graph displays the results for the SSP2 scenario, the parabolic impact model, and a Ramsey discount rate with a 1% pure rate of time preference and a risk aversion of one. It also shows results for a constant discount rate. I use two calibrations. In the first, the discount rate is 4.8% per year, so that the US social cost of carbon is \$0.15/tC as above. The global social cost of carbon is then \$28.76/tC, higher than above. In the second calibration, the discount rate is 5.7% so that the global social costs of carbon is \$24.02/tC as above. The US social cost of carbon then falls to \$0.13/tC. In either calibration, a constant discount rate as used in IAWGSCC (2013) puts a heavier weight on impacts in countries that are projected to grow faster than the USA. In the global calibration, US impacts are additionally suppressed.

4.4. Impact function

The default impact function is the parabolic one displayed in Table 1. That table also shows the global social cost of carbon. The Weitzman, Nordhaus and Hope models give similar results, with

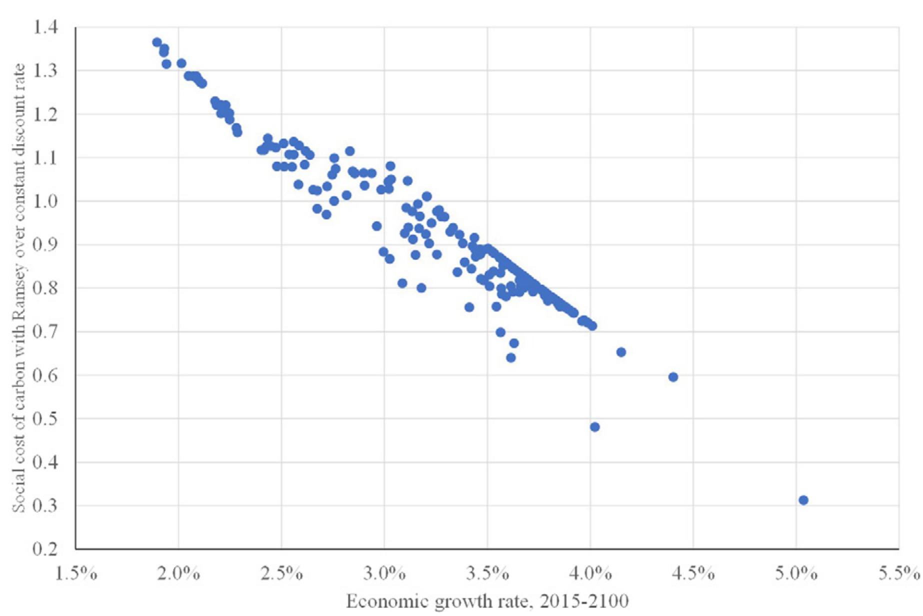

Fig. 5. The ratio of the social cost of carbon with a Ramsey discount rate to the social cost of carbon with a constant discount rate as a function of the assumed growth rate of the economy.

