

Lancker, Kira; Quaas, Martin

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Increasing marginal costs and the efficiency of differentiated feed-in tariffs

KIRA LANCKER *
MARTIN F. QUAAS †‡

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Abstract: We study optimal subsidies for renewable energy (RE) generation to internalize external benefits from intertemporal learning-by-doing spillovers, taking into account increasing marginal costs at the industry level due to limited availability of sites suitable for RE. We find that the optimal RE subsidy is differentiated according to productivity and derive a condition on production and spillovers under which less efficient, i.e. more costly, technologies should receive higher support, as common in actual policy-making. We show that such a support of technological diversification is optimal if (i) the elasticity of learning by doing is large, which means that technologies rapidly mature with little further scope for learning, and if (ii) productive sites are scarce, which limits future utilization of knowledge.

JEL Classification: D21, D24, D62, D83

Keywords: learning spillovers, subsidies, industrial policy, renewable energy, feed-in-tariffs, differentiation

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*Correspondence: Biodiversity economics, German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig, Deutscher Platz 5e, 04103 Leipzig, Germany. Email: kira.lancker@idiv.de.

†Correspondence: Biodiversity economics, German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig, Deutscher Platz 5e, 04103 Leipzig, Germany. Email: martin.quaas@idiv.de.

‡Kiel Institute for the World Economy (IfW)

1 Introduction

“In light of the pervasive market failures associated with innovation and learning, the commonly heard objection to industrial policies – the mantra that government should not be involved in ‘picking winners’ – is beside the point: the objective of the government is to identify, and ‘correct’ externalities and other market failures.” With this statement, Greenwald and Stiglitz (2013) argue in favor of government intervention to internalize knowledge spillovers, in particular in cases where innovation is fueled by the production of the good itself. Such learning-by-doing occurs when the production process is routinized and minor improvements aggregate gradually. If this learning is not fully appropriated by the individual firms, spillovers constitute a positive externality (Philippe and Xavier, 2015; Squires and Vestergaard, 2018).

In recent years, policies to internalize learning-by-doing spillovers have gained relevance in particular for, but not limited to, green technology, such as renewable energy (RE) (Fischer and Newell, 2008) or green transport (Fox et al., 2017). Many papers in the economic literature argue for technology-specific support rates (e.g. Haas et al., 2008; Schmalensee, 2012; Lehmann and Söderholm, 2018; Gawel et al., 2017). The major concern is the question how such support should be designed to avoid adverse effects from inadvertently “picking a winner” that might not be the long-term optimal choice. This is of particular importance if technologies exhibit path dependency (Acemoglu et al., 2016; Sandén and Azar, 2005; Kalkuhl et al., 2012; Jaffe et al., 2005).

The status quo in practical RE support policies is to grant technology-specific subsidies that are differentiated according to generation cost with costlier technologies receiving more subsidies. This contradicts an approach of static efficiency, that is, the subsidy for the same good – green electricity – should be the same. However, the question of optimal feed-in tariffs (FITs) has to be answered in its dynamic learning environment. The value of the spillover externality depends inter alia on the amount of future deployment of a technology. Even if a technology exhibits higher cost due to relative immaturity, it

may learn more in the future and be the optimal choice as a winner. Still, technology specific subsidies according to generation costs can hardly distinguish between ‘immaturity’ and ‘baseline costliness’ of a technology (for example due to the dependence on certain high-cost raw materials).

A related matter is the question of capacity constraints. It has previously been shown and is an intuitive result that if overall technology deployment is capped by an exogenous upper limit, this changes the optimal dynamic outcome of winning and losing technologies (Tahvonen and Salo, 2001; Nachtigall and Rübbelke, 2016; Wang and Zhao, 2018). Increasing marginal cost on sector level limits the value of spillovers. Then, technological diversification may be economically justified. Hence, economically sensible subsidies should take such capacity constraints into account.

In this paper, we use RE technologies as an example and develop a dynamic model to characterize how welfare-maximizing subsidies depend on current efficiency of technologies and the increasing marginal costs at the industry level that stem from overall limitations for deploying specific RE technologies. Learning leads to increased productivity and learning spillovers justify policy-intervention.

The results show that the optimal subsidy is technology-specific. Differentiation depends on learning- and production-related elasticities. We show that it is optimal to strongly support less advanced technologies, i.e. to promote diversification, if (i) marginal costs are strongly increasing, i.e. for each RE technology there is only a limited amount of suitable production sites available, and if (ii) the marginal benefit of learning-by-doing spillovers strongly decreases with experience. A necessary condition for an increasing relationship between costliness and optimal support is that sites are in limited supply. In quantitative terms, we find that for learning rates between 10-20% as typically found in empirical studies, the propensity for technological diversification is highest if the sector cost elasticity with respect to sites is at about 1.3, and thus relatively steep.

Our model thus provides a theoretical basis for the widespread and internationally

applied type of RE support differentiation. It offers policy guidance for situations where a relevant spillover externality exists and more than one technology compete in the learning process, and thus beyond the scope of RE.

The paper is structured as follows: After a short literature review in section 2, the model layout is presented in section 3 and the optimal FIT is derived. Section 4 analyses the link between costliness and optimal remuneration. The final section discusses some potential extensions and concludes.

2 Experience and related literature

2.1 Current practice of renewable energy support policies

In practice, renewable energy support is mostly technology-specific and differentiated according to production costs. In 2008, 19 of 22 European countries applied technology-specific tariffs (del Río, 2012). The German national action plan of 2009, for example, states that the calculation of tariffs for different technologies underlies the principle of cost-covering remuneration (Bundesumweltministerium , BMU). Rates are calculated to account for investment, operating and capital costs, tax write-off and other expenditure constituents (Fell, 2011). This induced highly differentiated tariffs. Since 2016, support is based on tendering, but auctions continue to be technology-specific (EEG 2016/2017). Ontario applied technology-specific FIT-rates as well, based on costs and a projected rate-of-return (Yatchew and Baziliauskas, 2011). According to Huang and Wu (2011), land scarcity is the primary reason for technology-specific tariffs and thus diversification in Taiwan. In China, a solar-exclusive subsidy came into effect in 2011 (Ye et al., 2017). Renewable energy certificates applied by Australia were complemented specifically by a Solar Credits Multiplier to support otherwise non-competitive small scale PV installations (Simpson and Clifton, 2014).

2.2 Economic models on RE subsidies

Technology-specific subsidies for RE technologies are also commonly advised in economic literature (e.g. Haas et al. 2008; Ragwitz et al. 2005; Schmalensee 2012; Lehmann 2013). According to a simulation study by Huber et al. (2004), differentiation leads to a more significant deployment of RE in the future and hinders a lockout of promising technologies. With differentiation, cost-recovery and investment security can be ensured for several technologies at the same time at overall lower cost. For this to occur, support is to be differentiated either according to the generation cost (Haas et al., 2011; Couture and Gagnon, 2010; Mendonça, 2009) or according to technological maturity¹ with respect to learning effects (e.g. IEA, 2011). Further empirical evidence finds that cost-differentiated support rates promote a “more homogeneous distribution among different technologies” Ragwitz et al. (2005), but low cost options are more effectively promoted in countries with technology-neutral systems (Böhringer et al., 2017; Johnstone et al., 2010). From an economic point of view, the trouble with this approach is that it does not expressly account for cost effectiveness. Del Río (2012) argues that while the improved adaptability of differentiated rates may lead to overall lower costs of support, technology-neutral tariffs may spur competition between technologies. If this competition is dampened, supporting less-mature and costlier technologies may lead to the massive diffusion of an expensive technology, incurring high costs in the long run.

