

THE RENEWABLE ENERGY INDUSTRY IN MASSACHUSETTS AS A COMPLEX SYSTEM¹

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Abstract

An abstract model of a local photovoltaic market was developed from a model-based field study. The system described by informants displays features of distributed and embedded agency: actors have the ability to take meaningful action, but that action and its effects are limited by the complexity of the system and by the actions of other actors. The structures necessary for dynamic growth are present, as expected in an industry that has had the growth of the PV market so far. Under several reasonable conditions, growth can be halted before reaching its potential: if reinforcing feedback processes saturate; if industry capacity grows too slowly; or if goals are too low or if they erode. Coordinated actions—multiple small interventions—are more effective than isolated large actions as a policy for market growth.

Key Words: Renewable energy, Photovoltaics, Industry growth, Mental models

Introduction

Renewable energy technology is a necessary part of the solution to major energy related problems: improving access to energy services, avoiding dangerous climate change, and reducing dependence on scarce resources. Deploying renewable energy has been a major challenge—despite the efforts of entrepreneurs and policy makers, and despite more than 30 years since the oil crises raised public interest, renewables represent a tiny fraction of energy consumed. Creating major change in the energy system will require coordinated action guided by an understanding of the complex system in which it occurs. This research is designed to develop that understanding, so that policy and strategy can work to deploy renewable energy. How does the renewable energy industry work as a system, and how could that system work better?

I address that question by collecting the mental models of experts in one segment of the renewable energy industry, and using system dynamics to organize the knowledge gained. I develop a behavioral theory of the photovoltaic (PV) market in Massachusetts which accounts for the full range of dynamic processes perceived by its participants. This theory is in the form of an abstract model of the system that can be used for policy analysis. Simulations using this

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model reveal that the future growth rate of the market is highly dependant on the strength of the feedback processes, initial conditions, and policy interventions. The strengths of the feedback processes in the industry are a more powerful influence on its behavior than the value of any variable. Although parameter values are too uncertain to make predictions on the state of growth, under a wide range of possible conditions policies that increase the attention paid to renewable energy are highly effective. The highest growth rates result from policy or strategic interventions that include multiple elements. Action that is both coordinated and sustained is important to getting the benefits from the multiple elements.

In this paper, I outline the methods and the data on informant mental models; a more complete description of these is found in (Jones, 2008). I describe an abstracted model of a local PV market which has high feedback complexity but low detail complexity. I analyze the behavior of two versions of that model: simulating observed market growth, and starting from equilibrium. I interpret the behavior to understand the interventions of industry actors, and to draw lessons regarding policy and strategy for industry growth.

Methods

The research design is a model-based field study: experts in the PV industry from private, public, and non-profit sectors were interviewed; the knowledge they conveyed was expressed as system dynamics models; those models were characterized, compared, combined, and analyzed. To view the renewable energy industry as a system in the system dynamics tradition is to see it as set of variables and the relations between them, changing over time, that exist because of choices and behavior of actors. This relates well to Garud & Karnøe's (2003) concept of distributed and embedded agency—what the actors are embedded in is a set of feedback processes, and each has awareness and power over only part of the system.

A model-based field study (Forrester, 1994; Lane, 1994) adds formal modeling language to the techniques exploratory qualitative research, making it possible to draw conclusions about system behavior from knowledge of system structure. The research drew on methods for grounded theory, particularly as applied to management research (Glaser & Strauss, 1967; Locke, 2001; Strauss & Corbin, 1994). Seventeen experts were interviewed, drawn from a deliberate or theoretical sample. Because their beliefs were a topic of research, the informants should be considered research subjects and I followed protocols for the protection of their rights including confidentiality and preventing disclosure of information with business value. Structured, open ended interviews were recorded; in addition, data included diagrams and sketches produced on oversize newsprint to provide a visual aid for feedback and initial analysis during the interviews. Questions probed each informant's knowledge about system structure and behavior, and their strategies and goals for their part of the system.

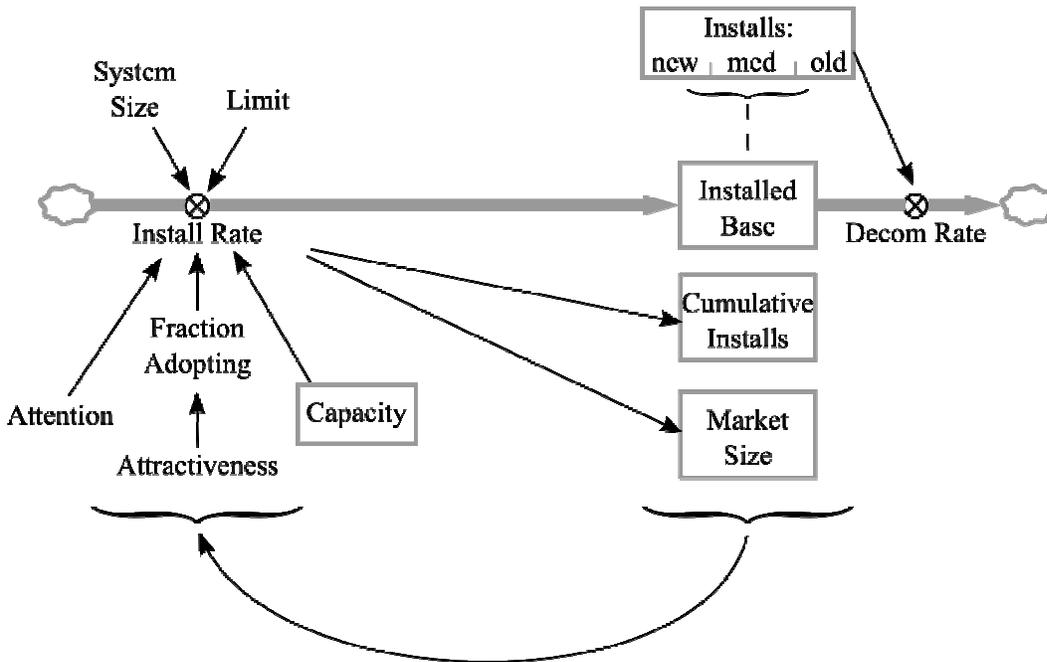
During analysis, system dynamics diagrams and models were constructed in place of the coding schema of more traditional grounded theory research. The information from each interview was examined for beliefs in causal links, feedback processes, dynamic hypotheses, and the structure implied by informants' descriptions. Based upon similarities in their mental models, informants were grouped into five clusters, four of which were the basis for building complete simulation models. Based on the lessons learned from these interim models, a combined model that incorporated all of the data and lessons from prior theory was constructed. The combined model, described below, was used to test policy and develop an understanding of the system as it is perceived by—and created by—those actors embedded in it.

Data

Informants described their industry as one of mostly dynamic growth processes pushing against static barriers. Each interview revealed several processes that depend on reinforcing feedback; on average, an informant described six of the fourteen reinforcing loops that were revealed in the data. In contrast, only seven of the seventeen informants identified one or two balancing loop processes. Most informants believed that feedback structures leading to falling cost were most important to market growth; a few believed that increasing capacity was more important, and two described a goal-seeking approach to some implicit desire for PV being the most important feedback process.

