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Article

Optimal Climate Policy and the Future of World Economic Development

Mark Budolfson, Francis Dennig, Marc Fleurbaey, Noah Scovronick, Asher Siebert, Dean Spears, and Fabian Wagner

Abstract

How much should the present generations sacrifice to reduce emissions today, in order to reduce the future harms of climate change? Within climate economics, debate on this question has been focused on so-called "ethical parameters" of social time preference and inequality aversion. We show that optimal climate policy similarly importantly depends on the future of the developing world. In particular, although global poverty is falling and the economic lives of the poor are improving worldwide, leading models of climate economics may be too optimistic about two central predictions: future population growth in poor countries, and future convergence in total factor productivity (TFP). We report results of small modifications to a standard model: under plausible scenarios for high future population growth (especially in sub-Saharan Africa) and for low future TFP convergence, we find that optimal near-term carbon taxes could be substantially larger.

JEL classification: Q5, Q1, O2, J11

Keywords: climate change, climate policy, carbon tax, total factor productivity, population growth

How much should present generations sacrifice to reduce emissions today, in order to reduce the future harms of climate change? Economists answer this question using Integrated Assessment Models of optimal carbon taxes, which balance near-term costs against future climate damages (Pizer et al. 2014; Interagency

Dean Spears (corresponding author) is an Assistant Professor in the Economics Department of the University of Texas at Austin and a visiting economist at the Indian Statistical Institute in Delhi; his email address is dean@riceinstitute.org. Mark Budolfson is an Assistant Professor in the Philosophy Department at the University of Vermont; his email address is Mark.Budolfson@uvm.edu. Francis Dennig is an Assistant Professor at Yale-NUS College in Singapore; his email address is fdennig@yale-nus.edu.sg. Marc Fleurbaey is Robert E. Kuenne Professor in the Woodrow Wilson School and the Center for Human Values at the University of Princeton; his email address is mfleurba@princeton.edu. Noah Scovronick is a Postdoctoral Research Associate in the Woodrow Wilson School of Public and International Affairs at Princeton University; his email address is Noah.Scovronick@princeton.edu. Asher Siebert is a postdoctoral research scientist at the International Research Institute for Climate and Society at Columbia University; his email is asiebert@iri.columbia.edu. Fabian Wagner is a Senior Research Scholar at the International Institute for Applied Systems Analysis in Laxenburg, Austria; his email address is fabian@iiasa.ac.at. We appreciate comments from participants at NEUDC, the Eastern Economic Association, the Population Association of America annual meeting, and Princeton University. Errors are our own. This paper received no specific funding. The research of Dean Spears was supported by grant P2CHD042849, Population Research Center, awarded to the Population Research Center at the University of Texas at Austin by the Eunice Kennedy Shriver National Institute of Child Health and Human Development. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. Supplementary online appendixes for this article can be found at *The World Bank Economic Review* website.

Working Group on Social Cost of Carbon 2013). Within climate economics, debate on this question has been largely focused on so-called "ethical parameters" of social time preference and inequality aversion. Although there is growing recognition of the importance of the climate vulnerability of the future poor (Hallegatte et al. 2015), leading models of climate economics make assumptions that do not reflect the full range of plausible future scenarios for economic and human development. It is therefore a priority for climate economics and policy to know how sensitive optimal carbon taxes are to other likely futures for the world's poor. We show that optimal climate policy importantly depends on the future of development, with effects that are comparable in size to large changes in ethical choices such as discounting.

The 2016 report of the US National Academies on the social cost of carbon highlighted that better socioeconomic models and projections are a critically needed input into assessing climate policies (National Academies 2016, 2017). In this paper, we investigate how important the contributions of *development economics*, in particular, may be to efforts to construct policy-relevant models of climate change and emissions policies: how much does optimal climate policy depend upon the answers to development economists' questions? We study the effects on optimal climate policy of two types of assumptions about the future of the developing world: different possibilities for population growth and its distribution worldwide, different possibilities for future convergence in aggregate productivity, and plausible interactions among these possibilities. The results make three contributions to the literature on optimal climate policy.

First, this paper theoretically emphasizes that population growth can play a role analogous to time discounting in determining optimal climate policy; this is because a larger future population increases the social importance of the future, relative to the present. However, despite this importance, population has not received the same systematic treatment as other aspects of the social welfare function, such as time preference or inequality aversion.

Second, this paper quantifies the effects on the optimal tax of population assumptions. Largely because of slow fertility decline in sub-Saharan Africa, the most recent global population projections now project that world population growth is likely to remain positive at the end of the 21st century (Gerland et al. 2014). We document a mechanism for the effect of population assumptions that changes over time: in the near term, greater future population growth increases optimal taxes because of its role in the social welfare function; in the long term, a larger realized population matters because of its effects on the economy and emissions. Future population growth influences optimal present-day Pigouvian taxes under a social welfare function that regards externality costs to more future people as a greater social cost. Under the UN's "low" projected future population path, the optimal global temperature is about 0.75°C *greater* than under the UN's "high" projected future population path; this is because a given level of climate damage registers as a greater social cost when more people will suffer from it.

Third, this paper computes optimal carbon taxes under assumptions of slower and faster convergence in Total Factor Productivity between the developing and developed world than is assumed by some leading models of optimal climate policy. Understanding the determinants of aggregate productivity is an active open research question in development economics (Easterly and Levine 2001). Indeed, historical literature on economic growth contains decades of predictions of macroeconomic convergence; however, evidence indicates that country-level income in fact has diverged (Pritchett 1997), or has failed to converge (Grier and Grier 2007), or has perhaps converged at best only very slowly (Deaton 2013). Lowering the assumed rate of convergence of poor countries' TFP growth to rich countries' has two effects: in the near term, it raises optimal carbon taxes because climate damages are hurting a future developing world that is poorer than it otherwise would be; in the long term, it lowers optimal taxes because the world can afford to pay less. We show that assumptions about population growth and TFP interact: if the future developing world were expected to have a large population and low TFP, then today's optimal carbon tax would increase considerably.

In many ways, life is getting better quickly for people in poor countries: infant mortality is falling, the fraction of people who are very poor is falling, populations are getting taller on average. But there are at least two important exceptions to these improving trajectories: one, that the fertility transition in sub-Saharan Africa is not following the same pattern as in other regions of the developing world, resulting in persistent positive population growth; and two, that despite decreasing inequality among individuals at the world level, aggregate economic convergence has been slow or absent, perhaps especially in TFP. The causes of these two facts are not fully agreed upon in their respective literatures; as a result, successive expert projections have proven subject to large revisions. These two facts matter here because—among the many positive and negative trends in the developing world—it turns out that these two trajectories are important determinants of optimal carbon taxes, as computed by economists' conventional models.

These findings are important for climate policy. Much of economists' debate about climate policy has considered the "ethical parameters" of time discounting and inequality aversion (Arrow et al. 2013). However, the future population and economic growth of the developing world are similarly important for optimal carbon taxes, are amenable to scientific refinement (through improved demographic projections, growth theory, and econometrics), and may be treated over-optimistically in the assumptions of influential models. Therefore, this paper advances a growing literature that documents the importance of the vulnerability of developing countries to climate change in the future (World Bank 2010), above and beyond the increasingly well-documented high levels of exposure of people in developing countries to environmental pollution today (e.g., Kumar and Foster 2007; Tanaka 2015). Our results underscore the inseparability of climate economics from development economics (Greenstone and Jack 2015).

1. Background: IAMs, Population, and TFP Growth

How much should society today be willing to sacrifice in order to prevent future climate damage? Under Executive Order 12866, US government agencies have been required to incorporate into regulatory decisions a "social cost of carbon," computed from economic Integrated Assessment Models (IAM). Such models incorporate economic optimization with scientific models of the climate and economic models of growth in order to inform regulation, and, in some models, compute a socially optimal tax on carbon, sometimes called a "carbon price" (Kossoy et al. 2015). In particular, IAMs weigh future climate damage against present-day mitigation costs to investigate optimal climate mitigation policy.

Debates over the social discount rate have proven important in economic valuations of climate change because most of the damage will happen decades or centuries in the future; a social planner that is less concerned about future well-being will be willing to incur lower costs today to prevent climate damages. It is well known that a lower social discount rate would recommend a greater reduction in carbon emissions. We introduce optimizing IAMs in order to show that assumptions about the future of the developing world can be of importance similar to choice of a social discount rate.

Any economic model to estimate an optimal tax[1] requires a *social welfare function* (SWF) in order to value the trade-offs society faces in its policy choices. For example, two forms of social welfare function that have been discussed in the population literature are *average utilitarianism*, which averages well-being over members of a population, and *total utilitarianism*, which adds well-being over members of a population, and therefore considers additional good lives to be an improvement in social welfare. Generically, all three cost-benefit optimization (DICE/RICE, FUND, and PAGE) IAMs use the same default social welfare function of a discounted total utilitarian form, as described by Pindyck (2013):

$$W = \frac{1}{1-\eta}\mathbb{E}\left[\int_{2015}^{2300} L_t C_t^{1-\eta} e^{-\rho t} dt\right], \tag{1}$$

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[1] Note that the optimal tax does not appear directly in equation 1, as it is neither subtracted from consumption nor redistributed to the population (Mankiw 2009); because our model, like other IAMs, uses a single representative agent within each region, carbon taxes are simply consumed like other output that is not invested as savings. Instead, a carbon tax indirectly reduces consumption by reducing economic output.

where $\mathbb{E}$ indicates an expectation over possible futures, t indexes time, ρ is the rate of social pure time preference, and η is a parametrization of the curvature of the within-period felicity function of period-average consumption C_t.[2] L_t is population size in period t.

If the social discount rate ρ is positive, costs to future generations are discounted in the computation of optimal present-day tax because these costs accrue to people living further in the future. As many observers have commented, much of the difference between the relatively high recommended carbon taxes of Stern's (2006) IAM and the relatively low carbon taxes of Nordhaus's Regionalized Integrated Climate Economy (RICE) IAM can be accounted for by the fact that RICE assumes a larger positive social discount rate, although this is not the only difference between these models and approaches. RICE, the model that we build upon in our analysis, is introduced in the next subsection.

Introducing the RICE Model

All analyses in this paper use the RICE model (Nordhaus and Boyer 2000). The RICE/DICE model family (DICE being the global counterpart) is one of three leading cost-benefit climate economy models capable of estimating the social cost of carbon (Policy Analysis of the Greenhouse Effect (PAGE) and Framework for Uncertainty, Negotiation and Distribution (FUND) are two others). RICE is highly representative of the set of leading cost-benefit IAMs that are used to estimate the social cost of carbon, so the results we find with RICE should not be qualitatively different if investigated with any of these models.

First developed in the 1990s, and updated several times subsequently, the RICE model consists of 12 regions, some of which are large countries and some of which are sets of countries. Each region has its own "damage function," an equation that translates the temperature change due to climate change into the damages that the region eventually experiences. The DICE/RICE models are freely available and have been used extensively in both academic research and policy analysis, including in the US governments Interagency Working Group on the Social Cost of Carbon, which recommends a carbon price for use in legally mandated cost-benefit analyses that evaluate relevant regulations. RICE has been described in detail elsewhere, but we also provide a detailed specification in the supplementary online appendixes.

Population Growth

Recent estimates by the UN World Population Prospects find that there is an important probability that population will be as high as 12.3 billion in 2100 (Gerland et al. 2014). These projections estimate that there is a 70 percent chance that population growth will still be positive in 2100. In particular, the median projection for Africa in 2100 is 4.2 billion people[3] and still growing, compared with less than one billion today. Population growth in Africa may be especially important for the social cost of carbon in regionally disaggregated models if climate damages are expected to be large there, or if evaluations of social welfare are sensitive to inequality or to the likelihood that poor Africans would be disproportionately harmed.

In this section, we introduce the importance of population projections to IAMs, and in particular the importance of population to some SWFs.[4] First, we note that the set of possible future population paths in the literature contains a wide diversity of possible futures. Over the past decades, demographers' best predictions about future population growth have been repeatedly revised under new information, and

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[2] Alternative models have relaxed some of these constraints. Strictly, Pindyck (2013), in his equation 1, omits L, implicitly assuming within-period average utilitarianism. Nordhaus (2011), in his equation 1, incorporates C and L as arguments into a within-period function U; although this is not discussed in the text, the only purpose for this flexibility could be to allow curvature over population size.

