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Abstract

Should Renewable Energy Sources (RES) auction systems support development of a wide range of different technologies or instead focus on supporting a select few? We review some of the approaches to RES technologies differentiation in relation to RES auction designs. Subsequently, we use an analytical model to examine the optimal differentiation of RES technologies when the future costs of RES installations are subject to uncertainty. We allow uncertainty to influence the cost function in two ways: (i) as an uncertain magnitude of the learning-by-doing effect and (ii) as a possibility for an exogenous random technological shock (such as an unexpected technological breakthrough). We find that uncertainty of learning rates increases the benefits of differentiation. This result, among other things, implies that optimal differentiation predicted by the energy models that assume fixed learning rates is biased downward. On the other hand, where exogenous shocks are present the differences between the costs of technologies are large and the planner has less incentive to commit to support a diversified pool of technologies and more incentive to favour the choice of a technology which is cheapest at the given moment in time. This last result is more pronounced when there is no learning-by-doing effect. We recommend that countries with potentially large learning rate effects - such as those countries at the technological frontier - should increase differentiation, while more peripheral countries should limit differentiation.

Keywords: Renewable Energy Sources, auction design, technological diversification, learning-by-doing, uncertainty

JEL Codes: O33, Q42

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1 Introduction

Growing recognition of the role renewable energy should play in the decarbonization process raises the importance of identifying the optimal portfolio of RES technologies. Within this theme, one of the most crucial research tasks is to understand the benefits associated with a more diversified portfolio, that is a portfolio which includes a larger number of RES technologies, even if some of them are not yet competitive. On the one hand, support for RES technologies that are currently more costly than the leading technologies involves larger costs with regard to the support system and/or less support for the leading RES technologies. This can result in slower growth of the share of RES in the total electricity mix. On the other hand, The Special Report on Renewable Energy Sources and Climate Change Mitigation by IPCC notes that diversity of RES technologies will facilitate decarbonization in the long run, and technologies that are currently in the stage of early development can potentially play an important role in the future. This view is supported by several studies focused on a range of climate-friendly technologies (Francek, Hekkert and Godfroij 2004, Richels and Blanford 2008).

This paper explores the benefits and costs of RES technologies differentiation when technological progress is subject to uncertainty. We shall address this research topic in two steps: first, we present the variety of approaches to RES differentiation existing among the most common RES support policies and examine what motivates policymakers to choose policies that lead to greater RES differentiation. Second, we shall set up an analytical model which examines the benefits (or costs) of increasing the number of technologies supported by the central planner when the parameters driving technological progress are random variables.

We focus on one particular type of RES support policy: competitive bidding, also referred to as tendering or auctioning. The number of countries using the auction mechanism has grown from nine in 2009 to 64 in 2015. Although the largest competitive procurements have occurred in emerging economies (e.g. in Latin American countries, China and India), the system is also gaining momentum in some developed countries (REN21 2014, REN21 2015, REN21 2016). This is especially the case in the European Union (EU), as the recent European Commission Guidelines on State aid for environmental protection and energy 2014–2020 indicates that RES competitive bidding will have to be implemented for almost all new installations in EU member states from 2017 onwards (European Commission 2014).

2 Description and examples of auction systems

2.1 Characteristics of the auction system

The main assumption of an auction system is that it lets the market decide which is the most competitive bid for the specified source of energy. It aims to reveal the real cost of a specific project/technology and ensure a cost-effective level of support (European Commission 2014). Auctions give a reliable and long-term income for RES investors as well as clear information for the public authority over the support provided. Therefore they are considered to deal with asymmetric information problem well, which can be severe, especially in technologies with large uncertainties about their cost trends (del Rio and Linares 2014). They also increase the transparency of the procurement process.

At the same time, the literature recognizes the potential failures of the auction mechanism. On the one hand, lack of competition may lead to high tariffs and overcompensation. On the other hand, in a very competitive area there is a risk of underbidding, resulting in high levels of contract failures (Maurer and Barroso 2011, European Commission 2014, IRENA 2013, REN21 2015). Auctions are also often criticized for being suitable only for large-scale established developers, as small-scale or new project developers are deterred by high transaction costs and uncertainty over auction results (IRENA 2013, del Rio and Linares 2014). Most empirical studies show that auctions are successful in reducing the price of RES, but problems with high transaction costs and contract failures seem to be rather common (e.g.: Elizondo-Azuela et. al. 2014, Held et. al. 2014, del Rio and Linares 2014).