The structure of the system arises from the decision processes of customers as much as the physical flow of components. Most importantly, in both residential and commercial segments of the market, informants perceived a separation between the processes that lead customers to consider PV, and those that lead to the final decision. The difference between attention and attractiveness was exemplified by one informant, who described the most important factor in PV as the price of gasoline, and “after they get started, then it’s an economic decision.” The decision processes of PV firms result in investments in capacity; the most common described heuristics were chasing subsidies, chasing market size, and steady growth. After testing several formulations of these decision processes and comparing the results with data, the following model was found to adequately capture both the behavior and description of the local market for PV.

Figure 1: Combined model structure (Central flow)



Model

The level of detail included in this version is designed to test policy and industry-level strategy, and develop common understanding. Figure 1 shows the central stock and flow of a system that matches informants' descriptions of the adoption process. Some fraction of people aware of the option decides to purchase a PV system, subject to capacity constraints; those decisions result in installations which accumulate in installed base. Panels last on average 30 years, which is modeled as a three-stage aging process. Tests with the interim models revealed no value in modeling an explicit stock of people considering PV, or of orders in process, since residence in those stocks is short compared to the timescale of industry dynamics.

Install Rate in kW/year is the product of *Attention*, *Fraction Adopting*, and *System Size* limited by *Capacity* using a soft minimum labeled as the *Limit* function:

$$\text{Install Rate} = \text{Capacity} * \text{Limit}(\text{Desired Install Rate} / \text{Capacity})$$

$$\text{Desired Install Rate} = \text{Attention} * \text{Fraction Adopting} * \text{System Size}$$

System Size is fixed at 5 kW per customer for most runs. *Attention*, in customers per year, varies depending on feedback and inputs. *Fraction Adopting* is an S-shaped function of *Attractiveness*, which in turn depends on feedback and inputs; both are dimensionless ratios. Finally, *Capacity* in kW per year adjusts over time, once again depending on feedbacks and inputs. These components incorporate the insight from the informants—that there exist some factors that potentially have a continuing positive effect and others that reach some maximum. While this model retains the names of processes described by informants, the same structure could apply to any processes with these properties. *Attractiveness* can drive *Fraction Adopting* only to one; *Attention* could reach any value; and *Capacity* can continue to grow but has delays.

Also in Figure 1 is the feedback from accumulations of installs to the components of *Install Rate*. Processes that depend on the current market are based on *Market Size*, a running average of *Install Rate* that represents industry reports or other sources of market information. Effects that depend on the physical existence of PV panels are based on *Installed Base*, the most obvious accumulation of installs. Effects like learning-by-doing are based on constructs representing accumulated knowledge. A few informants called this concept “local experience”, but others used “experience” to mean awareness about the benefits of PV from other projects in operation. This model avoids that term by defining two classes of *Cumulative Installs*—short term and long term—to capture learning or resources from past installations that persist for some finite time. *Market Size* is a simple smoothing function of the current install rate; *Cumulative Installs* builds up and decays over medium or long decay times:

$$\text{Market Size} = \text{SMOOTH}(\text{Install Rate}, \text{MktSizeSmthTime})$$

$$\text{MktSizeSmthTime} = 0.5 \text{ year}$$

$$\text{Cumulative Installs}[\text{term}]$$

$$= \int \text{Install Rate} - (\text{Cumulative Installs}[\text{term}]/\text{CI DecayTime}[\text{term}]) dt$$

$$\text{term} \in [\text{long term}, \text{short term}]$$

$$\text{CI DecayTime}[\text{short term}] = 5 \text{ years}$$

$$\text{CI DecayTime}[\text{long term}] = 25 \text{ years}$$

Each of these accumulations could affect the components of *Install Rate*, completing many feedback loops. Informants perceived several processes that would form such loops. I combined parallel loops to reduce complexity. Table 1 shows them sorted into a matrix of net feedback effects, justified by specific processes identified by informants. *Market Size*, *Cumulative Installs*, and *Installed Base* are called the “origin” of the feedback effect because those stocks are the logical cause of changes in mediating variables. The cells of Table 1 are associated with a matrix (symbolized by the Greek letter gamma, Υ) which represents the strengths of the feedback loops. This structure abstracts out inter-related effects such as cost and benefits, or detailed predictions of future markets by different methods. The model concentrates on total effect, with positive strength indicating a reinforcing loop and negative strength indicating a balancing loop. In this form, all of the feedback loops include an equation in the same form as a learning curve function (Argote & Epple, 1990).

Table 1: Loops by origin and component of *Install Rate*

	Market Size	Cum. Installs short	Cum. Installs long	Installed Base
Attention	Familiarity	Education Market maturity	Institutionalization	Experience <i>Goal seeking</i> <i>Perceived need</i>
	Net Reinforcing	Net Reinforcing	Net Reinforcing	Net Balancing
Attractiveness	Proximity <i>Supply Pressure</i>	Scale Technology Finance cost	Learning by doing Reputation	(none)
	Net Balancing	Net Reinforcing	Net Reinforcing	
Capacity	Capacity investment	Capacity investment	(none)	<i>Perceived need</i> <i>Siting</i>
	Net Reinforcing	Net Reinforcing		Net Balancing

Effect of origin on component = $(\text{origin} / \text{origin}_{\text{reference}})^{\Upsilon_{\text{component,origin}}}$

where $\text{origin}_{\text{reference}}$ is the base or goal value for the origin stock

and Υ is a matrix over [component,origin]

origin \in

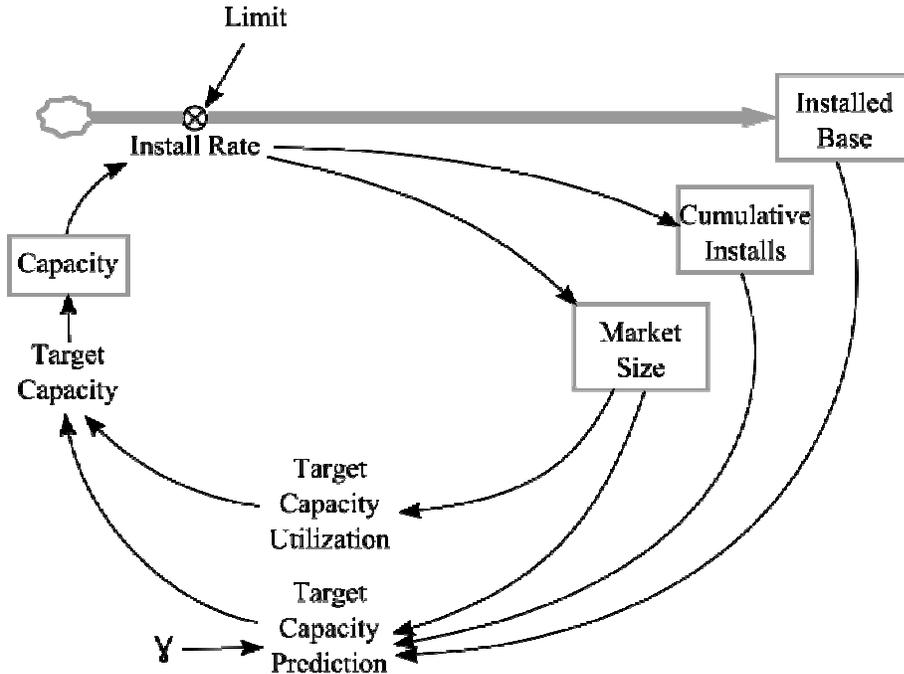
[Market Size, Cumulative Installs short, Cumulative Installs long, Installed Base]

component \in [Attention, Attractiveness, Capacity]

For most of the elements of Υ , a value of zero (no feedback) or a fraction represents realistic feedback rules. In the simulations below, values of 0.1-0.3 fit with complete feedback conditions, and values of 0.4-0.6 fit if there are only a few non-zero elements. The effect of *Market Size* on *Capacity* is the exception: a value of one represents the heuristic “grow capacity at the same rate as market growth”. Values slightly above or below one represent an exaggeration or discount of indicated growth. Within these guidelines, the magnitudes of Υ are varied in model testing.

