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Harnessing the uncertainty monster: Putting quantitative constraints on the intergenerational social discount rate

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Abstract

There is broad consensus among economists that unmitigated climate change will ultimately have adverse global economic consequences, that the costs of inaction will likely outweigh the cost of taking action, and that social planners should therefore put a price on carbon. However, there is considerable debate and uncertainty about the appropriate value of the social discount rate, that is the extent to which future damages should be discounted relative to mitigation costs incurred now. We briefly review the ethical issues surrounding the social discount rate and then report a simulation experiment that constrains the value of the discount rate by considering 4 sources of uncertainty and ambiguity: Scientific uncertainty about the extent of future warming, social uncertainty about future population and future economic development, political uncertainty about future mitigation trajectories, and ethical ambiguity about how much the welfare of future generations should be valued today. We compute a certainty-equivalent declining discount rate that accommodates all those sources of uncertainty and ambiguity. The forward (instantaneous) discount rate converges to a value near 0% by century's end and the spot (horizon) discount rate drops below 2% by 2100 and drops below previous estimates by 2070.

Harnessing the uncertainty monster: Putting quantitative constraints on the intergenerational social discount rate

In its guidance on public sector project appraisal, Her Majestys Treasury in the United Kingdom states that society "prefers to receive goods and services sooner rather than later, and to defer costs to the future" (HM Treasury Green Book, Para. 5.49). Such sentiment also influences social cost-benefit analysis guidelines in a wide range of countries across the world. This desire of governments to receive benefits early and defer costs to later underlies the concept of "social discounting"—that a dollar received tomorrow is worth less than a dollar received today even when ignoring the effects of inflation ("real discounting").

There are a variety of arguments that support this approach. First, it is clear that we are, by nature, impatient. When offered a reward of $15 right now, people on average would require $20 a month from now to delay their reward till then (Thaler, 1981), even though the accrual during that delay corresponds to an annualized interest rate of nearly 345%. Nearly indistinguishable results are obtained when respondents make intertemporal choices between goods, rather than monetary rewards. For example, Pender (1996) describes the strong desire of rural Indians to receive rice income sooner rather than later.

Although the particulars may vary across experiments, the basic finding that people heavily discount rewards over short time periods, forms a pervasively replicated benchmark finding in behavioral economics, with more than 3,000 articles on the topic being indexed by the PsycArticles data base at the time of this writing. (For a review, see Coller & Williams, 1999 or Frederick, Loewenstein, & O'Donoghue, 2002). This entrenched preference for the present, and the discounting of the future it entails, appears to be an immutable aspect not just of human cognition but of organisms more generally. When given the choice between a smaller reward now or a larger reward later, most animals generally prefer the immediate reward (Stevens & Stephens, 2010).

One reason for this impatience is, of course, that we may no longer be alive to enjoy future benefits, or pay future costs, by the time they are due. A million dollars 10 years hence may not appear worth terribly much to an 80-year-old, who might therefore rationally prefer an immediate $100,000. Accordingly, people's propensity to discount the future is found to increase with age (Trostel & Taylor, 2001). Contrary to the proverbial notion that impatience is a particular prerogative of the young, the data suggest that we become more impatient—that is, more insistent on receiving rewards immediately rather than later—as we age.

But impatience lies deeper than pure realization of our own mortalities. In humans, decisions relating to the present involve regions of the brain (viz. limbic and paralimbic cortical structures) that are also consistently implicated in impulsive behavior and cravings such as heroin addiction, whereas decisions that pertain to the future involve brain regions (viz. lateral prefrontal and parietal areas) known to support deliberative processing and numerical computation (McClure, Laibson, Loewenstein, & Cohen, 2004). Our strong preference for immediate rewards may therefore reflect the proverbial "reptilian brain," which competes with our "rational brain" that is telling us to consider and plan for the future.

When evaluating longer time horizons, not only do we continue to show impatience, even if at a lower annualized rate (e.g., Henderson & Bateman, 1995), we should also allow for the underlying economic situation to change. In general, societies have become wealthier over time, and this is also the forecast of most, but not all, experts for the future (Drupp, Freeman, Groom, & Nesje, 2016). Since the poor are not generally expected to subsidize the rich, societies should, all else being equal, prioritize the now over the future. Economic growth forecasts and the strength of our desire to reduce consumption inequality across time both affect governments decisions over discounting.

These underlying features also help determine how financial markets set interest rates; investors are also impatient and require capital growth that reflects changes in the underlying macroeconomy. But once these bond yields are set, then they present observable opportunity costs against which other projects can be appraised. For example, if one were so inclined, one could compare the present cost of one's education (tuition fees due today) against the delayed rewards (higher expected salaries upon graduation) using prevailing market interest rates.

Extending this markets-based approach to discounting in the public sector has been favored by a number of international governments, including the United States. This is described as the "positive" or "descriptive" approach to social discounting (e.g., Davidson, 2014). For example, suppose that the one year interest rate is 3%. Then, on the assumption that a government wishes to recognize the opportunity cost of capital, it would not choose to invest in a social project that cost \$100 today but only gives societal value of \$102 in a year. Accordingly, the discounting of future costs and benefits is part of the basic canon of economics. In general, an amount x_0 today is worth x_t in t years time, where $x_t = x_0 \times (1 + \rho)^t$, where ρ is the applicable discount rate. Equivalently, if we wish to determine the present value of an amount x_t that is due in t years time, then $x_0 = x_t/((1 + \rho)^t)$. A preference for smaller immediate rewards over delayed larger rewards is thus rational—and advisable—so long as social project appraisal decisions are calibrated to plausibly achievable interest rates.

Enter climate change. The situation changes dramatically when inter-temporal decisions cross generational boundaries and extend into the distant future. Today's policy decisions with respect to climate change will affect people who have not yet been born, and whom today's decision makers will never meet. The extended temporal horizon has particularly pronounced implications vis-a-vis the discount rate. We illustrate with an example provided by Dubgaard (2002) involving the future of Denmark. If the present value of real estate in Denmark is considered to be around \$238 billion, then applying a discount rate of 5%, \$6 invested now will be worth the same as the current value of the whole of the housing stock in Denmark in 500 years (Dubgaard, 2002). If we applied a discount rate of 1% instead, then the future Denmark around the year 2500 would be "worth" \$1.6 billion of mitigation efforts today. The striking difference between \$6 and \$1.6 billion reveals why "the biggest uncertainty of all in the economics of climate change is the uncertainty about which interest rate to use for discounting" (Weitzman, 2007, p. 705). Seemingly slight variations in the discount rate suffice to make climate mitigation efforts appear either very compelling and highly cost effective (Stern, 2007) or less pressing (Nordhaus, 2007).

The choice of an appropriate discount rate for climate economics has therefore been hotly contested in policy, economics, and ethics. This debate has failed to yield a consensual value, with some scholars proposing that the discount rate for climate change should be *negative* (Fleurbaey & Zuber, 2012) and others permitting a rate in excess of 6% (Nordhaus, 2007). Central to this argument has been whether the descriptive approach to discounting is appropriate in a social context when projects span generations. In particular the highly influential Stern Review (Stern, 2007) and a number of governments in Europe, prefer to estimate the social discount rate directly from its primitives rather than using market rates of interest. There are a number of reasons for this choice (see, e.g., Drupp et al., 2016). For example, while we know that individuals are impatient for themselves, many economists and philosophers would argue that we cannot be impatient with respect to future generations. In addition, those most affected by climate change—the poor, often in developing countries, who have not yet been born—cannot influence bond yields. This places a burden on governments to take a wider ethical perspective than investors do when trading in financial markets. This alternative approach to estimating the social discount rate, which underlies this paper, is called the “normative”, or “prescriptive”, approach (Davidson, 2014) and is often represented through the Ramsey Rule (Ramsey, 1928).

In this article we provide quantitative constraints on the discount rate for climate change by considering several sources of uncertainty and ambiguity about its appropriate value. Specifically, we report a simulation experiment that explored the parameter space underlying the social discount rate and computed a single “certainty-equivalent” rate (explained below) that integrates across all those sources of uncertainty. Figure 1 provides an overview of the experimental design and guides the discussion. To foreshadow our principal conclusion, when all those sources of uncertainty and ambiguity are considered simultaneously, the certainty-equivalent discount rate declines over time and converges to a value below that of various previous estimates by 2070.

Experimental design

Disentangling discounting

The social discount rate, also referred to as the consumption discount rate, is conventionally understood within the framework developed by Ramsey (1928), which expresses the social discount rate, ρ_s, as a function of two distinct components:

$$\rho_s = \eta \times g + \delta, \tag{1}$$

where g is the expected average annual real economic growth rate, δ represents a “pure time preference”, and η is a parameter that captures people’s risk aversion and inequality aversion. The rationale for inclusion of the growth rate, g, is that growing wealth makes a given cost for future generations more bearable than it appears to us now, in the same way that \$100 is valued a great deal more by a poor student than by a wealthy industrialist. The effect of future wealth is modulated by η, which variously describes risk aversion or inequality aversion.[1] The pure time preference component, δ, which is also referred to as the utility discount rate, reflects people's intrinsic preference for the present, or their "impatience" (e.g., Thaler, 1981).