The literature reveals a fairly broad range of overviews of the main features and performance of different types of RES support schemes. However, many papers focused on the comparison of feed-in tariffs and renewable purchase obligations, as these mechanisms were prevalent in public policy choices until recently (e.g. Menanteau, Finon and Lamy 2003, Lauber 2004, Ringel 2006, Rivers and Jaccard 2006, Fouquet and Johansson 2008, Jacobsson et. al. 2009, Fischer and Preonas 2010, Tamás, Bade Shrestha and Zhou 2010, Schmalensee 2012, Marschinksi and Quirion 2014). Del Rio and Linares (2014) even indicated that in some sense auctions had been widely dismissed. Yet the dissemination of the competitive bidding mechanism for RES support over the world has resulted in a visible increase in researchers' concerns about its characteristics, design options and performance (e.g.: Nielsen, Sorknæs and Østergaard 2011, Maurer and Barroso 2011, Mayr, Schmidt and Schmid 2014, Elizondo-Azuela et. al. 2014, del Rio et. al. 2015b).

2.2 Technological diversity as auction design option

A wide range of options exist for designing auctions, and implemented schemes differ a lot between countries. In fact, the design of an auction is the main determinant of its effectiveness (del Rio and Linares 2014). However, there is no "one-size-fits-all" type of auction design, and each time it has to be adapted to the specific conditions of a given country's power sector conditions (Maurer and Barroso 2011). Although the process of selection of individual auction system characteristics is challenging, the flexibility of the instrument gives public authorities the opportunity to achieve particular public policy objectives (IRENA 2013).

The design of an auction must take into account various factors. The most important are: the supply and demand specification (auctioned targets/scope/volume, technological specification, size, actors and geographical diversity, prequalification criteria); the criteria for selecting winners (price-only or multi criteria award, pricing rules, price ceilings and minimum prices); and contract characteristics (contract duration, penalties for non-compliance/delays, updating of remuneration over time) (Elizondo-Azuela et. al. 2014, del Rio et. al. 2015a). In the context of this paper, supply specification with regard to technological diversity is the key issue. In general, auctions can be either technology-neutral or technology-specific. In technology-neutral auctions, different technologies compete among each other in the same auctions. This results in the system achieving maximum cost-efficiency, as only the least costly technologies are successful. What is more, technology-neutral auctions reduce the risk of undercontracting due to lack of competition. However, in such auction systems, only mature (i.e. the cheapest) technologies are promoted. That discourages technological diversity and does not incentivize innovation for immature technologies. In technology-specific auctions, the bidding process is limited to a selected technology or group of technologies, usually defined as technology bands. This allows the public authority to drive multiple policy objectives and provides diversification of energy mix. Technology-specific auctions can reduce RES costs, since supported immature technologies may outperform more mature technologies in the future. They have also some disadvantages, as the fragmentation of the bidding process leads to lower competition (IRENA 2013, del Rio and Linares

2014, IRENA and CEM 2015).

Technology-neutral auctions have taken place is various countries, e.g. in the Netherlands and Brazil. The case of the Netherlands shows that the act of defining the technologies eligible for support is crucial. The auction system in this country allows competition between renewable electricity, renewable heat and renewable gas – all under one budget. As a result, low-cost heat technologies consume most of the budget available. The system has been criticized for not driving innovation; however, the main government's goal has been achieved, as the auction system resulted in a significant reduction of support costs, at least in the short run. Moreover, the less mature technologies can benefit from incentives outside the auction system, such as subsidies and tax benefits for R&D (Held et. al. 2014). In Brazil, auctions can be both technology-neutral and technology-specific. In the period 2007–2010 all auctions involving RES were technology-specific. This, together with high local content requirements (e.g. a minimum share of components had to be sourced from Brazilian suppliers), led to market development and rapid growth of domestic supply chains, especially in the wind power sector. As a result, wind technologies managed to become competitive in technology-neutral auctions, which also cover conventional sources. Yet there are concerns that wind may be crowding out other RE technologies (IRENA 2013, Elizondo-Azuela et. al. 2014, IRENA and CEM 2015).

Differentiating auctions between technologies is a widespread practice, and is applied more frequently than technology-neutral auctions. This is the case e.g. in India, Morocco, Peru and South Africa (IRENA 2013, del Rio and Linares 2014). In general, technology-specific auctions are recognized as being advantageous for less mature technologies and promoting energy-mix diversity. However, these features are not a given and their presence depends substantially on public policy choices. In South Africa, separate auctions were carried out in the years 2011–2013 for onshore wind, concentrated solar power, photovoltaics, biomass, biogas, landfill gas, small hydro and small projects (<5 MW). Maximum capacity limits were set for each technology in each auction, so there was no competition between different technologies. Yet the results of the auction were not satisfying, as the lack of competition led to high average prices and no successful bids in some of the technology bands (de Lovinfosse, Janeiro and Gephart 2013).

The technology-specific auction system is also currently being introduced in Germany. Pilot auctions for photovoltaics took place in 2015 and they have been assessed as successful, with intensive competition being their most important feature. From 2017 funding will be auctioned for onshore wind, offshore wind, photovoltaics and biomass projects (Müller 2016). The public authorities have indicated three main objectives for introducing the auction system. Firstly, support for renewable energy should be concentrated on the least expensive projects. Secondly, the targets for renewable energy capacity expansion and deployment corridors for each technology should be met. Thirdly, stakeholder diversity should be ensured (BMWi 2015). It is emphasized that different technologies require different conditions, therefore unified auctions for all technologies are pointless. Meeting the imposed objectives – especially the second one – is not possible under the technology-neutral auction system. However, to meet the objectives, the auctions' design, beyond being technology-specific, should also promote significant competition between the projects, provide high probability and assurance that the projects will be realized as well as ensure that the bidding process is simple, transparent and attainable for all actors (BMWi 2015, Ecofys 2015).

