Learning Rates and the Green Energy Deployment Game

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Abstract

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.

A simple game-theoretic model with three regions, (a region being a country or group of countries such as the EU,) is solved numerically to compare cost and deployment paths of solar photovoltaic (PV) energy under different assumptions. These assumptions include (1) un-coordinated myopic actions by all regions (2) un-coordinated actions by all regions but with some or all regions maximizing the present discounted value of current and next period utility, and (3) co-ordinated actions (maximization of the sum of present discounted utilities) by regions that sign a treaty with others responding myopically. Regional governments' utility functions are calibrated using observed deployment of solar PV under the assumption that they are myopic. 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. It is shown that an international treaty that includes the promotion of solar PV may result in significantly faster deployment and cost reduction than myopic unilateral actions. Forward-looking Nash behavior has a similar effect. In the reference scenario that assumes that fossil fuel prices remain constant, cost-competitiveness with fossil-fuel-based electricity is achieved 4-8 years sooner under forward-looking behavior that takes the learning rate into account than under myopic un-coordinated actions. In this scenario, under cooperation, PV accounts for 25% of world electricity output after 32 years.

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1 Introduction

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. This paper shows that policy coordination would enable acceleration of some existing unilateral policies and investigates the extent to which this could happen in the case of solar photovoltaic (PV) energy.

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

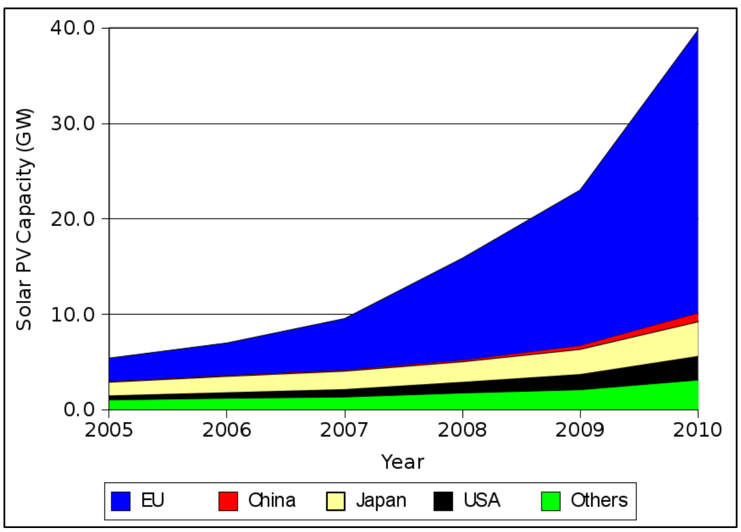

Figure 1: Growth of installed solar PV capacity between 2005 to 2010 [3].

We use data on deployments and costs of solar PV in the four-year period 2006-2010 to infer policy-makers' preferences for green energy. In this respect, we depart from most of the literature on modeling the effects of policies, which are either taken as exogenous, or are derived from a dynamic social welfare optimization problem. In contrast, we are interested in examining the gains from international cooperation *given* policy-makers' existing preferences.

The limited progress made by international negotiations in emissions reductions is partly 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 alternative 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. Yet, 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.

Below, we model a 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.

2 The Model

The policymaker of region i decides how much green energy to subsidize during her tenure. The regions modeled are China, the EU and the rest of the world (ROW). 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 and c_{oi}^t differ 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 benefit of green over fossil energy from the policymaker's perspective and $\mathcal{C}_i^t$ is the cost of green over 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 costs $\mathcal{C}_i^t$ are defined below:

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

The subsidy costs 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.

In the myopic case, the three regions 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. In the myopic strategy, the regions do not take into account 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

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

Using the observed data on deployment and costs in the period 2007-2010 [3, 1], B_i in that period can be inferred for three regions: the European Union (EU), China, and the Rest of the World (ROW). We find that B_i was highest for the EU at 16,290, and lowest for China at 949. B_i for the Rest of the World was 3,905. 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 1. 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.

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

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

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. 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 that would raise deployment above the Nash equilibrium level.