Some of these feedback effects, particularly balancing feedbacks, include the possibility of delay. Three auxiliary stocks are modeled to represent these effects. Their names reflect the most prominent construct in informant beliefs; however these variables can represent more general and multi-dimensional constructs with similar feedback processes. *Capacity* directly

Figure 2: Combined model structure (Capacity)



limits *Install Rate*; *Local Supply* acts as the reference for the balancing effect of *Market Size* on *Attractiveness*; *Desire* acts as the reference for the balancing effects of *Installed Base* on *Attention* and *Capacity*.

Capacity is one of the determinants of *Install Rate*, but unlike the others cannot change quickly. Workers have to be trained and equipment purchased to be able to install PV; informants report it takes about 6-18 months to add local capacity. Two rules for the investment in *Capacity* are defined, either or a combination could apply. Some informants perceived capacity growth from workload; this is formulated by having a target *Capacity Utilization*—if firms are too busy they expand, too idle they contract. Other informants perceived capacity growth arising from predictions of market size, often based on the scale of incentive programs, and subject to feedbacks from *Market Size*, *Cumulative Installs*, and *Installed Base*. The feedback structure of capacity is shown in Figure 2.

$$\text{Capacity} = \text{SMOOTH3i}(\text{Target Capacity}, \text{Cap Delay Time}, \text{Init Cap})$$

$$\text{Target Capacity} =$$

$$(\text{Cap Util Wt}) * \text{Target Capacity}_{\text{Utilization}} + (1 - \text{Cap Util Wt}) * \text{Target Capacity}_{\text{Prediction}}$$

$$\text{Target Capacity}_{\text{Utilization}} = \text{Market Size} / \text{Tgt Cap Utilization}$$

$$\text{Target Capacity}_{\text{Prediction}} =$$

$$\text{Init Cap} * \text{effects of } [\text{Market Size}, \text{Cumulative Installs}, \text{Installed Base}]$$

Figure 3: Combined model structure (Attractiveness)

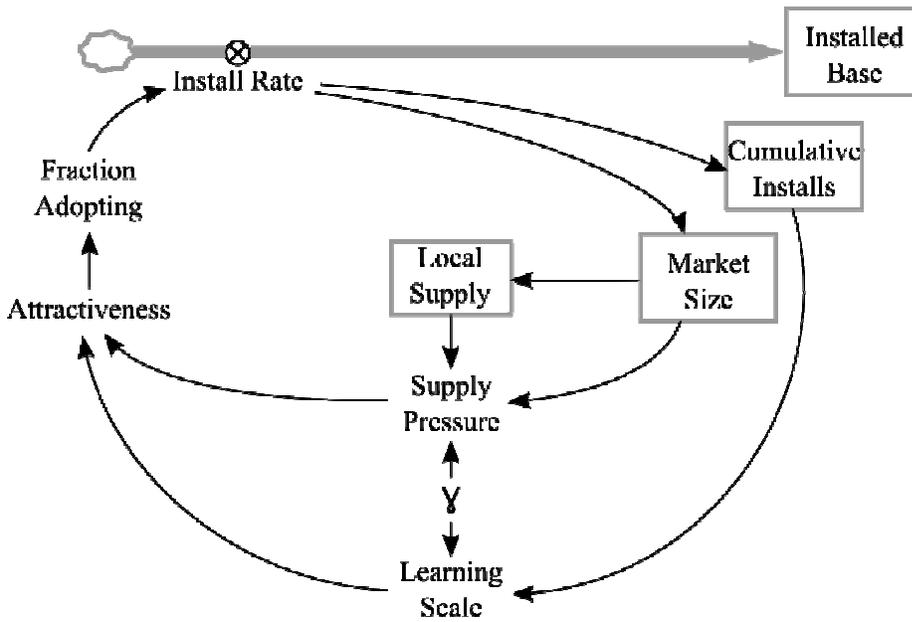
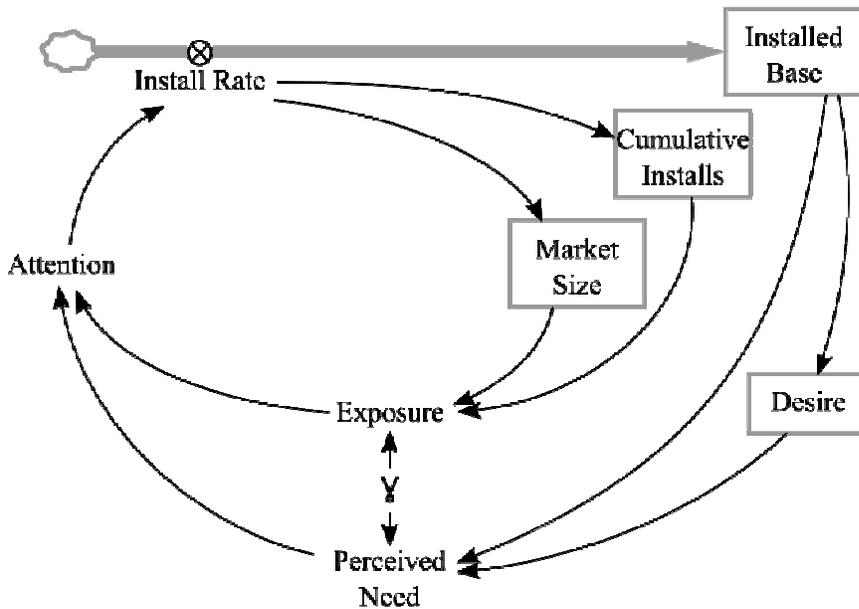


Figure 4: Combined model structure (Attention)



Local Supply represents the ability to source PV panels and other components; shortages of these have an impact on price, sales lead time, or other determinants of attractiveness. It is the interaction described by informants between the local and global markets—how much of the global supply chain can the local market capture. Absent other action, *Local Supply* adjusts to *Market Size* as a delay with a lag time of 6 months. *Local Supply* plays in the balancing effect on

Attractiveness from *Market Size*; the effects were described by informants as supply pressure. *Local Supply* and other feedback processes of attractiveness are shown in Figure 3.

The construct of *Desire* was a particular insight of informants in the *Desire* and *Actor* clusters. A gap between installed PV and some target creates a sense of urgency, a perceived need, which drives investments in the PV industry and sales PV systems. Success in getting PV installed can actually reduce that sense of urgency. The goal or target is vague and implicit and is perceived differently by different stakeholders; the variable *Desire* captures the net of these effects. Different options for the specification of *Desire* are tested, including a constant level, an eroding goal mechanism, an anchor on actual *Installed Base*, and a rising target. All the feedback loops acting on attention processes are shown in Figure 4.