[3] This would give Africa a population density comparable to China today.

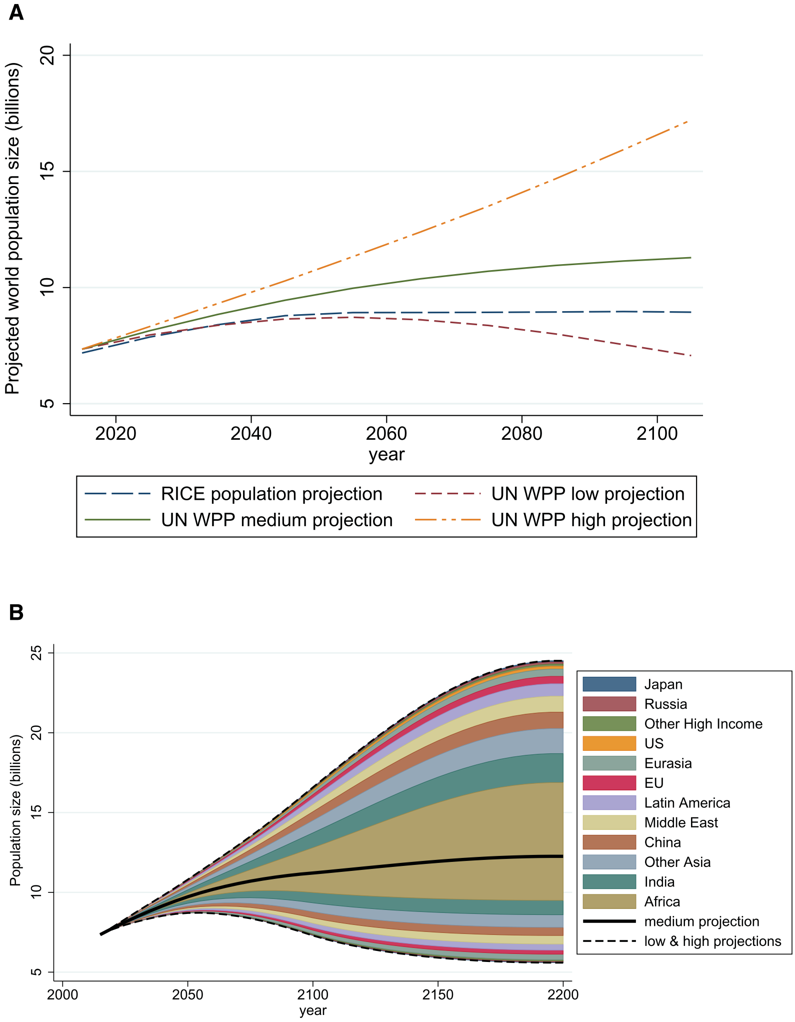
[4] Our purpose is to consider consequences of whatever *exogenous* population growth may be; we do not consider policy options to change population growth or what an optimal population policy would be (Spears 2015).

there is no reason to be sure that large revisions could not happen again. Second, we note that under the SWF used in leading IAMs, population growth plays a role formally analogous to time discounting. Third, we note that among SWFs used in the literature, there is indecision or implicit disagreement about how future population should be incorporated into climate policy. Our work on population in this paper builds on a shorter paper by the same authors in the climate science literature (Scovronick et al. 2017), which considers only the global population total, and is therefore unable to highlight the importance of the future of the developing world.

Population Growth: Assumptions and Projections

Possibilities for the future of human population size vary widely. Panel (a) of fig. 1 presents four population paths that we will use throughout this paper. The high, medium, and low paths are the most recent UN

Figure 1. Possible Future Population Paths: Global Totals and Alternative Distribution Across Regions



Source: Authors' computations from climate-economy model described in text.

Note: (A) global population totals. (B) decomposition of the differences between UN paths by RICE regions.

We updated the 2005–2015 RICE growth rates to match observed population growth. "Middle East" refers to Middle East and North Africa; "Africa" refers to sub-Saharan Africa.

aggregate population projections, taken from the 2015 round of the World Population Prospects. Note that in the medium projection, world population growth is still positive in 2100, largely because of positive population growth in Africa, as shown in panel (b).

The fourth projection is the population projection used in Nordhaus's (2011) implementation of RICE. Since that time, a newer version of RICE has slightly updated its population assumptions to more closely match the newest UN projections. Therefore, we emphasize that we do not use these figures to argue that RICE is "wrong." Rather, we include the comparison between the 2011 RICE assumptions and the most recent UN projection throughout our analyses in order to document the quantitative importance for optimal taxes of a modest change in population assumptions *that actually occurred* in the recent history of climate modeling.

Much of the uncertainty in future population size is from developing countries, especially from Africa, but also importantly from Asia (Gerland et al. 2014). This is largely because fertility decline in sub-Saharan Africa has lagged considerably behind the fertility transition in other developing regions for reasons that are not fully understood even by frontier demographic research (Kohler 2012). Reviews of past population projections show that even the most authoritative past projections have proven importantly incorrect or have subsequently been considerably revised (Lam 2011). In light of this history and of the considerable uncertainty in even the best demographic literature, it is plausible that future revisions in population projections could reflect differences as large or larger than the difference we study, between the 2011 RICE assumptions and the 2015 WPP projections.

We note that one important possibility is that climate change could endogenously influence world populations through net migration. Our population paths consider migration in the sense that the exogenously assumed World Population Prospects (WPP) projections themselves include migration assumptions. However, in this paper, we abstract away from any endogenous effect of climate change on net migration, to avoid further deviation from RICE.

Population Growth Can Be Theoretically Analogous to Time Discounting

For each time period t, define g_t as the population growth rate that correctly makes $L_t = e^{g_t t} L_{2015}$. Then the generic SWF of equation 1 can be rewritten:

$$W = \frac{1}{1-\eta}\mathbb{E}\left[\int_{2015}^{2300} \left(e^{g_t t} L_{2015}\right) C_t^{1-\eta} e^{-\rho t}\, dt\right] \tag{2}$$

$$= \frac{L_{2015}}{1-\eta}\mathbb{E}\left[\int_{2015}^{2300} C_t^{1-\eta} e^{(g_t-\rho)t}\, dt\right]. \tag{3}$$

This functional form emphasizes that the weight of the utility of a period's average consumption in the social welfare function depends on both the population growth rate and the time discount rate. If population growth is high enough relative to the discount rate, then average consumption in future periods is more important than average consumption in the present.[5]

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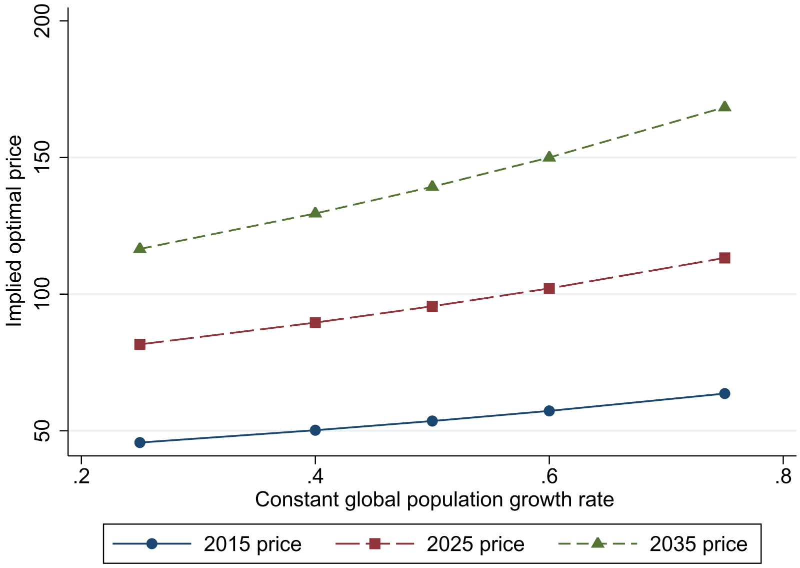
[5] In fact, not all studies of optimizing climate IAMs are explicit that they use an SWF of this total-population type; some papers do not describe an unambiguous assumption about population, because the economic or scientific focus of the research is on a different dimension of climate policy. Pindyck (2013), for example, omits population from his SWF, implicitly appearing to assume discounted within-period average utilitarianism. Anthoff and Tol (2010), in their IAM named FUND, use a population weighted SWF effectively identical to our equation 1. The results of this paper's analysis suggest that it could be useful for the IAM community to systemize assumptions on the role of population in social welfare.

As equation 2 shows, different population paths are important because they reweight the distribution over the total human population of economic costs and benefits. This reweighting happens over two dimensions: time and space.

The importance of the time dimension of population reweighting is visible in fig. 2, which illustrates this point by presenting optimal mitigation policies computed by RICE under the idealized assumption of constant global population growth rates. An increase in the constant worldwide population growth rate of 0.1 percentage points results in an approximately 7 percent higher near-term optimal tax.[6] This occurs because higher population growth means that the damages suffered by a (larger) future population are weighted more heavily in the social welfare function. This reweighting is precisely analogous to time discounting. In equation 2, a constant population growth rate would be represented by g without a time subscript, so the passage of time would be multiplied by the constant $g - \rho$: the difference between population growth, which makes the future more important, and time discounting, which makes the future less important. An equal percentage point increase in constant population growth and time discounting would exactly offset one another.

Population's role in reweighting across world regions is visible in panel (b) of fig. 1. This figure decomposes the differences across the UN population projections into the differences contributed by each of the 12 RICE regions. The large central section is sub-Saharan Africa (hereafter referred to as "Africa"), indicating that the population path that the world takes could not only differ substantially in the total numbers of people at different times; it could also differ considerably in the fraction of the world population at any one time that is in Africa. If the world follows a population path such that African population growth remains higher than population growth in the rest of the world for many decades, then the fraction of the population that lives in Africa could increase markedly. Whether this is projected to occur

Figure 2. Illustration: Optimal Carbon Price Under Idealized Constant Global Population Growth Rates



Source: Authors' computations from climate-economy model described in text.

Note: $\rho = 1.5\%$, $\eta = 1.5$. Standard RICE assumptions are used, other than for population growth. Population growth rate expressed in percentage points. Optimal price in units of $ per ton C.

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[6] We compute this semi-elasticity by regressing the log of optimal taxes in two on the constant population growth rate; $R2$ is greater than 99 percent.

will have a large effect on optimal climate mitigation policy because Africa is a climate-vulnerable region: larger mitigation costs are justified today if many more future people in Africa will be exposed to climate damage, all else being equal.

Economic Growth: How Quickly Will TFP Converge Globally?

The RICE IAM is a model of 12 global regions, some of which are large countries and some of which are sets of countries. Figure S2.3 in supplementary online appendix S2 presents the contemporaneous across-region inequality at each time period, computed from consumption levels in optimal paths for carbon emissions and carbon taxes. The figure plots several lines, each corresponding to a different combination of the “ethical parameters” for inequality aversion and social time preference, but differences among the lines are not visible as plotted. Rather, what the graph shows clearly is “convergence big time,” irrespective of the ethical parameter assumptions: a strong downward trend in inequality over time, across all modeled assumptions of the ethical parameters. In other words, the RICE model makes the strong assumption that global inequality will certainly fall dramatically over time.

However, some macroeconomists see evidence for a “disadvantage of poverty” (Ravallion 2012), which could counteract forces of convergence and cause it not to be the case that countries with high levels of poverty grow faster (López and Servén 2009). Whether or not overall global inequality is increasing or decreasing depends on whether one looks at country aggregates or attempts to look at person-level inequality and on whether or not country averages are weighted by population (Milanovic 2011): although person-weighted measures are dominated by the large, growing economies of China and India, it is clear that inequality of country-level aggregates (of the sort that climate IAMs model) has been non-decreasing over time or increasing.

