Learning Rates, Green Energy Deployment, and Feasible Climate Agreements

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Abstract

International climate negotiations. However, individual countries have implemented various policies related to emission reduction including promotion of renewable energy. This paper uses observed deployment and costs of solar photovoltaics (PV) to infer policy-makers' preferences for green energy in four regions, the EU, China, the USA, and the Rest of the World (ROW). The historical learning rate of 22%, slowing to 11% after three doublings of output, is used to model the effect of deployment on cost reduction. These preferences then imply that PV deployment will be scaled up sufficiently to drive the cost of green energy down to parity with new fossil energy within three decades (in our reference scenario with constant fossil-fuel prices and myopic behavior). It is shown that a stable (in a well-defined sense) international agreement on deployment of solar PV is feasible and would result in significantly faster deployment and cost reduction. In the reference scenario under cooperation, PV accounts for 25% of world electricity output after 32 years. With a modest increase in fossil-fuel prices, this fraction can be considerably higher. A similar conclusion follows even if an agreement is not reached as long as limited forward-looking behavior is triggered by the negotiation process.

Keywords: game theory | coalition games | solar PV | green investment
Abbreviations: EU, European Union; ROW, Rest of the World
JEL codes: F53, Q42, Q54, Q55

International climate negotiations have made limited progress toward the large greenhouse gas emission reductions required to stabilize the earth's climate. However, individual countries and regions have implemented various policies related to emission reduction including promotion of renewable energy [1]. The deployment of nascent technologies leads to cost reduction via learning-by-doing, economies of scale [2], and R & D that increases with market size [3, 4]. In the case of electricity generated by solar photovoltaic installations, the learning rate, that is, the percentage decline in the cost of generation for each doubling of output, has been observed to be about 22% [7].

The limited progress made by international negotiations in emissions reductions may in part be a reflection of the political influence of fossil-fuel industries that resist any moves that would reduce their profitability over the horizon of their managers, perhaps a decade or less. Solar PV promotion assumes importance in this context since it is still a very small fraction of world electricity output, and likely to remain so within the planning horizon of current managers. This makes it more politically feasible than the most favored policy instrument of economists: carbon pricing. This is one reason that several countries or regions including China, Japan, India, Malaysia and California have in the last year either introduced or expanded existing solar PV promotion policies. Due to the high learning rate in solar PV, current policies that increase deployment can, by lowering costs, have large effects on emissions in two or three decades.

Solar PV deployment has grown rapidly as a consequence of policy initiatives in some countries (See Table 1). These initiatives reflect policy-makers' preferences for green over fossil energy. Although the cost of PV has been

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falling rapidly, it is still about three times as expensive as fossil energy. Thus, promoting PV comes at a cost. The actual deployments in various regions are a result of trading off the preference for green energy against its cost, and thus provide a way to infer the strength of their respective policy-makers' preference for green energy. This paper uses the preferences thus inferred to develop scenarios for the deployment and cost of solar PV over the next three decades. If policy-makers have a short time horizon of a single four-year period, then in our basal scenario with constant fossil electricity costs, deployment takes place at a pace that results in cost parity with new fossil plants in 8 (four-year) periods. If policy-makers' horizon extends to another period, then their actions, through their effect on next-period costs, affect each others' net benefits. They are then engaged in a game. In this scenario, in a Nash equilibrium (when regions do not act cooperatively), cost parity is achieved four to eight years sooner. We show that a stable treaty in which regions engage in Pareto-optimal play exists. It improves on the Nash solution further, but the additional gain is relatively small.

Below, we model the game among policy-makers. Our motivation is that agreement or even negotiation on renewable energy promotion policies can make the effect of deployment on next-period costs salient for policy-makers, making them more likely to take the effects of their current-period actions on next-period costs into account. This, as our model simulations below show, can have significant effects on the speed with which costs fall and deployment occurs. The main contribution of this paper is to quantify this effect of the move from myopic to (limited to one-period ahead) forward-looking behavior. We eschew modeling behavior that looks further into the future for two reasons. First, we do not think it is realistic for actual policy-makers whose horizons are mostly quite short. Second, by confining forward looking behavior to be at most one period ahead, we ensure that our conclusions about the deployment path in the first few periods are not affected by any changes in model parameters in more distant periods. This lends a desirable robustness to the model that is not present in models involving long-horizon dynamic optimization.