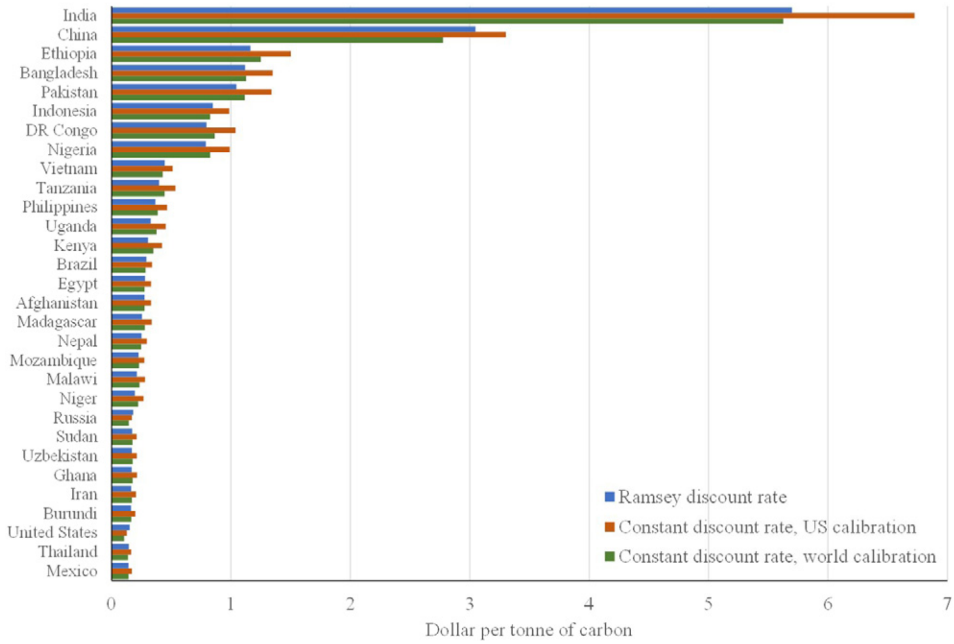

Fig. 6. The 30 largest national social costs of carbon with a Ramsey discount rate and two equivalent constant discount rates.

higher estimates for the more nonlinear specifications. This patterns breaks with the highly non-linear models of Ploeg and Golosov. The latter model has essentially zero damage below a threshold and infinite damage above. The social cost of carbon is therefore zero unless the extra tonne of carbon pushes the climate over the threshold. The Ploeg impact model is a less extreme version of this. The national pattern of social costs of carbon is very similar to the pattern from the parabolic model.

The piecewise linear model has a global social cost of carbon of $145.26/tC, 9.0 times as large as in the default. The pattern of national social costs is indistinct. For each country, the social cost is between 7.6 and 9.1 times as large for the parabolic model. The global social cost of carbon is so much higher because, when calibrated to the same data, a linear impact function gives higher impacts for moderate warming and lower impacts of substantial warming than a non-linear impact function (Peck and Teisberg, 1994, were the first to report this). The high income elasticity implies that later costs are relatively small, and the discount rate further emphasizes the impact of moderate warming in the short run.

4.5. Scenario dependence and convergence

There are two aspects to a scenario. First, how fast will climate change, and thus how much damage will be done? Second, how fast will incomes grow, and vulnerability to climate change fall? As economic growth drives emissions growth, these two effects at least partly offset each other. The separate effects are discussed below, climate in Section 4.7, growth in Section 4.6.

The SSP2 scenario is the default scenario. All scenarios are deemed equally unlikely. The default scenario is the median of the newer SSP scenarios. Table 3 shows the global social cost of carbon for all scenarios. Estimates range between $14.67/tC and $55.51/tC. The default scenario is somewhere in the middle. The earlier SRES scenarios are somewhat higher than the later SSP scenarios.

The national results scale with the global estimates. The social cost of carbon of countries rich and poor vary in almost the same way as the aggregate does. The pattern across countries is largely independent from scenario choice.

In the default scenarios, poorer countries grow faster. This is corroborated by some but not all data. Dropping this assumption, letting all countries grow at the same rate, leads to a global social cost of carbon of $28.57/tC, a slight increase. Fig. 7 plots the change in the national social cost of carbon against per capita income in 2015. Countries with an average income above (below) $28,000 per person per year see their social cost of carbon fall (rise). Poorer countries grow faster with convergence, and thus become less vulnerable and discount the future harder. The effects are small, however, because these effects become pronounced only in the more distant future.

4.6. Income elasticity

Table 4 shows the sensitivity of the global social cost of carbon to the income elasticity of the impact of climate change. The social cost of carbon falls is very sensitive to this parameter. If development does not affect vulnerability, the global social cost of carbon is $31.11/tC. The social cost of carbon initially falls, as society becomes less vulnerable with economic growth. However, the social cost of carbon starts rising for a higher income elasticity. This is because a higher income elasticity implies greater climate impacts in poorer countries in the near term. The social cost of carbon rises sharply as the income elasticity increases.

Changes in the national social costs of carbon are different from the changes in the global social cost. This is illustrated in Fig. 3. For the default income elasticity of −1.68, richer countries have

Table 3
The global social cost of carbon for nine alternative scenarios.

