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Efficient Feed-In-Tariff Policies for Renewable Energy Technologies

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Feed-in-tariff (FIT) policies aim at driving down the cost of renewable energy by fostering learning and accelerating the diffusion of green technologies. Under FIT mechanisms, governments purchase green energy at tariffs that are set above market price. The success or failure of FIT policies, in turn, critically depend on how these tariffs are determined and adjusted over time. This paper provides insights into designing cost-efficient and socially optimal FIT programs. Our modeling framework captures key market dynamics as well as investors' strategic behavior. In this framework, we establish that the current practice of maintaining constant profitability is theoretically rarely optimal. By contrast, we characterize a no-delay region in the problem's parameters, such that profitability should strictly decrease over time if the diffusion and learning rates belong to this region. In this case, investors never strategically postpone their investment to a later period. When the diffusion and learning rates fall outside the region, profitability should increase at least temporarily over some time periods and strategic delays occur. The presence of strategic delays, however, makes the practical problem of computing optimal FIT schedules very difficult. To address this issue, the regulator may focus on policies that disincentivize investors to postpone their investment. With this additional constraint, a constant profitability policy is optimal if and only if the diffusion and learning rates fall outside the no-delay region. This provides partial justifications for current FIT implementations.

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1. Introduction

Feed-In-Tariffs (*FITs*) are policy instruments that attract investments in renewable energy by offering long-term guaranteed purchase agreements to green power producers to sell their electricity into the grid (Klein 2008, Mendonça et al. 2009). Among existing policy mechanisms to stimulate the deployment of green energy, FIT policies are the most widely implemented and have proven to be the most promising of all, accounting for a greater share of renewable energy propagation than any other policy support scheme (European Commission 2008, Fouquet and Johansson 2008, Mendonça et al. 2009). FIT laws are responsible for approximately 75% of worldwide solar photovoltaic (PV) and 45% of global wind energy deployment by 2008 (Deutsche Bank 2010), and are in place in more than 87 jurisdictions across the world (REN21 2011).

Typically, FIT levels are amended downward for installations in subsequent years (Fell 2009, Klein et al. 2010, Couture et al. 2010, de Véricourt and Munigowda 2012). In most cases, feed-in prices fall annually by a fixed percentage, so as to trace the technology cost reduction and maintain the same level of profitability across years to newly commissioned projects. For instance, a 2010 report by the UK Department of Energy and Climate Change states the following (UK DECC 2010):

> Accordingly, the tariffs that are available for new installations will degrees each year, where they reduce to reflect predicted technology cost reductions to ensure that new installations receive the same approximate rates of return as installations already supported through FITs.

Depending on the technology, the intended rates of return lie in the 5%–8% range for the UK (UK DECC 2010) and FIT degressions are exerted to retain this nominal yield. Germany's "Renewable Energy Source Act" (EEG) is established based on an approximate 6%–7% rate of return for well-operated installations (Fell 2009, Deutsche Bank 2011). Profit margins in France rely, in a similar manner, on a *profitability index*, defined as the ratio between project's overall discounted payoff and its total discounted cost (Mendonça et al. 2009).

The success of FIT schemes critically depends on the tariffs at which governments decide to purchase green electricity, which, in turn, determine the level of profitability for investors (Mendonça et al. 2009, Fell 2009). Overall, too aggressive tariffs (higher levels of profitability) attract a wider range of investors by making less efficient projects financially viable (Lange 2012), at a cost to taxpayers. Too conservative remunerations, on the other hand, may not be sufficient for market expansion and limit the scope of the technology only to those who operate very efficiently.

The goal of this paper is to address the aforementioned fundamental trade-offs. We intend to provide insights on how to set feed-in tariffs for a renewable energy technology in order to accelerate its deployment, while optimizing specific policy objectives (e.g., containing the expenditure at a minimum level or maximizing the social welfare). To that end, we develop and analyze optimization models that capture the main market dynamics in the evolution of renewable technologies (i.e., learning and diffusion), while accounting for investors' strategic behaviors. In this framework, we establish that the current practice of maintaining constant profitability is theoretically rarely optimal. By contrast, we identify when profitability index (or, equivalently, rate of return) should decrease over time for the entire program duration, and when it should strictly increase, at least temporarily, over certain time periods. Increasing profitability, however, makes the practical computation of FIT schedules intractable. In this case, we provide conditions under which the current practice of maintaining constant profitability, although theoretically suboptimal, is justified.

The eventual goal of an FIT policy is to drive down the cost of renewables through technological improvements and toward commercial maturity. The maturity threshold for a renewable energy technology, often referred to as *grid parity*, is attained when the technology becomes cost-competitive. Once such a threshold is reached, market forces take over and no further government intervention is needed (see, for instance, Deutsche Bank 2012). In short, FIT policies aim at attracting private investments through subsidy to stimulate cost reduction just to the point of grid parity. This is possible because the cumulated adoption needed for the technology cost to reach this goal is typically not very large compared to the size of the underlying market. For example, in Germany, where the solar PV technology has just reached grid parity, the percentage of residential buildings with solar panels on their rooftop is still below 10%.[1]

In conjunction with the ultimate objective of grid parity, governments in practice may envision various intermediate targets along the way. Such targets underscore regulators' political will and priorities (Couture et al. 2010, Mendonça et al. 2009) and are typically in the form of installation capacity or cost reduction landmarks, or shares in total energy consumption. For example, France has mandated 5,400 MW of solar power (PV and thermal) by the end of 2020, whereas China has required its renewables to account for a 15% share in the nation's total energy consumption by 2020 (REN21 2011). Special consideration is also given to containing the overall policy cost to maintain its popularity and mitigate the burden on taxpayers/ratepayers (United Nations Environment Programme 2012, Deutsche Bank 2012).

In view of the common practice of minimizing program costs by governments, we study the policy design problem under two different scenarios: Problem (P1), exogenously imposed intermediate target with cost objective, and Problem (P2), endogenously induced grid parity with social welfare objective. In both settings we assume that the regulator can commit at the beginning of the horizon to all future FIT levels. Our models capture the two main market dynamics that FIT programs leverage on, and also accounts for possible strategic delays by investors:

- *Cost reduction due to technological learning.* The decline in technology cost as a function of its proliferation builds on a well-known concept in economics (see Arrow 1962 and also Yelle 1979), often interchangeably referred to as *experience curve*, *learning curve*, or *learning by doing*. This effect was later adopted in energy economics to describe cost-cutting trends in energy technologies (see, for example, International Energy Agency 2000, McDonald and Schrattenholzer 2001, Klein 2008).
- *Demand growth due to diffusion processes.* The way investors react to an incentive policy also hinges on their awareness of and confidence in the new technology and their perception of its future viability (see Jager 2006), which forms a second major dynamic factor influencing market conditions. The spread of information about a new technology or product in the market is governed by social learning and is formally referred to as *diffusion process* in the marketing literature (Bass 1969, Mahajan et al. 1990). This notion reflects that further penetration of a new technology into society enhances public perceptions of its value, which, in turn, creates a larger potential demand (see Geroski 2000, and Rao and Kishore 2010 for more on the penetration patterns of new technologies). More specifically, Bollinger and Gillingham (2012) study the diffusion of residential solar PV panels in California and show empirically that social interaction (peer) effects did indeed exist.
- *Strategic investor behavior.* Our models account for possible strategic delays by investors who may postpone their investment to a later period. Investors' choices, together with FIT levels set by regulators, determine the return on investment in different time periods. We do not find evidence suggesting that these strategic behaviors play a significant role in existing FIT programs. For instance, Bollinger and Gillingham (2012) do not report any such strategic delays, and existing studies based on model calibration (van Benthem et al. 2008, Wand and Leuthold 2011, Lobel and Perakis 2011) ignore them altogether. Nonetheless, the absence of strategic delays under current implementations can be attributed to the structure of the existing FIT polices, which actually disincentivize investors to postpone their purchase. Allowing investors to strategically postpone their investment in our model enables us to identify situations where preventing such strategic delays is justified.

Our analysis reveals the structures of optimal FIT policies. Specifically, in the setting of Problem (P1) where the regulator attempts to reach an installed capacity target at minimum cost, we identify a *no-delay region* of model parameters, within which the optimal FIT levels yields no delay from investors. This is because the profitability index, which is determined by both the tariff levels and technology costs, remains nonincreasing over time. Outside the region, by contrast, it is always optimal to let the profitability index increase in certain periods, thereby incentivizing some strategic delays. In fact, if the investors' discount factor is low enough (i.e., below a threshold), the optimal profitability index increases over the entire policy duration.

