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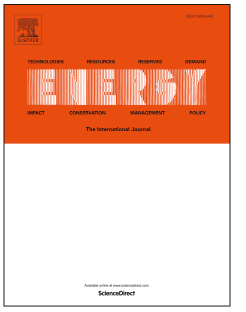

Defer option valuation and optimal investment timing of solar photovoltaic projects under different electricity market systems and support schemes

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Abstract

This paper applies the real options method to analyse the defer option value and optimal investment timing for solar photovoltaic projects in China. The main purpose of this paper is to examine investment behaviours under different market systems and support schemes. This paper further investigates the interaction of technological progress and support schemes. Four scenarios are designed, and the corresponding real options models are established. In the case study, we find that electricity market reform enhances the defer option value in the short term but makes the owners of solar PV projects postpone their investment. Nevertheless, the government can stimulate investment by implementing appropriate support schemes. Additionally, the impacts of different support schemes vary according to the market system. The impacts of feed-in tariffs and price premiums are similar in a regulated market but are different in a free market. The price premium scheme greatly promotes the defer option values in the short term, but the feed-in tariff scheme excels in the long term. A feed-in tariff has a greater impact on reducing the expected execution time and its variance than the price premium. In addition, more attractive support schemes are required when the technological level is improved.

Keywords: Optimal investment timing; Defer option values; Electricity marketing reform; Government support schemes; Technological progress; Solar photovoltaic project

1. Introduction

Similar to many other governments, the Chinese government faces a dilemma between developing the economy or protecting the environment. In past decades, extensive economic development has occurred in China, and China has received a tremendous boost to its economy at the sacrifice of its environment [1]. Coal, which provided approximately 67% of China's primary energy consumption during the past 10 years, plays a very important role in this process [2] and meets most of the energy demand that has been induced by economic development. However, the use of coal is associated with considerable environmental pollution. One of the largest sources of air pollution in China is coal combustion [3]. Industrial and residential coal combustion not only cause high levels of $PM_{2.5}$ and NO_X emissions in Central China but are also partly responsible for SO_2 emissions and acid rain in Southern China [1]. In the midst of these challenges, the Chinese government has promulgated several policies to mitigate the environmental pollution problems [4, 5]. These policies include (1) strengthening the supervision of environmental governance, (2) limiting coal consumption and promoting the industrial application of clean coal technology, and (3) increasing the application of clean energy, such as natural gas, solar energy, and wind energy. As part of its strategy, the Chinese government aims to achieve 15% non-fossil fuel energy by 2020.

Solar energy is one of the most promising clean energies for China for several reasons. First, China has abundant solar resources [6]; theoretically, solar energy in China could reach an annual output ranging from approximately 6900 to 70100 terawatt hours (TWh) [7]. Second, the cost of solar photovoltaic (PV) power has decreased. As an example, the PV module cost decreased to approximately 4 yuan/ peak watt in 2014, which is approximately one third of the cost in 2010 (13 yuan/ peak watt) [8]. Third, the domestic demand for solar power devices has continued to increase during the past few years. From 2010 to 2014, the cumulative installed PV power in China increased from 0.8 gigawatts (GW) to 28.2 GW [2], yielding a compounded annualized growth rate of 75.7%. Finally, the Chinese government has made several mid-term and long-term plans for solar energy expansion. In the 12th Five-Year Plan for National Economic and Social Development, the Chinese government projected reaching 50 GW of cumulative solar PV power by 2020 [9]. This figure was later increased to 100 GW to promote the development of the clean energy industry and to improve the environmental quality [4]. Several regulations have been approved to facilitate the development of solar energy from different perspectives, including the provision of government subsidies, market reform, public research and development, low rate loans, and the promotion of solar energy systems.

Abundant solar resources, decreasing manufacturing costs, rapid growth in the demand for solar power devices, and government plans and regulations guarantee that solar energy will become an important energy source in China in the future. Increasing numbers of companies are expected to participate in solar PV projects. However, the levelized cost of electricity for residential solar PV systems (without battery storage) in China is approximately 1.00 yuan/ kilowatt hour (kWh) [10], which is approximately 2.5 times more expensive than conventional power generation. Without government subsidies, this high cost results in very low profits for solar PV projects. In addition, solar PV projects have long payback periods and large investments that are characterized by uncertainties. Thus, companies should be cautious about investment timing to avoid losses. Additionally, the Chinese electricity market is undergoing market-oriented reform, in which the deregulation of electricity pricing is particularly important [11]. Therefore, decision makers should be aware of the possible effects of electricity price reform. Moreover, as the impacts of technological progress and support schemes on stimulating investment rely on each other, a quantitative analysis needs to be conducted to evaluate these interactions and how they affect the optimal investment timing of solar PV projects.

In this paper, we apply the real options method to evaluate the defer option value and optimal investment timing of PV projects from the perspective of a private investor. The main goals of this paper are to investigate the impacts that electricity market reform has on the defer option values and optimal investment timing, to analyse the defer option values and investment behaviours under different support schemes and market systems, and to examine the complex relationship between technological progress and support schemes. Four real options models that contain technological uncertainty, economic uncertainty and subsidy uncertainty are established in this paper. The changes in the investment behaviours induced by electricity price reform and different support schemes are observed by comparing the defer option values and the optimal investment timings of the different models. The impacts of the technological progress and support schemes are compared through a sensitivity analysis with respect to the optimal investment timing. The research results are also useful for policy makers and can support recommendations related to support schemes.

The layout of the rest of this paper is as follows. Section 2 discusses the related literature. Section 3 describes the methodology, which contains the economic assumptions, uncertain factors and real options models. In Section 4, an empirical analysis of China, including parameter estimation and scenario analyses, is presented, and Section 5 provides the concluding remarks for the paper.

2. Literature review

Solar PV projects have two distinct features: (1) the investment is irreversible and (2) the investment is not a now-or-never option. These two features grant a firm an option analogous to a financial call option, by which decision makers have the right but not the obligation to invest at a certain time in the future [12]. The net present value assessment does not consider these characteristics, so a real options analysis is applied to address these features. Companies that invest in solar PV projects pay more attention to the growth potential of solar energy. Capital budgeting and long-term planning can be integrated from the real options perspective [13], which will benefit the companies in the long run.

Real options theory can be traced back to 1977 when Myers studied the relationship between corporate debt and its value from the perspective of real options [14]. In the early development stage of this theory, scholars focused on the identification of new option types, their applications in different areas and the development of new methodologies [15]. Generally, real options are divided into five types [12, 16, 17]: (1) the defer option, in which decision makers wait until a positive environment arises (our analysis studies the defer option embedded in solar PV projects; therefore the option value implies the defer option value); (2) the alter operation scale option, in which decision makers expand or shrink the operation scale in accordance with the market situation; (3) the abandon option, in which decision makers sell the project when necessary; (4) the switch option, in which decision makers change the project's output or input; and (5) the growth option, which requires further investment decisions. Three methodologies are applied to solve real options questions: (1) partial differential equations (PDEs), which are used to solve real options questions under certain boundary conditions [12, 18] (the most widely used PDE is the Black-Scholes-Merton equation [19, 20]); (2) the binomial tree model, which is easy to understand and apply but can be used only in discrete scenarios [12, 21]; and (3) simulation, which can be applied to handle different types of real options [12] (the most useful simulation method is the least squares simulation method [22]).

Hoff et al. [23] were the first to apply real options analysis to solar PV. Since then, many relevant studies have been conducted by different scholars. These studies can be classified into 3 categories, namely, (1) project evaluation, (2) optimal investment timing, and (3) policy evaluation.

Project evaluation is an important application area for real options analysis in solar PV projects. Two methods (the binomial tree model and the simulation method) are commonly applied in these studies. (1) The binomial tree model, used in [23-25], was first applied by Hoff et al. [23], who set up a simple and instructional model to illustrate the application of real options. Sarkis and Tamarkin [25] extended the work of Hoff et al. [23] by setting up a quadrinomial tree model. Martinez-Cesena and Mutale [24] applied the binomial tree model to assess the value of applying demand response programs in off-grid PV systems. (2) The simulation method was applied in [26-28]. Martinez-Cesena et al. [26] and Weibel and Madlener [27] focused on the effect of technological impacts on the project value, while Gahrooei et al. [28] concentrated on the demand uncertainties. Unlike these studies, our study applies contingent claims to set up PDEs and to obtain analytical solutions; then, the Monte Carlo simulation method is applied to obtain numerical solutions.

The optimal investment timing is also an important application area. Real options analysis was applied in [29-31] to study optimal investment timing. The investment uncertainty and electricity price uncertainty are common uncertain factors considered in these studies [29, 31]. These uncertainties are very important, but policy uncertainty, which is also an influential factor that affects the economics of solar PV projects, was neglected in their model. Zeng et al. [30] considered investment uncertainty, electricity price uncertainty and renewable energy credit price uncertainty (which belongs to policy uncertainty) in their model. However, the common support schemes for solar PV projects in China are feed-in tariffs (FIT) and price premiums, as renewable energy credits are still not available in China. Unlike these previous studies, this paper establishes a model that is in line with the reality of China, considering the PV cost, electricity price and support scheme uncertainties (mainly FIT and price premium).

Policy evaluation is another important application area for real options analysis in solar PV projects [32-36]. Different policies have been discussed by different scholars, including a time-of-day price mechanism [33], FIT [32, 35, 36], and public research [34]. Lin and Wesseh [36] and Zhang et al. [32] applied binomial tree models to evaluate the current FIT in China and concluded that the current FIT can stimulate PV investment. However, their main research objectives were different: Lin and Wesseh [36] studied the impact of internalized external costs on the option value, and Zhang et al. [32] evaluated the FIT policy from the perspectives of both the investor and the government. Unlike these studies, we mainly studied the influence of ongoing electricity price market reform on the decision-making process. Additionally, the interaction between technological progress and the support schemes are studied using sensitivity analysis instead of system dynamics models, as was used in [34].

Moreover, unlike many other studies that apply learning curves [26, 29, 31, 32, 36] to research investment uncertainties and technological progress in the solar PV industry, we use historical data to measure the drift term and volatility term of the solar PV module cost. We also verify the calculated drift term by comparing it with results obtained from the learning curve method.

3. Methodology

3.1. Economic assumptions of solar PV project and uncertainties

3.1.1. Economic assumptions

Although the production of solar PV projects is uncontrollable in the short term, it is much more predictable on a yearly scale [7]. Therefore, we conduct our analysis on a yearly scale, and we assume that the annual production of a solar project is x kWh/ year. The feasibility of a solar PV project depends on the investment, electricity price and subsidy.

Investment in solar PV projects is divided into three parts: capital expenditure ($CAPEX$), operation and maintenance expenditure ($OPEX$) and assurance. Solar PV projects are capital-intensive projects, with $CAPEX$ accounting for approximately 70% of the total investment[1]. $CAPEX$ includes the PV system cost and the PV module cost. The PV system cost includes the costs for the inverter, structural installation, and wiring. The PV module cost includes the costs of the solar cells, ethylene vinyl acetate, and cover glasses, and usually account for approximately one third of $CAPEX$ [8]. Compared to the PV system cost, the module cost is much more likely to change and to have a greater impact on the investment [8, 10, 31]. $OPEX$ contains the costs for regular operation and maintenance, and assurance is used to compensate for losses incurred from contingencies.

