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Adoption of residential solar power under uncertainty: Implications for renewable energy incentives

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HIGHLIGHTS

- We examine household adoption of solar PV using the option value framework.
- Uncertainty in benefits and costs leads to delay in investment timing.
- Discounted benefits from solar PV have to exceed investment cost by 60% to trigger investment.
- Policy incentives that reduce uncertainty in returns from solar PV are most effective.

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ABSTRACT

Many incentives at the state and federal level exist for household adoption of renewable energy like solar photovoltaic (PV) panels. Despite generous financial incentives the adoption rate is low. We use the option value framework, which takes into account the benefit of delaying investment in response to uncertainty, to examine the decision by households to invest in solar PV. Using a simulation model, we determine optimal adoption times, critical values of discounted benefits, and adoption rates over time for solar PV investments using data from Massachusetts. We find that the option value multiplier is 1.6, which implies that the discounted value of benefits from solar PV needs to exceed installation cost by 60% for investment to occur. Without any policies, median adoption time is eight years longer under the option value decision rule compared to the net present value decision rule where households equate discounted benefits to installation cost. Rebates and other financial incentives decrease adoption time, but their effect is attenuated if households apply the option value decision rule to solar PV investments. Results suggest that policies that reduce the uncertainty in returns from solar PV investments would be most effective at incentivizing adoption.

1. Introduction

Solar energy has received growing support from the United States (US) government in the past several years. State governments, in particular have introduced various incentive programs in the form of rebates, tax incentives, and mandates (DSIRE, 2013). Many of these policies are targeted specifically to small residential installations, which is projected to be the fastest growing segment in solar installations in the US (GTM Research and Solar Energy Industries Association, 2014). In the state of Massachusetts, the combination of federal and state incentives has lowered the cost of a typical 6-kW residential system by over 50%, from about $33,000 to $16,000.[1] Despite generous incentives, adoption rates have been low. In 2012, less than 0.5% of households in Massachusetts that own their homes have solar panels.[2]

One possible reason for the low uptake of solar PV is the presence of uncertainty in the pay-off over the lifetime of the PV

[1] The average installed cost of PV systems under the Massachusetts Solarize II program that ran from 2010–2014 was $33,000 for a 6-kW system. The average rebate received for each installation was $4000. Adding the federal and state tax credits of $12,000 to the rebate amount gives the total incentive amount of $16,000 which is 48% of installation costs. Including payments for solar renewable energy credits (SRECs) which could vary from roughly $1000 to $2500 per year depending on the SREC price, increases the incentive amount to over 50% of installation cost (MassCEC, 2013).

[2] In 2012, an estimated 7256 homes have solar PV installed, out of about 1.6 million owner occupied housing units in Massachusetts (National Renewable Energy Laboratory, 2013; U.S. Census Bureau, 2012).

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system. Adopting solar PV involves large upfront costs with uncertain future benefits. Furthermore, the investment is irreversible or very costly to reverse. Thus, households may see a benefit or 'option value' to waiting to see how energy prices, government incentives, and solar PV technology will evolve before deciding to invest. The option value model for investment under uncertainty suggests that in the context of irreversible (or costly reversible) investments and uncertain future benefits, agents see a value to postponing the investment decision until uncertainty is resolved (Dixit and Pindyck , 1994). This implies that compared to investments whose returns are subject to less uncertainty, households may require a higher rate of return on their investment in solar PV. Thus, one would observe less adoption relative to the case where net benefits from solar PV adoption could be obtained with certainty. Since significant public funds are being expended on solar incentive programs, it is important to examine the effect of uncertainty on households' decisions to investment in solar power, and what this effect implies for policies that incentivize adoption of solar PV.

We find that uncertainty has a significant impact on the timing of investment in residential PV. When we assume that households take into account the option value of their investment dollars, the present value of benefits from solar PV needs to be 60% greater than installation costs for investment to occur. Compared to the net present value (NPV) decision rule that equates discounted benefits to initial investment cost, the median adoption time under the option value (OV) decision rule is 6–21 years longer depending on assumptions about what policies are in place. We find that financial incentives like rebates and tax credits decrease adoption times under both the NPV and OV decision rules, although the effect is weaker under the OV decision rule. Revenues from solar renewable energy credit markets have a modest effect on adoption times under the NPV decision rule, and may even increase adoption time under the OV decision rule. These results suggest that policies that reduce uncertainty of returns from solar PV investments would be most effective at encouraging adoption and diffusion of solar PV technology.

This paper is related to a number of previous studies that have examined the effect of uncertainty on technology adoption and energy investments. Hassett and Metcalf (1993) provide the first formal application of the option value framework to investments in energy efficiency. Using data on electricity prices and capital costs in the U.S. from 1955–1981, they conclude that the threshold rate of return on investment for energy efficiency investments is over four times that of the conventional rate of return. Isik (2004) uses the option value framework to examine the impact of policy uncertainty on the adoption of site-specific technologies by farmers in the state of Illinois. He considers the impact of policy changes, specifically the probability that an existing subsidy will be removed and the probability that a subsidy policy will be implemented when none currently exists. He finds that the expectation of a subsidy removal encourages investment, while the probability that a subsidy will be provided in the future delays investment. Ansar and Sparks (2009) also use the option value framework to examine the effect of uncertainty on the decision to invest in solar PV. They extend the model developed by Hassett and Metcalf (1993) by incorporating the effect of experience-curves on the drift and variance of benefits from solar PV adoption. They also consider the possibility of a downward jump in future benefits that would cause benefits to fall to zero. They conclude that the effect of experience-curves on threshold rates of return dominates the effects of the trend in energy prices and other possible shocks to future benefits.