The presence of strategic delays outside the no-delay region, however, makes it almost impossible to characterize, or even numerically calculate, the theoretically optimal FIT schedules. Technically, strategic delays gives rise to nonconvex optimization problems with equilibrium constraints that are intractable. This is particularly true in our setting, where each investor's profitability depends on all other investors' strategies through cost reduction and diffusion effects. Hence, determining when to join the program constitutes a very difficult problem for any rational investor. To obtain implementable FIT schedules, the regulator may thus only consider policies that actively preempt any strategic delays and hence reduce investors' choices to either join the program in the current period or leave. The resulting constrained optimization problem of the regulator then becomes easy to solve. When the model parameters are in the no-delay region, the additional no-delay constraint is redundant. That is, in this parameter region, the optimal policy has decreasing profitability, regardless of whether strategic investment delays are allowed. Outside the region, we show that the optimal policy (of the constrained problem) maintains constant profitability for investors. This also provides some justification for the current use of constant profitability policies, which, although theoretically suboptimal, are easy to implement.

Similar results extend to the social welfare maximization problem (Problem P2). In particular, we identify conditions under which profitability index should decrease over time and hence preclude strategic delays.

The area of sustainability in the operations management literature has been very active over the past few years (see Kleindorfer et al. 2005 for a review of earlier works). Closer to our work is a stream of research that studies investments in environmentally friendly technologies, both in the economics and operations literature. Ambec and Crampes (2010) and Garcia et al. (2012) investigate capacity investment decisions in two competing power generation technologies and how policymakers should design regulatory incentives to promote greater investment in renewable sources. Aflaki and Netessine (2015) highlight the importance of supply intermittency in renewable capacity investment when demand is stochastic. Wang et al. (2013) consider a dynamic setting and explore production and distribution capacity adjustments over time by a firm that has access to a portfolio of technology options. Plambeck and Taylor (2013) examine how variability in input and output prices may influence basic material manufacturers to invest in input versus capacity efficiency, and they conclude that a carbon tax or cap-and-trade regulation may reduce investments in improving energy efficiency.

Krass et al. (2013) address the impact of environmental taxation, subsidy, and rebate tools on green technology adoption by a monopolistic firm and the corresponding social welfare implications. Drake (2011) analyzes the effect of carbon tariffs on technology choice decisions for domestic and foreign firms in an asymmetrically regulated environment. Drake et al. (2012) study emission regulations such as tax and cap and trade and their influence on technology choice and capacity decisions by firms in a newsvendor setting. Shrimali and Baker (2012) focus on optimal design of FITs to reach a cost reduction target from learning by doing and economies of scale in a two period model. In the marketing literature, dynamic pricing of a new product or innovation in the presence of "word-of-mouth" effects has received a great deal of attention (see Krishnan et al. 1999 for a review, and Kalish and Lilien 1983 for an early study of subsidies for alternative energy innovations).

There is also a recent stream of empirical research on energy policy that relates closely to our work. In particular, van Benthem et al. (2008) explore the California solar market and examine the economic efficiency of the current subsidy schedule under California Solar Initiative (CSI) with and without learning by doing. In a similar vein, Wand and Leuthold (2011) study Germany's residential solar market from a social planner's perspective, and let the policy phase out optimally by extending the model over an infinite horizon. In a more recent working paper, Lobel and Perakis (2011) derive convexity properties of the cost function and suggest, based on their analysis, that FITs in Germany should be adjusted. The main approach of these papers is based on calibrating a model using real data on a specific technology and a specific market.

These precise calibration exercises allow their authors to derive exact numbers and explicit policy recommendations for the jurisdictions they study. By contrast, our intention is to gain general insights into the structure of efficient FIT policies and how they should account for different technology and market characteristics, as well as investors' strategic behaviors. In this respect, our analytical approach is complementary to the aforementioned calibration studies.

The remainder of this paper is organized as follows. We describe the model in §2. Analytical results on the structure of the optimal FIT policies are derived in §§3.1 and 3.2. Section 4 numerically examines the robustness of our results with respect to saturation effects. Section 5 concludes the paper. All proofs are presented in the e-companion (available as supplemental material at http://dx.doi.org/10.1287/opre.2015.1460) to this paper.

2. Model and Preliminary Results

Consider a government that aims at boosting a renewable energy technology in its jurisdiction through an FIT program over T periods. (The time horizon T indicates the program duration and can be endogenously determined.) We model the FIT design as a game in which the government first moves to announce and commit to a sequence of time-specific FIT contracts; investors, upon being informed about the program, decide whether and when to invest in response. In particular, we assume that the regulator can commit, at the beginning of the horizon, to all future contract terms over the entire policy duration.

The contract offered to a newly installed project in period $t \in \{1, \ldots, T\}$ specifies the electricity purchasing price ρ_t and the contract duration Γ (typically 15–25 years) over which ρ_t remains constant. This allows investors who join the FIT program in period t to sell their generated electricity to the grid at the locked-in price ρ_t for the duration of their contract, paid by the government. Investor awareness of the FIT program grows over time because of the word-of-mouth effect, whereas the installation cost of green technology decreases as the cumulated adoption increases.

Given the FIT contracts offered by the government, each investor evaluates her payoff p_t, which is the net present value of all payments she receives if she subscribes to the FIT program in period t and generates one unit of energy per time period. For ease of exposition, and without loss of generality, we assume that all payments are made at the *beginning* of the period. Therefore,

$$p_t = \sum_{i=0}^{\Gamma-1} r^i \rho_t = \frac{1-r^\Gamma}{1-r}\rho_t, \tag{1}$$

where $r \in [0, 1]$ is the investors' discount factor. In particular, payoff p_t is proportional to the purchasing price ρ_t enacted in period t. Given this one-to-one correspondence, and for expositional purposes, hereafter we capture the government's announcement of FIT contracts by the sequence $\mathbf{p} = \{p_t\}_{t=1,\ldots,T}$.

To account for heterogeneity in the investor population, we associate each individual investor with a *type* $\theta \in [0, 1]$, which represents her competence in utilizing the technology. More specifically, an investor's type (efficiency) reflects her intrinsic locational, technical, or informational characteristics with respect to exploiting the installed capacity. In the roof-mounted solar PV setting, for example, heterogeneity between investors captured by θ may include differences in location, maintenance capabilities, technical know-how, solar orientation of the house, slope of the roof, and shade from neighboring trees and buildings, all of which impact how much energy can be generated from one unit of installed capacity. An investor with efficiency θ, therefore, can only generate θ units of energy per period from one unit of installed capacity, and, therefore, collects a fraction θ of the per unit total payoff p_t when joining in period t.

Investor efficiency θ follows distribution $F(\cdot)$ and density $f(\cdot)$, which is positive and differentiable over its support $[0, 1]$. We impose no restrictions on this distribution except requiring it to hold the *increasing generalized failure rate* (*IGFR*) property.[2] This assumption is not restrictive at all since many of the commonly used distributions satisfy the IGFR condition, e.g., uniform, normal, exponential, gamma, Weibull, beta, and power distribution (see Lariviere and Porteus 2001 and Banciu and Mirchandani 2013 for more discussion).

We assume that acquiring one unit of energy generation capacity costs c_t in period t, which includes material, installation, administrative, and operations costs over the project's lifetime. That is, an investor with efficiency θ has to pay a present cost c_t in order to receive a present value θp_t when subscribing to the FIT program in period t. (Since each individual investor corresponds to one unit of capacity in our model, we use the words "investor" and "capacity" interchangeably throughout the paper.) In short, c_t and p_t represent lump-sum cost and payoff, respectively, both of which depend on discount factor r.

Finally, based on p_t and c_t, we introduce the notion of "profitability index," defined as the maximum payoff generated per monetary unit invested, and quantified as $\pi_t = p_t/c_t$ for investments made in period t. This financial measure is commonly used for ranking investment projects and appraising their profitability. In our setting, the change of profitability index over time also determines investors' subscribing/waiting decisions, which we introduce next.

2.1. Diffusion Process

The demand for a technology is often slim when it is first introduced to the market. As more adoptions take place and the technology penetrates, societal awareness and confidence about its value rise, which, in turn, generates more potential interest in subsequent years. We assume that an investor joins the pool of *active investors* upon being informed through the technology diffusion process and finding the FIT program attractive in the current period. Once becoming active, an investor further investigates all future periods and chooses to join in the period that maximizes her net payoff.

More precisely, in each period t, the information about the FIT program is disseminated to a new set of investors. Let n denote the *penetration coefficient*, defined as the number of uninformed investors that become aware of the FIT program in each period per unit of existing capacity. Assuming that the total installation base (cumulative capacity) at the end of period $t-1$ is M_{t-1}, the number of newly informed investors in period t is, therefore, nM_{t-1}. Among these investors, only those that earn nonnegative profit, that is, whose types θ satisfy $\theta p_t \geqslant c_t$, will find the program attractive and join the pool of active investors. Denote set A_t to represent the set of types that become active in period t. It follows that,

$$A_t = [c_t/p_t, 1]. \tag{2}$$

Therefore, the number of active investors added to the pool in period t is $nM_{t-1}\int_{\theta\in A_t} dF(\theta)$. This way of modeling the diffusion process ignores potential saturation effects. Our approach can be regarded as a special case of the *internal* *influence diffusion process* (Mahajan et al. 1990) in which the ultimate potential of the market (population size) is very large compared to the current cumulated adoption, implying that saturation effects are not prominent.[3] As a result, the prospective demand is approximately proportional to present adoption level. This modeling choice is justified in our domain, since FIT programs are often set up to stimulate adoption up to the level at which the technology becomes cost-competitive (grid parity). Once the grid parity goal is reached, this incentive policy is no longer needed, and the market forces can take over without requiring additional legislative support. Therefore, FIT policies are not intended to carry the adoption process too close to market saturation.

