Optimal Feed-in Tariff Schedules

Abstract

We analyze the design of optimal feed-in tariff schedules under production-based learning. We examine least cost policies in a simple two-period model that focuses on bringing down the levelized cost of renewable technologies to a predefined target under two well-known dynamics: learning-by-doing (LBD) and economies of scale (EOS). We show that, when the levelized cost reduction target is stringent, subsidies are required in both periods, regardless of the dynamic. However, when the target is moderate, the optimal policy is to subsidize only in one of the two periods: under the LBD dynamics it is optimal to subsidize as early as possible, whereas under the EOS dynamics it is optimal to subsidize as late as possible. Under the LBD dynamics the prevailing factor is the impact of early investment on cumulative experience, whereas under the EOS dynamics the prevailing factor is capital depreciation. The key takeaway is that, based on the underlying dynamics, the policy maker needs to adopt fundamentally different kinds of policies to promote renewable technologies.

Managerial Relevance

This paper provides guidelines for designing feed-in tariffs in such a way that they produce desired improvements in renewable technologies while being cost effective from the perspective of society. This is relevant to a wide range of policy makers, at national and sub-national levels, who are faced with questions about how to design renewable energy policies. The paper underlines the importance of understanding the cost dynamics of the particular technology that is being subsidized. In addition, policies such as feed-in tariffs are of great interest and import to firms in the renewable energy industry. This paper provides such firms with a policy-makers perspective on the costs and benefits of such policies, as well as some insight into how optimal investments in renewable energy technologies are effected by feed-in tariffs.

1 Introduction

1.1 Motivation

Climate change is perhaps the biggest problem faced by human beings in their history (Pew Center, 2008). It is caused by the accumulation of greenhouse gases (GHGs), such as carbon dioxide (CO_2), in the atmosphere. It has recently been established that human beings are responsible for the increased concentration of GHGs in the atmosphere (IPCC, 2007). This increased concentration may cause serious degradation of the earth's climate, requiring focused effort in controlling GHG concentrations in an expedited manner (Stern, 2007).

In order to achieve this transformation, the invention, innovation, and diffusion of new technologies to reduce GHG emissions will be critical (Goulder and Mathai, 2000). This phenomena, the so-called technology change (TC), occurs for a variety of reasons as firms compete in existing and new markets by producers *discovering* and utilizing new production methods that enable them to produce cheaper and better goods (Schumpeter, 1947), and is typically included in macroeconomic models as an endogenous factor (Romer, 1990). For example, ongoing innovations in propeller design continue to reduce the cost of wind-generated electricity considerably (Bolinger and Wiser, 2009; Neij, 1999), and recent improvements in solar photovoltaic (PV) cells continue to yield substantial cost reductions (Borenstein, 2008; Harmon, 2000).

However, in the context of climate change, market forces alone may not be enough to spur the required technology change (Jaffe et al., 2005). Under this situation policies can spur additional or "induced" technology change (ITC), a hypothesis first articulated by Hicks (1932) as follows: "a change in the relative prices of factors of production is a spur to invention – directed to economizing the use of a factor that has become relatively expensive." Attempts by Kennedy (1964), von Weizsacker (1965) and Ahmad (1966) to develop this hypothesis into a theory led to a sizeable literature (Binswanger and Ruttan, 1978; Thirtle and Ruttan, 1987), which faded from view after much criticism (Samuelson, 1965; Nordhaus, 1973). The topic has seen a revival thanks to Acemoglu's model of directed technical change (Acemoglu, 2002), which has direct relevance to climate policy (Smulders and Nooij, 2003).[1]

ITC can occur through two main channels: R&D leading to non-incremental technological change; and production effects, leading primarily to incremental reductions in cost (Goulder, 2004). Consequently, ITC can be achieved through technology "push" policies that boost the invention and innovation process, such as funding for R&D (Montgomery and Smith, 2005), and through policies that "pull" new technologies into the market, such as a GHG cap-and-trade program, or technology subsidies (European Commission, 2005). Depending on the maturity of a new technology, ITC policy may target any of the stages in its evolution (Grubb, 2004): basic R&D, applied R&D, demonstration (or prototyping), commercialization, market accumulation, and diffusion. Each of these stages may require different kinds of policy instruments (Martin and Scott, 2000). For example, basic and applied R&D may benefit from research grants and tax credits, whereas demonstration and commercial stages may benefit from demonstration grants and low-interest loans (Foxon et al., 2008).

It is well established that both push and pull policies are required to combat climate change effectively, given that it engenders a unique combination of multiple market failures (Jaffe et al., 2005): first, due to the unpriced "negative externality" from GHG emissions (Dales, 1968); and second, due to the "positive externality" from spillover effects related to R&D of low-emission technology (Arrow, 1959).

Though there is debate about the optimal policy instrument for ITC (for example, see Nemet and Baker (2009) for a discussion on the appropriate policy for organic PV), in this paper we focus on technology-subsidy-based pull policies, such as renewable portfolio standards (RPS) and feed-in tariffs (FiT) (Menanteau et al., 2003; Meyer, 2003), that promote technological change through production effects in the market accumulation stage of technology evolution. That is, our focus is on somewhat mature renewable technologies, such as wind and solar.

In particular, we focus on guaranteed minimum tariffs, also known as FiT. The main reason for focusing on FiT is simple: FiT have proven to be one of the most popular mechanisms for stimulating investment in renewable electricity generation worldwide (Gipe, 2006). Further, looking

[1] For a good theoretical background on modeling ITC in climate policy, see Weyant and Olavson (1999). ITC has relevance in other fields as well, such as agriculture (Staub and Blase, 1974).

at the effectiveness of current policies in Europe (Meyer, 2003) and California (Kema, 2008), it is clear that the popular RPS policies have not been as effective as hoped, and there is a need to (at least) incorporate FiT into the policy framework.

Under this policy (i.e., FiT), the renewable energy generator is guaranteed a minimum price for the electricity generated. This minimum price may not only cover the cost of production but also provide a surplus to encourage additional investment in the technology. The basic idea is that the additional investments would result in increased production capacity, which in turn would result in desired cost reduction through production effects (Mendonca, 2007).

This brings forth the critical issue of the optimal design of FiT schedules. In general, the design of FiT schedules from the perspective of a policy maker bears on the following (Kema, 2008). First, FiT schedules should be designed such that they result in the desired investment in renewable technologies. Second, they should account for the fact that the reductions in the cost of production are endogenous to the system under study. Finally, at the same time they should be designed such that the cost to the society is as little as possible. That is, they should be cost-effective.

1.2 Our Contribution

In this paper we focus on the issue of designing the optimal FiT schedules across time. We derive these schedules from the perspective of providing incentives to innovators to invest in renewable technologies – in order to achieve specified improvements in the technologies through production effects.

We assume that the policy maker has a goal of reducing the cost of renewable electricity through the use of FiT. The FiT gives producers of renewable energy a guaranteed surplus profit. This surplus profit leads producers to invest more in renewable technologies, causing the cost of production to decline over time, and eventually coincide with the cost of production of conventional technologies, such as coal-generated electricity. Given that FiT are used to incentivize producers of "costly" renewable technologies, they are useful only as long as these costs are higher than costs of conventional methods. Once cost parity is achieved, to avoid over-compensation (Klein et al, 2008), FiT are not required. Thus, the policy maker would like to set this surplus schedule to ensure that the objective is met with the minimum cost to society – for example, see Netherland's Spot-Market Gap Model (Cory et al., 2009) and Spain's Progression of Different Remuneration Components (Klein et al, 2008). That is, we minimize the surplus given to the producers of renewable technologies, subject to achieving pre-defined cost goals.[2]

It is typically believed that the cost of renewable (and many other) technologies are governed through learning-by-doing (LBD) dynamics (Yelle, 1977; Nemet, 2006). Studies have described the complex nature of the innovation process in which uncertainty is inherent (Freeman, 1994), knowledge flows across sectors are important (Mowery and Rosenberg, 1998), and lags can be long (Rosenberg, 1994). Perhaps because of such characteristics, theoretical work on innovation provides only a limited set of methods with which to predict changes in technology. The learning curve model offers an exception. It originates from observations that workers in manufacturing plants became more efficient, providing opportunities for cost reductions and quality improvements, as they produced more units (Wright, 1936; Alchian, 1963; Rapping, 1965). Arrow (1962) formalized a model explaining technical change as a function of learning (-by-doing), and referred to the learning curve as the changes in the productivity of labor, which were enabled by the experience of cumulative production. Though the basic idea remains the same, the concept has since been refined, including classification of different kinds of learning (Bahk and Gort, 1993); use of experience curves in many industries, including airplanes, automobiles, and integrated circuits among others (Conley, 1970; BCG, 1972; Dutton and Thomas, 1984); etc.

