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Integrated assessment of mitigation strategies using an agent-based model of the linked energy, economic, and climate system

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Abstract: An alternative to the typical application of rational choice models to climate policy is the coupling of agent-based modeling and exploratory approaches. Agent-based models (ABMs) represent the world as made up of heterogeneous, boundedly-rational agents who act in their own interests and yet engage in substantive communication. Rather than focusing on optimal outcomes, agent-based models are primarily concerned with the evolution of large-scale properties that 'emerge' from the lower-level behavior. Consequently, ABMs have the potential to address complex system properties and generate a wider array of plausible storylines than more traditional integrated assessment modeling methodologies. We provide an overview of a new agent-based model of economic growth, energy technology, and climate change, and demonstrate use of the model for scenario discovery. Scenario discovery generates ensembles of plausible futures under alternative assumptions and hypotheses concerning system behavior. Such scenarios can help identify policy vulnerabilities and opportunities, thus supporting the design of robust climate change mitigation strategies.

Keywords: integrated assessment model; climate policy; agent-based model; scenario discovery

1 INTRODUCTION

Attempts at addressing deep uncertainty concerning model structure and parameter values are typically pursued through scenario analysis. A scenario can be thought of as a "coherent, internally consistent, and plausible description of a possible future state of the world" (McCarthy et al., 2001). By illuminating the span of future outcomes with respect to key design variables, they can reduce decision-makers' overconfidence in their mental models, highlight the variables to which policies are most sensitive, and provide guidance to the robustness of policy options.

To date, the process of developing scenarios has focused the IAM community on the uncertainty of parameter values, while virtually ignoring issues of structural uncertainty. The Special Report on Emissions Scenarios (SRES) (Nakicenovic and Swart, 2000) is the most instructive example. Largely following the ‘scenario axis’ methods popularized by Schwartz (1991), it follows a sequential, piece-wise approach: (i) convene experts to identify significant driving forces, (ii) formulate a small set of scenario storylines which span the uncertainty space, and (iii) use these storylines to create detailed internally consistent futures. In the case of SRES, four storylines were developed and then used to quantify future pathways of population and economic output. The pathways serve as exogenous IAM inputs, resulting in model output scenarios of energy use, technology choice, greenhouse gas (GHG) emissions, and temperature change. IAM outputs are then used in further downstream applications of detailed climate system models and impact-adaptation-vulnerability (IAV) studies.

A consequence of scenario generation in the style of SRES is that considerable separation exists between the driving force identification process and use of storylines in downstream models and studies. Scenario storylines often contain implicit descriptions of structural shifts, such as changes in value systems, which are then used to quantify exogenous inputs for use in IAMs whose methodologies are not flexible and comprehensive enough to adequately engage the original storyline (the PoleStar model (Raskin et al., 2010) is one notable exception). Thus, the intent of the scenario storyline is ultimately obscured as results are passed to downstream applications. Additionally, it is difficult to create scenario storylines that are sufficiently diffuse but small in number and perceived not to be biased by the expert development panel. Contention has also remained as to whether probabilities should be assigned to the outcomes and how the ultimate results should support decision making. Experience in the scenario and modeling communities has shown that problems of the scenario axis method hinder the effective use of scenarios (Moss et al., 2010; Parson et al., 2007).

A suggested alternative to the combination of rational choice models and the scenario axis method is the coupling of agent-based modeling and exploratory approaches to interpreting model behavior (Robalino and Lempert, 2000). Agent-based models (ABMs) represent the world as made up of heterogeneous, boundedly-rational agents who act in their own interests and yet engage in substantive communication. These agents reside in an environment with multiple other agents and interact according to specified protocols of communication and decision making. Rather than focusing on optimal outcomes, agent-based models are primarily concerned with the evolution of large-scale properties that ‘emerge’ from the lower-level behavior (Miller and Page, 2007). Consequently, ABMs have the potential to address complex system and SoS properties and generate a wider array of plausible storylines than more traditional IAM methodologies,

Exploratory approaches to interpreting model behavior aid in searching and visualizing possible model outcomes and identifying robust policy options (Bankes, 1993). As compared to the scenario axis method, scenarios in exploratory modeling are constructed using statistical techniques to analyze an ensemble of plausible futures generated by the model under different assumptions and hypotheses about the ‘true’ system. Therefore, scenario assumptions, hypotheses, and model structure are fundamentally linked, providing a map of policy vulnerabilities and opportunities.