Among the many potential determinants of economic growth, RICE particularly assumes convergence in GDP because the model assumes rapid convergence across regions in Total Factor Productivity (TFP). TFP, famously described by Moses Abramowitz as a “measure of our ignorance,” is essentially a residual in growth accounting, the heterogeneity in long-run economic performance that is not accounted for by differences in factor inputs through the functional form of a growth theory. Much remains unknown about what TFP in fact measures, and why it varies so importantly across countries (Hsieh and Klenow 2010). Technology and productivity differences may be highly persistent over centuries (Comin, Easterly, and Gong 2010). As Grier and Grier (2007) show, other *inputs* such as physical and human capital are converging across countries, so divergence in *outcomes* appears particularly incompatible with strong convergence in a TFP-type residual. Although this does not mean it could not be useful to consider optimal climate policy in a world of rapid TFP convergence, the growth accounting literature is far from suggesting that such convergence is implied by the facts (Caselli 2005).

The Penn World Tables quantify TFP in each country over time (Feenstra, Inklaar, and Timmer 2015). These data give little reason to be confident that TFP will converge toward the United States in the future. In the past decade, TFP in India and China, relative to the United States, has hardly increased at all.[7] Over the full range of data in the Penn World Tables, TFP in Africa has *decreased* relative to TFP in the United States.[8] These data therefore suggest to us investigating a case in which TFP does not converge, as well as a case of TFP convergence only half as quickly as in the RICE model.

As in the case of population assumptions, it is not our intent to criticize the RICE IAM or any other. Instead, our goal is to *employ* the framework of RICE to investigate the sensitivity of optimal climate policy to assumptions about the future of the developing world. It is plausible that developing countries,

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[7] For example, TFP in China (relative to the United States) is 0.42 in 2007 and 0.43 in the most recent observation.

[8] In a regression of the TFP level at current purchasing power parity (so the United States is always one) on the year, with country fixed effects, for all available African country years, an additional year in the future is, on average, linearly associated with the TFP ratio being 0.0055 *lower*, with a standard error of 0.0018, clustered by country.

in the future, will not experience the dramatic catch-up that is implicitly assumed by some accounts of climate policy, such as RICE; we investigate the implications of this possibility by varying the assumed rate of TFP convergence. Combining different assumptions about TFP convergence with different assumptions about population growth allows us to investigate the plausible case where the future developing world contains many more people than today who will be exposed to climate change while living in economies that continue to lag considerably behind the richest.

2. Method: Small Modifications of a Leading, Publicly Available IAM

We produce new estimates of the social cost of carbon by making small modifications to the quantitative assumptions of RICE, a leading regionally disaggregated IAM, developed by Nordhaus (2011).[9] In particular, we vary two dimensions of the future of economic development: population growth[10] and TFP convergence.[11] In the IAM literature, much attention has been paid to the "ethical parameters" of pure time discounting (ρ) and inequality aversion (η); because our objective is to make minimal modifications to RICE, in our computations throughout the paper we maintain the RICE assumptions of $\rho = 1.5\%$ and $\eta = 1.5$.

Alternative Population Assumptions

As introduced in fig. 1, we consider four future population paths: the assumptions of Nordhaus's (2011) RICE and the high, medium, and low assumptions of the 2015 UN World Population Prospects (WPP). Although panel (a) plots the time path of global total population, in fact the regional composition of population additionally varies considerably across the paths, as seen in panel (b). The 12 RICE regions

[9] Our model is a Matlab implementation of the RICE2010 spreadsheet written for Dennig (2014). The original spreadsheet, by William Nordhaus, can be found at: http://www.econ.yale.edu/~nordhaus/homepage/RICEmodels.htm, last accessed August 27, 2017. In the supplementary online appendixes, we present equations that describe our model. Our model replicates all aspects of the original spreadsheet except for: (i) the objective function; (ii) the savings rate specification; and (iii) the implementation of the sea-level-rise damages. We use a population weighted discounted utilitarian objective while the original RICE2010 model uses Negishi-weights in addition to population weights. We use a fixed (Solow) savings rate while RICE2010 uses endogenous savings rates. Finally, we simplify the sea-level-rise damages by incorporating them into the quadratic damage function coefficients while in RICE2010 damages consist of a quadratic non–sea-level-rise component and a separate sea-level-rise component. The differences in savings rate and damage specifications are also described in full detail in the section "Modifications to RICE2010" in Dennig et al. (2015). Our model is additionally similar to NICE, a related IAM by Dennig et al. (2015) that was designed to extend RICE to within-region inequality; in the production of every estimate in this paper, our models are set to ignore within-region inequality.

[10] Our paper builds upon our prior work about aggregate global population in the climate science literature in Scovronick et al. (2017), a study that uses the globally representative model DICE rather than the regionally disaggregated RICE and, therefore, is unable to address the topics at the core of our paper: economic development, population growth in the developing world, the possible coincidence of population growth with poverty and climate damages across regions, and TFP convergence. Unlike the present paper, Scovronick et al. specifically study the policy implications for optimal climate mitigation of population and fertility policies and programs.

[11] A related recent paper by Gillingham et al. (2015) also studies variation in IAM output as a result of quantitatively differing inputs. Although the Gillingham study is an important contribution to the literature, our contribution differs in three ways: (i) we focus on uncertainty about the future of *development* while in contrast they use the DICE model that studies the world as a single representative-economy global whole; (ii) we study policy implications of focal cases of demographers' population projections while they randomly perturb a central growth rate in order to produce a statistical distribution of results; and (iii) a central focus of their paper is quantitatively assessing discrepancies across models while we focus on understanding the *economic role* of assumptions, such as in the effect of population growth on the SWF or the implications of TFP assumptions for future inequality.

are not identical to the UN regions for which the WPP are produced. Therefore, we aggregate country-level WPP population projections into the RICE regions. This method reproduces the global population exactly through 2100, the end of the projection horizon. In the weighted average, growth rates are weighted by the starting population of each country. These growth rates are applied forward to observed 2015 population levels to compute projected future population levels. Despite using this different regional aggregation, we find that our 2100 total population levels produced by this method closely match the 2100 population levels produced by WPP.[12]

Alternative TFP Convergence Assumptions

RICE assumes that TFP converges at a rate of 0.1 per decade, meaning that, as each decade passes, the gap between a developing region's TFP and the asymptotic value of that region's TFP reduces by 10 percent (for details, see supplementary online appendix S2). This assumption may be strong in light of a literature in development economics in which TFP is imperfectly understood and not certainly converging. We consider four TFP convergence rates: 0 (no convergence), 0.05 (half of RICE convergence), 0.1 (RICE), and 0.2 (convergence twice as fast as RICE).[13] We first consider the implications of these assumptions separately at the medium population path and then interact TFP assumptions with alternative population assumptions.

3. Optimal Tax and Population Projections

Result: Population Growth and Time Discounting

Figure 3 presents the main result of this section: optimal carbon taxes are considerably higher when high population growth paths are assumed rather than low population growth paths. As the difference between the RICE-2011 and UN WPP-2015 medium tax trajectories shows, even a relatively modest increase in projected population, of the magnitude that has in fact occurred in recent demographic updates, is sufficient to visibly increase optimal taxes: the optimal 2025 carbon tax is 25 percent greater under the revised population assumption. This update also moves closer in time by several decades the point at which the economy is projected to hit the "backstop" technology: exogenous future technological progress is assumed to make full decarbonization optimal once carbon taxes become large enough, which is visible in the graph as the common downward trend in prices after 2150. For larger differences in population assumptions, the impact on optimal carbon tax is larger still: the 2025 tax is 65 percent greater under the high trajectory, relative to the low, and this ratio rises to a maximum of the high population tax reaching 2.6 times the low population tax in 2085.

Figure 4 quantitatively confirms our theoretical intuition: increasing the projected population growth rate is analogous to reducing the social time discount rate. The bars on the left show that moving from the RICE to the medium population assumptions causes a change in the optimal carbon tax that is comparable to reducing the discount rate by half a percentage point; the bars on the right show that moving from

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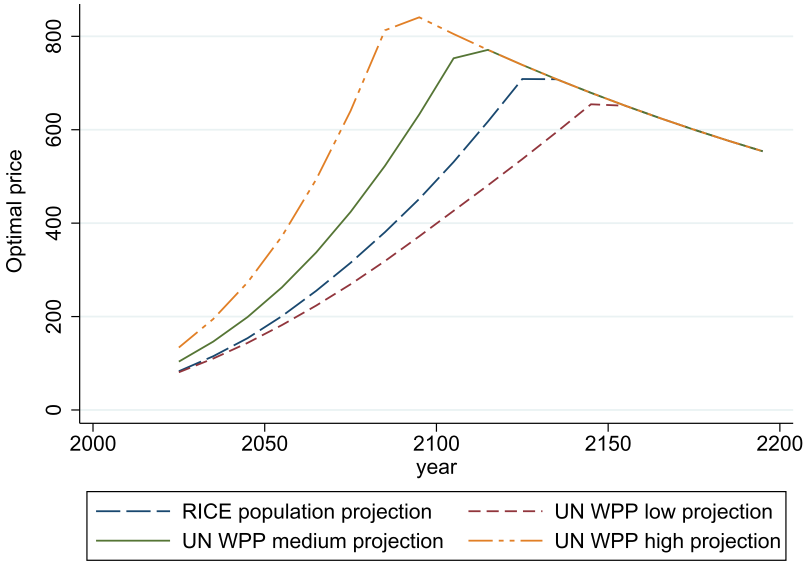
[12] WPP projections end at 2100, but RICE extends to 2300. We project regional growth rates from 2100 to 2200 by mechanically reducing the 2100 growth rate linearly to zero in ten steps, thus the 2110 growth rate is 0.9 times the 2100 growth rate and so on. We assume zero population growth in all WPP cases from 2200 onward. Note that the RICE population path assumes a slight decline in world population from 2100 to 2200 followed by a slight increase from 2200 to 2300. By the end of the period studied, the difference between the RICE and WPP medium population paths becomes large: 8.7 versus 11.4 billion people.

[13] The rate of convergence over time is only one source of heterogeneity across regions in TFP in the RICE model: regions also differ in their starting level of TFP and in their final TFP, specified in the model as a fixed final fraction of US TFP. Modifying these parameters would emphasize even more sources of uncertainty about future economic inequality.

Figure 3. Result: Optimal Carbon Tax Depends on Population Assumption

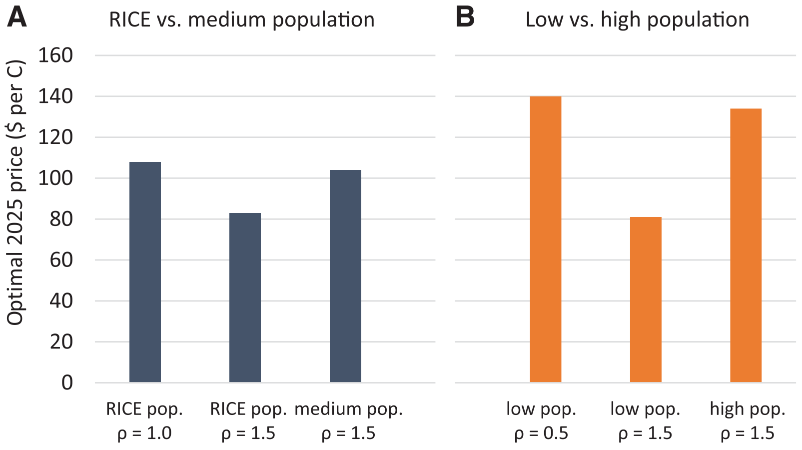


Source: Authors' computations from climate-economy model described in text.

Note: $\rho = 1.5\%$, $\eta = 1.5$. The time path of the optimal carbon tax eventually declines in all cases because the RICE model assumes that future technological progress will, over time, reduce the cost of an alternative "backstop" technology, which will eliminate an economic rationale for further net emissions. Optimal price in units of $ per ton C.

the low to the high population path increases the tax by as much as reducing the discount rate by a full percentage point. Because the full range of discount rates considered by the US government for carbon tax purposes spans only 2.5 percentage points, and because the well-known difference between the pure time preference assumptions of Nordhaus and Stern is 1.5 percentage points, these represent large effects, covering a sizeable portion of the range of climate policy debates.

Figure 4. Result: Changes in Population Assumptions Can Have Effects Similar to Changes in the Discount Rate



Source: Authors' computations from climate-economy model described in text.

