A Model of Energy Policy Impacts on Pollutant Emissions, Costs, and Social Benefits Developed for China's Central Government

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In partnership with China's National Center for Climate Change Strategy and International Cooperation (NCSC) and China's Energy Research Institute (ERI)

Abstract

Energy Innovation LLC has worked with China's central government to develop a System Dynamics model to assist in selecting policies that will allow China to achieve its emissions reduction goals. The model simulates years 2013-2030 and covers the Transportation, Electricity Supply, Buildings, and Industry sectors. It also handles District Heating and Carbon Capture and Sequestration. The effects of 35 energy policies, as well as increased technical progress through research and development (R&D), may be investigated in any combination. Numerous outputs are available, including: emissions of nine different pollutants; cash flow changes for government, industry, and consumers; monetized social benefits from avoided public health and climate damages; usage of nine fuels as well as electricity and heat; and the mix of power sources. A Python script can be used to identify optimized policy packages.

Quantitative results are described in the paper. Some qualitative conclusions: No single policy or technology is a silver bullet; the greatest emissions reductions at lowest cost are achieved via packages incorporating many policies that support a diverse set of technologies. It is possible for China to peak its carbon emissions in the early 2020s while achieving a net reduction in direct monetary outlays.

Keywords

China, pollution, emissions, policy, energy, climate change

Project Background and Motivation

The People's Republic of China has industrialized rapidly in the last two decades and is now the world's largest emitter of greenhouse gasses (GHGs). GHGs are the primary drivers of climate change, which if unchecked, will have devastating impacts on human societies and on the environment (Intergovernmental Panel on Climate Change Working Group II, 2014). Many Chinese cities also suffer from extremely high levels of localized air pollutants, including particulate matter (PM), nitrogen oxides (NO_x), sulfur oxides (SO_x), and volatile organic compounds (VOCs). These levels of pollution are harmful to public health. Chen et al. found that in northern Chinese cities, life expectancy is 5.5 years lower than in southern cities, due to their use of coal-fired heating in winter (Chen et al., 2013).

In response to these hazards, the Chinese central government desires to reduce China's pollutant emissions. Specifically, they wish to include policies to reduce emissions in China's forthcoming 13th Five-Year Plan, which will guide the country's economic development in the years 2016-2020, along with measures that will enable China to meet its recent, bilateral accord on emissions with the United States (Nakamura and Mufson, 2014).

A policymaker seeking to reduce emissions faces a dizzying array of policy options that might advance this goal. Policies may be specific to one sector or type of technology (for instance, light-duty vehicle fuel economy standards) or might be economy-wide (such as a carbon tax). Sometimes a market-driven approach, a direct regulatory approach, or a combination of the two can be used to advance the same goal. For instance, in order to improve the efficiency of home appliances, a government might offer rebates to buyers of efficient models, might mandate that appliance manufacturers meet specific energy efficiency standards, or both. In order to navigate this field of options, policymakers require an objective, quantitative mechanism to determine which policies will meet their goals and at what cost.

Many studies of energy policy have examined particular policies in isolation. However, it is of greater value to policymakers to understand the effects of a package of different policies, because the policies may interact. This can produce results different from the sum of the effects of the policies when studied individually. For example, a policy that promotes energy efficiency and a policy that reduces the cost of wind energy, enacted together, are likely to reduce emissions by a smaller amount than the sum of each of those two policies enacted separately. This is because some of the electricity demand that was eliminated via the efficiency policy would otherwise have been supplied by additional zero-emissions wind generation caused by the wind policy. In this case, the total effects are less than the sum of the individual effects. The opposite is also possible. For example, a policy that promotes the electrification of light-duty vehicles and a policy that makes wind cheaper are likely to do more together to reduce emissions than the sum of these policies' individual effects.

Thanks to the strength of computer models at simulating complex systems, we felt that a customized computer model would be a crucial tool with which we could assist Chinese policymakers in evaluating a wide array of different policies. Such a model would need to meet several requirements: it would need to represent the entire economy and energy system with an appropriate level of disaggregation, the code would need to be editable by us and sharable with the Chinese government, and it would need to be possible to represent many policies of diverse types in this model without unreasonable programming effort. We required outputs that included not only energy use and emissions, but also economic costs and benefits. Additionally, the model would need to capture the interactions of policies and other forces in a system whose parameters change dramatically over the 18-year model run, as China continues to grow and develop. We reviewed many models and model-creation platforms before determining that no existing model met our requirements.

Accordingly, we resolved to build a suitable model ourselves. We identified System Dynamics as the most appropriate intellectual and technical framework for this model, thanks to its focus on interactions within non-equilibrium systems, the visual presentation of model structure in most System Dynamics model editors (such as Vensim®), the ability to execute models rapidly (allowing for real-time experimentation and learning), and the comparative ease of training individuals without a programming background to use and edit the model.

We partnered with two organizations within the Chinese central government to develop a suitable model and populate it with data: the National Center for Climate Strategy and International Cooperation (NCSC) and the Energy Research Institute (ERI). In addition to input from our partners in China, we have benefitted from the advice of individuals from organizations in the U.S. with expertise in China's energy system or energy model development: the Massachusetts Institute of Technology, Stanford University, Lawrence Berkeley National Laboratory's China Energy Group, and Climate Interactive. The model has also been reviewed by individuals at a number of organizations (see the Acknowledgements section below for details), whose comments have helped to improve the model and expand its capabilities. We call this model the "Policy Solutions model."

Alongside the model, we have developed several custom tools to assist in obtaining and sharing output. First is a set of scripts written in the Python programming language. One script allows a user to specify policies and settings of interest (for instance, various carbon tax rates). The script will then perform many thousands of runs, combining policy settings in every unique combination, and log the output to a data file that can be easily imported and manipulated in statistical software. This script is useful for finding optimal policy packages that meet specific criteria. Other Python scripts enable the testing of the contribution of each individual policy to a given policy package and the logging of data from a set of predefined packages.

The other important custom tool is a web application written in Ruby that runs on a server and provides an internet-accessible, simple, but powerful front-end for selecting policy settings, running the model, and visualizing and exporting output. This tool will increase the model's accessibility to individuals who have limited technical skills or who do not wish to install Vensim software on their own computers.

Structure and Functionality of the Policy Solutions Model

The Policy Solutions model assesses the effects of 35 energy and environmental policies on a variety of metrics, including the emissions of nine pollutants; cash flow changes for government, industry, and consumers; the composition of the electricity generation fleet; the usage of various fuels; and monetized social benefits from avoided public health impacts and climate damages. The model is designed to operate at national scale and focuses on four sectors: transportation, electricity supply, buildings, and industry. The model reports outputs at annual intervals with an initial year of 2013 and a final year of 2030.

Unlike many energy and economic computer models, the Policy Solutions model does not construct a future business-as-usual or reference scenario. Instead, it uses a Reference scenario (based on the results of other scientists' studies and models) as input data. The Policy Solutions model then modifies the Reference scenario in response to the policy settings selected by the user.[i] This approach enables us to take advantage of the good work that has been done in this field, while providing novel capabilities to analyze policy options that are immediately useful to policymakers and suggest specific policy actions that could be undertaken.

System Dynamics

There exist a variety of approaches to representing the economy and the energy system in a computer simulation. The Policy Solutions model is based on a theoretical framework called "System Dynamics." As the name suggests, this approach views the processes of energy use and the economy as an open, ever-changing, non-equilibrium system. This may be contrasted with approaches such as computable general equilibrium (CGE) models, which regard the economy as an equilibrium system subject to exogenous shocks, or disaggregated technology-based models, which focus on the potential efficiency gains or emissions reductions that could be achieved by upgrading specific types of equipment.

System Dynamics models often include "stocks," or variables whose value is remembered from timestep to timestep, and which are affected by "flows" into and out of these variables. The Policy Solutions model uses stocks for two purposes: tracking quantities that grow or shrink over time (such as the total solar electricity generation capacity) and tracking differences from the BAU input data that tend to grow over the course of the model run (for instance, the cumulative differences caused by enabled policies in the potential fuel consumption of the light-duty vehicle fleet).

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[i] The electricity sector is an exception. Policies in the electricity sector can affect decisions about which types of power plants to build and how plants are dispatched, so a decision-making framework must be employed. The decisions made by this framework using Reference input data may result in different outputs from other models, so in order to ensure our policy case is identical to our Reference case when all of the policies are disabled, we need to run Reference input data through our decision-making logic to construct a Reference case.