2 MODEL DESCRIPTION

In ENGAGE, a diverse set of agents (negotiators, firms, and consumers) engages in purposeful behavior by observing and interacting with their surrounding environment and other agents. Their choices exhibit bounded rationality in the sense that the agents have limited cognitive abilities and incomplete information (Simon, 1955). They rely on decision heuristics that are based on theoretical and empirical findings from the literature (e.g., Thaler (1985), Heath and Soll (1996), and Gigerenzer and Brighton (2009) for consumers, Dosi, Fagiolo et al. (2010) for firms, and Lai and Sycara (2009) for negotiators). Regional economy-energy dynamics are based on the evolutionary macro-economic model of Dosi, Fagiolo et al. (2010).

ENGAGE is designed to serve robust decision-making in two capacities. The first is as a *policy discovery* tool. In this mode, policy formation is endogenous to the model and allows for the investigation of scenarios where policy formation and system structure co-evolve (Faber and Frenken, 2009) It allows one to ask questions such as, “What are the likely enhancing or retarding factors of international climate treaty formation and subsequent successful domestic implementation,” and has the ability to uncover plausible but unintuitive scenarios of discontinuous social and technological change. This mode is especially useful for testing robustness to structural uncertainties, such as the heuristics used in specifying agent decision rules and representation of the innovation process. The second capacity is as a *scenario discovery* tool, as outlined by Robalino and Lempert (2000), Lempert, Groves et al. (2006), Groves and Lempert (2007), and Bryant and Lempert (2010). This mode allows one to engage in a participatory, computer-based approach that achieves fully integrated scenario creation for exogenously supplied policies. A question such as, “What are the conditions under which a policy performs well or poorly?” can be investigated with scenario discovery. A particularly useful aspect of the scenario discovery mode is that policy solutions from other modeling frameworks can be used as an input into ENGAGE, allowing for testing of policy robustness to imperfect information and agent bounded rationality.

The starting point of our model is the ABM of endogenous growth and business cycles introduced by Dosi, Fagiolo et al. (2010), which we refer to as the DFR model (Figure 1). Our model significantly expands on the DFR model by adding energy as an input and cost factor in the production and use of goods and machines. We also add a simplified energy system, including energy technology and production firms. In the DFR model, the economy is composed of two types of agents, firms and workers, which observe their environment and make boundedly-rational decisions. Firms are divided into two types, capital-good and consumer-good. Furthermore, the number of each type of agent is fixed over time.

Capital-good firms produce machines that are sold to consumer-good firms, which use machines to produce homogenous consumer goods. Workers sell their labor to firms in exchange for the market wage and use all of their income to buy consumer goods. The public sector taxes wages and firm profits and uses the revenue to provide income to unemployed workers.

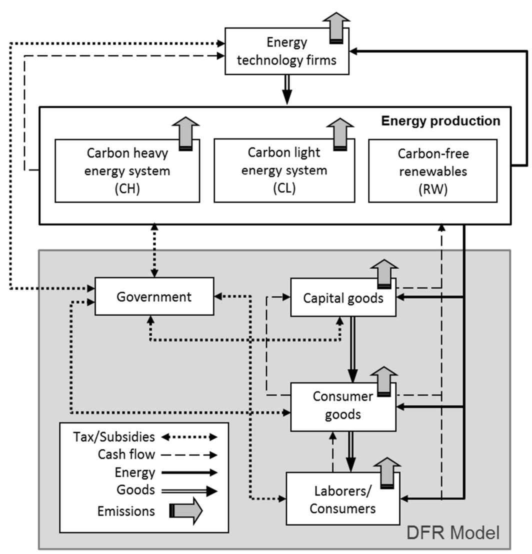

Figure 1. Schematic of agent-based model of the energy-economic system. Shaded box represents the scope of the original endogenous growth model by Dosi, Fagiolo and Roventini (2010).

In the original DFR model, firm production costs are only dependent on labor productivity and wage. The labor productivity of building a machine and producing consumer goods is linked directly to the machine vintage. Capital-good firms perform R&D in order to improve the labor productivity properties of their machines. Success of R&D is probabilistic; therefore the model can generate a wide range of technological futures. We add energy as an input and cost factor to the production of goods and machines and the use of goods by consumers. The amount of energy used for production activities and use of goods is determined by energy intensities that are subject to improvement through R&D.