Let C_t denote the solar PV module cost (whose units are converted to yuan/kWh; the details are shown in Appendix A) and $I(C_t)$ denote the investment. Since the module cost accounts for approximately 23.3% of the total investment and is the driving force for the investment volatility, we assume that the investment is determined by C_t. To be specific,

Assumption 1. $I(C_t) = (1/23.3\%) * C_t * x = 4.29 * C_t * x$

The profit of a solar PV project depends on the electricity price, subsidy, $OPEX$ and taxes. The assumptions about the electricity price change according to the market system. We assume that the electricity price is fixed in a regulated market, which conforms to the reality in China. In a free market, we assume that the electricity price is driven by the competitive electricity market. There are three types of support schemes in the renewable industry, namely, FIT, price premiums and renewable energy credits. $OPEX$ can be neglected (see other examples in [37, 38]). In the evaluation process, we assume that there are no taxes because

[1] The percentage was calculated according to data from table 2 in Ref [31].

many governments make great effort to establish a neutral tax system in which taxes do not influence a firm's decisions [38]. Therefore, the profit is assumed to be determined by the electricity price and subsidy. We denote profit as $\pi(P_t, S_t)$, where P_t and S_t represent the electricity price and subsidy payment at time t, respectively. Thus, the following assumption is made about the profit:

Assumption 2. $\pi(P_t, S_t) = (P_t + S_t) * x$

The lifetime for a solar PV project is usually very long, and extending its lifetime is often possible due to government' efforts to promote the development of clean energy. Therefore, referring to [37-41], we assume that the embedded option is perpetual[2], which not only facilitates the derivation process but also reflects the flexibility that decision makers have in the timing of projects.

3.1.2. Uncertainties

The uncertainties embedded in solar PV projects can be classified into three categories: (1) natural and technological uncertainty, which primarily influences the solar energy endowment and its utilization coefficient; (2) economic uncertainty, which mainly influences the earnings of projects; and (3) government regulation uncertainty, which influences different aspects of projects, such as the profitability, technology progress, and financing. These three types of uncertainty interact with each other and work together to affect the feasibility of solar PV projects. In our analysis, we use the PV module cost uncertainty, electricity price uncertainty and subsidy uncertainty to capture these three uncertainties. Moreover, market reform of the electricity price will make the previously fixed electricity price stochastic.

Geometric Brownian motion (GBM) is a continuous-time stochastic process that essentially implies that the distribution of future prices is lognormal. This process is frequently used to model output prices, security prices, and other economic and financial variables [12]. GBM is a Markov process, which implies that future prices are determined by today's prices rather than by past prices or the evolution of past prices. This is consistent with the weak form of market efficiency. The markets for the PV module, electricity and renewable energy credits are competitive and obey the weak form of market efficiency. Therefore, referring to [42, 43], we assume that the cost of the PV module, electricity price and subsidy follow GBM.

The PV module cost is used to measure the technological uncertainty because it is the driving force for the decline and volatility of the solar PV investment [8, 10]. PV modules have many regional markets and a global market, and there are many manufacturers in these markets. Thus, the market can be regarded as competitive. Under the competitive market assumption, we assume that the cost of a PV module is governed by a GBM process, that is:

$$dC_t = \alpha_c C_t dt + \sigma_c C_t dz_c, C_{t_0} = C_0 \tag{1}$$

where α_c and σ_c are the drift term and the volatility term of the PV module cost, respectively, dz_c is the increment of a standard Wiener process, and C_0 is the initial PV module cost. Equation (1) shows that the PV module cost follows GBM.

The electricity price is selected to measure the economic uncertainty. Electricity is a special commodity that is characterized by rigid demand, giving its price high volatility. Under the competitive assumption, we assume that the electricity price follows the GBM

[2] In section 4, the average time to investment is less than 9 years; therefore, this is not a restrictive assumption.

process, that is:

$$dP_t = \alpha_p P_t dt + \sigma_p P_t dz_p, P_{t_0} = P_0 \quad (2)$$

where α_p and σ_p are the drift term and volatility term of the electricity price, respectively, dz_p is the increment of a standard Wiener process, and P_0 is the initial electricity price. Equation (2) indicates that electricity prices follow GBM.

Traded assets, such as renewable energy credits, are used to represent the government regulation uncertainty and to establish a generalized real option model for solar PV projects. Renewable energy credits are publicly traded in a competitive market; therefore, referring to [30, 38], we again assume that this uncertainty follows the GBM process, that is:

$$dS_t = \alpha_s S_t dt + \sigma_s S_t dz_s, S_{t_0} = S_0 \quad (3)$$

where α_s and σ_s are the drift term and volatility term of the subsidy payment, respectively, dz_s is the increment of a standard Wiener process, and S_0 is the initial subsidy. Equation (3) indicates that the subsidy follows GBM.

Later in the analysis, we apply contingent claims to analyse the option values. Proper tradable assets must be selected to capture the characteristics (namely, the drift term and volatility term) of the stochastic assets [12]. A risk-free dynamic portfolio must be established to replicate the return and volatility of a solar PV project. The PV module, electricity and renewable energy credits are selected as the tradable assets in the portfolio. In the contingent claims, the risk-free rate is the discount factor, and the convenience yield is the difference between the expected return rate calculated by the Capital Asset Pricing Model (CAPM) and the expected change in the uncertain factors [12]. Let δ_c, δ_p and δ_s denote the convenience yields of the PV module, electricity and subsidy, respectively.

The results of the dynamic programming and contingent claims are the same in a risk-neutral world [12, 35, 38]. To simplify the deductions, we use a stochastic process in a risk-neutral world later in the analysis. Let the market prices of risk θ_c, θ_p and θ_s be defined as

$$\theta_c = \frac{\alpha_c + \delta_c - r}{\sigma_c}, \theta_p = \frac{\alpha_p + \delta_p - r}{\sigma_p}, \theta_s = \frac{\alpha_s + \delta_s - r}{\sigma_s}$$

where θ_c, θ_p and θ_s are the market prices of risk for the PV module cost, electricity price and subsidies.

By substituting the market prices of risk into Equations (1), (2) and (3), the stochastic processes of the PV module cost, electricity price and subsidy are rewritten as

$$dC_t = (r - \delta_c + \theta_c \sigma_c) C_t dt + \sigma_c C_t dz_c$$
$$dP_t = \left(r - \delta_p + \theta_p \sigma_p\right) P_t dt + \sigma_p P_t dz_p$$
$$dS_t = (r - \delta_s + \theta_s \sigma_s) S_t dt + \sigma_s S_t dz_s$$

where these equations are stochastic processes with market prices of risk.

As the market prices of risk are zero in a risk-neutral world, the stochastic processes in the risk-neutral world are rewritten as follows:

$$dC_t = \alpha_c^R C_t dt + \sigma_c C_t dz_c \quad (4)$$
$$dP_t = \alpha_p^R P_t dt + \sigma_p P_t dz_p \quad (5)$$
$$dS_t = \alpha_s^R S_t dt + \sigma_s S_t dz_s \quad (6)$$

where $\alpha_c^R = r - \delta_c$, $\alpha_p^R = r - \delta_p$ and $\alpha_s^R = r - \delta_s$. Equations (4-6) describe the GBM in a risk-neutral world.

3.2. Real options models

Let us consider a solar PV project that has just acquired government approval. The decision makers need to consider when the project should be performed. The real options approach can be applied in the decision-making process. Similar to many other projects, solar PV projects contain the defer option, which means that decision makers have the right but not the obligation to invest until positive market signals emerge. The value of this right and the optimal investment timing can be studied using real options methods. To simplify the model, we assume that the construction of the PV project is completed instantaneously [40] and that the decision makers are the price takers [40]. Additionally, we neglect any correlation between the PV module cost, electricity price and subsidy payment (see other examples in [32, 36]).

The option values and optimal investment timing of a solar PV project are studied under different market systems and support schemes. The electricity price market reform influences the risk exposure of the projects because the assumptions in the electricity price vary according to the market system. Support schemes also influence the risk exposure of the project: FIT eliminates the electricity price risk; the price premium leaves the investor completely exposed to the electricity price risk; and the renewable energy credits expose the investor to both electricity price and credit trading risks. As the Chinese market is not liberalized, implementing renewable energy credits is very difficult. Therefore, we focus on the first two types of support schemes, but we establish a generalized model that considers renewable energy credits. As the risk exposures are the same in a regulated market and a free market with the FIT scheme, the solutions are similar. For simplification, we incorporate the discussion of the real options model for a regulated market into that for the FIT scheme in a free market and mainly discuss real options models for the free market.

As both the investment cost and revenue have a linear relationship with the production x, the production x is offset in the derivation process. Therefore, referring to [12], [36], and [32], we conduct a unit decision analysis to facilitate the derivation process.

3.2.1. Value of operating project

Suppose that there exists an operating solar PV project. As we assume that the project has an infinite lifetime, the operating project value is independent of time t. Additionally, the PV module cost uncertainty is locked when the project is undertaken. Therefore, the operating project value is influenced by the electricity price and subsidy. Let $V(P_t, S_t)$ denote the value of an operating project when the electricity price and subsidy payment are P_t and S_t, respectively. During a short time interval dt, the return of this project comes from the capital gains and profits. According to the no arbitrage principle, we obtain

$$\mathrm{E}[dV] + \pi(P_t, S_t)dt = rVdt$$

where $\mathrm{E}[dV]$ and $\pi(P_t, S_t)\,dt$ are the capital gains and profits in the time interval dt, respectively, and $rVdt$ is the return of the project in the time interval dt.

Using Ito's lemma to expand the differential of the project value and deleting all the terms that go to zero more quickly than dt, we obtain

$$dV = \left[\alpha_p^R P_t \frac{\partial V}{\partial P_t} + \alpha_s^R S_t \frac{\partial V}{\partial S_t} + \frac{1}{2}\left(\sigma_p P_t\right)^2 \frac{\partial^2 V}{\partial {P_t}^2} + \frac{1}{2}(\sigma_s S_t)^2 \frac{\partial^2 V}{\partial {S_t}^2}\right] dt + \sigma_p P_t \frac{\partial V}{\partial P_t} dz_p + \sigma_s S_t \frac{\partial V}{\partial S_t} dz_s$$

where this equation is the expanded equation of Ito's lemma.

For simplification, let V_p and V_s denote $\frac{\partial V}{\partial P_t}$ and $\frac{\partial V}{\partial S_t}$, respectively, and let V_{pp} and V_{ss} denote $\frac{\partial^2 V}{\partial {P_t}^2}$ and $\frac{\partial^2 V}{\partial {S_t}^2}$, respectively. Then, taking the expectation of dV and substituting it into the equation above, we obtain the following PDE:

$$\frac{1}{2}\left(\sigma_p P_t\right)^2 V_{pp}(P_t, S_t) + \frac{1}{2}(\sigma_s S_t)^2 V_{ss}(P_t, S_t) + \alpha_p^R P_t V_p(P_t, S_t) + \alpha_s^R S_t V_s(P_t, S_t) - rV + \pi(P_t, S_t) = 0$$

which is the PDE for the value of an operating project.

The solution for this PDE is

$$V(P_t, S_t) = \rho_p P_t + \rho_s S_t$$

where $\rho_p = 1/\left(r - \alpha_p^R\right), \rho_s = 1/(r - \alpha_s^R)$ (see Appendix B for details).

Similarly, we obtain the value of an operating project in a regulated market, which is

$$V\left(P_f\right) = \rho_s\left(P_f + S_t\right)$$

where $\rho_s = 1/(r - \alpha_s^R)$ and P_f is the fixed electricity price in the regulated market.