Theoretical modeling studies link technology-specific subsidies to efficiency in reaching the policy goal, i.e. either abatement or spillover internalization. If the focus is on abatement, success may be technology-specific, thus justifying differentiated support rates (Wibulprasert, 2016; Streitberger et al., 2017; Lehmann and Söderholm, 2018). If the policy aims to internalize spillovers from learning, efficiency requires a differentiation according to, inter alia, learning and spillover rates and the mass of adopting

¹Arguably, a differentiation mode that targets cost-coverage will not be able to fully distinguish between immaturity-caused and inherent costliness of a technology.

firms (van Benthem et al., 2008; Lehmann, 2013; Lehmann and Söderholm, 2018; Bläsi and Requate, 2005; Reichenbach and Requate, 2012; van Benthem et al., 2008; Shrimali and Baker, 2012; Schmalensee, 2012). The models by Kalkuhl et al. (2012, 2013) and Kverndokk and Rosendahl (2007) show that the optimal FIT depends on parameters related to learning, production costs, and spillovers. They give an analysis on lock-in risks between technologies of different maturity levels, but no discussion on optimal differentiation strategies. Lehmann and Söderholm (2018) adds risk and uncertainty to the number of reasons why technology-specific subsidies may be cost-effective. Overall, the literature that studies technology-specific subsidies from the perspective of economic theory is limited. No study has yet resolved the question under which circumstances an optimal differentiation of FITs should give higher tariffs to more costly technologies. It remains unclear to what extent this practical approach is compatible with theoretical justification of cost effective differentiation. In addition, the impact of limited overall capacity on the optimal subsidy remains unclear.

2.3 Increasing marginal costs: Theory and empirical evidence

Increasing marginal cost is a standard assumption in economic models. For RE, it is realistic to assume increasing marginal cost on both plant and industry level. Site productivity on plant-level is subject to decreasing returns: Not all of the natural energy that a better site can provide can be as efficiently transformed as the first unit. Neither wind nor PV applications can deal with extreme wind or sun exposure. Wind turbines need to be switched off at too high wind speeds, while PV cells that become too hot lose efficiency (Radziemska, 2003; Machniewicz et al., 2015; IEA Wind, 2012). Even if that is not the case, eventually, some of the productive days with a large number of favorable wind or sun hours need to be sacrificed to do regular maintenance, that would otherwise be scheduled to occur on sub-optimal resource days (e.g. Scheu et al., 2012).

A limited overall potential for RE deployment, in particular scarce suitable sites

for windmills, hydro, PV etc., forms the basis for increasing marginal costs at industry level (Mercure and Salas, 2012). Taking into account economic limitations severely decreases this potential further (Moriarty and Honnery, 2012). Our interpretation is that increasing marginal costs stem from a higher price for the energy resource (e.g. wind full load hours), if the most efficient sites are occupied first (i.e. for those with equal costs, resource quality decides upon sequence of occupation).

Several studies estimate the impact of site constraints on wind energy costs or energy yield (e.g. Honnery and Moriarty, 2009; Hoogwijk et al., 2004; de Vries et al., 2007). All indicate increasing marginal costs and a limitation of suitable sites. Wisser and Bolinger (2017) document that the “Index of Built Wind Resource Quality at 80m” declined nearly continuously between 1998–2012. This shows a trend of building wind power projects in progressively lower-quality wind resource areas. Average capacity factors have only weakly increased for projects installed from 2009 through 2012. They rebound slightly afterwards, as old plants are gradually replaced. Söderholm and Klaassen (2007) specify an empirical model on wind power learning. They find that high FITs lead to more turbine installations at poorer (less windy) sites. For New Zealand’s hydro energy, Baines (1987) show that energy ratios (i.e. the ratio of energy output to energy input for an installation) started declining after roughly 1985. This is reflected in increasing and convex unit cost of production when plotted against cumulative installed capacity Kumar et al. (2011). Conventional energy production methodologies commonly show declining energy yield ratios as well (Hall et al., 2014).

Early economic models on RE supply have been based on the literature about clean backstop technologies that has been developed since the early 1970s (e.g. Nordhaus, 1973; Heal, 1976; Tahvonen, 1997). This literature typically assumed constant marginal costs of energy generation. An exception is made by Oren and Powell (1985), who assume that marginal costs decrease due to learning-by-doing. Later on, the dynamic literature features also papers that include increasing marginal costs on industry level

(Wang and Zhao, 2018), sometimes combined with decreasing marginal cost through technical change or learning (Tahvonen and Salo, 2001; Nachtigall and Rübbelke, 2016; Kalkuhl et al., 2012, 2013). Then, typically, different production technologies are used simultaneously for a long time horizon. This depends in particular on the size of the learning rate and the leniency of the capacity constraint. Notably, both characteristics depend heavily on the identity of the “winning” technology, which in turn depends on the regulators subsidy choice. As Wang and Zhao (2018) point out, capacity constraints may vary substantially between technologies and countries. This is not taken into account, except implicitly for Kalkuhl et al. (2012, 2013) who do not further discuss this trait. Similarly, in a two period dynamic model, Reichenbach and Requate (2012) incorporate industry-level increasing marginal cost via heterogeneous firms that reflect different plant locations. However, their focus is on market structure and the welfare loss when FITs are only second-best.

2.4 Evidence on learning by doing and spillovers

Empirical estimates on rates of learning-by-doing in green technologies vary widely, but most lie in a range of 10–20% and nearly all percentage quotes are positive (Söderholm and Sundqvist, 2007, Lindman and Söderholm, 2012, Fishedick et al., 2012, Nykvist and Nilsson, 2015, Rubin et al., 2015). For example, Rubin et al. (2015) review 18 studies on onshore wind power learning rates and find a mean learning by doing rate of 16%, 16 studies on solar/PV power with a mean rate of 23%, and two studies on biomass power generation with a mean learning-by-doing rate of 11%.

Learning rates are decreasing with the maturity of a technology, however, as shown by the empirical observation that immature technologies tend to have a significantly steeper learning curve than mature technologies (Grübler et al., 1999). This fact has been incorporated in previous modeling studies as well (e.g. Rivers and Jaccard 2006; Reichenbach and Requate 2012; Kverndokk and Rosendahl 2007).

Learning spillovers cause a positive externality which provides a reason for economic policy intervention. This RE subsidy justification is, among others, used in models of Reichenbach and Requate (2012); Helm and Schöttner (2008); Bläsi and Requate (2010) and Jaffe et al. (2005). Table 1 provides an overview of empirical evidence for learning spillovers in RE. A recent study utilizing patent data for various renewable energy technologies highlights that on average, about 60% of patent citations received by renewable patents come from patents in the same technological field (Noailly and Shestalova, 2017). Inter-technology spillovers were found to be positive, but very low for solar, wind and storage ($< 3\%$) technologies, while the share was slightly higher for waste, hydro and biomass energy technologies (Noailly and Shestalova, 2017).

Table 1: Empirical estimates of spillovers in energy related technologies

Author(s)	Technology	Spillover-rate
Bostian et al. (2010) (working paper)	PV cells	0.088
Braun et al. (2010) (working paper)	wind and solar plants	> 0
Dechezleprêtre and Glachant (2014)	wind energy	> 0
Irwin and Klenow (1994)	semiconductors	0.30
Noailly and Shestalova (2017)	RE patent data	> 0
Verdolini and Galeotti (2011)	energy supply and demand technologies (patent data)	> 0
Zimmermann (1982)	nuclear power plants	> 0

3 The model

We consider renewable energy (RE) production in a dynamic (two period) setting. The two main features of the model are (a) learning-by-doing spillovers that increase total factor productivity in the future period depending on the scale of present RE production and (b) increasing marginal costs at the industry level due to limited availability

of sites suitable for RE production. We consider both the market equilibrium under a feed-in tariff (FIT) and the social optimum to derive the optimal regulation. In the next step, we use a comparative static analysis of the market equilibrium to study the optimal differentiation of the FITs depending on technology parameters.