An RES auction system has also recently been introduced in Poland (since July 2016). In this case, the system chosen is a mix of technology-neutral and technology-specific auction designs. The Act on Renewable Energy Sources introduced seven categories of installations: with a capacity higher than 3504 MWh/MW/year; with a capacity higher than 3504 MWh/MW/year and CO2 emissions lower than 100 kg/MWh;

using waste in producing energy; using solely biogas in producing energy; owned by members of an energy cluster; owned by members of an energy cooperative; other. On the one hand, this means that the auction system in Poland is not fully technology-neutral, because there are some limitations on the participation of different technologies. On the other hand, the system is not fully technology-specific, because most of the bands are dedicated to more than one specific technology. The defined bands give high preference for some energy sources such as water, biogas and multi-fuel installations burning biomass together with coal, while the most common clean energy sources – wind and photovoltaics – can compete in principle only in the last of the seven categories listed. The government has stated that the system aims at providing more support for technologies which generate energy in a stable and predictable manner. It also leads to a better use of locally available resources (especially biomass) (Act on RES 2016). The Polish example shows that technology differentiation in auctions is not only a case of selection between technology-neutral and technology-specific systems, but can also be linked with more detailed auction design options, public policy choices and country-specific conditions.

3 The analytical model

The primary aim of this section is to examine the costs and benefits of RES differentiation when the outcome of the technology development process brings uncertain results. We abstract from the other benefits of differentiation, for instance, due to the intermittency of some RES.

The theoretical results are derived from the closed-form solution of a simple analytical model. The purpose of the analysis is to understand which policies minimize the expected price of renewable energy. In the model we assume that the expected price is given by the cost of the technologies, which in turn is determined by learning processes and exogenous technological shocks for a set of RES technologies. The learning rate parameters as well as the realizations of the exogenous technological shocks are random and distinct for each technology. Policies promoting a large number of technologies, which correspond to a wide range of technology-specific auctions, on the one hand will require support for technologies which are initially relatively costly, but on the other hand will allow a large number of technologies to benefit from the learning-by-doing process. Policies supporting only the cheapest technology, coresponding to technology-neutral auctions, will result in lower energy costs initially, but will limit the learning process for all remaining technologies. As we will demonstrate in this section, both, the costs and benefits of the differentiation depends on the variance of learning rates and the variance of exogenous shocks.

3.1 The set-up of the model

In the model we will consider two periods. The assumed timeline is presented in figure 1 and discussed below.

In the first period, which we index with $t = 1$, all technologies are still in the development stage. The government in this period takes two actions. First, by designing the auction system, it decides how many technologies will have a secured demand in period $t = 1$. The choice of a technology-neutral auction implies that only one technology is supported for this period. Large differentiation would correspond to a large number of technology-specific auctions. The commitment to organize an auction for technology i implies that the capacity of that technology will grow by $\Delta \ln (Capacity_{it}) = \Delta_{1i} > 0$. Technologies without a dedicated auction or, in the case of a technology-neutral auction system, technologies which do not win that auction, will have no growth of capacity. We will use $\mathcal{N}$ to denote the set of supported technologies, n to denote the number of supported technologies and $\mathcal{S}$ to denote the set of technologies which did not receive any support. Finally, Δ stands for the vector of Δ_i's. Note that this vector contains all the information of the policy (including information on the number of technologies supported by the policy). Importantly, in this paper we do not examine the consequnces of altering $\Delta_i's$ other than the choice between setting $\Delta_i = 0$ and $\Delta_i > 0$. In other words, in this paper we only examine the effects of increasing the number of supported technologies and not the effects of increasing or decreasing the size of this support. One consequnce of this is that we will not discuss the costs of differentiation in terms of lowering the support for already-supported technologies. This narrowing of the focus is discussed after proposition 1.

The second task of the government in the first period is to organize an auction and purchase electricity at a cost determined by the state of technology at that moment of time.

The cost of each technology in period 1 is determined by an exogenous shock, i.e. a shock which is independent of the learning-by-doing process in period 1. These shocks could be the outcome of the past learning-by-doing process or by technological breakthroughs. We label the shock as exogenous since it is independent of the current policy choices. The shock sets the cost of technology i at the level of $e^{-\eta_{1i}}$. We assume that it takes place before the government selects the supported technologies. The reason for the explicit modeling of this shock and its interpretation is presented in section 3.3.