System Dynamics models often use the output of the previous timestep's calculations as input for the following timestep. The Policy Solutions model follows this convention, with quantities such as the electricity generation fleet, the types and efficiencies of building components, etc. remembered from one year to the next. Therefore, an efficiency improvement in an early year will result in fuel savings in all subsequent years, until the improved vehicle/building component/etc. is retired from service. The Industry sector is handled differently: as the available input data come in the form of potential reductions in fuel use and process-related emissions by policy, we gradually implement these reductions (with corresponding implementation costs), rather than recursively tracking a fleet-wide efficiency. (Due to the diverse forms that input data take in the sectors we model, rarely does one approach work for all sectors. Accordingly, the Policy Solutions model attempts to use whichever approach makes the most sense in the context of each specific sector.)

One way in which the Policy Solutions model differs from many System Dynamics models is its handling of time delays. Many System Dynamics models explicitly implement delays before compliance with new policies or responses to other changing conditions, reflecting real-world factors related to human psychology, inertia in business practices and supply chains, etc. (Sterman, 2000, p.409). The Policy Solutions model does not explicitly implement these types of delays. Policy effects are implemented in one of two ways. Most policy effects are phased in linearly by the model's end year (2030). For example, if the user selects a carbon tax of $10/ton CO2e, then halfway through the model run, the carbon tax will be $5/ton CO2e. Human behavior in the year halfway through the model run will reflect the costs imposed by the $5/ton carbon tax: there is no delay that would cause people to base their decisions on a $3/ton or a $4/ton carbon tax, the prevailing rates a few years prior. Some policies are fully implemented in every model year when they are turned on. For example, a policy requiring improved labels that highlight the energy used by building components is implemented fully in the first modeled year (2013) and maintained through every year, because the meaningfulness of implementing one quarter or one half of an improved labeling policy is questionable. In these cases, people's behavior reflects the presence of the new labels in 2013; there is no delay of a year or two for them to notice and begin factoring the improved labels into their decisions.[ii]

Model Structure

The model's structure can be thought of as occurring along two dimensions: visible structure that pertains to the equations that define relationships between variables (viewable as a flowchart in Vensim) and behind-the-scenes structure that consists of arrays and their elements, which contain data and are acted on by the equations. For example, the transportation sector's visible structure consists of policies (such as a fuel economy standard), input data (such as the Reference cargo

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[ii] This model behavior need not be conceptualized as instantaneous compliance: each policy lever in the model need not refer to the legislative text of the policy, but could instead refer to people's delayed responses to the policy.

distance traveled- that is, passenger*miles or freight ton*miles), and calculated values, such as the quantities of fuels used by the vehicle fleet. The arrays in the transportation sector consist of vehicle categories (light-duty vehicles (LDVs), heavy-duty vehicles (HDVs), aircraft, rail, and ships), cargo types (passengers or freight), and fuel types (petroleum gasoline, petroleum diesel, electricity, etc.). The model generally will perform a separate set of calculations, based on a separate set of input data, for every combination of array elements. For example, the model will calculate different fuel economies for passenger HDVs, freight HDVs, passenger aircraft, freight aircraft, and so forth.[iii]

In Vensim, a single dimension of an array is called a "subscript," an array variable is called a "subscripted variable," and the possible values an array dimension may take are called "subscript elements." For example, the variable called "Fleet Aggregate Fuel Use[vehicle type, cargo type]" is a subscripted variable, "vehicle type" and "cargo type" are each subscripts, and the "vehicle type" subscript has the elements "LDVs," "HDVs," "aircraft," "rail," and "ships." Almost every variable in the Policy Solutions model is subscripted.

The model has four main sectors, plus a few supporting modules and sheets handling other functions (Figure 1).

[iii] Occasionally, a policy or other structural element of the model will cause a quantity to be shifted from one combination of array index values to another. For example, the vehicle electrification policy shifts fuel demand from non-electricity transportation fuels to electricity (with an efficiency adjustment).

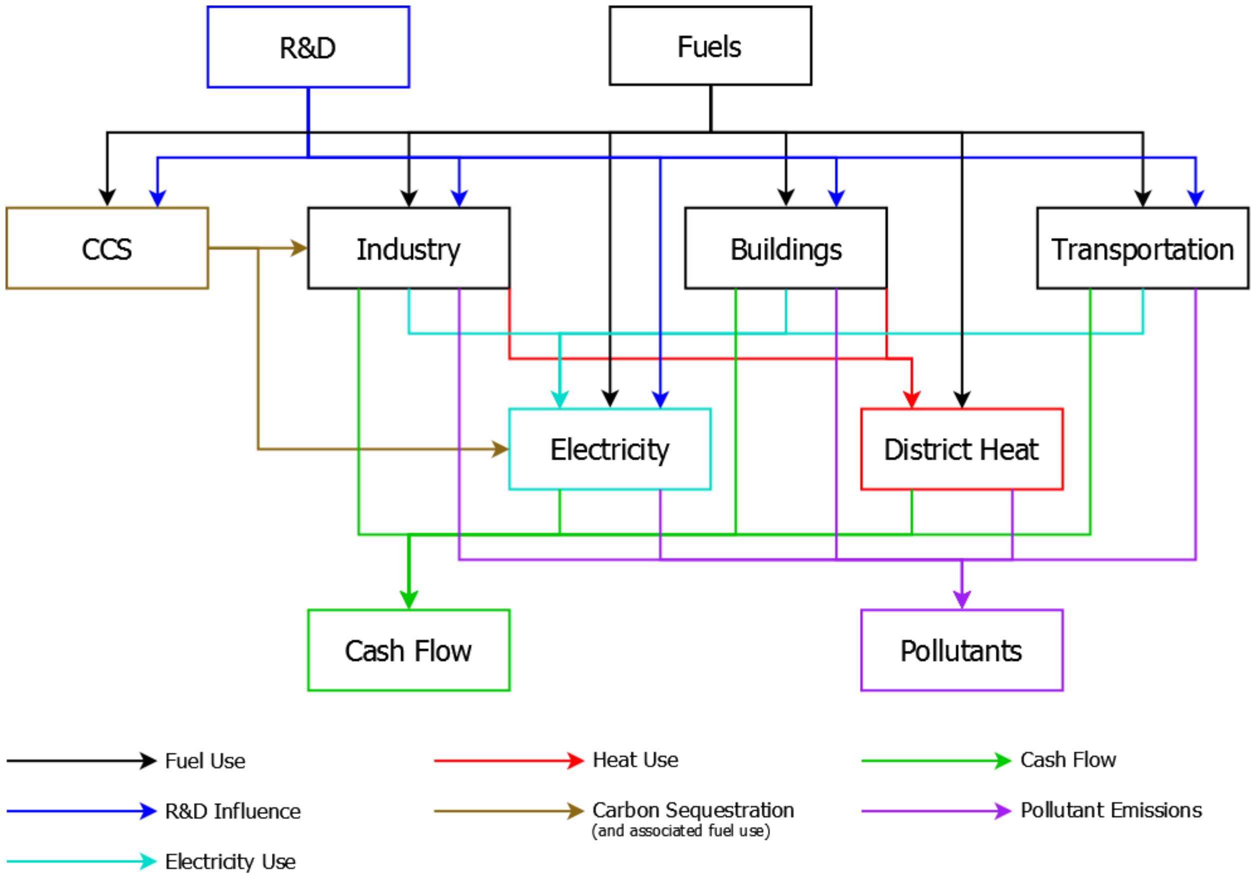

Figure 1: Diagram of the Policy Solutions model structure

The model's calculation logic begins with the Fuels sheet, where basic properties of all fuels are set and policies that affect the price of fuels are applied. Information about the fuels is used in the three "demand sectors": transportation, buildings, and industry. These sectors calculate their own emissions from direct fuel use- e.g. fossil fuels burned in vehicles, buildings, and industrial facilities. These sectors also specify a quantity of electricity or heat (energy carriers supplied by other parts of the model) required in each year. The electricity sector and district heat module consume fuel to supply the energy needs of the three demand sectors. All four sectors and the district heat module produce emissions of each pollutant, which are summed at the end. The same is true for cash flow impacts, which are calculated separately for particular actors (government, industry, consumers, and several specific industries). Calculation of changes in spending (for example, on capital equipment, fuel, and labor), as well as monetized social benefits from avoided public health impacts and climate damages, are also carried out at this stage.