1 The Model

The policymaker of region i decides how much green energy to subsidize during her tenure. The regions modeled are China, the EU, the US, and the rest of the world (ROW). We assume that the ROW consists of countries whose individual actions are too small to appreciably influence the cost of solar PV. Therefore, we assume that the ROW is always myopic. The policymaker weighs the perceived benefit of a new deployment of green energy against the cost of the annual stream of subsidies required to support it. In the case that she is myopic, the policymaker weighs the perceived benefit in the current period against the current period cost (during her tenure) of the stream of subsidies required. Assume that we know the energy demand E_i^t of a region i in period t. We denote the incremental demand in each period by e_i^t. The policymaker can meet the new demand e_i^t by deploying a combination of new green energy g_i^t at a levelized cost of c_{gi}^t, new fossil energy f_i^t at a cost of c_{fi}^t or by retiring old fossil plants (with operating costs of c_{oi}^t) early and replacing them with new green energy. c_{fi}^t exceeds c_{oi}^t by the stream of capital cost payments that the new plants have to make to pay off their capital investment. If $g_i^t > e_i^t$, some of the old fossil plants will be prematurely retired in the current period. We also assume that $g_i^t \leq \min(ME_i^t, E_i^t - G_i^{t-1})$, this caps the maximum green energy deployment to ME_i^t in a given period, where, $0 \leq M \leq 1$ (we use $M = 0.2$, i.e. at most 20% of energy demand can be replaced in the current period).

In the myopic case, the policymaker of region i in period t maximizes her utility:

$$\mathcal{U}_i^t = \mathcal{B}_i^t - \mathcal{C}_i^t$$

where, $\mathcal{B}_i^t$ is the additional benefit of green over fossil energy from the policymaker's perspective and $\mathcal{C}_i^t$ is the amount by which the cost of green energy exceeds that of fossil energy. We assume

$$\mathcal{B}_i^t = B_i^t \log(1 + g_i^t)$$

where B_i^t is the parameter that captures the strength of the policy-maker's preference for green energy in period t and g_i^t is the new green energy deployed in period t.
The subsidy cost $\mathcal{C}_i^t$ depends on the cost of c_{gi}^t relative to c_{fi}^t and c_{oi}^t.

$$\mathcal{C}_i^t = \begin{cases} g_i^t(c_{gi}^t - c_{fi}^t) & \text{if} \quad c_{oi}^t < c_{fi}^t \leq c_{gi}^t \text{ and } \quad g_i^t \leq e_i^t \\ e_i^t(c_{gi}^t - c_{fi}^t) + (g_i^t - e_i^t)(c_{gi}^t - c_{oi}^t) & \text{if} \quad c_{oi}^t < c_{fi}^t \leq c_{gi}^t \text{ and } \quad g_i^t > e_i^t \\ (g_i^t - e_i^t)(c_{gi}^t - c_{oi}^t) & \text{if} \quad c_{oi}^t \leq c_{gi}^t < c_{fi}^t \text{ and } \quad g_i^t \geq e_i^t \\ 0 & \text{if} \quad c_{gi}^t < c_{oi}^t < c_{fi}^t \end{cases}$$

The subsidy cost refers to the first in a stream of subsidies (in each subsequent period) that is required for a certain deployment of new green capacity to take place. Henceforth, we'll assume that the cost of green and fossil energy is independent of the region and a function of time (period) only, i.e. $c_{gi}^t = c_g^t$. The subsidy cost structure reflects the fact that the savings from not building new fossil plants are greater than the savings from ceasing to operate old fossil plants. Thus countries with fast growing energy demand will find it cheaper to rapidly expand green energy production than those with slow growing energy demand, as long as the cost of green energy remains above the operating cost of fossil energy.