3.2.2. Value of the defer option

As we have assumed that the defer option is perpetual, its value is not affected by time t. We denote the defer option value as $F(C_t, P_t, S_t)$, where the PV module cost, electricity price and subsidy payment are C_t, P_t and S_t, respectively. In the short time interval dt, the return of this option is the capital gain. Using the no arbitrage principle, we obtain

$$E[dF] = rFdt$$

where $E[dF]$ is the capital gain in the time interval dt and $rFdt$ is the return of this option in the time interval dt.

Using Ito's lemma to expand the differential of the option value and deleting all the terms that go to zero more quickly than dt, we obtain

$$dF = \left[\alpha_c^R C_t \frac{\partial F}{\partial C_t} + \alpha_p^R P_t \frac{\partial F}{\partial P_t} + \alpha_s^R S_t \frac{\partial F}{\partial S_t} + \frac{1}{2}(\sigma_c C_t)^2 \frac{\partial^2 F}{\partial {C_t}^2} + \frac{1}{2}\left(\sigma_p P_t\right)^2 \frac{\partial^2 F}{\partial {P_t}^2} + \frac{1}{2}(\sigma_s S_t)^2 \frac{\partial^2 F}{\partial {S_t}^2}\right] dt + \sigma_c C_t \frac{\partial F}{\partial C_t} dz_c + \sigma_p P_t \frac{\partial F}{\partial P_t} dz_p + \sigma_s S_t \frac{\partial F}{\partial S_t} dz_s$$

which is the expanded equation of Ito's lemma.

For simplification, let F_c, F_p and F_s denote $\frac{\partial F}{\partial C_t}$, $\frac{\partial F}{\partial P_t}$ and $\frac{\partial F}{\partial S_t}$, respectively, and let F_{cc}, F_{pp} and F_{ss} denote $\frac{\partial^2 F}{\partial {C_t}^2}$, $\frac{\partial^2 F}{\partial {P_t}^2}$ and $\frac{\partial^2 F}{\partial {S_t}^2}$, respectively. Then, taking the expectation of dF and substituting it into the equation above, we obtain the following PDE:

$$\frac{1}{2}(\sigma_c C_t)^2 F_{cc}(C_t, P_t, S_t) + \frac{1}{2}\left(\sigma_p P_t\right)^2 F_{pp}(C_t, P_t, S_t) + \frac{1}{2}(\sigma_s S_t)^2 F_{ss}(C_t, P_t, S_t) + \alpha_c^R C_t F_c(C_t, P_t, S_t) + \alpha_p^R P_t F_p(C_t, P_t, S_t) + \alpha_s^R S_t F_s(C_t, P_t, S_t) - rF = 0$$

which is the PDE for the defer option.

The following boundary conditions apply:

$$F({C_t}^*, {P_t}^*, {S_t}^*) = V({P_t}^*, {S_t}^*) - I({C_t}^*) \quad (7)$$

$$F_c({C_t}^*, {P_t}^*, {S_t}^*) = V_c({P_t}^*, {S_t}^*) - I_c({C_t}^*) \quad (8)$$

$$F_p({C_t}^*, {P_t}^*, {S_t}^*) = V_p({P_t}^*, {S_t}^*) - I_p({C_t}^*) \quad (9)$$

$$F_s({C_t}^*, {P_t}^*, {S_t}^*) = V_s({P_t}^*, {S_t}^*) - I_s({C_t}^*) \quad (10)$$

where ${C_t}^*$, ${P_t}^*$ and ${S_t}^*$ are the option trigger values, which depend on the trigger line.

The trigger line (or boundary) is called a “free boundary”. There is no difference between investment and waiting at the boundary; that is, the option value is equal to the termination value of the project at the boundary. Boundary conditions (7) and (8)-(10) are the value-matching condition and smooth-paste conditions, respectively [12]. These two conditions ensure that not only the values but also the derivatives of the option value and termination payoff match each other at the boundary.

3.2.2.1. Value of the defer option without subsidy

Assume that there is no subsidy for the project. There are two types of uncertainty in the project, namely, the uncertainties of the PV module cost and the electricity price. Therefore the corresponding PDE and boundary conditions are

$$\frac{1}{2}(\sigma_c C_t)^2 F_{cc}(C_t, P_t) + \frac{1}{2}\left(\sigma_p P_t\right)^2 F_{pp}(C_t, P_t) + \alpha_c^R C_t F_c(C_t, P_t) + \alpha_p^R P_t F_p(C_t, P_t) - rF = 0$$

$$F({C_t}^*, {P_t}^*) = \rho_p {P_t}^* - 4.29 * {C_t}^*$$

$$\frac{\partial F}{\partial C_t}({C_t}^*, {P_t}^*) = -4.29$$

$$\frac{\partial F}{\partial P_t}({C_t}^*, {P_t}^*) = \rho_p$$

By standard arguments, the value of the investment opportunity is $F(C_t, P_t) = B{C_t}^{1-\beta_1}{P_t}^{\beta_1}$ (see Appendix C),

where $\beta_1 = \frac{1}{2} - \frac{\alpha_p^R - \alpha_c^R}{{\sigma_c}^2 + {\sigma_p}^2} + \sqrt{\left(\frac{\alpha_p^R - \alpha_c^R}{{\sigma_c}^2 + {\sigma_p}^2} - \frac{1}{2}\right)^2 + \frac{2(r - \alpha_c^R)}{{\sigma_c}^2 + {\sigma_p}^2}} > 1$ and $B = \frac{4.29 * {\rho_p}^{\beta_1}(\beta_1 - 1)^{\beta_1 - 1}}{(4.29 * \beta_1)^{\beta_1}}$.

With the PV module cost and electricity price uncertainties, the trigger line for the project is:

$${H_t}^* = \frac{{P_t}^*}{{C_t}^*} = \frac{4.29 * \beta_1}{\rho_p(\beta_1 - 1)}$$

The analytical solution proves that the value of the option increases when the PV module cost decreases or when the electricity price increases. This solution implies that investment should be undertaken when the ratio of the electricity price to the PV module cost is high.

3.2.2.2. Value of the defer option with $\boldsymbol{FIT}$

The electricity price and subsidy uncertainty are removed in the FIT scheme, leaving only PV module cost uncertainty in the model. The corresponding PDE and boundary conditions are

$$\frac{1}{2}(\sigma_c C_t)^2 F_{cc}(C_t) + \alpha_c C_t F_c(C_t) - rF = 0$$

$$F({C_t}^*) = \frac{FIT}{r} - 4.29 * {C_t}^*$$

$$F_c({C_t}^*) = -4.29$$

By standard arguments, the solution to this PDE is $F(C_t) = B{C_t}^{\beta_2}$, where $\beta_2 = \frac{1}{2} - \frac{\alpha_c^R}{{\sigma_c}^2} - \sqrt{\left(\frac{\alpha_c^R}{{\sigma_c}^2} - \frac{1}{2}\right)^2 + \frac{2r}{{\sigma_c}^2}} < 0$ and $B = -\frac{4.29}{\beta_2}\left(\frac{\beta_2}{\beta_2 - 1}\frac{FIT}{4.29 * r}\right)^{1-\beta_2}$.

With the PV module cost uncertainty, the trigger line to undertake investment is

$${C_t}^* = \frac{\beta_2}{\beta_2 - 1}\frac{FIT}{4.29 * r}$$

The analytical solution proves that the value of the investment opportunity has a negative relationship with the PV module cost. The project should be undertaken when the PV module cost is below the trigger line.

As for projects in a regulated market, the project also contains only PV module cost uncertainty. Assuming that there is no subsidy in the regulated market, the electricity price is denoted by P_f, and the option value is $F(C_t) = B{C_t}^{\beta_2}$, where $\beta_2 = \frac{1}{2} - \frac{\alpha_c^R}{{\sigma_c}^2} - \sqrt{\left(\frac{\alpha_c^R}{{\sigma_c}^2} - \frac{1}{2}\right)^2 + \frac{2r}{{\sigma_c}^2}} < 0$ and $B = -\frac{4.29}{\beta_2}\left(\frac{\beta_2}{\beta_2 - 1}\frac{P_f}{4.29 * r}\right)^{1-\beta_2}$.

With PV module cost uncertainty, the trigger line for the project is

$${C_t}^* = \frac{\beta_2}{\beta_2 - 1}\frac{P_f}{4.29 * r}$$

3.2.2.3. Value of the defer option with price premium

The price premium scheme eliminates the subsidy uncertainty, leaving two types of uncertainty in the project: the uncertainties of the PV module cost and the electricity price. Let $P_t^r = P_t + premium$, where P_t^r is governed by GBM and has the same drift term and volatility term as P_t because the premium is a fixed parameter [44]. The corresponding PDE and the boundary conditions are

$$\frac{1}{2}(\sigma_c C_t)^2 \frac{\partial^2 F}{\partial {C_t}^2}(C_t, P_t^r) + \frac{1}{2}\left(\sigma_p P_t^r\right)^2 \frac{\partial^2 F}{\partial {P_t^r}^2}(C_t, P_t^r) + \alpha_c C_t \frac{\partial F}{\partial C_t}(C_t, P_t^r) + \alpha_p P_t^r \frac{\partial F}{\partial P_t^r}(C_t, P_t^r) - rF = 0$$

$$F\left({C_t}^*, P_t^{r*}\right) = \rho_p P_t^{r*} - 4.29 * {C_t}^*$$

$$\frac{\partial F}{\partial C_t}\left({C_t}^*, P_t^{r*}\right) = -4.29$$

$$\frac{\partial F}{\partial P_t^r}\left({C_t}^*, P_t^{r*}\right) = \rho_p$$

By standard arguments, the solution to this PDE is $F(C_t, P_t^r) = B{C_t}^{1-\beta_1}{P_t^r}^{\beta_1} = B{C_t}^{1-\beta_1}(P_t + Premium)^{\beta_1}$ (see Appendix D), where $\beta_1 = \frac{1}{2} - \frac{\alpha_p^R - \alpha_c^R}{{\sigma_c}^2 + {\sigma_p}^2} + \sqrt{\left(\frac{\alpha_c^R - \alpha_p^R}{{\sigma_c}^2 + {\sigma_p}^2} - \frac{1}{2}\right)^2 + \frac{2\left(r - \alpha_c^R\right)}{{\sigma_c}^2 + {\sigma_p}^2}} > 1$ and $B = \frac{4.29 * {\rho_p}^{\beta_1}(\beta_1 - 1)^{\beta_1 - 1}}{(4.29 * \beta_1)^{\beta_1}}$.

With the PV module cost and electricity price uncertainty, the trigger line for the project is:

$$H_t{}^* = \frac{P_t^{r*}}{C_t{}^*} = \frac{4.29 * \beta_1}{\rho_p(\beta_1 - 1)}$$

The above solution proves that the value of the option increases when the PV module cost decreases or when the electricity price increases. This solution implies that investment should be undertaken when the ratio of the electricity price to the PV module cost is high.

4. Results and discussion

4.1. Parameter estimation and scenario design

4.1.1. Parameter estimation

4.1.1.1. Parameters for PV module cost uncertainty

As we assume that the cost of the PV module is governed by GBM, we decide to use historical data to estimate the drift and volatility terms in Equation (1). The weekly cost data for the PV module are collected in the Wind database, which runs from 2012-02-01 to 2016-03-09, and the units are converted to yuan/kWh. By applying Ito's lemma to Equation (1), we obtain $dlnC_t = \left(\alpha_c - \frac{\sigma_c{}^2}{2}\right)dt + \sigma_c dz_c$, where the increment of lnC_t obeys a normal distribution. We use STATA to prove that C_t is governed by GBM, and we estimate α_c and σ_c. We conclude that the weekly drift term α_c is equal to -0.25% and that the weekly volatility term σ_c is equal to 0.63%. In annual terms, these values are -9.01% and 3.77%, respectively (details are provided in Appendix E).