Next, all active investors in the pool decide whether to join in period t or wait for future periods. Denote set D_t to represent the investor types who decide to make an investment in period t. Because joining in period t has to be profitable for these investors, we have $\theta p_t \geqslant c_t$ for $\theta \in D_t$, and hence, $D_t \subseteq A_t$. Those active investors who decide not to invest in the current period wait to join the program in a later period. Denote N^w_{t-1} to represent the number of waiting investors from the previous periods, and $F^w_{t-1}(\cdot)$ to represent the distribution of their types. Period t's new installation, denoted as m_t, can be expressed as

$$m_t = nM_{t-1}\int_{\theta\in D_t} dF(\theta) + N^w_{t-1}\int_{\theta\in D_t} dF^w_{t-1}(\theta). \tag{3}$$

The cumulated installation M_t after period t then becomes

$$M_t = M_{t-1} + m_t, \tag{4}$$

for $t = 1, 2, \ldots, T$, where the initial capacity M_0 is given. The total number of waiting investors after period t's adoption decisions is updated as

$$N^w_0 = 0, \quad \text{and} \quad N^w_t = N^w_{t-1} + nM_{t-1}\int_{\theta\in A_t} dF(\theta) - m_t, \quad \text{for } t > 0. \tag{5}$$

Next, the corresponding distribution of waiting investors after period t's adoption decisions evolves according to

$$F^w_t(\theta) = \frac{1}{N^w_t}\left[nM_{t-1}\int_{x\in[0,\theta]\cap\bar{D}_t\cap A_t} dF(x) + N^w_{t-1}\int_{x\in[0,\theta]\cap\bar{D}_t} dF^w_{t-1}(x)\right], \tag{6}$$

in which notation $\bar{D}_t$ is the complement of set D_t, and the region $[0,\theta]\cap\bar{D}_t$ captures the types below θ and not joining FIT in period t. The first term in Equation (6) captures the number of newly informed investors in period t who decide not to join in this period, whereas the second term is the number of existing active investors who continue to wait in period t.[4] Equations (3)–(6) fully specify the diffusion process in our model, for given sequences of payments $\mathbf{p}$ and costs $\mathbf{c}$. (See section EC.3 in the e-companion for an example of how the distribution of waiting investors evolves over time.)

An immediate consequence of a highly unsaturated market is that efficiency composition of newly informed investors in each period does not change with time. Considering the fact that the market is far from saturation, there remain a significant number of efficient investors who can be potentially attracted to join. Therefore, the absorption of a small population of efficient investors is not going to have meaningful impact on the general heterogeneity structure represented by distribution $F(\cdot)$. Nonetheless, we relax this assumption in §4 by embedding a more general diffusion process in the model, and we numerically examine the robustness of our results with respect to such effects.

Next we discuss how the technology cost c_t decreases in time.

2.2. Learning Curve

We borrow the notion of learning curve from the economics literature to formalize the decline in technology cost due to expansion of its usage. This phenomenon corresponds to the cost reductions resulting from innovation, competition, and economies of scale as well as improvements in knowledge, skills, techniques, and procedures.

Among various functional forms that have been proposed to represent the learning curve, exponential decay (power function) is the most common approach (Yelle 1979, Wand and Leuthold 2011). Under this paradigm, the technology cost drops exponentially as a function of its proliferation. In particular, the cost of acquiring one unit of technology in period t is given by

$$c_t = c_0\left(\frac{M_{t-1}}{M_0}\right)^{-\alpha}, \tag{7}$$

where c_0 and M_0 are the initial cost and the aggregate adoption before the introduction of FIT, respectively, and M_{t-1} is the cumulative capacity installed by the end of period $t-1$. Also, $\alpha \in (0, 1)$ is the *learning parameter*,[5] representing how fast the proliferation of the technology pushes down its cost. In the literature, the *learning rate* is defined as the percentage drop in cost when the cumulative adoption of the technology doubles. In our context, the learning rate equals $1-2^{-\alpha}$. Given the monotonic one-to-one correspondence between α and learning rate, we will henceforth use these two interchangeably when referring to the magnitude of learning.

When α is close to zero, little learning occurs and cost reduces very slowly as the capacity grows. On the other hand, α close to one describes a situation where doubling the technology penetration cuts its cost in half. We consider α to be no more than 1 in our framework, which can be supported by available empirical evidences suggesting learning rates between 10%–30% for renewable energy technologies (van der Zwaan and Rabl 2003).

Whereas typical learning rates of 10%–30% have been reported for different technologies, the rate is closer to 20% for solar PV systems (van der Zwaan and Rabl 2003; also see Wand and Leuthold 2011, van Benthem et al. 2008, Nemet 2006 for more analysis on solar technology learning curve). Moreover, recent studies have come to the conclusion that the cost of electricity from wind turbines falls by 7%–19% for each twofold increase in wind power generation capacity (Krohn et al. 2009; also see Bolinger and Wiser 2009, Junginger et al. 2005 for more specific details on the wind power technology learning curve). In a longer time perspective, the cost of wind and solar electricity generation has dropped by more than 50% over the last decade, which is attributable to learning effects (Mendonça et al. 2009).

2.3. Investors' Decisions

Now we consider individual investors' decisions. The aggregate decision from investors in period t is captured by the decision rule D_t, which is the foundation of the diffusion process dynamics.

For a type θ investor who has entered the pool in period τ, the joining decision can be formulated as the following optimal stopping problem,

$$J_t(\theta;\mathbf{p},\mathbf{c}) = \max\{\theta p_t - c_t, rJ_{t+1}(\theta;\mathbf{p},\mathbf{c})\}, \quad t=\tau,\ldots,T \qquad (8)$$

with $J_{T+1}=0$. Here the first term in the maximization represents joining the FIT program (and therefore stopping) in period t and the second term continuing into the next period.

Proposition 1. *Given the government's payoff schedule* $\mathbf{p}=\{p_t\}_{t=1,\ldots,T}$, *and a sequence of nonincreasing costs* $\mathbf{c}=\{c_t\}_{t=1,\ldots,T}$, *solutions to the optimal stopping problem* (8) *have the following threshold structure: in each period t there is a threshold* $\hat{\theta}_t(\mathbf{p},\mathbf{c})$ *such that an investor with efficiency* θ *joins the FIT program if and only if* $\theta \geqslant \hat{\theta}_t(\mathbf{p},\mathbf{c})$.

Proof. Optimization problem (8) can be equivalently recast as

$$\max_{t=\tau,\ldots,T+1}\{r^{t-\tau}(\theta p_t - c_t)\},$$

with boundary condition $p_{T+1}=c_{T+1}=0$ to capture the decision of not joining the program at all. Consider any type θ investor such that it is optimal for her to join the FIT program in period τ rather than waiting to a later period $t>\tau$. We must have $\theta p_\tau - c_\tau > r^{t-\tau}(\theta p_t - c_t)$ for any $t>\tau$, or, $\theta(p_\tau - r^{t-\tau}p_t) > c_\tau - r^{t-\tau}c_t > 0$, where the last inequality follows from c_t nonincreasing. This further implies that $p_\tau - r^{t-\tau}p_t > 0$. Therefore, for $\theta' > \theta$, we have $\theta'(p_\tau - r^{t-\tau}p_t) > \theta(p_\tau - r^{t-\tau}p_t) > c_\tau - r^{t-\tau}c_t$. Hence, it must be optimal for type θ' to join in period τ as well. Q.E.D.

Proposition 1 implies that it is sufficient to consider decision rule D_t in period t to be in the form of $[\hat{\theta}_t, 1]$ for some threshold $\hat{\theta}_t$. The thresholds further influence the evolution of the market diffusion (3)–(6) and, eventually, the sequence of costs $\mathbf{c}$ through (7). Therefore, given the payoffs $\mathbf{p}=\{p_t\}_{t=1,\ldots,T}$, there is a game among investors in which each investor forms a rational expectation of how the cost and FIT levels should evolve over time as a function of all other investors' joining/waiting decisions. This *rational expectation equilibrium* concept (also referred to as *recursive competitive equilibrium*) arises in the macroeconomic literature (Prescott and Mehra 1980, Ljungqvist and Sargent 2004). It has also been adopted in the dynamic pricing and operations literature in recent years (see, for example, Su 2010, and references therein). In our setup this corresponds to the following definition.