There are two model components that affect the operation of various sectors. A set of R&D levers allows the user to specify improvements in fuel economy and decreases in capital cost for technologies in each of the four sectors and in the carbon capture and sequestration (CCS) module. The CCS module alters the Industry and Electricity sectors by reducing their CO_2 emissions (representing sequestration), increasing their fuel usage (to power the energy-intensive CCS process), and affecting their cash flows.

Lastly, there are a number of sections that are not part of the model's calculation flow but serve other purposes. The "Policy Control Center" and the "R&D Control Center" are pages where the user can conveniently view and set all of the policy levers. The "Output Variables and Graphs" page provides certain outputs of interest, converted to more commonly-used units (for example, converting BTUs of natural gas to trillion cubic feet of natural gas). A "Debugging Assistance" page provides the means to easily check certain totals that should sum to zero in the absence of bugs.

Available Policies

The policies that the model is able to simulate are listed below. To provide a thorough description of each of these policies is beyond the scope of this paper, but a very short definition (emphasizing the way the policy is implemented in the Policy Solutions model) is provided below each policy.

<u>Electricity Sector</u>

1. Renewable Portfolio Standard
   This policy requires that a percentage of potential electricity generation come from non-hydro renewables (wind, solar, and biomass).

2. Additional Growth of Demand Response
   This policy increases the capacity for temporally relocating electricity demand, represented here as a reduction in peak demand and an increase in grid flexibility, without affecting total demand.

3. Subsidy for Electricity Production
   The government pays money to producers of electricity per quantity of electricity generated and dispatched to the grid. (Set separately for each electricity source.)

4. Early Retirement of Generation Capacity
   An amount of electricity generating capacity retires each year in excess of the amount that retires due to the completion of that capacity's natural lifetime. (Set separately for each electricity source.)

5. Lifetime Extension
   This policy increases the natural lifetime of electricity generating capacity by a number of years, thereby reducing retirements during the model run. (Set separately for each electricity source.)

6. Mandated Capacity Construction Policy (a schedule can be defined by the user)
   This policy causes specific quantities of generation capacity to be built in specific years.

7. Additional Growth of Battery Electricity Storage
   This policy increases the amount of chemical battery electricity storage available, providing flexibility that enables more variable renewables to be used on the grid.

8. Use Least-Cost Dispatch (rather than contract-based dispatch, as is done in China today)
   Electricity is dispatched from sources in order from least to greatest marginal cost, rather than guaranteeing certain plants a number of hours they may run to recover their costs.

<u>Industry Sector</u>

9. Reduction in Industrial Production
   This policy represents a gradual shift of China's economy away from manufacturing and toward services, as well as other targeted measures, such as improving product quality (so that products, particularly building materials, do not need to be replaced so often) and shutting down excess industrial capacity that is run despite insufficient demand for the products. (Set separately for each industry.)

<u>Policies to Reduce Process Emissions</u>

10. Reduction of Vented Non-Methane Byproduct GHGs
    This policy requires improvements in production processes or final products that reduce the release of non-methane, non-CO_2 GHGs, such as hydrofluorocarbons (HFCs), to the atmosphere.

11. Methane Destruction (flaring)
    This policy requires methane that is currently being vented to instead burned before venting, converting it mostly to CO_2 without adding economic value.

12. Worker Training
    Workers are trained to use more efficient processes or to better maintain equipment, which can reduce process emissions in some cases.

13. Cement Clinker Substitution
    Clinker, the main component in cement, is made by breaking down limestone, which releases large amounts of CO_2. This policy requires other materials to be substituted for some of the clinker, reducing the amount of limestone that must be broken down.

14. Methane Capture
    This policy requires methane that is currently being vented or leaked to the atmosphere to instead be captured. It will ultimately be burned, offsetting the need to burn other methane.

<u>Policies to Reduce Fuel Consumption</u>

15. Early Retirement of Inefficient Facilities
    The least efficient industrial facilities of each type are retired and replaced with modern, highly efficient facilities, with equivalent production capacity.

16. Improved Installation and System Integration
Sometimes efficiency losses are not internal to industrial components like motors or pumps, but arise because of poor facility design or poor integration of various components. This policy represents promotion of principles for holistic design, pipe layout, etc. that reduce fuel use.

17. Waste Heat Recovery and Combined Heat and Power (CHP)
Many industrial facilities generate heat, which is lost to the atmosphere. CHP allows some of the heat to be used to do useful work, such as creating hot steam to warm a building or turn a turbine.

18. Replacement of Coal with Other Fuels
This policy requires industrial facilities to purchase new equipment or retool existing coal-burning equipment to use natural gas or electricity.

19. Industrial Equipment Energy Efficiency Standards
This policy requires industrial equipment to reduce energy use by a percentage relative to the Reference case. (Set separately for each industry.)

<u>Transportation Sector</u>

20. Fuel Economy Standards
This policy requires new vehicles to reduce their fuel consumption per unit distance that passengers or tons of freight are transported by a percentage relative to the Reference case. (Set separately for each vehicle type.)

21. Feebate (for LDVs)
This policy imposes a fee on the sale of inefficient LDVs rebated to buyers of efficient LDVs.

22. Transportation Demand Management, or TDM
This is a package of urban design and pricing policies designed to reduce motor vehicle use, such as improvements to public transit, construction of walking and biking paths, zoning for high density along transit corridors, congestion pricing, and parking fees.

23. Vehicle Electrification
This policy causes a percentage of the fleet of specified types of vehicles to be powered by electricity. (Set separately for each applicable vehicle type and cargo type.)

<u>Buildings Sector</u>

24. Rebate Program for Efficient Building Components
This policy causes utilities to pay a rebate to consumers who buy particularly efficient models of particular building components. $50-$100 for a clothes washer and $25-$50 for a dishwasher or refrigerator are typical values. (Set separately for each applicable building type and component type.)

25. Energy Efficiency Standards for Building Components
    This policy requires new building components to reduce their energy need (while providing the same level of services) by a percentage relative to the Reference case. (Set separately for each component type.)

26. Improved Appliance Labeling
    Improved labels disclose energy use, causing consumers to buy more efficient models and manufacturers to opt to produce more efficient models.

27. Improved Contractor Education and Training (for HVAC and envelope installation)
    Improved training allows contractors to construct buildings and install building systems (such as insulation or low-emissivity windows) with greater skill, preventing thermal leaks and improving performance.

28. Building Component Electrification
    This policy causes new electricity-using building components to be purchased in lieu of a percentage of new building components that use a different fuel in the Reference case.

29. Accelerated Retrofitting
    This policy causes a percentage of building components in existing buildings to be replaced each year by new components, on top of lifetime-based retirement and replacement. (Set separately for each component type.)

<u>Cross-Sector</u>

30. Additional Fuel Taxes
    This policy increases the price of a fuel by a specified percentage, with tax revenues going to the government. (Set separately for each applicable sector and fuel type combination, including electricity and heat.)

31. Carbon Tax
    This policy increases the price of fuels according to their carbon content, and it increases the price of equipment according to its embedded carbon content (carbon that was released in the course of manufacturing and shipping of the item prior to purchase). (Set separately for each sector.)

32. Phase-Out of Reference Case Subsidies
    This policy removes fuel subsidies that exist in the Reference case, including indirect subsidies, such as those that reduce the cost of drilling for oil or gas.

33. Additional Growth of Carbon Capture and Storage (CCS)
    This policy increases the amount of CCS used by the electricity supply and industry sectors, thereby increasing their fuel use and reducing their CO_2 *emissions.*

34. Use Market-Based Electricity Prices (rather than government-set prices)
    Electricity prices are allowed to vary from year to year based on the policy-driven change in costs for electricity suppliers.

35. Obtaining a Greater Fraction of District Heat from CHP Plants
    This policy increases the fraction of heat, an energy carrier like electricity in the model, that is generated from waste heat or CHP plants and therefore does not require fuel to be burned for the purpose of generating the heat (as the plant is run to provide electricity in any event).

In addition to the 35 policies listed above (over 200 policies listed above if each subscripted setting is counted as its own policy), there are 43 R&D policy levers that cause reductions in fuel use or capital costs for various technologies.

Input Data

The model has significant input data requirements, necessitating the use of a variety of data sources. Whenever they are available, the model uses data provided by NCSC and ERI. These often include quantities of specific things, such as the number of miles that passengers are traveling via different vehicle types or the quantity of fuel used by different industries. Future year projections come from NCSC and ERI's other models, such as those based on the Stockholm Environmental Institute's "Long range Energy Alternatives Planning System" (LEAP) (Heaps, 2012) and the International Energy Agency's "The Integrated MARKAL-EFOM System" (TIMES) (International Energy Agency Energy Technology Systems Analysis Program, 2015).