Parameter α_c can also be calculated using the learning curve method. To be specific,

$$\alpha_c = \frac{\ln(1 - LR)}{ln2} * GR$$

where LR is the learning rate and GR is the growth rate. Lin and Wesseh [36] note that LR in China is 50%. By assuming that GR is 10% (see examples in [31]), we conclude that α_c is -10%, which is close to -9.01%. Later in the analysis, we assume that α_c is equal to -9.01%.

4.1.1.2. Parameters for electricity price and subsidy

(1) Parameters for a regulated market

We assume that if there are no support schemes for solar PV projects, the owner will sell the electricity at the FIT for coal-fired power generation. Let P_f denote the weighted FIT for coal-fired power generation in 2015. Using the data collected from the Wind database and the National Development and Reform Commission (NDRC), we conclude that P_f is equal to 0.41 yuan/kWh in the regulated market.

(2) Parameters for a free market

As the generated electricity price in China is now under regulation, it does not follow a stochastic process, and there are not sufficient data to estimate the parameters for Chinese power systems. However, the Chinese government has decided to perform electricity market reform based on the electricity market in Europe, which is much more liberalized than that in China. Therefore, referring to [38], we assume that α_p^R and σ_p are equal to 2.15% and

29.20%, respectively, in annual terms. Considering that there is a decreasing tendency in support schemes, we assume that the FIT and price premium are 0.78 yuan/kWh and 0.23 yuan/kWh, respectively[3].

4.1.1.3. Risk-free rate and convenience yield

(1) Risk-free rate

We use spot rates for the 10-year government bonds to calculate the risk-free rate. Monthly data from 2013-03 to 2016-03 are obtained from the Wind database. During this period, the interest rate ranges from 2.84% to 4.61%. We use the average as the risk-free rate, so r is equal to 3.74%.

(2) Convenience yield of the PV module

The convenience yield of the PV module is estimated as the difference between the PV manufacturing industry's expected return and the PV module's cost drift term. Specifically, $\delta_c = \mu_c - \alpha_c$. μ_c is calculated using the CAPM model:

$$\mu_c = r + \beta_c(E(r_m) - r)$$

where r is the risk-free rate, β_c is the β for the PV manufacturing industry, and $E(r_m)$ is the expected return of the market portfolio.

We use the Shanghai-Shenzhen 300 index (CSI 300 index) as the market portfolio and use daily logarithm returns, which run from 2013-3-24 to 2016-3-13, to calculate the value of $E(r_m)$, which is 3.95%. β_c is calculated as the equity-weighted β of the listed companies in the solar PV manufacturing industry (details are shown in Appendix F). After the calculation, we conclude that β_c and δ_c are equal to 1.182 and 13.00%, respectively. Hence, α_c^R equals -9.26%.

(3) Convenience yield of electricity

The convenience yield of electricity is difficult to estimate directly because electricity is not storable. Therefore, the future price of electricity is widely used to estimate the convenience yield [38, 45, 46]. However, as α_p^R is a risk-neutral drift term for the electricity price, we do not need to calculate δ_p.

All of the parameters for the regulated market and free market are summarized in Table 1.

Table 1

4.1.2. Scenario design

Four scenarios are discussed in the subsequent analysis, and each has different parameters and assumptions. Table 2 lists the details of the scenarios.

Table 2

[3] The newest FIT and price premium in China are 0.90 yuan/kWh (average FIT for the whole country) and 0.35 yuan/kWh, respectively. The data are obtained from the website of the NDRC - http://www.sdpc.gov.cn/

4.2. Scenario analysis on option values

4.2.1. Sensitivity analysis

To analyse the different option values, we use MATLAB to simulate the GBM process and to calculate the values for the parameters in the analytical solutions. Then, we conduct several analyses based on the results. Using Ito's lemma, Equations (4) and (5) can be rewritten as follows:

$$dlnC_t = (\alpha_c^R - \sigma_c{}^2/2)dt + \sigma_c dz_c \tag{11}$$

$$dlnP_t = \left(\alpha_p^R - \sigma_p{}^2/2\right)dt + \sigma_p dz_p \tag{12}$$

To simulate the GBM process in MATLAB, we discretize the risk-neutral processes in Equations (11) and (12). We assume that the lifetime for the option is T, which is split it into N equal intervals of Δt. Thus, Equations (11) and (12) can be discretized as

$$ln(C_t/C_{t-1}) = (\alpha_c^R - \sigma_c{}^2/2)\Delta t + \sigma_c\sqrt{\Delta t}\epsilon_{ct} \tag{13}$$

$$ln(P_t/P_{t-1}) = \left(\alpha_p^R - \sigma_p{}^2/2\right)\Delta t + \sigma_p\sqrt{\Delta t}\epsilon_{pt} \tag{14}$$

where ϵ_{ct} and ϵ_{pt} are independent standard normal random variables.

We simulate several paths using Monte Carlo sampling based on Equations (13) and (14) and obtain the parameters in the analytical solutions in Section 3.2. Then, we use the analytical solutions to conduct a sensitivity analysis in order to determine how the option value changes with varying initial values of different uncertain factors. The result is shown in Fig. 1. As both the PV module cost uncertainty and electricity price uncertainty influence the option value in Scenarios 2 and 4, the option values for these scenarios are dependent on C_t and P_t. For example, the changes in Scenario 2 with respect to C_t and P_t are shown in Fig. 1(a). The option approaches infinity when the PV cost module tends to zero or the electricity price tends to infinity. Observing the changes in the option value on the longitudinal section of the C-axis, we conclude that the option value for Scenario 2 decreases when the initial PV cost increases. Similarly, we infer that the option value increases when the initial electricity price increases. The results of the other sensitivity analyses are shown in Figs. 1 (b) and 1 (c). These figures confirm the expected relationship between the uncertain factors and real option values, namely, that the real option value has a negative relationship with costs and a positive relationship with revenues.

A high cost and low electricity price will decrease the profits of solar PV projects, thus decreasing the option value. This phenomenon also conforms to option theory. The cost is related to the investment, which is analogous to the execution price in option theory, and the execution price has a negative impact on the option value. The electricity price is relevant to the value of an operating project, which is analogous to the price of an underlying asset in option theory, and the price of an underlying asset has a positive influence on the option value. These results are useful for investors because they imply that the cost and electricity price are the market signals for investment. Investors can undertake projects when the ratio of the electricity price to the PV module cost is high.

Figure 1

4.2.2. Expected option values

The above analysis studies how the option values change in response to varying values of different uncertain factors in a static way. To study how the option values dynamically change with respect to C_t and P_t, we need to calculate the expected option values. By taking the expectations of Equations (11) and (12), the expected C_t and P_t are expressed as follows:

$$\mathrm{E}C_t = C_0 e^{\alpha_c^R t} \tag{15}$$

$$\mathrm{E}P_t = P_0 e^{\alpha_p^R t} \tag{16}$$

The Monte Carlo simulation results of C_t and P_t are shown in Fig. 2. The expected C_t has a negative relationship with t, whereas the expected P_t has a positive relationship with t. For C_t, the costs continue decreasing because of technological progress, large-scale production, and production optimization [10]. The simulation result confirms the expected behaviour of the PV module cost. P_t increases slightly when t increases but is very volatile, which is in line with reality. Compared to the process of P_t, the process of C_t demonstrates a more significant long-term trend. The expected C_t decreases to approximately one-half of its initial value in ten years, while the expected P_t increases by only approximately 22%. Nevertheless, the volatility of P_t is much higher than that of C_t. As shown in Fig. 2, the sample path for C_t fluctuates around the expected path for C_t, whereas the sample path for P_t indicates that P_t is more volatile. These features have a great influence on the option values and optimal investment timing.

Figure 2

The expected option values are shown in Fig.3. All of the expected option values increase when t increases, which confirms the expected behaviour of the options. As the time period increases, positive market signals are more likely to emerge. Therefore, the option value has a positive relationship with time. Although the option values in all four scenarios increase over time, there are some obvious differences among them, which are caused by the different market reform assumptions and support scheme assumptions in the scenarios. Three rules are summarized[4]:

Figure 3

(1) Support schemes have similar impacts on the option value in a regulated market, and the minimum π in the regulated market is 0.56 yuan/kWh.

The option value $F(C_t)$ and B are governed by π in the regulated market, and they have a positive relationship with π. Both the FIT and price premium have linear relationships with π, so their impacts are similar in the regulated market. By implementing the support schemes, the value of π increases, thus increasing the option value. To stimulate investment in solar PV projects in the regulated scenario, the most important thing for the government is to determine the minimum π^* that will encourage investors to invest at the initial time, i.e., $C_t^* = C_0$. The calculations show that π^* is equal to 0.56. In other words, the minimum price premium should be 0.15 yuan/kWh or the minimum FIT should be 0.56

[4] One important thing that should be noted is that the rules that are summarized here are ideal (which assumes that the option is not executed). As we will see in Section 4.3, the projects will usually be executed in ten years, and the option values embedded in the projects go to zero when the projects are executed.

yuan/kWh in the regulated market.

(2) Support schemes have different impacts on the option values in a free market.

Compared to the option values of Scenario 2, the option values of Scenario 3 decrease after FIT is implemented in the short term but surpass those of Scenario 2 in the long term (as shown in Fig. 4). Moreover, compared to the option values of Scenario 2, the option values of Scenario 4 increase when a price premium is executed. By comparing the option values of Scenarios 3 and 4, we conclude that compared to the FIT, the price premium greatly enhances the option value in the short term, but its impact on the promotion of the option value decreases in the long run.

Figure 4

The expected option values for Scenarios 3 and 4 are $B_3 \mathrm{E}C_t{}^{\beta_2}$ and $B_4 \mathrm{E}C_t{}^{1-\beta_1} \mathrm{E}P_t{}^{\beta_1}$, respectively. As $B_4 > B_3$, the option value for Scenario 3 is smaller than that of Scenario 4 in the short term. However, things will change in the long run. As $|1-\beta_1| < |\beta_2|$, it can be inferred that the positive effect of $\mathrm{E}C_t$ on $\mathrm{E}F_4$ is smaller than that on $\mathrm{E}F_3$. Moreover, as we discussed above, the process of C_t exhibits a more significant long-term trend than that of P_t. The relative change in $\mathrm{E}C_t$ is much greater than that of $\mathrm{E}P_t$ during the same period because $|\alpha_c^R| > \alpha_p^R$. Therefore, the expected option value of Scenario 3 will surpass that of Scenario 4 in the long run.

(3) Electricity market reform will enhance the option value in the short term.

The projects are additionally exposed to electricity price uncertainty after electricity market reform is accomplished. Hence, compared to the option values in the regulated market, the option values are enhanced in the short term. However, the additional uncertainty decreases the impact that C_t has on the option value, whereas C_t has a great impact on the option value in the long run because of its obvious long-term trend. Therefore, the option values in the regulated market will eventually exceed those in the free market (without subsidy). This result is shown in Fig. 5(a) and (b), in which the option values for Scenario 1 surpass those for Scenario 2.

Figure 5

4.3. Scenario analysis of optimal investment timing

4.3.1. Optimal investment conditions

To determine the optimal investment timing, the optimal investment conditions must be identified. The analytical solutions to the optimal investment conditions are derived in Section 3.2. The numerical optimal investment conditions are obtained by simulations and are listed in Table 3.