In the last several years, many states have put in place policy incentives for residential solar PV. Many of these incentives change over time and are subject to uncertainty. For example, the average rebate in Massachusetts was $1.34 per watt in 2010, while in 2014 the average amount has been reduced to $0.36 per watt (MassCEC, 2014). States have also implemented solar-specific mandates. These mandates have led to the creation of markets for solar renewable energy credits (SRECs) that are priced in the marketplace.[3] While these policies increase the financial benefit available to PV adopters, they also add additional uncertainly to the level of net benefits. In 2012, SREC prices in Massachusetts were over $500 per 1000 kWh, which would yield a household owning a 5-kW system $2750/yr in benefits.[4] In early 2014, with an SREC price of about $200, projected SREC revenues were $1100. Existing studies have not accounted for the effect of policy uncertainty on the adoption of solar PV. This paper fills this gap in the literature.

We develop a dynamic stochastic model of household adoption of solar PV systems using the option value framework to examine the impact of uncertainty on households' decisions to invest in solar PV. Using data from Massachusetts on electricity prices, installation costs, rebates (including tax credits), SREC prices, and energy production of solar PV systems, we estimate drift and volatility parameters for benefits and costs over time, and derive the optimal investment rule for solar PV adoption. We then derive the threshold value of discounted benefits that trigger adoption and the length of time for investment to occur under the net present value (NPV) and option value (OV) decision rules. We also simulate adoption rates over time and examine the impact of different incentive mechanisms on adoption decision and timing. Finally, we discuss the implications of the option value decision rule on the effect of various policy incentives for solar PV.

We extend the analysis by Ansar and Sparks (2009) in a number of ways. First, we account for the effect of government policies on net benefits. As discussed earlier, these policies significantly alter the benefits and costs of solar power, as well as the uncertainty in net benefits. Second, we consider trends in both benefits and costs of solar PV adoption. Ansar and Sparks (2009) do not consider changes in installation costs over time. A significant portion of uncertainty in net benefits may come from uncertainty in future installation costs, which include not only the price of materials but also labor and managerial costs that are related to the level of expertise of installers and economies of scale. Finally, we examine the effect of applying the option value decision rule on the impact of policy incentives for solar power. If households take into account option values when making investment decisions, the level of uncertainty associated with policy incentives will affect the way households respond to these policies. Since policy incentives play a crucial role in a household's decision to invest, it is important to examine how uncertainty affects the effectiveness of different incentives.

The remainder of this section provides a brief background on the solar PV market in the US and in the state of Massachusetts. Section 2 presents the model we use to derive the optimal investment decision rule. Section 3 discusses data sources and presents results and Section 4 concludes.

[3] SRECs are commodities that are traded on SREC markets. In principle, SREC sales can be transacted directly by buyers and sellers, provided that the seller is certified by the state. However, residential PV owners typically contract with SREC aggregators and brokers who then sell SRECs on spot markets, through forward contracts, or at auction. SREC prices are determined by supply and demand, and the level of the Alternative Compliance Payment, the fee that electricity suppliers have to pay if they do not meet state-mandated requirements for solar-generated electricity.

[4] Assuming energy production of 1100 kWh per 1-kW capacity.

1.1. Background

Solar PV capacity has experienced dramatic growth in the last several years. The compounded annual growth rate in the US from 2005 to 2013 for all applications (residential, commercial, utility) is 64%, with 79 total installations in 2005 and 4751 installations in 2013. The residential segment accounts for 19% of total installed capacity and is forecasted to be the fastest growing market segment for PV installations in 2014. The compounded annual growth rate for residential applications is 57% from 2005 to 2013, growing from 27 MW (Mega-watts) to 792 MW in capacity (GTM Research and Solar Energy Industries Association, 2014). The growth in the PV market can be attributed to several factors including the decreasing cost of PV systems and the increase in available incentives.

In 2010 the federal government spent $1.1 billion to support solar energy development, representing more than a 5-fold increase from 2007 levels (U.S. Energy Information Administration, 2011). The federal government has also provided a tax credit for residential and commercial solar energy investments since 1978. The Energy Policy Act of 2005 set the tax credit at 30% of installation costs. Under the Emergency Economic Stabilization Act of 2008, the solar tax credit is authorized until 2016.

Since the numerical portion of this paper will be based on data from Massachusetts, we focus the discussion below on specific policies in that state. In 2013, Massachusetts was 6th in total cumulative solar capacity by state with a total capacity of 440 MW (GTM Research and Solar Energy Industries Association, 2013). At the end of 2012, cumulative residential capacity was about 37 MW which means that residential installations are at least 8% of overall capacity in the state.[5] Massachusetts has a renewable portfolio standard (RPS) that is designed to meet the goal of reaching 15% renewables by 2020, with the percentage continuing to increase by 1% in succeeding years. Within the RPS, a solar carve-out program exists with an initial goal of reaching 250 MW installed capacity by 2017 and 400 MW by 2020 from systems that have less than 6-kW of capacity. Since the goal for 2017 was met in 2013, the state government increased the 2020 goal to 1600 MW. In 2013, the minimum compliance standard under the solar carve-out program is approximately 135,495 MWh or 0.2744% of 2011 electricity load (MA-EEA, 2013). Massachusetts has an active SREC market. The market price of SRECs is determined by supply and demand. In 2010 and 2011, SREC prices were upwards of $500, reaching $570 per MWh of solar energy produced. However, in 2013, the average SREC price was only around $230 per MWh (SRECTrade, 2013).

State tax credits are available and amount to 15% (up to $1000) of installation costs. A generous system of rebates also exist. From 2010 to the second quarter of 2014, $29 million in rebates were distributed, with $18 million going to residential installations (MassCEC, 2014). In 2013, rebates from the state's Commonwealth Solar program (applicable to the first 5-kW of capacity) include a base incentive of $0.4 per watt, an additional $0.05 for using components produced in-state, and $0.4 if the value of the home where the panels are being installed qualify as moderate or if family income is below a set threshold. In addition, a $1 per watt Natural Disaster Relief incentive is available to homes that were damaged by a hurricane or tornado. Rebates have been declining in the past years. In 2010, the average rebate for residential projects was over $6000 per installation, while in 2013, the average rebate was down to roughly $2200 per installation (MassCEC, 2014). Rebates under MassCEC are also not guaranteed. A set amount of funds are allocated per funding cycle. Those who do not qualify for a round of funding must wait until the next round opens. In addition to mandates, rebates, and tax credits Massachusetts also offers a sales tax exemption for the cost of solar equipment. Furthermore, solar rights regulation also exists, which prohibit local governments from passing regulations or ordinances restricting a home owner's ability to install a solar energy system.