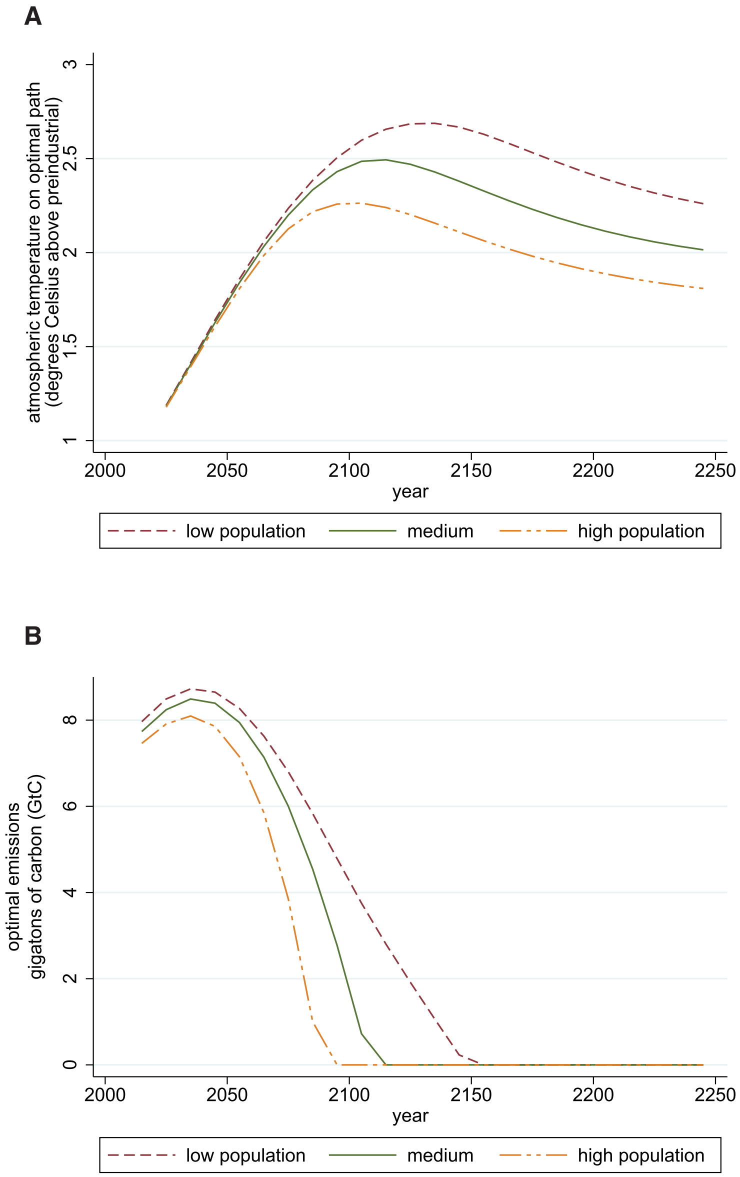
Note: ρ is expressed in terms of percentage points. Optimal price in units of $ per ton C.

Mechanisms: Near-Term Through Social Welfare, Long-Term Through the Economy

Why does a larger future population imply that climate policy should be more aggressive today? There can be at least two possibilities: first, through the social welfare function, a larger future population makes average costs in the future socially more *important*; second, through the economy, a larger future population can be expected to emit more (O'Neill et al. 2012), consuming more of an intertemporal carbon budget and leaving less for today.

Figure 5 offers a way to understand the importance of population in the social welfare function, in the spirit of the envelope theorem or Hotelling's Lemma: it shows how the optimal time path of global

Figure 5. Mechanisms: An Increased Future Population Reduces Optimal Peak Temperature and Emissions



Source: Authors' computations from climate-economy model described in text.

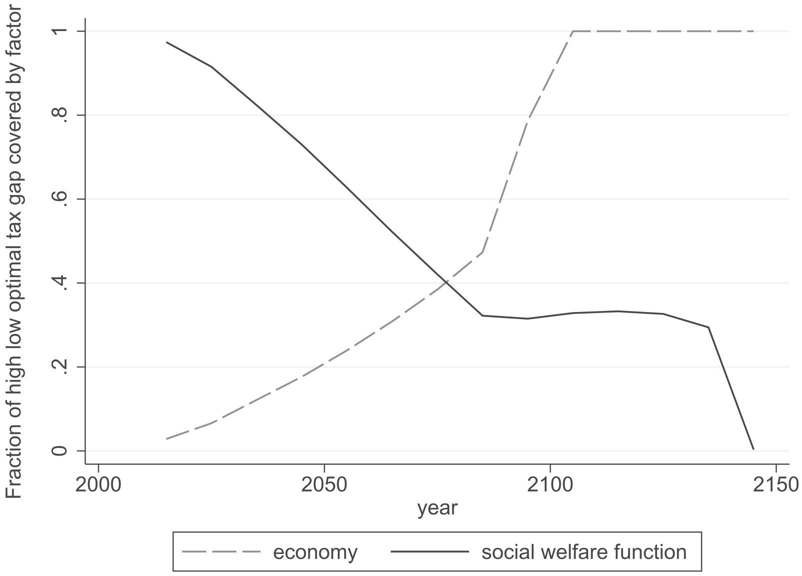
Note: (A) Optimal temperature path depends on exogenous population path. (B) Optimal global emissions depend on exogenous population path. $\rho = 1.5\%$, $\eta = 1.5$.

temperature changes as the assumed exogenous future population growth is increased. The temperature lines for lower population scenarios are above the lines for higher population scenarios.[14] In other words, it is optimal to allow the world to grow hotter and to permit climate change to be more damaging if we assume there will be fewer future people to be hurt by climate damages. Moreover, the effect of this reduced "price" of climate change is so large as to outweigh the mechanically increased carbon "budget" of a smaller population.

Thus, we have seen that the discounting-like role of population growth in the social welfare function is one important mechanism; it is further the case that the relative importance of population in the social welfare function to population in the economy changes over time. Figure 6 presents two ways of visualizing this change over time. The top panel (a) concentrates on our baseline case of ethical parameters, where $\eta = 1.5$ and $\rho = 1.5\%$. To produce this figure, two further optimizations of the carbon tax were computed, each with a different mixed combination of population path assumptions:

- SWF: Assuming population will follow the WPP high path in the social welfare function, but the low path in the economy.
- Economy: Assuming population will follow the WPP high path in the economy, but the low path in the SWF.

Figure 6. Mechanisms: Fraction of Difference in Optimal Tax Between High and Low Population Cases Accounted for by Separating the Roles of Population in the Economy and in the Social Welfare Function



Source: Authors' computations from climate-economy model described in text.
Note: Computed according to equation (III.1).

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[14] Note that *none* of these scenarios keep the temperature change under the two-degree or 1.5-degree targets highlighted by some international policymakers, as these would require very rapid mitigation regardless of population or TFP convergence.

Both paths are named here after the portion of the model in which population is assumed to be high. Each mixed combination produces a fraction for each year:

$$fraction_t^{mix} = \frac{tax_t^{mix} - tax_t^{low}}{tax_t^{high} - tax_t^{low}}, \tag{III.1}$$

where mix is either SWF or $Economy$, as above, and tax_t is the optimal carbon tax in year t. Thus, this fraction reports the fraction of the difference in the optimal carbon tax between the high and low population paths that is covered by only changing to the high population in either the economy or the SWF.

Figure 6 plots the results. In the short run, the role of future population growth in the social welfare function is very important; future population growth does not yet matter in the economy because it has not yet been realized.[15] This impact reflects the social welfare function judging the future to be more important and therefore more demanding of our emission reductions today.

Mechanisms: Allocation of the World Population into Regions

The RICE model upon which our results are ultimately built splits the world into 12 regions; some other IAMs consider the world as a single representative economy. Representing climate economics as a single economy could either overstate or understate the effects of population growth, depending on the convexity or concavity of the damages, and on how climate damages are distributed throughout the world. If, for any global average of damages and population growth, damages are relatively large in the places where population growth is relatively high, then non-linear models such as ours would appropriately find a larger social cost of carbon if regionally disaggregated than if globally aggregated. This is especially important if we are interested in the future of developing countries: population growth is projected to be high throughout the 21st century in sub-Saharan Africa, where climate change is expected to be costly and where poor people are vulnerable. Similarly, large and growing populations are exposed to climate damages in developing countries in Asia. Population growth is low in the northern areas of Europe and North America where climate change may be less harmful.

Figure 7 compares the optimal carbon taxes resulting from our population projections with optimal carbon taxes from alternative projections in which the world total population is the same as in the projections, but each region's population is, by hypothesis, set to grow at the same global rate. Thus, for each of the WPP projections (low, medium, high), an equal growth projection (low^e, medium^e, high^e) is created in which population growth within time periods is equal across regions. Therefore, substituting these equal growth projections for the original WPP projections preserves any consequences of the total future world population, while eliminating any consequences of unequal future population growth rates across regions. In particular, fig. 7 plots the ratio in each year of the optimal tax with the WPP projections to the optimal tax with the equal growth projections. The fact that these ratios are greater than one indicates that the distribution of population growth across regions raises the near-term social cost of carbon, relative to a world in which it were not the case that population growth would be particularly concentrated in developing countries. The ratios fall toward one (and sometimes briefly slightly below it as the backstop is hit) as time passes, and it becomes more relevant that the world population is poorer, just as in fig. 6 the social welfare weighting becomes relatively less important over time.

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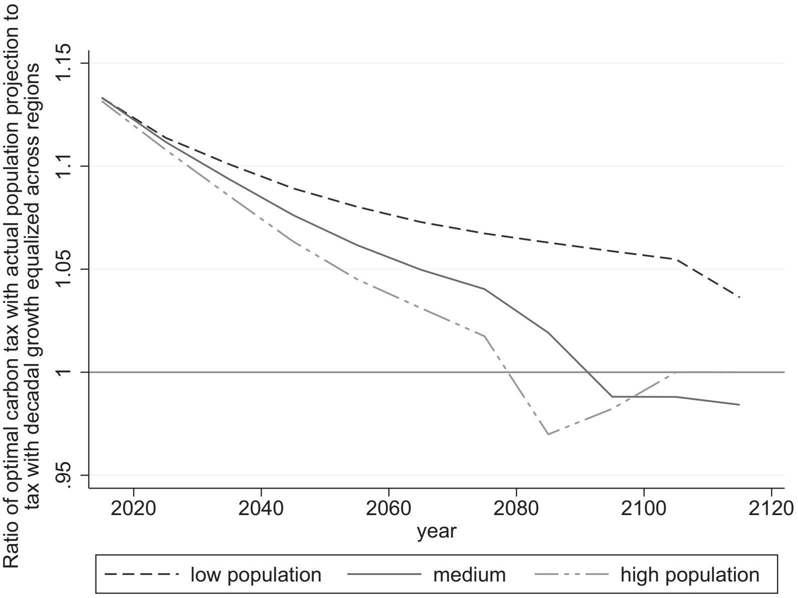
[15] Note that, because the IAM is highly nonlinear, there is no reason to expect these fractions to add up to one in any particular year.

Figure 7. Mechanisms: Optimal Carbon Taxes Are Higher Than They Would Be in a Hypothetical World in Which Population Growth Were Evenly Distributed Across the World's Regions



Source: Authors' computations from climate-economy model described in text.
Note: Computed according to equation (III.1).