Within the Ramsey framework we thus have to consider three quantities to determine the social discount rate: Future economic growth (g), risk aversion (η), and pure time preference (δ). All three of those quantities are at least partially amenable to quantitative estimation. Future growth rates can be estimated by economic modeling (e.g. Nordhaus, 2007), risk aversion can be inferred from asset markets (Epstein & Zin, 1991) and behavioral surveys (Barsky, Kimball, Juster, & Shapiro, 1997), and pure time preference can be inferred by behavioral experiment (e.g., Zauberman, Kim, Makoc, & Bettman, 2009). It is therefore in principle possible to estimate the social discount rate—with some degree of uncertainty—using the earlier descriptive approach (Davidson, 2014).

However, because of the far-reaching implications of the discount rate, many scholars have argued against a descriptive solution and in favor of a *prescriptive* approach, whereby the social discount rate is determined, at least in part, by ethical and moral considerations (e.g., Adler & Treich, 2015; Davidson, 2014; Stern, 2007). To illustrate, assume that $g = 0$ in Equation 1 and that empirical estimates of δ are in the range of 5%. In that case, we would burden our descendants with the disappearance of Denmark because we were unwilling to expend more than $6 on climate mitigation, based entirely on estimates of how strongly people prefer instant gratification over a delayed reward (because with $g = 0$ future generations are assumed to be no wealthier than us). Ethical considerations also apply to determining the value of η: risk aversion and inequality aversion are moral constructs, and Hume's dictum that the "ought" cannot be derived from the "is" therefore casts doubt on the relevance of its estimability.

We next briefly discuss those ethical ambiguities and other sources of uncertainty about the discount rate. This defines the multi-dimensional variable space which we then explore in our simulation experiment (Figure 1).

Ethical ambiguities of discounting

We abhor slavery and other forms of domination, defined as situations in which one group of persons can determine arbitrarily and without significant reciprocation the conditions of another group's lives (Nolt, 2011). Because "future people have no power to resist or retaliate against our emission of greenhouse gases" (Nolt, 2011, p. 67), some ethicists have argued that the adverse future effects of climate change (e.g., the risk of displacement of up to 187 million people through sea level rise; Nicholls et al., 2011) constitutes unacceptable inter-generational domination. Considerations along those lines are frequently taken to imply that δ should be set to zero. Ramsey (1928) himself called it "ethically indefensible" to "discount later enjoyments in comparison with earlier ones" (p. 543). Likewise, Adler and Treich (2015) argue that any value $\delta > 0$ "embodies a clear violation of the attitude of impartiality that is foundational to ethics" (p. 283).

The notion of "stewardship" towards future generations is also intrinsic to most world religions and was articulated poignantly in the recent encyclical of Pope Francis (2015). Accordingly, (Stern, 2007) set $\delta = 0.1\%$, with the residual positive value representing a presumed risk of human extinction.

However, the seemingly attractive idea of treating all generations equally by setting $\delta \cong 0$ entails some unnerving consequences (Pearce, Groom, Hepburn, & Koundouri, 2003). In general, the lower the discount rate, the more future consumption matters and hence the more we should set aside for the benefit of future generations. When $\delta = 0.1\%$ and $\eta = 1$, as favored by Stern (2007), the mathematically implied savings rate is 97% (Dasgupta, 2008). That is, out of \$100 we may only consume \$3, with the remainder being taxed away for the benefit of our children. Our children, in turn, would also only be allowed to spend \$3 of their considerably greater wealth, with the remainder being passed on to their children, and so on ad infinitum. An implication of zero discounting therefore is the impoverishment of each current generation for the benefit of the succeeding one.

To avoid this conundrum, scholars have variously proposed an alternative, rank-based discounting schemes (Zuber & Asheim, 2012) or have argued for a higher value of δ on the basis of moral considerations. For example, Nordhaus (2007) assumed $\delta = 1.5\%$. Because this ethical debate is ongoing, we explore values of δ of 0% (with 65% weighting) and 3.15% (with 35% weighting); see top left of Figure 1. Those estimates of δ and their probability weighting are based on a recent survey of 200 experts by Drupp et al. (2016) and are thus empirically constrained vertices of this ethical space.

Similarly, we let η take on values of 0.5 and 2.2 with equal probability. Although risk aversion and inequality aversion are informed by ethical considerations, these boundaries are broadly consistent with findings from the expert survey by Drupp et al. (2016). The values of η and δ were fully crossed (top left of Figure 1), thereby providing an exploration of the space of likely ethical considerations.

Uncertainties about future growth

Modeling the effects of warming on economic production. Application of Equation 1 requires knowledge of future economic growth. Conventionally, those estimates may be obtained by economic modeling of the future (e.g., Nordhaus, 2007) or by extrapolation from historical data on the assumption of a steady-state economy. Here we rely on a recent empirical model reported by Burke, Hsiang, and Miguel (2015) that examined the marginal effects of temperature on gross domestic product (GDP) for more than 160 countries during the last 50 years (1960–2010) while controlling for a host of other variables (e.g., secular trends, country-specific idiosyncracies, and so on). Burke et al.'s principal finding was that temperature has a curvilinear relationship with economic production, with an optimum at around $13°C$. All other variables being equal, economic production declines with lower or higher average temperatures. The curvilinear relationship holds equally for rich and poor countries, and it holds equally for the early part of the period examined (1960–1989) and the late period (1990–2010). The relationship is also robust to a wide variety of other variables (Burke et al., 2015, Supplementary Methods).

The empirical model permits projection of economic growth through the end of the century as a function of three variables that are the source of considerable uncertainty: the sensitivity of the climate to carbon emissions, the emissions trajectory that results as a result of policy choices, and the socio-economic development pathway that the world is following. We orthogonally combine those three variables to examine their effect on projected global growth (top-right panel of Figure 1).

Scientific uncertainty about climate sensitivity. There is no doubt about the fact that the globe is warming in response to greenhouse gas emissions from human economic activity, and that this warming has been ongoing without notable interruption or cessation (Cahill, Rahmstorf, & Parnell, 2015; Lewandowsky, Risbey, & Oreskes, 2016, 2015). There is, however, some uncertainty about *how much* warming can be expected in response to emissions. This scientific uncertainty is encapsulated in the standard deviation of the estimate of a quantity known as climate sensitivity, which refers to the amount of warming (in $°C$ or, equivalently, K) that is expected in response to a doubling of atmospheric CO_2 concentrations compared to preindustrial levels. Estimates of sensitivity have ranged from around $1.5°C$ to $4.5°C$ for more than 4 decades (Freeman, Wagner, & Zeckhauser, 2015, see also further discussion below). There are compelling reasons, relating to feedback loops, why this uncertainty range is unlikely to be substantially reducible (Roe & Baker, 2007).

We represent uncertainty by the standard deviation of the (lognormal) distribution of possible realizations of climate sensitivity in our climate model, which we varied in 6 steps; $0.26°C$, $0.37°C$, $0.64°C$, $0.83°C$, $1.17°C$, and $1.66°C$. Mean sensitivity was kept constant. Exploring the effects of different levels of uncertainty about climate sensitivity is important in light of the fact that greater uncertainty translates into *greater* risks and damage costs in nearly all circumstances (Freeman et al., 2015; Lewandowsky, Risbey, Smithson, Newell, & Hunter, 2014; Lewandowsky, Risbey, Smithson, & Newell, 2014). It is unknown, however, how the effects of uncertainty interact with other variables that contribute to global growth paths.

Policy uncertainty about emissions trajectories. We compared the "Representative Concentration Pathways" (RCPs) that are used by the IPCC to explore different climate futures (Bindoff et al., 2013). Although RCPs are not directly interpretable as policy choices and emissions trajectories (because they are defined by the atmospheric concentrations of greenhouse gases rather than emissions), they represent the likely *consequences* of policy choices.

We employed the climate forcings (i.e., the imbalance of incoming and outgoing energy that results from atmospheric greenhouse gases) provided by RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 for the period 2000 through 2100 as input to our climate model. These RCPs span the range from aggressive mitigation and limiting global temperature rises to approximately 2° (RCP 2.6), to continued business as usual and extensive warming (RCP 8.5). (Data available at: `http://tntcat.iiasa.ac.at:8787/RcpDb/dsd`).

Uncertainty about future economic development. We compared two "Shared Socio-Economic Pathways" (SSPs). SSPs form the basis of the IPCC's projections of future global development in Working Group 3. We employed two scenarios, SSP3 and SSP5, also used by Burke et al. (2015). SSP3 assumes low baseline growth and slow global income convergence between rich and poor countries; SSP5 assumes high baseline growth and fast global income convergence. (Data available at: `https://secure.iiasa.ac.at/web-apps/ene/SspDb/dsd`). The SSPs provide the "baserate" growth rates that were entered into the empirical model described above to obtain climate-adjusted growth projections.