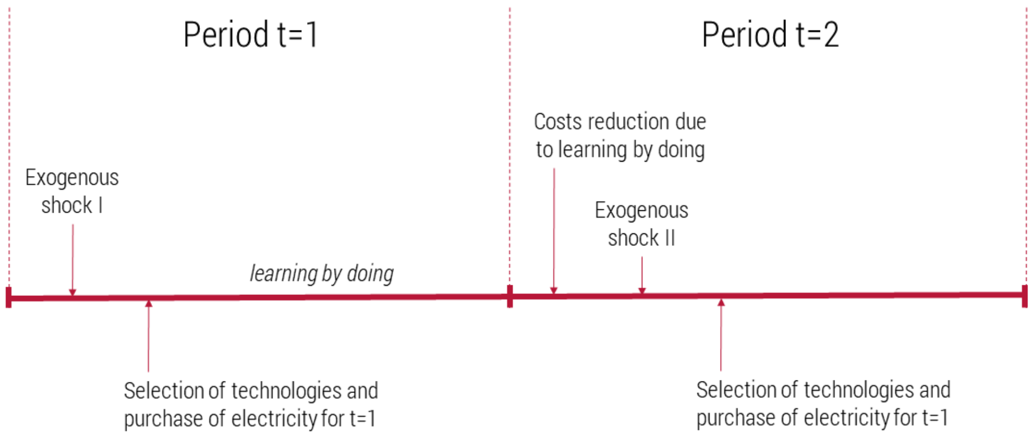
The firms will manufacture the technologies which received funding through auctions; this manufacturing is accompanied by the learning-by-doing process. The learning process will result in the reduction of the cost of a given technology for the period 2 by a factor $e^{\gamma_i \Delta_{1i}}$, where γ is the slope of the learning curve[1]. We allow the parameter γ to be random, independent and identically distributed (i.i.d.) across technologies with a distribution defined by the cumulative density function $G(x)$. In order to ensure the tractability of the derivations, whenever we consider random learning we assume that γ is positive and $0 < G(x) < 1$ for any positive finite number, which implies that there is a positive probability that the learning rate is zero and that there is no upper bound for the learning rate. This last assumption is discussed in detail in section 3.2.

In addition, the cost of technology in period 2 is affected by the second exogenous shock, which takes place at the beginning of period 2. Thus, the final cost of the technology at the time it is purchased in period 2 is given by $e^{-\gamma_i \Delta_{1i} - \eta_{1i} - \eta_{2i}}$. For mathematical convinience we will use $A_i \equiv e^{-\eta_{1i} - \eta_{2i}}$ to denote the total effect of the two exogenous shocks. Let $H(x)$ denote the cumulative density function of the shock η_{2i}. Whenever we consider the random exogenous shock in period 2, we assume that $0 < H(x) < 1$ for any positive finite number, which implies that there is a positive probability that the shock is zero and that the shock has no upper bound.

In the second period (indexed with $t = 2$), the central planner chooses the winning technology - the optimal (most productive) technology to serve the entire market. We fix the demand in the second stage and normalize it to unity. Thus, the demand for the technologies is $\Delta_{2i} = 1$ for the optimal technology and $\Delta_{2i} = 0$ for all the remaining technologies.

[1] The slope is directly related to the well-known learning rate parameter: $learning\ rate = 1 - 2^{-\gamma}$

Figure 1. Model timeline



3.2 Random learning rate - general result

The standard learning curve is the relation between the total cumulative installed capacity of the technology and its instalation cost

$$\ln\left(Cost_i\right) = -\gamma_i \ln\left(Capacity_i\right)$$

The curve is built on the presumption that reduction in costs of technology depends on the demand for instalations (i.e. a change in cumulative capacity) in a given period of time. This dependence could be explained by either the concept of learning-by-doing, i.e. a reduction in manufacturing costs due to the accumulation of experience, or by an increase in investment in R&D when firms are guaranteed demand over a given period of time (Witajewski-Baltvilks et al. 2015). In our set-up the manufacturing takes place in period 1 and its fruits are harvested in period 2.

Note that in this set-up the uncertainty of the learning process does not have any impact on the costs of electricity in period 1. For example, if two, otherwise identical, countries face different variances of the learning process the two countries will experience exactly the same costs/benefits of differentiation in the first period. However, the optimal policy in the two countries could be different due to differences in the benefits of differentiation in the second period. Consequently, to examine the effect of the variance of the learning on the optimal policies, it is sufficient to examine the relation between the differentiation and the expected electricity cost in the second period[2].

Since $\Delta_{1i} = \Delta \ln\left(Capacity_{1i}\right)$, the unit instalation cost for technology i at time $t = 2$ is $A_i e^{-\gamma_i \Delta_{1i}}$, where

[2] More formally, if the objective is to select policy which minimizes the weighted cost of energy in the two periods $\min_n W = \omega_1 c_1\left(n, v\right) + \omega_1 c_1\left(n\right)$ where c_1, c_2 are the costs of renewable electricity in the two periods, ω_1 and ω_2 are the weights and v is the variance of learning rates, then the optimal policy is given by the sign of $\omega_1 \frac{dc_1(n,)}{dn} + \omega_2 \frac{dc_2(n,v)}{dn}$ or by the condition $\omega_1 \frac{dc_1(n,)}{dn} + \omega_2 \frac{dc_2(n,v)}{dn} = 0$. Thus a change in v could affect the optimal choice of n only through a change in $\frac{dc_2(n,v)}{dn}$.