Scenario	Social cost of carbon
SRES A1	$19.69/tC
SRES A2	$55.51/tC
SRES B1	$25.39/tC
SRES B2	$34.46/tC
SSP1	$17.78/tC
SSP2	$24.02/tC
SSP3	$42.02/tC
SSP4	$25.59/tC
SSP5	$14.67/tC

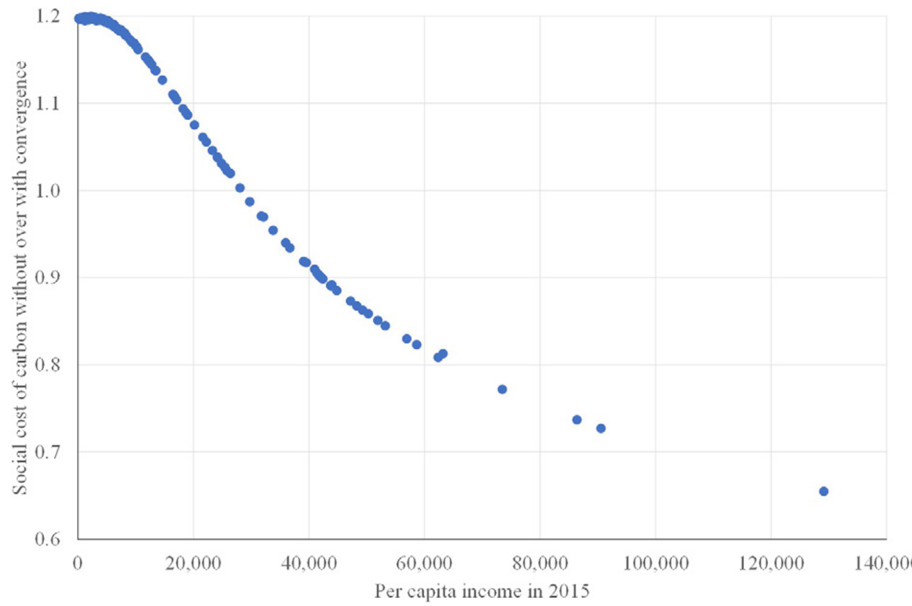

Fig. 7. The ratio of the social cost of carbon with income convergence to the social cost of carbon without income convergence as a function of per capita income in 2015.

lower social costs of carbon. For an income elasticity of −0.88, richer countries have higher social costs of carbon.

4.7. Climate sensitivity

Table 4 shows the sensitivity of the global social cost of carbon to the climate sensitivity. The social cost of carbon rises steeply with the assumed equilibrium warming due to a double of atmospheric carbon dioxide.

National social costs of carbon go up and down with the global estimate. The spatial pattern does not change. This follows from the functional form; see Table 1. National impact models have different parameters but the same specification at the global impact model, and therefore respond in the same way to a change in temperature.

4.8. Weighted regression

In the default model, I assume that the primary impact estimates shown in Fig. 1 are independent. They are not, but it is hard to quantify how the estimates relate to one another. For instance, 11 of the estimates are by Nordhaus and co-authors. Some the later estimates are updates of earlier ones, while other estimates use different data and methods. Instead of trying of specify exactly how different estimates relate to one another, I make an assumption that is just as extreme as the assumption of now dependence whatsoever: I group all estimates by Nordhaus; by Mendelsohn; by Maddison; by Bosello, Roson and Tol; and by Betz and Fankhauser; I assign a weight equal to one over the number of group members to each estimate in that group; and re-estimate the parabolic model using weighted least squares.

The results are hardly affected: The global social cost of carbon falls to \$21.70/tC. It falls because the weighted least squares de-emphasizes the estimates by the relatively pessimistic Nordhaus. The spatial pattern of the national social costs of carbon is not affected.

4.9. Imputation and calibration

In the base specification, the parameters of the national impact functions are derived from the global parameters, per capita income, and the income elasticity. However, Eq. (1) has two elements, income and temperature. I therefore recalibrate the national impact functions using both. The problem with this procedure is that it changes signs. Always negative impacts become always positive for 55 countries and 7 out of 8 impact function. The inverted-U-shape of the piecewise linear impact function becomes a U-shape.

It is therefore no surprise that the global social cost of carbon falls to \$15.93/tC. India's social cost of carbon falls from \$5.74/tC to \$4.58/tC, because its high vulnerability is now explained by heat and poverty rather than by poverty alone. The US social cost of carbon falls from \$0.15/tC to − \$0.78/tC, a carbon subsidy.

In the base specification, the impact functions are calibrated on the global impact estimates and national impact estimates imputed from the global estimates, using the estimated income elasticity. There is no obvious reason to do things in this order. I therefore use the income elasticity to impute national impacts from the primary

Table 4
The global social cost of carbon for alternative climate sensitivities and alternative income elasticities of impact.