When data are not available from NCSC or ERI, the model uses published estimates specific to China from reputable sources, such as the International Energy Agency (IEA), the U.S. Environmental Protection Agency, and Lawrence Berkeley National Laboratory's China Energy Group. When no data specific to China is available at all, the model uses United States data to represent China. This is most common for coefficients that relate certain (less commonly-studied) policies to their real-world responses, such as the Percentage Efficiency Improvement due to Contractor Education and Training (for the installation of heating, ventilation, and air conditioning (HVAC) systems and building envelope components).

Model Limitations

One model limitation arises because of its reliance on various scientific studies and modeling results to establish the effects of policies on physical quantities and costs. The studies typically investigated these relationships under a particular set of real-world conditions. These conditions cannot reflect all possible sets of policy settings a user might select. Therefore, the relationships between policies and the quantities they affect might be different in different scenarios. This is not captured in the Policy Solutions model. Generally, the model's Reference case is likely to be closest to the conditions under which the various policies were studied by the creators of the input data. Therefore, the uncertainty of policy effects is likely smallest when policy levers are set at low values, and uncertainty increases as the policy package includes a greater number of policies and the settings of those policies become more extreme.

Another limitation of the model is the difficulty of characterizing uncertainty numerically. Almost all of the input data lacked numerical uncertainty bounds. Even if such bounds had been available, it would have been difficult to carry them through the model to establish uncertainty bounds on the final result. As a replacement, the Policy Solutions model supports Monte Carlo analysis, which can highlight the sensitivity of the model results to changes in any particular input or set of inputs. A user who lacks confidence in a particular value may run a Monte Carlo simulation, varying the suspect value within the range that he/she believes is reasonable, to obtain a probability distribution for any output.

The model generally contains policy levers that imply specific actions (e.g. setting a renewable portfolio standard, retiring industrial facilities early, etc.) rather than setting targets to be met via unknown actions (e.g. defining a cap on carbon emissions, a total allowable quantity of energy use by industry, etc.). The model is designed to predict the outcomes of specific combinations of policy actions, not to seek an "optimal" set of policy actions to meet a specific target within Vensim. However, using the Python script developed for use with the model, it is possible to search large policy design spaces for combinations of settings that optimize particular outputs. For example, if a user has a maximum allowable carbon emissions in mind, he/she can perform thousands of runs of the model while varying policies of interest, discard all of the results with carbon emissions in excess of the cap, and sort the remaining scenarios by another metric of interest (such as change in capital and fuel expenditures).

Policy Scenarios

While a strength of the Policy Solutions model is the ability to simulate and compare many thousands of policy packages efficiently, it was necessary to construct a small number of specific scenarios that could be presented to senior Chinese policymakers. With NCSC and ERI, we developed three policy packages, as well as two scenarios that represent upper and lower bounds on emissions:

- A **Reference scenario (RS)** represents the future if no additional emissions-reducing policies are enacted. This scenario provides the upper bound on emissions for this study.
- A **Low Carbon scenario (LC)** was designed by NCSC and ERI to be politically feasible and to complement their own modeling work on achievable emissions reductions. This scenario was developed by considering only energy-related emissions (that is, excluding process emissions from the Industry sector), and it aims to achieve national targets in addition to emissions reduction, such as greatly increasing the share of natural gas in China's energy mix.

- An **Enhanced Low Carbon scenario (ELC)** is similar to the low carbon scenario above, but with stronger policy settings that achieve peak CO_2e emissions in an earlier year.

- An **Energy Innovation LLC Recommended scenario (EI)** was designed with the goals of reducing CO2e emissions and limiting the number and strength of different policies that must be enacted. This scenario uses only the ten most effective policies, at settings no stronger than international best practice, to achieve great emissions reductions while reducing monetary expenditures in 2030.

- A **CO2e-Minimizing scenario (CO2eMin)** sets each policy to a setting that, in combination with all of the other policies, minimizes economy-wide CO2e emissions in the last year of the model run.[iv]

The minimum-emissions package was identified by searching through combinations of policy settings using the Python script. An exhaustive search of the policy design space would be impossible. (Testing just 3 settings for each of 35 policies would be 3^35 model runs, which at the rate of 10 runs per second, would take 159 billion years.) However, we were able to optimize policies in logical chunks, noting which policies were only conditionally effective, and then perform a second optimization phase in which we freeze the clearly helpful or not-helpful policies at their final values and vary only the conditionally effective policies.[v] Finally, we manually test every policy in proximity to this "tentative" best package, as a double-check in case some policies that are helpful or harmful in proximity to this package exhibited the opposite behavior in the first-pass optimization phase. While this procedure does not provide a guarantee that we have found the one optimal policy package, it is likely close enough to optimal to be within the model's margin of error.

[iv] Each policy's maximum allowable setting was bounded by international best practice. Without such bounds, the concept of a CO2e-minimizing scenario is meaningless, as it would be possible to strengthen policy settings without limit.

[v] For example, we might exhaustively search a space in which we test three settings of eight policies (3^8 or 6561 model runs, or about 11 minutes at 10 runs per second). We find that some of these eight policies are always set to a particular setting in the best-performing runs, and it is likely that the overall optimal package will include these policies at these settings. We similarly find that some of these eight policies are always disabled in the best-performing runs, and it is likely they will be similarly disabled in the optimal package. One or two policies might vary amongst the top-performing runs. We call these "conditionally effective" policies: whether these policies are worthwhile depends on the settings of other policies around them. Once we've established the final values for the majority of all policies, we do a run in which we exhaustively test the settings of the conditionally-effective policies, while the other policies are held constant at their final values.

Results and Discussion

Greenhouse Gas Emissions

Figure 2 shows greenhouse gas emissions by year for all of the tested scenarios. The LC and ELC scenarios were designed by NCSC and ERI only considering energy-related CO_2 emissions (e.g. from fuel combustion) and did not make use of policies to lower industrial sector process emissions, so they are graphed in terms of non-process CO_2. In contrast, the EI scenario and the CO2eMin scenarios were designed to minimize overall CO_2e and to include industrial sector process emissions. The reference scenario is shown on both graphs.

All of the emissions curves show a visible bend at the year 2020. This occurs because input data for most variables provided by NCSC and ERI came only in decadal timesteps (2010, 2020, and 2030 values), while the Policy Solutions model uses an annual timestep. Linear interpolation was used to obtain input data for these variables for the years 2013-2019 and 2021-2029. Since many trends change between 2010-2020 and 2020-2030, sharp bends are evident. This is an artifact of the input data format and is not meaningful. We chose not to smooth the curves so as to provide an accurate view of our outputs, but it may be advantageous to remember that in the real world, the bend around 2020 would instead be a smoother curve.