4. Optimal Tax and TFP Convergence

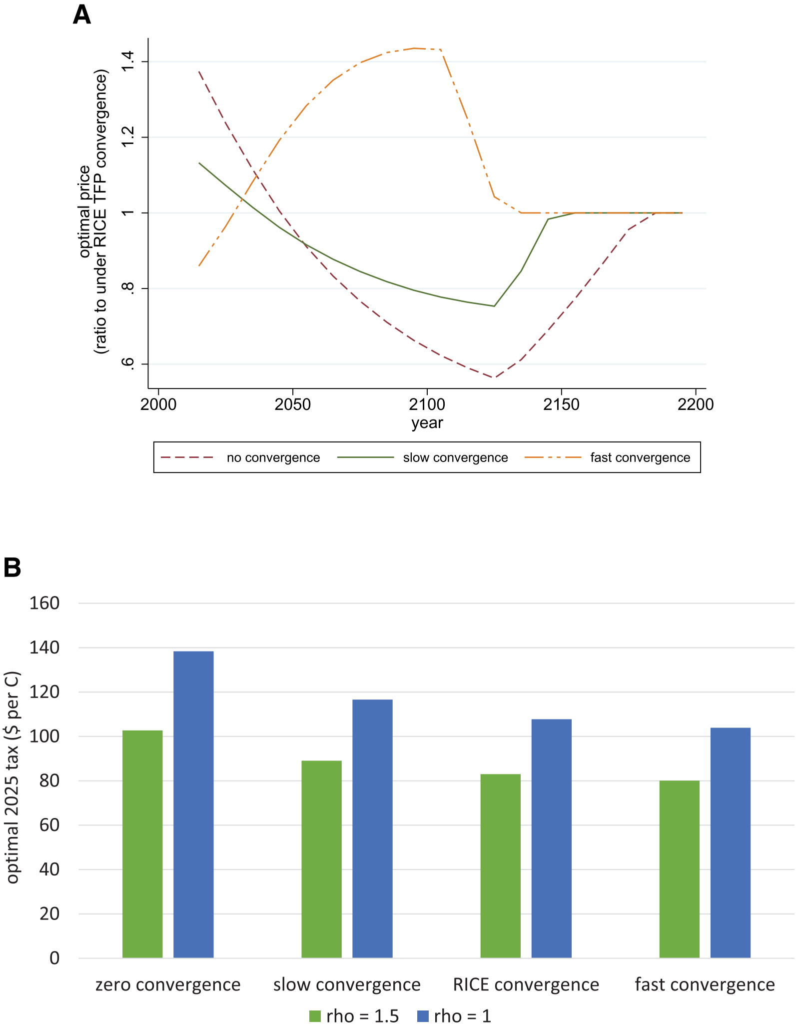
Widely used computations of an optimal carbon tax assume a large decrease in future country-level global inequality, driven by rapid global convergence in Total Factor Productivity. Such convergence may not occur, especially in TFP. This section considers optimal carbon taxes under the assumption that future TFP convergence is slow. One argument against substantial spending to avoid climate change is that its future victims will be much richer than today's world population; if future TFP convergence is much slower, this may not be true.

Result: Slower Convergence Increases Near-Term Taxes, Decreases Long-Term Taxes

Figure 8 presents the results of alternative assumptions for TFP convergence, which has different implications over the course of the 21st century. In the near term, as panel (a) shows by comparing the ratio of the social cost of carbon under alternative TFP assumptions to the results under the standard RICE convergence rate, *slower* assumed TFP convergence translates into *higher* optimal carbon taxes. This is because the future people in developing countries who will be harmed by climate change will be poorer than otherwise if TFP convergence is slower, so their losses are more socially costly. As the 21st century progresses, this pattern reverses, and each path crosses one: higher TFP convergence comes to emphasize higher optimal carbon tax, because a richer world is able to afford more climate mitigation.

Panel (B) compares the magnitude of the consequences for the optimal 2015 carbon tax of changing TFP convergence assumptions with the consequence of reducing the rate of pure time discounting. Each of our four TFP assumptions is computed with a lower and higher discount rate. Comparing the optimal tax with zero convergence with the optimal tax under the original RICE convergence speed, we find that eliminating TFP convergence increases the optimal tax by a magnitude about as large as decreasing the rate of pure time discounting by 0.5. This computational result is consistent with Gollier's (2015)

Figure 8. Result: Optimal Carbon Tax Depends on Assumption About Future Developing World TFP



Source: Authors' computations from climate-economy model described in text.

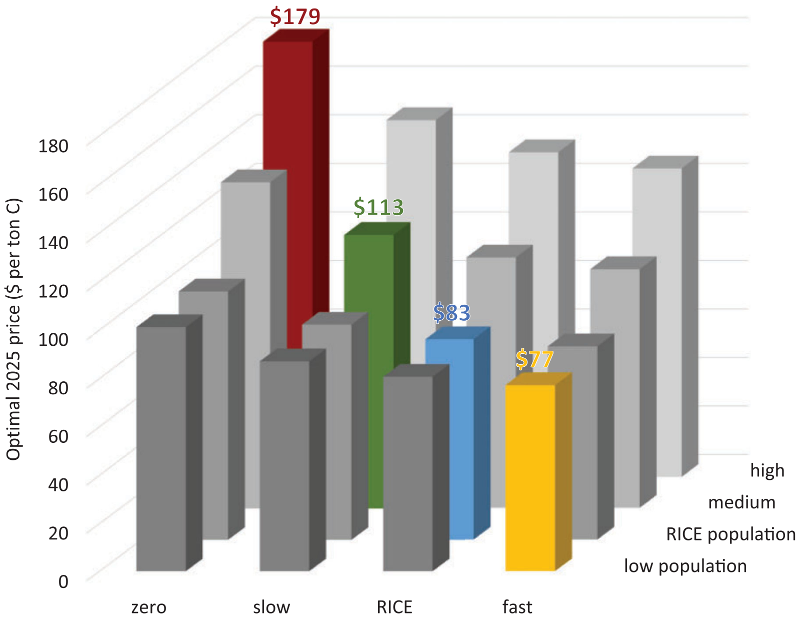
Note: (A) Effects of TFP convergence are reversed as future growth and climate damages are realized ($\eta = 1.5$, $\rho = 1.5\%$). Panel (A) is computed using the original RICE population assumptions. In panel (A), TFP assumptions eventually cease to matter (all lines go to 1) as all regions hit the backstop and fully decarbonize. Optimal price in units of $ per ton C (B) Reducing convergence from RICE's assumption to zero has an effect on the optimal present-day tax comparable to reducing ρ by 0.5. Panel (B) is computed using the RICE population assumptions and $\eta = 1.5$.

theoretical observation that economic convergence has consequences for the valuation of future losses that are similar to increasing the rate of pure time preference.

Interaction: TFP Convergence and Population Growth

We have seen that faster future population growth, especially as it is expected to be concentrated in the developing world, and slower future TFP convergence both would raise today's optimal carbon taxes. This section asks how these predictions about the future of the developing world interact—by which we mean, does the effect of changing population growth or TFP assumptions depend upon the level of the other input? This would be an especially important question to ask if economic growth and fertility

Figure 9. Interaction: Assumptions About Future Population Growth and TFP Convergence Interact



Source: Authors' computations from climate-economy model described in text.
Note: $\rho = 1.5\%$, $\eta = 1.5$. Optimal price in units of $ per ton C.

reduction were not independent but instead were causally linked to one another, as many demographers and economists have suggested (Foster and Rosenzweig 2006; Vogl 2015).

Figure 9 presents 16 combinations of the assumptions that we have considered: population growth that is high, medium, low, or on the RICE path, crossed with TFP convergence that is fast, slow, zero, or at the original RICE speed. The figure shows that these assumptions are not merely linearly additive but, in fact, interact: the effect of reducing TFP convergence is greater when future population growth is projected to be faster and vice versa. Moving from the baseline RICE assumptions to the case where the optimal carbon tax is greatest (no TFP convergence, high population growth) increases the optimal 2015 tax from $90 to $200. Starting from the RICE assumptions and our baseline ethical parameters of $\eta = 1.5$ and $\rho = 1.5\%$, this is equivalent to reducing the rate of pure time preference, ρ, to something below 0.5 percent. This is close to some of the lowest discount rates in the climate economics literature.

The highlighted diagonal row emphasizes the steep consequences for climate mitigation policy if population growth and TFP convergence are correlated across world economic development scenarios. Moving from the baseline assumptions in the 2011 version of RICE to the medium population projection update and a modestly pessimistic TFP convergence rate increases the near-term social cost of carbon by 36 percent. The social cost of carbon is more than doubled under the combination of high population growth and no TFP convergence.

5. Robustness

Supplementary online appendix S2 demonstrates that our result is qualitatively robust to two changes to the model: allowing each world region to have its own, separate optimal tax instead of a single global price, as RICE assumes (Anthoff 2009; Budolfson and Dennig forthcoming), and modeling intraregion economic inequality, such that climate damages could be disproportionately harmful to the regional poor or rich (Dennig et al. 2015).

6. Conclusion: Optimal Climate Policy Depends on the Future of Developing Countries

There is broad consensus that climate change will be costly to future generations and that today's generation should make economic sacrifices to reduce carbon emissions. But how much should be sacrificed? How bad should we value future climate damages to be, relative to today's economic output? Answering these questions requires assumptions about the future of the developing world. Our paper is not intended to settle the matter of the social cost of carbon. To the contrary, we demonstrate quantitatively that choosing the best climate policy depends critically on the answers to open questions in development economics.

If today's poor economies will grow into richer countries with relatively small future populations, then fewer future people will be hurt by climate change, and they will be better able to financially sustain the damages. However, if today's poor economies remain poor, and if population growth is high in poor populations, then potentially very many future people will be exposed to climate damage, which will be deeply costly on top of their poverty. This conclusion resonates with Hallegatte et al.'s (2015) argument that the costliness of climate change for well-being will depend critically on what is achieved for economic and human development in the coming few decades.

This paper has identified a potentially important reason for more aggressive emission reduction policy, even using moderately large social discount rates. If policymakers have good reason to believe that future population growth might be high or concentrated in poor regions, that TFP convergence will be slow or zero, or that both of these might happen, then today's emission reductions should be greater. We use the methods of traditional optimizing IAMs, which ignore poverty and inequality within world regions (Dennig et al. 2015), and which focus only on expected outcomes, and not on the risk of extreme disasters (Wagner and Weitzman 2015); making either of these modeling changes could recommend even more mitigation.

Unlike the ethical parameters upon which debates about climate economics have substantially focused, assumptions about TFP convergence and population projections are in principle amenable to improved economic and demographic theory and forecasting. This means that our results are a reason to invest in better understanding the future of the developing world. Finally, as a policy implication, our results imply that near-term investments in accelerating human and economic development, including accelerating the demographic transition, could pay dividends in reduced necessary spending on optimal climate mitigation.

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Optimal climate policy and the future of world economic development

Supplementary Online Appendix S1: Model Details

The model used in this paper is a Matlab implementation of the RICE2010 spreadsheet model developed by William Nordhaus. A complete description of the original model can be found in Nordhaus and Boyer (2000), and more recently in the Supporting Information to Nordhaus (2010). Those publications, and particularly Nordhaus and Boyer (2000), not only describe all equations, but also explain the calibration of the major sectors. Below we describe the essential features of the original model, along with the modifications implemented in our Matlab version.

The Original RICE2010 Model

The RICE model is made up of twelve macro-region economies (some of which are in fact countries, like China, India, the United States, Russia, and Japan). In the RICE model (as in the DICE model it is based on), the basic policy trade-off is between output today—through greater or smaller mitigation cost—and output tomorrow—through greater or lower climate damages. The *net* output function, in region *i* and period *t,* is given by

$$Y_{it} = \left(\frac{1-\Lambda_{it}(\mu_{it})}{1+D_i(T_t)}\right) A_{it}K^{\alpha}L^{1-\alpha} \tag{1}$$

where A_{it} is (gross) total factor productivity (TFP), K_{it} is capital, and L_{it} is labor. Labor is equal to the region's population size and is an exogenous variable. The mitigation rates $\mu_{it} \in [0,1]$ result in a region- and time-specific mitigation cost:

$$\Lambda_{it}(\mu_{it}) = \theta_{it}\mu_{it}^{2.8} \tag{2}$$

The parameters θ_{it} are exogenous, region specific, and declining over time. They are calibrated so that the marginal cost of abatement of the first ton of CO_2 is zero and the marginal cost of the last ton of abatement is a backstop price, which is the price at which non-fossil sources of energy are competitive with fossil fuels (see **Backstop prices** below).

One minus μ_{it} is the proportion of baseline (business-as-usual) industrial CO_2 emissions in that period and region that make it into the atmosphere. The emissions of all regions add to the atmospheric stock of CO_2 which, via the greenhouse gas effect, increases the radiative forcing of the atmosphere and increases the global average temperature.

The damage functions $D_i(T_t)$ are (quadratic) functions with temperature that quantify the economic damage of climate change. These are described in more detail in the section *Sea-Level Rise and Climate Damages* below.

