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Population, uncertainty, and learning in climate change decision analysis

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Brian O'Neill (1) and Warren Sanderson (2,1)

1 International Institute for Applied Systems Analysis, A-2361 Laxenburg, Austria
2 State University of New York, Stony Brook, NY 11794-4384, USA.

Abstract

The question of whether to act now or wait to learn more is central to the climate change issue. Previous work has reached no firm conclusions on either the direction or the magnitude of the effect on optimal emissions reductions of incorporating the potential for learning in climate change decision analysis. Here we use a well known, simple integrated assessment model to investigate how learning about the outlook for future population growth could affect optimal climate policy. We draw on recent work showing that, because population growth is path dependent, we can learn about the long term outlook for population size by waiting to observe how population changes in the short term. We find that learning about population growth can affect optimal policy, and that the timing and scope for learning are a key determinant of the magnitude of the effect.

Background

The question of whether to act now or wait to learn more is central to the debate over climate change policy. The climate change issue is characterized by both long timescales – today's emissions of greenhouse gases will affect climate for decades to centuries – and substantial uncertainties in climate impacts on society and costs of emissions reductions. Many argue that it would be beneficial to wait to learn more (and reduce uncertainties) before deciding whether, and how much, to reduce emissions. This strategy would avoid investments in emissions reductions that may turn out to be unnecessary. Others argue that reductions should begin now, because if climate change turns out to be serious, we would later regret not acting early. The question of how the potential for learning about various aspects of the problem affects today's optimal decision remains unresolved (Webster 2002). It is possible that learning about the outlook for future population growth could impact such decisions. Population is one factor affecting the outlook for future greenhouse gas emissions. If, by waiting a decade or two, we learn that population is likely to be much lower in the future than we currently expect, our outlook for future emissions will likely also be revised downward, reducing the urgency of emissions reductions. If we learn that population is likely to be much higher, our outlook for emissions will also be higher, justifying more aggressive action to reduce emissions.

The potential for learning about future population growth by waiting for more information was investigated by Sanderson et al. (2004). Using the IIASA probabilistic population projections (Lutz et al., 2001), conditional probabilistic forecasts with future jump-off dates were constructed. Such forecasts are conditional on what happens between the beginning of the current forecast period (the year 2000) and the future jump-off date. Sanderson et al. (2004) investigated, for example, how projections of population in 2050 would differ conditional on trends between 2000 and 2010. The outlook for 2050 would depend on events between 2000 and 2010 for several reasons. At a minimum, the values of demographic variables like population size, fertility, mortality, and migration in that ten-year period will be observed. Other factors such as new policies, economic trends, or social conditions that are relevant to the outlook for future demographic rates will also be observed. It is possible as well that demographic theory will be improved through research, that new breakthroughs in health (or new epidemics of disease) will occur, or that new contraceptive technology will be developed. All of these types of learning could change the outlook for the future. Sanderson et al. (2004) analyze only learning based on the observation of demographic variables, finding that there is substantial scope for this kind of learning (sometimes called "passive learning") to affect the outlook for future population growth. For example, in the IIASA projections, the median projected global population size in 2010 is 6.8 and in 2100 is 8.4. However, projections that are above the median in 2010 have a median in 2100 of 9.3, while projections that are below the median in 2010 have a median in 2100 of only 7.6. Waiting just 10 years, and making a very coarse observation about a single variable (global population size) leads to a difference in the median long term population of nearly +/- 1 billion.

Methods

In this paper we analyze whether learning about future population growth affects "optimal" climate change policy within a simple integrated assessment model of climate change. We use a simplified version of the Dynamic Integrated Climate-Economy (DICE) model (Nordhaus, 1994) as a framework for analysis due to its simple and transparent structure, and because it is well known in the climate change literature, having been applied to many different types of analyses. DICE is a one-region, global model consisting of a Ramsey-type economic growth model that also produces carbon emissions, linked to a carbon cycle model that simulates the buildup of carbon dioxide concentrations in the atmosphere due to these emissions. It also contains a mitigation cost function which estimates the economic costs of reducing emissions. We assume that in the future, atmospheric concentration must be kept below a given limit, consistent with the objective of the UN Framework Convention on Climate Change. DICE is used to solve for the optimal emissions path that meets the concentration constraint, where optimal is defined as the emissions path that implies the smallest net present value of emissions reduction costs.

We consider optimal climate change policy under uncertainty in future population growth, where population uncertainty is based on the IIASA projections. Uncertainty matters in this case because if population is high, meeting a given concentration target requires larger reductions. If population is low, meeting the same target will require smaller reductions, or perhaps even none at all (i.e., uncontrolled emissions in a low population world may not even be high enough to exceed the concentration constraint). We compare three types of optimal solutions: (1) the certainty equivalent case, where the uncertainty distribution in population is replaced by its expected value; (2) the optimal solution under full uncertainty, in which it is the expected value of mitigation costs that is minimized; and (3) the optimal solution under uncertainty with learning. In this third case, we solve a two-period, sequential decision-making problem, in which population uncertainty in the second period is partially resolved, contingent on the population path followed in the first period. The conditional population projections for this component of the analysis are derived from the IIASA population projection as discussed above, except that we assume that learning consists of observing whether, at a given point in time, the global population is in the top, middle, or bottom third of the full uncertainty distribution.