3.1 Technology and Learning Spillovers

We consider an endogenous mass n_t of RE generation devices (e.g. wind turbines or photovoltaic panels) in period $t \in \{1, 2\}$, where $t = 1$ is the ‘present’ period and $t = 2$ is the ‘future’ period. We consider each of these devices as operated by a single firm, and think of each of these firms as being very small compared to the overall size of the market. Each RE device is operated on an individual site, and RE output y (e.g., kilowatt hours per year) depends on site productivity s (e.g., the wind full load hours, or hours of sunshine) and total factor productivity A_t according to

$$y = A_t f(s), \tag{1}$$

where $f(s)$ with $f'(s) > 0$ describes how output depends on site productivity.

Productive sites are scarce. We assume that the most productive sites are used for RE generation, and use $S(n_t)$ to denote the productivity of the last site in use if n_t is the total mass of RE devices, which equals the total mass of sites occupied. Total RE output in period t thus is

$$Y_t = A_t \int_0^{n_t} f(S(j)) dj. \tag{2}$$

While total factor productivity in the first period, A_1 , is given, total factor productivity in period $t = 2$ depends on production decisions in the first period due to learning-by-doing with spillovers between firms (Arrow, 1962). In terms of the model, A_2 depends on cumulative output in the first period, Y_1 . This assumption also means that the spillover

rate is uniform and that there is no private learning, consistent with the assumption that the RE sector is competitive with a continuum of many small firms involved.

Learning-by-doing is positive, $A_2'(Y_1) > 0$, but at a diminishing rate $A_2''(Y_2) < 0$. We focus on the case in which the elasticity of the marginal increase of future productivity with present output is smaller than unity,

$$-\frac{Y_1 A_2''(Y_1)}{A_2'(Y_1)} < 1. \quad (3)$$

The interpretation is that productivity is not bounded from above, A_2 goes to infinity when Y_1 goes to infinity. Instead, Y_1 is restrained by diminishing productivity, which also constrains learning in the sense that learning becomes costly.

3.2 Market equilibrium

RE firms are price takers on output and input markets. To set up one RE device, the firm has to pay the price F_t for the device and rent the site at a price r_t , which we assume to be the same, independently of site productivity for RE generation, i.e., r_t captures the opportunity costs of using the site for RE generation.

On the output market, the RE firms compete with each other and with other firms on the overall electricity market. Let p_t denote the (wholesale) market price of electricity². There may be a subsidy Δ_t paid by the regulator, such that the producer price for RE firms becomes $p_t + \Delta_t$. Under constant prices within the first period, Δ_t can be interchangeably interpreted as a feed-in premium or the markup on the price under a FIT, where $p_t + \Delta_t$ would be the FIT. In the following, we will work under the

²Electricity prices are exogenous. In practice, dampening effects on the wholesale electricity price have been shown for increased RE production (Traber and Kemfert, 2011; Mulder and Scholtens, 2013). Also, the subsidy itself may have an impact on consumer electricity prices (Traber and Kemfert, 2009). For the question of this paper – the optimal differentiation of subsidies – these effects are disregarded. It is assumed that, since the price is the same across technologies, their influence would primarily concern the overall optimal level of support, and not the differentiation between FITs.

assumption that the government pays a FIT, as this is the prevailing support scheme in Europe (Kitzing et al., 2012).

Hence, the profit $\pi_t(j)$ for firm j in period t is

$$\pi_t(j) = (p_t + \Delta_t) A_t f(S(j)) - r_t - F_t \quad (4)$$

Profit is positive for the firms occupying the most productive sites. The overall mass n_t of RE devices is determined by the condition that the marginal firm earns no profit,

$$(p_t + \Delta_t) A_t f(S(n_t)) = r_t + F_t. \quad (5)$$

We allow for late entry and early exit, i.e. $n_2 \geq n_1$ and $n_2 \leq n_1$ are both possible, depending in particular on market price development. Since firms do not appropriate learning, we do not have to distinguish between incumbents and late entrants. We further assume that market prices are such that the number of firms in both periods is strictly positive, as otherwise, there would be no benefit from learning and the optimal subsidy was zero.

3.3 Social optimum and optimal RE support

Let δ denote the discount factor, such that $\delta = 1/(1+i)$, where we use the market interest rate i as the discount rate. The social optimum is found by maximizing welfare

$$W = \max_{n_1, n_2} \left\{ p_1 Y_1 - n_1 (r_1 + F_1) + \delta (p_2 Y_2 - n_2 (r_2 + F_2)) \right\} \quad (6)$$

where Y_t is given by (2) for both periods and where total factor productivity in period $t = 2$ depends on first period's output as $A_2(Y_1)$. By our assumptions, the social welfare function is jointly concave in n_1 and n_2 , such that the first-order conditions characterize a welfare optimum.

The conditions that determine the welfare-maximizing masses of firms in both periods can be written as

$$\left(p_1 + \delta p_2 A_2'(Y_1) \int_0^{n_2} f(S(j)) dj \right) A_1 f(S(n_1)) = r_1 + F_1 \quad (7)$$

$$p_2 A_2(Y_1) f(S(n_2)) = r_2 + F_2 \quad (8)$$

In the Appendix, we show that both n_1 and n_2 increase with the total factor productivity in period 1, i.e. $\frac{dn_1}{dA_1} = n_1'(A_1) > 0$ and $n_2'(A_2) > 0$. The more productive the RE technology is the more firms will enter the market in period 1. Furthermore, as productivity increases output in period 1, and thus also productivity in period 2 – due to learning by doing – also the mass of RE devices in period 2 increases with A_1 .

We derive the optimal RE subsidies by comparing the masses of RE devices in the market equilibrium under the subsidy (condition 5) and the conditions for the socially optimal masses of RE devices (conditions 7 and 8). We find that it is optimal not to intervene in the market in the second period, i.e. to set $\Delta_2 = 0$, which is a result of the assumption that there will be no third period that would benefit from further learning-by-doing.

The optimal mass of firms in the first period will be implemented by a RE subsidy

$$\Delta_1^* = \delta p_2 A_2'(Y_1) \int_0^{n_2} f(S(j)) dj \quad (9)$$

It is just equal to the marginal external benefit of output in the first period in terms of learning-by-doing spillovers – this is the discounted present value of extra output in period 2 due to extra output in period 1. With no subsidy or a subsidy below Δ_1^* , the mass of RE devices in period 1 is smaller than socially optimal. Note that the social planner need not decide whether it is optimal to support a technology at all: As long as $\Delta_1^* > 0$, a positive FIT should be offered to the technology. Whether the technology

is actually deployed then depends on whether the most productive site is productive enough to yield a non-negative profit, $(p_1 + \Delta_1^*)A_1 \int_0^1 f(S(j))dj \geq r_1 + F_1$.

We now turn to our main question how Δ_1^* should be differentiated according to different technologies. In particular we are interested in the question how the initial productivity A_1 affects Δ_1^* .

4 Optimal differentiation of FITs: Should costlier technologies receive higher support?

We are now ready to derive the main equation of this paper. The elasticity of the optimal RE subsidy with respect to the first period's productivity is (see Appendix):

$$\frac{A_1}{\Delta_1^*} \frac{d\Delta_1^*}{dA_1} = \overbrace{\frac{Y_1 A_2''(Y_1)}{A_2'(Y_1)} \left(1 + \frac{n_1 f(S(n_1))}{\int_0^{n_1} f(S(j)) dj} \frac{A_1 n_1'(A_1)}{n_1} \right)}^{\text{decreasing-marginal-learning-effect}} + \overbrace{\frac{n_2 f(S(n_2))}{\int_0^{n_2} f(S(j)) dj} \frac{A_1 n_2'(A_1)}{n_2}}^{\text{learning-utilization-effect}} \quad (10)$$

If this elasticity is negative, the conclusion is that less productive, i.e. more costly, technologies should receive higher support. If this elasticity is positive, more productive technologies should receive higher support. Equation (10) shows that there is no general conclusion with respect to the optimal differentiation of RE subsidies. The two terms in equation (10) have opposite signs: The sign of the first term is negative, the sign on the second one is positive. We associate these two terms with two counteracting effects.