However, there is recent disagreement – in particular, as related to cost reductions in organic PV systems being governed by economies of scale (EOS) dynamics (Nemet, 2006; Nemet and Baker, 2009) as opposed to LBD, as conventionally believed (Bolinger and Wiser, 2003; Benthem et al., 2008). EOS is different from LBD in the sense that improvements from EOS come from increase in current capacity, whereas improvements from LBD come from increase in cumulative production

[2]The pre-defined goal may mean many things. For example, it could be the cost of electricity from conventional sources, such as coal. It could also be the cost to reach grid parity, which is the cost of electricity from a mix of sources. Finally, it could be a price that would make it competitive, given a carbon tax. In this paper, though we have not explicitly defined this goal, we implicitly refer to the first definition – however, we mention the context every time numerical values are used, as in Sections 3.2 and 4.2.

(Nemet, 2006). Note that, in microeconomics, EOS refers to the cost advantages that a business obtains due to expansion (Stigler, 1958). In effect, the results in Nemet (2006) support previous findings by Dutton and Thomas (1984) that "sometimes much of what is attributed to experience is due to scale"; by Argote and Epple (1990) which proposed economies of scale as one of four alternate hypothesis to LBD for observed technical improvements; and by Gruber (1996) which went a step further and derived an equation governing cost reductions due to scale effects in the semiconductor industry.

Though this debate is far from over, instead of leaning either way, we take a neutral stance and examine both of these production effects in deriving FiT schedules. That is, our contribution is not in further developing the concepts of LBD or EOS. The novelty of our work derives from application of these dynamics in deriving optimal subsidy schedules. Given that our work matches subsidies to production dynamics, it is also related to the generic resource-based view (RBV) literature that, according to the firm's capabilities, optimizes the application of resources at the firm's disposal to sustain long-term competitive advantage (Wernerfelt, 1984; Rumelt, 1984).

We model the policy maker's decision under realistic assumptions – in terms of capital depreciation and investment efficiency – on firms' investment dynamics. We find that the optimal schedule varies depending on assumptions about whether the cost reductions come from LBD or EOS. In particular, we show the following.

When the cost reduction target is stringent, subsidies are required in both periods under both dynamics. Further, as the target becomes increasingly stringent, optimal subsidies under both dynamics show similar behavior: not only subsidies are required in both periods but also it is optimal to subsidize more heavily earlier. However, when the target is moderate, the optimal policy is to subsidize only in one of the two periods: under LBD dynamics it is optimal to subsidize in the first period only, whereas under EOS dynamics it is optimal to subsidize in the second period only.

Except for the case when the target is very stringent, the key difference between the two dynamics is related to how the subsidies are spread over time. If cost reductions come from LBD, it is optimal to provide incentives early in order to take advantage of learning dynamics. That is, the optimal FiT schedule under LBD is non-increasing. On the other hand, if cost reductions come from EOS, then it is optimal to provide incentives later in order to avoid capital depreciation, and to maximize the scale of the enterprise. That is, the optimal FiT schedule under EOS is typically non-decreasing, except for the case when the target is very stringent – in this case, the optimal FiT schedule becomes non-increasing as scale effects start to dominate.

1.3 Related Work: ITC Instruments for Climate Change

Our work is related to a variety of literature, including ITC, innovation, and LBD. We have provided relevant literature synthesis on these topics in Section 1.1.

In this sub-section we limit ourselves to comparison with literature on FiT design as well as other ITC instruments for renewable technologies. We do so since our work entails a unique combination of the following. First, we focus specifically on ITC instruments – in particular, on a production based subsidy (i.e., FiT). Second, this subsidy is targeted towards cost reduction of renewable technologies, based on LBD and EOS. For example, though literature exists on evaluating impacts of production based subsidies in agriculture (Ahmed and Sampath, 1992; Sunding and Zilberman, 2001), the second component is usually missing.

1.3.1 FiT Design

There are a great variety of potential FiT policy design options, such as appropriate tariff structure, eligibility, and pricing (Cory et al., 2009; Klein et al, 2008; Kema, 2008; Lesser and Sua, 2008). For example, Cory et al. (2009) provides a good overview of various FiT structures used worldwide, including fixed-price tariffs and premium-price tariffs. Similarly, Klein et al (2008) examines FiT design options, such as stepped tariff designs; tariff level depending on location, plant size, and fuel type; incorporating technological learning and experience curves; and tariff degression. Further, some work focuses on FiT schedule design in specific geographies, such as Kema (2008), which is specific to California. It focuses on heuristics, such as cost-plus pricing, for setting FiT schedules. However, all of this work is either empirical or heuristics based.

Several papers have examined the provision of technology subsidies under LBD and have come to similar conclusions regarding subsidizing renewable technologies earlier than later (Kverndokk and Rosendahl, 2007; Benthem et al., 2008). Kverndokk and Rosendahl (2007) studied the role of technology subsidies in climate policies, using a simple dynamic equilibrium model with LBD, and found that the optimal subsidy rate (e.g., through FiT) of a carbon-free technology should be high when the technology is first adopted but falls over time. Similarly, Benthem et al. (2008) developed a model to analyze the economic efficiency of solar subsidy policies in California, and emphasized the need for the necessity of subsidies (e.g., through FiT) as early as possible under LBD. However, this result – the need to subsidize early under LBD – was surmised in both the papers, not proven.

Therefore, by analyzing the design of FiT schedules from a theoretical perspective, our paper fills a gap in the literature on FiT.

1.3.2 FiT vs. Other ITC Instruments

A number of papers have compared various policies for promoting ITC, and examined various aspects of FiT.

A popular theme is comparison between FiT and obligatory renewable energy quotas with green certificates trading, also known as RPS. Previous literature has compared these two policies along various dimensions, such as efficiency, fairness, and effectiveness (Toke, 2007; Menanteau et al., 2003; Gipe, 2006; Meyer, 2003); and found FiT to be more efficient and RPS to be more fair. Moreover, RPS systems favor large, vertically integrated generators and multinational electric utilities, and are more difficult to design and implement than FiT systems (Gipe, 2006).

Another theme has compared pull policies, such as FiT, with push policies, such as R&D funding and found R&D funding to be more effective for solar energy technologies due to their relative immaturity (Nemet and Baker, 2009).

However, our paper has intentionally stayed away from such comparison and has instead focused on a specific aspect of FiT, namely the design of optimal FiT schedules.

1.4 Organization

The rest of the paper is organized as follows. Section 2 presents the basic model used in this paper. Section 3 presents the results under LBD dynamics whereas Section 4 presents the results under EOS dynamics. In section 5, we examine the robustness of our results under different models. Finally, Section 6 discusses the implication of our results, explores alternative models, and concludes.

2 The Model

Our model takes the perspective of a policy maker who would like to promote renewable technologies by providing a FiT schedule. Under this schedule producers are guaranteed that all the production in a period is bought at the pre-specified FiT. The goal is to increase production of the technology, thus spurring cost decreases due either to LBD or EOS.

We analyze a minimum-cost FiT schedule such that the renewable technologies achieve cost parity with conventional ones over a finite time horizon. We first examine the firm's investment dynamics in Section 2.1 and then analyze the policy maker's decision in Section 2.2.

2.1 The Firm's Investment Dynamics

A key unit of analysis in our model is the Levelized Electricity Cost (LEC). LEC is the cost of generating electricity for a particular system, amortized over the total electricity produced during its lifetime, and is generally measured in \$/kWh. It includes all costs, such as initial investment, operations and maintenance, cost of fuel, cost of capital, etc. The LEC is the minimum price at which energy must be sold for an energy project to break even. This metric is commonly used to compare different types of electricity generation, since some technologies, such as solar and wind, have large initial costs but no fuel costs; while other technologies, such as coal and gas, have different characteristics. Nemet and Baker (2009) provides an excellent description of calculating LEC from various system parameters.