The energy supply sector we add to the DRF model is highly stylized. It is comprised of three energy technology firms and one energy production firm. Each energy technology firm produces one type of energy production technology and undertakes R&D in order to improve the unit costs of building its technology. The energy production firm buys energy technologies and uses them to produce and sell energy to all other firms and households. The level of energy technology detail in our model follows other proof-of-concept models, such as Robalino and Lempert (2000), that specify three stylized energy technologies: 'carbon-heavy', 'carbon-light', and 'renewable'. The technologies differ significantly by cost, with carbon-heavy and renewable initially the cheapest and most expensive, respectively. For simplicity, we specify only one fossil fuel source for use as an input to the carbon-heavy and carbon-light energy technologies. Although our current proof-of-concept model is relatively simple, it allows for the production of scenarios in which prices, wages, energy use, and technological change are determined endogenously.

3 RESULTS

3.1 Policy Projections

To provide a preliminary demonstration of the flexibility of our model, we run 50 simulations from year 2000 to 2300 for a business-as-usual (*BAU*) and three policy scenarios: *R&D shift*: switching all baseline energy R&D funding to the renewable technology; *Tax*: a moderate, increasing carbon tax; and *Tax + R&D*: a moderate, increasing carbon tax with revenue recycling into renewable technology R&D. For policy experiments *Tax* and *Tax + R&D*, we also maintain baseline subsidies to energy R&D. The carbon tax is based on the optimal carbon tax trajectory from the DICE model (Nordhaus, 2008), which starts at approximately zero and increases to values of 24, 54, and 136 \$ per tonne CO_2 in years 2025, 2050, and 2100. Our baseline simulation assumes a continuation of selected current U.S. climate policies into the future: no carbon tax combined with subsidization of energy technology R&D. In line with U.S. R&D trends over the past decade, we assume that the carbon-light technology receives roughly double the amount of R&D funds of the renewable technology (Sissine, 2011).

Comparison of the emissions pathways (Figure 2) against the pattern of energy technology market shares (Figure 3) indicates that the energy system structure is the casual link between the evaluated policies and the overall carbon intensity of the economy. In *BAU*, carbon-light begins to penetrate the market around 2050 and reaches saturation about 50 years later. Due to the lack of climate policy, renewable does not begin to be cost-competitive until 2300. As a result, *BAU* emissions continue to grow steadily over time. For the policy scenarios, the entry of renewable in the energy system coincides with declining emissions, with the timing dictated by the policy specifics.

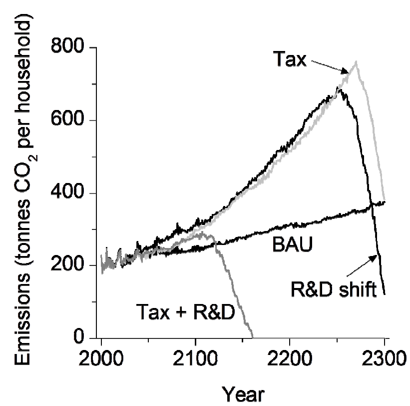

Figure 2. Median annual emissions per household for *BAU* and policy scenarios, estimated from 50 simulations.

Shifting R&D spending from carbon-light to renewable has the effect of delaying the market penetration of carbon-light by about 10 years, increasing near and medium-term energy prices, and speeding up the introduction of renewables. Implementing only a carbon tax moves up the penetration of carbon light and renewables compared to *BAU*. However, compared to *R&D shift*, the *Tax* scenario yields much higher energy prices, but is roughly as effective at spurring renewable development. This points to the importance of having a model that can assess the coupled effects of increased R&D spending and a carbon tax. As shown in Figure 3, Panel D, the entry of renewables into the market improves considerably when revenue raised from a carbon tax is recycled to renewable R&D.