The first is the “decreasing-marginal-learning-effect”. For a more productive technology, output in period $t = 1$ is higher. This increases learning-by-doing. The technology advances faster to a more mature state. Due to decreasing marginal productivity of learning, the marginal extra contribution of the FIT to spillovers will thus be smaller the more productive the technology is. The magnitude of this effect depends on the elasticity

of marginal future productivity gain with respect to present output, $-Y_1 A_2''(Y_1)/A_2'(Y_1)$. If this elasticity is large, the industry learns faster at the beginning, but rapidly becomes mature with little further scope for learning benefits.

The second is the “learning-utilization-effect”. The mass of firms that benefit from per-firm-spillovers changes over time. All n_2 firms active in period $t = 2$ (or RE devices, as in the model’s interpretation), benefit from increased productivity due to the learning in the period before. The important feature is that knowledge is non-rival and its value for one firm will not dilute just because more firms use it. Again, limits on technology utilization would put a limit on this effect.

To further specify conditions under which it is reasonable to differentiate FITs according to costliness, we further look at the relevant elasticities. An assumption of constant elasticities, which is not required for the subsequent analysis, is common in theoretical models that include learning-by-doing (e.g. Nachtigall and Rübhelke, 2016).

Specifically, we assume that, at least locally, $f(S(j)) \propto j^{\alpha-1}$ is a power function of j , with $0 < \alpha < 1$, such that α is defined as the elasticity

$$\alpha = \frac{n f(S(n))}{\int_0^n f(S(j)) dj} \quad (11)$$

In a similar fashion consider that $A_2(Y_1)$ is, at least locally, iso-elastic, i.e. $A_2(Y_1) \propto \frac{Y_1^{1-\beta}}{1-\beta}$, such that

$$\beta = -\frac{Y_1 A_2''(Y_1)}{A_2'(Y_1)} \quad (12)$$

with $0 < \beta < 1$.

Both (11) and (12) are inputs into the “experience parameter”, $-\frac{1-\beta}{\alpha}$. The estimation of this experience parameter is standard in empirical work concerning learning rate estimation (see Rubin et al. (2015) for an overview). Learning follows a power law: If output Y_1 doubles, the fractional cost reduction equals $2^{\frac{1-\beta}{\alpha}}$. The learning rate then is

defined as $LR = 1 - 2^{-\frac{1-\beta}{\alpha}}$. This model of learning by doing, related to unit cost, was first suggested by Wright (1936).

With this specification, still the model is not solvable in closed form, but from (8) we find that under the assumptions (11) and (12),³

$$\frac{n'_2(A_1)}{n_2} = (1 - \beta) \frac{\alpha}{1 - \alpha} \frac{n'_1(A_1)}{n_1}. \quad (13)$$

Thus, using (11) and (12) in (10), we get

$$\frac{A_1}{\Delta_1^*} \frac{d\Delta_1^*}{dA_1} = -\beta \left(1 + \alpha \frac{A_1 n'_1(A_1)}{n_1} \right) + \alpha \frac{A_1 n'_2(A_1)}{n_2} \quad (14)$$

$$= -\beta + \alpha (1 - \beta) \frac{A_1 n'_1(A_1)}{n_1} \left(\frac{\alpha}{1 - \alpha} - \frac{\beta}{1 - \beta} \right). \quad (15)$$

If $\alpha < \beta$, the bracket in (15) is negative. Thus, knowing that $n'_1(A_1) > 0$ (see Appendix A), $\alpha < \beta$ is a sufficient condition such that the less productive, or more costly, technologies should receive higher support. Furthermore, it can be shown that the necessary condition for this, i.e. (15) < 0 , is:

$$\beta > \alpha \left(\frac{1}{1 + (1 - \alpha)/\alpha\eta} \right) \quad (16)$$

with $\eta \equiv A_1 \frac{n'_1(A_1)}{n_1}$.

This shows that the elasticities of aggregate production with respect to the mass of firms and the elasticity of the learning curve are key parameters that determine whether more or less productive technologies should receive stronger support. A low value for α and a high value for β favor a higher FIT for costlier technologies:

- (i) A high value of β means that the marginal benefit of current output in terms of future productivity decreases fast. If the current technology is already rather

³This can be shown by constructing an example using the specifications above in (8). We obtain $n_1^{\alpha(1-\beta)} n_2^{\alpha-1} = k$ with some constant $k > 0$. Thus, $n_2 = k^{-\frac{1}{1-\alpha}} n_1^{(1-\beta)\frac{\alpha}{1-\alpha}}$.

productive, there is not much scope for future learning spillovers. A high value of β means that the “decreasing-marginal-learning-effect” is large, thus favoring the support of technologies that are not yet advanced.

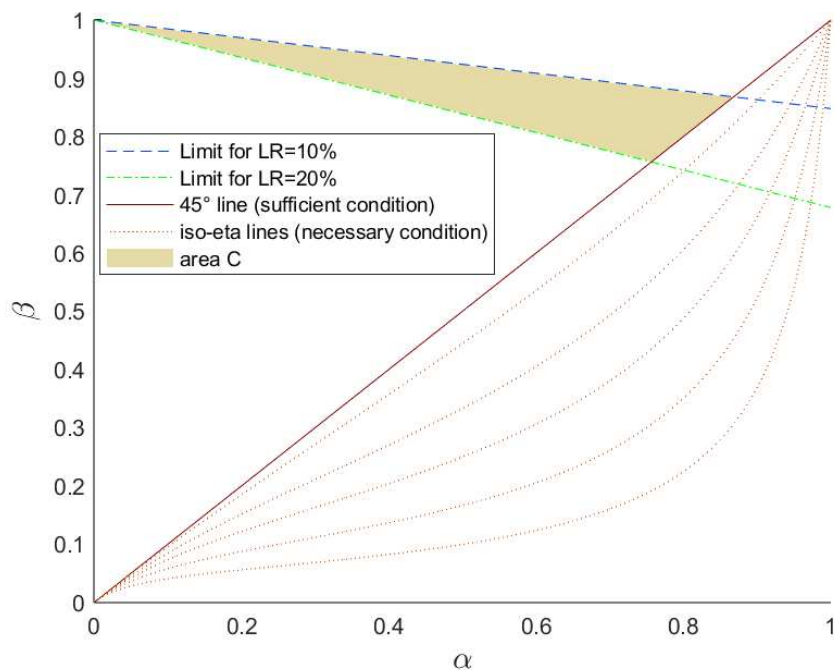
- (ii) A low value of α means that marginal costs are strongly increasing – or, equivalently, marginal productivity is strongly decreasing – at firm and industry level. Scarcity of productive sites for one type of RE technology calls for diversification of RE technologies in use and thus for support of currently less advanced technologies. The low value of α leads to a small “learning-utilization-effect”.

This result can provide guidance for policy-makers: Optimal differentiation depends (inter alia) on generation costs, but the sign of this dependence can be both positive or negative. Whenever sites are in strongly limited supply and sites are an important production factor, countries should tend to give a higher FIT to costlier technologies. If the limits to learning as well as the limits to utilization restrict learning benefits, diversification is optimal. By contrast, when sites are not very scarce (as for example for some countries that are especially suited for solar technology, where the entire regional energy consumption could be produced from one technology), concentration on the cheaper technology is preferable (*ceteris paribus*). Condition (15) shows that the more efficient technologies should always receive the higher support if α is close to one.