In our model (see Figure 1), the quantity of electricity produced during period n is given by q_n, for periods $n \in \{0, 1, 2\}$, respectively. This electricity is produced at LEC lc_{n-1}. That is, the total

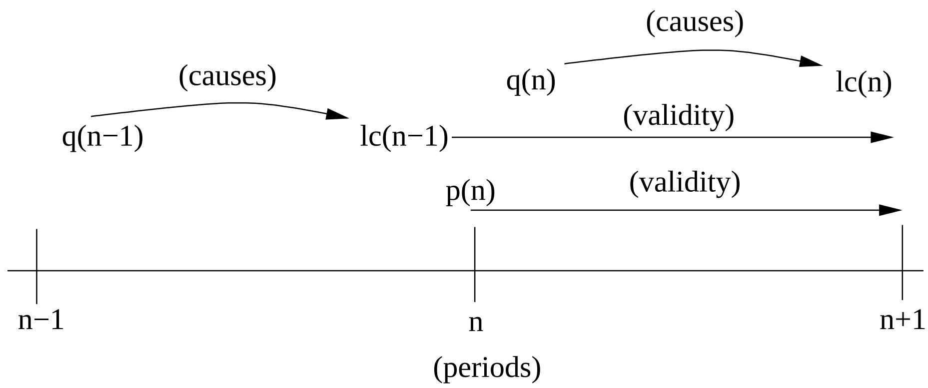

Figure 1: The sequencing of variables. Representative variables for periods $n-1$ and n are shown. The quantity produced in period $n-1$ (i.e., q_{n-1}) causes the LEC to change to lc_{n-1} at the end of the period. This LEC, i.e, lc_{n-1} is what the producer sees in period n. Further, the FiT for period n (i.e., p_n) is valid for the whole period n.

cost of producing q_n in period n is given by $lc_{n-1}q_n$. The production of q_n, however, will reduce the LEC at the end of period n to lc_n, due to learning or scale effects. This LEC will then apply to the electricity produced in period $n+1$.

The FiT applicable in period n is given by p_n, for $n \in \{1, 2\}$. It is assumed to be announced at the beginning of period $n-1$ and is valid for the whole period n (see Figure 1). The firm's per-unit profit or surplus in period n is then given by

$$s_n = p_n - lc_{n-1}.$$

We assume that firms are myopic and only invest to maximize profits for one period at a time, where a period may represent 5 or 10 years. Specifically, a period would correspond to the duration a given value of feed-in tariff is active. Given the expected surplus s_n in period n, firms invest an amount I_{n-1} in period $n-1$ in order to increase capacity in period n. Given a constant LEC, firms will produce up to capacity as long as their surplus is positive. Then, we just have one variable, q_n that represents both the quantity produced and the capacity in the period n.[3]

[3]That is, we assume that the capacity for a period is the same as the quantity produced in that period. It is possible to differentiate between the two by denoting the capacity as the quantity produced in one year – then given m years in a period, the quantity produced in a period would be m times the capacity. Though this may change the actual parameters describing our solutions by a factor m, it can be easily verified that the essential insights remain

The firm chooses investment I_{n-1} to *maximize* its perceived profit in period n:[4]

$$\pi_n = s_n q_n - I_{n-1}. \tag{1}$$

We assume there is some cost to investing, so we make a distinction between the cost of investment to the firm, termed gross investment I, and the productive amount of investment, termed net investment J. Further, we assume that the capacity in the current period (q_n) is related to the capacity in the previous period (q_{n-1}) and *net* investment in the previous period (J_{n-1}) through the discrete dynamics

$$q_n = \delta q_{n-1} + \gamma J_{n-1}, \tag{2}$$

where $0 < \delta \leq 1$ is the capital depreciation factor, $0 < \gamma \leq 1$ is a factor that translates investment dollars into units of capacity, and J_n is related to the *gross* investment I_n via the quadratic adjustment cost model (Uzawa, 1969) as

$$I_n = J_n(1 + \phi \frac{J_n}{q_n}), \tag{3}$$

where $\phi \geq 0$ represents the strength of the cost of investment. Note that this formulation assumes that rapid changes in the physical capital stock are costly and the cost (i.e., $(1 + \phi \frac{J_n}{q_n})$) of net investment is related to the size of the net investment. Specifically, it means that there are decreasing returns to investment in any given period, but that it is less costly for a large firm to increase capacity than for a small firm.

By solving for J_n and substituting it into (2) we get an expression for capacity as a function of gross investment (see Appendix I for details):

$$q_n = q_{n-1}[\delta + \frac{\gamma}{2\phi}(\sqrt{1 + \frac{4\phi I_{n-1}}{q_{n-1}}} - 1)], \tag{4}$$

the same, and we prefer to use the simpler notation that the quantity produced in a period is the same as the capacity.

[4] This, somewhat myopic, assumption implies that firms act as if they are going to go out of business at the end of the next period. That is, they don't recognize that investment aimed at the first period will benefit them in the second period. They are missing two effects: first, that the extra capacity will benefit them in the second period by lowering the LEC, and by earning revenues; and second, because of the extra capacity further investments will be lower in the second period.

Then, combining (1) and (4) we get the producer's problem as follows:[5]

$$\max_{I_{n-1}} \pi_n = s_n q_n(I_{n-1}) - I_{n-1}, \tag{5}$$

Given $s_n \geq 0$ (i.e., the subsidy is never in the form of a tax), then $\frac{d^2\pi_n}{dI_{n-1}{}^2} \leq 0$ (see Appendix I for details). That is, the producer's problem is concave in I_{n-1}. Next, noting that

$$\frac{d\pi_n}{dI_{n-1}}(0) = \gamma s_n - 1,$$

the optimal investment is given by

$$I^*_{n-1} = \begin{cases} [(\gamma s_n)^2 - 1]\frac{q_{n-1}}{4\phi} & \text{if } s_n \geq \frac{1}{\gamma} \\ 0 & \text{if } s_n < \frac{1}{\gamma}, \end{cases} \tag{6}$$

where the first term is derived from the first order condition

$$s_n\gamma(1 + \frac{4\phi I_{n-1}}{q_{n-1}})^{-\frac{1}{2}} - 1 = 0.$$

(6) essentially says that if the surplus profit is not high enough, then the firm has no incentive to invest, and it simply allows the capital stock to depreciate. Given (6), the optimal capacity dynamics (4) can be written as

$$q^*_n = \begin{cases} q_{n-1}[(\delta - \frac{\gamma}{2\phi}) + \frac{\gamma^2}{2\phi}s_n] & \text{if } s_n \geq \frac{1}{\gamma} \\ q_{n-1}\delta & \text{if } s_n < \frac{1}{\gamma}. \end{cases} \tag{7}$$

[5] This assumes that there are no constraints on funds available for investment. In a normally functioning financial system this may be true in a lucrative and relatively risk-free) market, such as the one created by feed-in tariffs. This assumption allows us to focus on the policy maker's subsidy decision. However, in Section 5.2 we relax this assumption and qualitatively investigate the effect of limited investment availability. To put this in context, consider the venture capital (VC) investment in the clean tech industry before and after the financial crisis of 2008. During the crisis, total VC investments in clean tech quickly dropped from \$8.5 billion in 2008 to \$5.5 billion in 2009 (Clean Tech Group, 2010), indicating a shift from an abundance of external funds to limited investment availability.

Here we provide a definition to simplify calculations. Denoting

$$S_n \triangleq \begin{cases} a + bs_n & \text{if } s_n \geq \frac{1}{\gamma} \\ \delta & \text{if } s_n < \frac{1}{\gamma}. \end{cases} \tag{8}$$

where

$$a = \delta - \frac{\gamma}{2\phi} \text{ and } b = \frac{\gamma^2}{2\phi} > 0, \tag{9}$$

we can then write[6]

$$q_n^* = q_{n-1} S_n, \tag{12}$$

and, iteratively

$$q_n^* = q_0 \prod_{i=1}^{n} S_i. \tag{13}$$

2.2 The Policy Maker's Problem

Given the firm's investment dynamics, we now focus on the policy maker's problem under different LEC dynamics, such as LBD and EOS.

The Policy Maker's (PM) goal is to achieve a LEC equal to a predetermined target: $lc_2 = lc \leq lc_0$, where lc is a predetermined target, and lc_0 and lc_2 are the initial and final LECs, respectively.

We assume that the firm has no market power. That is, the firm has no influence on setting the subsidy, and it essentially acts as a price-taker. This implicitly means that there is no gaming going on, and the firm does not mis-report either the investment or the quantity produced.

Further, we assume that the renewable technology is the marginal technology, so the market price for electricity is equal to the LEC of the renewable technology.[7] Thus, if the PM guarantees

[6]Note that, (8) essentially indicates

$$a + b = \delta - \frac{\gamma}{2\phi}(1 - \gamma) \leq \delta \tag{10}$$

as well as

$$S_n \geq \delta \geq a + b \geq 0. \tag{11}$$

[7]The assumption that renewable technology is marginal may seem rather strong. We have used this simplifying assumption to get valuable insights. In Section 5.1, we relax this assumption, and show that the intuition still holds. Further, it may be possible for a renewable technology to be marginal in some markets. For example, solar could be marginal with respect to the typically used diesel generator sets in the off-grid markets in developing countries,

a price of p_n to the producer, the PM can recoup the cost of electricity in the market lc_n; therefore the cost to the PM is precisely the surplus of the producer: $s_n = p_n - lc_{n-1}$.