Table 3

These results show that support schemes are very helpful for stimulating investment. The support schemes directly influence the optimal investment conditions in the scenarios that consider only the PV module cost uncertainty. However, in the scenarios that consider both the electricity price and PV module cost uncertainty, the price premium does not influence the optimal investment conditions but rather influences the initial conditions, which in turn influence decision making.

Investment should be undertaken when the optimal investment conditions are met. Based on our assumptions, the project should be undertaken immediately in Scenario 3, whereas for Scenarios 1, 2 and 4, the decision makers should wait until the investment can be compensated by future profits.

4.3.2. Expected optimal investment timing

To determine the optimal investment timing, we calculate the time at which the optimal investment conditions are triggered. As both C_t and P_t are stochastic, the optimal time t^* is also stochastic, so we need to use the expected values in the calculation. For Scenarios 1 and 3, in which only the cost uncertainty is considered, the optimal time can be calculated as

$$\mathrm{E}(t^*) = A_1\left[ln\left(\frac{\beta_2}{\beta_2 - 1}\frac{P_f}{4.29 * r}\right) - ln(C_0)\right]$$

where $A_1 = 1/\left(\alpha_c^R - \frac{1}{2}\sigma_c^2\right)$ and the variance of t^* is equal to $\frac{(C_t^* - C_0){\sigma_c}^2 A_1^3}{2}$ (with reference to [41], see Appendix G).

For Scenarios 2 and 4, in which both the PV module cost and price uncertainty are considered, the optimal time can be calculated as

$$\mathrm{E}(t^*) = A_2\left[ln\left(\frac{4.29 * \beta_1}{\rho_p(\beta_1 - 1)}\right) - ln\left(\frac{P_0}{C_0}\right)\right]$$

where $A_2 = 1/\left[\frac{1}{2}\sigma_c^2 + \alpha_p^R - \alpha_c^R - \frac{1}{2}\sigma_p^2\right]$ and the variance of t^* is equal to $\frac{(H_t^* - H_0)({\sigma_p}^2 + {\sigma_c}^2)A_2^3}{2}$ (see Appendix G).

Figure 6

The expected execution times for different scenarios are shown in Fig. 6. As the initial condition is below the optimal investment condition in Scenario 3, investments are undertaken immediately; thus, the expected execution time is equal to 0. The expected execution times for Scenarios 1, 2, and 4 are 3.38 years, 8.59 years and 2.42 years, respectively. Three rules are summarized.

(1) The expected execution time and its variance decrease once suitable support schemes are implemented.

Comparing Scenarios 2 and 4, we conclude that the investment is expected to be undertaken approximately 6.17 years earlier due to the implementation of a price premium in the free market, and the variance of the execution time also becomes much smaller. A sensitivity analysis is conducted with respect to the support schemes to study the relationship between the support schemes and the expected execution time, as shown in Fig. 7(a) and (b). The results show that the expected execution time and its variance decrease when proper support schemes are applied in both the regulated market and free market. The results in Fig. 7 indicate that the government expenditure under the price premium scheme is smaller than that under the FIT scheme. The government needs to pay 0.56 yuan/kWh to encourage owners to invest under the FIT scheme, whereas it needs to pay only approximately 0.35

yuan/kWh to stimulate investment under the price premium scheme. However, the impacts of the FIT scheme on decreasing the expected execution time and its variance are greater than those of the price premium scheme. As shown in Fig. 7, when the increaces in the price premium and FIT are the same, the reduction of the expected execution time and its variance with the FIT are greater than those with the price premium.

Figure 7

(2) The investment will be postponed after electricity market reform, but the execution time and its variance will be reduced if proper support schemes are implemented.

Unlike the regulated scenario, the electricity market reform scenario includes electricity price uncertainty. As shown in Fig. 6, the expected execution time and its variance for Scenario 2 are greater than those for Scenario 1. This indicates that investment will be postponed in the free market. However, as shown in Fig. 7(b), the expected execution time and its variance are reduced after a price premium is implemented. Moreover, the government can choose to execute a FIT scheme to simulate investment.

(3) The impacts that support schemes have on the promotion of the optimal execution time are restrained by technological progress.

Decreasing PV module cost is mainly caused by technological progress, large-scale production and production optimization [10]. Technological progress refers to improvements in both material efficiency and conversion efficiency. Excluding the decline in polysilicon prices, technological progress accounts for approximately 52% of the cost decrease [10]. Therefore, we use α_c^R to represent the technological level. As demonstrated in Sections 3.2.2 and 4.3.2, the optimal investment condition H_t^* increases when $|\alpha_c^R|$ increases and is independent of the price premium in the free market. On the other hand, the initial investment condition H_0 increases when the premium increases and is independent of α_c^R in the free market. α_c^R and the price premium interact with each other when determining the expected execution time. To study their quantitative relationship, a sensitivity analysis of the optimal execution time with respect to these variables is conducted.

Fig. 8(a) and (c) shows that a low price premium greatly reduces the expected execution time when $|\alpha_c^R|$ is small. However, as $|\alpha_c^R|$ increases, a much higher price premium should be applied to stimulate investment. Maintaining the price premium at 0.15 yuan/kWh can encourage investors to invest when $|\alpha_c^R|$ is small. However, the optimal execution time first increases and then decreases as $|\alpha_c^R|$ increases. Therefore, we conclude that the effects of the support schemes are suppressed when $|\alpha_c^R|$ become greater. This change is caused by the unequal impacts the support schemes have on the optimal investment conditions, as shown in Fig. 8(b). α_c^R influences the optimal investment condition H_t^*, whereas the price premium influences the initial investment condition H_0. As shown in Fig. 8(b), H_t^* changes much faster than H_0 when the changes in α_c^R and the price premium are the same. Assuming that the price premium is 0.195 yuan/kWh, H_t^* is smaller than H_0 (0.605) when $|\alpha_c^R|$ is smaller than 5.5%, indicating that investors will invest right now. However, when $|\alpha_c^R|$ increases to 6.5%, H_t^* changes to approximately 0.65, which is greater than H_0; therefore, a rational investor will wait to invest. Technological progress results in a faster decline in PV costs, making the project more profitable in the future. Therefore, a rational investor will wait.

There is a minimum price premium pr^* for each α_c^R. When the price premium is larger than pr^*, rational investors will invest right now. The quantitative relationship between pr^* and α_c^R is described by

$$\frac{4.29}{\rho_p}\left(1+\frac{1}{-\frac{1}{2}-\frac{\alpha_p^R-\alpha_c^R}{{\sigma_c}^2+{\sigma_p}^2}+\sqrt{\left(\frac{\alpha_c^R-\alpha_p^R}{{\sigma_c}^2+{\sigma_p}^2}-\frac{1}{2}\right)^2+\frac{2(r-\alpha_c^R)}{{\sigma_c}^2+{\sigma_p}^2}}}\right)-\frac{P_f+pr^*}{C_0}=0$$

The relationship between pr^* and α_c^R is shown in Fig. 8(a) and is the borderline between the surface where the expected execution time is greater than zero and the surface where the expected execution time is equal to zero, that is, the borderline of the dark purple area and light purple area in Fig. 8(a). This rule also applies to regulated situations.

Figure 8

5. Conclusions

This paper presents a real options framework to determine the option value and optimal investment timing for solar PV projects under different market systems and different support schemes. The PV module costs, electricity prices, and support schemes are considered in our model. According to the proposed model, we analyse the unit decision value and the optimal investment timing in four different scenarios. The impacts of technological progress and the support schemes are also examined. Solar PV projects in China are analysed as an empirical study. Three conclusions are drawn with respect to our main research objectives:

(1) Electricity market reform enhances the option value in the short term because the projects are additionally exposed to electricity price uncertainty after market reform. Although electricity market reform makes owners postpone the execution of solar PV projects, the government can apply an appropriate support scheme to stimulate instantaneous investment. Based on the results, the price premium scheme may be preferred because it reduces the necessary government expenditure.

(2) The impacts of different support schemes on the option value and optimal execution time are similar in the regulated market because they directly influence the profits. However, these impacts are different in the free market: the option value under the price premium is higher than that under the FIT in the short term, but the option value under the FIT is greater in the long run. The impact that the FIT has on reducing the expected execution time and its variance is also greater than that for the price premium. Therefore, government should balance the expenditure and the expected execution time for solar PV projects when they decide which support scheme should be implemented.

(3) More attractive support schemes are necessary when there is a promotion in technology because the impacts that technological progress and support schemes have on the optimal investment conditions are unequal; H_t^* changes much faster than H_0 when the changes in α_c^R and the price premium are the same. Therefore, the government should adjust their support schemes when there is a technological breakthrough.

In addition to the above conclusions, the optimal investment timing is very important for investors, and we conclude the following: (1) The solar PV project will be undertaken immediately in only Scenario 3; the investors in Scenarios 1, 2 and 4 are expected to wait approximately 3.38, 8.59 and 2.42 years, respectively. (2) The expected execution time is decided by the difference between the optimal investment conditions and the initial conditions, the drift terms and the volatility terms. (3) Electricity market reform will increase the expected execution time when there are no changes in the support schemes. (4) Implementing support schemes, especially the FIT, can decrease the expected execution time and its variance.

Appendixes

Appendix A. Unit conversion process for solar PV module cost

Let S_t denote the price for crystalline silicon PV modules at time t, in units of $/W. Then, let C_t denote the price for PV modules at time t, in units of yuan/kWh. We assume that the exchange rate E is a constant 6.6 yuan/$, and we also assume that the high production efficiency of a solar module can be maintained for 15 years. Suppose that y is the module capacity.

$$C_t = \frac{Total\ module\ cost}{\sum_{t=1}^{15} electricity_t} = \frac{S_t * y * E * 1000}{\sum_{t=1}^{15} x * sd} = \frac{S_t * E * 1000}{15 * sd}$$

where sd denotes the annual sunshine duration in China.

To estimate sd, we use data from the BP Statistical Review of World Energy (2015). As electricity is an important resource for development in China, the demand for electricity, especially for renewable energy, is greater than the supply. Therefore, we assume that the annual production of solar energy equals its annual consumption. The annual solar production is determined by sd and the PV operating power:

$$Pro = sd * OPP$$

where Pro denotes the annual production of solar energy and OPP denotes the PV operating power, which can be represented by the cumulative installed PV power.

By applying an ordinary least squares (OLS) regression model (with the results shown in Fig. A.1), we obtain the value of sd, which equals 986 hours/year.

Figure A.1

Therefore,

$$C_t = \frac{S_t * E * 1000}{15 * 986}$$

Using this method, we conclude that the average C_t during the first quarter of 2014 is 0.304 yuan/kWh, and the cost for a solar PV project is 1.30 yuan/kWh. This value is close to the 1 yuan/kWh reported in [10], which excludes the battery storage costs. The conversion factor (ignoring the exchange rate) calculated by our methods is approximately 0.0676, which is close to the conversion factor (approximately 1/14) between S_t and C_t in [10].