To explore which is the the empirically relevant case of RE subsidy differentiation, we consider the following numerical example. Empirical estimates of learning rates concerning the reduction in unit costs were most often between 10–20% (cf. Section 2.4). For this range, the experience parameter would lie between 0.152 and 0.322. Area C in figure 1 illustrates combinations of α and β in this range for which the sufficient condition, $\alpha < \beta$ holds, denoted by area C. Thus, for all combinations in area C, costlier technologies should receive more support. A necessary condition for an increasing relationship between costliness and optimal support is that sites are in moderately limited

supply, i.e. $\alpha < 1$. The higher the learning rate, the stronger would site scarcity have to be. For a sector cost elasticity with respect to sites of 1.3 ($\alpha = 0.77$), the propensity for technological diversification is highest. The figure also depicts the necessary condition (16) for different values of $\eta \equiv A_1 \frac{n_1'(A_1)}{n_1}$.

Figure 1: The shaded area indicates the combinations of α (the elasticity of aggregate output with respect to the mass of firms) and β (the elasticity of marginal future productivity with respect to current output) for which costlier technologies should receive higher support. Iso-eta-lines drawn for the following (arbitrary) values of η : 0.5, 2, 4, 8, 16.



5 A model with two technologies

In this section, we expand the model to two technologies. While the single-technology model is sufficient, this expansion has two advantages. First, a two-technology-model can be used to make the relationship between initial cost ratios and first-period FIT

ratios more explicit. Second, we can introduce inter-technology spillovers and discuss the consequences for FIT differentiation. We distinguish variables concerning the second technology by a bar. To simplify notation, we set $A_1 = 1$, $\bar{A}_1 = \gamma$ and write A, \bar{A} instead of A_2, \bar{A}_2 . Then, total RE output is

$$Y_1 = y_1 + \bar{y}_1 \int_0^{n_1} f(S(j)) dj + \gamma \int_0^{\bar{n}_1} \bar{f}(\bar{S}(\bar{j})) d\bar{j}, \quad (17)$$

$$Y_2 = y_2 + \bar{y}_2 = A \int_0^{n_2} f(S(j)) dj + \bar{A} \int_0^{\bar{n}_2} \bar{f}(\bar{S}(\bar{j})) d\bar{j}. \quad (18)$$

Assume that the firm in the original technology (bar technology) has to pay the price F_t (\bar{F}_t) for the device and rent the site at a price r_t (\bar{r}_t). Different types of sites are used for different technologies, such that technologies are independent from each other concerning sites. For both technologies, the overall masses n_t and \bar{n}_t of RE devices are determined by the condition that the marginal firm earns no profit. The objective function reads:

$$W = \max_{n_1, n_2} \left\{ p_1 (Y_1 + \bar{Y}_1) - n_1 (r_1 + F_1) - \bar{n}_1 (\bar{r}_1 + \bar{F}_1) \right. \\ \left. + \delta (p_2 (Y_2 + \bar{Y}_2) - n_2 (r_2 + F_2) - \bar{n}_2 (\bar{r}_2 + \bar{F}_2)) \right\} \quad (19)$$

Now, we can derive how the optimal relative FIT $\frac{\bar{\Delta}_1^*}{\Delta_1^*}$ depends on the relative costliness γ . A higher γ means that the original technology is more costly compared to the bar-technology. Concentrate first on the case where inter-technology-spillovers are zero, i.e. $A_{\bar{Y}_1} = \bar{A}_{Y_1} = 0$. As before, we use comparative statics and derive (20).

$$\begin{aligned}
\frac{\gamma}{\delta p_2 \bar{\Delta}_1^*} \frac{d \left(\frac{\bar{\Delta}_1^*}{\Delta_1^*} \right)}{d\gamma} &= \frac{\gamma}{\delta p_2 \bar{\Delta}_1^*} \frac{d \bar{\Delta}_1^*}{d\gamma} \\
&= \underbrace{\frac{\bar{n}_2 \bar{f}(\bar{S}(\bar{n}_2))}{\int_0^{\bar{n}_2} \bar{f}(\bar{S}(\bar{j})) d\bar{j}} \frac{\gamma}{\bar{n}_2} \frac{\partial \bar{n}_2}{\partial \gamma}}_{\text{learning-utilization-effect}} + \underbrace{\frac{\bar{Y}_1 \bar{A}_{\bar{Y}_1, \bar{Y}_1}(Y_1, \bar{Y}_1)}{\bar{A}_{\bar{Y}_1}(Y_1, \bar{Y}_1)} \left(1 + \frac{\bar{n}_1 \bar{f}(\bar{S}(\bar{n}_1))}{\int_0^{\bar{n}_1} \bar{f}(\bar{S}(\bar{j})) d\bar{j}} \frac{\gamma}{\bar{n}_1} \frac{\partial \bar{n}_1}{\partial \gamma} \right)}_{\text{decreasing-marginal-learning-effect}}
\end{aligned} \tag{20}$$

The first equality stems from the fact that without technology spillovers and assuming that both technologies are small enough to be price takers, the two FITs are indeed independent from each other. For the same reason, one can show that $\frac{\partial \bar{n}_1}{\partial \gamma} > 0$ and $\frac{\partial \bar{n}_2}{\partial \gamma} > 0$ in the same way as for the single-technology-model.

Comparing (20) with (10) shows that adding a second technology to the model does not alter the condition derived in section 4, as long as the two technologies are independent from each other. Again, the question whether both, one or none of the technologies get deployed is decided on the market, and need not be determined by the social planner.

Now suppose that the two technologies are able to learn from each other. The empirical finding by Noailly and Shestalova (2017) shows that for some RE technologies (see section 2.4), innovations find outside applications in other RE technologies. Larger-scale deployment of one RE technology can benefit the other for example by reducing the cost for complementary infrastructure. If such inter-technology knowledge spillovers occur, the ensuing externality from production encompasses the benefits generated in both technologies, which is reflected in the optimal FIT ratio:

$$\frac{\bar{\Delta}_1^*}{\Delta_1^*} = \frac{A_{\bar{Y}_1}(Y_1, \bar{Y}_1) \int_0^{\bar{n}_2} f(S(j)) dj + \bar{A}_{\bar{Y}_1}(Y_1, \bar{Y}_1) \int_0^{\bar{n}_2} \bar{f}(\bar{S}(\bar{j})) d\bar{j}}{A_{Y_1}(Y_1, \bar{Y}_1) \int_0^{\bar{n}_2} f(S(j)) dj + \bar{A}_{Y_1}(Y_1, \bar{Y}_1) \int_0^{\bar{n}_2} \bar{f}(\bar{S}(\bar{j})) d\bar{j}} \tag{21}$$

Inter-technology spillovers of learning-by-doing are modeled as $A_{Y_1}(Y_1, \bar{Y}_1) > 0$,

$A_{\bar{Y}_1}(Y_1, \bar{Y}_1) > 0$, $\bar{A}_{Y_1}(Y_1, \bar{Y}_1) > 0$ and $\bar{A}_{\bar{Y}_1}(Y_1, \bar{Y}_1) > 0$, with $A_{Y_1, Y_1}(Y_1, \bar{Y}_1) < 0$ and $A_{\bar{Y}_1, \bar{Y}_1}(Y_1, \bar{Y}_1) < 0$. Furthermore, $A_{Y_1, \bar{Y}_1}(Y_1, \bar{Y}_1) < 0$ and $\bar{A}_{Y_1, \bar{Y}_1}(Y_1, \bar{Y}_1) < 0$ if we assume that technological learning in one technology is a substitute for learning in the other technology, and $A_{Y_1, \bar{Y}_1}(Y_1, \bar{Y}_1) > 0$ and $\bar{A}_{Y_1, \bar{Y}_1}(Y_1, \bar{Y}_1) > 0$ if we assume inter-technological learning to be complementary. Due to the technical complexity of this case, we refer the reader to Appendix section C for technical details, and will only discuss the main points of interest here.

Each FIT (see (21)) now additionally depends on utilization and learning spillovers of the other technology. Both the learning-utilization-effect as well as the decreasing-marginal-learning-effect are now split into two, one part for each technology's utilization (equation (A.52)).