Definition 1. For a given sequence of payoff levels $\mathbf{p}$, a sequence of costs $\mathbf{c}(\mathbf{p})$ is "equilibrium costs" in the investors' game if optimal thresholds $\{\hat{\theta}_t(\mathbf{p},\mathbf{c}(\mathbf{p}))\}_{t=1,\ldots,T}$ (following the optimization problem (8)) generate the same sequence $\mathbf{c}(\mathbf{p})=\{c_t(\mathbf{p})\}_{t=1,\ldots,T}$ through dynamics (3)–(7). We call the corresponding sequence of thresholds $\hat{\Theta}(\mathbf{p})=\{\hat{\theta}_t(\mathbf{p})\}_{t=1,\ldots,T}$ in which $\hat{\theta}_t(\mathbf{p})=\hat{\theta}_t(\mathbf{p},\mathbf{c}(\mathbf{p}))$, the "equilibrium thresholds" for the investors' game given payoff levels $\mathbf{p}$.

The next result establishes the existence and uniqueness of the equilibrium in the investors' game.

Proposition 2. *For any sequence of payoff levels* $\mathbf{p}$ *under the FIT program, there exists a unique sequence of equilibrium thresholds* $\hat{\Theta}(\mathbf{p})$ *and a unique sequence of equilibrium costs* $\mathbf{c}(\mathbf{p})$ *for the corresponding investors' game.*

Given the existence and uniqueness of the equilibrium, the government can evaluate any sequence $\mathbf{p}$ as long as we specify the government's objective function, to which we now turn.

2.4. The Government's Problem

When crafting FIT regulations, the policy makers may pursue different objectives in light of their ultimate goal of achieving market integration for the green technology. In practice, special emphasis is often placed on minimizing the policy expenditure while envisaging an intermediate adoption target to be accomplished by a specified deadline. In this section, we first form the government's optimization problem for this case. From a central planner's perspective, however, maximizing the social welfare must be the primary objective for the legislators, as commonly assumed in the economics literature (van Benthem et al. 2008, Wand and Leuthold 2011). This corresponds to our second formulation of the government's problem.

2.4.1. Exogenous Intermediate Target with Cost Objective. In practice, most FIT-implementing jurisdictions incorporate targets on renewable generating capacity or its share of the total energy consumption, to be accomplished at minimum cost, as is currently being done in most of the European Union countries (see REN21 2011). In the context of our model, this corresponds to having a capacity target $\tilde{M}$, which has to be surpassed by an exogenous deadline T.

To construct the government's optimization problem, we note that the amount of electricity produced by an investor is a function of her efficiency, θ. Following Equation (3) and Proposition 1, new installations in period t consist of investors (newly informed as well as those waiting from previous periods) whose efficiency is above the equilibrium threshold $\hat{\theta}_t(\mathbf{p})$. In each period over their lifetime, the installations launched in period t, therefore, generate the total power of

$$G_t(\mathbf{p}) = nM_{t-1}\int_{\hat{\theta}_t(\mathbf{p})}^{1} \theta\, dF(\theta) + N_{t-1}^{w}\int_{\hat{\theta}_t(\mathbf{p})}^{1} \theta\, dF_{t-1}^{w}(\theta), \qquad (9)$$

in which M_t, N_t^w, and $F_t^w(\cdot)$ evolve according to dynamics (3)–(6) and are hence all functions of $\mathbf{p}$. Multiplying G_t with ρ_t gives us the annual compensation that the government has to pay through the FIT program for installations occurring in period t.

Denote δ to represent the government's discount factor. The present value (from the government's perspective) of the FIT payments to an investor who joins in period t is, therefore,[6]

$$\sum_{i=0}^{\Gamma-1}\delta^i\rho_t = \frac{1-\delta^\Gamma}{1-\delta}\rho_t = \gamma p_t,$$

in which p_t is defined in (1), and parameter γ is defined as

$$\gamma = \frac{(1-\delta^\Gamma)(1-r)}{(1-r^\Gamma)(1-\delta)}.$$

It follows that the present value of the government's expenditure on all projects initiated in period t equals $\gamma p_t G_t(\mathbf{p})$. Thus, the government's objective of minimizing total expected expenditure over the planning horizon of T periods can be expressed as

$$z(\tilde{M}, T) = \min_{\mathbf{p}} \gamma \sum_{t=1}^{T} \delta^{t-1} p_t G_t(\mathbf{p}) \qquad \text{(P1)}$$

$$\text{subject to:} \quad M_T \geqslant \tilde{M}$$

in which $z(\tilde{M}, T)$ denotes the minimum cost when the target on cumulative capacity is $\tilde{M}$ and the planning horizon is T periods.

Note, finally, that changing c_0 corresponds to rescaling the unit of money, since c_0 is the only input parameter in the model that is measured in money. As a result, the optimal solution $\mathbf{p}^*$ rescales with c_0 so that the corresponding profitability index and market diffusion processes do not change. In this sense, Problem (P1) is "independent" of the initial cost c_0. This insight has important implications for our characterization of the optimal policy, a result that we formalize in the next section.

2.4.2. Social Welfare Objective. Alternatively, we study a welfare objective function and consider three main elements contributing to social surplus in each period. The first element corresponds to the value of renewably generated electricity and includes all the benefits to the society from the electricity being produced by the operational installations. The electricity from FIT-supported projects in each period, in effect, saves the society the negative externalities of otherwise conventionally generated electricity. Simply put, this consists of all benefits attributable to the replacement of dirty power plants with clean sources (van Benthem et al. 2008, Wand and Leuthold 2011). We assume that one unit of newly installed green electricity generating capacity leads to a social surplus of β_1 over the project's lifetime. Note that the realized surplus for each project depends on its *actual* electricity production, which is a function of the investor's efficiency type. Hence, the total surplus generated by installations launched in period t is $\beta_1 G_t$, where G_t is defined in (9). This term can also cover cases in which there exists a social/economic value intrinsic to the installed capacity itself beyond the actual power generated.

The second component of the social surplus is the implementation cost of the FIT program. We introduce deadweight loss factor $\beta_2 > 0$ to denote the disutility incurred for each currency unit spent on the program. This parameter captures the economic distortion caused by FIT transfers and/or the administrative costs inflicted on the society in implementing the policy; its value can vary between 0 (no deadweight loss as in van Benthem et al. 2008, Wand and Leuthold 2011) and 1 (attributing the entire FIT payments to social costs as in Lobel and Perakis 2011).

Finally, the total cost borne by society in expanding the industry in period t is given by $\beta_3 c_t m_t$. Parameter β_3 is often set equal to one in the literature (van Benthem et al. 2008, Wand and Leuthold 2011), but for the sake of generality, we allow β_3 to take values between 0 and 1.

Further, in this general setup, the termination of the FIT program is determined endogenously. More specifically, the program ends once grid parity is achieved. This happens when the cost of technology falls to a level where it can compete with conventional power production methods without requiring any additional legislative support (see, for instance, Deutsche Bank 2012). In effect, grid parity can be quantified as a threshold on technology cost, which we denote by $\tilde{c}_*$.[7] Once technology cost falls below this threshold, generating renewable electricity becomes less expensive than conventionally produced power.[8] At this point, the technology matures, i.e., it becomes self-sustainable in a free market. This is also in parallel with Lange (2012) who models FIT policy design as an optimal stopping problem. We consider the lump sum utility Π to represent the long-run discounted social value along the growth trajectory of the technology once the FIT program is terminated. This corresponds to the value of letting the system evolve after grid parity, without any policy intervention as in Wand and Leuthold (2011).

Putting all together, the lawmaker's optimization problem can be cast as

$$\zeta(\tilde{c}_*) = \sup_{\mathbf{p},\,T} \left\{ \sum_{t=1}^{T} \delta^{t-1}(\beta_1 G_t(\mathbf{p}) - \beta_2 \gamma p_t G_t(\mathbf{p}) - \beta_3 c_t m_t) + \delta^T \Pi \right\} \tag{P2}$$

subject to: $c_{T+1} \leqslant \tilde{c}_*$,

where function $\zeta(\cdot)$ denotes the highest attainable social surplus. The decision variable T in the above formulation specifies the period at which unit cost falls below $\tilde{c}_*$ for the first time, implying that grid parity has been reached. Finally, note that Problem (P1) is a special case of Problem (P2) with $\beta_1 = \beta_3 = \Pi = 0$ and fixed T, because any technology cost target corresponds to an installed capacity target following the learning curve (7).

3. Optimal FIT Policies

In this section, we present analytical results from the model introduced in the last section. To characterize the structure of the optimal policy[9] for either problems presented in §2, one needs to solve a game between the government and the investors. Such a game is generally very hard to analyze, because the population size, efficiency composition, and investment behavior of active investors in each period depend on other individual investors' choices in both preceding and subsequent periods. In fact, our problem is not tractable even numerically for the time horizon T exceeding a few periods.