The PM wants to minimize the cost of achieving the goal LEC target, as follows:

$$\begin{aligned} \underset{s_1,s_2}{\text{minimize}} \quad & \textstyle\sum_{n=1}^{2} s_n q_n^* \\ \text{subject to} \quad & s_n \geq 0,\ n \in \{1,2\} \\ & lc_2 \leq lc. \end{aligned} \tag{14}$$

We now consider this problem under two different assumptions about cost dynamics, LBD and EOS.

3 FiT under LBD Dynamics

In this section, we assume that the LEC dynamics is given by the well-known (and empirically verified) LBD relationship (Yelle, 1977)

$$lc_n = lc_{n-1}\left(\frac{\sum_{i\leq n} q_i^*}{\sum_{i\leq n-1} q_i^*}\right)^{d_L}, \tag{15}$$

where the cost-reduction occur due to cumulative production so far, and the exponent d_L represents the effectiveness of learning. This equation essentially says that the (logarithmic) incremental change in the LEC in period n is related to the (logarithmic) incremental change in cumulative production. Further, d_L is negative (i.e., $-1 < d_L < 0$), and the effectiveness of learning increases as d_L decreases.

Using (13), (15) can be written as

$$lc_n = lc_{n-1}\left(\frac{1 + \sum_{j=1}^{n} \prod_{i=1}^{j} S_i}{1 + \sum_{j=1}^{n-1} \prod_{i=1}^{j} S_i}\right)^{d_L} \tag{16}$$

such as India (Kolhe at al, 2002). As another example, solar may be marginal with respect to tiered power pricing, such as the one used by the electric utility PG&E in the state of California in the USA (Borenstein, 2008), where the retail price can go all the way up to 60 cents/kWh.

as well as

$$lc_n = lc_0(1 + \sum_{j=1}^{n} \prod_{i=1}^{j} S_i)^{d_L}. \tag{17}$$

Note that the LEC in period n is independent of the initial quantity q_0. This is due to the fact that the optimal capacities (and hence quantities produced) are linear in q_0 – this results in q_0 getting cancelled out in (15). This linear relationship can be traced all the way back to the quadratic cost adjustment model (3) since it results in optimal investment (i.e., I^*_{n-1} in (6)) as well as the new quantity (i.e., q_n in (4)) being linear in the previous quantity (i.e., q_{n-1}).

Given the evolution of the capacity and LEC dynamics described in (12) and (15), we define the objective function as (14). Further, noting the condition in (7), it is possible that, given $s_n < \frac{1}{\gamma}$, a firm does not invest and there are no additions to capacity. This is captured by the modified problem

$$\begin{aligned} \underset{s_1,s_2}{\text{minimize}} \quad & \textstyle\sum_{n=1}^{2} s_n q^*_n \\ \text{subject to} \quad & s_n \geq \tfrac{1}{\gamma}, \; n \in \{1,2\} \\ & lc_2 \leq lc. \end{aligned} \tag{18}$$

Given a solution $s_n = \frac{1}{\gamma}$ for the modified problem (18), the firm would not invest in period n, and the policy maker would simply set $s_n = 0$ in the original problem (14) – that is, the policy maker would not do anything in period n.

Now, given the linear relationship in (8), we reformulate the problem so that the decision variables are S_n instead of the s_n, and using (13) and (8), rewrite (18) as

$$\begin{aligned} \underset{S_1,S_2}{\text{minimize}} \quad & \textstyle\sum_{n=1}^{2} q_0(\frac{S_n - a}{b}) \prod_{i=1}^{n} S_i \\ \text{subject to} \quad & S_n \geq \delta, \; n \in \{1,2\} \\ & lc_2 \leq lc. \end{aligned} \tag{19}$$

At this point it is instructive to look at the terminal condition $lc_2 \leq lc$. Using (17), the terminal condition $lc_2 \leq lc$ gives

$$lc_2 = lc_0(1 + S_1 + S_1S_2)^{d_L} \leq lc. \tag{20}$$

Given $-1 < d_L < 0$ and $S_n \geq 0$, this implies

$$(1 + S_1 + S_1 S_2) \geq (\frac{lc}{lc_0})^{\frac{1}{d_L}}. \tag{21}$$

Note that inequality is reversed from (20) since d_L is negative. We also get

$$S_2 \geq \frac{(\frac{lc}{lc_0})^{\frac{1}{d_L}} - 1}{S_1} - 1 \triangleq \frac{\alpha}{S_1} - 1, \tag{22}$$

where $\alpha = (\frac{lc}{lc_0})^{\frac{1}{d_L}} - 1$.

Then we can write (19) as

$$\begin{aligned} \underset{S_1, S_2}{\text{minimize}} \quad & \mathcal{P} = q_0[\tfrac{S_1 - a}{b} S_1 + \tfrac{S_2 - a}{b} S_1 S_2] \\ \text{subject to} \quad & S_1 \geq \delta \\ & S_2 \geq \delta \\ & (1 + S_1 + S_1 S_2) \geq (\tfrac{lc}{lc_0})^{\frac{1}{d_L}}. \end{aligned} \tag{23}$$

Given $S_n \geq 0$, the objective in (23) is clearly increasing in both the variables and, in the absence of the terminal condition (21), the optimal solution would be trivial – i.e., $S_0 = \delta$ and $S_1 = \delta$. The presence of the cost target (21) is what makes the analysis interesting.

The Lagrangian corresponding to (23) is given by,

$$\mathcal{L} = \mathcal{P} + \mu_1(\delta - S_1) + \mu_2(\delta - S_2) + \lambda[(\frac{lc}{lc_0})^{\frac{1}{d_L}} - (1 + S_1 + S_1 S_2)],$$

where $\lambda \geq 0,\ \mu_1 \geq 0,\ \mu_2 \geq 1$. Then the Karush-Kuhn-Tucker (KKT) conditions corresponding to

(23) are given by

$$\frac{\partial \mathcal{L}}{\partial S_1} = \frac{\partial \mathcal{P}}{\partial S_1} - \mu_1 - \lambda(1+S_2) = \frac{(2S_1 - a)q_0}{b} + \frac{(S_2 - a)S_2 q_0}{b} - \mu_1 - \lambda(1+S_2) = 0 \tag{24a}$$

$$\frac{\partial \mathcal{L}}{\partial S_2} = \frac{\partial \mathcal{P}}{\partial S_2} - \mu_2 - \lambda S_1 = \frac{S_1(2S_2 - a)q_0}{b} - \mu_1 - \lambda S_1 = 0 \tag{24b}$$

$$\lambda[(\frac{lc}{lc_0})^{\frac{1}{d_L}} - (1 + S_1 + S_1 S_2)] = 0 \tag{24c}$$

$$\mu_1(\delta - S_1) = 0 \tag{24d}$$

$$\mu_2(\delta - S_2) = 0. \tag{24e}$$

λ is the KKT multiplier on the LEC constraint – it is zero when the final LEC is strictly lower than the goal LEC; it is non-zero when the constraint is met with equality. μ_1 and μ_2 are the KKT multipliers on the first and second period subsidy constraint. These shadow prices are zero if the respective subsidy is positive and non-zero when the subsidy is zero.

3.1 Results

There are a total of eight potential scenarios due to the three KKT multipliers taking binary values (zero and non-zero). In order to analyze this type of problem, we consider each possible case in turn; however, many of the cases are similar to each other and the eight cases can be grouped into five key cases. Here we discuss the results and provide a summary of the feasible cases in Table 1: the detailed calculations are presented in online Appendix II (Section 8).

In the first case, the objective is surpassed with positive subsidies. This refers to the situation where $\lambda = 0$ and $\mu_1\mu_2 = 0$. This, not surprisingly, is not a valid solution to the problem. It is never optimal to subsidize more than the amount required to just hit the target.

In the second case the objective is met or surpassed with no subsidy ($\lambda \geq 0$; $\mu_1\mu_2 > 0$). This happens when the target subsidy is not sufficiently stringent. The LEC reduces through time through the process of LBD to meet or surpass the target with no subsidies. This case obtains when $(\frac{lc}{lc_0})^{\frac{1}{d_L}} < (1 + \delta + \delta^2)$.