Summary

The orthogonal combination of the variables just described yields an experimental design for uncertainties about future growth that fully crosses 6 levels of scientific uncertainty with 4 levels of policy uncertainty (RCPs) and 2 levels of uncertainty about future global development (SSPs). For each of the 48 cells of this design, 1,000 simulation replications were performed by sampling a realization of climate sensitivity from the appropriate lognormal distribution. For each realization, global temperatures were projected to the end of the century and the economic effects of climate change were derived by considering the relevant SSP in conjunction with the empirical model relating temperature to economic production. Cumulative average growth rates for the remainder of the century were then computed across the 1,000 replications in each cell of the design.

These 48 projected global economic trajectories to the end of the century, each of which represented the expectation under one set of experimental conditions, were then converted into candidate social discount rates. At this stage the ethical considerations (top left Figure 1) were applied to each trajectory, by combining each of the 48 projected global economic growth rates (g) with the four combinations of δ and η using Equation 1. This yielded 192 candidate discount rates (48×4) across all combinations of experimental variables. In a final step, those candidates were integrated into a single certainty-equivalent declining discount rate (CE-DDR) using a process known as "Gamma discounting" (K. Arrow et al., 2013; Pearce et al., 2003; Weitzman, 2001), which is sometimes known instead as "Expected Net Present Value".

Gamma discounting: Harnessing uncertainty about the discount rate

If the future discount rate is uncertain, what is the appropriate way to handle this uncertainty? Suppose we believe that future interest rates could be 1% or 7% with equal probability? How do we best plan for that future? Recent work in economics has yielded considerable progress on this issue (e.g., K. Arrow et al., 2013; K. J. Arrow et al., 2014; Freeman, 2010; Gollier, 2002; Weitzman, 1998, 2001). One outcome of this research has been that it is not the discount rates that are to be averaged (e.g., by computing the mean of 1% and 7%, viz. 4%), but the (discounted) net present values associated with those rates at various points in the future. Weitzman (2001) termed this Gamma discounting and we use his terminology here.

Table 1 illustrates Gamma discounting using an example provided by K. Arrow et al. (2013). The table shows discounted values of \$1,000 at various times in the future for three different discount rates (ρ). For example, if $\rho = 4\%$, then the present value of \$1,000 after 50 years is \$135.34, and so on. Uncertainty about the discount rate is represented by the heterogeneity among the discounted values across the entries for each time t. For example, assuming an equal probability of ρ being 1% or 7%, then 50 years from now our $\$1,000$ can be worth either \$606.53 or \$30.20. It follows that the average of those two uncertain values represents the probability-weighted expectation for our $\$1,000$, which 50 years from now is $(\$30.20 + \$606.53)/2 = \$318.36$. These mean expected present values are shown in the column labeled MEV in Table 1 for our $\$1,000$ at various points in the future on the assumption that the discount rate is either 1% or 7% with equal probability. The temporal relationship between successive MEVs, finally, yields a single certainty-equivalent discount rate (CE-DDR) for any given point in time. For example, the MEV at $t = 50$ is \$318.36, and the MEV at $t = 51$ is \$314.33. The ratio between those successive values, \$318.37/\$314.33 = 1.0128 = 1.28%, provides the *instantaneous* CE-DDR at time $t = 50$ (also known as "forward" rate), and those values are shown in the second-to-last column of Table 1. This single declining discount rate can be applied with 100% certainty, and will yield the same discounted values as application of multiple rates with less than 100% certainty (K. Arrow et al., 2013).

While the forward (or instantaneous) CE-DDR captures the slope of the declining discount rate function between times t and $t + 1$, those rates cannot be used to discount an amount from the present to time t—that is, the MEV at time $t = 50$, for example, cannot be obtained by discounting \$1,000 at a rate of 1.28%. This requires a different certainty-equivalent discount rate, which is also declining but has generally higher values than the instantaneous rate. This rate is called the "spot" (or "horizon") CE-DDR and is shown in the final column of the table. Application of this rate to our present-day \$1,000 (or any project amount that is small relative to the size of the economy; Dietz & Hepburn, 2013) for time t will yield the MEVs for that time shown in the table. We report both forward (instantaneous) and spot (horizon) CE-DDRs from our experiment.

Gamma discounting has been applied in a variety of contexts where the discount rate is uncertain, including situations in which there is uncertainty about future economic growth (Fleurbaey & Zuber, 2012). The theoretical grounding for Gamma discounting is particularly firm when the candidate fixed discount rates (first three columns in Table 1) arise from irreducible heterogeneity among expert opinions rather than from random variation about an imprecise estimate (Freeman & Groom, 2015). Different ethical positions about risk aversion (η) and pure time preference (δ) are clear instances of irreducible heterogeneity, and we likewise consider the different levels of the remaining variables in our experimental design to represent the views of different hypothetical experts: Some experts might opine that the world will follow an SSP5 trajectory whereas others argue that the world will follow an SSP3 trajectory and so on. By contrast, the replications within each cell of the design are not considered to constitute irreducible heterogeneity but realizations of the future under a homogeneous, but noisy, scenario. It is for these theoretical reasons that we integrate across replications within each experimental cell to obtain a single expected growth trajectory that is then entered into Gamma discounting together with its counterparts, as noted earlier.

Simulation procedure and results

Emulating global climate change

Global temperature projections were obtained from a climate emulator proposed and tested by Raupach et al. (2011). Unlike a general circulation model (GCM), which models the atmosphere (and/or oceans) at a high resolution and therefore requires immense computing power, an emulator captures the behavior of a GCM at a global level and can be computed more rapidly.

The emulator converts radiative forcings into global temperatures, using a climate step-response function that is characterized by (in this case) three terms, obtained by inverting the Laplace transform of the climate response function for the HadCM3 model reported by Li and Jarvis (2009). The climate response function includes a parameter for climate sensitivity, represented by λ_q. (See Equation A6 and Table A2 in Raupach et al., 2011).

There are different ways in which climate sensitivity—i.e., warming in response to CO_2 doubling—can be operationalized, depending on how much time elapses after CO_2 doubling before the temperature increase is measured. The IPCC relies primarily on equilibrium climate sensitivity (ECS), which involves timescales of years to decades after CO_2 doubling, during which the atmosphere and upper oceans have had time to come into temperature balance. There are, however, numerous other feedback loops that operate at longer time scales, such as ice sheets and ocean circulation (Lunt et al., 2010), and the ultimate warming in response to CO_2 doubling may be greater and much delayed compared to ECS. This ultimate sensitivity to greenhouse gas emissions is labeled earth system sensitivity (ESS) and has been estimated to be 30-50% greater than ECS (Lunt et al., 2010).

Because the longest time scale in the three-term climate response function in our emulator is nearly 1500 years, the modeled climate sensitivity is best understood as ESS rather than ECS. We kept ESS constant at $\lambda_q = 4.6°C$ ($1.235KW^{-1}m^2$), the value used by Raupach et al. (2011) in a validation of the emulator against the IPCC's projections. This value is higher than estimates of ECS, which typically range from $1.5°C$ to $4.5°C$ (Freeman et al., 2015). For each simulation replication, a realization of ESS was sampled from a lognormal distribution with mean $\mu_{ESS} = 4.6$ and standard deviation σ_{ESS}, where the value of σ_{ESS} depended on the experimental condition.

Figure 2 illustrates the combined effects of scientific uncertainty (changes in σ_{ESS}) and climate policy uncertainty (RCPs) on global temperature projections from our emulator.

Relating global temperature to economic production

Using the data made available by Burke et al. (2015), we estimated regression weights for their (unlagged) base model with per capita GDP growth as the criterion. Our estimates of 0.0103 for temperature and -0.0004 for the square of temperature correspond closely to the values reported by Burke et al. (see their Extended Data Table 1; first column).

Projected global temperatures were obtained from the emulator for 2010–2100 and expressed as anomalies relative to 2010. Those global projections were converted into country-specific projections using the relationships observed under the RCP8.5 scenario for the mean projections of the CMIP5 model ensemble (Taylor, Stouffer, & Meehl, 2012). That is, the mean projected temperature increases for the CMIP5 ensemble between the reference periods 2080–2100 and 1986–2005 were used to estimate the factor by which each country differed from the global average (e.g., Botswana is expected to warm by 1.45 times the global average, whereas Argentina is only expected to experience 0.90 of the average, and so on). Those factors translated projected global temperatures into expected warming for each country, which in turn were converted into country-specific marginal effects of climate change on economic growth. That is, the economic growth trajectory expected for each country from the relevant pathway (SSP3 or SSP5) was adjusted upward or downward by the temperature-determined marginal effect of climate change.

Global GDP projections. Global GDP trajectories, obtained by summing the country-specific trajectories, are shown in Figure 3 for the two most extreme RCPs (RCP 2.6 and RCP 8.5, in the top and bottom row of panels, respectively) and the two most extreme values of uncertainty about climate sensitivity ($\sigma_{ESS} = 0.24°C$ and $\sigma_{ESS} = 1.66°C$ in the left-hand and right-hand column of panels, respectively).

Note that global GDP is expected to increase under most circumstances, except in Panel **d**, when scientific uncertainty is greatest ($\sigma_{ESS} = 1.66°C$), expected growth smallest (SSP3), and mitigation absent (RCP 8.5).