The model is constrained to have a globally uniform carbon price. The price is globally uniform so that there is no implicit redistribution across regions via different abatement efforts.[1] In each period, this price fixes the distribution of abatement effort across regions as follows. Given the price, each region mitigates the amount at which the regional marginal cost of mitigation is equal to the global price. The relationship depends on exogenous parameters that vary by region and period. We refer to this as the carbon tax, because at a country by country level it could be achieved by a carbon tax, but we do not explicitly compute any actual carbon tax revenue, only the implied (reduced form) regional reduction in GDP resulting from the global carbon price. Moreover, within regions there is only a representative agent. As a result, there is no revenue redistribution from any carbon tax, within or across regions.

Output in different periods of time are linked by a capital accumulation process and the greenhouse gas effect whereby the accumulation of past emissions (affected by past mitigation rates) in the atmosphere leads to increased radiative forcing and greater global mean temperatures. Capital accumulation in one region only affects future output in that same region, while emissions in one region affect future output in all regions through climate damages.[2] The model is optimized in order to choose the carbon price path that maximizes an intertemporal welfare function of the consumptions in each region and time period.

The objective function (see next section) is concave in consumption, thus weighing costs and benefits more heavily if they are incurred in regions and periods with less consumption. The most important (exogenous) determinant of consumption in the model is gross Total Factor Productivity (TFP), A_{it}. TFP values are calibrated in 2005 as the residuals of a Cobb-Douglass production function with capital share $\alpha = 0.3$. For all other periods, TFP growth rates are computed as follows. For Region 1 (the United States), a long-run growth rate $g_l = 0.33\%$ per annum is assumed to which the current growth rate declines at a rate of $\Delta = 10\%$ per decade. As a result, the annual growth rate in Region 1 during the decade beginning in 1995+10t is given by

$$g_{1t} = (1-\alpha)[g_l + \exp(-\Delta)^{t-1}(g_{11} - g_l)] \tag{3}$$

In regions other than the United States, the TFP growth rate is determined by a process of convergence from the regional growth rate in 2005 to a fraction κ_i of US growth rate:

$$g_{it} = g_{1t} + (1-\gamma)^{t-2}\gamma[\log(y_{11}/y_{i1}) + \log\kappa_i + 10(g_{11} - g_{i1})] \tag{4}$$

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[1] In the Robustness Checks Appendix we consider a relaxation of this constraint. For more details about the implications of this, see Dennig and Emmerling (2017).

[2] There is, in fact, a second-order effect of capital accumulation in one region affecting future output in other regions. Greater capital accumulation in region *i* and period *t* leads to greater output in region *i* and period *t+1.* All else being equal, this leads to greater emissions in region *i* and period *t+1* and thus to greater damage to all other regions from period *t+1* onward. But this is a second-order effect, and has almost no impact on optimal carbon taxes.

where y_{it} is the per-capita GDP in region *i* and period *t,* and γ is the rate of convergence to the United States (per decade).[3] By default, the RICE model sets $\gamma = 0.1$. In section IV of the main paper, we consider different values.

The Social Welfare Function

A discounted utilitarian social welfare function is the standard social objective used by all three leading IAMs for the social cost of carbon—RICE/DICE, FUND, and PAGE—as well as many other studies of climate policy. We preserve that same social objective in our study.

Regional output is split between savings that are invested into the future capital stock, and consumption, which is assumed to be distributed equally as per capita consumption amongst the individuals of the region. The RICE objective is the maximization of the following social welfare function:

$$W(c_{it}) = \sum_{it} \frac{L_{it}}{(1+\rho)^t} \frac{c_{it}^{1-\eta}}{1-\eta} \tag{5}$$

where L denotes population, c per capita consumption, ρ the rate of pure time preference, and η inequality aversion. This discounted, population-weighted (total) utilitarian objective is the standard objection function in all leading cost-benefit climate-economy IAMs. There is a significant debate on the values of the parameters ρ and η, but very little disagreement about the functional form. The function we use differs slightly from the original RICE spreadsheet model, as the original uses the same function but with regional and time dependent Negishi weights, which have the effect of, in every period, equalizing the marginal per capita contribution to welfare from consumption across regions. The inclusion of these weights is often justified as necessary to avoid the model yielding optima with large explicit (via interregional money transfers) or implicit (via a differentiation of regional carbon prices) regional transfers. We exclude these weights because in a model with explicit constraints against international transfers and against differential carbon prices across regions, these weights are not necessary (Dennig et al. 2015). Furthermore, such weights distort the optimum in ways that seem hard to justify morally (see Dennig and Emmerling 2017).

Capital Accumulation and the Savings Rate

The calibration for the RICE model yields annual rates for several variables, which are then cumulated to the decadal time step of the model. In particular, in the RICE2010 spreadsheet the assumed capital depreciation rate of 10% per annum is cumulated geometrically to the 10-year time step, while savings are accumulated arithmetically. Specifically, capital is accumulated over the 10-year time step as:

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[3] The equation for the TFP growth rate of regions other than the United States is only valid for t>1. At t=1 (2005), the historic GDP growth rate times the labor share is used.

$$K_{t+10} = K_t * (1-\delta)^{10} + 10 * I_t \tag{6}$$

where I_t is annual investment. If one puts faith in the calibration of annual rates, this combination of geometric depreciation and arithmetic accumulation quite significantly overstates capital accumulation at the ten-year step, while combining geometric accumulation and depreciation or arithmetic accumulation and depreciation is more accurate.[4] In our version of the model, we have made both accumulation as well as depreciation arithmetic, yielding

$$K_{t+10} = K_t * (1-10\delta) + 10 * I_t \tag{7}$$

which is closer to the correct accumulation over the 10-year time step.

We also modify the savings rates. In RICE2010 the regional savings rates are chosen to maximize the Negishi weighted global welfare function, taking optimal carbon taxes as given. This is computationally cumbersome, and unlikely to be a reasonable description of savings rates, as it overstates the savings rates of regions with high growth rates and understates savings rates of regions with low growth rates relative to what representative agents in such regions would choose.[5] Instead, we apply a fixed Solow savings rate of 25.8% in every time period and every region. This vastly simplifies the modeling, and could even be considered an improvement over the savings rates in the original model, since it can be rationalized as the optimal savings rate as determined by an infinitely lived agent with logarithmic utility and a utility discount rate of 1.5% per annum.[6]

The net effect of the two changes to savings and capital accumulation is that there is slightly less capital accumulation in our version than in RICE2010. In fact, if our model had a fixed rate of 30%, the capital accumulation in our version would be approximately equal to that in RICE2010 for most of the model horizon. Having the lower savings rate of 25.8% affects the values of aggregate variables such as GDP and emissions at the optimum, but it barely changes the value of the optimal carbon tax, as you can see in fig. S1.1 below.

Sea-Level Rise and Climate Damages

RICE2010 implements sea-level rise (SLR)-related damages in addition to the regular damages to GDP. For simplicity, our Matlab version does not implement this exact damage specification. Instead, we estimate new coefficients for a quadratic function of temperature to get similar quantitative effects (Dennig et al. 2015).

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[4] To see this, notice that the correct first-order approximation is

$$K_{t+10} = K_t(1-\delta)^{10} + I_t \sum_{j=0\ to\ 9} (1-\delta)^j$$

When $\delta = 0$ all three variants yield the same capital stock ten periods later. But if δ becomes large enough for the linear approximation of the logarithm to become inaccurate, then the version used in RICE2010 diverges significantly from the correct accumulation.

[5] See Dennig and Emmerling (2017) for this result.

[6] See Golosov et al. (2014) for this result.

Denoting by D^{nonS} the non-SLR component and by D^{S} the SLR component, the original specification consists of a damage function D such that

$$D_{it} = D_{it}^{nonS} + D_{it}^{S} \tag{8}$$

with

$$D_{it}^{nonS} = \beta_{1i} T_t + \beta_{2i} T_t^2 \tag{9}$$

$$D_{it}^{S} = (b_{1i} S(T_t) + b_{2i} S(T_t)^2)\left(G_{i,0,t-1}\right)^{\frac{1}{4}}. \tag{10}$$

Here T_t is the temperature increase above preindustrial levels, $S(T_t)$ is the amount of SLR as a function of temperature increase, and $G_{i,0,t-1}$ is the economic growth factor (one plus cumulative growth rate) of region *i* between period 0 (2005) and period *t-1* (2005+10(t-1)).

From this specification, we estimate a new specification

$$\widetilde{D}_{it} = \lambda_{1i} T_t = \lambda_{2i} T_t^2 \tag{11}$$

by computing the damage from the spreadsheet model for a couple of runs (BAU and optimum). Then, for every region, these terms are regressed by ordinary least squares against temperature by the specification (11). The result is an estimate of the total damage term that only depends on temperature.

The estimates of the non-SLR economic damages come from Nordhaus and Boyer (2000). The study estimated, for different regions, the impacts of rising temperatures on several economic sectors ranging from agriculture and health to nonmarket amenities; migration effects are not included since population is exogenous. Figure S1.2 displays climate damages as a fraction of output for each RICE region with and without sea-level rise.

Backstop Prices

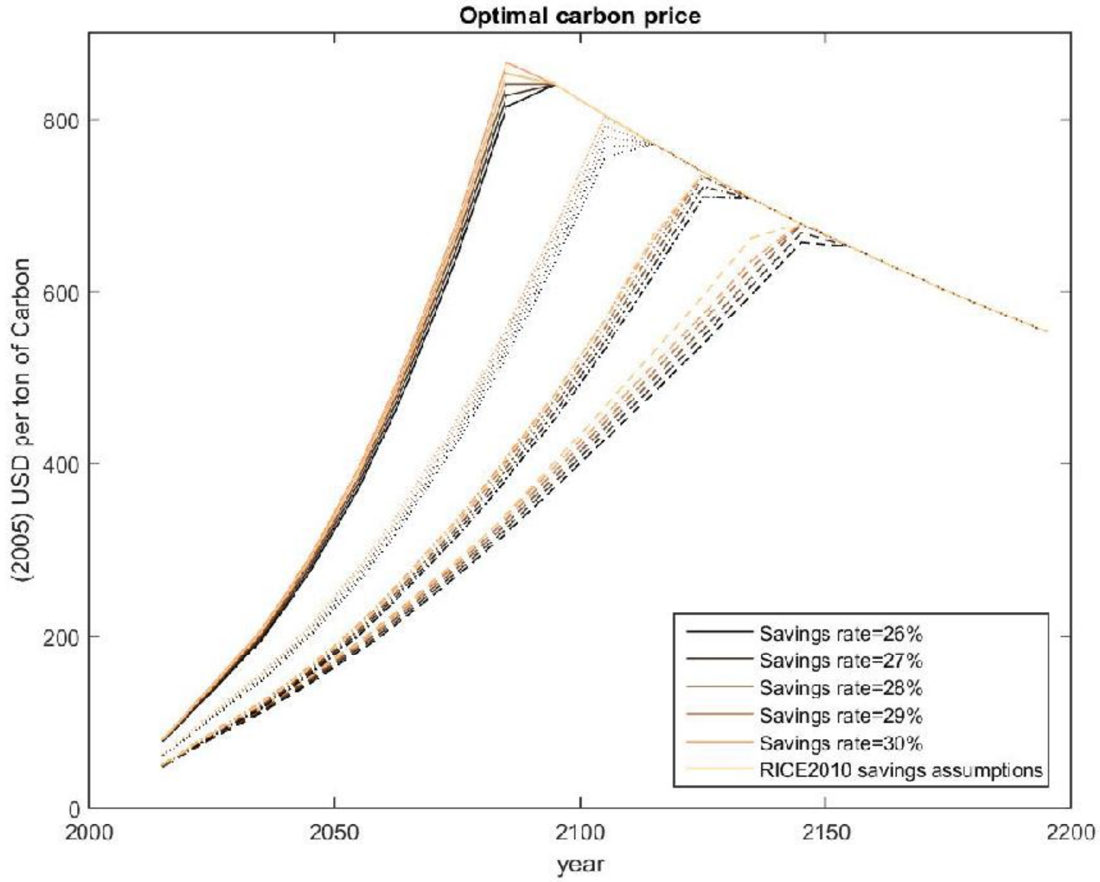
The backstop price is the carbon price at which full abatement takes place. The idea is that at such a high penalty for emissions, non-fossil sources of energy become competitive. This is a standard concept in the theory of exhaustible resources (Dasgupta and Heal 1979). The RICE model posits a global backstop price that declines over time, and attributes to each region a fraction (or multiple) of that price. The United States, for instance, has a backstop of 0.9 times the world backstop, and India has a backstop of 1.1 times the world backstop. For the runs in this paper, we have set the backstop prices of all regions to equal the world backstop price. This is done because having different backstops leads to non-differentiabilities in the objective as the carbon price passes from below the backstop of a region to above the backstop.