In the third case, the objective is met and there is a non-zero subsidy in only the first period

Table 1: Optimal feed-in tariffs under LBD dynamics.

Condition	s_1	s_2
$(\frac{lc}{lc_0})^{\frac{1}{d_L}} < (1+\delta+\delta^2)$	0	0
$(1+\delta+\delta^2) < (\frac{lc}{lc_0})^{\frac{1}{d_L}} < 1+\delta+\frac{3}{2}\delta^2+\frac{1}{2}\delta^3$	$\frac{S^{max}-a}{b}$	0
$(\frac{lc}{lc_0})^{\frac{1}{d_L}} > 1+\delta+\frac{3}{2}\delta^2+\frac{1}{2}\delta^3$	$\frac{S_1^*-a}{b}$	$\frac{S_2^*-a}{b}$

$(\lambda > 0,\ \mu_1 = 0,\ \mu_2 > 0)$. This case obtains when $(1+\delta+\delta^2) < (\frac{lc}{lc_0})^{\frac{1}{d_L}} < 1+\delta+\frac{3}{2}\delta^2+\frac{1}{2}\delta^3$.

In the fourth case, the objective is met and there are non-zero (i.e., strictly positive) subsidies in both periods $(\lambda > 0,\ \mu_1 = 0,\ \mu_2 = 0)$. This case obtains when $(\frac{lc}{lc_0})^{\frac{1}{d_L}} > 1+\delta+\frac{3}{2}\delta^2+\frac{1}{2}\delta^3$. Further, in this case it can be verified that the first period subsidy is always higher than the second period subsidy.

Finally, in the fifth case, the objective is met and there is a non-zero subsidy only in the second period $(\lambda > 0,\ \mu_1 = 0,\ \mu_1 > 0)$. This case is not a valid solution to this problem: it provokes a contradiction, as is shown in online Appendix II (Section 8). When cost reductions come through LBD, it is never optimal to delay subsidies.

In online Appendix II (Section 8) we derive the values of the optimal feed-in subsidies, which after defining

$$S_1^* = \frac{1}{6}[-1+\frac{1}{(-1+54\alpha^2+6\sqrt{3}\sqrt{\alpha^2(-1+27\alpha^2)})^{\frac{1}{3}}}+(-1+54\alpha^2+6\sqrt{3}\sqrt{\alpha^2(-1+27\alpha^2)})^{\frac{1}{3}}], \quad (25)$$

$S_2^* = \frac{(\frac{lc}{lc_0})^{\frac{1}{d_L}}-1}{S_1^*} - 1$, and $S^{max} \triangleq \frac{(\frac{lc}{lc_0})^{\frac{1}{d_L}}-1}{1-\delta}$, we present in Table 1. Further, it is straightforward to show that $S_1^* \geq S_2^*$ when $(\frac{lc}{lc_0})^{\frac{1}{d_L}} > 1+\delta+\frac{3}{2}\delta^2+\frac{1}{2}\delta^3$.

Essentially, $(\frac{lc}{lc_0})^{\frac{1}{d_L}}$ represents the stringency of the goal. When it is low, no subsidies are necessary. When it is moderate, subsidies are required only in the first period. When it is high, subsidies are required in both periods, with the first period subsidy being always higher than the second period one. This is explained in detail in Section 3.2.

As an example, when $\delta = 0.95,\ \gamma = 1,\ \phi = 0.5$ and $d_L = -0.27$, [8] we get

$$(s_1, s_2) = \begin{cases} (0,0) & \text{if } lc > 0.76lc_0 \\ (\frac{S^{max}-a}{b}, 0) & \text{if } 0.70lc_0 < lc < 0.76lc_0 \\ (\frac{S_1^*-a}{b}, \frac{S_2^*-a}{b}) & \text{if } lc < 0.70lc_0. \end{cases}$$

If $lc_0 = 1.10,\ lc = 1$ (i.e., the goal is weak), there are no subsidies; if $lc_0 = 1.35,\ lc = 1$ (i.e., the goal is moderate), we get a non-zero subsidy of 1.10 in first period only; and if $lc_0 = 1.50,\ lc = 1$ (i.e., the goal is ambitious), we get non-zero subsidies of 1.73 and 1.14 in the first and second period, respectively.

3.2 Analysis

In this section we interpret the conditions necessary to obtain the three possible cases.

The expression $(\frac{lc}{lc_0})^{\frac{1}{d_L}}$ represents the stringency of the goal. The more stringent the goal, the lower is the ratio between the final and initial cost – i.e., $\frac{lc}{lc_0}$. That is, for fixed d_L, the ratio $\frac{lc}{lc_0}$ also represents the stringency of the goal. Recall that the exponent d_L is negative and lies between 0 and -1. Thus $\frac{1}{d_L}$ is negative and less than -1. Therefore, the lower the ratio $\frac{lc}{lc_0}$, the higher $(\frac{lc}{lc_0})^{\frac{1}{d_L}}$.

If the goal is not stringent enough, then $(\frac{lc}{lc_0})^{\frac{1}{d_L}} < (1 + \delta + \delta^2)$ and we will be in the case where no subsidies are necessary. If the goal is very stringent, then $(\frac{lc}{lc_0})^{\frac{1}{d_L}} > 1 + \delta + \frac{3}{2}\delta^2 + \frac{1}{2}\delta^3$, and it will be optimal to subsidize in both periods. If the goal is between these two extremes, it is optimal to subsidize only in the first period.

As the effectiveness of learning increases, d_L becomes more negative, and $(\frac{lc}{lc_0})^{\frac{1}{d_L}}$ decreases. Thus, for a given goal lc, the optimal policy will move from subsidizing in both periods, to subsidizing in one period, to not subsidizing at all, as learning becomes more effective. For a fixed goal, subsidies decrease in the effectiveness of learning. While this may first appear odd, it is a result of focusing on a predetermined goal. In a larger context, the stringency of the goal itself should be considered a choice variable. It is likely that if learning is found to be of very little effect, then this

[8] This is the value of d_L found using Strategic Unlimited data, one of the most comprehensive world surveys of PV prices (Strategic Unlimited, 2003; Nemet, 2006).

particular technology would not be targeted.

The other key parameter in the condition is the depreciation of capital. If there were no depreciation then $\delta = 1$ and the condition for the intermediate case of a subsidy only in the first period would reduce to $3 < (\frac{lc}{lc_0})^{\frac{1}{d_L}} < 4$. Under this assumption, and if learning is assumed be $d_L = -0.27$, then there would be no subsidy if $lc > 0.74lc_0$; there would be a subsidy in both periods if $lc < 0.69lc_0$; and a subsidy in the first period only otherwise.

As way of comparison, the LEC for solar is about 36 cents/kWh (Baker et al., 2009) and the LEC for wind is about 6 cents/kWh (IEA, 2005), compared to fossil fuels that are at about 5 cents/kWh (IEA, 2005). Thus, assuming learning as above and no depreciation, and assuming that the pre-determined cost goal is the current LEC of fossil fuels, it would not be optimal to subsidize wind at all (since it will get down to the target price without a subsidy), and it would be optimal to subsidize solar in both periods (since it is quite far from the target price).

Generally there is some depreciation and $\delta < 1$. For a given goal, as the rate at which capital loses value increases (i.e. δ decreases), the optimal policy will move from no subsidy, to subsidizing in the first period, to subsidizing both periods.

To summarize, if the cost target is too weak, there is no subsidy; if it is intermediate, there is a subsidy in the first period only; and if it is strong there is a subsidy in both periods. We see the same pattern as depreciation increases (δ decreases) and the opposite pattern as learning becomes more effective.

Of particular interest are the following two results: first, if there is a subsidy in the second period there must be a subsidy in the first period; and second, even if there are subsidies in both periods, the first period subsidy is always higher than the second period one. This characterizes optimal subsidies under LBD dynamics: an earlier investment in capacity contributes to the cumulative experience in all subsequent periods, and helps bring down the LEC, and it is always optimal to subsidize earlier than later.

4 FiT under EOS Dynamics

We now look at the same problem when the LEC dynamics are driven by EOS dynamics (Nemet and Baker, 2009). In this case,

$$lc_n = lc_{n-1}(\frac{q_n^*}{q_{n-1}^*})^{d_R}, \tag{26}$$

where the cost-reduction occur due to increase in production capacity, and the exponent d_R represents the effectiveness of EOS. This equation essentially says that the (logarithmic) incremental change in the LEC in period n is related to the (logarithmic) incremental change in production capacity. Further, d_R is negative (i.e., $-1 < d_R < 0$), and the effectiveness of EOS increases as d_R decreases.