Figure 4 summarizes the average global GDP growth rates through the end of the century across all conditions of the experiment. The greatest source of difference again arises from which shared socioeconomic pathway that the world will follow (SSP3 vs. SSP5), with all other sources of uncertainty being subsumed under that primary variable. When year-to-year growth is considered, it is clear that under SSP3 without mitigation overall global growth may be negative for decades towards the end of the century (Panel **a**). When the cumulative average annual growth is considered, as required for computation of discount rates (Panel **b**), growth no longer turns negative (because the annual rates late in the century are averaged into all rates leading up to that point) but nonetheless declines late in the century.

By the year 2099, the cumulative average growth rate across the 48 cells of the experimental design is 1.60%, with a standard deviation of 0.88% (Figure 4 panel **b**). These values are almost identical to the mean (1.70%) and standard deviation (0.91%) of expert opinions on future long-term economic growth rates reported by Drupp et al. (2016).

Country-specific GDP projections. The aggregation at the global level obscures considerable variability among countries: Although some cool countries are expected to benefit from climate change, countries that are already near or beyond the optimum temperature will suffer. Figure 5 shows the proportion of countries (out of 165) whose year-to-year per capita GDP growth rate is projected to be negative, again showing the most extreme levels of climate uncertainty (in columns) and the most extreme RCPs (rows).

Except in the most favorable circumstances (SSP5 with strict mitigation; Panels **a** and **b**), a notable share of countries will experience economic decline at some point during the remainder of the 21st century. Under unfavorable conditions (SSP3 without mitigation; Panels **c** and **d**) around two thirds of all countries will experience decline by the end of the century.

Notably, even under stringent mitigation (RCP 2.6, top panels), when uncertainty about climate sensitivity is large (Panel **b**), under SSP3 more than 20% of countries experienced decline late in the century for at least 10% of the realizations (solid red line in Panel **b**). For the same mitigation path, when uncertainty was at its lowest (Panel **a**), this proportion was notably less and even the most extreme realization (dotted red line in Panel **a**) caused less than 20% of countries to decline. This pattern (comparing columns of panels) extends earlier results showing that greater uncertainty about the value of climate sensitivity creates greater adaptation and mitigation risks (Freeman et al., 2015; Lewandowsky, Risbey, Smithson, Newell, & Hunter, 2014; Lewandowsky, Risbey, Smithson, & Newell, 2014).

Relating uncertain future economic production to the social discount rate

The certainty-equivalent discount rates obtained from the projected growth rates via Equation 1 are shown in Figure 6 for various ethical scenarios. In an all inclusive scenario, all conjunctions of δ (0; 3.15%, probability-weighted 65% and 35%, respectively) and η (0.5; 2.2) contribute to the distribution of candidates for Gamma discounting; this scenario is labeled "Gamma" in the figure. In the remaining 4 scenarios, δ and η are set to the values indicated in the legend.

It can be seen that when all ethical ambiguities are considered, the forward (instantaneous) rate declines very rapidly, falling below 2% by around 2040 and heading towards a value near 0 by century's end. The spot (horizon) rate, which integrates across all intervening values of the forward rate and is applicable when seeking to discount the costs and benefits of a present project, naturally falls off less rapidly but dips below 2% by century's end. Note that this result is obtained using a realistic probabilistic weighting of the alternative values of the ethical variables based on expert responses (Drupp et al., 2016).

The declining schedule obtained by our experiment is placed into a broader context in Figure 7. The figure compares our results to relevant precedents that also estimated the social discount rate applicable to climate change. Previous estimates were variously based on analysis of historical interest rates (Groom, Koundouri, Panopoulou, & Pantelidis, 2007; Newell & Pizer, 2003), analysis of expert surveys (Freeman & Groom, 2015; Weitzman, 2001), or policy recommendations (e.g., the U.K. Treasury's "Green Book").

Our approach differs from those precedents by relying on explicit modeling of the impact of future climate change on economic production. When the likely impact of climate change on the global economy is considered, a more rapid decline of the discount rate is observed than in previous work. By 2070, our estimates of the spot (horizon) rate dips below the other past benchmark estimates considered here.

Discussion

We conclude from the experiment that when the full range of uncertainties is considered, then irrespective of one's ethical stance towards inter-generational discounting, the computationally-constrained value of the social discount rate declines steeply across the remainder of the century and dips below 2% for the end of the century, when the effects of climate change will be felt most acutely. This meshes well with the median long-run social discount rate elicited from experts (Drupp et al., 2016). We consider our work to provide a proof of concept, with much further exploration remaining to be performed. Potential limitations of our work must be noted before we can suggest some implications.

Potential limitations

Limitations of the climate emulator. Two caveats apply to our climate emulator that concern the conversion of emulated global temperatures into country-specific warming. Those conversion factors were calibrated against the ensemble mean of the CMIP5 model projections for RCP8.5. However, the regional details of warming are quite uncertain given that they depend on dynamical climate responses, such as the El Niño Southern Oscillation (ENSO) or changes in atmospheric circulation patterns related to the Arctic Oscillation, which vary widely across models. Therefore, a logical extension of our analysis would add yet another degree of freedom to the phase space where we explore the varying spatial footprints of predicted warming across models within the CMIP5 ensemble.

Moreover, it is unknown whether the global-to-country conversion factors estimated for RCP8.5 remain invariant under different warming scenarios, such as the other RCPs examined here. Future work has to examine the robustness of this calibration across warming scenarios, as well as across models.

Limitations of the empirical model. Several caveats also apply to the empirical model relating temperature to economic productivity (Burke et al., 2015). First, our simulation used a point estimate of the regression parameters for temperature (and its square), as did Burke et al.. This ignores a further source of uncertainty, namely the parametric uncertainty in the empirical model. Future work might usefully include that additional source of uncertainty in an experiment. A second caveat concerns the upper limit on temperatures in the empirical model: To avoid out-of-sample predictions, Burke et al. limited all future temperatures to the maximum observed in their historical sample, and we followed that practice here. Accordingly, the consequences of extreme future warming would have been curtailed by the model for countries that are already hot or warm. It remains to be seen whether removal of this ceiling would exacerbate the economic consequences already seen with RCP 8.5 towards the end of the century.

The final caveat concerns the presumed benefits of warming that is expected for cool countries from the empirical model. The model is limited in two ways: First, it considers only the effects of average temperature, which ignores the increase of extreme weather events (including floods, storms, and heat waves) that even cool countries are arguably already beginning to experience (e.g., AghaKouchak, Cheng, Mazdiyasni, & Farahmand, 2014; Coumou & Rahmstorf, 2012; Seneviratne, Donat, Mueller, & Alexander, 2014). Those extreme events may increasingly offset the benefit of slightly warmer temperatures in the historical record. Similarly, in a globalized economy, cool countries may suffer economic losses when hitherto unprecedented climatic events occurring elsewhere disrupt supply chains (Levermann, 2014). Second, the empirical model is based on historical data and its application to the future thus tacitly assumes a stationary environment. It is therefore unclear whether the model can deal with historically-out-of-sample effects when the environment becomes increasingly non-stationary. Non-stationary environments provide a particular challenge to estimating return-periods and return-levels of extreme events, although some promising developments exist (e.g., Cheng, AghaKouchak, Gilleland, & Katz, 2014). An extreme form of non-stationarity involves tipping points, beyond which irreversible large-scale impacts become inescapable. Expert elicitation reveals that at least five potential tipping points—reorganization of the Atlantic meridional overturning circulation; collapse of the Greenland Ice Sheet; collapse of the West Antarctic Ice Sheet; dieback of the Amazon rainforest; and an increase in the amplitude of ENSO—are consensually considered to constitute a significant risk (Kriegler, Hall, Held, Dawson, & Schellnhuber, 2009). Specifically, Kriegler et al. put the lower bound on the probability of triggering at least one of those events in response to $2°C - 4°C$ warming at 16%, and at 56% (i.e., better than even) if global temperatures exceed $4°C$ warming relative to 2000 temperatures. A conservative estimate of the impact of such tipping points is in the vicinity of 10% of global GDP (Lontzek, Cai, Judd, & Lenton, 2015).

We therefore suggest that the model may underestimate the adverse impact of climate change on future economic activity.

Assumptions about mitigation costs. We used the same empirical model to relate temperatures to economic production in all cells of the experimental design. This may be potentially problematic for any RCP other than 8.5 because we do not model mitigation costs explicitly. We believe that this omission is justified for several reasons: first, because the projected growth rates for the other RCPs are consistently above those for RCP 8.5, the declining discount rates rates we obtain in the end are conservative and constitute an upper bound—that is, they could not be *higher* if mitigation costs are considered. If mitigation reduced growth rates compared to RCP 8.5 then Gamma discounting would yield even lower declining rates. We find this unlikely based on indicative work by van Vuuren et al. (2011).