Climate sensitivity	Social cost of carbon	Income elasticity	Social cost of carbon
$0.5°/2\times CO_2$	\$1.35/tC	0	\$31.11/tC
$1.5°/2\times CO_2$	\$7.23/tC	−0.08	\$23.90/tC
$2.5°/2\times CO_2$	\$17.36/tC	−0.88	\$6.48/tC
$3.0°/2\times CO_2$	\$24.02/tC	−1.68	\$24.02/tC
$4.5°/2\times CO_2$	\$50.35/tC	−2.48	\$445.02/tC
$6.0°/2\times CO_2$	\$86.24/tC	−3.28	\$21889.04/tC

estimates, making sure that the national numbers add up to the primary estimates for the regions, and calibrate the impact function to the imputed national estimates.

The base specification has imputation *after* calibration, the alternative imputation *before* calibration. A pragmatic advantage of the base specification is that sensitivity analysis on the income elasticity (see above) is trivial. The alternative specification uses more information from the primary impact studies, and may thus be seen as the preferred order. However, the regional details in the primary studies are very uncertain, and this is carried over into the parameters of the national impact functions. The base specification regularizes the primary estimates and is thus less sensitive to outliers.

The global impact function has two negative parameters and is thus always negative. So are the national impact functions imputed from this. In contrast, only 31 of the calibrated national impact functions are always negative. 35 have an inverted U-shape, with the typical optimal temperature relatively close to today's. The remaining 123 countries' impact functions are U-shaped, but with the worst temperature much above today's; that is, these countries see negative impacts of climate change, their impacts worsen with greater warming, but the incremental impacts fall with greater warming. This specification is strange. Under extreme warming (not considered here) incremental impacts and, eventually, impacts will turn positive. Marginal impacts (the focus here) are sensitive to the curvature of the impact function. I therefore prefer imputation *after* calibration.

As could be expected from the above, the estimates are quite sensitive to the change in order. The global social cost of carbon is \$3.38/tC for imputation before calibration, instead of \$24.02/tC for imputation after calibration. Fig. 8 shows the national results. The national cost of carbon falls by an order of magnitude for China and India, the two top countries. For 34 countries, the sign flips: The national cost of carbon is negative, calling for a carbon subsidy. These carbon subsidies are small. The main effect is the sharp reduction in the bigger countries.

The other impact functions show a sensitivity to the calibration procedure that is similar to that of the parabolic function. The piecewise linear function shows a greater sensitivity: While the default has a social cost of carbon of \$145/tC, the calibration-with-temperature has a social cost of carbon of \$839/tC and the imputation-before-calibration procedure leads to a social cost of carbon of \$4/tC.

5. Discussion and conclusion

This paper presents estimates of the national cost of carbon for almost every country. Such estimates are relevant if governments pursue "my country first" policies. I imputed national climate change impact functions from global impact functions and the income elasticity implied by regional estimates of the impact of climate change. The national social cost of carbon is largest in poor countries with large populations—India, China, Ethiopia, Bangladesh, Pakistan, and Indonesia. The EU and the USA rank 7th and 8th. The national social cost of carbon is less sensitive to the pure rate of time preference in faster growing economies, and more sensitive to the rate of risk aversion. The global social cost of carbon is sensitive to the assumed impact function, climate sensitivity, and scenario, but the pattern of national social costs is not. The assumption of income convergence raises (lowers) the national social cost of carbon of poorer (richer) countries. The assumed income elasticity of climate change impacts is the key parameter, more important than the assumed discount rate, for both the global social cost of carbon and the pattern of national social costs.

Unfortunately, although there is near universal agreement that poorer countries are more vulnerable to climate change, few have estimated an income elasticity. A key parameter in the analysis is thus poorly constrained by empirical evidence. This should be a high priority in future research. Another priority is to replace the impact function used here by impact functions. This is important because different attributes of climate change—carbon dioxide fertilization, ocean acidification, sea level rise, actual climate change—have different dynamics and different net present marginals. Different components of the impact function respond differently to development—air conditioning rises faster than income, agriculture slower; air conditioning is affected by the urban heat island effect, agriculture is not. The estimates above ignore uncertainty, about emissions, climate change, and impacts. Estimates ignore distributional issues within countries, and empathy towards people from other countries. All that is deferred to future research.

Two findings of this paper will withstand the refinements of further research. National social costs of carbon are much smaller than the global social costs of carbon. Large, poor countries would impose the highest carbon taxes if acting in the national self-interest.