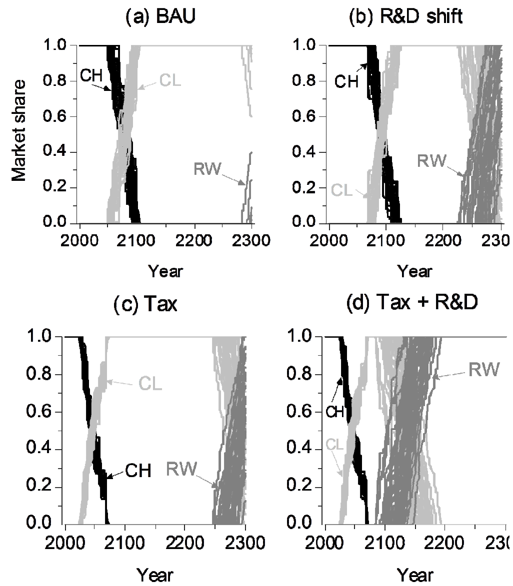

Figure 3. Energy technology market shares for *BAU* and selected policies: (CH) carbon-heavy, (CL) carbon-light, and (RW) renewable. Each line represents 1 of 50 simulations.

3.2 Scenario Discovery

One of the ENGAGE model's capabilities is to support the identification of scenarios under which a given policy may perform particularly well or poorly. Conceptually, scenario discovery involves identifying and classifying groups of simulation results that have similar characteristics, which then become individual 'discovered' scenarios. These scenarios might then be related to the values of stochastic factors or model parameters to understand the most important drivers generating each scenario. In general, the methodology and statistical techniques used depend on the question being asked and the characteristics of the simulations (see Bryant and Lempert, 2010; Groves and Lempert, 2007; Lempert et al., 2006). For example, a decision-maker might want to know not only how the economy is likely to respond to a specific climate policy, such as *Tax + R&D*, but also what specific turn of events might lead to strong versus weak performance under this policy. One procedure to answer this question with ENGAGE is to use hierarchical clustering (see Everitt et al., 2011) of model simulations to identify distinct scenarios followed by classification and regression tree (CART) analyses (see Breiman et al., 1984) to identify scenario drivers.

The first step in the procedure is to choose the dependent and independent variables relevant to the policy question. As an example, for the *Tax + R&D* policy simulations, we select GDP per household average growth rate, energy use average growth rate, and normalized cumulative emissions as the dependent variables, and labor productivity (*A* and *B*) average growth rates, energy intensity (*EFA*, *EFB*, and *EFG*) average growth rates, and energy technology improvement efficiency as the independent variables. For energy technology improvement efficiency, a learning-by-searching metric is derived for each technology by dividing the cumulative cost reduction until market entry by cumulative R&D expenditures until market entry. A learning-by-doing metric divides cumulative cost reduction between market entry and saturation by cumulative energy produced between market entry and saturation.

Using the dependent variables, we start by applying a hierarchical clustering algorithm to identify combinations of simulations that form statistically meaningful groups. An advantage to hierarchical clustering is that a decision-maker or analyst can use a tree-like plot of results to select the number of groups—hence, scenarios—to investigate. The technique works by first assigning each simulation to its own cluster. The algorithm then proceeds iteratively, at each stage joining the two most similar clusters until there is just a single cluster. The dissimilarity between two clusters at each step is computed as the increase in the error sum of squares (ESS) that would result from aggregating two clusters into a single cluster (Figure 4). The commonly employed Ward's Method then chooses successive clustering steps so as to minimize the increase in ESS at each step. The vertical length of the branches in the plot represents the distance between adjacent clusters, thus providing a graphical basis for choosing the number of clusters which would result from cutting the tree at a particular height.

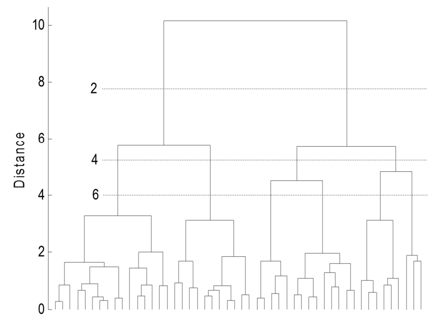

Figure 4. Cluster tree for 50 simulations of *Tax + R&D* policy. Horizontal lines identify cuts of the tree that define the indicated number of scenarios.

To keep our example simple, we chose to define four scenarios, labeled A, B, C, and D. Boxplots (Figure 5, Panels A-C) show that these scenarios are most strongly delineated by cumulative emissions. However, two scenario groupings of GDP and energy use growth also emerge, with scenarios *A* and *C* achieving relatively lower growth and scenarios B and D yielding relatively higher growth in each.