A_i is determined by the exogenous technological shocks (for future reference, let us define A as the vector of A_i's for the set of all available technologies). There will be one "winner of the race" - the technology with the lowest cost among all technologies. We wish to determine how the expected cost of this "winning" technology depends on the planner's choice of n in period $t = 0$.

In this subsection we assume that learning is the only source of uncertainty. This implies that $Var\left(\eta_i\right) = 0$ and thus the realization of η_{2i} is known to the planner in Period 1.

The probability that the cost of the best technology in period 2 will be larger than z is the probability that $e^{-\gamma_i \Delta_{1i}} A_i > z$ for every i. Since γ's are independent, the cumulative density function of the winner's cost in period 2 conditional on the realization of the exogenous shocks and policy choices, $F\left(z|A, \Delta\right)$ will be then defined by

$$1 - F\left(z|A, \Delta\right) = \prod_{i \in N \cup S} P\left(A_i e^{-\gamma_i \Delta_{1i}} > z|A, \Delta\right) \tag{1}$$

where $P\left(X\right)$ denotes the probability of an event X.

Now consider two alternative policy choices. The first choice, indexed with $p1$, is given by the vector Δ^{p1}. The second choice sets $\Delta_{1i}^{p2} = \Delta_{1i}^{p1}$ for every $i \in N^{p1}$, that is every technology which received support under the first choice receives the same support under the second policy choice. In addition, the second policy choice sets $\Delta_{1k}^{p2} > 0$ for technology k from the set S^{p1}, that is $p2$ supports one technology which did not receive the support under the first policy choice.

Now suppose for a moment that at the start of the learning process all technologies are symmetric, i.e. $A_i = \overline{A}$ and for every $i \in N \cup S$. Then, recalling that $\gamma_i > 0$, 1 could be expressed as

$$1 - F\left(z|A, \Delta^{p2}\right) = G\left(\frac{1}{\Delta_{1k}} \ln\left(\frac{A_k}{z}\right)\right) \prod_{i \in N^{p1}} G\left(\frac{1}{\Delta_{1i}} \ln\left(\frac{\overline{A}}{z}\right)\right) \leq$$

$$\prod_{i \in N^{p1}} G\left(\frac{1}{\Delta_{1i}} \ln\left(\frac{\overline{A}}{z}\right)\right) = 1 - F\left(z|A, \Delta^{p1}\right)$$

with the inequality being slack for every $z \leq A$ (otherwise both sides of an equality may be equal to zero). Consequently, the policy which excludes investment in technology k results in a cumulative density function which first order stochastically dominates the cdf resulting from the policy which includes investment in technology k. In other words, the probability that the expected cost is larger than z under larger differentiation is never larger than under low differentiation and is strictly smaller for some values of z. This implies that the expected cost of renewable electricity in the second period must be lower under larger differentiation.

In the case of no uncertainty, the expected value is $E_n\left(z\,|\Delta_{i1}\right) = \max\left\{A_i e^{\gamma \Delta_{i1}}\right\}$, which does not depend on the number of technologies.

For the general case (relaxing the assumption on symmetry), we find the following result:

Proposition 1 Consider the set-up outlined in section 1.1. An increase in the number of technologies with positive investment which does not affect the level of investment for the already supported technologies decreases the expected cost of the winner technology. When there is no uncertainty, there is no benefit from the larger differentiation between technologies.

Proof The proof for the symmetric case is presented in the text. Below we derive the proof for the general case.

Using 1, we find that

$$1 - F\left(z|A, \Delta^{p2}\right) = \prod_{i \in N^{p2} \cup S^{p2}} P\left(A_i e^{-\gamma_i \Delta_{1i}} > z\right)$$

$$= \prod_{i \in N^{p1}} P\left(\gamma_i < \frac{1}{\Delta_{1i}} \ln\left(\frac{A_i}{z}\right)\right) P\left(\gamma_k < \frac{1}{\Delta_{1k}} \ln\left(\frac{A_k}{z}\right)\right) \prod_{i \in S^{p2}} P\left(A_i > z\right)$$

$$= G\left(\frac{1}{\Delta_{1k}} \ln\left(\frac{A_k}{z}\right)\right) \prod_{i \in N^{p1}} G\left(\frac{1}{\Delta_{1i}} \ln\left(\frac{A_i}{z}\right)\right) \prod_{i \in S^{p2}} P\left(A_i > z\right)$$

$$\leq P\left(A_k > z\right) \prod_{i \in N^{p1}} G\left(\frac{1}{\Delta_{1i}} \ln\left(\frac{A_i}{z}\right)\right) \prod_{i \in S^{p2}} P\left(A_i > z\right)$$