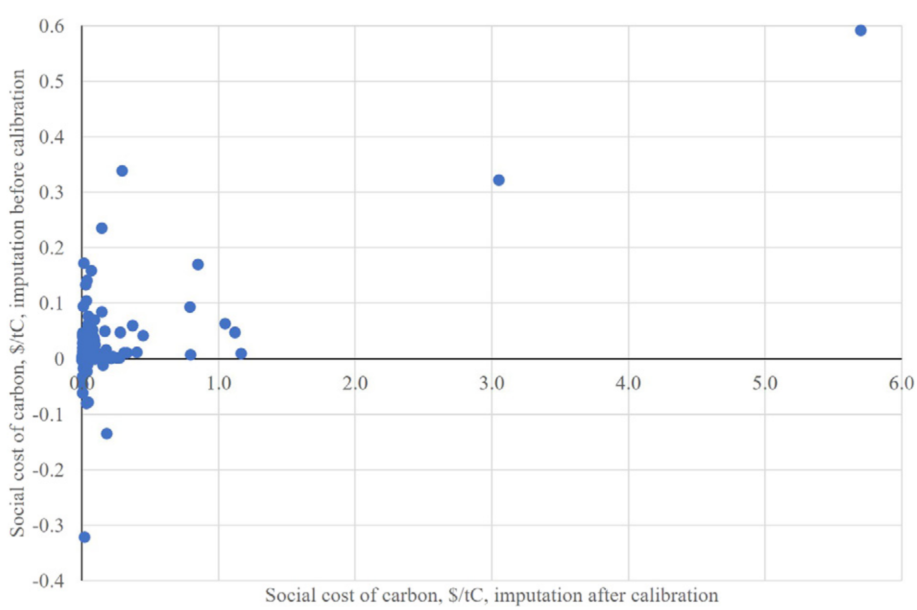

Fig. 8. The national cost of carbon for imputation *after* calibration against imputation *before* calibration.

Appendix A. Regions in primary impact studies

Berz, Fankhauser (1995) European Union • USA • Other OECD • former Soviet Union • China • Rest of the World

Tol (1995, 2002) OECD America • OECD Europe • OECD Pacific • Eastern Europe and former Soviet Union • Middle East • Latin America • South and South East Asia • East Asia • Africa

Hope (2006), Plambeck and Hope (1996) European Union • USA • Other OECD • Eastern Europe and former Soviet Union • China • South Asia • Africa and Middle East • Latin America

Nordhaus and Yang (1996) USA • Japan • European Union • former Soviet Union • China • Rest of the World

Nordhaus and Boyer (2000) USA • Japan • OECD Europe • High Income OPEC • High Income • Eastern Europe • Russia • India • China • Middle Income • Lower Middle Income • Africa • Low Income

Bosello et al. (2012) USA • Mediterranean Europe • Northern Europe • Eastern Europe • former Soviet Union • South Korea, South Africa and Australia • Canada, Japan and New Zealand • North Africa • Middle East • Sub-Saharan Africa • South Asia • China • Other Asia • Latin America

Roson and van der Mensbrugghe (2012) China • Japan • Other East Asia • India • Other South Asia • USA • Brazil • Russia • Other Eastern Europe and Central Asia • Europe • Sub-Saharan Africa • Middle East and North Africa • Other Annex I (Kyoto Protocol) • Other High Income • Rest of the World

References

Adger, W.N., 2006. Vulnerability. Glob. Environ. Chang. 16 (3), 268–281. ISSN 0959-3780. http://www.sciencedirect.com/science/article/pii/S0959378006000422.

Arrow, K., Cropper, M., Gollier, C., Groom, B., Heal, G., Newell, R., Nordhaus, W., Pindyck, R., Pizer, W., Portney, P., Sterner, T., Tol, R.S.J., Weitzman, M., 2013. Determining benefits and costs for future generations. Science 341 (6144), 349–350. ISSN 0036-8075. https://doi.org/10.1126/science.1235665.

Arrow, K.J., Cropper, M.L., Gollier, C., Groom, B., Heal, G.M., Newell, R.G., Nordhaus, W.D., Pindyck, R.S., Pizer, W.A., Portney, P.R., Sterner, T., Tol, R.S.J., Weitzman, M.L., 2014. Should governments use a declining discount rate in project analysis? Rev. Environ. Econ. Policy 8 (2), 145–163. https://doi.org/10.1093/reep/reu008.

Berz, G. Insuring against catastrophe. Disasters. URL http://www.ourplanet.com/imgversn/113/berz.html.