Learning by Doing and technological innovation can lead to a decrease in the cost of green energy with increasing total deployment. It has been empirically observed in many technologies that the cost of the technology per unit of production roughly changes as:

$$c_g^t = c_g^0 \left(\frac{G^{t-1}}{G^0} \right)^{\alpha} \quad \text{where} \quad 2^{\alpha} = 1 - l$$

The cost of green energy in period t depends on the cumulative deployment G^{t-1} in period $t-1$. The learning rate l is the fraction by which the cost decreases when cumulative deployment doubles. c_g^0 is the initial cost of green energy and G^0 and G^t are the initial and current cumulative green energy deployment worldwide. More complicated learning functions are possible if the technology goes through a succession of learning regimes with different learning rates.

1.1 Myopic behavior

By myopic behavior, we mean that policy-makers do not consider net benefits that extend beyond the current four-year period. They maximize their utilities $\mathcal{U}_i^t$ and deploy new green energy according to the cost of green energy at the beginning of the current period which, as we saw above, is a function of the total green energy deployment in the last period. Under myopic behavior, the regions do not take into account the fact that their current period deployment can lead to cost reduction in the next period. Consequently, the actions of policy-makers in other regions are irrelevant for policy-maker i's decision.

So far, it has been the case that $c_f^t \leq c_g^t$ and in all regions of the world, $g_i^t \leq e_i^t$. Using this fact, and assuming that policy-makers have so far acted myopically, we can infer that in each region the optimal g_i^t has been given by

$$g_i^t = \frac{B_i^t}{c_g^t - c_f} - 1. \tag{1}$$

Using the observed data on deployment and costs in the period 2007-2010 [5, 6], B_i^0 in that period can be inferred for the four regions: China, the EU, the US and the ROW. We find that B_i^0 was highest for the EU at 16,290, and lowest for China at 949.3. B_i^0 for the US was 1602.5, and 2761 for the ROW. Despite its low preference parameter, China is considered separately because additions to total energy demand are expected to be larger in China than anywhere else, as seen in Table 3. Consequently, China will account for a large share of g once the cost of green energy reaches near parity with new fossil energy but still remains significantly more expensive than existing fossil energy.

Preliminary data on deployments in 2011 allow us to test the accuracy of our model's prediction of 2011 deployments made using the values of B_i^0 derived above under the assumption of myopic behavior (See Table 2). It is clear that the model under-predicts deployments, especially in China. This could be due to cost reductions in 2010 and 2011 that were larger than usual, and perhaps also due to an increase in China's preference parameter. It would not be surprising if China's preference parameter were to increase as it has only recently become a large supplier of solar modules. Conversely, as the EU's domestic suppliers' market share shrinks, it is possible that the EU's preference parameter could decrease. Looking ahead, we might expect all countries' preference parameters to increase over the next few decades as the adverse effects of global warming loom larger and nearer. We do not, however, formally model this.

Jumping ahead a bit (See 1.2), we could also ask if the EU was forward-looking in the period 2007-2010 even if the other regions were myopic. The EU would then be able to predict the deployment of the other regions, and deploy its 2007-2010 deployment for a lower preference parameter. We calculate the EU's preference parameter, B_i^0 to be 12,232 instead 16,290 in this case. This low figure seems unlikely, especially given the 2011 deployments.

1.2 Forward-looking behavior: Nash equilibria

In scenarios with two-period strategies, the policymaker maximizes the two period utility

$$\mathcal{V}_i^t = \mathcal{U}_i^t + \delta \mathcal{U}_i^{t+1}, \tag{2}$$

where δ is the discount factor for a single period.

With this forward-looking behavior, policy-makers are playing a game. In this game, the choice of deployment g_i^t in the current period would lower the cost of green energy for all policy-makers in the next period due to learning. Thus, compared to the myopic problem, in a Nash equilibrium of this game, policy-makers would choose higher levels of g_i^t in order to reap the benefits of cheaper green energy next period.

1.3 International Agreements

Since deployment this period is a public good that lowers costs for *all* players next period, policy-makers could further increase their payoffs by entering an agreement specifying current-period deployments by each player that would raise total deployment above the Nash equilibrium level. We will assume, in keeping with the literature [8, 9], that once players enter into such an agreement, it will be adhered to. We will consider only agreements between the EU, China, and the USA, and will assume throughout that the rest of the world (ROW) plays myopically, that is, according to Eq. (1). This assumption is made for tractability. Any subset of these three players will be referred to as a *coalition*. If singleton coalitions form, that is, if there is no agreement, then it is assumed that the EU, China and the USA will play a Nash equilibrium while the ROW plays myopically.