[5] This is likely an underestimate since residential installations also increased in 2013.

2. Methods

2.1. Model

In this section, we present a theoretical model of a household's decision to invest in a PV system based on the option value framework. The representative household is assumed to minimize the cost of energy required to obtain a fixed comfort level. Before installing a PV system, the household derives energy from the electrical grid. The household also has the option to invest in a solar PV system to provide all or part of its energy demand. Once the investment is made it is considered irreversible. The trade-off faced by the household is between energy savings from the electricity produced by solar PV and the initial cost of installation. Energy savings are uncertain and depend on the price of electricity and energy output of solar panels. If the price of electricity increases, energy savings will be high, and conversely if electricity prices fall, energy savings over the lifetime of the system will be low and may not be sufficient to offset the upfront investment cost. The investment cost is also uncertain because of changes in the price of PV modules and available financial incentives.[6]

Let ω denote the difference in energy cost between the scenarios with and without a solar PV system.

$$\omega = \int_0^L Q_E P_t^E e^{-rt}\,dt - \left[\int_0^L (1-\phi) Q_E P_t^E e^{-rt}\,dt - I\right] \tag{1}$$

where L is the lifetime of the solar PV system, Q_E is fixed electricity consumption, P_t^E is the price of electricity, ϕ is the proportion of energy from solar PV expressed as the ratio of total energy output from solar PV and Q_E, r is the discount rate, and I is the initial investment cost. The first term on the right-hand side of the equation above is the total cost of energy over L-time periods without solar PV, and the second term is the net cost with a solar PV system. If $\omega \geq 0$, total energy cost is lower with the installation of solar panels.

Let $V = \int_0^L \phi Q_E P_t^E e^{-rt}\,dt$ denote the present value of energy savings over L time periods at time t (time subscripts are suppressed for V and I). The value of V varies over time depending on changes in P_t^E. The initial investment cost also varies over time and depends on installation cost (N_t) and government rebates (R_t) offered at time of installation. Thus, the initial investment cost at time t is $I = (N_t - R_t)$. We assume that V and I are stochastic and follow geometric Brownian motion (GBM) according to:

$$dV = \alpha_V V\,dt + \sigma_V V\,dz_V \tag{2}$$

$$dI = \alpha_I I\,dt + \sigma_I I\,dz_I \tag{3}$$

where dz is the increment of the Wiener process that follows a normal distribution with zero mean and unit variance. The drift and volatility parameters are denoted by α and σ respectively. We assume no correlation between dz_V and dz_I, $E[dz_V dz_I] = 0$, because the underlying causes of uncertainty for the two series are

[6] Our base simulations do not include SREC revenues. Policy simulations with SRECs are discussed in Section 3.3.

different. Energy savings is primarily affected by energy prices and the location of PV installation while investment cost is primarily affected by the cost of materials and labor, and government policy. While in principle the installed base and thus the installation cost of PV modules could affect energy prices, this is not likely to have a significant effect given the limited share of solar power in electricity generation.

Substituting V in Equation (1) leads to $\omega = V - I$. Under the NPV rule, the household will invest in solar panels if $\omega \geq 0$ or the value of energy savings is equal to or greater than the value of investment cost. However, the NPV decision rule ignores the effect of irreversibility and uncertainty in the investment decision, and the value of waiting to invest at a later period. Unlike the NPV rule that ignores the potential value of waiting to invest, the option value framework recognizes that the household can maximize its pay-off from investing by waiting to exercise its option to invest at a future optimal time. The value of the investment opportunity in solar panels is $F(V, I) = \max_T E[V - I]e^{-\rho T}$, where ρ is the risk-adjusted discount rate and T is the optimal investment time. The household maximizes the expected present value of the pay-off from investing by choosing the optimal time to make the investment given in (2) and (3). The solution takes the form of a threshold ratio of V and I that makes it optimal to invest, and is obtained by dynamic programming (Dixit and Pindyck , 1994).

The solution reveals that it is optimal to invest when the following condition holds:

$$V = h^* I \tag{4}$$

The term h^* is often referred to in the literature as the option value multiplier, i.e. it gives the ratio of V to I that would trigger investment. Put differently, the value of V has to be at least h^*-times that of I to trigger investment. The option value multiplier is calculated as $h^* = {}^{\beta}\!/_{\beta - 1}$. The value of β (and hence h^*) depends on the drift and volatility associated with V and I. The methodology for obtaining β and deriving Equation (4) is fairly standard (see Dixit and Pindyck, 1994). A sketch of the procedure is given in Appendix A.

Equation (4) above shows that uncertainty in future benefits and costs of installing solar PV cause a divergence in the NPV rule of $V = I$. If $\beta > 1$, the present value of benefits has to exceed investment cost by a factor that depends on the option value multiplier in order to induce investment.

2.2. Data

This section presents data used to estimate drift and volatility parameters for V and I.

2.2.1. Energy savings

Annual energy savings are calculated using data on electricity prices and energy output of installed systems. Monthly residential retail electricity prices from 1985 to 2013 for Massachusetts towns of Boston, Brockton, and Nashua were obtained from the Bureau of Labor Statistics (BLS, 2013). The price series is seasonally adjusted and indexed using 1982–1984 as base years. Energy output per kW installed capacity can vary for each installation based on factors that affect solar insolation[7] such as location of the house, orientation of the roof or area where solar panels are installed, and the presence of trees and other objects that could prevent exposure of the panels to the sun's rays. We use PVWatts, a tool developed by the National Renewable Energy Laboratory to estimate the energy output per 1 kW installed capacity for six different zip codes in the state of Massachusetts representing different geographical regions in the state.[8] We find that the average energy output of solar panels in the six locations is 1100 kilo-watt hours (kWh) per year for every 1-kW capacity (kWC). We use this value as our central estimate, and examine robustness of results to a range of energy output levels from a low of 800 kWh/kWC/yr to a high of 1400 kWh/kWC/yr. In addition, we consider a scenario where there is technological improvement such that energy production increases by 2% per year.