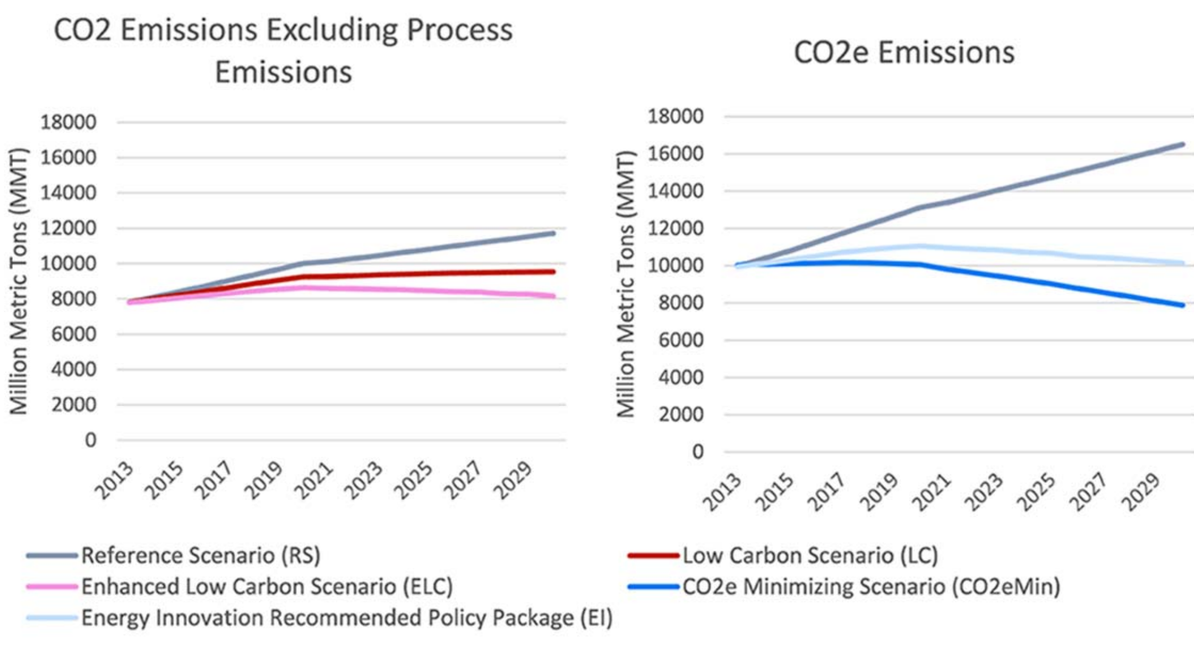

Figure 2: CO2 and CO2e Emissions by Scenario

The CO_2e-minimizing scenario uses nearly all of the 35 policy levers to achieve its deep reductions. The Energy Innvoation recommended scenario uses only 10 policy levers and is able to achieve 77% of the CO_2eMin scenario's reduction in annual CO_2e emissions in 2030. It also achieves this at lower cost (as measured by expenditures on capital equipment, fuel, and labor), because many of the policies it does not use are relatively expensive per ton CO_2e abated.

Contributions of Specific Policies to Emissions Reductions

The model only reports the combined effects of a package of policies, to capture their interactions. However, it can be of utility to policymakers to understand the relative contributions of different policies to emissions reduction. We have developed two methodologies to estimate policy contributions to emissions reduction; both can be executed in an automated manner via one of the Python script support tools. The first procedure enables the policies of a given package one-at-a-time, each time performing a model run and recording the emissions reduction due to that component policy. The sum of the policies' individual effects can then be calculated, and each policy accounts for a particular percentage of that total. We assume the same percentage holds true when testing the policies in combination.[vi] This methodology is likely to be of greatest interest to policymakers who anticipate being able to enact a small handful of energy policies (perhaps due to limits on time or political capital), so the policies' individual effects in proximity to the Reference scenario are of greater relevance than their individual effects in the context of an integrated package of many policies.

The second procedure starts with all of the policies of a given package enabled, then disables policies one-at-a-time and records the resulting increases in emissions. From here, the procedure is similar to that used above. We total these increases, determine the percentage each policy contributed to the sum of the individual increases, and assume that this is the percentage that the policy contributes to the abatement achieved by the package as a whole. This methodology is likely to be most useful for policymakers who anticipate being able to enact the majority of an integrated policy package, and so the policies' effects in the context of that package are more relevant than their effects in proximity to the Reference scenario.

Figure 3 shows the contributions of the ten policies that compose the EI policy package to the overall reductions achieved by the package. This figure uses the first of the two procedures detailed above.

[vi] For example, suppose a particular policy package reduces emissions in 2030 by 80 MMT, and the sum of the policies' individual effects is to reduce emissions by 100 MMT. If a policy accounts for 10% of the 100 MMT reduction based on individual testing, we assume it also accounts for 10% of the reduction achieved by the package when interactions are accounted for (that is, it is responsible for an 8 MMT reduction).

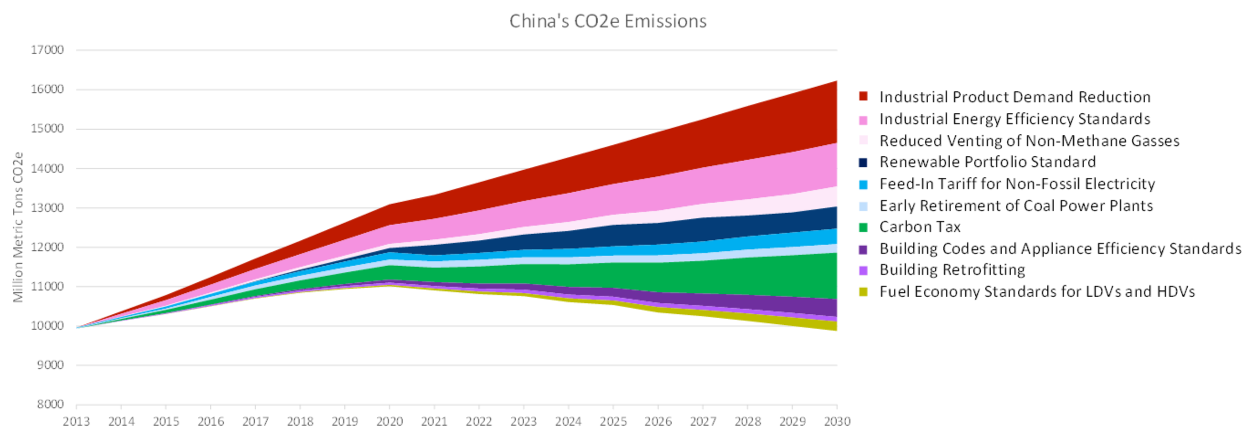

Figure 3: Individual policy contributions to abatement from the Energy Innovation LLC recommended policy package

Many policies' results are self-explanatory, but a few policies deserve comment. Industrial product demand reduction is the single strongest policy, in part because it reduces both fuel use and process emissions from Industry (the highest-emitting sector in China). Note that insofar as this policy represents a shift of the Chinese economy from manufacturing to services, it might slightly increase energy demand in the buildings and appliances sector, and it might slightly decrease energy demand in the transportation sector. Neither of these secondary effects from the rise of the service sector is captured in the model.

"Building Codes and Appliance Efficiency Standards" as well as "Fuel Economy Standards for LDVs and HDVs" are phased in linearly throughout the model run and only apply to newly-sold building components or vehicles, so only the items sold in 2030 (a small fraction of the total fleet) comply with those standards at full stringency. For that reason, the full abatement potential of these policies is not realized by 2030, making them look less effective than they really are. Figure 4 shows the CO_2e abatement that is achieved by vehicle fuel economy standards on a timeframe that extends to 2050 rather than 2030. The policy reaches full strength in 2030 and is held constant thereafter. In 2030, the policy causes less than half of the annual emissions abatement that it will ultimately achieve, if time is provided for vehicle fleet turnover. The same is true of the building and appliance efficiency standards policy.

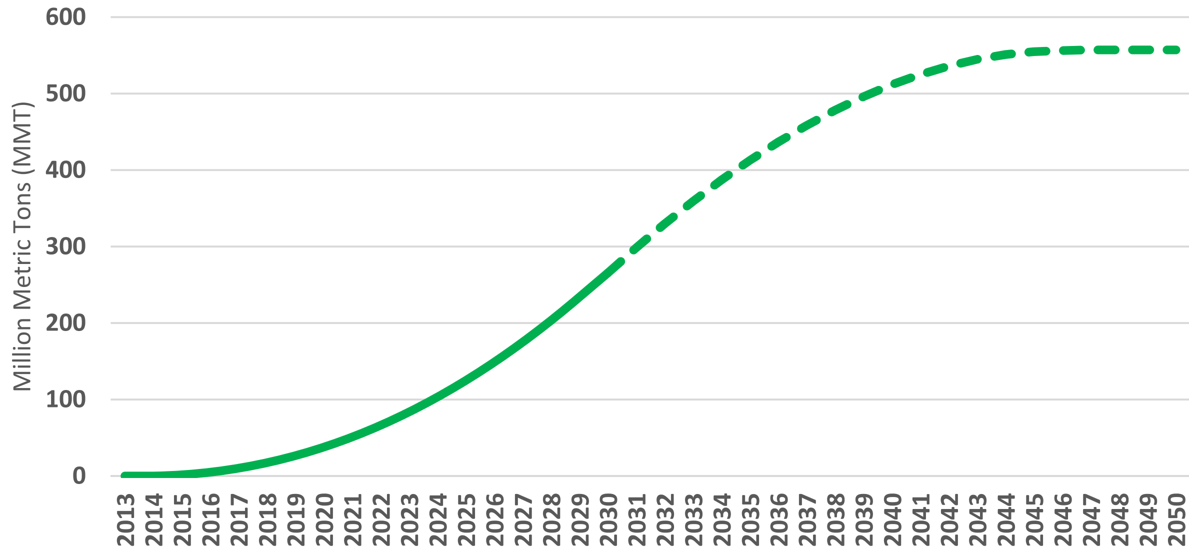

Figure 4: CO_2e abatement from vehicle fuel economy standards. The standards phase in linearly through 2030 and are held constant thereafter.