Nonetheless, as we will demonstrate in this section, the problem becomes numerically tractable when no investors are waiting. Thus, in what follows, we first identify necessary and sufficient conditions under which the FIT schedules at the equilibrium prevent any strategic delays. We further characterize the structure of the corresponding optimal policies. We then study the case in which the regulator seeks to prevent any strategic behavior so as to make the policy computationally feasible. We present our results for the two regulator's objectives in two separate subsections.

3.1. Exogenous Target with Cost Objective (P1)

In Problem (P1), the capacity target $\tilde{M}$ and policy duration T are imposed exogenously. For an arbitrary T, the diffusion rate may not be sufficiently high for FIT to reach the desired goal $\tilde{M}$. This is because even under the most generous tariffs, the maximum adoption growth in each period is still bounded from above by n duplications. In this case, we call the target *infeasible*. For any given target, the next lemma specifies a lower bound on n above which the target becomes feasible.

Lemma 1. *Consider the optimization Problem (P1). The target $\tilde{M}$ is feasible and can be achieved in T periods if and only if $n > \hat{n}$, where $\hat{n}$ is defined as*

$$\hat{n} = (\tilde{M}/M_0)^{1/T} - 1.$$

The lower bound $\hat{n}$ is associated with the most extreme FIT regime, in the sense of being too generous. It relates to a scenario where staggering tariffs are enacted in each period to attract the entire potential demand.

We have the following characterization of the equilibrium and the optimal policy.

Theorem 1. *Consider Problem (P1). Fixing model parameters M_0, α, $F(\cdot)$, δ, $\tilde{M}$, and T, there exist thresholds $\check{n} > \hat{n}$ on the penetration coefficient n (where $\hat{n}$ is defined in Lemma 1):*

(i) *If $n \in [0, \hat{n}]$, the target $\tilde{M}$ is infeasible and cannot be achieved in T periods.*

(ii) *If $n \in (\hat{n}, \check{n}]$, the optimal profitability index, π_t^*, is nonincreasing in t. In particular, π_t^* strictly decreases over time when $n \in (\hat{n}, \check{n})$, whereas it remains a constant when n equals $\check{n}$. Furthermore, the equilibrium thresholds $\hat{\theta}_t(\mathbf{p}) = 1/\pi_t^*$.*

(iii) *If $n \in (\check{n}, \infty)$, there exists a nonempty time interval in which π_t^* strictly increases in t. Furthermore, there exists a threshold $\hat{r}_n$ such that if $r \leqslant \hat{r}_n$, then π_t^* strictly increases in t over the entire time horizon.*

(iv) *Both thresholds $\hat{n}$ and $\check{n}$ are independent of c_0 and r, increase in $\tilde{M}$ and decrease in T.*

Theorem 1 indicates that in a certain range of penetration coefficient n, the optimal FIT levels should be set up such that the profitability index monotonically decreases or remains constant. When this happens, no informed investors would defer their investment to a later period. In each period, a new investor decides between joining the FIT program immediately without waiting and not joining at all. The investment decision problem (8) therefore reduces to a myopic one, i.e., $\max\{\theta p_t - c_t, 0\}$. This explains why the equilibrium threshold, $\hat{\theta}_t(\mathbf{p})$, becomes the inverse of the optimal profitability index, $1/\pi_t^*$. Furthermore, under such settings, dynamics (3)–(6) can be simplified to

$$m_t = nM_{t-1} \int_{\theta \geqslant c_t/p_t} dF(\theta) \quad \text{and} \quad M_t = M_{t-1} + m_t. \tag{10}$$

Theorem 1 also indicates that the current practice of maintaining a constant profitability over time may be optimal only if the penetration coefficient n takes value $\check{n}$.

When $n > \check{n}$, Theorem 1 states that π_t^* is not monotonically nonincreasing. Therefore, there must be a nonempty time interval over which the optimal profitability index strictly increases, incentivizing some investors to delay their investment. And, if discount factor r is below a certain threshold, this time interval actually extends to the whole program duration $\{1, \ldots, T\}$.

Finally, threshold $\check{n}$ depends on neither the initial cost c_0 nor the time discount factor r. This is because when investors do not wait, their time discount factor does not enter the calculation of their payoffs. Note that discount factor r does impact input parameter c_0, which is the total net present cost of all costs incurred over the project lifetime. As discussed in §2.4.1, however, the optimal profitability index, and hence threshold $\check{n}$, are independent of c_0.

We further have similar results for the impact of learning rate α on the optimal policy, as stated below.

THEOREM 2. *Consider Problem (P1), and assume that the target is feasible. Fixing model parameters M_0, $n > \hat{n}$, $F(\cdot)$, δ, $\tilde{M}$, and T, there exist two thresholds $\hat{\alpha}$ and $\check{\alpha}$ $(0 \leqslant \hat{\alpha} \leqslant \check{\alpha} \leqslant 1)$, on the learning parameter $\alpha \in (0,1)$:*

(i) *The optimal profitability index, π_t^*, is (strictly) decreasing in t if and only if $\alpha \in (\hat{\alpha}, \check{\alpha})$. If $\alpha = \hat{\alpha}$ or $\alpha = \check{\alpha}$, the profitability index remains a constant. Furthermore, $\hat{\theta}_t(\mathbf{p}) = 1/\pi_t^*$ if $\alpha \in [\hat{\alpha}, \check{\alpha}]$.*

(ii) *If $\alpha \notin [\hat{\alpha}, \check{\alpha}]$, there exists a nonempty time interval in which π_t^* strictly increases in t. Furthermore, there exists a threshold $\hat{r}_\alpha$ such that if $r \leqslant \hat{r}_\alpha$, then π_t^* strictly increases in t over the entire time horizon.*

(iii) *Threshold $\hat{\alpha}$ decreases with $\tilde{M}$ and increases with T, whereas $\check{\alpha}$ increases with $\tilde{M}$ and decreases with T. Both thresholds are independent of c_0 and r.*

Theorems 1 and 2 essentially describe a set in the α-n space, denoted as $\mathscr{D}$, and referred to as the *no-delay region* hereafter, such that $(\alpha, n) \in \mathscr{D}$ is necessary and sufficient for the index to be nonincreasing (see our illustrative example below, Figure 2). In this region, investors never postpone their investment to a later period, and discount factor r has no impact on the optimal policy, as is formally stated below.

THEOREM 3. *Fixing model parameters M_0, $F(\cdot)$, δ, $\tilde{M}$, and T, there exists a region $\mathscr{D}$ in the α-n space such that any strategic delay by investors is eradicated under the optimal policy if and only if $(\alpha, n) \in \mathscr{D}$, where*

$$\mathscr{D} = \{(\alpha, n) \mid \alpha \in (0,1);\ \hat{n} < n \leqslant \check{n}(\alpha);\ \check{n}(\alpha) \text{ is a unimodal function}\}.$$

In particular, the optimal profitability index strictly decreases if and only if (α, n) is in the interior of set $\mathscr{D}$. Furthermore, the optimal profitability index remains constant if and only if (α, n) sits on the frontier of set $\mathscr{D}$ and the problem is feasible.

Finally, the boundary of region $\mathscr{D}$, $\check{n}(\alpha)$, is characterized by the following equation:

$$((1+\hat{n})^\alpha - \delta(1+\hat{n}))(1+\xi(n)) = \delta n(\alpha - 1)\xi(n)\lambda(n) f(\lambda(n)), \quad (11)$$

where

$$\lambda(n) = \bar{F}^{-1}(\hat{n}/n), \quad \text{and} \quad \xi(n) = \frac{\int_{\lambda(n)}^1 x f(x)\, dx}{(\lambda(n))^2 f(\lambda(n))},$$

which is independent of c_0 and r, and has a unique solution $\check{n} \in [\hat{n}, \infty)$ for any given $\alpha \in (0,1)$.

According to this theorem, the current practice of maintaining profitability constant is optimal only when (α, n) is such that $n = \check{n}(\alpha)$. Setting the sequence of optimal profitability index as constant yields the closed-form expression (11), which fully characterizes the entire boundary $\check{n}(\alpha)$ of the no-delay region $\mathscr{D}$. The expression demonstrates that the boundary $\check{n}(\alpha)$ depends on $\hat{n}$, and hence on parameters M_0, $\tilde{M}$, and T, as well as the government's discount factor δ and the distribution of investors $F(\cdot)$. The expression also clearly indicates that the boundary does not depend on c_0 and r, as discussed earlier.

It follows that the policymaker can easily establish a priori whether a nonincreasing policy is optimal by computing the no-delay region $\mathscr{D}$ and verifying if a particular (α, n) belongs to $\mathscr{D}$, irrespective of the value of r. When $(\alpha, n) \in \mathscr{D}$, solving Problem (P1) only involves a single dimensional search for π_1^* (see Corollary EC.1 in the e-companion).