2.2.2. Investment cost

Investment cost is the installation cost minus available rebates from the federal and state government. Data on installation cost for 1998–2011 are from the Lawrence Berkeley National Lab (Barbose et al., 2012). Rebates received by over 3000 residential installations from 2008 to 2013 were obtained from the Massachusetts Clean Energy Center (MassCEC, 2013).

3. Results and discussion

3.1. Estimated parameters

Using data on electricity prices and energy output, we estimate the drift (α_V) and standard deviation rate (σ_V) for the present value of energy savings (V). Similarly, using installation costs, rebates, and tax credits, we estimate the drift (α_I) and standard deviation rate (σ_I) for the net installation cost (I). Table 1 shows the annual estimates for α_V, σ_V, α_I, and σ_I. The estimates for α_V and σ_V are identical for both No Policy and Rebate scenarios because the Rebate does not affect the trend in benefits from solar PV, but only the trend in net installation costs. Under the No Policy scenario, only the trend and volatility of installation costs are considered in estimating α_I and σ_I, while under the Rebate scenario, the trend and volatility of financial incentives (rebates and tax credits) are also taken into account. The drift terms show that discounted benefits are increasing over time, while net investment costs are decreasing over time. The value of benefits is more uncertain than that of investment costs, as indicated by the volatility parameter of benefits being almost double that of installation costs.

3.2. Critical values for V and adoption time

Given the estimated parameter values and a risk-adjusted discount rate of $\rho = 0.15$ we calculate β to be 2.7 for both the No Policy and Rebate scenarios.[9] The equivalence of β for the two scenarios does not mean the two cases are identical. As seen in Table 1, parameters for V in both the No Policy and Rebate cases are the same. The parameters for I in both scenarios are slightly different, but the difference in not large enough to affect the value of β. However, the rebate still reduces the level of net installation costs and thus leads to different critical values and adoption times compared to the No Policy case, as discussed below.

Given the derived value of β, the option value multiplier, $h^* = {}^{\beta}\!/_{\beta - 1}$ is 1.6, implying that under the option value decision rule, the present value of energy savings needs to be 60% greater than the initial investment cost for investment to be triggered. The

[7] Also called solar irradiation, this is a measure of solar radiation energy received by a given surface area at a particular time.

[8] We use default assumptions for derate factor (0.77), tilt (42.2° latitude), and azimuth (180°).

[9] The risk-adjusted discount rate (RADR) is obtained by adding an expected risk premium to the "risk-free" discount rate. We do not make assumptions about the exact values of the two components of the RADR. Our assumption for ρ is based on values assumed in earlier studies (Ansar and Sparks , 2009; Carey and Zilberman , 2002). We conduct sensitivity analysis with $\rho = 0.1$ and $\rho = 0.2$. Results are reported in Section 3.3.1.

Table 1
Estimates of parameters governing stochastic process of returns (V) and investment (I) on solar PV.

	No Policy	Rebate
α_V	0.0228	0.0228
	(0.0000)	(0.0000)
σ_V	0.0921	0.0921
	(0.0000)	(0.0000)
α_I	−0.0403	−0.0391
	(0.0117)	(0.0131)
σ_I	0.0405	0.0417
	(0.0120)	(0.0131)

Note: standard errors in parentheses. αs are drift parameters while σs are volatility parameters.

decision rule used to trigger investment, whether NPV or OV has implications for the expected adoption time and critical value of V that will trigger adoption. To determine the expected adoption time and the critical value of V, we run a simulation model. Using the estimated drift and volatility parameters and starting values for V and I, we generate 10,000 paths for V and I by forward-simulating over a 40-year period. We determine the initial value of V to be $1244 (in 2010 prices). This is based on forward-simulating prices over an expected solar PV lifetime of 20 years, starting with the average residential electricity price in 2010 of $0.146 per kWh, and assuming energy savings of 1100 kWh per kW installed capacity (kWC) per year.[10] For the No Policy scenario, we use the 2010 value of average installation cost ($6487 per kW-capacity) as the starting value for I. For the Rebate scenario, we subtract the average rebate amount (inclusive of state and federal tax credits) of $3473 per kW-capacity from the installation cost to obtain the starting value for I of $3014 per kW-capacity.

To determine adoption time and critical value of V, we determine the time and value of V the first time at which $V \geq I$ (for the NPV framework) or $V \geq h^*I$ (for the OV framework) for each realization of V and I. Fig. 1 shows one realization of V and I under the No Policy scenario. The figure shows an increasing trend for V and a decreasing trend for I, as expressed by the parameter estimates presented in Table 1. The increase in V is based on increasing prices for electricity as observed in the data.[11] The decreasing trend in I reflects a reduction of installation costs over time observed in our data. Because of these opposite trends it is clear that with rational consumers adoption of solar panels will happen eventually; in the case of the NPV framework this point will be reached earlier (i.e. as soon as $V \geq I$) than under the OV decision rule (i.e. when $V \geq h^*I$).

Table 2 shows the adoption times and critical values of V for the median realization of V and I under the No Policy scenario for different levels of energy output. Results show that without financial incentives, adoption time under the NPV decision rule ranges from 23 to 33 years. Adoption times under the OV decision rule are 22–34% longer, ranging from 31 to 40 years, depending on the level of energy output. For the case with medium energy output, the critical value of benefits is $2933 (in 2010 dollars) per kW capacity under the OV decision rule, which is 27% greater than the critical value under the NPV decision rule. This result implies that for a 5-kW system, the present value of benefits has to be $14,664 for investment to occur. Given Equation (4), this also implies that net installation cost has to fall to $9165.