Second, it is far from clear that the impact of mitigation on economic growth can be modeled with any degree of reliability. Recent work has suggested that even the direction of the effect—i.e., whether mitigation accelerates growth or decreases it—cannot be firmly established (Rosen & Guenther, 2015). We therefore believe that a demonstrably robust (Burke et al., 2015) empirical model that is not adjusted for mitigation costs may yield better insights into the future than attempts of explicit modeling that are associated with greater uncertainty (Rosen & Guenther, 2015).

Assumptions underlying the social discount rate. Several assumptions underlying our approach need to be highlighted. First, the candidate distribution of discount rates determines the value of the CE-DDR. If the distribution of candidates shifts, so does the CE-DDR. In the experiment, we estimated the values and weights associated with δ and η based on expert responses (Drupp et al., 2016). However, for the uncertainty variables and their conjunctions (top-right panel in Figure 1), we have no information about the likelihood of the realization of their various values (e.g., whether RCP 2.6 is more or less likely to materialize than RCP 8.5) and in the absence of such knowledge all levels of were considered to be equally likely. It remains for future research to determine whether this assumption is plausible. Likewise, the consequences of adding intermediate levels to the experimental factors (e.g., intermediate values of η) remain to be observed.

Second, our main result relied on the gamma discounting proposed by (Weitzman, 2001). The boundary conditions of gamma discounting are a source of active debate (e.g., Freeman & Groom, 2016; Jouini & Napp, 2014), although it can be theoretically defended in many situations; for example, when experts have irreducibly different ethical opinions (e.g., about pure time preferences; see Freeman & Groom, 2016). It is, however, theoretically less well-established whether gamma discounting is also applicable when experts differ in risk aversion (cf. Jouini & Napp, 2014).

Third, our analysis has focused on a single global CE-DDR. This may be an over-simplification and some researchers have argued for its disaggregation into country-specific (and indeed person-specific) discount rates. One analysis along those lines has converged on the conclusion that the discount rate should be negative for climate change (Fleurbaey & Zuber, 2012). Further work along those lines is particularly important for ethical reasons (Singer, 2006): A single global discount rate tacitly presumes that the beneficiaries of current and future wealth are the same—after all, discounting according to Equation 1 presumes that our descendants are sufficiently wealthy to cope with the damages that we cause by limiting mitigation costs. Given that it is poor countries that will bear a disproportionate burden from climate change whereas rich countries benefit from avoiding mitigation (Costello et al., 2009), the global discount rate carries considerable hidden ethical baggage (Singer, 2006).

Implications

There has been much recent work on declining discount rates. A common theme of this work is the convergence to a low value over time (e.g., K. Arrow et al., 2013; K. J. Arrow et al., 2014; Freeman, 2010; Freeman & Groom, 2015; Gollier, 2002; Gollier & Hammitt, 2014; Groom et al., 2007; Newell & Pizer, 2003; Pearce et al., 2003; Weitzman, 2001). Our results confirm this convergence under a new set of circumstances, when various different sources of uncertainty and ambiguity are considered and when future growth rates are modeled based on a robust historical relationship between temperatures and economic production.

The suggested value of the CE-DDR that arises from our analysis is considerably lower than some previous estimates (e.g. Freeman & Groom, 2015; Groom et al., 2007;

Newell & Pizer, 2003). This meshes with the results of Burke et al. (2015), who found that their projected economic damages from climate change were far greater than estimates obtained from conventional economic models. We suggest that this difference reflects the fact that our modeling, like Burke et al.'s, explicitly takes into account the non-stationarity of economic production that arises under climate change. Whenever non-stationarity has been explicitly considered in previous work, the anticipated consequences have been far more dire than anticipated under stationary modeling (e.g., Lontzek et al., 2015; Moyer, Woolley, Matteson, Glotter, & A, 2014).

One immediate implication of the lower estimate yielded by our analysis is that it will further strengthen the impetus for climate mitigation by increasing the social cost of carbon. Compared to a constant discount rate of 4%, a declining discount rate that reaches 2% somewhere around 2100, doubles or triples the social cost of carbon emissions (K. Arrow et al., 2013). If our even lower value turns out to be robust, this would further increase the social cost of carbon although the magnitude of the effect remains to be determined.

However, at least one note of caution applies to declining discount rates because they may engender unexpected resource depletion in a "tragedy-of-the-commons" situation (Hepburn, 2003, cited in Pearce et al., 2003). It remains to be seen whether this result is robust, but it would be of particular concern in the context of climate change, which is perhaps the greatest "tragedy-of-the-commons" problem faced by humanity to date.

Conclusion

We aimed to provide quantitative constraints on the social discount rate that is applicable to climate change. Our estimates decline rapidly to below 2% at the end of the century when we integrate across a range of contrasting ethical positions about pure time preference and risk aversion.

Although this estimate is lower than that obtained by related previous work, it may nonetheless be conservative in light of the fact that possible tipping points in the climate system are not considered. Moreover, our work does not resolve other equally pressing ethical issues arising from cost-benefit economics in climate change, such as the valuation of environmental goods. We may be able to put a (discounted) price tag on all the real estate in Denmark, but that tells us nothing about the value of natural goods such as the natural beauty of the Danish country side, the existence of song birds, or species diversity (e.g., Ackerman & Heinzerling, 2004; Freeman & Groom, 2013; Funtowicz & Ravetz, 1994).

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Footnotes

[1] The role of η is quite nuanced and intricate, as it can in turn be decomposed into various additional components (K. J. Arrow et al., 2014; Atkinson, Dietz, Helgeson, Hepburn, & Slen, 2009; Gollier, 2002; Kaplow & Weisbach, 2011; Pearce et al., 2003). For present purposes those details need not concern us because our analysis explores a range of values of η and the precise underlying factors that determine those values do not affect the outcome.

Table 1

Present value of $1,000 received or expended after t *years with various discount rates and their certainty-equivalent declining discount rate obtained by Gamma discounting*

	$1,000 at time t [a]				*CE-DDR (%)* [c]	
t	*1%*	*4%*	*7%*	*MEV* [b]	Forward	Spot
1	990.05	960.79	932.39	961.22	3.94	4.03
10	904.84	670.32	496.59	700.71	3.13	3.62
50	606.53	135.34	30.20	318.36	1.28	2.32
100	367.88	18.32	0.91	184.40	1.02	1.71
150	223.13	2.48	0.03	111.58	1.01	1.47
200	135.34	0.34	0	67.67	1.01	1.36
300	49.79	0.01	0	24.89	1.01	1.24
400	18.32	0	0	9.16	1.01	1.18

[a] Column entries are values of $1,000 at time t (years hence) discounted by the rate (ρ) for that column.

[b] MEV = Mean expected present value if $\rho = 1\%$ or $\rho = 7\%$ with equal probability.

[c] CE-DDR = Certainty-equivalent declining discount rates.

Figure Captions

Figure 1. Overview of experimental design. The variables in the top panels are combined in an orthogonal design. Full crossing of levels of each factor is represented by the $\bigotimes$ operator, and factor levels are shown in each box. Sampling from all combinations of sources of uncertainty (top right panel) yields a probability distribution of projected economic growth rates (shown by the shaded distribution), whose average is combined with the parameters determined by ethical considerations (top left panel) to yield candidate social discount rates, ρ_s. Candidate rates are then combined into a single certainty-equivalent declining social discount rate (CE-DDR) using the process known as gamma discounting (Table 1).

Figure 2. Representative emulator output. Panel **a** shows 1,000 realizations for each RCP drawn from a lognormal distribution with $\sigma_{ESS} = 0.24°C$, and Panel **b** uses $\sigma_{ESS} = 1.66°C$. In each panel, the mean projection across the 1,000 realizations is shown by a bold solid line with the shaded polygon representing the observed variation across realizations. Observations for 1950–1999 (drawn in black) are based on historical forcing estimates (Hansen, Sato, Kharecha, & von Schuckmann, 2011) and observations from 2000 onward are based on RCP projections.