Appendix B. Value of an operating project in a free market

The value of an operating project is the net present value of the future net cash flows:

$$V(P_t, S_t) = \mathrm{E}_{p_t, S_t}\left[\int_0^T e^{-rt}(P_t + S_t)dt | P_t, S_t\right]$$
$$= \mathrm{E}_{p_t}\left[\int_0^T e^{-rt}P_t dt | P_t\right] + \mathrm{E}_{S_t}\left[\int_0^T e^{-rt}S_t dt | S_t\right]$$

As P_t and S_t are independent, we can assume that $V(P_t, S_t) = G_p(P_t) + G_s(S_t)$, where $G_p(P_t)$ and $G_s(S_t)$ are the solutions to the following PDEs:

$$\frac{1}{2}\frac{\partial^2 G_p}{\partial {P_t}^2}\left(\sigma_p P_t\right)^2 + \frac{\partial G_p}{\partial P_t}\alpha_p^R P_t - rG_p(P_t) + P_t = 0$$
$$\frac{1}{2}\frac{\partial^2 G_s}{\partial {S_t}^2}(\sigma_s S_t)^2 + \frac{\partial G_s}{\partial S_t}\alpha_s^R S_t - rG_s(S_t) + S_t = 0$$

Using standard arguments, the solutions are:

$$G_p(P_t) = A_1 {P_t}^{\alpha_1} + A_2 {P_t}^{\alpha_2} + \rho_p P_t$$
$$G_s(S_t) = B_1 {S_t}^{\beta_1} + B_2 {S_t}^{\beta_2} + \rho_s S_t$$

where $\rho_p = 1/\left(r - \alpha_p^R\right)$; $\rho_s = 1/(r - \alpha_s^R)$; A_1, A_2, B_1 and B_2 are undetermined constants; α_1 and α_2 are the roots of the fundamental quadratic equation $\frac{1}{2}{\sigma_p}^2\alpha(\alpha - 1) + \alpha_p^R\alpha - r = 0$; and β_1 and β_2 are the roots of the fundamental quadratic equation $\frac{1}{2}{\sigma_s}^2\beta(\beta - 1) + \alpha_s^R\beta - r = 0$.

After ruling out investment bubbles, we obtain $G_p(P_t) = \rho_p P_t$ and $G_s(S_t) = \rho_s S_t$. Thus, the value of the operating project is determined by $V(P_t, S_t) = G_p(P_t) + G_s(S_t) = \rho_p P_t + \rho_s S_t$.

Appendix C. Value of the defer option without subsidy

In the case where the project faces PV module cost and electricity price uncertainties, the PDE is:

$$\frac{1}{2}(\sigma_c C_t)^2\frac{\partial^2 F}{\partial {C_t}^2}(C_t, P_t) + \frac{1}{2}\left(\sigma_p P_t\right)^2\frac{\partial^2 F}{\partial {P_t}^2}(C_t, P_t) + \alpha_c^R C_t\frac{\partial F}{\partial C_t}(C_t, P_t) + \alpha_p^R P_t\frac{\partial F}{\partial P_t}(C_t, P_t) - rF = 0$$

As the value of the option is homogeneous of degree 1 in (C_t, P_t), $F(C_t, P_t)$ can be written as $F(C_t, P_t) = C_t f(P_t/C_t) = C_t f(H_t)$. Therefore, $\frac{\partial^2 F}{\partial {C_t}^2}(C_t, P_t) = \frac{{H_t}^2 f''(H_t)}{C_t}$, $\frac{\partial^2 F}{\partial {P_t}^2}(C_t, P_t) = \frac{f''(H_t)}{C_t}$, $\frac{\partial \mathrm{F}}{\partial \mathrm{C}_t}(C_t, P_t) = f'(H_t)$, and $\frac{\partial \mathrm{F}}{\partial \mathrm{P}_t}(C_t, P_t) = f(H_t) - H_t f'(H_t)$.

Substituting these values into the PDE and grouping them, we obtain

$$\frac{1}{2}\left({\sigma_c}^2 + {\sigma_p}^2\right){H_t}^2 f''(H_t) + \left(\alpha_p^R - \alpha_c^R\right)H_t f'(H_t) - (r - \alpha_c^R)f(H_t) = 0$$

The boundary conditions become

$$f({H_t}^*) = \rho_p {H_t}^* - 4.29$$
$$f'({H_t}^*) = \rho_p$$
$$f({H_t}^*) - {H_t}^* f'({H_t}^*) = -4.29$$

By standard arguments, $f(H_t) = B{H_t}^{\beta_1}$

where β_1 is the positive root of the fundamental quadratic equation

$$\frac{1}{2}\left({\sigma_c}^2+{\sigma_p}^2\right)\beta(\beta-1)+\left(\alpha_p^R-\alpha_c^R\right)\beta-\left(r-\alpha_c^R\right)=0$$

The trigger line and B are obtained by the boundary conditions

$$H_t{}^*=\frac{P_t{}^*}{C_t{}^*}=\frac{4.29*\beta_1}{\rho_p(\beta_1-1)}$$

$$B=\frac{4.29*{\rho_p}^{\beta_1}(\beta_1-1)^{\beta_1-1}}{(4.29*\beta_1)^{\beta_1}}$$

Therefore, $F(C_t,P_t)=C_tf(H_t)=C_tBH_t{}^{\beta_1}=BC_t{}^{1-\beta_1}P_t{}^{\beta_1}$.

Appendix D. Value of the defer option with price premium

In this case, the project faces both PV module cost and electricity price uncertainties. Let $P_t^r=P_t+Premium$. Using Ito's lemma, we infer that P_t^r is also governed by GBM, which has the same drift term and volatility term as P_t. The PDE and boundary conditions are

$$\frac{1}{2}(\sigma_cC_t)^2\frac{\partial^2F}{\partial {C_t}^2}(C_t,P_t^r)+\frac{1}{2}\left(\sigma_pP_t^r\right)^2\frac{\partial^2F}{\partial {P_t^r}^2}(C_t,P_t^r)+\alpha_c^RC_t\frac{\partial F}{\partial C_t}(C_t,P_t^r)+\alpha_p^RP_t^r\frac{\partial F}{\partial P_t^r}(C_t,P_t^r)-rF=0$$

As the value of the option is homogeneous of degree 1 in (C_t,P_t^r), $F(C_t,P_t^r)$ can be written as $F(C_t,P_t^r)=C_tf(P_t^r/C_t)=C_tf(H_t)$.

Therefore, $\frac{\partial^2F}{\partial {C_t}^2}(C_t,P_t^r)=\frac{{H_t}^2f''(H_t)}{C_t}$, $\frac{\partial^2F}{\partial {P_t^r}^2}(C_t,P_t^r)=\frac{f''(H_t)}{C_t}$, $\frac{\partial \mathrm{F}}{\partial \mathrm{C}_t}(C_t,P_t^r)=f'(H_t)$, and $\frac{\partial \mathrm{F}}{\partial P_t^r}(C_t,P_t^r)=f(H_t)-H_tf'(H_t)$.

Substituting these values into the PDE and grouping them, we obtain

$$\frac{1}{2}\left({\sigma_c}^2+{\sigma_p}^2\right){H_t}^2f''(H_t)+\left(\alpha_p^R-\alpha_c^R\right)H_tf'(H_t)-\left(r-\alpha_c^R\right)f(H_t)=0$$

The boundary conditions become

$$f(H_t{}^*)=\rho_pH_t{}^*-4.29$$

$$f'(H_t{}^*)=\rho_p$$

$$f(H_t{}^*)-H_t{}^*f'(H_t{}^*)=-4.29$$

Using standard arguments, $f(H_t)=BH_t{}^{\beta_1}$

where β_1 is the positive root of the fundamental quadratic equation

$$\frac{1}{2}\left({\sigma_c}^2+{\sigma_p}^2\right)\beta(\beta-1)+\left(\alpha_p^R-\alpha_c^R\right)\beta-\left(r-\alpha_c^R\right)=0$$

The trigger line and B are obtained by the boundary conditions

$$H_t{}^*=\frac{P_t^{r*}}{C_t{}^*}=\frac{4.29*\beta_1}{\rho_p(\beta_1-1)}$$

$$B=\frac{4.29*{\rho_p}^{\beta_1}(\beta_1-1)^{\beta_1-1}}{(4.29*\beta_1)^{\beta_1}}$$

Therefore, the value of the option is

$$F(C_t,P_t^r)=C_tf(H_t)=C_tBH_t{}^{\beta_1}=BC_t{}^{1-\beta_1}P_t^{r\,\beta_1}=BC_t{}^{1-\beta_1}(P_t+Premium)^{\beta_1}$$

Appendix E. Estimation of the drift term and volatility term of the PV module cost uncertainty

We apply STATA to prove that C_t is governed by GBM and to estimate α_c and σ_c

using the following details:

(1) Normality test: If C_t is governed by GBM, $dlnC_t = (\alpha_c - \sigma_c{}^2/2)dt + \sigma_c dz_c$. We can infer that the increment of lnC_t obeys a normal distribution. To verify this, we calculate the natural logarithm value of C_t and let $r_t = lnC_t - lnC_{t-1}$. Then, we conduct a normality test for r_t by plotting a quantile-quantile plot (see Fig. E.1), and the result shows that r_t fits the normal distribution well.

Figure E.1

(2) Augmented Dickey-Fuller (ADF) unit root test: The ADF test is used to test whether or not a time series variable is stationary. It can also be used to verify whether lnC_t is governed by Brownian motion (BM). The regression model for the ADF test is $lnC_t - lnC_{t-1} = \alpha + \beta C_{t-1} + \sum_{j=1}^{k} \gamma_j r_{t-j} + \epsilon_t$. The null hypothesis is that lnC_t follows a BM with drift, namely, $\alpha \neq 0$ and $\beta = 0$. The p-value for the ADF test is approximately 0.09, so the null hypothesis cannot be rejected at the 5% level; hence, lnC_t statistically follows a BM process.

(3) Parameter estimation: As lnC_t is governed by a BM process, $\sigma_c{}^2$, which is the variance of r_t, can be calculated. As $r_t = \left(\alpha_c - \frac{\sigma_c{}^2}{2}\right)\Delta t + \sigma_c\sqrt{\Delta t}\varepsilon_t$, we apply the OLS method to estimate α_c.

We conclude that the weekly drift term α_c is equal to -0.25% and that the weekly volatility term σ_c is equal to 0.63%.

Appendix F. β for the solar PV manufacturing industry

β for solar PV module manufacturers is listed in Table F.1, and the weighted β for the PV module manufacturing industry (β_c) is 1.182.

Table F.1

Appendix G. Estimation of the optimal investment timing

The optimal investment timing t^* is stochastic because C_t or the ratio P_t/C_t is stochastic. However, we can estimate the expected t^* and its confidence interval using Ito's lemma.