Stability: We use the notion of stable agreements given by [10]. This is more demanding than that commonly used in the literature because it requires not only that an agreement between a coalition of players be immune to defection by a single member of the coalition but also that it be immune to defection by all stable sub-coalitions. Stability is thus defined recursively. A singleton coalition will always be deemed to be *stable*. A two-player coalition will be called stable if an agreement between its members specifying their current-period deployments can guarantee each of its members a utility (given by Eq. (2)) that is at least as high as it would get if it were to instead play a Nash equilibrium. In this case, it is assumed that the third player plays a best response to the coalition (the ROW is always assumed to play myopically). If a two-player coalition is stable, it is further assumed that its members would not enter into an agreement that they could both improve upon, so that only Pareto-optimal agreements are considered. Finally, the *grand coalition* of China, the EU, and the USA will be called stable if no stable sub-coalition of its members exists that improves the utilities of all members of the sub-coalition (over and above what they get in a Pareto-optimal agreement among the members of the grand coalition). Finally, in our simulations, we pick the deployment on the Pareto-frontier of all stable grand coalitions that leads to the maximum decrease in the cost of green energy.

2 Simulations

In our simulations, we consider a set of scenarios using electricity demand projections from the IEA [6] for China, the EU, the US, and the rest of the world (ROW) (See Table 3.). 2010 Solar PV deployments in the four regions are given in Table 4. We assume that the learning rate of solar PV will stay at 22% for the next three doublings of global capacity and be 11% thereafter (We follow the assumptions used by the Energy Information Administration but with a higher learning rate, see [7, 11]). This is because most of the initial cost reduction comes from learning in the photovoltaic cell part of the plant. The learning and cost reduction has been slower in the 'balance of the system' part that will come to constitute a larger and larger share of the cost as the cost of the photovoltaic cell falls. Each period is four years long, the typical tenure of a policymaker. We assume that all new deployments are in green energy when the cost of green energy falls below the cost of new fossil energy. We also assume that when the cost of green energy approaches and falls below that of old fossil energy, new green energy is deployed and old fossil energy is retired prematurely, subject to the cap in new green deployments stated above. This cap is set to 20% of the total energy demand in that period. By allowing green energy to grow at this rate, we are implicitly assuming that complementary institutional infrastructure (such as time-of-day pricing) to shift demand to the daytime when solar energy is available, and physical infrastructure such as long-distance lines for transmitting solar energy from sunlit to night-time areas will be put in place by the time solar energy accounts for a significant fraction of electricity generation. The simulation runs for 8 periods from 2011 to 2042. We use the same cost parameters in all regions but we will consider different cost trajectories in different simulations. We also consider simulations where a region's preference for green energy changes over time. In each simulation we consider the following deployment strategies (or scenarios): 1. all are myopic [MYOPIC], 2. China, the EU, and the US always play the Nash equilibrium [NASH], and 3. China, the EU and the US form the best possible stable grand coalition, or play Nash if the grand coalition is an empty set [COALITION]. We again note that the ROW is always myopic.

2.1 The Reference Simulation

The Reference (R) simulation (Table 5) uses c^0_{gi} = \$300/MWh, c^t_{fi} = \$100/MWh and c^t_{oi} = \$65/MWh. The fossil energy costs are assumed constant throughout. We also assume that the preference for green energy, determined from the 2007-2010 deployment, is constant throughout. Most of the initial investment in reducing the cost of green energy comes from the region with the highest preference for it: the EU. These investments require support in the form of subsidies. The 'baton' is passed to fast growing regions like China and the ROW as the cost of green energy approaches, and subsequently, falls below the cost of new fossil energy. Compare the green energy deployment in Table 5 in periods 6 and higher between COALITION, NASH and MYOPIC. Looking ahead leads to 5-10% reduction in the cost of green energy with coalitions providing marginal improvements over Nash. In scenarios where regions look ahead one period, there is more subsidy provided in all regions though the subsidy per unit of green energy is reduced. Finally, we note that in the COALITION scenario the deployment in period 7 is according to Nash equilibrium play. There is no stable coalition that Pareto-dominates the Nash equilibrium when the cost of green energy has fallen below that of new fossil energy. The reason is that China and the USA have low preference parameters and in a Nash equilibrium are already deploying only green energy. They will not start retiring old fossil plants at a high cost in order to deploy more green energy even if the EU were to increase its deployment further.