Using (13), this can be written as

$$lc_n = lc_{n-1}(\frac{\prod_{i=1}^{n} S_i}{\prod_{i=1}^{n-1} S_i})^{d_R} \tag{27}$$

as well as

$$lc_n = lc_0(\prod_{i=1}^{n} S_i)^{d_R} \tag{28}$$

Then we can write (23) as

$$\begin{aligned} \underset{S_1,S_2}{\text{minimize}} \quad & \mathcal{P} = q_0[\tfrac{S_1-a}{b}S_1 + \tfrac{S_2-a}{b}S_1S_2] \\ \text{subject to} \quad & S_1 \geq \delta \\ & S_2 \geq \delta \\ & S_1S_2 \geq (\tfrac{lc}{lc_0})^{\frac{1}{d_R}}. \end{aligned} \tag{29}$$

Given $S_n \geq 0$, the objective in (29) is clearly increasing in both the variables and, again, the presence of the cost target is what makes the analysis interesting.

Notice that the key difference from (23) is the third constraint. This drives all the differences between this problem and the LBD problem. The Lagrangian corresponding to (29) is given by,

$$\mathcal{L} = \mathcal{P} + \mu_1(\delta - S_1) + \mu_2(\delta - S_2) + \lambda[(\frac{lc}{lc_0})^{\frac{1}{d_R}} - S_1 S_2],$$

where $\lambda \geq 0,\ \mu_1 \geq 0,\ \mu_2 \geq 1$. Then the KKT conditions corresponding to (23) are given by

$$\frac{\partial \mathcal{L}}{\partial S_1} = \frac{\partial \mathcal{P}}{\partial S_1} - \mu_1 - \lambda S_2 = \frac{(2S_1 - a)q_0}{b} + \frac{(S_2 - a)S_2 q_0}{b} - \mu_1 - \lambda S_2 = 0 \tag{30a}$$

$$\frac{\partial \mathcal{L}}{\partial S_2} = \frac{\partial \mathcal{P}}{\partial S_2} - \mu_2 - \lambda S_1 = \frac{S_1(2S_2 - a)q_0}{b} - \mu_1 - \lambda S_1 = 0 \tag{30b}$$

$$\lambda[(\frac{lc}{lc_0})^{\frac{1}{d_R}} - S_1 S_2] = 0 \tag{30c}$$

$$\mu_1(\delta - S_1) = 0 \tag{30d}$$

$$\mu_2(\delta - S_2) = 0, \tag{30e}$$

where λ and μ play similar roles as before.

4.1 Results

Again, there are a total of eight potential scenarios, and many of the cases are similar to each other and the eight cases can be grouped into five key cases. Here we discuss the results and provide a summary of the feasible cases in Table 2: the detailed calculations are presented in online Appendix III (Section 9).

Note that, similar to the LBD problem, it is never optimal to surpass our objective; however in contrast to the LBD case, it is possible to meet the objective with no subsidies only when the goal LEC is equal to the current LEC and when there is no depreciation (more on this below).

In the first case, the objective is surpassed. This refers to any situation in which $\lambda = 0$. The case $\lambda = 0,\ \mu_1\mu_2 = 0$, not surprisingly, is not a valid solution to the problem: it is never optimal to subsidize more than the amount required to just hit the target. Further, the case $\lambda = 0,\ \mu_1\mu_2 > 0$ is not a valid solution since it essentially requires the final LEC to be higher than the initial LEC – clearly something that we are not interested in.

In the second case the objective is met with no subsidy ($\lambda > 0;\ \mu_1\mu_2 > 0$). This case obtains when $(\frac{lc}{lc_0})^{\frac{1}{d_R}} < \delta^2$. Note that, given our original requirements that $lc \leq lc_0$ and $\delta \leq 1$, this condition is equivalent to $(\frac{lc}{lc_0})^{\frac{1}{d_R}} = \delta^2 = 1$, which is the same as $lc = lc_0$ and $\delta = 1$. That is, this happens only when the target LEC is equal to the initial LEC (i.e., $lc = lc_0$) and $\delta = 1$. While this case is possible, it is of little practical interest due to the razor-thin edge condition.

In the third case, the objective is met and there is a non-zero subsidy in only the second period ($\lambda > 0,\ \mu_1 > 0,\ \mu_2 = 0$). This case obtains when $\delta^2 < (\frac{lc}{lc_0})^{\frac{1}{d_R}} < \delta\sqrt{\delta + \frac{\gamma}{2\phi}}$.[9]

In the fourth case, the objective is met and there are non-zero (i.e., strictly positive) subsidies in both periods ($\lambda > 0,\ \mu_1 = 0,\ \mu_2 = 0$). This case obtains when $(\frac{lc}{lc_0})^{\frac{1}{d_R}} > \delta\sqrt{\delta + \frac{\gamma}{2\phi}}$. However, there is no clear relationship between the subsidies. Though an analytical result is difficult to obtain, numerical simulations show that the second period subsidy is higher when $(\frac{lc}{lc_0})^{\frac{1}{d_R}} \approx \delta\sqrt{\delta + \frac{\gamma}{2\phi}}$; however, as $(\frac{lc}{lc_0})^{\frac{1}{d_R}}$ increases the first period subsidy becomes higher.

Finally, in the fifth case, the objective is met and there is a non-zero subsidy only in the first period ($\lambda > 0,\ \mu_1 = 0,\ \mu_1 > 0$). We show in online Appendix III (Section 9) that this case is not a valid solution to this problem. When cost reductions come through EOS, it is typically not optimal to expedite subsidies.

In online Appendix III (Section 9) we derive the values of the optimal feed-in subsidies, which after defining

$$S_1^* = \frac{a}{6} + \frac{a^2}{(6(a^3 + 54c^2 + 6\sqrt{3}\sqrt{a^3c^2 + 27c^4})^{1/3}} + \frac{1}{6}(a^3 + 54c^2 + 6\sqrt{3}\sqrt{a^3c^2 + 27c^4})^{1/3}, \qquad (31)$$

$S_2^* = \frac{(\frac{lc}{lc_0})^{\frac{1}{d_R}}}{S_1^*}$, and $S^{max} \triangleq \frac{(\frac{lc}{lc_0})^{\frac{1}{d_R}}}{\delta}$, we present in Table 2.[10]

Essentially, $(\frac{lc}{lc_0})^{\frac{1}{d_R}}$ represents the stringency of the goal. When it is low, no subsidies are necessary. When it is moderate, subsidies are required only in the second period. When it is high, subsidies are required in both periods – however, the relationship between the subsidies depends on $(\frac{lc}{lc_0})^{\frac{1}{d_R}}$: when it is lower (higher) the second (first) period subsidy is higher. This is explained in detail in Section 4.2.

[9]Note that, given $\delta \leq 1$, $\gamma \leq 1$ and (9), it can be easily shown that $\delta^2 < \delta\sqrt{\delta + \frac{\gamma}{2\phi}}$.

[10]Though the case of no subsidies is of little practical interest, it is presented here nevertheless, to draw similarities with the LBD case.

Table 2: Optimal feed-in tariffs under EOS dynamics.

Condition	s_1	s_2
$(\frac{lc}{lc_0})^{\frac{1}{d_R}} < \delta^2$	0	0
$\delta^2 < (\frac{lc}{lc_0})^{\frac{1}{d_R}} < \delta\sqrt{\delta + \frac{\gamma}{2\phi}}$	0	$\frac{S^{max}-a}{b}$
$(\frac{lc}{lc_0})^{\frac{1}{d_R}} > \delta\sqrt{\delta + \frac{\gamma}{2\phi}}$	$\frac{S_1^*-a}{b}$	$\frac{S_2^*-a}{b}$

As an example, using the parameters used in Section 4.2, when $\delta = 0.95,\ \gamma = 1,\ \phi = 0.5$ and $d_R = -0.2$, [11] we get

$$(s_1, s_2) = \begin{cases} (0, 0) & \text{if } lc > 1.02lc_0 \\ (0, \frac{S^{max}-a}{b}) & \text{if } 0.94lc_0 < lc < 1.02lc_0 \\ (\frac{S_1^*-a}{b}, \frac{S_2^*-a}{b}) & \text{if } lc < 0.94lc_0. \end{cases}$$

If $lc_0 = 0.90,\ lc = 1$ (i.e., the goal is weak), there are no subsidies; If $lc_0 = 1.05$ and $lc = 1$ (i.e., the goal is moderate), we get a non-zero subsidy of 1.39 in the second period only; if $lc_0 = 1.10$ and $lc = 1$ (i.e., the goal is ambitious), we get non-zero subsidies of 1.13 and 1.53 in the first and second period, respectively. Further, when the goal is ambitious, we observe the following: if $lc_0 = 1.325$ and $lc = 1$, we get non-zero subsidies of 2.7 in both periods; if $lc_0 = 1.5$ and $lc = 1$, we get non-zero subsidies of 3.11 and 2.53 in the first and second period, respectively. That is, as the goal becomes more ambitious, we go from the second period subsidy dominating to the first period subsidy dominating.