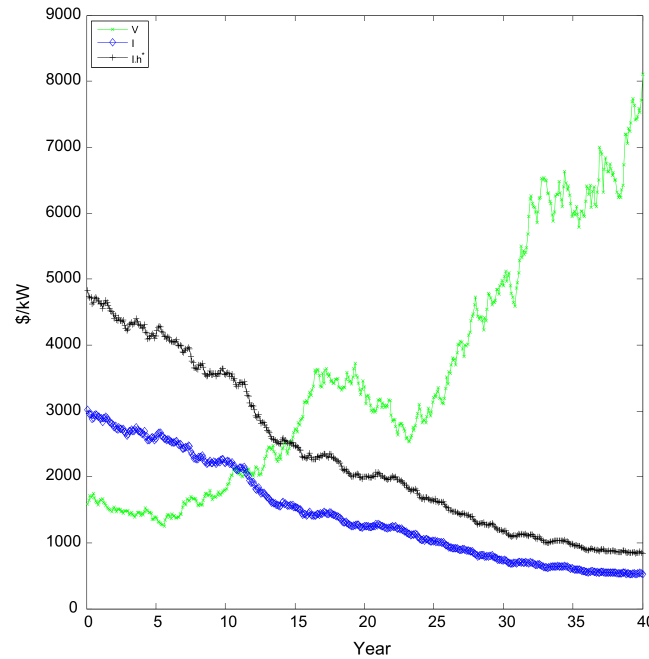

Fig. 1. One instance of simulated values of V and I under the no-policy scenario with medium energy output.

Table 2
Adoption time and critical values of V under the no-policy scenario for different levels of energy output.

	Energy output		
	Low	Medium	High
Adoption time in years			
NPV	32.8	27.2	23.1
OV	40.0	35.1	31.0
Critical value of V ($/kWC in 2010 prices)			
NPV	1961	2312	2645
OV	2598	2933	3261

Note: low, medium, and high energy output assume 800 kWh, 1100 kWh, and 1400 kWh per kW-capacity per year respectively.

3.2.1. Rate of adoption over time

To further examine the effect of incentives under NPV and OV decision rules, we turn to predicted rates of adoption. For the simulated values of V and I under the No Policy scenario, we calculate the expected cumulative adoption rates at each point in time. Figs. 2–4 show simulated adoption rates over time for NPV and OV decision rules assuming different levels of energy output per KW installed capacity.

For low and medium energy output levels, the proportion of adopters at 20 years are 4% and 16.2% respectively under the NPV rule. In contrast, under the option value rule, the proportion of adopters at 20 years are 0.24% and 2% under low and medium levels of energy output. For the high energy scenario, over 34% have adopted at year 20 under the NPV rule, while under the OV rule, only 6.4% have adopted. These figures show the significant effect of uncertainty in delaying diffusion of solar PV technology.

[10] We run robustness checks with varying lifespans up to 30 years. While absolute numbers change (adoption times for both No Policy and Rebate scenarios decrease), our results regarding the effect of using the OV decision rule instead of the NPV decision rule, and the impact of policy scenarios are robust with respect to this change.

[11] Increasing electricity prices are consistent with forecasts presented by the U. S. Energy Information Administration (2015) and the ISO New England (2014).

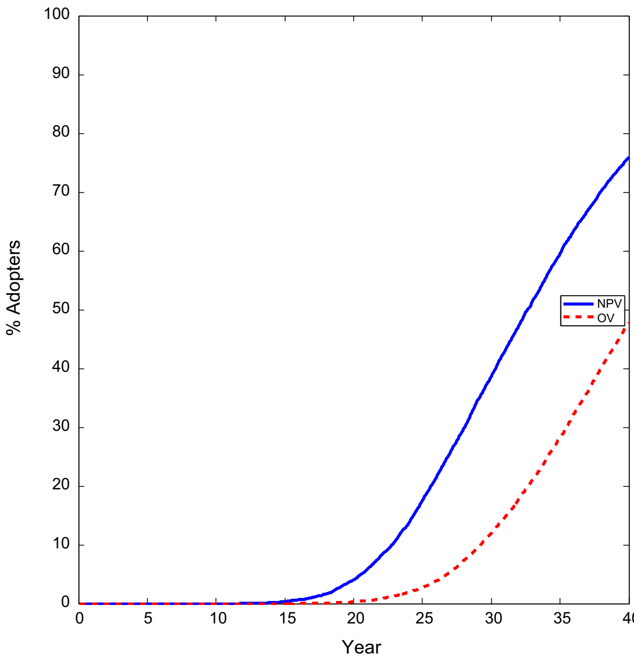

Fig. 2. Adoption rate for NPV and OV decision rules in no-policy scenario with low energy output (800 kWh/kWC/yr).

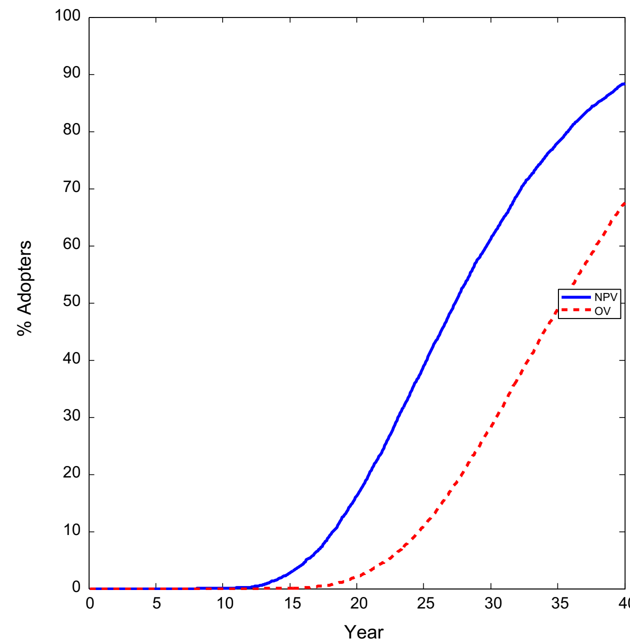

Fig. 3. Adoption rate for NPV and OV decision rules in no-policy scenario with medium energy output (1100 kWh/kWC/yr).