As shown in fig. S1.3, the optimal prices for the model with different backstops are almost identical to the optimal prices that we report in fig. 4 in the main paper up to the point where they hit the backstop.

Sub-Regional Inequality: The NICE Model

The RICE model assumes that there is no inequality within regions, but as a robustness check (Robustness Checks Appendix of the main article) we wanted to ensure that the main results of our paper are not sensitive to a more detailed description of sub-regional distribution of income. In order to investigate this issue, we used the “NICE” model, described in detail in Dennig et al. (2015). NICE is essentially the version of the RICE model described above, except that in each region we assign five income groups, or quintiles, of equal population. Using World Bank income distribution data, we establish the income distributions of the 12 regions of the RICE model, to establish the quintile shares of consumption for each region. In Dennig et al. (2015), this is used to highlight the importance of the distribution of damages across sub-regional income groups for the optimal carbon price.

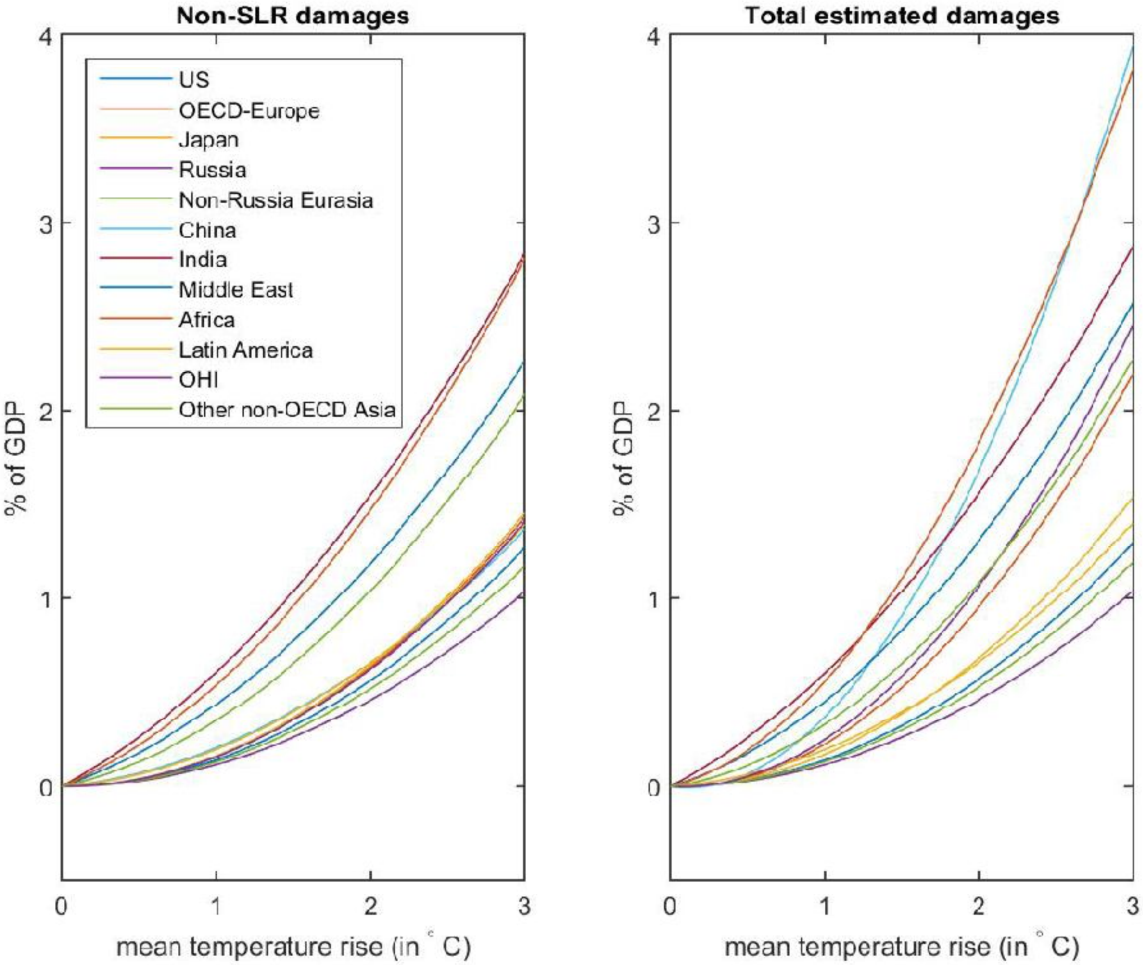
Figure S1.1. Optimal Carbon Taxes from fig. 3 of the Main Article, for Different Assumptions on Capital Accumulation



Source: Author model runs

Note: Four groups of carbon tax paths for six different assumptions on capital accumulation are displayed. Five assumptions correspond to fixed savings rates (of different magnitudes) along with full capital depreciation over a decade. The sixth corresponds to the exact savings rates and capital depreciation assumptions of the original RICE2010 spreadsheet. The four groups correspond to the different population projections in descending order: UN WPP High, UN WPP Medium, RICE population, and UN WPP Low.

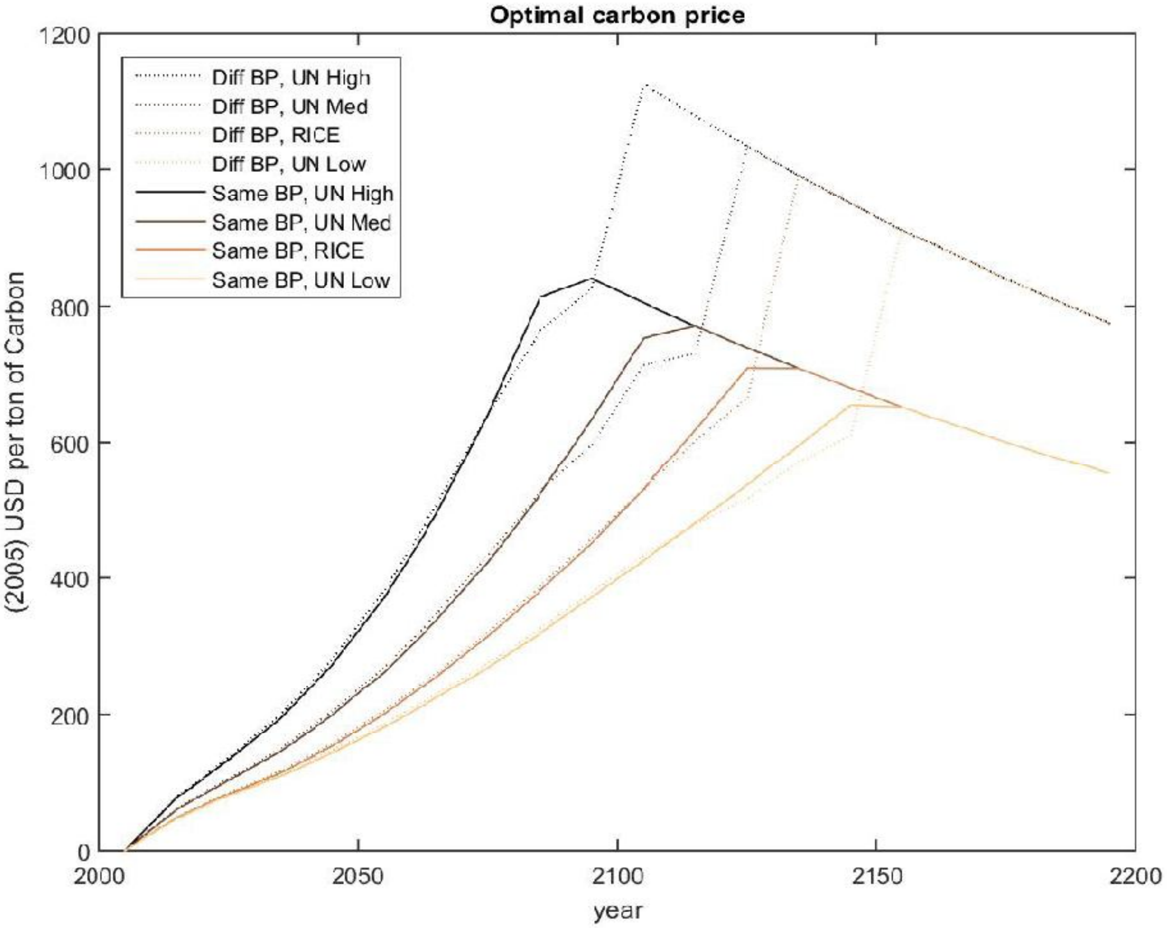
Figure S1.2. Climate Damage Functions with (right panel) and without (left panel) Sea-Level Rise Damages



Source: Author calculations

Note: Economic damages from global mean temperature increases, by region, as a proportion of GDP. The left panel displays the damages from the original RICE2010 model *excluding* damages from Sea-Level-Rise, while the right panel displays the damage function computed by the authors which include Sea-Level-Rise.

Figure S1.3. Optimal Carbon Taxes from fig. 3 of the Main Article, the Original (different by region) Backstop Prices of the RICE Model, and the Equal Backstop Price Assumption Used in the Main Paper



Source: Author model runs

Note: Optimal carbon taxes from Fig. 3 of the main article. The solid lines reproduce the paths from Fig. 3 and are computed under the assumption that all regions in the world have the same backstop price, while the dashed lines are computed using the assumption from the original RICE2010 model that regions have varying backstop prices. It is clear that before hitting the backstop, the two assumptions yield very similar results.

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Supplementary Online Appendix S2: Robustness Checks

Convergence of TFP across Regions Assumed by RICE

The RICE model upon which our investigations are based assumes convergence across regions in Total Factor Productivity, which is an important determinant of convergence across regions in economic outcomes. The table below presents, for each region, the ratio of that region's TFP to TFP in the United States; this is done for 2015 and for the asymptotic position toward which they converge over time. The analysis in the paper varies the rate at which regions' TFP converge to their asymptotic level. Note that, for each non-US region, the ratio increases from 2015 to the asymptotic value and the standard deviation across regions decreases over time.

Robustness

Separate Prices by Region

The RICE (Nordhaus and Boyer 2000) IAM, like the FUND (Anthoff and Tol 2010) and PAGE models, computes a single, global social cost of carbon. However, Chichilnisky and Heal (1994) show that a single global price is only optimal, under a social welfare function that attends to inequality across regions, if there are lump-sum transfers across regions. This is because the rich and poor regions of the world differ considerably in their ability to pay for climate mitigation, as reflected in their marginal utility of consumption. Because the cross-region economic transfers in the actual world may be below the optimal size, this section verifies that our results are qualitatively robust to allowing the social planner to choose a time path of optimal taxes for each region of the world, rather than a single global tax. Prior papers have used FUND (Anthoff 2009) and a variant of RICE (Budolfson and Dennig forthcoming) to investigate the consequences for optimal prices and climate outcomes of allowing different prices by region, rather than imposing a uniform global price.

Figure S2.1 presents the results for India and Africa, two large regions representative of the developing world.[1] Unsurprisingly, the optimal tax is greater in India, which is richer, than in Africa, which is poorer. But in both cases, our two main results are qualitatively preserved. First, optimal mitigation is greater when future population growth is projected to be greater. Second, the impact of TFP convergence changes over time: slower convergence, in which developing countries will therefore be poorer in the future, translates into higher mitigation in the near term and lower mitigation in the long term.