$$= 1 - F\left(z|A, \Delta^{p1}\right)$$

The assumption that $G(0) > 0$ (there is a positive probability that a learning rate is positive) implies that if $z \leq \min_{i \in N \cup S}\{A_i\}$, then $\prod_{i \in N^{p1}} G\left(\frac{1}{\Delta_{1i}} \ln\left(\frac{A_i}{z}\right)\right) \prod_{i \in S^{p2}} P\left(A_i > z|A, \Delta^{p2}\right) > 0$. In addition, it implies that $z < A_k$ and thus $P\left(A_k > z\right) = 1$. Finally, the assumption that $G(x) < 1$ for any finite positive x (which means that there is no upper bound for the learning rates) ensures that $G\left(-\frac{1}{\Delta_{1k}} \ln\left(\frac{z}{A_k}\right)\right) < 1$. Together, these results imply that for $z \leq \min_{i \in N^{p1}}\{A_i\}$, the condition above is slack: the cumulative density function for the policy choice which excludes investment in technology k first order stochastically dominates the cdf for the policy choice that includes investment in technology k. That is, as in the symmetric case, the probability that the expected cost is larger than z under larger differentiation is never larger than under low differentiation and is strictly smaller for some values of z.

The stochastic dominance then implies the strict inequality for expectation of cost: $E\left(z\left|\Delta^{p1}\right.\right) > E\left(z\left|\Delta^{p2}\right.\right)$. In our case this can be easily demonstrated using the fact that the cost must be positive:

$$E\left(z\left|\Delta^{p2}\right.\right) = \int_0^\infty z f\left(z\left|\Delta^{p2}\right.\right) dz$$

$$= \int_0^\infty \left(1 - F(z)\right) dz$$

$$= \int_0^{\min_{i \in N^{p1}}\{A_i\}} \left(1 - F\left(z\left|\Delta^{p2}\right.\right)\right) dz + \int_{\min_{i \in N^{p1}}\{A_i\}}^\infty \left(1 - F\left(z\left|\Delta^{p2}\right.\right)\right) dz <$$

$$\int_0^{\min_{i \in N^{p1}}\{A_i\}} \left(1 - F\left(z\left|\Delta^{p1}\right.\right)\right) dz + \int_{\min_{i \in N^{p1}}\{A_i\}}^\infty \left(1 - F\left(z\left|\Delta^{p1}\right.\right)\right) dz = E\left(z\left|\Delta^{p1}\right.\right)$$

In the case of no uncertainty, the expected value is $E_n\left(z\left|\Delta_{i1}\right.\right) = \max\left\{A_i e^{\gamma \Delta_{i1}}\right\}$, which does not depend on the number of technologies.

QED

The proposition involves two important assumptions, which we discuss below.

Fixed investment for remaining supported technologies In the proposition we compare two policies which differ only in the number of supported technologies. This set-up implicitly implies that support for an additional technology does not require a reduction in demand for the technologies which are already supported under smaller differentiation. There are two reasons why in this paper we have focused on this case. The first reason is its mathematical tractability. The second reason is that this dependency is already accounted for in the bottom-up models on optimal differentiation. The primary aim of our paper is to discuss the costs of benefits of differentiation that were not previously discussed by the literature and to understand in what direction they may bias the previous modeling results and encourage accounting for them in the new generation of energy models. Since the costs of differentiation in terms of lower support for other technologies has been already covered in the literature, we do not elaborate on it further in our study.

Nevertheless, to illustrate the potential trade-off between insurance provided by differentiation and its cost in terms of lowering the scale of the learning-by-doing for selected technologies, in section 3.3 we sketch a simplified model of optimal RES mix which allows Δ_{1i} to depend on the total number of supported technologies.

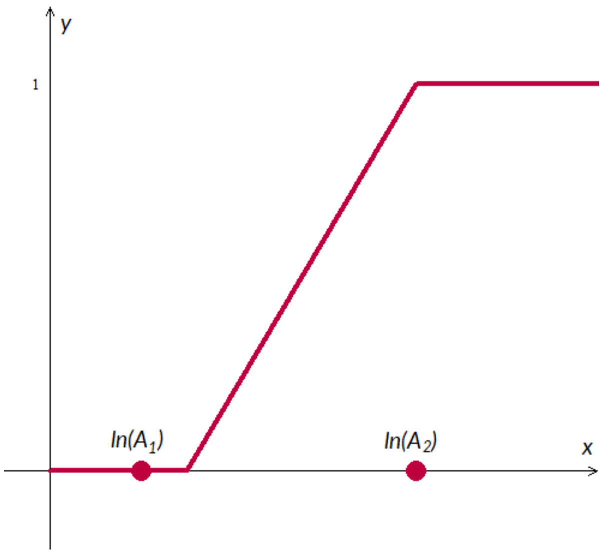
No upper bound for the learning rates The second important assumption, which ensures that Proposition 1 holds, is the assumption of no upper bound for the learning rate. This assumption cannot hold in the presence of floor costs, which can arise when the productivity of a given technology is constrained by physical limits. The presence of floor costs has been challenged by some studies. For instance, Young (1993) argues that while in the short run the learning process could indeed be bounded, in the long run these bounds can be shifted by research (or a learning-by-searching process). Nevertheless, even if there are no long run limits on productivity improvement (e.g. because the constrained physical processes that a given technology currently relies on can be replaced by processes that are not yet known or understood by scientists at the moment), the physical limits may imply a bound on learning processes in the short run, particularly for narrowly defined technologies.