2.2 Sensitivity Analysis

We also construct scenarios where we change one or more assumptions of the Reference simulation. The cost of fossil energy can rise as a result of scarcity due to resource exhaustion, and/or carbon taxes. Indeed, this is more likely than a constant cost of fossil energy because costs are expected to rise with cumulative extraction [12]. We assume a CO_2 intensity of 0.5 tCO_2/MWh, about halfway between coal and gas. As noted above, the preference for green energy can also change in the near future, especially in China and the EU. We consider the following simulations:

- Rising fossil costs (F): Table 6 has the numbers for a simulation with rising fossil fuel costs , assumed to be constant across regions.
- Green China (C): In this simulation, we assume that China's preference for green energy is 4 times the reference (R) scenario, and the EU's preference in halved (See Table 7).
- Simulation FC: In this simulation, we combine the assumptions of rising fossil costs (F) with the change in preferences of China and the EU (C).

The costs of new fossil energy and old fossil energy are two significant thresholds of the model. A region with a low preference for green energy will deploy significant amounts of green energy only when the cost of green energy approaches or goes below the cost of new fossil energy. At the second threshold, new green deployment not only meets incremental energy demand but also replaces old fossil capacity which is prematurely retired. A region with a high preference for green energy is less affected by these thresholds directly. For example, in the Reference case the EU, with its high preference for green energy, retires fossil capacity before the cost of green energy falls below the cost of new fossil energy.

We find that for all scenarios (R, F, C and FC) the total annual subsidy costs are higher in COALITION: about 25%-30% more than in MYOPIC, and 10% higher than NASH. The extra subsidy is effective as it leads to a higher deployment of green energy and the average annual current period subsidy cost per unit of green energy (henceforth, S_g) is lower in most periods. Typically, S_g in MYOPIC is indistinguishable from NASH or COALITION in the first period. Subsequently, when the cost of green energy is higher than the cost of new fossil capacity, S_g is lower in COALITION or NASH in all simulations. Forward looking behavior gives more "bang for the buck". See Table 8 for more.

Finally, we would like to compare the green energy deployments of China and the EU in the simulations, Reference (R) and Green China (C). We can see in Table 9 that an increase in the preference of China can make a big difference, and can make up for a fall in the preference of the EU. More importantly, global subsidy costs are lower. A China with a higher preference for green energy can spend less by deploying green energy instead of new fossil energy whereas Europe might have to prematurely retire old fossil capacity to provide for the same level of deployment. Therefore, "*Learning by Doing*" is achieved at a lower global cost.

3 Discussion

The estimated preference parameters of policy-makers lead to increasing deployment of green energy even in the Reference scenario with myopic policy-makers. This is sufficient for cost parity with fossil energy to be reached in a thirty-year horizon. Very recent figures on deployment provide suggestive evidence that, in fact, the preference parameter of China may increase and deployments therefore proceed even faster than this scenario suggests. In the scenario with rising fossil costs and an increased preference parameter for China (albeit a lower one for the EU), PV deployments result in 60% of world electricity output being solar in the thirty-two year horizon of the model.

The model produces a large number of possible trajectories for the evolution of green energy. This is a result of the interplay of the various parameters, model inputs and options: changing preference for green energy, no or limited foresight and the changing cost of fossil fuels. The learning rate for green energy is another important variable though we have preferred to keep it unchanged throughout all simulations. We have also kept the cap on maximum green deployment in a given period constant across all simulations. Some robust conclusions that can be drawn form the simulations are:

- A policy making environment with some foresight can produce a faster decline in the cost of green energy. The cost reaches parity with the cost of new fossil energy 4-8 years before a scenario with only myopic policymakers.
- Scenarios with a one period look ahead (a foresight of 4 years) lead to costs that are 5%-10% lower than the corresponding myopic scenario, especially in the initial stages of the model when the fastest declines occur.
- As expected, full cooperation between regions (the COALITION scenario) produce the fastest decline in the cost of green energy.
- The progress achieved by the NASH scenario is quite close to that of the COALITION scenario.