4.2 Analysis

In this section we interpret the conditions necessary to obtain the three possible cases.

First, if the goal is not stringent enough, then $(\frac{lc}{lc_0})^{\frac{1}{d_R}} = \delta^2$, and no subsidies are necessary. However, based on the discussion above, this is a razor-thin edge condition $(\frac{lc}{lc_0})^{\frac{1}{d_R}} = \delta^2 = 1$, and may be of little interest from a practical perspective. Next, if the goal is very stringent, then

[11] This is the standard value of d_R found in most literature on EOS for solar PV (Nemet and Baker, 2009).

$(\frac{lc}{lc_0})^{\frac{1}{d_R}} > \delta\sqrt{\delta + \frac{\gamma}{2\phi}}$, and it will be optimal to subsidize in both periods. Finally, if the goal is between these two extremes, then $\delta^2 < (\frac{lc}{lc_0})^{\frac{1}{d_R}} < \delta\sqrt{\delta + \frac{\gamma}{2\phi}}$, and it is optimal to subsidize only in the second period. To summarize, the case of no subsidies is not interesting from a practical perspective, and we deal with only two cases going forward: subsidy in both periods and subsidy in the second period only.

As the strength of EOS increases (i.e., d_R becomes more negative) $(\frac{lc}{lc_0})^{\frac{1}{d_R}}$ decreases. Then, similar to Section 3.2, for a given goal, the optimal policy will move from subsidizing in both periods to subsidizing in one period (but the second period as opposed to the first period for LBD) only, as EOS becomes more effective.

The other key parameters are the depreciation of capital (i.e., δ), the strength of the cost of commitment (i.e., ϕ), and the (net) investment to capacity conversion factor (i.e., γ). In fact, effectively there are two parameters: δ and the ratio $\frac{\gamma}{2\phi}$, which is essentially the efficiency of the conversion from (gross) investment to capacity. We look at the effect of each of these in some detail next.

First, note that the ratio $\frac{\gamma}{2\phi}$ did not affect the analysis under LBD dynamics, whereas it is important in this case. To understand this, first note that the presence of $\frac{\gamma}{2\phi}$ is related to the terminal constraint on LEC (i.e., the relationship between lc and lc_0). Various bounds on the cost target are essentially bounds on the shadow prices of this constraint. This effect is related to the fact that investments under EOS dynamics have an immediate effect only whereas those under LBD dynamics have a long term effect. Thus, the cost of investment is relevant under EOS dynamics (and not relevant under LBD dynamics) due to its close relationship in bringing the LECs down immediately.

In order to observe the effect of the (gross) investment efficiency (i.e., $\frac{\gamma}{2\phi}$), we fix δ. If there were no depreciation (i.e., $\delta = 1$) then the condition for the intermediate case of a subsidy only in the second period would reduce to $1 < (\frac{lc}{lc_0})^{\frac{1}{d_R}} < \sqrt{1 + \frac{\gamma}{2\phi}}$: as the (gross) investment efficiency improves for a fixed target, investments become more effective in bringing about additional capacity, and this interval becomes wider, meaning it is more likely that we only need to subsidize in one period. Now, given that γ is simply a scaling factor, without loss of generality, we assume $\gamma = 1$

to focus on the effect of the cost of commitment. If learning is assumed be $d_R = -0.2$ as before, and $\phi = 1.0$ (i.e., $\frac{\gamma}{2\phi} = 0.5$) then there would be a subsidy in both periods if $lc < 0.96 lc_0$; and a subsidy in the second period only otherwise. Thus, assuming no depreciation and EOS as above, and using the LEC numbers from Section 3.2, it would be optimal to subsidize both wind and solar in both periods. However, if the cost of commitment decreases to 0.05 (i.e., $\frac{\gamma}{2\phi}$ increases to 10), then there would be a subsidy in both periods if $lc < 0.79 lc_0$; and a subsidy in the second period only otherwise. Thus, it would be optimal to subsidize solar in both periods and wind only in the second period.

Depreciation has the same effect in this case as in the LBD case: as depreciation increases the optimal policy moves from subsidizing in the second period to subsidizing in both periods.

To summarize, this case is similar to the LBD case in the following ways: first, a stringent cost target leads to subsidies in both periods, while a weaker cost target leads to a subsidy in only one period; second, when the cost target is very ambitious, this case requires a higher subsidy in the first period.

In contrast to the LBD case, however, given that the final LEC is required to be lower than the initial LEC, it is unlikely that no subsidy will be optimal. This is simply a result of the underlying dynamics. It is possible to achieve the required cost reduction in the absence of subsidies under LBD due to the effect of cumulative production on cost reduction even when capacity is not increasing. Such an effect is not possible under EOS since cost reduction under EOS requires an increase in capacity and, therefore, non-zero subsidies. This case is interesting since it says that it would almost always be right to subsidize a firm under EOS, but not always so with LBD.

Finally, the key contrast between the cases is that, under EOS, if there is a subsidy in the first period there must be a subsidy in the second period, whereas a subsidy in the second period does not necessitate a subsidy in the first period. Further, whereas under LBD it is never optimal to subsidize later, under EOS it may be the optimal policy, especially when the goal is not very stringent. This is because, under EOS dynamics, there are two competing effects. When the goal is low to moderately ambitious, depreciation effects dominate: an earlier investment in capacity would depreciate more than a later investment, which indicates that a later investment would have a greater impact on the final capital and hence the final LEC. However, when the goal is very ambitious, the policy maker needs to subsidize aggressively to build the required capacity, and the first period subsidy is higher.

5 Extensions

5.1 Premium FiT

As established in Section 2, our model focuses on minimizing the subsidy, defined as the extra amount the policy maker has to pay over the LEC of production. This assumes that there exists a mechanism that ensures that renewable energy was bought at its LEC. Note that under this mechanism the subsidy is the same as the producer's surplus.

This model, though informative, may not be the only one of interest to a policy maker. Cory et al. (2009) provides a comprehensive list of different types of FiT mechanisms. Our model is the closest to the "fixed" FiT mechanism where the FiT is independent of the market price of electricity.

In this section we explore an alternative model, also defined as the "premium" FiT in Cory et al. (2009). Under this model, the subsidy is defined as the extra amount a policy maker pays on top of a market price p. Then the producer surplus in period n is given by

$$\tilde{s}_n = (p + s_n - lc_{n-1}). \tag{32}$$

Under this mechanism, the policy maker's problem (14) (Section 2.2) remains the same. Further, replacing the subsidy s_n by the producer's surplus $\tilde{s}_n$, the analysis of Section 2.1 holds. However, this problem turns out to be hard to solve analytically. Therefore, we focus on solving it numerically, and leave a detailed analysis to future work. The following two examples show that the intuition derived in Section 3.2 holds.

The first example looks at how changing the cost targets affects the optimal FiT schedule under LBD. When $\delta = 0.5,\ b = 0.64,\ d = -0.5,\ (\frac{lc}{lc_0})^{\frac{1}{d_R}} > 1.87$, the optimal solution is to subsidize in both periods. However, when the target is relaxed to $1.75 < (\frac{lc}{lc_0})^{\frac{1}{d_R}} < 1.87$, the optimal solution is to subsidize in first period only. When the target is relaxed further to $(\frac{lc}{lc_0})^{\frac{1}{d_R}} < 1.75$, the target is met without any subsidies.

Similarly, the second example looks at how changing the depreciation affects the optimal FiT schedule. When $\delta < 0.5,\ b = 0.82,\ d = -0.5,\ (\frac{lc}{lc_0})^{\frac{1}{d_R}} = 1.82$, the optimal solution is to subsidize in both periods. However, when δ increases such that $0.5 < \delta < 0.53$, the optimal solution is to subsidize in the first period only. When δ increases further such that $\delta > 0.53$, the target is met without any subsidies.