Table 1 and Figures 1 through 4 depict the combined model which is used for policy testing. *Attention*, *Attractiveness*, and *Capacity* each depend on the product of ratios of stocks to reference points raised to exponents; the reference points and exponents can be varied to change the effective feedback structure of the system. In addition to the equations describing the system, exogenous inputs are used during model testing, or the behavior of variables is overridden, to simulate the actions of agents through policy or strategic intervention. A model in Vensim format is included as a supplemental file; an excel file is also included which includes both the values of Υ and the parameters used in model runs.

Behavior of the Combined Model

Although depicting a local market, in building an endogenous model the feedback loops incorporate changes that occur on the global scale. This is in effect an assumption that many local markets are acting similarly. The combined model can reproduce the observed growth of the Massachusetts photovoltaic market under conditions which imply a wide range of future trajectories. To illustrate the model behavior, I fit output to past data under several feedback conditions; I then test the sensitivity of future trajectory to key model parameters and policy interventions. Later, I present policy testing using counterfactual equilibrium market conditions to more clearly measure policy impact.

Massachusetts energy regulators estimate that there were approximately 500 kW of PV in service in 2000, and 4 MW at the beginning of 2008 (EOEEA, 2007). This constitutes an average growth of 29.5% per year in installed base; if the growth is steady, there would be a similar growth rate in market size. Figures 5 and 6 show plots of Installed Base (in kW) for several feedback conditions fitted to that data. Fitting was done using Vensim's optimization function, set to adjust *Base Attention* and *Base Attractiveness*, and the reference points and initial conditions on *Market Size*, *Cumulative Installs*, and *Installed Base*, but holding feedback strengths and policy inputs fixed.

Even for the same model parameters and feedback conditions, more than one trajectory can match past data. In general, any *Install Rate* could be the result of high *Attention* with low *Fraction Adopting*, or vice versa—*Attention* and *Attractiveness* can substitute for each other. Since *Fraction Adopting* can only rise to one, future growth is higher if *Attractiveness* starts low than if *Attention* starts low; changes in both variables take advantage of reinforcing feedback loops for longer. The different trajectories diverge rapidly, but over the limited time early in the market growth for which we have data they cannot be distinguished. This path dependence is one of the features seen in the model behavior.

Figure 5: Behavior of combined model – Positive feedback only

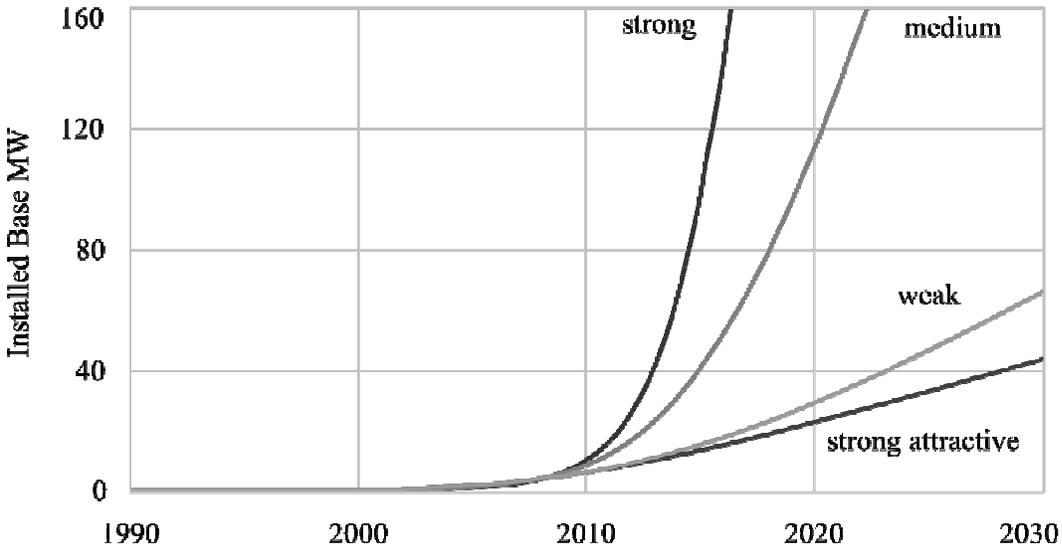


Figure 5 shows simulations with only positive feedbacks, representing a simple system. These runs have non-zero values of Υ only for learning-by-doing, education, and capacity investment type effects—only one reinforcing feedback loop for each component. The “strong” and “weak” feedback conditions have overall feedback strengths 20% higher or lower than the “medium” case; all of these start in 1990 with high *Attention* (~100 people/year) and low *Fraction Adopting* (~2%). The “strong / attractive” case has the same feedback parameters as “strong”; but starts with ~17 lookers per year of whom ~10% adopt. Even though all these simulations fit with prior data, the “strong / attractive” case is slightly closer to informants’ descriptions of the “tire kicking” rate.