Bosello, F., Eboli, F., Pierfederici, R., 2012. Assessing the economic impacts of climate change. Rev. Environ. Energy Econ. 1–9.

Burke, M., Davis, W.M., Diffenbaugh, N.S., 2018. Large potential reduction in economic damages under UN mitigation targets. Nature 557 (7706), 549–553. https://doi.org/10.1038/s41586-018-0071-9.

Burke, M., Hsiang, S.M., Miguel, E., 2015. Global non-linear effect of temperature on economic production. Nature 527 (7577), 235–239. https://doi.org/10.1038/nature15725.

Cai, Y., Lontzek, T., 2019. The social cost of carbon with economic and climate risks. J. Polit. Econ. 0 (ja), null. https://doi.org/10.1086/701890.

d'Arge, R., 1979. Climate and economic activity. World Meteorological Organization, Geneva. 652–681.

Dell, M., Jones, B.F., Olken, B.A., 2012, July. Temperature shocks and economic growth: evidence from the last half century. Am. Econ. J. Macroecon. 4 (3), 66–95. https://doi.org/10.1257/mac.4.3.66.

Dell, M., Jones, B.F., Olken, B.A., 2014. What do we learn from the weather? The new climate-economy literature. J. Econ. Lit. 52 (3), 740–798.

Deryugina, T., Hsiang, S., 2017, November. The marginal product of climate. National Bureau of Economic Research.

Dietz, S., Stern, N., 2015. Endogenous growth, convexity of damage and climate risk: how Nordhaus' framework supports deep cuts in carbon emissions. Econ. J. 125 (583), 574–620. https://doi.org/10.1111/ecoj.12188.

Fankhauser, S., 1995. Valuing Climate Change—The Economics of the Greenhouse. 1. EarthScan, London., pp. 1–180. 1-85383-237-5.

Fankhauser, S., Tol, R.S.J., 2005. On climate change and economic growth. Resour. Energy Econ. 27 (1), 1–17.

Gayer, T., Viscusi, W., 2016. Determining the proper scope of climate change policy benefits in U.S. regulatory analyses: domestic versus global approaches. Rev. Environ. Econ. Policy 10 (2), 245–263. https://doi.org/10.1093/reep/rew002.

Greenstone, M., Kopits, E., Wolverton, A., 2013. Developing a social cost of carbon for us regulatory analysis: a methodology and interpretation. Rev. Environ. Econ. Policy 7 (1), 23–46.

Griliches, Z., Ringstad, V., 1970. Error-in-the-variables bias in nonlinear contexts. Econometrica 38 (2), 368–370. ISSN 00129682, 14680262. http://www.jstor.org/stable/1913020.

Guivarch, C., MÃl'jean, A., Pottier, A., Fleurbaey, M., 2016. Social cost of carbon: global duty. Science 351 (6278), 1160.

Hahn, R.W., Ritz, R.A., 2015. Does the social cost of carbon matter? Evidence from US policy. J. Leg. Stud. 44 (1), 229–248.

Havranek, T., Irsova, Z., Janda, K., Zilberman, D., 2015. Selective reporting and the social cost of carbon. Energy Econ. 51, 394–406. http://www.sciencedirect.com/science/article/pii/S0140988315002327.

Heyes, A., Morgan, D., Rivers, N., 2013. The use of a social cost of carbon in canadian cost-benefit analysis. Can. Public Policy 39 (SUPPL.2), S67–S79.

Hope, C.W., 2006. The marginal impact of CO2 from PAGE2002: an integrated assessment model incorporating the IPCC's five reasons for concern. Integr. Assessment J. 6 (1), 19–56.

Howard, P.H., Sterner, T., 2017, Sep. Few and not so far between: a meta-analysis of climate damage estimates. Environ. Resour. Econ. 68 (1), 197–225. https://doi.org/10.1007/s10640-017-0166-z.

IAWGSCC, 2013. Technical support document: technical update of the social cost of carbon for regulatory impact analysis under executive order 12866. Interagency Working Group on the Social Cost of Carbon, United States Government, Washington, D.C..

Lemoine, D., 2018, September. Sufficient statistics for the cost of climate change. National Bureau of Economic Research.

Lemoine, D., Kapnick, S., 2015. A top-down approach to projecting market impacts of climate change. Nat. Clim. Change 6, 51. https://doi.org/10.1038/nclimate2759.

