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POLICY RESPONSES TO CLIMATE CHANGE IN A DYNAMIC STOCHASTIC ECONOMY

Allocation: GLCPC/250 Knh
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EXECUTIVE SUMMARY

We extended our DSICE (Dynamic Stochastic Integration of Climate and the Economy) framework for evaluating policy responses to future climate change, to control the global average temperature anomaly so as not to exceed 2°C, with a stochastic economic production process [1]. We find that the social cost of carbon should be significantly greater in order to meet the 2°C target with a high probability [2].

We are extending DSICE to incorporate spatial structure of temperature and economy, sea level rise, thawing of permafrost, partial competition and collaboration, and adaptation. Our preliminary results show that rich countries in the region above 30 degrees north latitude should enact higher carbon taxes than poor countries in the tropic region [3]. Another extension of DSICE is to incorporate dirty/clean energy sectors. We find that we should significantly increase investment in clean energy and reduce investment in dirty energy, and very soon [4].

RESEARCH CHALLENGE

There are significant uncertainties in the climate and economic systems. Integrated Assessment Models (IAMs) of climate and the economy aim to analyze the impact and efficacies of policy responses to climate change. DICE (Dynamic Integrated model of Climate and Economy) is the benchmark IAM model developed over the past 20 years [5] and used frequently in the literature, e.g., by the United States Interagency Working Group on Social Cost of Carbon [6]. It is a simple perfect foresight forward-looking model that assumes we know all future information and that there is no heterogeneity. Ignoring heterogeneity in the economy as well as uncertainty in economic and climate conditions, or giving a relatively primitive treatment of uncertainty and heterogeneity, is often excused on the grounds that computational limitations make it impossible to do better. Our work from recent and previous Blue Waters projects clearly shows otherwise. We develop and solve new computational IAMs that merge the basic elements necessary, such as the spatial temperature system, climate tipping points, economic risks, clean energy usage, regional economic activities, and so on. We then use their solutions to do economic analysis about the optimal climate policy under uncertainty and risks and how such a policy will impact economic activities.

METHODS & CODES

In the past three years, Cai, Judd, and Lontzek used GLCPC allocations to build a prototype computational framework, called DSICE [1], to address these issues. DSICE allows shocks to both the economic and climate systems, and uses recursive preferences that isolate the intertemporal elasticity of substitution and risk aversion. Cai, Brock, and Xepapadeas are working on a spatial DSICE model [3], based on DSICE and the energy balance model developed by Brock and his collaborators. The spatial DSICE model incorporates heat and moisture transport between poles and tropics, sea level rise, and regional economic entities with interaction, as well as climate adaptation. Cai and his collaborators are also working on clean energy usage and Bayesian learning of uncertain critical parameters in DSICE.

We have developed three general parallel code packages for stochastic dynamic programming (DP), nonlinear certainty equivalent approximation (NLCEQ), and supergames, respectively, with high parallel efficiency. For stochastic DP models, we use the value/policy function iteration method (backward iteration) and the master-worker structure; the master assigns N tasks for workers to solve in parallel, and then gathers the results of these tasks from workers, and repeats this process until our iteration stops. For NLCEQ, it can be implemented in parallel naturally, and we have used Blue Waters allocations to solve huge-dimensional (up to 400 state variables) dynamic stochastic problems [7]. While tasks in the DP method are of small or moderate size, the tasks in NLCEQ are solving large-scale optimization problems that could take hours for each solution. Moreover, the number of tasks could also be large, but they are naturally parallelizable, so parallelization over these tasks is efficient in Blue Waters. The algorithm for solving supergames uses iteration methods until convergence, and each iteration consists of solving an enormous number of linear programming problems (of moderate size) [8].

RESULTS & IMPACT

In the past year, we published three papers based on the support of Blue Waters. In the first paper, published in *Nature Climate Change*, we extended DSICE to study the impact of multiple interacting tipping points. It is a large-size stochastic dynamic programming model with up to 10 continuous-state variables and five discrete-state variables. The paper showed that the five multiple interacting tipping points increases the social cost of carbon nearly eightfold.

In the second paper, published in *Quantitative Economics*, we used Blue Waters to develop an NLCEQ method to solve huge-dimensional dynamic stochastic problems efficiently and in parallel. NLCEQ has also been implemented to analyze the effect of climate and technological uncertainty in crop yields on the optimal path of global land use by Cai, Judd, Hertel and their collaborators [7].

In the third paper, published in *Operations Research*, we used Blue Waters to develop a parallel algorithm that can solve super games with states, which model strategic interactions among multiple players.

Economics, particularly when integrated with climate change science, is a field with many problems that have the size and complexity that justify the use of massively parallel computer systems. Our work using Blue Waters has allowed some economists to attack those computationally intensive economics problems.

WHY BLUE WATERS

Our parallel algorithms use the master-worker structure, and the communications among the master and workers are frequent and of small or moderate sizes, so the high latency inherent in a commodity cluster limited the ability to solve large problems in a reasonable amount of time. Moreover, the number of tasks could be huge. For example, the largest DP problem (for DSICE) we solved using Blue Waters had 372 billion of such tasks. Blue Waters allows us to use MPI (Message-Passing Interface) and solve far larger problems efficiently, as we have already shown in our previous work using Blue Waters.

PUBLICATIONS AND DATA SETS

Cai, Y., T.M. Lenton, and T.S. Lontzek, Risk of multiple climate tipping points should trigger a rapid reduction in CO_2 emissions. *Nature Climate Change* 6 (2016), pp. 520–525.

Cai, Y., K.L. Judd, and J. Steinbuks, A nonlinear certainty equivalent approximation method for stochastic dynamic problems. *Quantitative Economics*, 8:1 (2017), pp. 117–147.

Yeltekin, S., Y. Cai, and K. L. Judd, Computing equilibria of dynamic games. *Operations Research*, 65:2 (2017), pp. 337–356.