Economic Effects of Policy Packages

The Policy Solutions model calculates the change in the amount of money paid by several economic actors (government, industry, consumers, and several specially-broken-out industries) to each one of these actors. The sum of all changes in spending and receipts always adds to zero, because every time money is spent, someone else receives that money. It's important to note that when seeking to find the "cost" of a policy package, there are several reasonable, potential cost metrics that can be defined by summing various combinations of these cash flows. For example, one metric reported by the model is the total change in outlays, which is the sum of all changes in spending (i.e. disregarding changes in receipts). However, in this paper, we will use a different metric: the change in spending on capital equipment, fuel, and labor. This differs from "total change in outlays" in that it excludes certain cash flows, like payments of subsidies, which are not concrete costs in the same sense as buying equipment or fuel. Figure 5 shows the change in capital, fuel, and labor expenses for each scenario in each year of the model run.

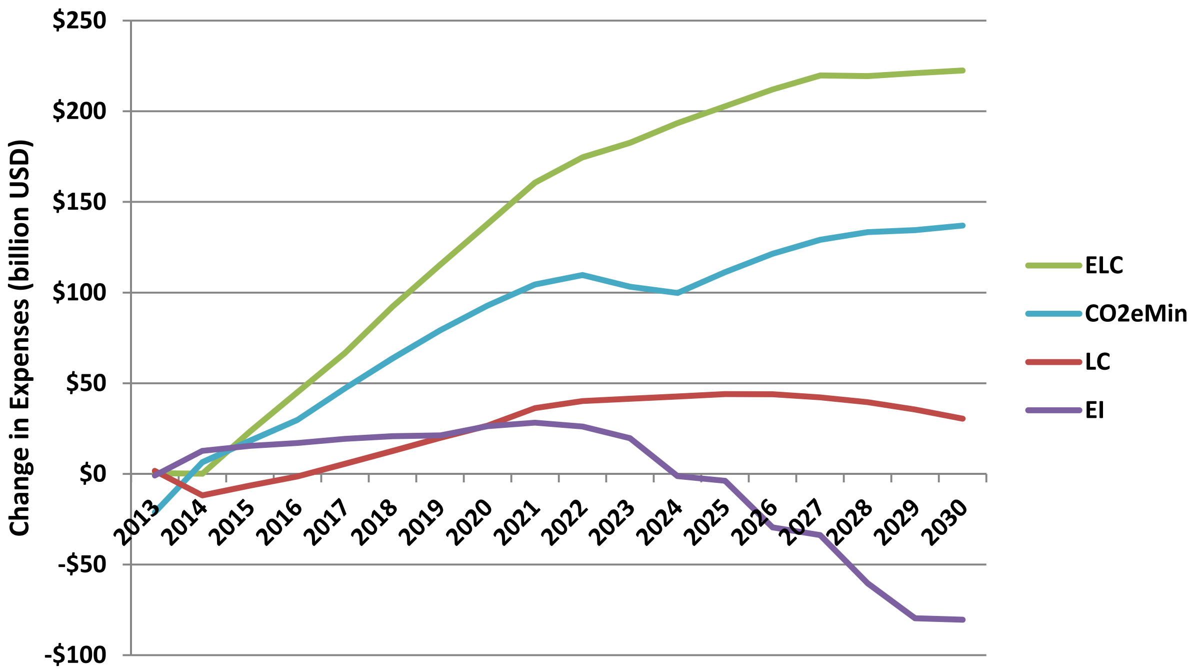

Figure 5: Change in capital, fuel, and labor expenses by scenario

Generally, the scenarios have a greater slope in the early years of the model run, and the slope begins flattening out or even becomes negative in the early 2020s. This happens because investments in improved equipment generally are made at a similar rate in all years of the model run, but fuel savings grow larger over time, as more and more equipment has been replaced.

The policies that have the largest impact on expenses tend to be taxes on commonly-used fuel types and the carbon tax. This is because the taxes' effect on reducing fuel consumption (saving money) is outweighed by increasing the price of the fuel that is still consumed. The LC and ELC cases use both a carbon tax and a tax on petroleum fuels, which together account for most of the cost. As an illustration, disabling the carbon tax and the petroleum fuel tax in the ELC package changes the cost of the package in 2030 from positive $222 billion (an expense) to negative $39 billion (a savings).

The EI package is the only one that reduces costs in 2030. This is in large part because the EI package forgoes fuel taxes: most reductions in the EI package are driven by standards. However, the EI package does include a substantial carbon tax (reaching $45/ton CO_2e in 2030), and it is this policy that accounts for most of the EI package's costs.

These model results make taxes appear to be expensive, but in the real world, it is possible to achieve the emissions reduction from fuel taxes or a carbon tax while offsetting the cost with an equivalent reduction in other taxes, such as income or payroll taxes. This option is beyond the scope of the Policy Solutions model, but it is worth highlighting, because a revenue-neutral carbon tax is a policy that is favored by some policymakers (Rosner, 2014). One finding of this work is that while such a tax would be a powerful way to drive down emissions, it functions best as one element in a package of policies, which collectively can achieve greater emissions reductions and save more money than the carbon tax alone.

It is possible to attribute costs to particular policies within a package in the same manner as it is possible to attribute emissions reductions to particular policies (described above). Putting these things together allows us to construct a policy cost curve, with abatement potential on the X-axis and cost per ton abated on the Y-axis. Figure 6 is such a curve for the CO_2eMin scenario, which we show here because it includes more policies than the other scenarios. Note that a policy cost curve is simply another way to visualize the component policies within a package; the curve changes depending on which policies are enabled and what specific settings they are given. There does not exist a single "correct" curve or policy cost ordering.

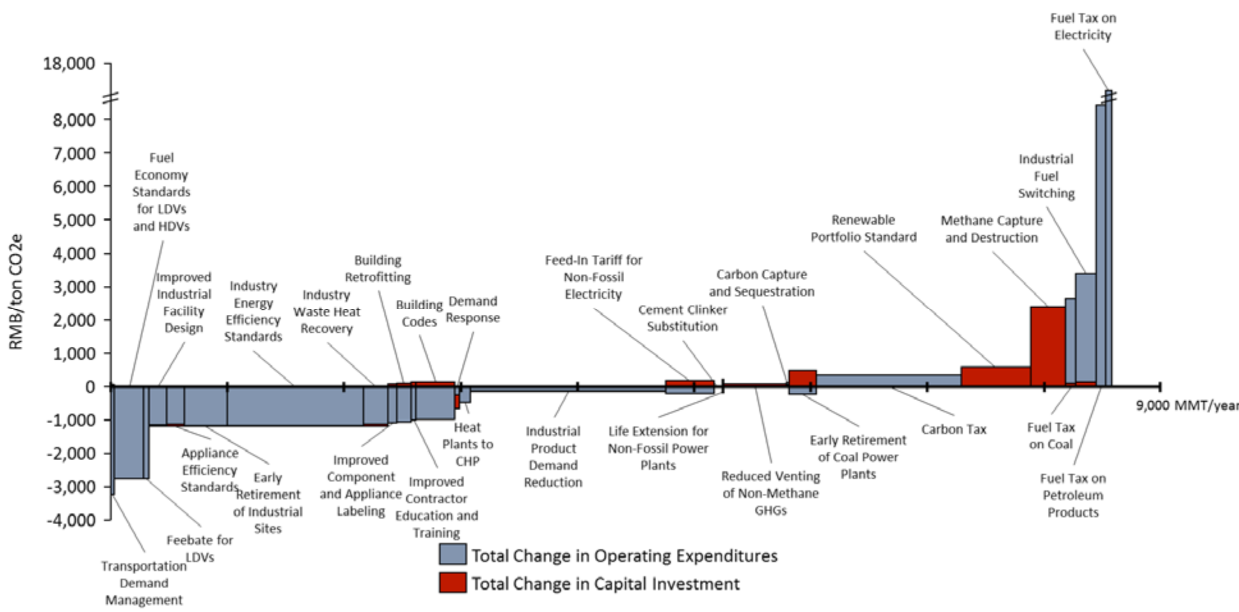

Figure 6: Abatement potential and cost per ton abated by policy for the CO_2eMin scenario

Calculation of Monetized Social Benefits

Change in spending is not the only relevant metric for policymakers. The model also estimates the monetized values of avoided public health damages and climate impacts. Public health damages are based solely on mortality (not morbidity). Monetization of these damages is based on figures from the U.S. EPA (U.S. Environmental Protection Agency, 2015), adjusted upward to reflect China's larger population and therefore likely larger human exposure per ton of pollutant emitted, then adjusted downward to account for differences in median income (as a proxy for a direct adjustment based on Value of a Statistical Life (VSL)[vii], because we felt that available VSL figures for China were unreasonably low). Climate impacts are based on the United States' social cost of carbon figures, since China does not have a comparable statistic.