When $(\alpha, n) \notin \mathscr{D}$ and $r > 0$, however, the computation of the optimal policy becomes intractable. First, the term $G_t(\mathbf{p})$ in (9) is in general nonconvex under dynamics (3)–(7), and thus (P1) is a nonconvex optimization problem. Second, when investors can strategically delay their investment, evaluating the objective functions for a given sequence of payoffs $\mathbf{p}$ involves solving a game among investors to obtain equilibrium thresholds $\hat{\Theta}(\mathbf{p})$. Searching for the optimal sequence is therefore computationally difficult.[10]

To design practical policies, the regulator may preempt any strategic delays by eliminating incentives to defer investments. In our framework, this corresponds to solving Problem (P1) under the additional constraint

$$\theta p_t - c_t \geqslant r^{\tau - t}(\theta p_\tau - c_\tau) \quad \text{for all } t \geqslant 1,\ \tau > t \text{ and } \theta \in A_t. \quad (12)$$

Note that constraint (12) is a necessary and sufficient condition for eradicating any strategic delays. The constraint is not binding if model parameters belong to set $\mathscr{D}$ and yields a constant profitability index policy otherwise, as stated below.

PROPOSITION 3. *Consider Problem (P1) with $r > 0$ and additional constraint (12), and assume that the target is feasible. The optimal profitability index, π_t^*, is strictly decreasing in time if and only if (α, n) is in the interior of set $\mathscr{D}$, and remains a constant otherwise.*

In the proof of Proposition 3, we first establish that constraint (12) is equivalent to $\pi_t \geqslant \pi_{t+1}$ for all t. This is because an investor for whom the payoff is infinitesimal in period t would always prefer to defer if $\pi_t < \pi_{t+1}$, irrespective of her discount factor. Then, Proposition 3 claims that when $(\alpha, n) \notin \mathscr{D}$, the set of constraints in (12) are all *simultaneously* binding, and hence, $\pi_t = \pi_{t+1}$ for all t, which is not a trivial result.

Finally, note that although Proposition 3 provides conditions under which π_t^* is monontone in t, we do not have monotonicity of π_t^* (for a specific t) with respect to model parameters α and n. For example, since the capacity target constraint is binding at optimality, π_t^*'s cannot all increase or decrease with α.

Illustrative Example: The German Solar PV Industry. In the following, we gather data from various sources on the evolution path for the solar PV industry in Germany under their "Renewable Energy Source Act" (EEG) during 2001–2012 period, and calibrate our model to gain insight into the structure of their FIT policy. The data for our analysis come from the following sources: International Energy Agency (2012), Deutsche Bank (2011), BMU (2007), BSW Solar (2013), Lobel and Perakis (2011), and references therein. Rather than conducting a thorough empirical analysis, our focus here is on the *structure* of the implemented policy and comparing it against our findings.

To calibrate our model, we first assume a uniform distribution over $[0, 1]$ to represent the heterogeneity of investors' efficiency. Our data on c_t and m_t are directly collected from the available sources, whereas p_t's are calculated as the NPV of the FIT income flow. In particular, p_t equals the NPV of the 20-year cash flow offered by the FIT policy in year t; we use a discount factor 0.96 and maximum annual full load hours of 1,050 (Hoefnagels et al. 2011).

The FIT policy implemented in Germany under their EEG law anticipates a 7% internal rate of return (IRR) for projects launched in different years (Fell 2009, Deutsche Bank 2011). This implies, in our model, a constant profitability index of 1.283.[11] Given this constant profitability index, it is reasonable to assume no strategic waiting behavior in the data. We then apply the ordinary least squares method together with Equations (7) and (10) to estimate learning parameter (α) and penetration coefficient (n), respectively. This leads to point estimates of $\alpha^0 = 0.194$ (learning rate 12.56%) and $n^0 = 1.78$ for these two parameters (see section EC.2 in the e-companion for details).

In this exercise, we consider the intermediate capacity target of 52 GW, which was passed in Germany Renewable Energy Action Plan (2010), and is envisioned to be achieved by 2020. For the purpose of illustration, we consider the hypothetical scenario where this target is set as early as the inception of EEG law in 2001. This corresponds to taking $T = 20$ years in our framework (between 2001 and 2020). In accordance with our formulation, we also set c_0 and M_0 as the prevailing cost and existing cumulative capacity of solar PV in Germany at the end of 2000, respectively. To solve Problem (P1) for the German solar PV market, we first use the estimated model parameters to compute the no-delay region $\mathcal{D}$. Next, we verify that $(\alpha^0, n^0) \in \mathcal{D}$, which implies that investors do not strategically delay under the optimal policy and enables us to compute the optimal policy accurately.

Figure 1 depicts the corresponding optimal policy as well as the constant policy implied by German FIT regulations. The solid line in the figure demonstrates the optimal sequence of profitability index during the 2001–2020 period. The dashed line, which remains constant at 1.283, represents the profitability index corresponding to a 7% internal rate of return. As is evident from the graph, the optimal solution from our model is a decreasing curve of profitability index from 1.349 in 2001 to 1.255 in 2020, and leads to a 9.6% reduction in cost compared to the constant policy represented by the dashed line.

Figure 1. Profitability index for solar PV in Germany corresponding to our model (solid curve) and the FIT regulations (dashed line).

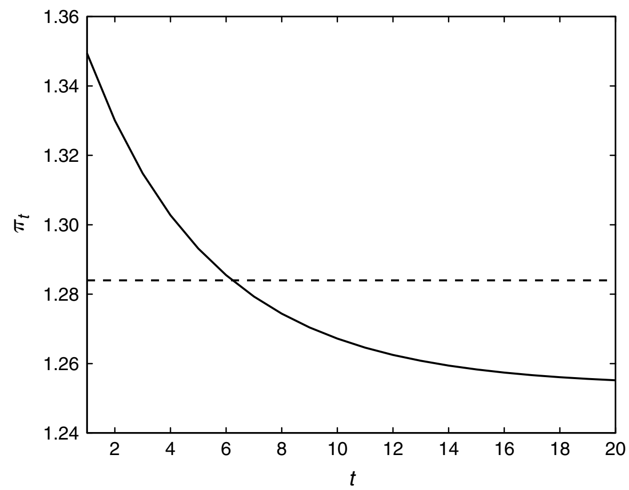
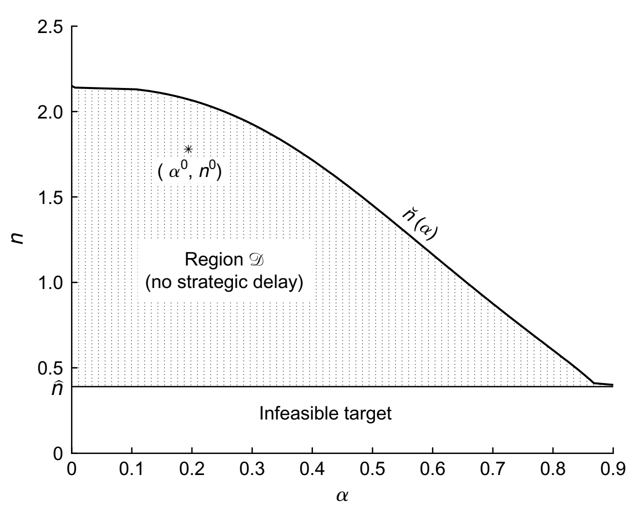


Figure 2 further depicts our theoretical results for the German solar PV market. In particular, the figure specifies the no-delay region $\mathcal{D}$ in the α-n space using curve $\check{n}(\alpha)$, which is unimodal, consistent with Theorem 3. Alternatively, the region could be characterized using thresholds $\hat{\alpha}(n)$ and $\check{\alpha}(n)$, which are defined in Theorem 2 for any given n. In this example, note that $\hat{\alpha}(n) = 0$ for all values of $n > \hat{n}$, and is thus not attainable by $\alpha \in (0, 1)$. For any given (α, n) in the figure, the corresponding optimal policy is strictly decreasing when the point is in the interior of $\mathcal{D}$, and constant if $n = \check{n}(\alpha)$. The current characteristics of the German solar PV market, marked by point $(\alpha^0, n^0) = (0.194, 1.78)$

Figure 2. Illustration of region $\mathcal{D}$ for the German solar PV market in (α, n) space, with $\alpha^0 = 0.194$ and $n^0 = 1.78$.



in the figure, is in the interior of region $\mathscr{D}$. In particular, $n^0 = \check{n}(0.373)$, which means that everything else being equal, the optimal policy remains decreasing for a learning parameter that almost doubles α^0. Similarly, $\check{n}(\alpha^0) = 2.09$, which means that the optimal policy remains decreasing as long as n_0 does not increase by more than 17%.