The bar-technology is now cheaper in period one, and the related increase in learning-by-doing will make both technologies cheaper in the second period. Due to this, both technologies will be utilized more in the second period. This means that the direct learning utilization effect is again positive for both technologies. However, inter-technology-learning is also utilized more, which accounts for the other term in each of the two small brackets. For example, an increase in \bar{n}_2 leads to a positive learning utilization effect but also a negative effect on the optimal FIT ratio $\frac{\bar{\Delta}_1^*}{\Delta_1^*}$, since the original technologies' learning is worth more as well. The two learning-utilization-effects' signs are necessarily different (unless both are zero): if (22) holds, then the bar technologies' learning-utilization-effect is negative and the original technologies' learning-utilization-effect is positive and vice versa.

$$\frac{\bar{A}_{\bar{Y}_1}(Y_1, \bar{Y}_1)}{\bar{A}_{Y_1}(Y_1, \bar{Y}_1)} < \frac{A_{\bar{Y}_1}(Y_1, \bar{Y}_1)}{A_{Y_1}(Y_1, \bar{Y}_1)} \tag{22}$$

Thus, the effect of n_2 (learning-utilization in the original technology) competes with

the effect of a larger \bar{n}_2 (learning utilization in the bar technology).

The signs of the two decreasing-marginal-learning-effects depend on whether inter-technology learning is substitutable or complementary. In case of complementary learning, the term in square brackets is negative for the bar technology and positive for the original technology. For the bar technology, the effect found in the single-technology model is now reduced in absolute terms by the two complementary effects and increased by the decreased marginal cross-effect. For the original technology, this is similar. In case of substitutive learning, the sign of each decreasing-marginal-learning-effect part is ambiguous and in addition, the sign of $\frac{\partial n_1}{\partial \gamma}$ cannot be easily determined.

6 Discussion and Conclusion

In this paper we have set up a theoretical model to study the optimal differentiation of renewable energy (RE) support policies. The rationale for RE subsidies are learning-by-doing spillovers. We have further taken into account the limits to expand individual RE technologies that come about due to the limited availability of sites suitable for RE generation. This translates into increasing marginal costs of RE production at firm- and industry-level. Thus, two competing forces drive the dynamic development of a technology, and both depend on cumulative production in the first period: Increasing marginal costs and increasing productivity due to learning-by-doing. Using comparative statics with regard to differences in generation costs, we have provided a theoretical analysis of a very common practice in politics: The differentiation according to the level of generation cost.

FITs should be differentiated between technologies, if cost, learning rates and spillover rates differ. We have shown that simple, linear differentiation on the basis of generation costs, as is often applied in practice, is not an efficient support regime. This results because the optimal support level depends on costs in several different and non-linear

ways. However, the sign of optimal differentiation, so to say, the direction of differentiation, can be derived. The negative decreasing-marginal-learning-effect captures that a cheaper industry will optimally learn more, but the effect on the margin is lower. This effect tends to favor the support of less advanced technologies. The positive learning-utilization-effect goes in the opposite direction. It comes about, as more productive technologies tend to attract more firms in the future, thus extending the external benefit of learning-by-doing spillovers.

We have shown that it is optimal to give higher support to more costly technologies, as it is common practice, if the elasticity of learning by doing is large and marginal costs are steeply increasing, i.e. if productive sites are scarce. In such a case, the policy-maker should seek to support a differentiated set of technologies.

Several model extensions are possible. First, we have not considered variable inputs in production, such as labor needed for maintenance of RE devices. Including such variable inputs, the model would further allow for the possibility of learning being either driven by aggregate output or by specific inputs such as wind turbines or PV panels. Most empirical studies use installed capacity as independent experience variable, this includes turbine number and size. In addition, learning could also be caused by progress in the operational management (Neij, 1997, 1999). In such a setting, a FIT on RE output can only reach a second-best outcome. A similar analysis as done in the present paper can be applied nevertheless. Second, we have studied a two-period setting only. The present model can be extended to an arbitrary number of periods, considering total factor productivity as a state variable that changes with current output. Such an approach would allow to study how the optimal RE subsidy changes over time, although analytical results would most likely be restricted to a steady-state analysis. Furthermore, the model could be refined to include finite absorptive capacity, such that the appropriation of external knowledge is no longer costless.

Despite the abstractions necessary to generate clear insights, our analysis led to the-

oretical results that could inform empirical research and policy making. In terms of empirical research, an advantage of our results is that conditions on optimal differentiation of RE support are formulated in terms of elasticities, which are typically well measurable in statistical analyses. In terms of policy-making, we provide the background for the common differentiation according to the costliness of RE technologies. Specifically, we find that considering the scarcity of sites suitable for RE generation under the different technologies is an important driver for such a differentiation and the resulting diversification of RE technologies.

Appendix

A Comparative statics

The assumption that the social welfare function W is jointly concave in n_1 and n_2 , implies

$$\begin{aligned}W_{n_1 n_1} &< 0 \\W_{n_2 n_2} &< 0 \\W_{n_1 n_1} W_{n_2 n_2} - W_{n_1 n_2}^2 &> 0.\end{aligned}\tag{A.23}$$

It is straightforward to check that the social welfare function (6) satisfies these conditions. The conditions for the social optimum, or equivalently the market equilibrium under the optimal RE subsidy, can be written as $W_{n_1} = 0$ and $W_{n_2} = 0$. Differentiating with respect to A_1 , we get the following conditions

$$W_{n_1 n_1} n_1'(A_1) + W_{n_1 n_2} n_2'(A_1) + W_{n_1 A_1} = 0\tag{A.24}$$

$$W_{n_2 n_1} n_1'(A_1) + W_{n_2 n_2} n_2'(A_1) + W_{n_2 A_1} = 0\tag{A.25}$$

Solving leads to

$$n_1'(A_1) = \frac{W_{n_1 n_2} W_{n_2 A_1} - W_{n_2 n_2} W_{n_1 A_1}}{W_{n_1 n_1} W_{n_2 n_2} - W_{n_1 n_2}^2}\tag{A.26}$$

$$n_2'(A_1) = \frac{W_{n_1 n_2} W_{n_1 A_1} - W_{n_1 n_1} W_{n_2 A_1}}{W_{n_1 n_1} W_{n_2 n_2} - W_{n_1 n_2}^2}\tag{A.27}$$

For the welfare function (6) we have

$$W_{n_1 A_1} = \delta p_2 A_2''(Y_1) \left(\int_0^{n_1} f(S(j)) dj \right) \left(\int_0^{n_2} f(S(j)) dj \right) A_1 f(S(n_1)) \\ + \left(p_1 + \delta p_2 A_2'(Y_1) \int_0^{n_2} f(S(j)) dj \right) f(S(n_1)) \quad (\text{A.28})$$

$$= \left(p_1 + \delta p_2 A_2'(Y_1) \left(\int_0^{n_2} f(S(j)) dj \right) \left(1 + \frac{Y_1 A_2''(Y_1)}{A_2'(Y_1)} \right) \right) f(S(n_1)) \quad (\text{A.29})$$

Thus, condition (3) implies $W_{n_1 A_1} > 0$. Moreover,

$$W_{n_2 A_1} = p_2 A_2'(Y_1) \left(\int_0^{n_1} f(S(j)) dj \right) f(S(n_2)) > 0. \quad (\text{A.30})$$

Thus, $n_1'(A_1) > 0$ and $n_2'(A_1) > 0$.

Differentiating (9) with respect to A_1 , we obtain

$$\frac{1}{\delta p_2} \frac{d\Delta_1^*}{dA_1} = A_2''(Y_1) \left(\int_0^{n_1} f(S(j)) dj + A_1 f(S(n_1)) n_1'(A_1) \right) \left(\int_0^{n_2} f(S(j)) dj \right) \\ + A_2'(Y_1) f(S(n_2)) n_2'(A_1) \quad (\text{A.31})$$

Rearranging leads to (10).