Table 3
Adoption time and critical values of *V* under different policy scenarios.

	No policy	Rebate	CO_2 subsidy	SREC	SREC and rebate
Adoption time in years					
NPV	27.2	13.9	26.3	27.1	13.3
OV	35.1	21.8	34.1	40.0	34.5
Critical value of *V* ($/kWC in 2010 prices)					
NPV	2312	1722	2256	2296	1670
OV	2933	2016	2836	4197	2844

Note: medium level of energy output is assumed.

3.3. *Effect of uncertainty on solar incentives*

The effect of uncertainty in delaying adoption has implications for which policies would be more effective at incentivizing adoption. To examine the effect of various policy options on adoption under the NPV and option value frameworks, we simulate several policy scenarios. Adoption time and critical values for different policy scenarios assuming medium energy output from solar panels are in Table 3.

In the No Policy scenario, there are no financial incentives from the government so that the initial investment cost faced by households is equal to the installation cost. The drift and volatility of investment cost are determined by the trend in gross installation cost (see Table 1). As discussed above, adoption time under the OV rule is 8 years longer compared to the NPV rule.

In the Rebate scenario, the installation cost is reduced by over half (from $6487 to $3014) due to policy incentives like rebates and tax credits.[12] The drift and volatility of investment cost are determined by the trends in both installation cost and rebates (see Table 1). Table 3 indicates that with the rebate, adoption time under the NPV rule decreases by 49% compared to the No Policy scenario, from 27 years to 14 years. Under the OV decision rule, adoption time decreases by 38% compared to the No Policy scenario. The predicted adoption time under the OV decision rule is 58% longer compared to that under the NPV decision rule (22 years versus 14 years). The reduction in adoption times under both decision rules indicates that financial incentives have been effective in incentivizing adoption of solar PV. However, the effect of financial incentives is attenuated under the OV decision rule. In terms of adoption rates, the proportion of adopters at year ten is 22% under the NPV rule. In contrast, under the OV rule, the proportion of adopters at ten years is 1% for medium levels of energy output. For the high energy scenario, over 50% have adopted at year 10 under the NPV rule, while under the OV rule, less than 7% have adopted. These results illustrate the difference in the impact of a financial incentive when the OV decision rule is applied, compared to the NPV rule. Hassett and Metcalf (1993) also find that financial incentives like the tax credit for residential energy efficiency improvements had limited effectiveness due to households considering the option value of their investment dollars.

One of the most attractive features of solar power is its low greenhouse gas (GHG) emissions compared to electricity produced from fossil-fuels. We consider a carbon subsidy scenario, where owners of solar PV systems are given an annual subsidy equal to the value of GHG emissions reductions from solar electricity production relative to other sources of electricity such as oil, natural gas and coal.[13] The mean life-cycle GHG emissions for electricity production from different fuel sources are: 1000 gCO_2/kWh for coal, 800 gCO_2/kWh for oil, 560 gCO_2/kWh for natural gas, and 56 gCO_2/kWh for solar PV (Weisser, 2007). These numbers imply a reduction of over 90% from solar power compared to fossil-fuel inputs. A $100 annual subsidy per kW installed capacity approximates the case with a carbon tax of $100 per ton CO_2 and electricity from solar replacing coal. A $20 subsidy per kW installed

[12] Although tax credits need to be claimed during tax season after the solar PV has been installed, we assume that this financial benefit decreases investment cost at the time of installation.

[13] A carbon tax on all sources of emissions is the first best policy for dealing with GHG externalities, not a clean energy subsidy. However, an analysis of the effects of a carbon tax versus a clean energy subsidy is beyond the scope of this paper.

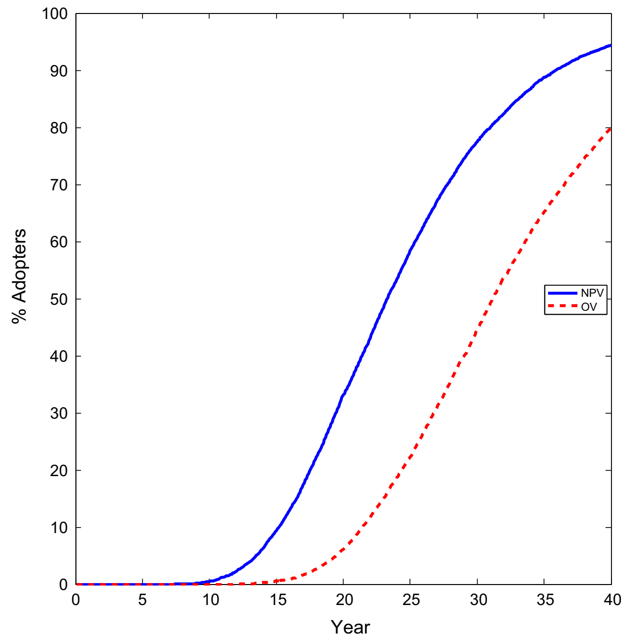

Fig. 4. Adoption rate for NPV and OV decision rules in no-policy scenario with high energy output (1400 kWh/kWC/yr).

Table 4
Adoption time and critical values of *V* under different policy scenarios and discount rates.