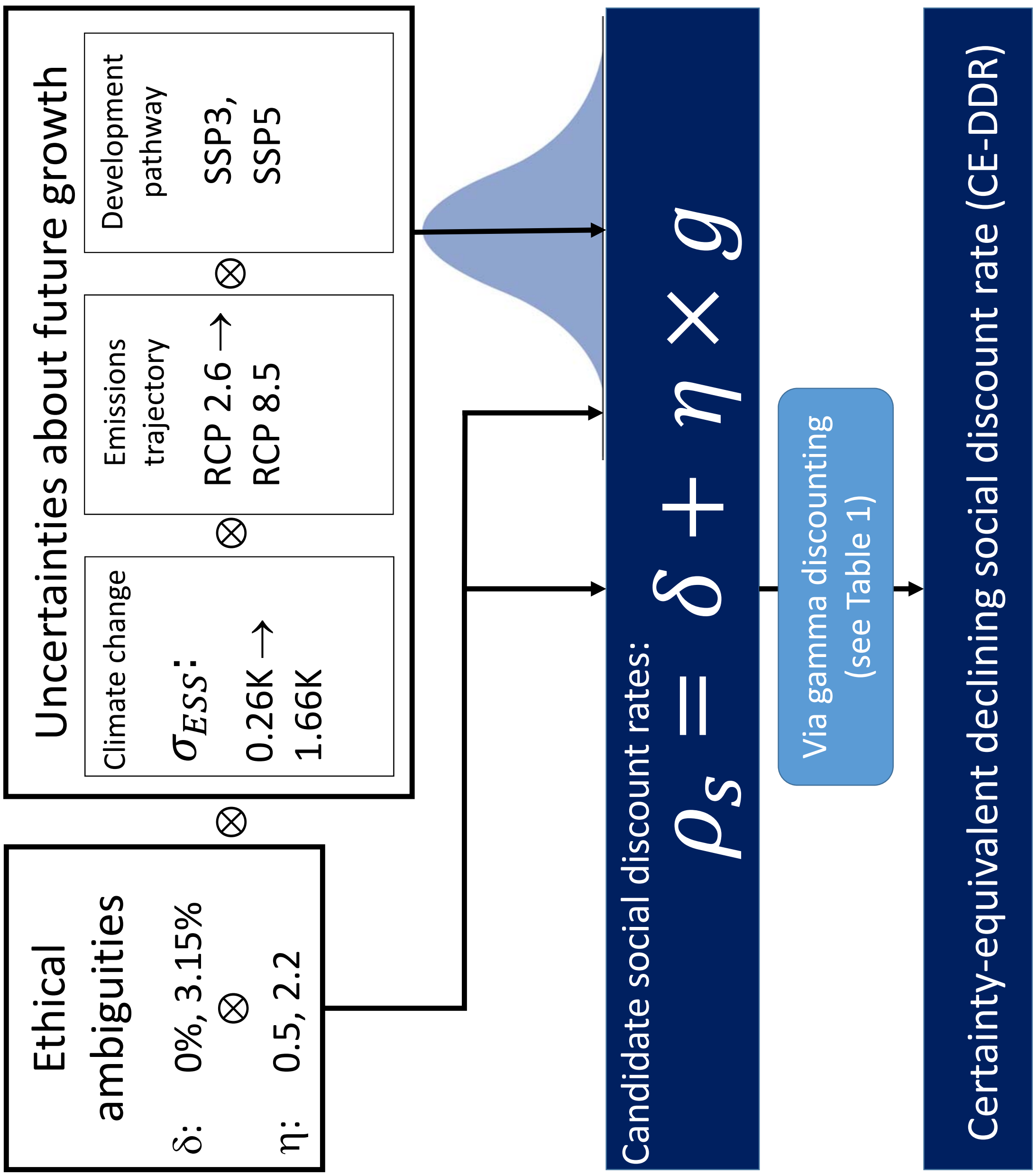
Figure 3. Global GDP trajectories for two RCPs (RCP 2.6 in the top row and RCP 8.5 in the bottom row) and two levels of uncertainty about climate sensitivity ($\sigma_{ESS} = 0.24°C$ in the left-hand column of panels and $\sigma_{ESS} = 1.66°C$ in the right-hand panels). Each panel presents two scenarios of economic development (SSP3 and SSP5). Plotting symbols represent mean trajectories across 1,000 realizations of climate sensitivity, solid lines represent the 10th percentile of realizations, and the dashed lines the minimum of the 1,000 realizations.

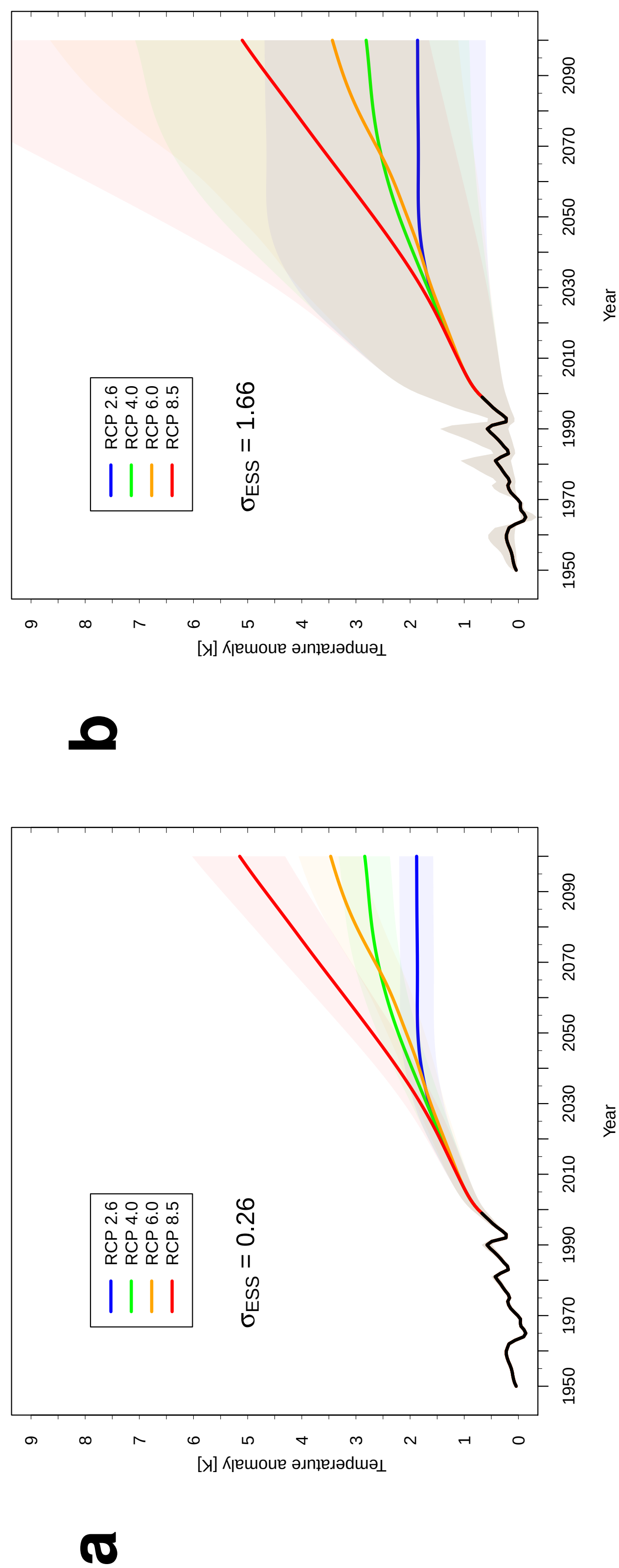
Figure 4. Global growth rate trajectories for year-to-year annual growth (left panel) and cumulative average annual growth from 2010 onward (right panel). The socio-economic pathways (SSP3 and SSP5) are represented by the two pairs of lines as indicated.

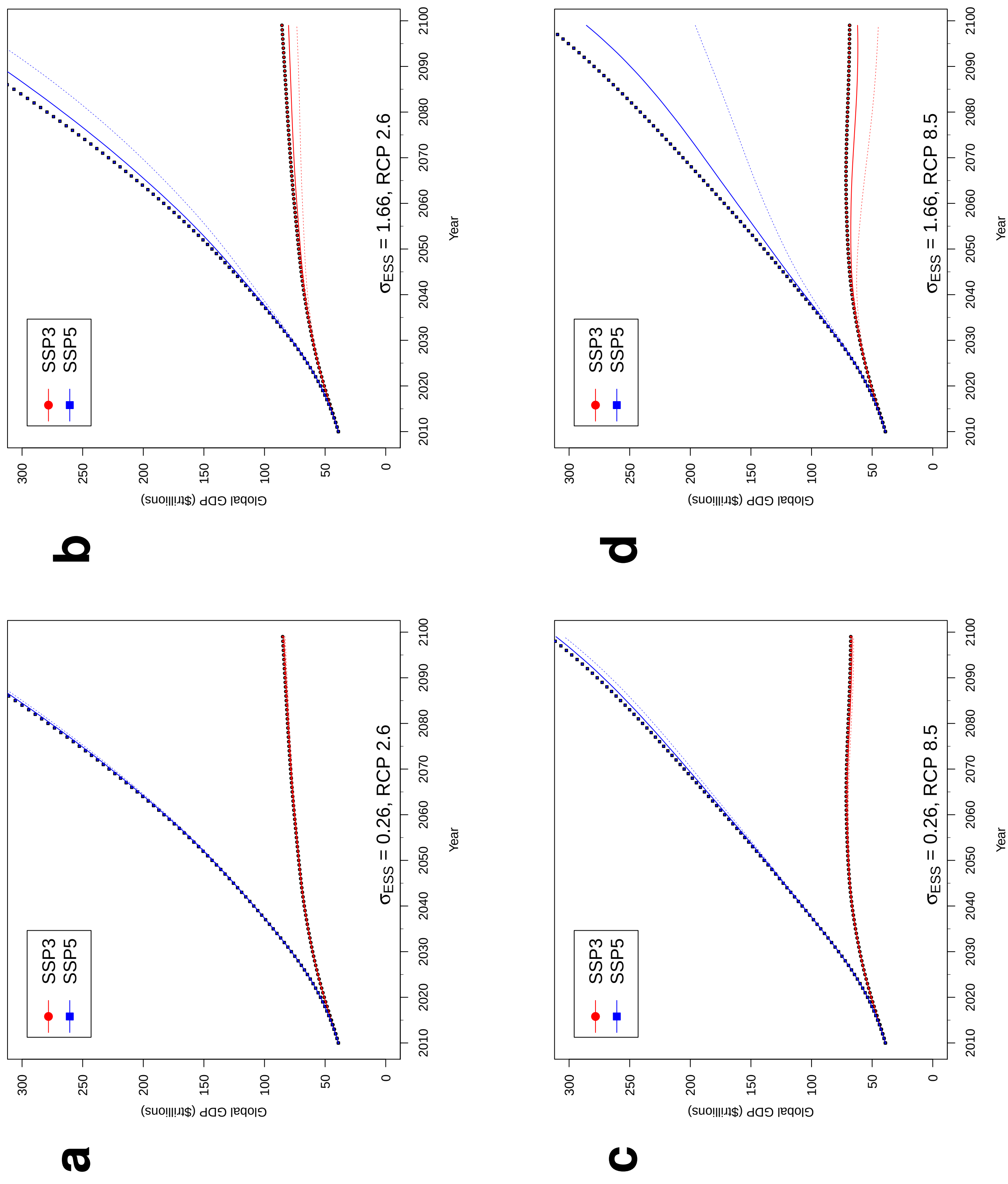
Figure 5. Proportion of countries (out of 165) with a net negative growth rate for two RCPs (RCP 2.6 in the top row and RCP 8.5 in the bottom row) and two levels of uncertainty about climate sensitivity ($\sigma_{ESS} = 0.24°C$ in the left-hand column of panels and $\sigma_{ESS} = 1.66°C$ in the right-hand panels). Each panel presents two scenarios of economic development (SSP3 and SSP5). Plotting symbols represent mean trajectories across 1,000 realizations of climate sensitivity, solid lines represent the 90th percentile of realizations, and the dashed lines the maximum of the 1,000 realizations.