Letta, M., Tol, R.S.J., 2018. Weather, climate and total factor productivity. Environ. Resour. Econ. ISSN 1573-1502. https://doi.org/10.1007/s10640-018-0262-8.

Maddison, D., Rehdanz, K., 2011. The impact of climate on life satisfaction. Ecol. Econ. 70 (12), 2437–2445. http://www.sciencedirect.com/science/article/pii/S0921800911003028.

Maddison, D.J., 2003. The amenity value of the climate: the household production function approach. Resour. Energy Econ. 25 (2), 155–175.

Maier-Reimer, E., Hasselmann, K., 1987, Aug. Transport and storage of CO2 in the ocean - an inorganic ocean-circulation carbon cycle model. Clim. Dyn. 2 (2), 63–90. https://doi.org/10.1007/BF01054491.

Mendelsohn, R.O., Schlesinger, M.E., Williams, L.J., 2000. Comparing impacts across climate models. Integr. Assessment 1 (1), 37–48.

Metcalf, G.E., Stock, J.H., 2017. Integrated assessment models and the social cost of carbon: a review and assessment of U.S. experience. Rev. Environ. Econ. Policy 11 (1), 80–99.

Moore, F.C., Diaz, D.B., 2015. Temperature impacts on economic growth warrant stringent mitigation policy. Nat. Clim. Change 5 (2), 127–131. ISSN 1758-678X. https://doi.org/10.1038/nclimate2481.

Moyer, E.J., Woolley, M.D., Matteson, N.J., Glotter, M.J., Weisbach, D.A., 2014. Climate impacts on economic growth as drivers of uncertainty in the social cost of carbon. J. Leg. Stud. 43 (2), 401–425. https://doi.org/10.1086/678140.

Nakicenovic, N., Swart, R. (Eds.), 2000. Special report on emissions scenarios: a special report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.

Newell, R.G., Prest, B.C., Sexton, S., 2018. The GDP temperature relationship: implications for climate change damages. Resources for the Future. 2018/07/05/.

Nordhaus, W.D., 1982. How fast should we graze the global commons? Am. Econ. Rev. 72 (2), 242–246.

Nordhaus, W.D., 1991. To slow or not to slow: the economics of the greenhouse effect. Econ. J. 101 (444), 920–937.

Nordhaus, W.D., 1994a. Expert opinion on climate change. Am. Sci. 82 (1), 45–51.

Nordhaus, W.D., 1994b. Managing the Global Commons: The Economics of Climate Change. The MIT Press, Cambridge.

Nordhaus, W.D., 2006. Geography and macroeconomics: new data and new findings. Proc. Natl. Acad. Sci. 103 (10), 3510–3517. http://www.pnas.org/cgi/doi/10.1073/pnas.0509842103.

Nordhaus, W.D., 2008. A Question of Balance—Weighing the Options on Global Warming Policies. Yale University Press, New Haven., pp. 1–234.

Nordhaus, W.D., 2017. Revisiting the social cost of carbon. Proc. Natl. Acad. Sci. 114 (7), 1518–1523. http://www.pnas.org/content/114/7/1518.

Nordhaus, W.D., Boyer, J.G., 2000. Warming the World: Economic Models of Global Warming. The MIT Press, Cambridge, Massachusetts - London, England., pp. 1–232. 0-262-14071-3.

Nordhaus, W.D., Moffat, A., 2017, August. A survey of global impacts of climate change: replication, survey methods, and a statistical analysis. National Bureau of Economic Research.

Nordhaus, W.D., Yang, Z., 1996. Rice: a regional dynamic general equilibrium model of optimal climate-change policy. Am. Econ. Rev. 86 (4), 741–765.

Peck, S.C., Teisberg, T.J., 1994, Nov. Optimal carbon emissions trajectories when damages depend on the rate or level of global warming. Clim. Change 28 (3), 289–314. ISSN 1573-1480. https://doi.org/10.1007/BF01104138.

Pigou, A., 1920. The Economics of Welfare. Macmillan, London.

Pindyck, R.S., 2017a. Coase lecture—taxes, targets and the social cost of carbon. Economica 84 (335), 345–364.

Pindyck, R.S., 2017b. The use and misuse of models for climate policy. Rev. Environ. Econ. Policy 11 (1), 110–114. 21097.