3 Simulations

In our simulations, we consider a set of scenarios using electricity demand projections (See Table 1) from the IEA [1] for China, the EU, and the rest of the world (ROW). Solar PV deployments in the three regions are:

Region	Initial Green Energy (TWh)
China	1.15
EU	38.98
ROW	12.92

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 [2, 4]). 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

	Annual Total Energy (TWh)			
Period	China	EU	ROW	World
0	4245	3332	13748	21325
1	5238.9	3442	15045.4	23726.2
2	6465.5	3555.6	16465.1	26486.2
3	7605.3	3675.6	17952	29232.9
4	8526.6	3802.5	19500.5	31829.6
5	9559.6	3933.7	21182.6	34675.8
6	10552	4061.1	22991.7	37604.8
7	11647.4	4192.6	24955.4	40795.4
8	12856.5	4328.4	27086.7	44271.6

Table 1: Electricity demand projections (TWh) from the International Energy Agency ([1])

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. In 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 the bulk of electricity consumption. The simulation runs for eight periods from 2010 to 2041. 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 myopic, 2. the EU looks ahead one period, 3. EU and CHINA play Nash, 4. all play Nash, 5. EU and CHINA cooperate, and 6. all cooperate.

3.1 The Reference Simulation

The Reference(R) simulation 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. The preferences of the three regions have been calibrated to reflect their 2006-2010 deployments, assuming a 1. 22% learning rate, 2. 2010 cost of green energy of \$300/MWh, and 3. that deployments were myopic. We also assume that the preference for green energy is constant. Most of the initial investment

Period	Myopic	EU looks ahead	China EU Nash	All Nash	China EU co-operate	All co-operate
0	300.00	300.00	300.00	300.00	300.00	300.00
1	203.91	193.89	193.86	193.38	192.61	188.04
2	158.11	147.47	147.42	146.52	145.72	142.37
3	135.39	130.87	130.85	130.29	130.01	127.52
4	124.60	120.91	120.88	120.22	120.09	117.04
5	116.41	113.18	113.13	112.20	112.32	107.67
6	109.56	106.50	106.41	**100.21**	105.40	**100.00**
7	103.15	**99.68**	**99.57**	88.95	**98.01**	88.85
8	**94.52**	88.15	88.10	82.39	87.37	82.33

Table 2: c^t_g 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. We note that looking ahead one period can lead to an additional 5%-10% reduction in the cost of green energy. The numbers in boldface show when the cost of green energy is at or below the cost of new fossil energy.

in reducing the cost of green energy comes from the region with the highest preference for it: the EU. This can be seen by comparing the global green energy deployment in the **EU looks ahead** scenario with the **China EU Nash** or the **All Nash** scenarios in the early periods. These investments require support in the form of subsidies. The 'baton' is passed to fast growing regions like

Period	Myopic	EU looks ahead	China EU Nash	All Nash	China EU co-operate	All co-operate
0	53.1	53.1	53.1	53.1	53.1	53.1
1	155.8	179.3	179.4	180.6	182.6	195.3
2	316.8	384.7	385	391.7	397.7	424.4
3	572.3	700.2	700.9	718.9	728.4	817.3
4	937.9	1121.4	1123.1	1160.3	1167.6	1360.6
5	1405.5	1661.7	1665.7	1749.7	1738.8	2235.3
6	2015.3	2385.4	2397.1	3425.9	2536.9	3469.5
7	2885.4	3535.9	3558.7	**6961.1**	3910.3	**7007.6**
8	4851.7	**7345.1**	**7369.3**	10980.7	**7743.3**	11030

Table 3: G^t, the global green energy deployment increases considerably when regions look ahead one period and, either play Nash or cooperate. The numbers in boldface show the jump in deployment when the cost of green energy at the end of the previous period (see Table 2 is equal to or below the cost of new fossil energy. The global deployment of green energy increases from 11% in the Myopic case to 25% when all three regions cooperate.

China and the rest of the world as the cost of green energy approaches, and subsequently, falls below the cost of new fossil energy. Compare the green energy deployment in periods 6 and higher between **All Nash**, **All cooperate** and the others. Here, deployment of green energy replaces the deployment of new fossil energy. This holds true for all scenarios. 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 substantially reduced due to the higher deployment, and lower cost of green energy.

3.2 Sensitivity Analysis

We construct simulations 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. We assume a CO_2 intensity of 0.5 tCO_2/MWh, about halfway between coal and gas. Finally, the cost can also fall with the discovery of new resources or technologies to extract currently uneconomical resources (e.g. shale gas in the US). We consider the following cost numbers (see Table 4) for simulations with falling and rising fossil fuel costs, assumed to be constant across regions.

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 re-

Period	Reference (R) New	Old	Rising Fossil Costs (F) New	Old	Falling Fossil Costs (C) New	Old
1	100	65	100	65	100	65
2	100	65	100	65	100	65
3	100	65	105	70	95	60
4	100	65	110	75	95	60
5	100	65	120	85	90	55
6-8	100	65	120	85	85	50

Table 4: Cost assumptions for the Reference, Rising Fossil Costs (C) and Falling Fossil Costs (F) simulations.