B Comparative statics for the two-technologies-case

The conditions for the social optimum, or equivalently the market equilibrium under the optimal RE subsidy, can be written as $W_{n_1} = 0$, $W_{\bar{n}_1} = 0$, $W_{n_2} = 0$ and $W_{\bar{n}_2} = 0$.

Differentiating with respect to γ , we get the following conditions

$$W_{n_1 n_1} n_1'(\gamma) + W_{n_1 \bar{n}_1} \bar{n}_1'(\gamma) + W_{n_1 n_2} n_2'(\gamma) + W_{n_1 \bar{n}_2} \bar{n}_2'(\gamma) + W_{n_1 \gamma} = 0 \quad (\text{A.32})$$

$$W_{n_2 n_1} n_1'(\gamma) + W_{n_2 \bar{n}_1} \bar{n}_1'(\gamma) + W_{n_2 n_2} n_2'(\gamma) + W_{n_2 \gamma} = 0 \quad (\text{A.33})$$

$$W_{\bar{n}_1 n_1} n_1'(\gamma) + W_{\bar{n}_1 \bar{n}_1} \bar{n}_1'(\gamma) + W_{\bar{n}_1 n_2} n_2'(\gamma) + W_{\bar{n}_1 \bar{n}_2} \bar{n}_2'(\gamma) + W_{\bar{n}_1 \gamma} = 0 \quad (\text{A.34})$$

$$W_{\bar{n}_2 n_1} n_1'(\gamma) + W_{\bar{n}_2 \bar{n}_1} \bar{n}_1'(\gamma) + W_{\bar{n}_2 n_2} n_2'(\gamma) + W_{\bar{n}_2 \gamma} = 0 \quad (\text{A.35})$$

$$W_{n_1 n_1} n_1'(\gamma) + W_{n_1 \bar{n}_1} \bar{n}_1'(\gamma) + W_{n_1 n_2} n_2'(\gamma) + W_{n_1 \bar{n}_2} \bar{n}_2'(\gamma) + W_{n_1 \gamma} = 0 \quad (\text{A.36})$$

$$W_{n_2 n_1} n_1'(\gamma) + W_{n_2 \bar{n}_1} \bar{n}_1'(\gamma) + W_{n_2 n_2} n_2'(\gamma) + W_{n_2 \gamma} = 0 \quad (\text{A.37})$$

$$W_{\bar{n}_1 n_1} n_1'(\gamma) + W_{\bar{n}_1 \bar{n}_1} \bar{n}_1'(\gamma) + W_{\bar{n}_1 n_2} n_2'(\gamma) + W_{\bar{n}_1 \bar{n}_2} \bar{n}_2'(\gamma) + W_{\bar{n}_1 \gamma} = 0 \quad (\text{A.38})$$

$$W_{\bar{n}_2 n_1} n_1'(\gamma) + W_{\bar{n}_2 \bar{n}_1} \bar{n}_1'(\gamma) + W_{\bar{n}_2 n_2} n_2'(\gamma) + W_{\bar{n}_2 \gamma} = 0 \quad (\text{A.39})$$

Solving leads to

$$n_1'(A_1) = \frac{W_{n_1 n_2} W_{n_2 A_1} - W_{n_2 n_2} W_{n_1 A_1}}{W_{n_1 n_1} W_{n_2 n_2} - W_{n_1 n_2}^2} \quad (\text{A.40})$$

$$n_2'(A_1) = \frac{W_{n_1 n_2} W_{n_1 A_1} - W_{n_1 n_1} W_{n_2 A_1}}{W_{n_1 n_1} W_{n_2 n_2} - W_{n_1 n_2}^2} \quad (\text{A.41})$$

C Inter-technology spillovers

Inter-technology spillovers of learning-by-doing are modeled as $A_{Y_1}(Y_1, \bar{Y}_1) > 0$, $A_{\bar{Y}_1}(Y_1, \bar{Y}_1) > 0$, $\bar{A}_{Y_1}(Y_1, \bar{Y}_1) > 0$ and $\bar{A}_{\bar{Y}_1}(Y_1, \bar{Y}_1) > 0$, with $A'_{Y_1, Y_1}(Y_1, \bar{Y}_1) < 0$ and $A'_{\bar{Y}_1, \bar{Y}_1}(Y_1, \bar{Y}_1) < 0$. Furthermore, $A_{Y_1, \bar{Y}_1}(Y_1, \bar{Y}_1) < 0$ and $\bar{A}_{Y_1, \bar{Y}_1}(Y_1, \bar{Y}_1) < 0$ if we assume that technological learning in one technology is a substitute for learning in the other technology, and $A_{Y_1, \bar{Y}_1}(Y_1, \bar{Y}_1) > 0$ and $\bar{A}_{Y_1, \bar{Y}_1}(Y_1, \bar{Y}_1) > 0$ if we assume inter-technological learning to be complementary.

The objective function reads:

$$W = \max_{n_1, n_2} \left\{ p_1 (Y_1 + \bar{Y}_1) - n_1 (r_1 + F_1) - \bar{n}_1 (\bar{r}_1 + \bar{F}_1) \right. \\ \left. + \delta (p_2 (Y_2 + \bar{Y}_2) - n_2 (r_2 + F_2) - \bar{n}_2 (\bar{r}_2 + \bar{F}_2)) \right\} \quad (\text{A.42})$$

The relative FIT

$$\frac{\bar{\Delta}_1^*}{\Delta_1^*} = \frac{A_{\bar{Y}_1}(Y_1, \bar{Y}_1) \int_0^{n_2} f(S(j)) dj + \bar{A}_{\bar{Y}_1}(Y_1, \bar{Y}_1) \int_0^{\bar{n}_2} \bar{f}(\bar{S}(\bar{j})) d\bar{j}}{A_{Y_1}(Y_1, \bar{Y}_1) \int_0^{n_2} f(S(j)) dj + \bar{A}_{Y_1}(Y_1, \bar{Y}_1) \int_0^{\bar{n}_2} \bar{f}(\bar{S}(\bar{j})) d\bar{j}} \quad (\text{A.43})$$

now depends on relative costliness γ in multiple different ways. We differentiate with respect to relative costliness γ and multiply both sides by $\frac{1}{\delta p_2} \frac{(\Delta_1^*)^2}{\Delta_1^*}$ leads to:

$$\frac{(\Delta_1^*)^2}{\delta p_2 \bar{\Delta}_1^*} \frac{d \left(\frac{\Delta_1^*}{\bar{\Delta}_1^*} \right)}{d\gamma} = \frac{1}{\delta p_2} \underbrace{\left(\frac{\Delta_1^*}{\bar{\Delta}_1^*} \frac{d \bar{\Delta}_1^*}{d\gamma} - \frac{d \Delta_1^*}{d\gamma} \right)}_{\text{decreasing-marginal-learning-effect}} \quad (\text{A.44})$$

$$= - \underbrace{\left[\left(A_{Y_1, Y_1}(Y_1, \bar{Y}_1) - \frac{\Delta_1^*}{\bar{\Delta}_1^*} A_{\bar{Y}_1, Y_1}(Y_1, \bar{Y}_1) \right) \int_0^{n_2} f(S(j)) dj \right]}_{\text{decreasing-marginal-learning-effect}} \quad (\text{A.45})$$

$$+ \underbrace{\left(\bar{A}_{Y_1, Y_1}(Y_1, \bar{Y}_1) - \frac{\Delta_1^*}{\bar{\Delta}_1^*} \bar{A}_{\bar{Y}_1, Y_1}(Y_1, \bar{Y}_1) \right) \int_0^{n_2} \bar{f}(\bar{S}(\bar{j})) d\bar{j}}_{\text{decreasing-marginal-learning-effect}} \left[f(S(n_1)) \frac{\partial n_1}{\partial \gamma} \right] \quad (\text{A.46})$$