Discount rate	No policy			Rebate		
	10%	15%	20%	10%	15%	20%
Adoption time in years						
NPV	22.0	27.2	31.5	8.8	13.9	18.1
OV	33.2	35.1	37.8	20.0	21.8	24.3
Critical value of *V* ($/kWC in 2010 prices)						
NPV	2760	2312	2018	2121	1722	1443
OV	3762	2933	2505	2637	2016	1647

Note: medium level of energy output is assumed.

capacity represents the case with a carbon tax of $25 per ton CO_2 and electricity from solar replacing oil.[14] Results show that compared to the No Policy scenario, carbon subsidies between $20–100 per ton CO_2 do not have a significant impact on adoption times. Table 3 shows that under the both NPV and OV decision rules, adoption time decreases by roughly 3% with a carbon subsidy of $100 per ton CO_2. The preceding analysis is based on specific alternative sources of energy to show how solar-generated electricity compares to different electricity sources. In reality, solar power replaces a mix of energy sources. Baker et al. (2014) report that CO_2 savings for solar PV, given the energy mix in the Northeast is 1.44 lbs/kWh (653 g/kWh). This translates to a subsidy of $66/kWC per year, which is between the subsidy rates analyzed above. Thus, basing the subsidy on energy generation mix does not alter our results that a carbon subsidy is unlikely to have a significant effect on investment timing.

In addition to energy savings, another significant benefit that is available to households owning solar PV systems is revenue from

Table 5
Adoption time and critical values of *V* under different policy scenarios and assumptions about efficiency gains.

	No efficiency gain		With efficiency gain	
	No policy	Rebate	No policy	Rebate
Adoption time in years				
NPV	27.2	13.9	26.8	13.6
OV	35.1	21.8	37.6	24.1
Critical value of *V* ($/kWC in 2010 prices)				
NPV	2312	1722	2291	1707
OV	2933	2016	3202	2132

Note: medium level of energy output is assumed.

the sale of SRECs. SREC revenues can vary widely depending on the prevailing SREC price, which is determined in the SREC market, and which has shown considerable volatility since SREC markets opened in the state of Massachusetts. We assume that including SRECs in V results in V following a combined GBM and jump process, i.e. V follows a GBM process but a positive probability exists that V will take a discrete jump downward. We allow for the possibility of jumps to account for drastic price reductions observed in our data; for instance, the SREC price in our data dropped from $545 in June 2012 to $210 in August 2012.[15]

Formally, we modify the expression for dV to: $dV = \alpha_V V\,dt + \sigma_V V\,dz_V - V\,dq$, where dq is the increment of a Poisson process with a mean arrival rate given by λ. We assume that dz and dq are independent, i.e. $E[dz\,dq] = 0$. The solution process is similar to that outlined in Appendix A, however, the fundamental quadratic equation that must be satisfied by β changes to: . Using bi-monthly data on SREC prices in Massachusetts from February 2011 to August 2013, we employ maximum likelihood estimation to uncover parameters describing a generalized Brownian motion process with jumps. Based on our estimation, we set $\lambda = 1/31$ and $\phi = 0.5$, and solve for β numerically.

We use the data on SREC prices to predict expected SREC payments to owners of solar installations taking policy details such as the 10-year limit on SREC payments and the Alternative Compliance Payment into account. The initial value is set to $236 per 1000 kWh of electricity production based on the SREC price for August 2013. The inclusion of SREC revenues increase the drift of benefits by 178% from 0.023 to 0.064 relative to the scenarios with no SRECS, and the volatility parameter is more than four times greater at 0.472 with SRECs than without SRECs. This suggests that the benefits grow faster over time with SRECs, but that the benefits are also very volatile. The corresponding option value multiplier (h^*) increases to 3.4 which is more than double the value of h^* in scenarios without SRECs.

The last two columns in Table 3 show scenarios that include revenues from SREC sales. Under the NPV rule, the reduction in adoption times is only a fraction of a year when we compare the scenario with SRECs (but no rebates) to the No Policy scenario, and the scenario with SREC and Rebates to the Rebate scenario. It is possible that the high degree of volatility in SRECs leads the model to generate a very small realized benefit from SRECs. In contrast to the NPV case, with the OV decision rule, adoption times increase substantially. Compared to the No Policy scenario, the case with SRECs increase adoption time by 40%. The scenario with both

[14] GHG subsidy for coal is calculated as: $100 /ton$CO_2$*(1000−56) g$CO_2$/kWh*1/1,000,000 ton/g*1100 kWh/kWC/yr=$103.8 /kWC/yr. Similar calculations apply to other energy sources.

[15] Jump processes have been found to describe price data well in many settings, e.g. common stocks (Ball and Torous , 1985), exchange rates (Jorion, 1988), and electricity prices (Weron et al., 2004). We confirm through simulations that the GBM process with jump generates realistic price patterns in the context of SRECs.

SRECs and rebates has an adoption time that is 58% longer than the scenario with only rebates. This result is likely due to the high value of h^* when SRECs are present. As discussed earlier, the volatility parameter with SRECs increases by over 400% compared to the Rebate and No Policy scenarios, and the resulting h^* in the SREC scenarios is more than double compared to scenarios without SRECs. With very uncertain returns, the benefits have to be much larger than initial costs to induce investment.

3.3.1. Sensitivity analysis

We test the robustness of our results to assumed discount rates (see Table 4) and possible efficiency gains (see Table 5).

A. Discount rate

The effect of the assumed discount rate is straightforward in the NPV case. A lower discount rate increases the value of V because households discount future monetary gains less heavily (see Table 4). Thus, faster adoption is observed with a 10% discount rate, compared to the baseline 15% discount rate (and vice versa for 20% discount rate). The effect of discount rates under OV decision rule is not so straightforward since lower discount rates also increase the magnitude of h^*, thus driving up the wedge between V and I and leading to longer adoption times. With a 10% discount rate, the value of h^* is 1.5 while with a 20% discount rate, the value of h^* is 2.5. Our numerical results show that under the OV decision rule, the effect of the discount rate on V dominates, and we observe longer adoption times with higher discount rates, and vice versa.