The last conclusion is particularly pertinent, since it is unlikely that all regions or countries of the world will sign on to an agreement. We conclude that negotiation on co-ordinating policies among a few large jurisdictions can have a significant effect on the time by which cost parity with new fossil plants is achieved, if, as seems likely, coordination triggers forward-looking behavior. Since any one region's actions, by itself, have a more modest effect on cost reduction, forward-looking behavior in the absence of coordination is less likely.

Methods

The preferences used in the model are obtained by applying Eq. (1) to 2007-2010 data on deployments and costs of solar PV. Projections are based on data from [6]. The model is coded in Python, and makes extensive use of Scipy, a library of mathematical software in Python. The MYOPIC scenario is straightforward. In the NASH scenario we coarsely discretize the search region of green energy deployment of China, the EU, and the US, and numerically calculate the best response surfaces of each region [S1, S2, S3]. The intersection of the three best response surfaces ($N = S1 \cap S2 \cap S3$, the Nash equilibrium set) is numerically determined, a sufficiently large bounding cuboid around the intersection is selected, and the process is repeated with finer discretizations till the desired tolerance is reached. The definition of the model limits the intersection of the three surfaces to either a surface or a line or a point. In the case of degenerate intersections (surfaces or lines), a point in the intersection set is picked at random. Since this is a one period look-ahead model, the last period deployment is myopic and solved in the determination of the Nash equilibrium in the penultimate period.

The program for the COALITION scenario is fairly close to NASH. In every period the Nash equilibrium is first determined. A discretization of the search region is picked such that the grid size is less than 4% of the smallest deployment. The three best response surfaces [S1, S2, S3], and set of stable sub-coalitions [SC1, SC2, SC3] on each surface are determined. Finally, the set of points in the search volume, GC, that Pareto dominate 1. the Nash equilibrium and, 2. the three sets of stable coalitions [SC1, SC2, SC3] are determined. We pick the point on the Pareto frontier of GC that maximizes the reduction in the cost of green energy as the stable coalition. We pick the Nash equilibrium, N, if the sets GC, SC1, SC2 and SC3 are empty.

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Table 1: Solar PV capacity (in GW) from BP Statistical Review of World Energy([5])

Year	EU	China	USA	Japan	Others
2005	2.4	0.1	0.5	1.4	1.0
2006	3.4	0.1	0.6	1.7	1.2
2007	5.4	0.1	0.8	1.9	1.3
2008	10.7	0.1	1.2	2.1	1.8
2009	16.3	0.4	1.6	2.6	2.1
2010	29.6	0.9	2.5	3.6	3.1

Table 2: Predicted and reported 2011 deployments (in GW, assuming 15% efficiency)

Source	EU	China	USA	ROW	World
Predicted(MYOPIC)	15.3	0.7	1.3	2.4	19.7
PV Magazine [13]	21	2	1.6	3.1	27.7
ELECTROIQ [14]	-	1.7	2.7	-	23.8

Table 3: Electricity demand projections (TWh) from the International Energy Agency ([6])

Period	China	EU	US	ROW	World
0	4245.0	3332.0	4326	9422.3	21325.3
1	5238.9	3442.0	4499.2	10536.7	23716.7
2	6465.5	3555.5	4679.3	11782.9	26483.2
3	7605.3	3675.6	4851.1	13101.7	29233.7
4	8526.6	3802.5	5013.4	14485.6	31828.0
5	9559.6	3933.7	5181.1	16015.6	34689.9
6	10552.0	4061.1	5316.7	17686.5	37616.2
7	11647.4	4192.6	5455.9	19531.7	40827.6
8	12856.5	4328.4	5598.7	21569.4	44353.0

Table 4: Annual Green Energy (Solar PV) generation in 2010

Region	Generation (TWh)
China	1.15
EU	38.98
US	3.31
ROW	8.87

Table 5: Results for the REFERENCE simulation. The cost of green energy, c_g^t, decreases over time with increasing cumulative capacity. Recall that deployment of green energy in the current period is determined by the cost in the previous period. Period 0 refers refers to the initial condition data at the start of the simulation. The costs given for period *i* are the end of period costs that determine the next period's deployment. The numbers in boldface show when the cost of green energy is at or below the cost of new fossil energy.