Figure 6: Behavior of combined model – Complete feedback

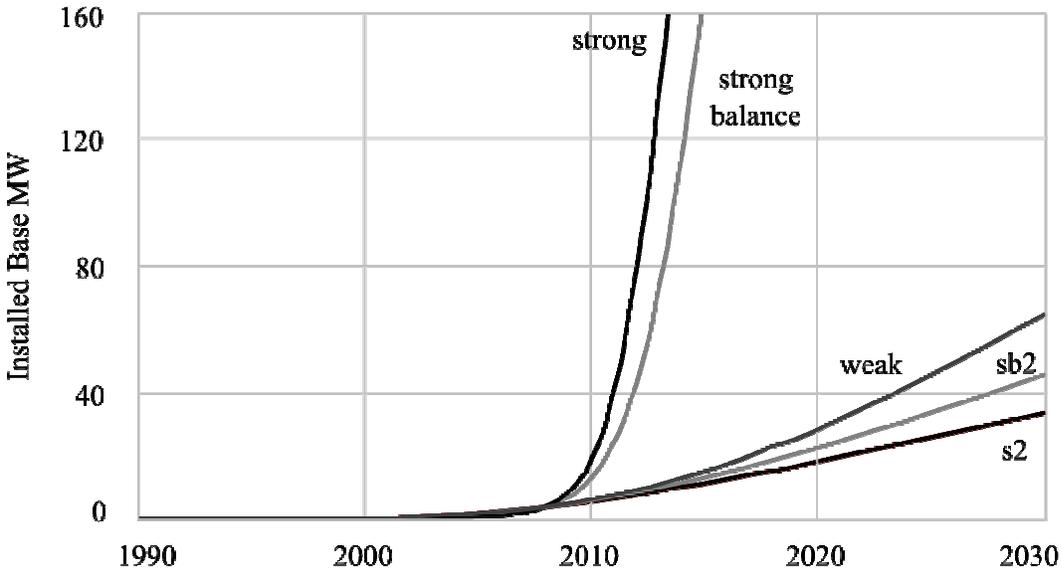


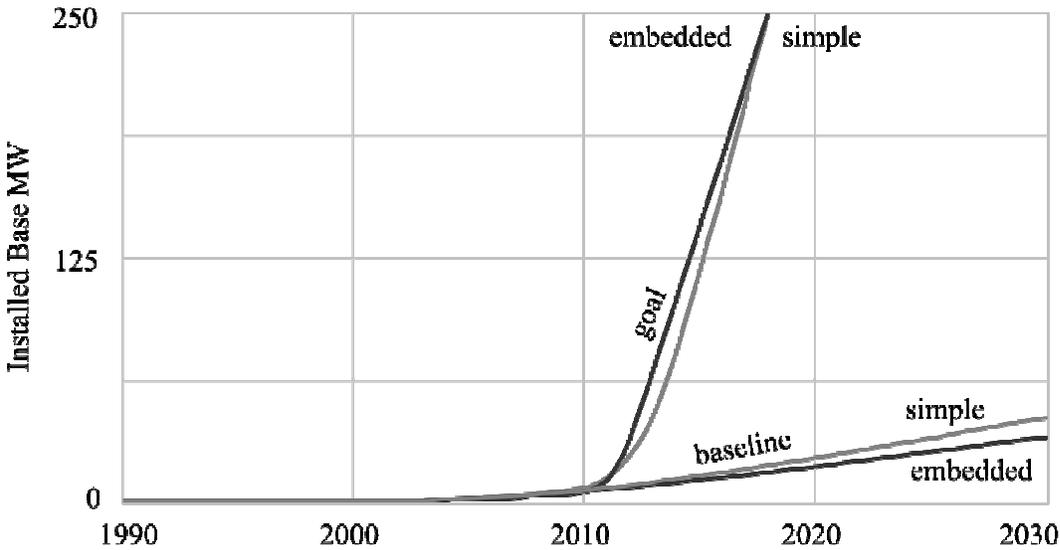
Figure 6 shows simulations with the full range of reinforcing and balancing feedback loops active, a more fully embedded system than in Figure 5. Here, the “strong” and “weak” feedback conditions have a slightly higher sum over the positive elements of Υ as “strong” and “weak” in the simple cases, but the values are spread over all the feedback loops and there are negative entries for balancing feedbacks. The values of Υ for all these cases are shown in Table 2. Also tested is a “strong balance” condition, with the same strength positive feedback loops as the “strong”, but triple the strength of balancing feedback. As in the simulations with positive feedback only, simulations with complete feedback can match past data with high *Attention*, implying higher future growth, or low *Attention*, with lower future growth. The “strong balance” feedback has lower future growth than “strong” from high *Attention* but faster growth from low *Attention* (curves labeled s2 and sb2).

Table 2: Feedback strength for model runs

		Simple				Embedded			
		MS	CI s	CI 1	IB	MS	CI s	CI 1	IB
weak	Attn	0	0.4	0	0	0.1	0.2	0.1	(0.1)
	Attr	0	0	0.4	0	(0.1)	0.2	0.2	0
	Cap	1	0	0	0	1	0.05	0	(0.05)
medium	Attn	0	0.5	0	0	0.2	0.2	0.2	(0.1)
	Attr	0	0	0.5	0	(0.1)	0.3	0.3	0
	Cap	1	0	0	0	1	0.1	0	(0.1)
strong	Attn	0	0.6	0	0	0.2	0.2	0.2	(0.3)
	Attr	0	0	0.6	0	(0.3)	0.3	0.3	0
	Cap	1	0	0	0	1	0.1	0	(0.3)

The trajectories represented by weak feedback strengths and by low initial *Attention* clearly are the more challenging for industry and for policy makers. For example, a proposal by Massachusetts Governor Patrick set a goal to have 250 MW of PV installed by end of 2017 (EOEEA, 2007). Specific interventions were not detailed, but assuming that systemic changes could be accomplished by 2010, there would have to be an increase in the growth rate to about 63% per year, more than twice the current rate, or even higher if it takes longer to ramp up. The higher trajectories under both simple and embedded cases reach that goal without further intervention—we would interpret the Governor’s announcement and subsequent incentives as part of the evolution of the system rather than a change of trajectory.

Figure 7: Response to aggressive policy



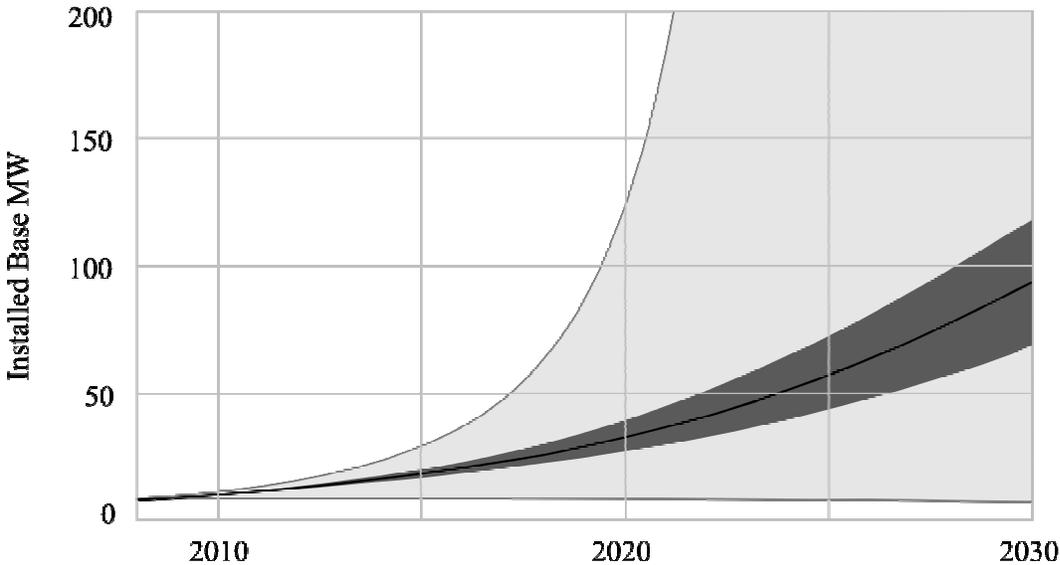
If conditions are such that the trajectory does need to change, multiple interventions are required to reach the goal. Figure 7 shows two similar trajectories that accomplish the same goal. The feedback conditions are the “strong simple” and “strong embedded” from Table 5.2; initial conditions are high *Attractiveness* and low *Attention*. The minimum changes required to reach 250 MW at the end of 2017 depend on the feedback conditions. In the simple, pure reinforcing condition, *Target Capacity* must rise by 2000 kW/year in 2008 anticipating future sales, and in 2010, programs attract an additional 7000 people per year in *Attention*. For the more embedded case extra *Desire* must be generated equal to the 250 MW goal, which attracts attention and spurs capacity building; and in 2010 an extra 5700 people per year worth of *Attention*. In neither feedback condition can any one parameter change shift the trajectory to reach 250 MW by the end of 2017.

Both of these feedback conditions are optimistic, in that without further intervention the systems they describe would grow rapidly into the future. These two scenarios start from unfavorable initial conditions compared to other possibilities that fit past data, and we are unable to distinguish which conditions are more accurate. Even so, large parameter inputs, representing large and multifaceted policy or strategic interventions, are needed to have them match stated goals. These particular policy interventions—focusing on attention and capacity—work because under these initial conditions attractiveness does not have far to grow before changes in attention are worthwhile. Under conditions such that the market has not moved past its “tire-kicking” phase, interventions in attractiveness are more important.