Figure 7 shows the monetized social benefits for each scenario. Avoided climate damages only account for 9-16% of the total value of the benefits (varying by scenario and by year). The vast majority of the benefits come from avoided mortality.

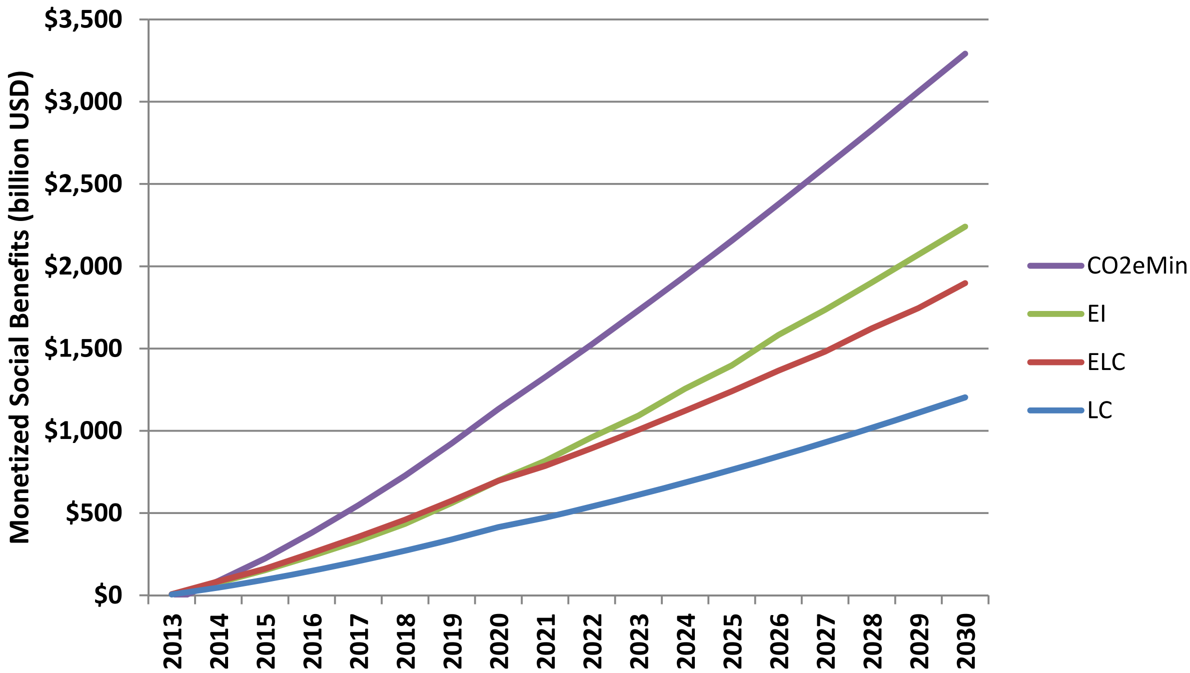

Figure 7: Monetized social benefits by scenario

[vii] VSL is a means of valuing risk reductions or deaths in monetary terms. It can be estimated from surveys that ask people how much they would be willing to pay to reduce their risk of dying in the next year. For a discussion of VSL as used by the U.S. EPA, see the EPA's "Frequently Asked Questions on Mortality Risk Valuation" at http://yosemite.epa.gov/EE%5Cepa%5Ceed.nsf/webpages/MortalityRiskValuation.html.

The values of social benefits tend to greatly outweigh the direct costs of policy packages. For example, in 2030, the LC scenario costs $30 billion but generates $1200 billion in social benefits, and the CO_2eMin scenario costs $137 billion but generates $3293 billion in social benefits. However, in one sense, the figures are not comparable, because the costs refer to actual payments that are made, while nobody pays money to account for the value of social benefits. Instead, people simply live who otherwise would have died. The main factor that causes the social benefits to be so large is the size of the monetary value placed on human life for policy analysis purposes.

Effects of Policies on Electricity Generation

We also examine the quantity of electricity provided by each modeled energy source in each scenario (Figure 8). In the Reference scenario, most new electricity output is from coal-fired generation. Solar, wind, and biomass also grow and account for 13.7% of output in 2030. In the Low Carbon scenario, there is very little growth of coal after 2020. Relative to the Reference scenario, there is significantly more natural gas output, as well as slightly more nuclear, wind, solar and biomass. Overall output in the LC scenario is also lower than in the Reference scenario by 750 TWh. The Enhanced Low Carbon scenario is the first scenario to exhibit a coal peak, which occurs around 2020. The ELC scenario includes less coal and natural gas output than the LC scenario, and more nuclear, hydro, wind, and solar. The EI scenario is the first one to aggressively drive down coal, slowly through about 2018 and then faster through 2030. Demand is lower in the EI scenario than the Reference scenario by 2,491 TWh in 2030. Wind, solar, and biomass account for 35.6% of output in 2030. The CO2eMin scenario is similar in many respects to the EI scenario, but coal is reduced faster, and there is more growth of hydro and nuclear, two of the more expensive, zero-carbon power plant types.