For scenarios in which only the PV module cost is uncertain, t^* can be estimated by calculating the average time that the process C_t takes to satisfy the investment condition C_t^*. Using Ito's lemma, we obtain

$$dlnC_t = (\alpha_c^R - \sigma_c{}^2/2)dt + \sigma_c dz_c \tag{G.1}$$

With reference to [41], the probability density function of t^* is given by

$$\phi(t^*) = \frac{ln(C_t^*/C_0)}{\sigma_c\sqrt{2\pi t^{*3}}} e^{-\left[ln(C_t^*/C_0) - (\alpha_c^R - \sigma_c{}^2/2)t^*\right]^2 / 2\sigma_c{}^2 t^*} \tag{G.2}$$

and the Laplace transform of t^* is

$$\mathrm{E}\left(e^{-\theta t^*}\right) = \int_0^{\infty} e^{-\theta t^*}\phi(t^*)dt^* = e^{-\left[\sqrt{\left(\alpha_c^R - \frac{\sigma_c{}^2}{2}\right)^2 + 2\sigma_c{}^2\theta} - \left(\alpha_c^R - \frac{\sigma_c{}^2}{2}\right)\right] ln(C_t^*/C_0) \Big/ \sigma_c{}^2} \tag{G.3}$$

Based on Equation (F.3), we obtain the expected execution time of the option and its variance:

$$\mathrm{E}(t^*) = \int_0^\infty t^* \phi(t^*) dt^* = -\lim_{\theta \to 0} \frac{\partial \mathrm{E}\left(e^{-\theta t^*}\right)}{\partial \theta} = \frac{ln(C_t^*/C_0)}{\alpha_c^R - \frac{\sigma_c{}^2}{2}} \tag{G.4}$$

$$\mathrm{Var}(t^*) = \frac{(C_t^* - C_0)\sigma_c{}^2}{2\left(\alpha_c^R - \frac{\sigma_c{}^2}{2}\right)^3} \tag{G.5}$$

For scenarios in which both the electricity and PV module cost are uncertain, t^* can be estimated by calculating the average time that the process P_t/C_t takes to satisfy the optimal investment condition $H_t^* = P_t^*/C_t^*$. By using Ito's lemma, we obtain

$$dlnH_t = \left(\sigma_c{}^2/2 + \alpha_p^R - \alpha_c^R - \sigma_p{}^2/2\right)dt + \sigma_p dz_p - \sigma_c dz_c \tag{G.6}$$

Using the same method, we can obtain the expected execution time of the option and its variance:

$$\mathrm{E}(t^*) = [lnH_t^* - lnH_0]\Big/\left(\frac{1}{2}\sigma_c^2 + \alpha_p^R - \alpha_c^R - \frac{1}{2}\sigma_p^2\right)$$

$$\mathrm{Var}(t^*) = \frac{(C_t^* - C_0)\left(\sigma_p{}^2 + \sigma_c{}^2\right)}{2\left(\frac{1}{2}\sigma_c^2 + \alpha_p^R - \alpha_c^R - \frac{1}{2}\sigma_p^2\right)^3}$$

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Table 1 describes the parameters in our analysis.

Table 1

Input parameters for the scenario analysis.

1. Public parameters				
Parameter	Symbol	Unit	Value	Notes
Risk-free rate	r	%/year	3.74	Data from Wind database; discount factor
Initial PV module cost	C_0	yuan/kWh	1.00	Adjusted data from [32]
2. Parameters for the regulated market				
Parameter	Symbol	Unit	Value	Notes
Risk-neutral drift term of PV module cost	α_c^R	%/year	-9.26	Calculated in 4.1.1
Standard deviation of PV module cost	σ_c	%/year	3.77	Calculated in 4.1.1
Electricity price without subsidy	P_f	yuan/kWh	0.41	Data from Wind database and NDRC
3. Parameters for the free market				
Parameter	Symbol	Unit	Value	Notes
Risk-neutral drift term of PV module cost	α_c^R	%/year	-9.26	Calculated in 4.1.1
Standard deviation of PV module cost	σ_c	%/year	3.77	Calculated in 4.1.1
Risk-neutral drift term of electricity price	α_p^R	%/year	2.15	Data from related literature [38]
Standard deviation of electricity price	σ_p	%/year	29.2	Data from related literature [38]
Feed-in tariff	FIT	yuan/kWh	0.78	Adjusted data from NDRC
Price premium	$Premium$	yuan/kWh	0.23	Adjusted data from NDRC
Initial electricity price	P_0	yuan/kWh	0.41	Data from Wind database and NDRC

Table 2 describes the scenario design in our analysis.

Table 2
Scenario description.

No.	Scenario	Description
1	Regulated market without subsidy	There are no support schemes in this scenario, so the only uncertain factor is the PV module cost. The electricity uncertainty is not considered because of the market system assumption, and the electricity price P_f is assumed to be 0.41 yuan/kWh.
2	Free market without subsidy	There are no support schemes in this scenario, so the uncertain factors include the PV module cost and electricity price. The parameters for these factors are listed in Table 1.
3	Free market with FIT	The support scheme is FIT, which eliminates the electricity uncertainty. The FIT is assumed to be 0.78 yuan/kWh.
4	Free market with price premium	The support scheme is price premium, and both PV module cost uncertainty and electricity price uncertainty are considered. The premium is assumed to be 0.23 yuan/kWh.

Table 3 describes the optimal investment conditions and initial conditions in our analysis.

Table 3
Optimal investment conditions.

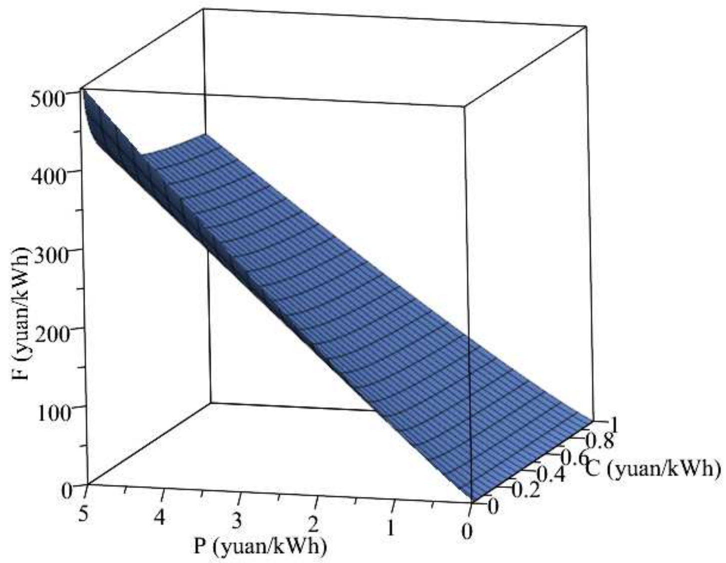
No.	Optimal investment condition	Initial condition	Description
1	$C_t^* = 0.73$	$C_0 = 1$	Investment should be undertaken immediately when the PV module cost is less than 0.73 yuan/kWh.
2	$P_t^*/C_t^* = 0.76$	$P_0/C_0 = 0.41$	Investment should be undertaken immediately when the ratio of the electricity price to the PV module cost is greater than 0.76.
3	$C_t^* = 1.39$	$C_0 = 1$	Investment should be undertaken immediately when the PV module cost is less than 1.39 yuan/kWh.
4	$P_t^{r*}/C_t^* = 0.76$	$P_0^r/C_0 = 0.65$	Investment should be undertaken immediately when the ratio of the electricity price to the PV module cost is greater than 0.76.

Table F.1 describes the estimation of β for different solar module manufacturers and the β for the PV module manufacturing industry.

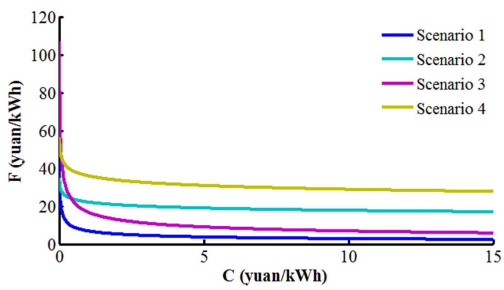
Table F.1.
β for the solar PV module manufacturing industry.

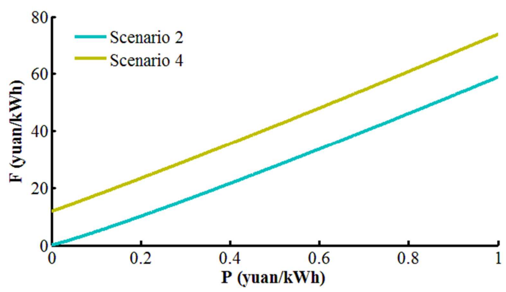
Stock code	Adjusted β	β	Equity (billion yuan)	Weight	Weighted β
601727.SH	1.186	1.278	21.498	45.5%	0.581
002129.SZ	1.226	1.337	4.809	8.8%	0.118
601012.SH	1.026	1.039	3.061	8.4%	0.087
600151.SH	1.015	1.023	7.105	5.4%	0.055
601908.SH	1.132	1.197	3.857	5.3%	0.063
300274.SZ	1.039	1.058	5.834	5.2%	0.055
600885.SH	0.815	0.723	10.132	4.4%	0.032
300118.SZ	1.015	1.023	12.639	4.2%	0.042
002610.SZ	1.111	1.166	13.177	2.9%	0.034
600537.SH	1.170	1.253	6.882	2.8%	0.035
300111.SZ	1.124	1.184	10.730	2.4%	0.028
002218.SZ	0.984	0.976	20.424	2.0%	0.019
300080.SZ	1.032	1.048	111.058	1.6%	0.017
002580.SZ	1.170	1.254	12.815	1.3%	0.016
β_c					1.182

Figure 1 presents the sensitivity analysis of the defer option values with respect to the electricity price and the PV module cost using a static analysis.



(a)

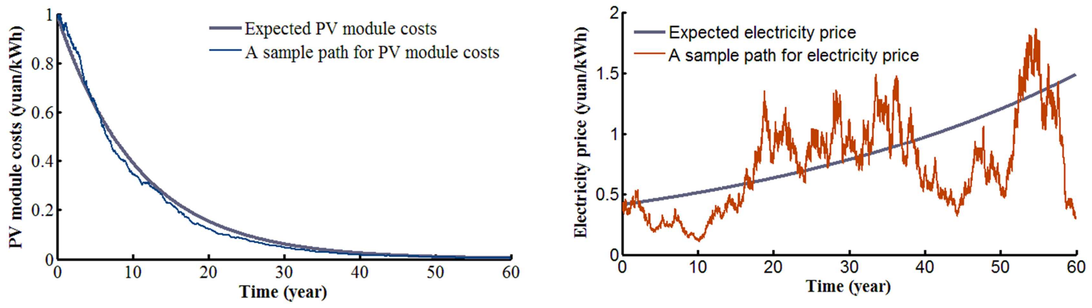




(b) (c)

Fig. 1. Sensitivity analysis results. (a) Option values as a function of the PV module cost and electricity price in Scenario 2; (b) Option values as a function of the PV module cost; (c) Option values as a function of the electricity price.

Figure 2 presents the expected value and a sample path for PV module cost and electricity price.



(a) (b)

Fig. 2. Monte Carlo simulation of C_t and P_t; (a) Expected C_t as a function of t; (b) Expected P_t as a function of t.

Figure 3 presents the expected option value with respect to time in the four scenarios.

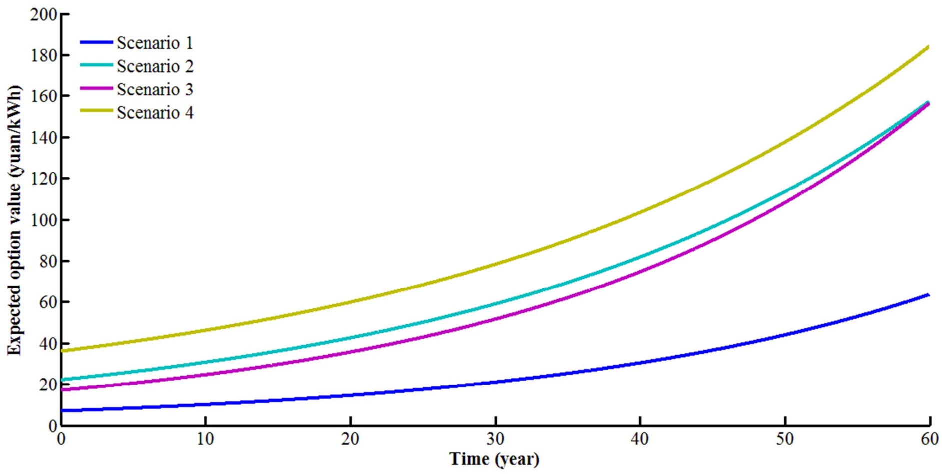


Fig. 3. Expected option values for different scenarios.