Sensitivity testing

Sensitivity analyses measure the relative impact of various changes in a more systematic way. Starting in year 2008 from a midpoint of possible fits to historic data, with moderate *Attention* and room for improvement in *Fraction Adopting*, the following tests vary parameters one at a time to measure the impact on market outcomes. These tests are centered on the “strong embedded” feedback condition, and vary the magnitudes of γ between 0 to 0.5 (0.8 to 1.2 for

Figure 8: Sensitivity analysis



$\gamma_{cap,MS}$). Also tested are inputs to *Attention* and *Attractiveness*, both positive and negative, to represent problems or policy interventions.

Figure 8 shows the range of possible trajectories that result from changes in single parameters, starting from the same initial conditions. The central trace reaches 29 MW in 2020 and over 90 MW by 2030, in the middle of the simulations shown in Figures 5 and 6. Half of all trajectories (the dark grey band) are within 30% of the central trace. The extremes on the high-growth end all result from very strong feedback loops on *Attention*. The lowest traces, which peak early and decline to below the 2008 *Installed Base*, can result from absent or extremely weak feedbacks on *Attractiveness*, or strong negative inputs to *Attractiveness*; missing feedback loops on *Attention* lead to trajectories nearly as bad. From these particular initial conditions, the market may reach its upper limit based on *Capacity* for short periods of time, but the overall trajectory is only limited by *Capacity* in the extremely high growth conditions.

Examining the outliers in the sensitivity analysis illustrates what are potentially the worst problems and most transformative areas for improvement. For static barriers, a reduction in *Attractiveness* is worse than a reduction in *Attention*, but a simple improvement in either one offers relatively little compared to the base case on its own. For dynamic changes, breaking any of the reinforcing feedback loops can prevent the growth of the market, and strengthening positive feedback loops that act on *Attention* are by far the most powerful single actions. Informants' self-described actions also make sense in light of these tests: much of the work of the institutional entrepreneurs in this system can be interpreted as ensuring that positive feedback processes exist. For example, publicizing success stories helps the feedback from installations to familiarity; convening market participants and sharing best practices helps the feedback from installations to learning and lower cost.

Extreme changes in parameter values represent major problems or major interventions. For more moderate action, *policy elasticities* (Sterman, 2000: 854) are a guide to the relative

Table 3: Policy elasticity from sensitivity analysis

Parameter	Normal case	Supply constrained
Attention Input	1.53	0.22
Attractiveness Input	0.92	0.33
Υ [Attn,MS]	2.24	0.45
Υ [Attn,CI s]	2.21	0.47
Υ [Attn,CI l]	2.39	0.51
Υ [Attn,IB]	-0.057	-0.002
Υ [Attr,MS]	-0.007	-0.001
Υ [Attr,CI s]	1.8	0.54
Υ [Attr,CI l]	1.92	0.55
Υ [Cap,MS]	0.94	2.89
Υ [Cap,CI s]	0.075	0.23
Υ [Cap,IB]	-0.046	-0.17

power of various changes in the system. Policy elasticity is defined as the change in a policy relevant outcome resulting from a change in a model parameter; if a 10% increase in price results in a 10% decrease in growth rate, the policy elasticity for growth rate on price is -1.0. In Table 3, the outcome of interest is the level of *Installed Base* in 2020, chosen because goals often target that year. Policy elasticities are shown for two initial conditions, two classes of policy inputs, and the values of feedback loop strength. These elasticities only apply to small changes near the center trace because growth has a non-linear response to each of these parameters, but the ranking of elasticities applies over a much wider range. The normal case is the same sensitivity test as shown in Figure 8; the supply constrained case has slightly lower *Initial Capacity* balanced with higher *Base Attention* to result in the same trajectory, but the limiting factor is capacity growth.

When capacity is sufficient for growth, the parameters of greatest impact are the strengths of reinforcing feedback processes that act on *Attention*. After feedbacks on *Attention*, the next most powerful changes are the reinforcing feedbacks on the *Attractiveness* of PV, followed by direct inputs to *Attention*. Direct inputs to *Attractiveness* and changing the feedback strength for capacity investment each have moderately strong impact. In terms of strategic and policy actions, these parameter changes correspond to changing the *process* by which PV becomes familiar, then the *process* of economies of scale or learning, then a direct program of raising attention, followed by a tie between the cost effect of an incentive program and adjusting how capacity investments follow market growth. If the market starts from a condition where the capacity to deliver PV is the limiting factor, than changing how capacity decisions are made is by far more effective than any other intervention. In the conditions tested here, the industry is not overly affected by balancing feedback effects—price is not strongly increased by supply-

demand imbalance, the desire for clean energy or lack thereof does not come to dominate the market. Like the supply constrained case, the model can be manipulated into a condition where those do become limiting, in which case the balancing feedback strengths have higher policy elasticities.

These simulations and sensitivity tests indicate the importance of structure, in the form of feedback strengths, over other parameters. Changing the process by which people come to consider PV is much more powerful than injecting new people interested in PV. The relative effectiveness of single changes can be judged from the policy elasticities, but it is difficult to evaluate more complex strategic moves. All these cases are based on parameters fitted to past data, and therefore must already incorporate existing policy into their feedback strengths. In the growing systems it is particularly difficult to separate the components of *Install Rate*—until *Fraction Adopting* reaches its limit, changes in *Attractiveness* and *Attention* can substitute for each other. The simulations in Figures 5 and 6 show the sensitivity of the future to baseline values—which are uncertain as seen by the diversity in the trajectories that fit observed data. To more carefully explore the policy space I take advantage of the ability inherent in formal modeling to simulate counterfactual conditions and test the system’s response as changes are made from an equilibrium condition.

Policy testing

With no changes to the structure, the combined model is set into equilibrium conditions, with installations exactly making up for decommissioning. This could only occur if market size were held constant for several lifetimes of PV systems. Despite the departure from reality, testing from equilibrium has several advantages. From equilibrium, it is easier to compare small changes. Testing allows looking at the system without confounding current policies with the natural system response. We can examine different policy and feedback conditions to see which have permanent effect and which are only transient. And, since we suspect we are actually in a growing system, we can get an idea of the way actors must currently be affecting the system in order for that to be so.

Table 4: Feedback strength for policy testing

		MS	CI _s	CI _l	IB
simple	Attn	0	0.6	0	0
	Attr	0	0	0.6	0
	Cap	1	0	0	0
embedded	Attn	0.2	0.2	0.2	(0.1)
	Attr	(0.1)	0.3	0.3	0
	Cap	1	0.1	0	(0.1)
high inertia	Attn	0.2	0.2	0.2	(0.3)
	Attr	(0.3)	0.3	0.3	0
	Cap	1	0.1	0	(0.3)

Table 5: Policy elements for policy testing

Policy Element	Parameter change
Marketing	Attention
Incentive	Attractiveness
Installer	Target Capacity
Distributor	Local Supply
Vision	Extra Desire

The model is simulated for 30 years, from 2005 to 2035, and various policies are changed in the year 2010. These runs start from a *Market Size* of 1000 kW per year, approximately the current value; *Attractiveness* is such that 30% of people looking buy; *Capacity* and *Attention* are at the levels to sustain these rates. For the same level of *Attractiveness*, two equilibrium cases, normal and supply constrained, are constructed by changing the bases on *Attention* and *Initial Capacity*. In equilibrium, *Desire* must be equal to *Installed Base* and the installs are equally distributed among vintages; equilibrium *Installed Base* is *Market Size* times *Lifetime* or 30 MW.