$$- \underbrace{\left[\left(A_{Y_1, \bar{Y}_1}(Y_1, \bar{Y}_1) - \frac{\Delta_1^*}{\bar{\Delta}_1^*} A_{\bar{Y}_1, \bar{Y}_1}(Y_1, \bar{Y}_1) \right) \int_0^{n_2} f(S(j)) dj \right]}_{\text{decreasing-marginal-learning-effect}} \quad (\text{A.47})$$

$$+ \underbrace{\left(\bar{A}_{Y_1, \bar{Y}_1}(Y_1, \bar{Y}_1) - \frac{\Delta_1^*}{\bar{\Delta}_1^*} \bar{A}_{\bar{Y}_1, \bar{Y}_1}(Y_1, \bar{Y}_1) \right) \int_0^{n_2} \bar{f}(\bar{S}(\bar{j})) d\bar{j}}_{\text{decreasing-marginal-learning-effect}} \quad (\text{A.48})$$

$$\underbrace{\left(\int_0^{n_1} \bar{f}(\bar{S}(\bar{j})) d\bar{j} + \gamma \bar{f}(\bar{S}(n_1)) \frac{\partial n_1}{\partial \gamma} \right)}_{\text{learning-utilization-effect}} \quad (\text{A.49})$$

$$- \underbrace{\left(A_{Y_1}(Y_1, \bar{Y}_1) - \frac{\Delta_1^*}{\bar{\Delta}_1^*} A_{\bar{Y}_1}(Y_1, \bar{Y}_1) \right) f(S(n_2)) \frac{\partial n_2}{\partial \gamma}}_{\text{learning-utilization-effect}} \quad (\text{A.50})$$

$$- \underbrace{\left(\bar{A}_{Y_1}(Y_1, \bar{Y}_1) - \frac{\Delta_1^*}{\bar{\Delta}_1^*} \bar{A}_{\bar{Y}_1}(Y_1, \bar{Y}_1) \right) \bar{f}(\bar{S}(n_2)) \frac{\partial n_2}{\partial \gamma}}_{\text{learning-utilization-effect}} \quad (\text{A.51})$$

Assume (in the same fashion as was assumed in section 4) that, at least locally, $f(S(j)) \propto j^{\alpha-1}$ is a power function of j (resp. $\bar{f}(\bar{S}(\bar{j})) \propto \bar{j}^{\bar{\alpha}-1}$ a power function of \bar{j}), with $0 < \alpha < 1$ ($0 < \bar{\alpha} < 1$). With this specification

$$\alpha = \frac{n f(S(n))}{\int_0^n f(S(j)) dj}$$

$$\bar{\alpha} = \frac{\bar{n} \bar{f}(\bar{S}(\bar{n}))}{\int_0^{\bar{n}} \bar{f}(\bar{S}(\bar{j})) d\bar{j}}$$

Furthermore, we assume again that the productivity parameters $A(Y_1, \bar{Y}_1)$ and $\bar{A}(Y_1, \bar{Y}_1)$ are, at least locally, iso-elastic such that we can define the following eight elasticities (which lie strictly between zero and one):

$$\begin{aligned}
\epsilon_{Y_1, Y_1} &= -\frac{Y_1 A_{Y_1, Y_1}(Y_1, \bar{Y}_1)}{A_{Y_1}(Y_1, \bar{Y}_1)} \\
\bar{\epsilon}_{Y_1, Y_1} &= -\frac{Y_1 \bar{A}_{Y_1, Y_1}(Y_1, \bar{Y}_1)}{\bar{A}_{Y_1}(Y_1, \bar{Y}_1)} \\
\epsilon_{\bar{Y}_1, \bar{Y}_1} &= -\frac{\bar{Y}_1 A_{\bar{Y}_1, \bar{Y}_1}(Y_1, \bar{Y}_1)}{A_{\bar{Y}_1}(Y_1, \bar{Y}_1)} \\
\bar{\epsilon}_{\bar{Y}_1, \bar{Y}_1} &= -\frac{\bar{Y}_1 \bar{A}_{\bar{Y}_1, \bar{Y}_1}(Y_1, \bar{Y}_1)}{\bar{A}_{\bar{Y}_1}(Y_1, \bar{Y}_1)} \\
\epsilon_{Y_1, \bar{Y}_1} &= -\frac{\bar{Y}_1 A_{Y_1, \bar{Y}_1}(Y_1, \bar{Y}_1)}{A_{\bar{Y}_1}(Y_1, \bar{Y}_1)} \\
\bar{\epsilon}_{Y_1, \bar{Y}_1} &= -\frac{\bar{Y}_1 \bar{A}_{Y_1, \bar{Y}_1}(Y_1, \bar{Y}_1)}{\bar{A}_{\bar{Y}_1}(Y_1, \bar{Y}_1)} \\
\epsilon_{\bar{Y}_1, Y_1} &= -\frac{Y_1 A_{\bar{Y}_1, Y_1}(Y_1, \bar{Y}_1)}{A_{Y_1}(Y_1, \bar{Y}_1)} \\
\bar{\epsilon}_{\bar{Y}_1, Y_1} &= -\frac{Y_1 \bar{A}_{\bar{Y}_1, Y_1}(Y_1, \bar{Y}_1)}{\bar{A}_{Y_1}(Y_1, \bar{Y}_1)}
\end{aligned}$$

Using these elasticities in (A.44) gives:

$$\begin{aligned}
& \frac{1}{\delta p_2} \left(\frac{\Delta_1^*}{\bar{\Delta}_1^*} \frac{d \bar{\Delta}_1^*}{d \gamma} - \frac{d \Delta_1^*}{d \gamma} \right) \tag{A.52} \\
&= - \left(\left(\frac{\Delta_1^*}{\bar{\Delta}_1^*} \epsilon_{\bar{Y}_1, Y_1} - \epsilon_{Y_1, Y_1} \right) \frac{Y_2}{A} A_{Y_1} + \left(\frac{\Delta_1^*}{\bar{\Delta}_1^*} \bar{\epsilon}_{\bar{Y}_1, Y_1} - \bar{\epsilon}_{Y_1, Y_1} \right) \frac{\bar{Y}_2}{\bar{A}} \bar{A}_{Y_1} \right) \frac{\alpha}{n_1} \frac{\partial n_1}{\partial \gamma} \\
&- \left[\left(\frac{\Delta_1^*}{\bar{\Delta}_1^*} \epsilon_{\bar{Y}_1, \bar{Y}_1} - \epsilon_{Y_1, \bar{Y}_1} \right) \frac{Y_2}{A} A_{\bar{Y}_1} + \left(\frac{\Delta_1^*}{\bar{\Delta}_1^*} \bar{\epsilon}_{\bar{Y}_1, \bar{Y}_1} - \bar{\epsilon}_{Y_1, \bar{Y}_1} \right) \frac{\bar{Y}_2}{\bar{A}} \bar{A}_{\bar{Y}_1} \right] \left(\frac{1}{\gamma} + \frac{\bar{\alpha}}{n_1} \frac{\partial \bar{n}_1}{\partial \gamma} \right) \\
&- \frac{Y_2}{A_2} \left(A_{Y_1}(Y_1, \bar{Y}_1) - \frac{\Delta_1^*}{\bar{\Delta}_1^*} A_{\bar{Y}_1}(Y_1, \bar{Y}_1) \right) \frac{\alpha}{n_2} \frac{\partial n_2}{\partial \gamma} \\
&- \frac{\bar{Y}_2}{\bar{A}_2} \left(\bar{A}_{Y_1}(Y_1, \bar{Y}_1) - \frac{\Delta_1^*}{\bar{\Delta}_1^*} \bar{A}_{\bar{Y}_1}(Y_1, \bar{Y}_1) \right) \frac{\bar{\alpha}}{\bar{n}_2} \frac{\partial \bar{n}_2}{\partial \gamma}
\end{aligned}$$

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