	Reference (R)			Pref 1 (P1)		Pref 2 (P2)	
Period	China	EU	ROW	China	EU	China	EU
1	949.3	16290	3905	949.3	16290	949.3	16290
2	949.3	16290	3905	3905	16290	3905	8145
3-8	949.3	16290	3905	3905	16290	7810	8145

Table 5: Data for simulations with 1. China's preference level increased to match the rest of the world's (ROW) and 2. China's preference level increased to twice ROW's and EU's preference is halved. ROW's preference remains constant across scenarios.

places old fossil capacity which is prematurely retired. A region with a high preference for green energy is less affected by these thresholds directly.

Another set of parameters that we vary is the preference for green energy B_i^t in the three regions. In simulation Pref 1 (P1), we raise the preference parameter of China to that of the rest of the world. In simulation Pref 2 (P2), we raise China's preference parameter to twice that of the ROW and halve the EU's preference for green energy. In Pref 1 we see that a higher preference for green energy in China leads to a faster decrease in the cost of green energy. This is due to the higher deployment in the initial periods as China is more willing to subsidize green energy. In Pref 2 we see that higher preference for green energy in China can even compensate for a reduction in the preference parameter in Europe.

	Rising Fossil Costs (F)				Falling Fossil Costs (C)			
	Myopic		All Optimized		Myopic		All Optimized	
Period	Cost	Deploy.	Cost	Deploy.	Cost	Deploy.	Cost	Deploy.
0	300	53.1	300	53.1	300	53.1	300	53.1
1	203.91	155.8	188.02	195.4	203.91	155.8	188	195.4
2	158.11	316.8	142.36	424.5	158.11	316.8	142.37	424.4
3	134.69	590.1	125.37	904	136.02	556.7	128.66	774.8
4	122.13	1056.5	**112.62**	1711.1	125.79	886.4	119.36	1210.9
5	**99.28**	3621.3	93.85	**5060.1**	118.74	1249.1	113.02	1675.2
6	88.38	**7235.1**	***85***	9121.8	113.58	1627	108.4	2147.6
7	***82.2***	11132.7	76.34	***17280.9***	109.25	2050.1	104.42	2681.8
8	74.5	***19987***	71.21	26135.2	105.51	2522.2	101.22	3228

Table 6: The numbers in boldface and underlined italics mark the periods when the cost of green energy crosses 1. cost of new fossil ($120/MWh) and 2. cost of old fossil ($85/MWh) respectively. Note the jump in green energy deployment in the subsequent period. These thresholds are not reached in the case of Falling Fossil Costs so the progress in cost reduction is slow.

3.3 Observations and Discussion

The model proposed in this paper 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 myopic policymakers only.
- 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 produce the fastest decline in the cost of green energy.
- The progress achieved by the two or three-region Nash games are quite close to that of the full cooperation 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

Period	Reference (R) Cost	China	EU	Pref 1 (P1) Cost	China	EU	Pref 2 (P2) Cost	China	EU
0	300	1.2	39.0	300.0	1.2	39.0	300	1.2	39.0
1	193.86	5	143.0	193.8	5.2	142.8	197.03	5.3	134.7
2	147.43	14.4	298.6	143.0	50.9	296.4	150.81	55.7	235.0
3	130.85	33.7	513.9	127.1	148.5	522.3	129.8	233.6	355.1
4	120.88	64.1	780.0	116.3	309.6	801.7	117.6	562.1	484.0
5	113.13	110.3	1090.4	107.1	626.0	1136.8	106.24	1281.2	641.8
6	106.41	187.6	1448.0	**98.5**	1174.9	1536.2	**96.7**	2273.2	840.3
7	**99.57**	334.7	1854.7	88.1	**2270.3**	2038.0	87.74	**3368.7**	1099.5
8	88.1	**1543.8**	2324.9	81.9	3479.4	2741.8	82.05	4577.8	1456.7

Table 7: We compare the Reference, Pref 1 and Pref 2 simulations for the scenario where China and EU play a two period Nash game and ROW is myopic. Note the difference between the numbers in boldface between the different simulations. In the Reference simulation, China's green energy deployments increase drastically only when the cost goes below the cost of new fossil capacity. In the other two cases, China has a higher preference for green energy and deploys early.

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.

References

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[4] *Assumptions to the Annual Energy Outlook (2011).* Energy Information Administration, 2011.