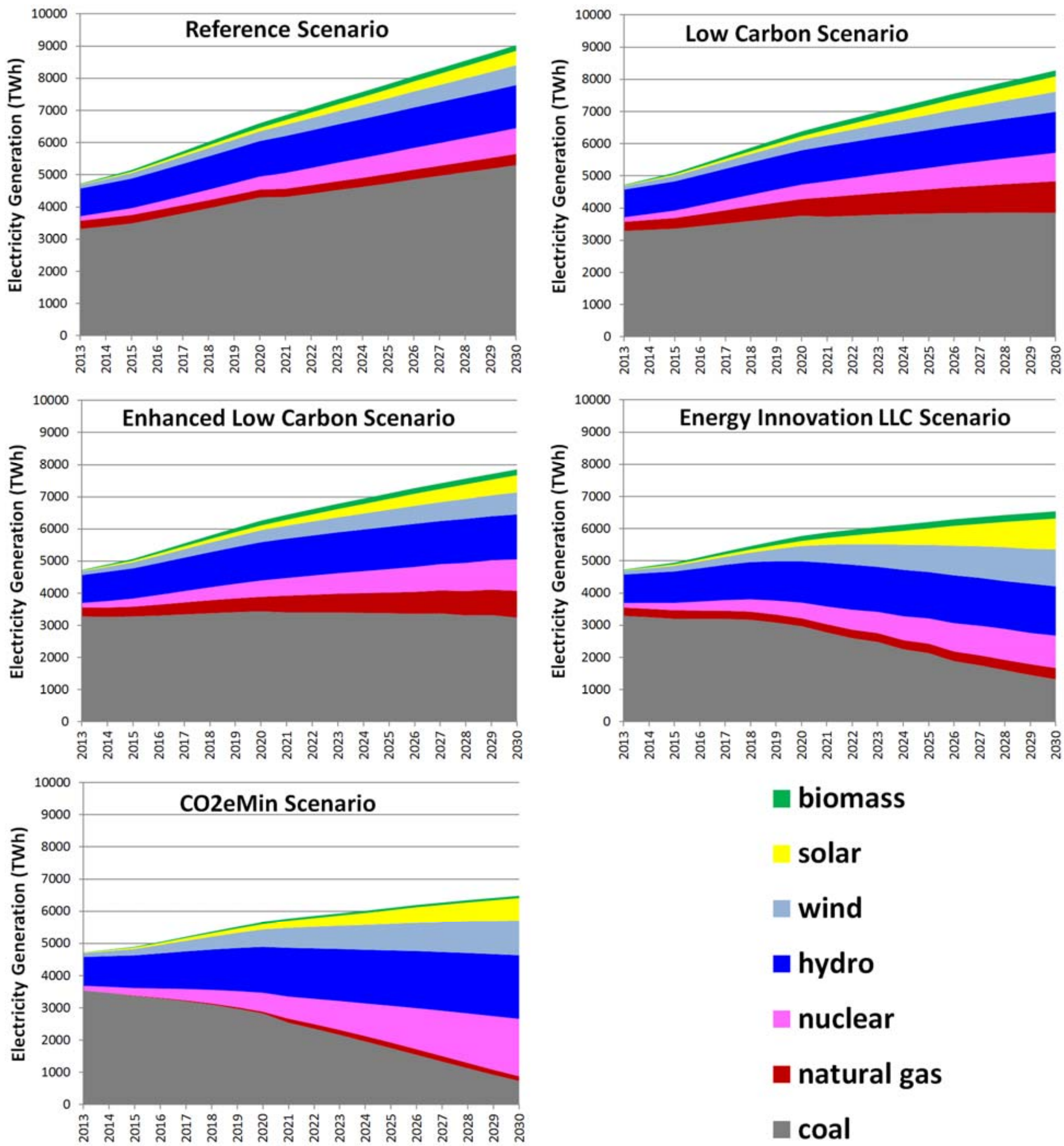

Figure 8: Electricity generation (TWh) by energy source in each scenario

Additional Outputs of Interest to Policymakers

The results in this paper are a sampling of some particularly relevant and important results; a complete overview of all interesting or useful results would be impossible, due to the diversity of different model outputs that are available, as well as the fact that we only review five specific policy packages in this paper. It is worth briefly mentioning other model results that might be of use to policymakers or researchers but are not shown numerically here:

- Policymakers might consider outputs other than CO_2e and monetary outlays to be goal or decision metrics. For instance, if energy security is a primary concern, policy packages can be designed with an eye toward reducing economy-wide consumption of petroleum fuels and natural gas, which are mostly imported in China.

- We do not utilize enhanced research and development (R&D) in our policy scenarios, but the model is equipped with 43 levers that allow R&D-based cost reductions and fuel efficiency improvements beyond the Reference case for 26 different classes of technologies. This can enable a user or policymaker to explore which policies would be effective in the context of different levels of R&D success in different areas. For example, perhaps a solar subsidy becomes less effective if there is more R&D advancement of the coal and natural gas technologies, but the Renewable Portfolio Standard policy remains effective irrespective of the level of coal and natural gas R&D advancement. This would imply that the RPS policy is more robust against different fossil fuel R&D outcomes than the subsidy policy. It is important to consider which policies work in a range of R&D environments, because the future of scientific advancement is not knowable with precision.

- While we used the Python script to identify an approximate minimal emissions policy package, it can be used to seek a policy package to suit any number of conditions. For example, one could find the policy package that minimizes monetary outlays while keeping emissions below a certain, fixed level, thus determining a least-cost method of complying with a carbon cap.

- Sometimes, it is interesting to see not just what is effective, but what is ineffective, at least through the 2030 timeframe. For example, the policy that allows for the achievement of additional CCS potential does not tend to have much effect, because CCS is such a new technology that its maximum potential by the year 2030 is not very high. Some policies are conditionally effective, depending on their setting and sometimes the settings of other policies. One example is a subsidy for electricity production from a particular energy source: there is a price range where the subsidy alters the model's decisions about what to build, but above and below that range, the subsidy makes no difference (because the subsidized energy source is either far too expensive to build or far too cheap not to build). Policies that increase the amount of flexibility on the electric grid are effective when the RPS is high (because they help bring more renewables onto the system), but they have no effect otherwise (because there is already sufficient flexibility to allow for the integration of as many renewables as the model wishes to build).

These examples help to illustrate that the model's greatest utility isn't in providing the specific results for the four policy packages discussed in this paper, but to rapidly answer a tremendous range of questions that policymakers might have about their options for affecting the energy system.

Web Application Model Interface

In order to provide access to key model results and improve the usability of the model for non-technical users, Energy Innovation has produced a web application that provides a means of interacting with the model, creating policy packages, and visualizing output in a web browser. The web application was developed by Todd Fincannon. This web application has particular value because much of the input data provided by the Chinese government may not be publicly distributed, preventing us from releasing a functional version of the model for China. The web application provides a means for the public to use the China version of the model without violating the restriction on sharing of input data. (We are publicly releasing a United States version of the Policy Solutions model.) Figure 9 is a screenshot of the web application with several annotations in red.

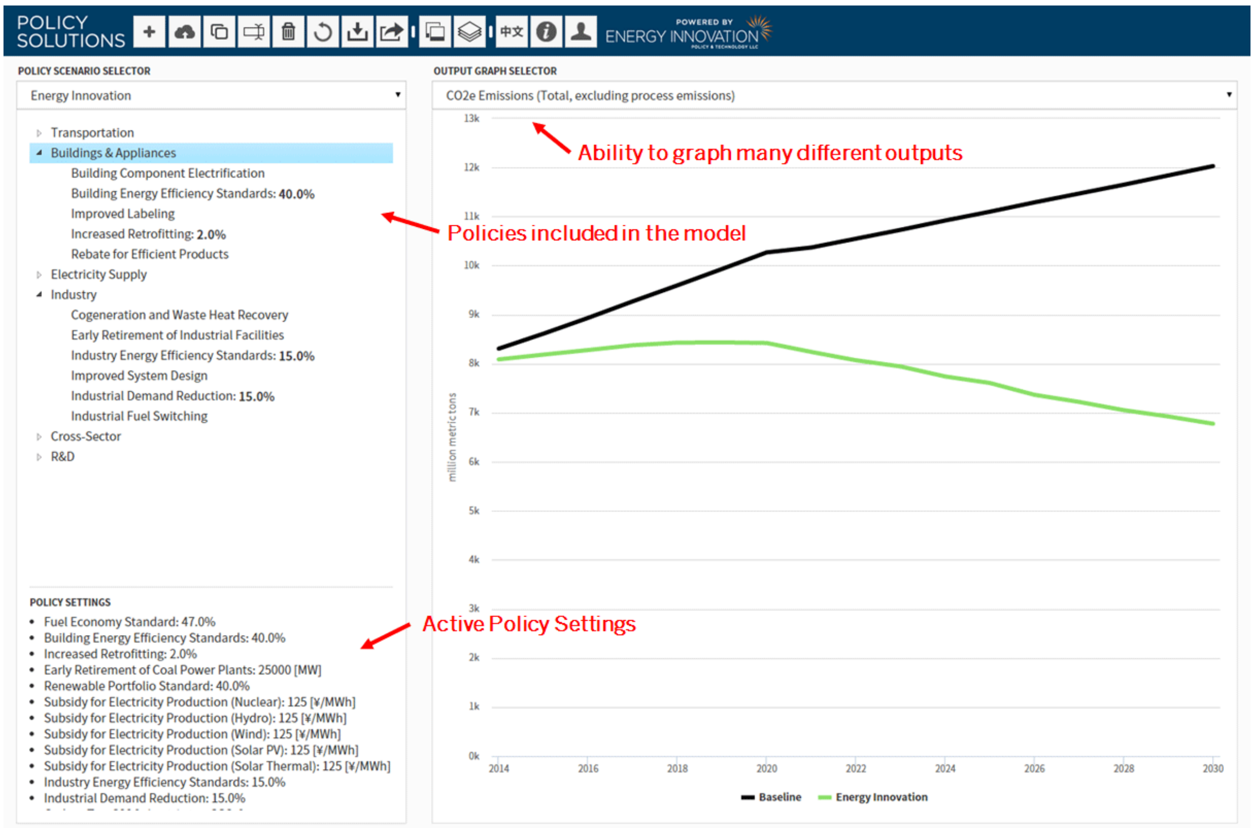

Figure 9: Screenshot of the web application interface for the Policy Solutions model (China version)

Conclusion

With the right set of policies, China will be able to cut its emissions dramatically and cost-effectively. A System Dynamics model provides the ideal tool to help policymakers understand the range of policy options at their disposal and quantitatively estimate their effects. It is our hope that the Policy Solutions model will assist the Chinese central government in selecting policies that will achieve their emissions reduction targets. But more than that, we hope that seeing that large emissions cuts are possible with reasonable policy options will inspire China to set more aggressive targets. Strong emissions cuts will pay for themselves through fuel savings, public health benefits, and reduced damages from climate change. Climate change may be the most serious problem we presently face, but with dedication and smart policy choices, China can be a leader in meeting this challenge.

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