3.2. Grid Parity with Social Welfare Objective (P2)

We now turn our attention to Problem (P2), and study the optimal FIT schedule when a central planner wishes to maximize the social welfare. First, we note that if the cost of reaching grid parity is too high or its benefit too low, it may be optimal for the government not to implement the FIT program. Formally, we say a technology is *desirable* if it is optimal to achieve grid parity for Problem (P2) within finite time.[12]

Lemma 2. *Consider Problem (P2) with model parameters α, n, c_0, Π, M_0, $F(\cdot)$, r, and δ. Keeping all model parameters fixed except α, there exists threshold $\underline{\alpha}$ so that the technology is desirable if and only if $\alpha \geqslant \underline{\alpha}$. Similar thresholds $\underline{n}$, $\bar{c}_0$, and $\underline{\Pi}$ exist for parameters n, c_0, and Π, so that the technology is desirable if and only if $n \geqslant \underline{n}$, $c_0 \leqslant \bar{c}_0$, and $\Pi \geqslant \underline{\Pi}$, respectively.*

The implication of Lemma 2 is that a desirability frontier surface can be established in the (α, n, c_0, Π) space, dividing it into two desirable and undesirable regions. Similar desirability thresholds exist for other model parameters as well. In the remainder of this section, we focus on the case where the technology is desirable, and study the structure of the optimal policy surrounding it.

Similar to §3.1, we next characterize conditions on the model parameters for which strategic delays by investors disappear in Problem (P2). Note that when the target is set on technology cost, the total capacity installation required to reach the target becomes α-dependent (see Equation (7)). This creates additional complications in the analysis. In particular, for lower values of α, deeper market penetrations are required to reach the same cost reduction goal. As it turns out, this new effect is a key factor in determining the structure of the optimal FIT policy. Although deriving the optimal policy for Problem (P2) is more involved, we can still carry the analysis under some mild conditions and present the following result in parallel to Theorems 1 and 2.

Theorem 4. *In Problem (P2), fix model parameters c_0, $\tilde{c}_*$, M_0, $F(\cdot)$, δ, r, β_1, β_2, β_3, and Π, such that $\Pi \geqslant \Pi_b$ and $c_0/\tilde{c}_* \geqslant c_b$ for some lower bounds Π_b and c_b (which are independent of α and n). For any given n, there exists a threshold $\breve{\alpha} \geqslant \underline{\alpha}$ ($\underline{\alpha}$ as introduced in Lemma 2) on the learning parameter α, such that the optimal profitability index, π_t^*, is strictly decreasing in t if and only if the learning parameter $\alpha \in [\underline{\alpha}, \breve{\alpha})$.*

Similarly, for any given α, there exists a threshold $\check{n} \geqslant \underline{n}$ on the penetration coefficient n, such that the optimal profitability index, π_t^*, is strictly decreasing in t if and only if $n \in [\underline{n}, \check{n})$.

Furthermore, thresholds $\underline{\alpha}$, $\breve{\alpha}$, $\underline{n}$, and $\check{n}$ are all decreasing in $\tilde{c}_*$.

The conditions on Π and $c_0/\tilde{c}_*$ required in Theorem 4 pertain to situations where the social value of the renewable energy technology is high enough, and the technology is still in its early stages of development (far from grid parity). Under these conditions, a region akin to set $\mathscr{D}$ in §3.1 can be specified so that the investors do not defer their investment. Unlike the case of Problem (P1), however, such a no-delay region does depend on the discount factor r, because γ, which depends on r, appears in the coefficient of some but not all terms in the objective function. Despite this slight complication, inside the no-delay region, the market dynamics (3)–(6) still reduce to (10), which allows for simple computation. When (α, n) is outside this region, however, there must exist a nonempty time interval over which the regulator (strictly) increases the profitability index with time. Some investors would therefore defer, which tremendously complicates the computation.

To overcome this issue of computational intractability, similar to Problem (P1), the policy maker may again wish to preempt any strategic waiting by investors. This can be done by imposing the additional constraint (12), which eradicates investors' incentive to defer. We wish to emphasize again that the constraint is necessary and sufficient to preclude any strategic waiting from investors and is equivalent to $\pi_t \geqslant \pi_{t+1}$ for all t.

It can be shown that the optimal profitability index with this new constraint takes a constant-then-decreasing form. That is, there exists a period τ^{**} such that the optimal profitability index remains constant for $t \leqslant \tau^{**}$ and strictly decreases for $t \geqslant \tau^{**}$. Note that this result is not trivial, because any nonincreasing policy is feasible to constraint (12). However, we claim that under the optimal policy, the constraint $\pi_t \geqslant \pi_{t+1}$ is binding for all $t \leqslant \tau^{**} - 1$, and nonbinding otherwise.

Lastly, recall that parameter β_1 (corresponding to the social value of green energy over conventionally generated power) does not depend on time in our setup. In fact, it is possible to relax this assumption and generalize our result on Problem (P2) for time-dependent β_1 as long as the ratio $(\beta_1)_t/c_t$ is nondecreasing.

4. Diffusion Process with Saturation Effects

One of the key features in our theoretical formulation is the absence of saturation effects in the diffusion of the technology. This simplifying assumption is consistent with the objective of current FIT policies, and it allows mathematical tractability. In this section, we attempt to generalize our model by allowing for saturation effects in the dynamics of the adoption process and demonstrate that saturation effects do not change the fundamental insights obtained from our model.

Throughout this numerical exercise, we assume away strategic waiting, which makes computation possible. Because strategic delays in investment actually weaken saturation, ignoring them in our study can only strengthen our conclusion that saturation effects do not significantly impact our results.

In our framework, there are two different dimensions over which saturation takes place: *market saturation* and *efficiency saturation*. Market saturation refers to the slowing of the adoption process due to decline in the number of nonadopters, and it is commonly used in the marketing literature to describe the contagion of a new product or technology. To capture this effect, we use the canonical Bass model (Bass 1969), in which the total population of potential investors is finite and given by parameter N. The prospective demand in period t is formed by the interaction between adopters (M_{t-1}) and nonadopters ($N-M_{t-1}$), so that each interaction generates a potential interest with probability χ. Then, P_t, prospective demand for the technology in period t, is given by

$$P_t = \chi M_{t-1}(N-M_{t-1}) = \chi N M_{t-1}\left(1-\frac{M_{t-1}}{N}\right) = nM_{t-1}\left(1-\frac{M_{t-1}}{N}\right), \qquad (13)$$

where $n=\chi N$ is the revised penetration coefficient.

As stated above, each potential investor in period t is attracted to join FIT if her type exceeds the threshold c_t/p_t. On the other hand, the unfulfilled demand (investors of types lower than c_t/p_t) remain in the pool of nonadopters and can be potentially attracted again in subsequent periods. Since the investors who subscribe to the FIT program each period are those of higher types, the efficiency heterogeneity of the market also changes over time. This phenomenon, which we refer to as efficiency saturation, causes distribution $F(\cdot)$ to skew to the left with further dissemination of the technology. Given that demand in each period is a random sample from the pool of nonadopters, we have to update the efficiency distribution dynamically to account for those who have left the pool and joined the FIT program. Let $F_t(\cdot)$ denote the efficiency distribution of nonadopters in period t, where $F_0(\cdot)$ is the initial distribution of efficiency for the whole population. Then, the adoption growth in period t becomes

$$m_t = P_t\bar{F}_t(c_t/p_t) = nM_{t-1}\left(1-\frac{M_{t-1}}{N}\right)\bar{F}_t(c_t/p_t), \qquad (14)$$

and the distribution should be updated according to

$$F_{t+1}(\theta) = \frac{N-M_{t-1}-P_t}{N-M_t}F_t(\theta) + \frac{P_t-m_t}{N-M_t}\min\left\{\frac{F_t(\theta)}{F_t(c_t/p_t)}, 1\right\}. \qquad (15)$$

In the above equation, the first term corresponds to the pool of uninformed investors carried from period t to $t+1$, and the second term adjusts for the leftover demand from period t. So in effect, $F_{t+1}(\cdot)$ is a convolution of $F_t(\cdot)$ and a revised $F_t(\cdot)$ where the right tail is truncated at c_t/p_t.

Putting all together, in the presence of saturation effects and nonstrategic investors, the government's optimization problem can still be represented by Problems (P1) and (P2), with the only difference that Equation (3) must be replaced with Equation (14), and all integrals must be taken with respect to the corresponding period's distribution.

Now, let $\tilde{M}_*$ be the generation capacity required to reach grid parity.[13] When $\tilde{M}_*$ is small compared to N (which also implies that $M_t \ll N$ for all t), it immediately follows that $P_t \approx nM_{t-1} \ll N$. This further implies that $F_{t+1}(\cdot)\approx F_t(\cdot)$ and hence, $m_t \approx nM_{t-1}\bar{F}_0(c_t/p_t)$. On the other hand, it is not hard to show that when investors are not strategic, Equation (3) also reduces to $m_t = nM_{t-1}\bar{F}(c_t/p_t)$. In other words, Equation (3) offers a reasonable approximation of the diffusion process with saturation as long as N is sufficiently large compared to $\tilde{M}_*$.

Without such an approximation, incorporating the saturation effects into the model makes our mathematical formulation extremely complex and analytically intractable. The complexity comes primarily from the convolution of two different distributions, which, in general, does not lead to a closed-from solution. In fact, the convolution presented in Equation (15) turns out to be challenging even numerically, and revising the distribution in each period becomes computationally very slow as t grows.