Preliminary results

Initial results demonstrate that learning about population can matter to optimal emissions. As shown in Figure 1, the optimal emissions with uncertainty and learning in 2020 (red lines) are higher in the initial period (2000-2020) relative to the case with uncertainty and no learning. (Of course, after the learning occurs, optimal emissions take a number of different paths, contingent on what was learned.) In this case, the potential for learning about population leads to the conclusion that it would be beneficial to reduce emissions less in the short term, and wait to learn more about future population growth before (possibly) making further emissions cuts.

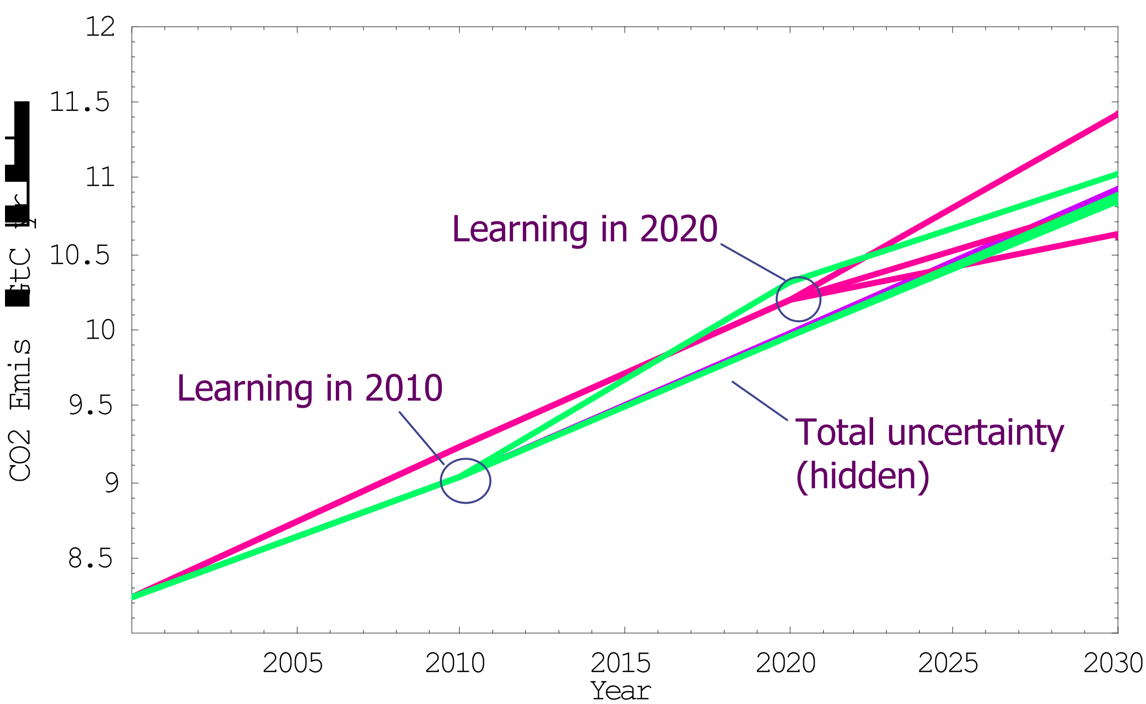

Figure 1: Optimal carbon emissions for the case of total uncertainty (purple line, hidden), and assuming learning about future population growth either in 2010 (green lines) or 2020 (red lines).

This result is dependent on many factors. Figure 1 shows one of those factors: the assumed timing of learning. If the learning is assumed to occur in 2010, rather than 2020, it has no effect on optimal emissions (relative to the total uncertainty case). Essentially, not enough is learned by observation in the first 10 years to affect the optimal near term decision. This result emphasizes that how much can be learned, and how fast, is a key determinant of how important population learning might be to climate change decision analyses.

Further work will explicate the basic results more fully, and will explore the sensitivity of results to a number of key assumptions, including:

- The assumed constraint on future atmospheric carbon concentrations (i.e., a low vs. high stabilization level);
- The nature of the assumed mitigation cost function. A crucial factor in determining the effect of learning is irreversibility. We will test cost functions that explore results of various assumptions regarding the irreversibility of investments in emissions reductions;
- The nature of the objective function. E.g., it may be desirable to minimize not the expected value of mitigation costs, but the risk that costs could exceed a given threshold viewed as unachievable;
- Alternative policies, including the effect of learning assuming that climate policy takes the form of optimal taxes versus on optimal emissions cap.

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