Piontek, F., Kalkuhl, M., Kriegler, E., Schultes, A., Leimbach, M., Edenhofer, O., Bauer, N., 2018. Economic growth effects of alternative climate change impact channels in economic modeling. Environ. Resour. Econ. ISSN 1573-1502. https://doi.org/10.1007/s10640-018-00306-7.

Pizer, W., Adler, M., Aldy, J., Anthoff, D., Cropper, M., Gillingham, K., Greenstone, M., Murray, B., Newell, R., Richels, R., Rowell, A., Waldhoff, S., Wiener, J., 2014. Using and improving the social cost of carbon. Science 346 (6214), 1189–1190.

Plambeck, E.L., Hope, C.W., 1996. Page95 - an updated valuation of the impacts of global warming. Energy Policy 24 (9), 783–793.
Pretis, F., Schwarz, M., Tang, K., Haustein, K., Allen, M.R., 2018. Uncertain impacts on economic growth when stabilizing global temperatures at 1.5° c or 2° c warming. Philos. Trans. R. Soc. Lond. A 376 (2119). http://rsta.royalsocietypublishing.org/content/376/2119/20160460. https://doi.org/10.1098/rsta.2016.0460.
Ramsey, F.P., 1928. A mathematical theory of saving. Econ. J. 38 (152), 543–559. http://www.jstor.org/stable/2224098.
Rehdanz, K., Maddison, D.J., 2005. Climate and happiness. Ecol. Econ. 52 (1), 111–125.
Revesz, R., Greenstone, M., Hanemann, M., Livermore, M., Sterner, T., Grab, D., Howard, P., Schwartz, J., 2017. Best cost estimate of greenhouse gases. Science 357 (6352), 655. http://science.sciencemag.org/content/357/6352/655.abstract.
Riahi, K., van Vuuren, D.P., Kriegler, E., Edmonds, J., ONeill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J.C., KC, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpender, F., Silva, L.A.D., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J.C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A., Tavoni, M., 2017. The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview. Global Environ. Change 42, 153–168. ISSN 0959-3780. https://doi.org/10.1016/j.gloenvcha.2016.05.009.
Ricke, K., Drouet, L., Caldeira, K., Tavoni, M., 2018. Country-level social cost of carbon. Nat. Clim. Change 8 (10), 895–900. ISSN 1758-6798. https://doi.org/10.1038/s41558-018-0282-y.
Rose, S.K., 2012. The role of the social cost of carbon in policy. WIREs Clim. Change 3, 195–212.
Roson, R., van der Mensbrugghe, D., 2012. Climate change and economic growth: impacts and interactions. Int. J. Sustain. Econ. 4 (3), 270–285.
Schneider, S.H., Thompson, S.L., 1981. Atmospheric CO_2 and climate: importance of the transient response. J. Geophys. Res. 86 (C4), 3135–3147.
Sunstein, C.R., 2014. On not revisiting official discount rates: institutional inertia and the social cost of carbon. Am. Econ. Rev. 104 (5), 547–551.
Tol, R.S.J., 1995. The damage costs of climate change toward more comprehensive calculations. Environ. Resource Econ. 5 (4), 353–374.
Tol, R.S.J., 2002. Estimates of the damage costs of climate change - part i: benchmark estimates. Environ. Resour. Econ. 21 (1), 47–73.
Tol, R.S.J., 2005. The marginal damage costs of carbon dioxide emissions: an assessment of the uncertainties. Energy Policy 33, 2064–2074.
Tol, R.S.J., 2009. The economic effects of climate change. J. Econ. Perspect. 23 (2), 29–51.
Tol, R.S.J., 2011. The social cost of carbon. Ann. Rev. Resour. Econ. 3, 419–443.
Tol, R.S.J., 2013. Targets for global climate policy: an overview. J. Econ. Dyn. Control 37 (5), 911–928.
Tol, R.S.J., 2018. The economic impacts of climate change. Rev. Environ. Econ. Policy 12 (1), 4–25. https://doi.org/10.1093/reep/rex027.
Wang, P., Deng, X., Zhou, H., Yu, S., 2018. Estimates of the social cost of carbon: a review based on meta-analysis. J. Cleaner Prod. ISSN 0959-6526. https://doi.org/10.1016/j.jclepro.2018.11.058.
Yohe, G.W., Tol, R.S.J., 2002. Indicators for social and economic coping capacity - moving towards a working definition of adaptive capacity. Global Environ. Change 12 (1), 25–40.