For the purposes of policy testing, three of the strong feedback conditions from Table 2—strong simple, strong embedded, and strong balancing—are tested against several policies. Table 4 reproduces the values of Υ with the names used in this section. No matter what the feedback parameters, all values remain constant until interventions occur. Possible policy or strategic

Table 6: Policy elasticities from policy testing

Normal case			
Policy Element	simple	embedded	high inertia
Marketing	0.092	0.11	0.10
Incentive	0.085	0.10	0.094
Installer	0	0	0
Distributor	0	0.008	0.023
Vision	0	0.007	0.022

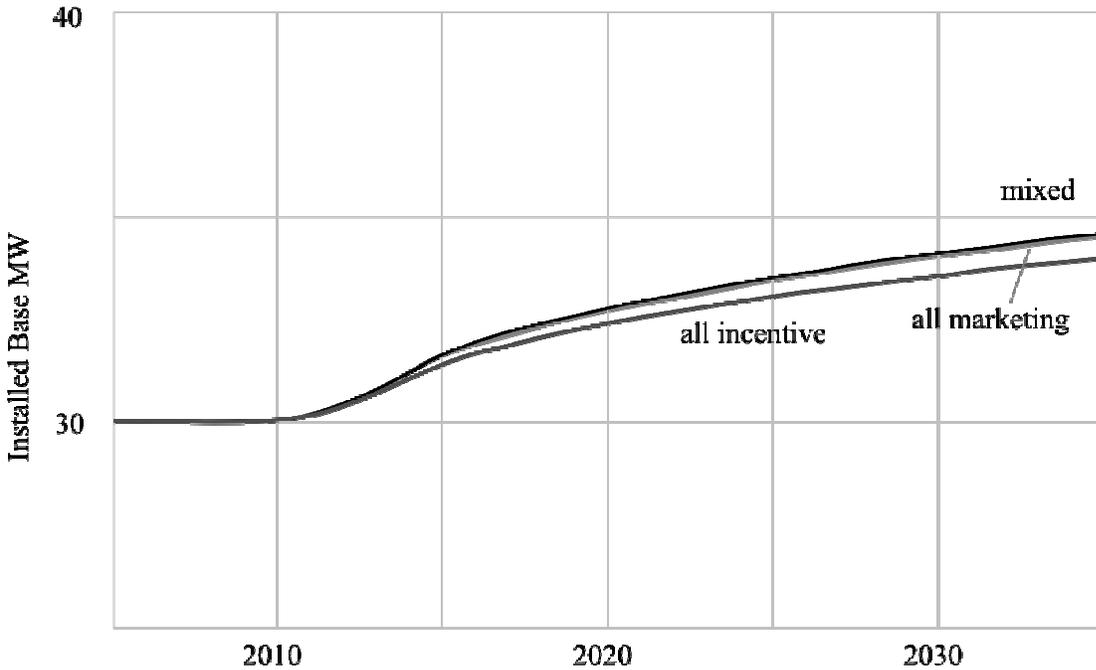
Capacity constrained case			
Policy Element	simple	embedded	high inertia
Marketing	0.082	0.098	0.093
Incentive	0.075	0.088	0.083
Installer	0.023	0.027	0.026
Distributor	0	0.007	0.021
Vision	0	0.011	0.032

interventions are represented by temporary inputs that increase model parameters; Table 5 gives intuitive names for the policies along with the model parameter affected. Thus, policy testing includes two capacity cases (normal and constrained), three feedback conditions (simple, embedded, and high inertia), and five policy elements.

Table 6 shows sensitivity tests on these thirty combinations. A marketing policy—raising *Attention*—is the most effective single intervention under all conditions tested; an increase in *Attention* results in a greater change in the *Installed Base* in year 2020 than an equal change in other parameters. An incentive type of program that raises *Attractiveness* is the second most effective in all cases. A policy to increase installers has no effect if *Capacity* is already sufficient, but that becomes a moderately effective policy in the capacity constrained case. Interventions on *Local Supply* and *Desire* have no effect in the simple feedback condition—those balancing feedbacks are simply not active—and limited effectiveness in the embedded feedback condition. They are moderately effective however in the high inertia condition where balancing feedbacks are strong.

Note that these measures of effectiveness, policy elasticities, compare equal relative changes in parameter values, not equivalent effort. It may be less expensive, for example, to make a large change in the implicit variable *Desire* by setting forth a bold vision than to change *Attractiveness* by a few percent through a rebate program. Lacking information on how achieve a given change in parameter, we can still use the change in the parameter as a proxy for the size of intervention. For the policy tests below, I mix multiple policy elements to demonstrate the effects of combined and coordinated action. The size of each element is defined as a percent change from the base value; the programs are temporary and can vary by duration and start time.

Figure 9: Effect of combined policy elements



For example, an incentive program might raise *Attractiveness* by 10% its equilibrium value for five years, meaning a few more percent of those who look will adopt.

Combinations of policy elements are usually more effective than elements in isolation. In Figure 9, combinations of incentive and marketing programs are implemented from 2010 to 2015, in a world of capacity constraint and high inertia. As expected from sensitivity testing, a marketing program that raises *Attention* by 30% results in higher growth than an incentive program that does the same for *Attractiveness*. The difference in *Installed Base* increase is 12%, approximately the percent difference in their policy elasticities. What could not be seen from policy elasticities is that a mix of marketing with incentives is above marketing alone; the best ratio of about 27% effort into incentives results in a 2% higher *Installed Base* than marketing alone. Even though marketing is the best single action to take based on system response, transferring some of that effort to a less effective action mobilizes additional reinforcing feedback loops. For changes on this scale, a combination of marketing and incentive is the best policy under any of the capacity or feedback conditions, even though the best ratio and the resulting growth is different for each.

For large interventions, combined policy is even more important, since growth can actually lead to new problems. A ten-year marketing program that can raise *Attention* by 200% will lead to 85.6 MW of installed PV by 2035 in the capacity constrained high inertia case, but the market is suppressed for many years by being at the absolute limit of capacity, waiting for investments to catch up. As seen in Table 7, combinations of marketing and installer policies beat marketing alone or marketing and incentives, which is never the case for smaller interventions. A combination of all three policies is even better, and the best intervention that could be found includes diverting even more effort from marketing to make a small investment