To understand why the result in the proposition might not hold when the learning rate is bounded, consider the following example. Suppose that there are only two technologies: technology 1 and technology 2 characterized by A_1 and A_2, and learning rates γ_1 and γ_2 respectively. Assume also that the learning rates have the uniform distribution $\gamma \sim Uniform\left[0, \overline{\gamma}\right]$. The government considers whether to support both technologies or to limit the support to technology 1. Suppose also that $\frac{A_1}{A_2} < 1$, i.e. prior to learning-by-doing technology 1 is cheaper than technology 2. This is presented in figure 2. The dashed line represents the probability that the logarithm of the cost of technology 2 is smaller than x . If $A_1 < A_2 e^{\Delta_2 \overline{\gamma}}$, that is if the bound of the learning rate $\overline{\gamma}$ is small relative to the distance between $\ln\left(A_1\right)$ and $\ln\left(A_2\right)$, then technology 2 cannot compete with technology 1 even if it reaches maximum learning-by-doing for a given support Δ_2.

The example above shows that the benefits of differentiation are questionable mark when the differentiation involves support for technologies whose costs are currently much higher than the costs of the cheapest renewable technologies. If experts agree that these technologies will never be able to compete with other RES technologies, supporting them will be a waste of resources.

Consequences for energy modeling In the current generation of bottom-up models the predictions of an optimal policy which involves support for more than one technology is usually achieved by adopting a series of physical constraints on renewable energy sources. For instance, while the models often indicate

Figure 2. Example of the problem with bounded learning rates



that hydroelectric power is the cheapest renewable energy source, they also indicate benefits from investing in other sources since the large-scale deployment of hydro-power is constrained by the availability of appropriate sites. Since the models assume constant learning rates, they do not take into account the benefits of differentiation resulting from the uncertainty of the learning rates. Consequently the optimal level of differentiation predicted by these models is biased downward.

3.3 A simple model of the optimal RES mix

In this section we illustrate the prediction of proposition 1 using a simple stylized model of optimal differentiation between RES technologies. We show that ignoring the uncertainty of learning curves causes the bias of model prediction: according to the model the optimal differentation is smaller than the differentiation when uncertainty on the learning curves is taken into account.

In this section we introduce several additional assumptions in order to improve the mathematical tractability of the model. These assumptions facilitate the exposition of the key forces driving the benefits and costs of differentiation under uncertainty of the learning rate and allow for simple graphical illustration of the results. However, it is important to stress that the general result in proposition 1 is independent of these additional assumptions.

Suppose that the planner must supply the following fixed quantities of electricity: Q_1 in period 1 and Q_2 in period 2. In period 2, the planner will deliver the electricity by employing the cheapest available technology. In period 1, the planner will need to design an auction system which distributes the demand Q_1 across n technologies. The task of the planner will be to choose the optimal number of supported technologies with an objective of minimizing the expected value of the total cost of electricity produced from renewables.

In order to simplify the model, in this section we assume that all technologies face the same marginal cost in period 1: $A_i = 1$ for every i. This assumption implies that if the planner decides to support n technologies, the demand will be spread equally across all these supported technologies: $q_{1i} = \frac{Q_1}{n}$.

In this case the planner's minimization problem can be stated as

$$\min_{n}\left\{\sum_{i}^{n}\frac{Q_1}{n}+E_n\left(z\right)Q_2\right\} \quad (2)$$

where $E_n\left(z\right)$ is the expected cost of the cheapest technology in the second period. The next step is to express this expectation in terms of the number of supported technologies, n.

Each technology that is granted an auction will experience a growth of its cumulative capacity by a positive factor $\Delta_{1i}>0$. Since Δ_{1i} stands for the growth relative to the capacity at the beginning of period 1, we need to make an additional assumption regarding that initial capacity. To preserve the symmetry of the problem we will assume that the initial capacity is given by q_0 and is the same across all technologies. This implies that $\Delta_{1i}=\frac{q_{1i}}{q_0}=\frac{Q_1}{q_0 n}=\Delta_1$, which is invariant between all supported technologies.

As in the set-up proposed in the previous section, we assume that firms then build the capacity, according to planner's decision determining Δ_{1i} , and improve the technology through learning-by-doing. The improvements will increase the productivity of the technology and reduce its cost to the level of $e^{-\gamma\Delta_1}$.