5.2 Budget Constraints

In our original model (5), we assume that the producer does not face any constraints in obtaining funds for investments. As mentioned earlier, this may be a valid assumption in the context of a small and lucrative market in a normally functioning financial system. However, it is instructive to investigate what would happen if these conditions are no longer true and the firm becomes budget constrained. To do so, we use the following form for the producer's problem:

$$\max_{I_{n-1} \leq \beta\pi_{n-1} + I_e} \pi_n = s_n q_n(I_{n-1}) - I_{n-1},$$

where $0 \leq \beta \leq 1$. Note that the only difference from the original problem (5) is the presence of the constraint $I_{n-1} \leq \beta\pi_{n-1} + I_e$, where I_e represents externally available funds, and $\beta\pi_{n-1}$ (i.e., a fraction of previous period's profits) represents internally available funds.

When I_e is large, it means that there is essentially no limit on external fund availability. This may happen, for example, when the investor confidence is high due to absence of various risks, including technology risk. In this case it is as if the constraint did not exist, and this problem is the same as (5), with the same results.

However, when I_e is small, the firm is limited in terms of procuring funds for investment. This may happen, for example, when the investor confidence is low due to presence of a speculative technology. In this case, despite potential *future* earnings promised by feed-in tariffs, the firm is restricted in its capacity build-up due to limited *current* fund availability. In particular, given $I_e = 0$, this essentially requires the firm to bootstrap. This suggests the following.

First, giving high subsidies early to encourage early capacity buildup may not be optimal, and subsidies targeted towards LBD dynamics may not be as effective as hoped for. In fact, as I_e becomes smaller, even under LBD, it may become optimal to delay subsidies. This can be illustrated via an example. Consider LBD dynamics with (see Section 3.1) $\delta = 0.95$, $\gamma = 1$, $\phi = 0.5$, $d_L = -0.27$, $lc_0 = 1.50$, $lc = 1$, $q_0 = 1, \beta = 1$. When $I_e > 1$, plenty of external funds are available due to high investor confidence, the firm is not budget-constrained, and we get non-zero subsidies of 1.73 and 1.14 in the first and second period, respectively. However, when $I_e < 1$, external funds are limited due to reduced investor confidence, the firm becomes budget-constrained: when $0.62 < I_e < 1$, we still get a higher first period subsidy; however, when $I_e < 0.62$, the second period subsidy becomes higher.

Second, meeting a given cost target is not guaranteed anymore. Continuing with the above example, when $I_e < 0.33$, it is not possible to meet the cost target anymore. This can also be demonstrated by the trivial case when for example, a technology is too speculative, and no external investors want to invest, resulting in $I_e = 0$: we get $I_0^* = I_1^* = 0$, the firm will have no funds available for investment in either period, and there will be no cost reductions due to the absence of capacity build up. That is when no one wants to invest no amount of subsidies can help.

It is instructive to build on this insight further. In a bad economy, due to lack of availability of private-sector finance, production based subsidies (such as the FiT) may not be the best policy option to promote renewable energy. Instead, upfront lump sum subsidies may be more useful. The 1603 program, a part of the recent US Recovery Act, is an example: it allowed renewable energy projects to claim upfront cash grants in place of the usual tax incentives based on investment and production (US Treasury, 2009).

6 Conclusions

In this paper, we provide a framework for calculating optimal FiT schedules. We focus on the case of firm-level cost reductions due to production based activities. Our work shows the importance of designing a subsidy with the characteristics of the underlying technology in mind. This complements (and adds to) the RBV literature that shows that it is important to match resources to the characteristics of the firm.

In particular, we look at a simple two-period model and examine two production dynamics for the underlying technology: LBD and EOS. The optimal subsidy schedule under the two dynamics provide the following insights.

These dynamics provide similar results either when the cost goal is stringent or when the capital depreciates quickly: subsidies are required in both periods to build up capacity. Further, when the goal is very stringent, a higher subsidy is required in the first period. However, the interesting split happens either when the cost goal is moderate or when capital does not depreciate quickly: the optimal policies involve providing all the subsidies in one period only – the first period under LBD and the second period under EOS. Further, when the cost goal goes from moderate to high, though both dynamics require subsidies in both periods, they differ in how the subsidies are spread over time: under LBD, the optimal subsidies are higher in the first period whereas under EOS they are higher in the second one. Finally, we find that it always optimal to subsidize under EOS but not always so under LBD.

In summary, except for the case when the target is very stringent, it is always optimal to provide subsidies – and promote investments – earlier under LBD and later under EOS. The results crucially depend on interactions between capital accumulation, capital depreciation, and investment efficiency. Under EOS dynamics, the driving force is capital depreciation under which it is always better to delay investments – and capital accumulation – as late as possible to maximize the impact of increasing production capacity on reducing LEC. Whereas, under LBD dynamics, though the capital depreciation effect is still relevant, it is overcome by the stronger effect of earlier investments contributing to cumulative experience in subsequent periods, and it is always better to expedite subsidies. Finally, the behavior of subsidies under EOS displays a very interesting, and perhaps non-intuitive, pattern: when the cost target is not very stringent, the optimal subsidies are back-loaded to avoid depreciation effects; however, when the target becomes very stringent, the optimal subsidies become front-loaded, similar to LBD, since the scale effects dominate.

Our models are not only positive but also normative in that they not only provide a description of regulatory behavior – in particular, in terms of decreasing subsidies in the presence of LBD (Klein et al, 2008; Wand et al, 2009) – but also provide a framework for designing future policies. In particular, our results demonstrate that, based on the underlying dynamics, the policy maker needs to adopt a fundamentally different policy approach to promote renewable technologies. This relates to answering questions, such as whether subsidies should be provided at all, and how subsidies should be timed. For example, the policy maker should use the EOS based FiT schedule for solar photo-voltaics (PV) if she is convinced that the cost of production is governed through the EOS dynamics (Nemet, 2006; Nemet and Baker, 2009) as opposed to the LBD dynamics, as conventionally believed (Bolinger and Wiser, 2003; Benthem et al., 2008). Further, given the dependence of the optimal FiT schedules on the capital depreciation factor as well as the strength of the cost of investment, in order to set optimal FiT schedules, our results require the policy maker to have a good understanding not only of the underlying technology but also of the underlying investment dynamics.

We acknowledge that our model uses some simplifying assumptions that allow us to derive these insights. A more thorough analysis would require relaxation of these assumptions. We have already partially investigated the relaxation of the fixed feed-in tariff assumption in Section 5.1, and have shown that the insights derived under the simpler model still hold. We have also partially investigated the relaxation of the unconstrained budget assumption in Section 5.2, and have shown that the results can potentially change when financial markets become tight – in particular, it may not be optimal to subsidize early under LBD. Another assumption in the paper is that the firm is myopic. That is, it does not optimize beyond one period. However, in reality a rational firm may be forward looking and may optimize over multiple periods. Relaxing these assumptions further would be the focus of future work.

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7 Appendix I: Detailed Calculations for Section 2

7.1 The Optimal Level of Capacity

Here we relate the capacity of production q_n to gross investment I_n, and derive (4) using (2) and (3). From (3), we get

$$\frac{\phi}{q_n}{J_n}^2 + J_n - I_n = 0.$$

That is,

$$J_n = \frac{q_n}{2\phi}(-1 \pm \sqrt{1 + \frac{4\phi I_n}{q_n}}).$$

Given that $J_n \geq 0$, it must be that

$$J_n = \frac{q_n}{2\phi}(\sqrt{1 + \frac{4\phi I_n}{q_n}} - 1). \tag{33}$$

Now, substituting for J_n in (2), and simplifying, we get (4).

7.2 Concavity of the Firm Profit Function

Here we derive the first and second order derivatives of the firm profit function in (5). First, (4) indicates

$$\frac{dq_n}{dI_{n-1}} = \gamma(1 + \frac{4\phi I_{n-1}}{q_{n-1}})^{-\frac{1}{2}} \tag{34a}$$

$$\frac{d^2 q_n}{d{I_{n-1}}^2} = -\frac{\gamma}{2}(1 + \frac{4\phi I_{n-1}}{q_{n-1}})^{-\frac{3}{2}} \leq 0. \tag{34b}$$

Using (34) in (5), we then get

$$\frac{d\pi_n}{dI_{n-1}} = s_n \frac{dq_n}{dI_{n-1}} - 1 = \gamma s_n (1 + \frac{4\phi I_{n-1}}{q_{n-1}})^{-\frac{1}{2}} - 1 \tag{35}$$

$$\frac{d^2\pi_n}{d{I_{n-1}}^2} = s_n \frac{d^2 q_n}{d{I_{n-1}}^2} = -\frac{\gamma s_n}{2}(1 + \frac{4\phi I_{n-1}}{q_{n-1}})^{-\frac{3}{2}} \leq 0. \tag{36}$$