Figure 4 presents the option value for the free market scenarios with different support schemes.

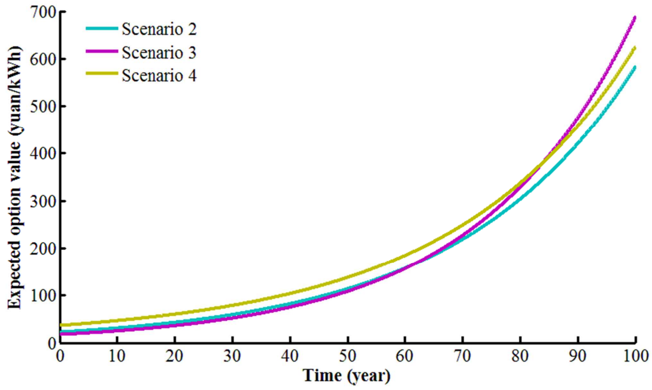
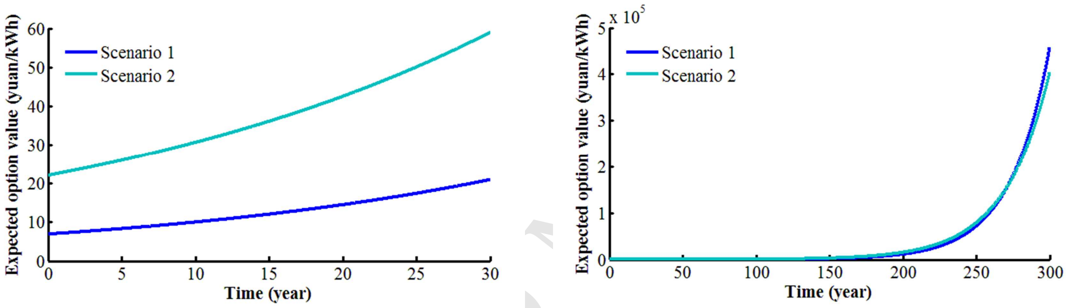


Fig. 4. Expected option values for the free market scenarios.

Figure 5 presents the expected option values for Scenarios 1 and 2. There are no support scheme in either scenario. The electricity price is stochastic in Scenario 2 but is fixed in Scenario 1.



(a) (b)

Fig. 5. Expected option values for Scenarios 1 and 2.

Figure 6 presents the expected execution time in the four scenarios.

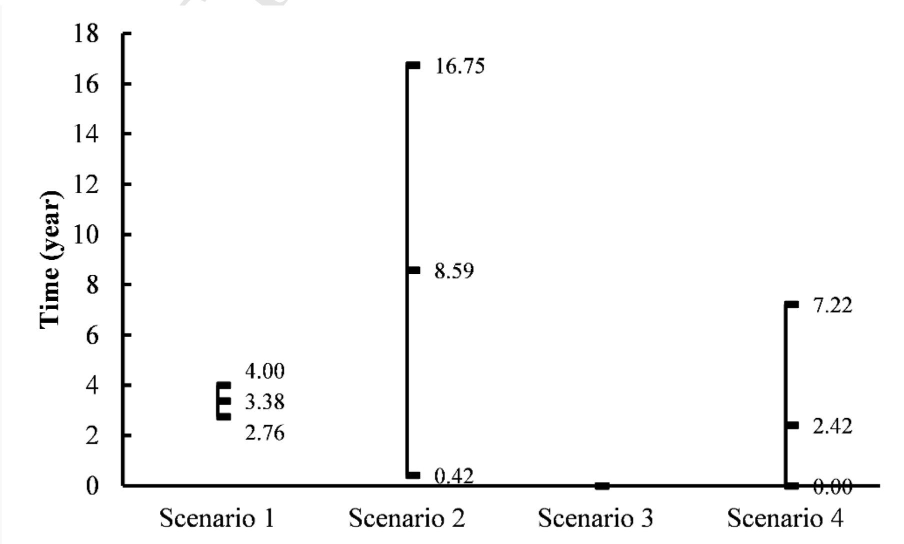


Fig. 6. Expected execution time range (90% confidence level).

Figure 7 presents the impacts of different support scheme on reducing the expected execution time and its variance.

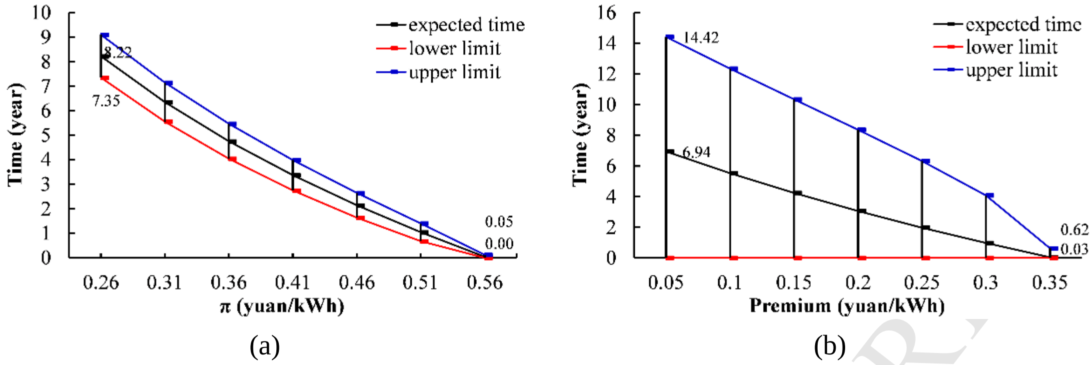
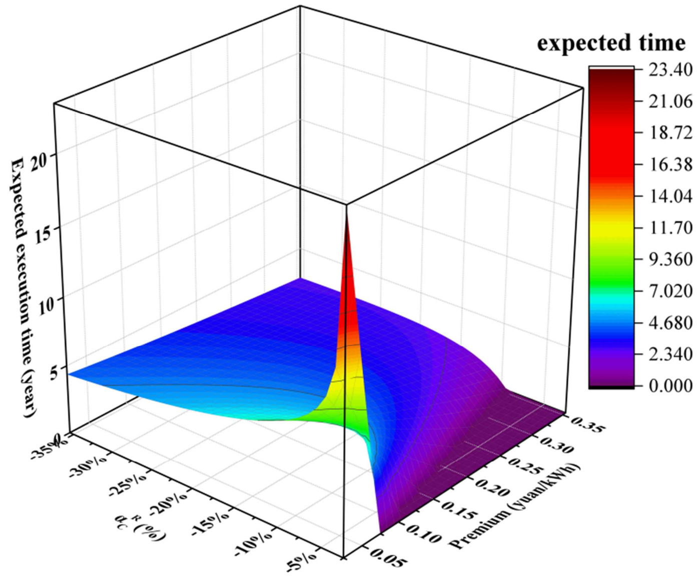
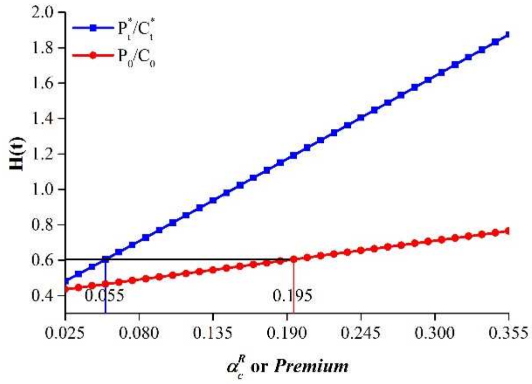


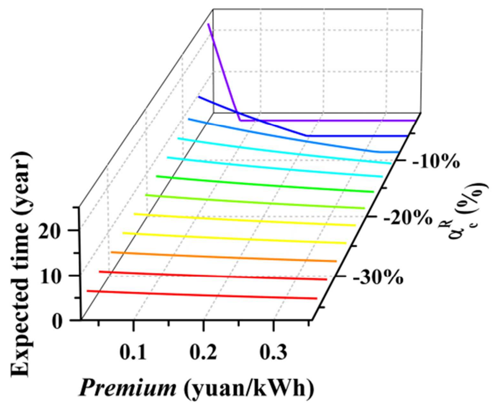
Fig. 7. Sensitivity analysis with respect to support schemes. (a) Sensitivity analysis with π in the regulated market; (b) Sensitivity analysis with $premium$ in the free market.

Figure 8 presents the relationship between technological progress and support schemes in the free market. Figure 8(b) also analyses the reasons for these results.



(a)





(b) (c)

Fig. 8. Sensitivity analysis with respect to α_c^R and support schemes (a) sensitivity analysis of expected execution time with α_c^R and *premium*; (b) sensitivity analysis of H_t^* and H_0 with α_c^R and *premium*; (c)sensitivity analysis of execution time with *premium*.

Figure A.1 presents the estimated sunshine duration in China.

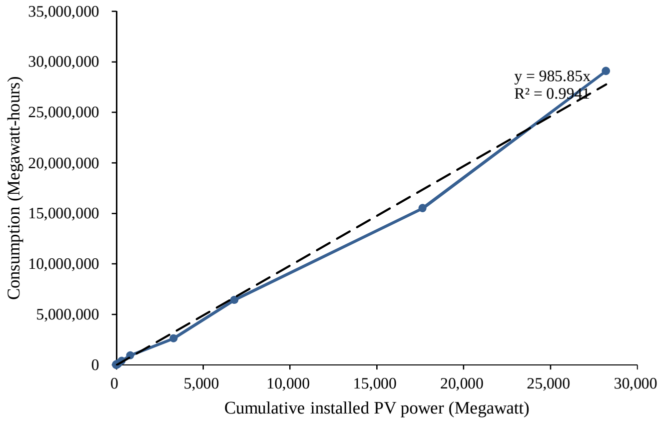


Fig. A.1. Estimated sunshine duration in China

Figure E.1 presents the test for normality of r_t.

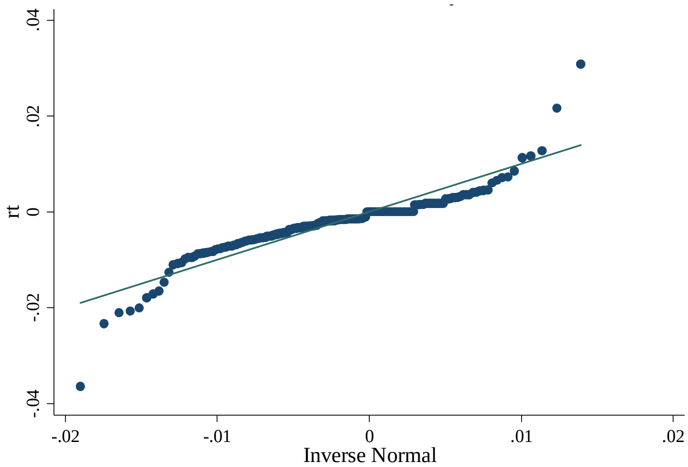


Fig. E.1. Quantile-quantile plot for r_t.

Highlights:

- Contingent claims are applied to establish multi-factor real options models.
- Investment will be postponed when marketization reform is performed.
- The effects of feed-in tariff are the same in regulated market and free market.
- The effects of price premium are different in the regulated market and free market.
- The interaction between technological progress and support schemes is studied.