	MYOPIC				NASH				COALITION			
Period	Cost	Gen.	Share	Subsidy	Cost	Gen.	Share	Subsidy	Cost	Gen.	Share	Subsidy
0	300	52.3	0	-	300	52.3	0	-	300	52.3	0	-
1	202.63	156.3	0.01	20.8	192.56	180.2	0.01	25.6	189.05	189.7	0.01	27.5
2	156.31	322.5	0.01	38.0	145.65	392.7	0.01	46.8	142.08	423.4	0.02	50.4
3	134.33	591.2	0.02	55.1	129.73	727.5	0.02	65.6	127.36	811.6	0.03	71.3
4	123.45	976.9	0.03	72.1	119.65	1176.7	0.04	83.9	117.21	1330.6	0.04	91.8
5	115.15	1478.1	0.04	89.0	111.73	1768.7	0.05	102.1	108.94	2055.2	0.06	112.7
6	108.12	2149.6	0.06	106.0	104.75	2595.7	0.07	120.2	**99.99**	3422.7	0.09	137.5
7	101.56	3120.2	0.08	122.5	**97.66**	3937.6	0.10	136.8	88.7	6981.8	0.17	149.7
8	**90.77**	6086.1	0.14	137.9	87.01	7825.0	0.18	148.6	82.1	11057.9	0.25	162.7

Units: Cost [$/MWh], Generation [TWh], (Annual Cumulative Global) Subsidy [$Billion (2010)]

Table 6: Cost assumptions for the Reference (R) and Rising Fossil Costs (F).

Period	Reference (R) New	Old	Rising Fossil Costs (F) New	Old
1	100	65	100	65
2	100	65	100	65
3	100	65	105	70
4	100	65	110	75
5	100	65	120	85
6-8	100	65	120	85

Units: Cost [$/MWh]

Table 7: Preference for green energy (B_i^t) in the Reference (R) and the Green China (C) simulation. The US and ROW preferences remains constant across scenarios.

	Reference (R)				Green China (C)	
Period	China	EU	US	ROW	China	EU
1	949.3	16290	1602.5	2761.1	3797.2	16290
2-8	949.3	16290	1602.5	2761.1	3797.2	8145

Table 8: Comparison of S_g, the average current period subsidy cost of green energy, across scenarios and simulations when the cost of green energy, c_g^t, is more than the cost of new fossil energy, c_f^t. For example, NASH/MYOPIC is the ratio of S_g in NASH w.r.t S_g in MYOPIC for the same period. Each cell of the table shows the range and the typical value in parentheses. Green energy subsidy costs in the COALITION scenario are typically 11% less than MYOPIC and about 5% less than NASH.

	S_g ratios between various scenarios		
Period	NASH/MYOPIC	COALITION/MYOPIC	COALITION/NASH
1st	$\sim$1	$\sim$1	$\sim$1
$c_g^t \geq c_f^t$	0.87-0.98 (0.94)	0.75-0.97 (0.89)	0.86-0.99 (0.95)

Table 9: Green energy deployment (in TWh) in the COALITION scenario for the Reference (R) and the Green China (C) simulations. In this particular case, the increase in China's preference for green energy makes up for the decline in the EU's preference.

	Reference (COALITION)			Green China (COALITION)		
Period	Cost	China	EU	Cost	China	EU
0	300	1.2	39	300	1.2	39
1	182.33	5.2	150.3	189.05	27.9	149.2
2	141.57	15.4	322.1	142.08	83.2	262.4
3	128.13	39.8	574.1	127.36	197.2	387.3
4	117.92	78.2	880.6	117.21	377.9	539.9
5	108.62	145.9	1252.1	108.94	725.3	713.8
6	100	587.4	1738.3	99.99	1410.7	902.1
7	89.24	1682.7	2217.7	88.7	2505.9	1136.6
8	82.87	2891.9	2904.1	82.1	3715.1	1471.7

Units: Cost [$/MWh], Generation [TWh]