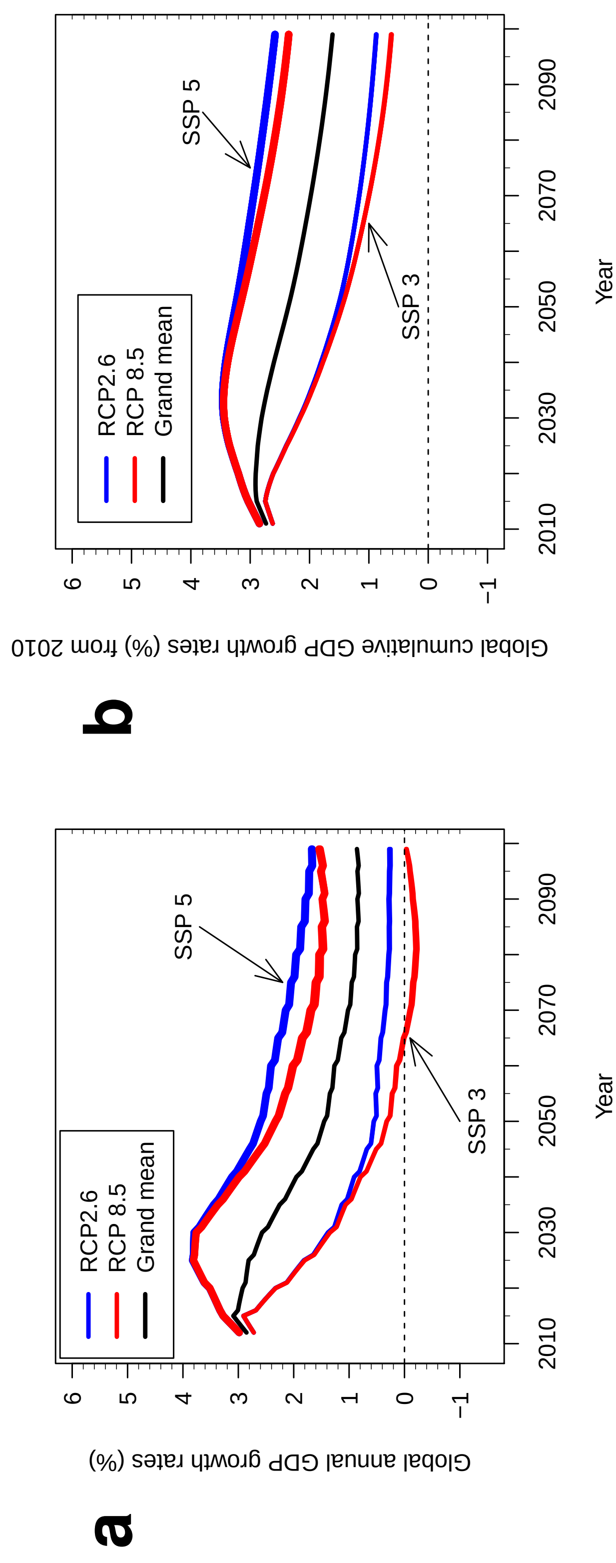
Figure 6. Certainty-equivalent declining discount rates obtained in the experiment. Panel **a** shows forward (instantaneous) rates and panel **b** spot (horizon) rates. The different parameters in each panel refer to different ensembles of candidate rates that are integrated by Gamma discounting. The line labeled "Gamma" integrates across all sources of uncertainty and ambiguity using 192 candidates, and the remaining 4 lines integrate across 48 candidates using the particular conjunction of η and δ as indicated in the legend. Rates are quoted on a continuously compounded basis for comparability with previous research.

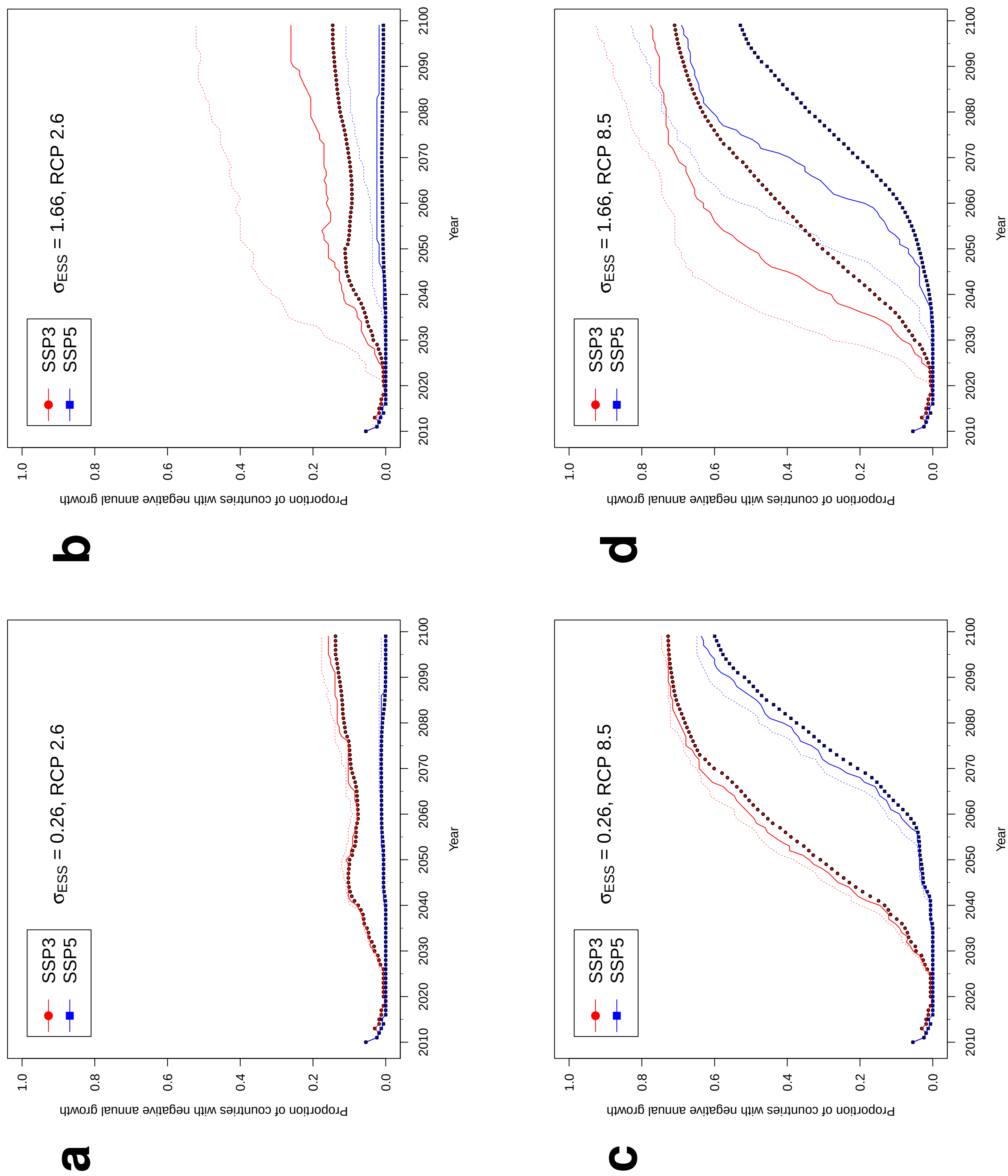
Figure 7. Comparison of spot (horizon) CE-DDRs obtained in the experiment in this paper to current practice (U.K. Treasury) and previous research by Freeman & Groom (2015), Weitzman (2001), Newell & Pizer (2003), and (Groom et al., 2007). The line for our experiment represents Gamma integration across all 192 candidate rates; see Figure 6, panel **b**.