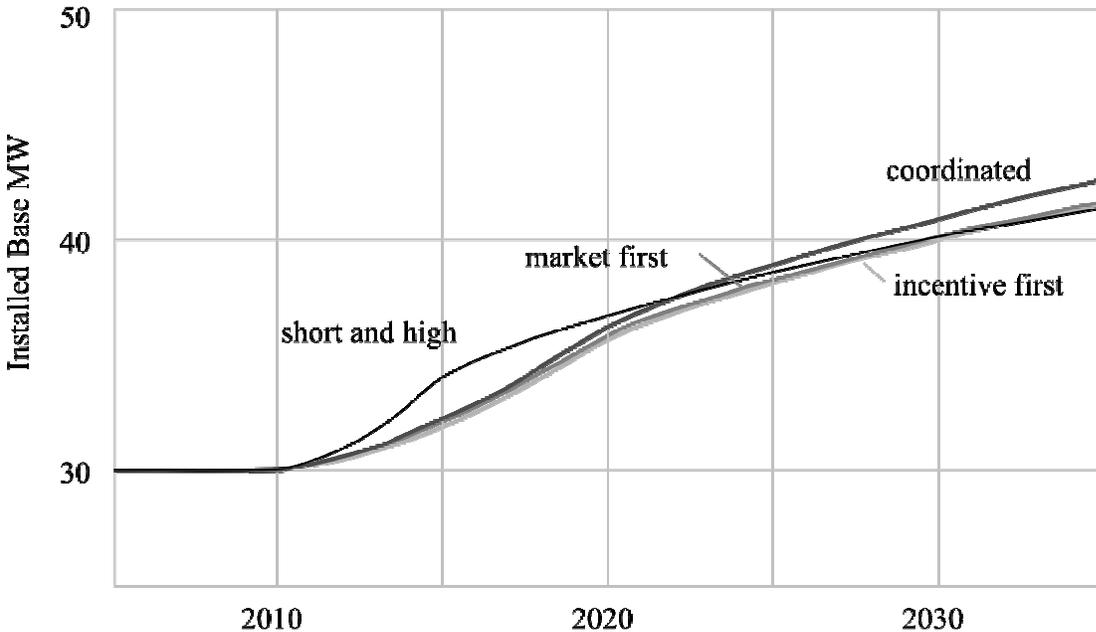
Table 7: Combined policy elements for high growth

Policy Elements (% change)	Installed Base in 2035 (MW)
Marketing (200)	85.6
Marketing (180) + Incentive (20)	90.3
Marketing (180) + Installer (20)	95.4
Marketing (160) + Incentive (20) + Installer (20)	100.3
Marketing (130) + Incentive (30) + Installer (35) + Vision (5)	103.5

in raising the level of *Desire*. For large changes from equilibrium, the best policy is sensitive to feedback and initial capacity conditions, since different limiting factors are reached in each case, but some combinations of several policy elements are always better than a single large parameter change.

Timing plays a role in the effectiveness of combined action as well. Coordinated action results in higher growth than sequential action, and large interventions of short duration are inferior to sustained small interventions of the same total magnitude. Figure 10 shows both features of the system for combinations of incentive and marketing policy elements. A 20% increase in both parameters sustained for ten years is the best combination, superior to sequential five year programs raising *Attention* and *Attractiveness* by 40% each, in what ever order, despite the same total intervention and duration. All of these ten-year policies are superior to raising *Attractiveness* and *Attention* by 40% for five years together.

Figure 10: Effect of coordinating policy elements



Taken together, these behavioral tests indicate the system as modeled does match the behavior of the photovoltaic market as described by informants, and that a system with the structure they describe has features common to many complex systems. The structure of the system, its feedback strengths and initial conditions, is far more important in determining future trajectories than other parameter values. In the system as modeled, feedback strengths and policy actions that affect the attention paid to renewable energy are more important than those that affect the attractiveness or capacity to install it. Though policies on attention are higher leverage than others, combined and coordinated action is important—particularly when growth leads to reaching new limiting conditions. Interventions with many policy elements, that occur concurrently, and that spread the effort over longer durations are superior to other policies.

Conclusion

The large scale behavior of the renewable energy industry results from the fine scale structure of individual and organizational decisions. A behavioral theory of the Massachusetts photovoltaic market, in the form of a system dynamics model which incorporates the details described by industry experts, matches the observed behavior of the market and gives important insights for policy and strategic action. Details of the PV market—the difference between exploration and adoption, the way firms invest in capacity, the perception of solar power by potential customers—interact with higher order phenomena to determine the trajectory of the system. There is no simple relationship for market penetration as a function of cost; the diffusion of photovoltaics follows a path that depends on initial conditions, policy, strategic action, and system structure. The best interventions include multiple elements and coordinated and sustained action at several points in the system. The strengths of the feedback processes in the industry exert a more powerful influence on its behavior than any other factor.

Although parameter values are too uncertain to allow for predictions of market growth, policy testing reveals lessons about policy that are robust to changes in assumptions. Over different feedback and capacity conditions, an intervention that raises attention is the highest leverage single change, but a combination of increases in attention and attractiveness will outperform a single intervention. The faster the market grows, the more important multiple policy elements becomes, because growth can lead to the system reaching new limiting conditions. Timing of interventions plays a role as well: low level sustained interventions are superior to short-lived high impact interventions, and multiple element interventions are more effective if concurrent than if they are sequential.

The models developed here are insufficient to determine what size of incentive produces what change in market trajectory. The responses of model behavior to different combinations of policy elements, and the difference between the responses of combined programs under different sequences, show how effects other than the size of an intervention matter. It is more important to consider the many effects of any strategic or policy choice, and to consider all the choices that are needed to have a single effect, than it is to select the correct value for a rebate program.

An intervention of the scale of Germany's feed-in tariff law is likely to work in any system with positive feedback. But the lesson is not that it is sufficient to encourage growth to institute a large subsidy. Considering the behavior shown in simulations, the situation in Germany was more than a single action. The German market had for years been building supply; the announcement of the new rules attracted great attention and spurred investment in capacity; the commitment to renewable energy changes both explicit and implicit goals for the system. These factors are likely to be as meaningful as the economic value of the rules.

Massachusetts has set a goal of 250 MW of installed PV by the end of 2017 (EOEEA, 2007). Simple calculations show the magnitude of the challenge of meeting that goal—an increase in growth rate from an already high 30% per year to 63% per year, if that increase can suddenly happen in 2010. Simulations reveal that, in the system described by informants, no single intervention is likely to work. Instead, it requires coordinated action, including a preemptive increase in capacity, so that the ability to deliver and install panels in place before the demand for them is generated.

The behavior of models in this research depends more strongly on the feedback parameters used than the interventions made. Feedback loops that act via attention and attractiveness have the highest policy elasticities—unless capacity is a limiting factor in which case its main loop has the highest sensitivity. What the policy sensitivities mean is that the highest leverage actions are changing the processes by which accumulations of market choices lead to greater attention, greater attractiveness, and, greater investment. These model results correspond with some of the activities that informants described, particularly those informants who get projects done or grow the market. Publicizing success stories, convening industry actors, sharing information, and building confidence are all means of connecting elements of the system. The real work done by institutional entrepreneurs is the model equivalent of building and maintaining critical links in the feedback loops—which turns out to be the highest leverage activity.

The observed growth of the photovoltaic market indicates that reinforcing structures must be present, and informants' mental models include plausible mechanisms by which reinforcing loops act. Individual and firm decisions accumulate to cause higher order phenomena, which in

turn affect the trajectory of the industry, mediated by decision processes. Feedback loops like familiarity and learning are assumed to be a natural part of the system, but informants also describe the difficult work that goes into creating and maintaining links. Incentives and awareness programs make use of reinforcing feedback processes; the best policy would be to support the people who strengthen feedback processes.

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