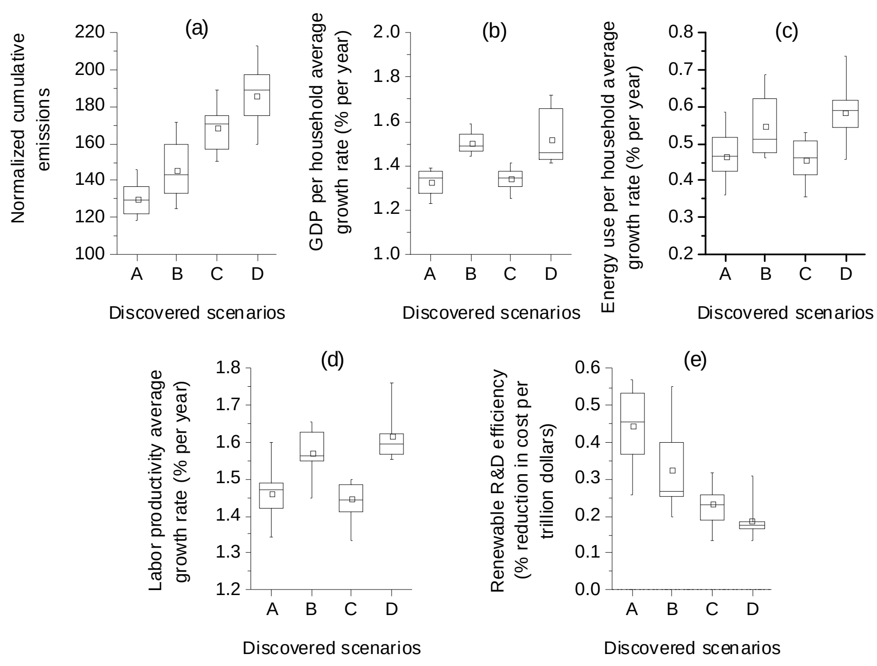

Figure 5. Scenarios discovered by hierarchical cluster analysis (Panels a-c) and the driving factors identified by CART analysis (Panels d and e). Boxplot centerline, square marker, box edges, and whisker ends represent the median, mean, 25-75[th] percentile range, and 5-95[th] percentile range, respectively.

The next step of our scenario discovery, CART analysis, is used to identify the underlying factors that generate the groupings identified by the cluster analysis. CART analysis consists of finding splits of the independent variables that yield the strongest possible predictions of a dependent variable. Independent variables are not required to follow any specific distribution, and nonlinear relationships as well as interaction effects are readily captured. When the dependent variable belongs to a category or class (as is the case for our scenario groupings), the underlying statistical methods are those of classification (Breiman et al., 1984).

Our CART results indicate that labor productivity growth in the consumption good sector and renewable technology learning-by-searching efficiency are the primary driving factors behind the discovered scenarios. Visual comparison of the dependent (Figure 5, Panels a-c) and independent (Figure 5, Panels d and e) variable box plots confirms this finding. The ranking of cumulative emissions clearly mirrors the renewable learning-by-searching efficiency. With regard to identified grouping of low and high GDP and energy use growth scenarios, the CART analysis finds this to be a result of labor productivity growth, which also exhibits low and high growth scenario pairing. Therefore, an insight gleaned from this simple scenario discovery example would be that scenarios of low and high GDP and energy use growth (driven primarily by improvements in labor productivity) can each bifurcate into relatively low or high emissions pathways depending on the success of renewable energy technology R&D. This is an example of how an evolutionary economic model can reveal the sometimes unanticipated outcomes that may emerge from a system of interacting systems.

4 DISCUSSION

While relatively simple, we have shown that our prototype economic-energy model is responsive to policy details, such as revenue recycling, that are not able to be addressed by many aggregated neoclassical economic models. The model can also be used to discover a set of distinct economic and technological scenarios. Because these scenarios are defined by endogenously generated simulations, the scenario drivers, model structure, and macro-level outcomes are mutually consistent. We exemplify the process of scenario discovery for only one of four simulated policies for only a handful of possible influential variables. Clearly there is opportunity to explore model sensitivity and policy robustness to a more diverse set of assumptions and hypotheses. Specifically, the functionality of the ENGAGE framework can be extended by considering population and firm growth and by introducing heterogeneity in household behavior and values. We would also like to consider more adaptive rules for firm and household decision-making.

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