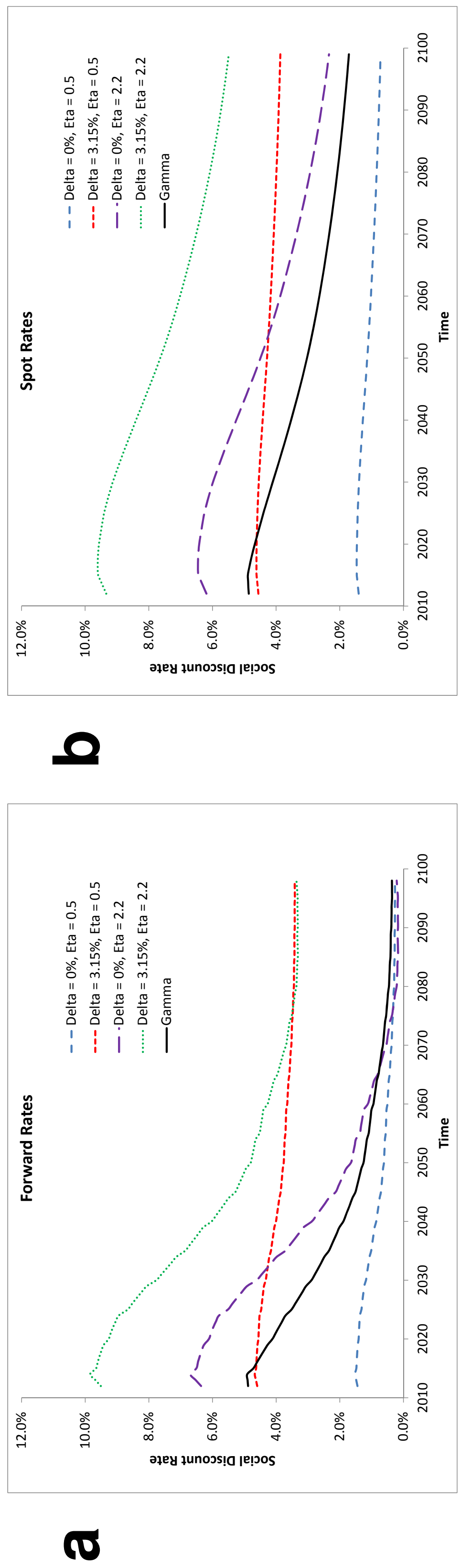

Ethical ambiguities
δ: 0%, 3.15%
⊗
η: 0.5, 2.2
⊗
Uncertainties about future growth
Climate change
σ_{ESS}:
0.26K → 1.66K
⊗
Emissions trajectory
RCP 2.6 → RCP 8.5
⊗
Development pathway
SSP3, SSP5
Candidate social discount rates:
$\rho_s = \delta + \eta \times g$
Via gamma discounting (see Table 1)
Certainty-equivalent declining social discount rate (CE-DDR)

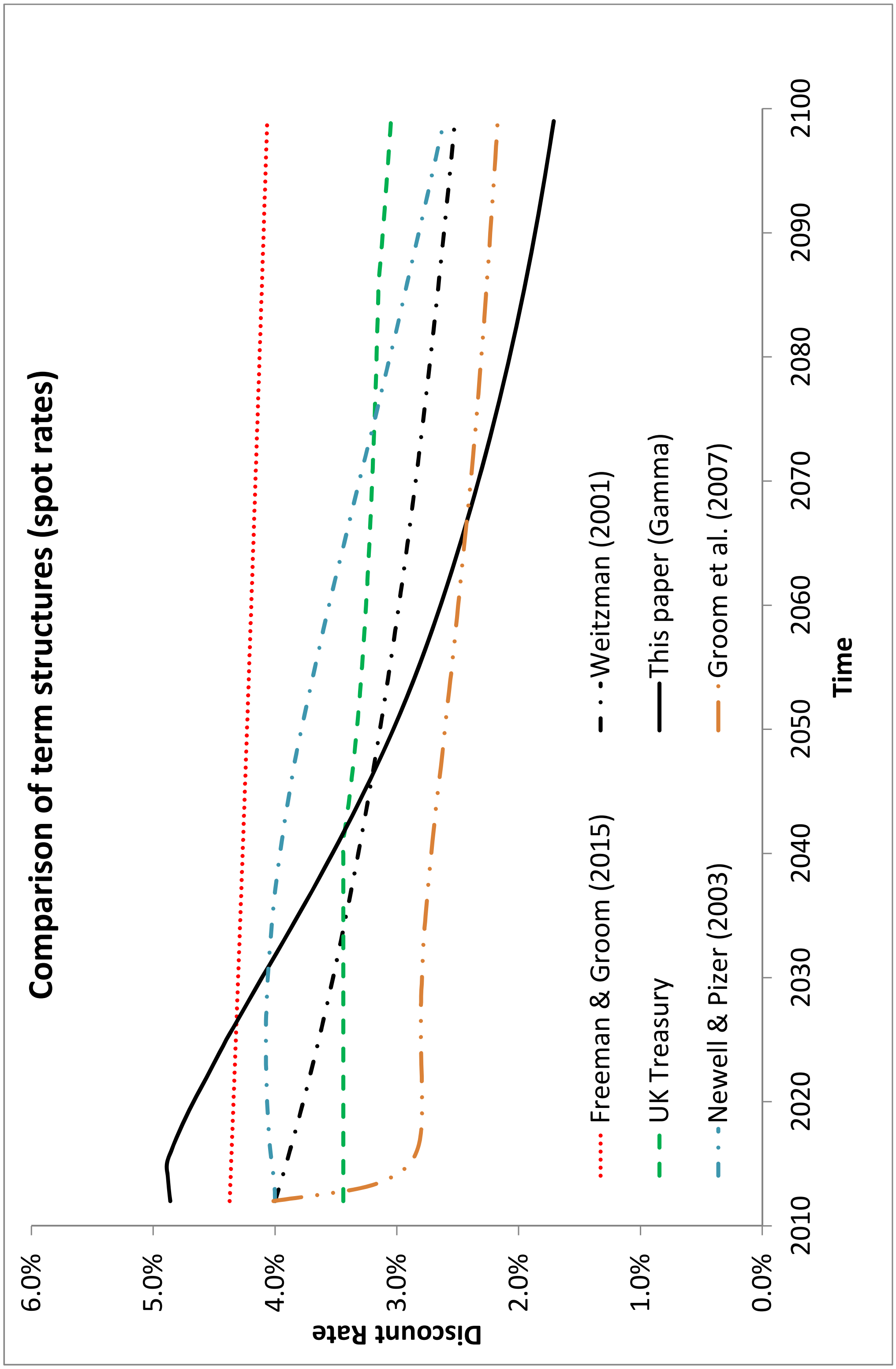

a
RCP 2.6
RCP 4.0
RCP 6.0
RCP 8.5
σ_{ESS} = 0.26
Temperature anomaly [K]
Year
b
RCP 2.6
RCP 4.0
RCP 6.0
RCP 8.5
σ_{ESS} = 1.66
Temperature anomaly [K]
Year


a
b
c
d
SSP3
SSP5
Global GDP ($trillions)
Year
σESS = 0.26, RCP 2.6
σESS = 1.66, RCP 2.6
σESS = 0.26, RCP 8.5
σESS = 1.66, RCP 8.5


a
b
Global annual GDP growth rates (%)
Global cumulative GDP growth rates (%) from 2010
Year
RCP2.6
RCP 8.5
Grand mean
SSP 5
SSP 3


a
b
c
d
σESS = 0.26, RCP 2.6
σESS = 1.66, RCP 2.6
σESS = 0.26, RCP 8.5
σESS = 1.66, RCP 8.5
SSP3
SSP5
Proportion of countries with negative annual growth
Year


a
Forward Rates
Social Discount Rate
Time
Delta = 0%, Eta = 0.5
Delta = 3.15%, Eta = 0.5
Delta = 0%, Eta = 2.2
Delta = 3.15%, Eta = 2.2
Gamma
b
Spot Rates
Social Discount Rate
Time
Delta = 0%, Eta = 0.5
Delta = 3.15%, Eta = 0.5
Delta = 0%, Eta = 2.2
Delta = 3.15%, Eta = 2.2
Gamma


Comparison of term structures (spot rates)
Discount Rate
6.0%
5.0%
4.0%
3.0%
2.0%
1.0%
0.0%
2010
2020
2030
2040
2050
2060
2070
2080
2090
2100
Time
Freeman & Groom (2015)
UK Treasury
Newell & Pizer (2003)
Weitzman (2001)
This paper (Gamma)
Groom et al. (2007)