B. Efficiency gains

We consider a case where the efficiency of solar panels improve such that energy production increases by 2% per year. Efficiency gains increase the drift of V because of greater expected benefits as solar panels become more efficient. The drift term increases by 90% from 0.0228 to 0.0432 relative to the case without efficiency gains (see Table 5). This in turn increases h^* by 17% from 1.6 to 1.9. Under the OV framework, the expectation of future efficiency gains increases adoption times, as households delay investment to take advantage of more efficient panels. On the other hand, under the NPV framework, greater efficiencies increase V at each time period, thus leading to slightly shorter adoption times and lower critical values of V.

The predicted adoption times and critical values presented above are based on the parameters estimated for the electricity and solar markets in Massachusetts. Changes in the trend of electricity prices and installation costs of solar PV (for example, due to technological change or policy changes) would alter adoption times and critical values of V that would trigger adoption. However, the result that decisions about investment timing made based on the OV decision rule will differ from that made using the NPV decision rule would still hold. Furthermore, increased uncertainty in benefits and costs of solar PV would lead to larger gaps between timing decisions under the NPV and OV decision rules.

4. Conclusion and policy implications

In this article we demonstrate the effect of uncertainty on households' adoption of solar PV when they consider the option value of their investment decision. Unlike a simple net present value decision rule where the household equates the discounted value of benefits with the investment cost, under the option value decision rule, the present value of benefits must exceed the investment cost by a factor that takes into account uncertainty in net benefits, and the potential benefit of waiting to invest until uncertainty has been resolved. Using data from the solar market in Massachusetts, we find that under the OV decision rule, the present value of benefits has to exceed net installation cost by 60% for investment to occur. Without policy incentives from the government this will take 35 years, and net installation cost has to fall to \$2933 per kW-capacity (less than half of the average installation cost in 2010 for Massachusetts).

Policy incentives are effective at decreasing adoption times. Under the both the NPV and OV decision rules, Massachusetts' current rebate program would reduce adoption times significantly. However, the effect of rebates (and other financial incentives) are attenuated under the OV decision. The difference in the effect of SREC revenues under the NPV and OV decision rules is especially notable: under the NPV decision rule, adoption time decreases slightly; under the OV decision rule, adoption times increase significantly due to the volatility in benefits introduced by SRECs.

Our results show that financial incentives could be effective at inducing solar PV adoption, although their effectiveness is somewhat limited, especially if there is uncertainty associated with the incentive. It is possible that other non-financial incentives would be more effective. Studies by Bollinger and Gillingham (2012), Noll et al. (2014), and Steward et al. (2014) have pointed to the effectiveness of peer-to-peer marketing and general market development supports in increasing solar PV diffusion. Policy-makers can also explore strategies to reduce uncertainty in financial incentives, such as paying for SREC credits up-front or setting a fixed schedule for rebate availability.

Future research could explore the welfare implications of solar incentive policies like rebates and SRECs, since these policies cause distortions in the market. Whether the welfare cost of these policies outweigh the environmental and energy security benefits of solar PV is an important empirical question.

Although the market application of our model focuses on the solar PV market, the conclusion that uncertainty may attenuate the effect of financial incentives applies to other renewable energy investments, most of which receive government incentives, and are subject to large upfront investment costs and uncertain stream of benefits that are affected by energy prices and energy output.

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Appendix A

This appendix presents an outline of the methodology used to derive the expression in Equation (4). The procedure is discussed extensively in Dixit and Pindyck(1994). An intuitive discussion can also be found in Chapter 7 of Conrad (2010). First note that for values of V and I for which it is not optimal to invest, the Bellman equation is:[16]

$$\rho F(V,\ I)\,dt = E[dF(V,\ I)] \tag{A.1}$$

The equation above shows that the total expected return of the investment opportunity (shown on the left-hand side) has to be equal to the rate of capital appreciation (shown on the right-hand side) if the option to invest is not exercised. Intuitively, the rate of capital appreciation is the threshold below which the investor

[16] A Bellman equation is a recursive formulation of a dynamic programming problem, making use of the fact that the outcome of future states will be based on then-optimal decisions.

would forgo (at least for the time being) the investment opportunity. Since the optimal adoption time only depends on the ratio of V and I, we use the property that $F(V, I)$ is homogeneous of degree one in V and I (i.e. $F(V, I) = If(v)$, $v = {}^{V}/_{I}$) to simplify the problem to one dimension.

Using Ito's Lemma is used to expand $f(v)$, the Bellman equation is re-written as[17]:

$$\frac{1}{2}\left(\sigma_V^2 + \sigma_I^2\right)v^2 f''(v) + (\alpha_P - \alpha_I)vf'(v) - (\rho - \alpha_I)f(v) = 0. \tag{A.2}$$

where $'$ and $''$ denote first and second derivatives. The Bellman equation above must be satisfied subject to boundary conditions, which defines the region (values of V and I) where the option is immediately exercised:

$$f(v) = v - 1 \tag{A.3}$$

$$f'(v) = 1;\; f(v) - vf'(v) = -1 \tag{A.4}$$

(A.3) is the value-matching condition which states that at the region where it is just optimal to invest, the value of the option is equal to the discounted benefits minus the investment cost. The smooth pasting conditions (A.4) state that the derivatives of the option value function and the discounted benefits minus the investment cost are equal at the investment threshold. The form of the solution that satisfies (A.2) is given by $f(v) = Av^{\beta}$ where A and v are unknowns, and β is the positive root of the following quadratic equation:

$$\frac{1}{2}(\sigma_V^2 + \sigma_I^2)\beta(\beta - 1) + (\alpha_V - \alpha_I)\beta - (\rho - \alpha_I) \tag{A.5}$$

Noting that $f(v) = Av^{\beta}$, the boundary conditions can be used to obtain a two-equation system that allows us to solve for A and v. Using the first smooth pasting condition to obtain an expression for A, and substituting back to the expression for the value matching condition yields Equation (4).

The numerical value of β used to calculate h^* is obtained by substituting parameter estimates given in Table 1 and assumptions about the value of ρ into (A.5), and solving for the positive root of the quadratic equation.

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[17] Ito's lemma is an identity used to derive the differential of a time-dependent function of a stochastic process.