Intra-Region Economic Inequality

In the RICE, FUND, and PAGE regionally disaggregated IAMs, each region of the world is modeled as a single representative agent; DICE (Nordhaus 2017) is a global integrated assessment model in which the entire world's consumption is a representative agent. Therefore, none of these models consider economic inequality within world regions. However, NICE, a recent modification of RICE by Dennig et al. (2015), divides the twelve RICE regions into their economic quintiles. Using NICE, optimal mitigation

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[1] Richer regions such as the United States or Europe would not be informative to depict because, in the utilitarian optimum represented by our social welfare function, the model recommends that they fully decarbonize quickly, as the marginal cost (to that region) of climate mitigation is greater in the developing world.

policy can be computed under the assumption that future climate damages are independent of income across quintiles in a region (an assumption roughly comparable to the representative agent approach), that damages are increasingly proportional to income (hurting the rich within a region most), or that damages are inversely proportional to income (harming the poor within a region most). As Dennig et al. show, the social cost of carbon is highly sensitive to the future within-region economic incidence of climate damages. In fig. S2.2, we use NICE instead of RICE, in order to verify that our results are qualitatively robust to these possible assumptions about future within-region inequality. For all three assumptions about the incidence of damages, the social cost of carbon is greater for a larger future population path, by an amount that is increasing over the near future.

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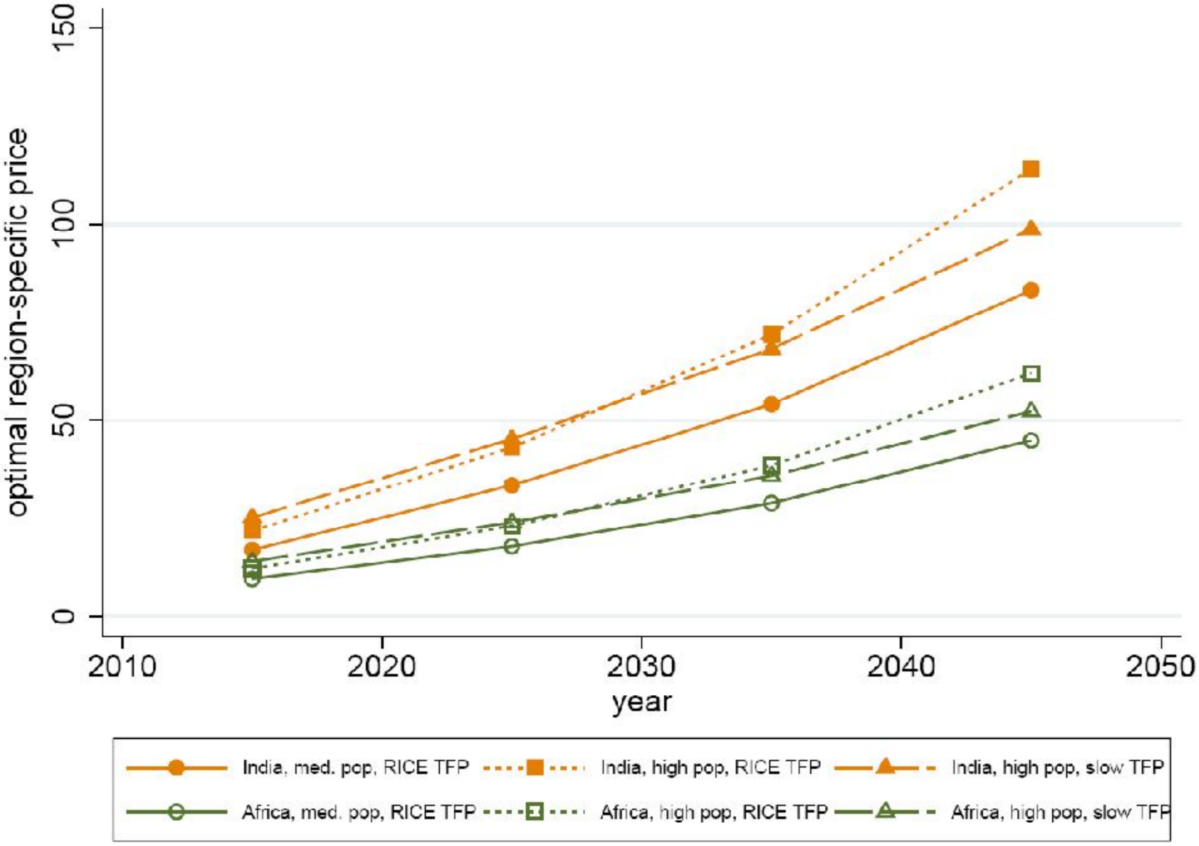
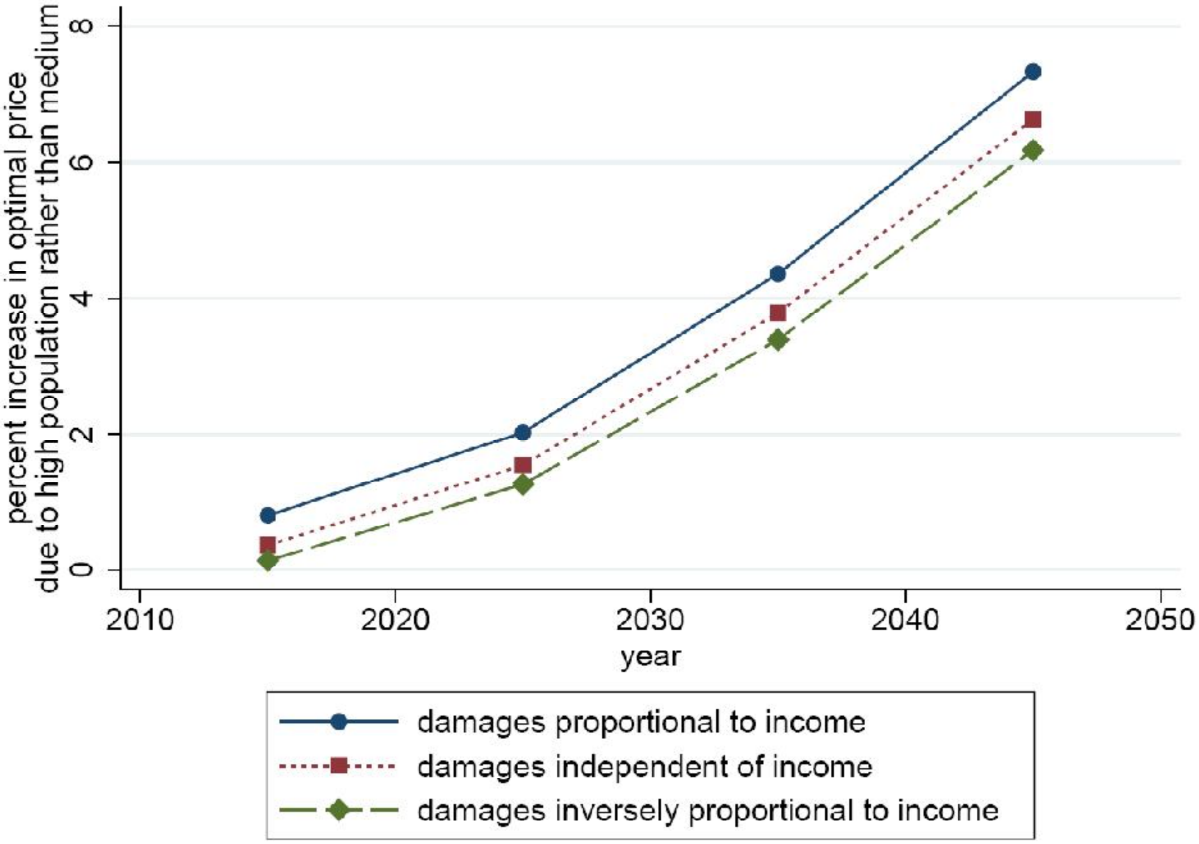
Figure S2.1. Robustness: Effects of Population and TFP Are Qualitatively Similar if Each Region Is Assigned a Separate Optimal Price



Note: $\rho = 1{:}5\%$; $\eta = 1{:}5$. Optimal price in units of $ per ton C.

Source: Authors’ computations from climate-economy model described in text.

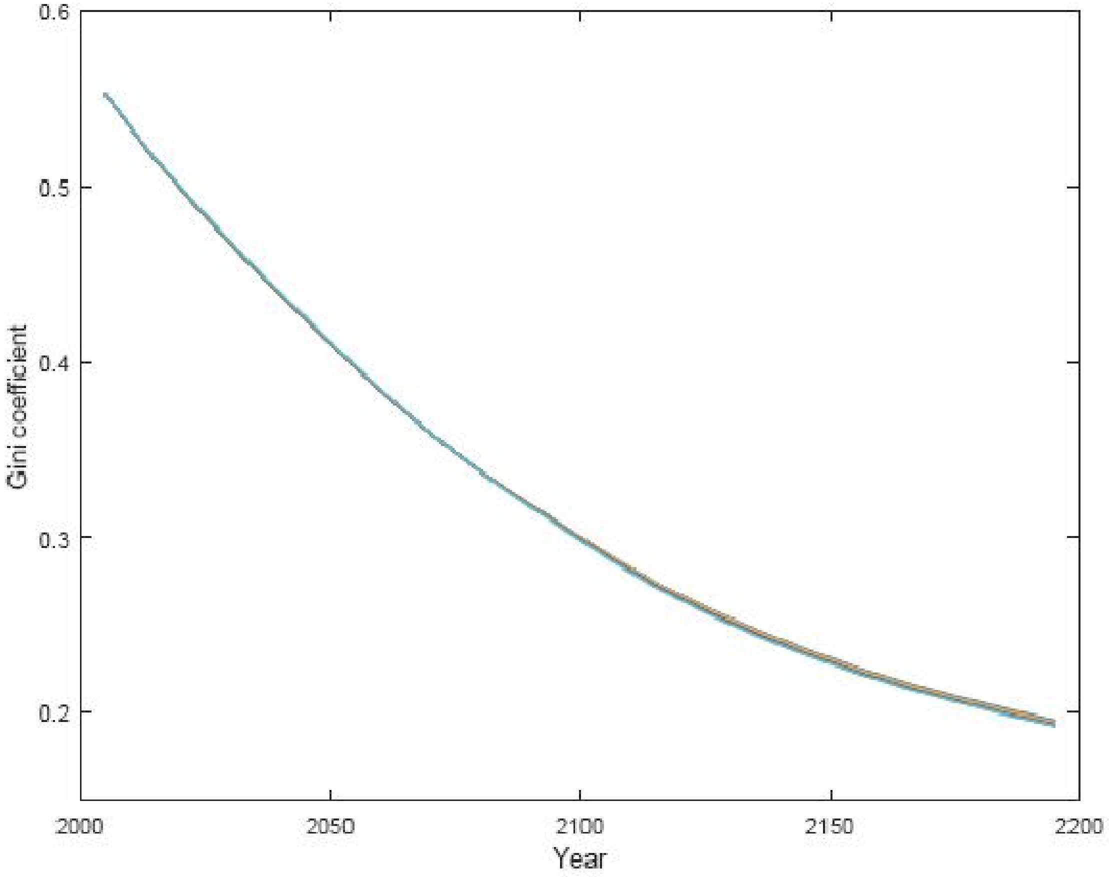
Figure S2.2. Robustness: Effects Are Qualitatively Similar if Damages Interact with Within-Region Economic Inequality



Note: η = 1:5%; η = 1:5. Estimated using the NICE variant of RICE, described in Dennig et al. (2015). Optimal price in units of $ per ton C.

Source: Authors' computations from climate-economy model described in text.

Figure S2.3. Convergence, Big Time: Future Within-Decade Gini Coefficients Implied by RICE Assumptions



Note: Each line is a time path of the across-region, within-period Gini coefficients for one of 20 optimal paths yielded by RICE under 20 combinations of "ethical parameters": each combination of ρ in {0; 0:5; 1; 1:5; 2} in percentage points and η in {1; 1:5; 2; 3}.

Source: Authors' computations from climate-economy model described in text.

Table S2.1. Ratio of Region-Specific TFP to US TFP, 2015 and Asymptotically

RICE region	TFP ratio to US: asymptotically	TFP ratio to US: 2015
US	1	1
OECD Europe	0.9	0.74
Japan	0.9	0.8
Russia	0.6	0.43
Non-Russia Eurasia	0.6	0.24
China	0.6	0.2
India	0.5	0.13
Middle East	0.5	0.34
Africa	0.4	0.11
Latin America	0.7	0.33
Other high income	0.9	0.8
Other non-OECD Asia	0.6	0.15
Standard deviation	*0.19*	*0.31*

Source: Authors' computations from climate-economy model described in text.