We conduct an extensive numerical analysis by generating random instances where model parameters are uniformly drawn from intervals listed in Table 1. These intervals are formed based on our best estimates for lowest and highest possible values for each parameter and are gathered from the empirical evidences in the literature. In addition, we use three different $\mathscr{B}$eta distributions with parameters (2, 2), (2, 4), and (4, 2) for $F_0(\cdot)$ to capture symmetric, left-skewed, and right-skewed distributions, respectively. Since the distribution updating step, as described by Equation (15), quickly becomes challenging after the first few periods, we reapproximate the outcome of the convolution by fitting the

Table 1. Model parameters for the numerical study.

Parameter	Uniform distribution
α	[0.15, 0.5]
n	[0.8, 3]
δ	[0.9, 0.97]
c_0	[2,000, 10,000]
M_0	[10, 100]
$\tilde{M}_*$	$[4\times 10^4, 1.5\times 10^5]$
N	$[2\times \tilde{M}_*, 20\times \tilde{M}_*]$
β_1	[200, 800]
β_2	[0, 1]
β_3	[0, 1]
Π	$[4.5\times 10^7, 1.8\times 10^{10}]$

Table 2. Distribution of relative suboptimality gap for ignoring saturation effects.

Percentile	10th	25th	50th	75th	90th	Mean
Suboptimality gap %	0.0024	0.124	0.608	1.986	4.516	1.973

$\mathscr{B}$eta distribution that best describes investor heterogeneity structure in each period.

In Table 1, note that the range $[0.15, 0.5]$ for the learning parameter α, translates into learning rates between 10% and 30%. Also, the range for N is constructed so that the ratio $\tilde{M}_*/N$ varies between 0.05 and 0.5, i.e., reaching grid parity may require a market penetration as low as 5% and as high as 50% of the total population of investors. Finally, the Π values we choose yield the optimal policy duration, T^*, to be in the $[10, 25]$ range.

For each $F_0(\cdot)$ distribution, we generate 1,000 random instances, and record the optimal FIT schedule and the optimal objective value in settings with and without saturation effects. The focus of this numerical study is only on Problem (P2) since it is more general and covers Problems (P1) as a special case.

Table 2 summarizes our findings for the suboptimality gap of all 3,000 instances, measured as the relative suboptimality of the model that ignores saturation compared to the general model developed in this section. According to these numbers, in more than 75% of the cases, the relative suboptimality is below 2%. Moreover, the average across all cases does not exceed 2%, which seems tolerable for large-scale public policy problems of this sort. Intuitively, ignoring saturation should be more costly when the ratio $\tilde{M}_*/N$ is larger, since a higher market penetration occurs under the FIT program. This is also consistent with our numerical results. In particular, the average suboptimality gap for cases with $\tilde{M}_*/N \leqslant 0.1$ is around 1.2%. That is, the suboptimality gap shrinks as the adoption mass required by grid parity comprises a smaller percentage of the total population.

Moreover, we also evaluate the optimal FIT schedules in our numerical tests to explore the impact of saturation effects on the structure of the optimal policy. For example, in the absence of saturation, we can prove that if $r = 0$ in Problem (P2), the optimal sequence of profitability index possesses a unimodal structure, i.e., it first increases and then decreases (see Proposition EC.5 in the e-companion). We observe in our numerical analysis that the optimal policy in 96% of the cases with saturation effects also exhibits such a structure. More importantly, in the remaining 4%, violations of the unimodal structure always appear toward the end of the horizon, when the saturation effects start to take hold. To be more precise, the unimodal structure is violated only by (at most) the last three p_t/c_t ratios (e.g., $p_{T^*-1}/c_{T^*-1} > p_{T^*-2}/c_{T^*-2}$), and the structure can be retrieved if we change these variables by no more than 1% of their values.

In short, our numerical analysis suggests that ignoring saturation effects in the diffusion process does not impair the FIT policy performance significantly, and our results appear quite robust with respect to changes in the assumptions governing the diffusion process.

5. Conclusion

This paper studies the dynamic control of remuneration rates (prices) of feed-in tariff policies, the most widely implemented policy instrument for promoting renewable energy technologies. Under this mechanism, the government attracts investments and stimulates demand for the technology by sponsoring a certain compensation level for purchasing electricity from those who have adopted the technology. The objective is to make renewables cost-competitive—before the market saturates—so as to let private investment foster deployment of these energy sources. In current practice, legislators typically attempt to maintain the same level of profitability across years by dynamically adjusting the feed-in tariffs offered to newly commissioned projects.

Our analysis, however, shows that maintaining profitability at a constant level is in theory rarely optimal. By contrast, we characterize a no-delay region in the problem's parameters, such that the profitability index should strictly decrease over time if the diffusion and learning rates belong to this region. In this case, investors never strategically postpone investment to a later period. When the diffusion and learning rates fall outside the region, the optimal profitability index may increase, which would incentivize some investors to strategically delay joining the FIT program.

Nonetheless, our work offers some justifications for the use of constant profitability index in practice. Indeed, even though these policies may be theoretically suboptimal, the corresponding FIT levels can be easily calculated and hence implemented. This is because, as with decreasing policies, maintaining a constant profitability index precludes strategic delays, which makes computation of FIT schedules feasible. We show that when the regulator also requires the policy to prevent any strategic delays, the constant profitability index policy is optimal if the diffusion and learning rates fall outside the no-delay region. However, when the model parameters are in the no-delay region, a decreasing profitability policy should be preferred.

From a technical standpoint, although we have assumed a fixed cost threshold for achieving grid parity, our model allows this threshold to be time-dependent. This speaks to power-generating costs associated with oil and gas prices, which may change the cost parity goal over time.

Our setup can also help address the important issue of disruptive events, such as technological disruptions or sudden influxes of foreign and inexpensive technologies. A complete treatment of these issues requires a Bayesian approach, in which the regulator dynamically updates her belief about the occurrence of such events and dynamically varies tariffs according to this belief. Nonetheless, the key decisions when confronting disruptive events are mainly the size and duration of the program, for which our current setup offers simpler and more practical heuristic approaches. For instance, using our formulation (P1) as building blocks, policy makers can conduct cost/benefit analyses to trade off the timing and cost of an FIT policy against the possible occurrence of a disruptive event.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/opre.2015.1460.

Endnotes

1. Own calculation based on Hoefnagels et al. (2011), International Energy Agency (2002), and Eurostat EC (2012).
2. The IGFR property implies that the ratio $xf(x)/(1-F(x))$ is increasing in x.
3. In parallel to this analogy, the parameter n is equivalent to "coefficient of imitation" in the Bass (1969) model.
4. Because $N_0^w = 0$, distribution $F_0^w(\cdot)$ can be set arbitrarily.
5. $(-\alpha)$ is sometimes referred to as *learning elasticity* (van der Zwaan and Rabl 2003) or *learning index* (Yelle 1979).
6. Note that as before, we assume all payments are made at the beginning of the period.
7. In particular, threshold $\tilde{c}_*$ can be interpreted as the prevailing cost of traditional energy production power plants such as those fueled by coal or natural gas.
8. The cost parity threshold associated with grid parity is type dependent, and will not be reached for all investor types at the same time. Our analysis carries over regardless of how this threshold is defined, e.g., for the highest efficiency or for the average efficiency.
9. Since we are dealing with a game, using the term "optimal policy" is with a slight abuse of language. Rigorously speaking, by optimal policy we are referring to the regulator's best response in equilibrium.
10. It is possible to introduce binary variables into the optimization model to address the equilibrium issue. Nonconvex integer optimization problems are notoriously hard to solve to optimality.
11. For this, we first consider a cash flow with unit initial cost and a constant annual payment of 0.094 over 20 years. The value of the payment is set so that the cash flow delivers the internal rate of return of 7%, that is $1=\sum_{i=1}^{20}(0.094/(1.07)^i)$. We then calculate the net present value of these payments at discount rate 96% to obtain the profitability index corresponding to the cash flow: $\sum_{i=1}^{20}(0.094/(1.04)^i)=1.283$.
12. Note that the optimal objective value $\zeta(\tilde{c}^*)\geqslant 0$, while not implementing FIT at all yields an objective function value of 0. This implies that as long as a technology is "desirable" according to our definition, it is indeed optimal for the government to achieve grid parity rather than not implementing the FIT program at all. To see $\zeta(\tilde{c}^*)\geqslant 0$, consider a particular sequence of feasible solutions $p_t=(1+\epsilon)c_t$ with ϵ approaching zero in the limit. Any positive ϵ guarantees that grid parity is achieved within finite time T, while in the limit T approaches infinity and the objective function value approaches 0.
13. In view of the one-to-one correspondence between cost and capacity, as provided in Equation (7), $\tilde{M}_*$ is the capacity equivalent of the cost target $\tilde{c}_*$ and satisfies

$$\tilde{c}_* = c_0\left(\frac{\tilde{M}_*}{M_0}\right)^{-\alpha}.$$

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