Finally, to ensure that the solution to the minimization problem takes a closed form, we assume that γ follows the Gumbel distribution. In this case its cumulative density function is given by $G\left(x\right)=e^{-e^{-\frac{x-\mu}{\beta}}}$, where $\beta>0$ is the scale parameter and μ is the location parameter. The variance of γ is given by $Var\left(\gamma\right)=\frac{\pi^2}{6}\beta^2$.

Under these assumptions it can be shown that the expected value of the cost of the cheapest technology in period 2 is given by (for detailed derivations, see the appendix)

$$E\left(z\right)=n^{-\beta\Delta_1}e^{-\mu\Delta_1}\Gamma\left(1+\beta\Delta_1\right) \quad (3)$$

where $\Gamma\left(.\right)$ is the well-known gamma function. This expression allows us to identify two contradicting effects of technological differentiaiton.

First, for the fixed Δm the expression is clearly decreasing in n, implying that a larger number of varieties reduces the expected cost of the most effective technology in the second period. This captures the notion that every additional technology in the basket of auctioned technologies carries a positive probability that its learning rate will be larger than any other technology.

Second, differentiation increases the expected price through its negative effect on Δ_1. To understand this, suppose that at the beginning of period $t=1$ all technologies have a capacity equal to $\frac{Q}{N}$ and suppose that the planner expects that over this period the total capacity will increase to $Q\left(1+g\right)$. Since the total auctioned capacity is spread equally across technologies, the change in capacity for each technology between period 0 and 1 is given by $\frac{Q(1+g)}{n}-\frac{Q}{N}$ and the growth of capacity for each technology is given by $\Delta_1=\frac{gN}{n}$, which is inversely proportional to n. Since for $\beta<\xi=1.44$ (ξ is the argument minimizing the Gamma function in its positive domain) the expected costs are decreasing in Δ_1, an increase in n will lead to an increase in costs through this channel.

The simple intuition for this dependency is that for a fixed increase in total capacity, more technologies involves a smaller increase in capacity per technology reducing the scale of learning-by-doing. As a result we shall expect a smaller drop in the cost for each technology.

The presence of these two counteracting effects implies the first trade-off between widening and narrowing

Figure 3. Optimal number of supported technologies as a function of $Var\left(\gamma\right)$

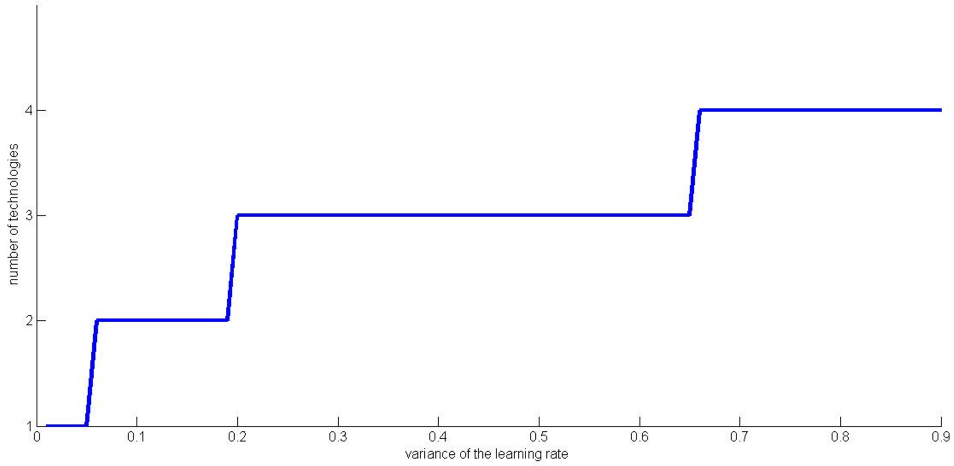


Table 1. Optimal auction design for the various levels of learning rate variance

Variance of the learning parameter	Optimal auction design
$Var\left(\gamma\right) \in (0, 0.06)$	technology-neutral auction or auction for one technology
$Var\left(\gamma\right) \in [0.06, 0.20)$	auction with separate baskets for two technologies
$Var\left(\gamma\right) \in [0.20, 0.66)$	auction with separate baskets for three technologies
$Var\left(\gamma\right) > 0.66$	auction with separate baskets for four technologies or more

technological differentiation. The First Order Conditions to the problem stated in euqations (2) using (3) implies that (for the interior solution) the optimal choice of n will satisfy

$$\ln\left(n\right) = 1 - \frac{\mu}{\beta} + \psi\left(1 + \beta\Delta_1\right)$$

where ψ is a digamma function. The optimal number of supported technologies for different values of the variance of the learning parameter γ, which measures the degree of uncertainty associated with the realization of the learning rates, is plotted in figure 3 and presented in table 1.

Notice that when there is no uncertainty ($\beta = 0$), then the planner's minimization problem takes the form $\min_n \left\{Q_1 + e^{-\mu\Delta_1}Q_2\right\}$, which is clearly decreasing in Δ_1 and thus increasing in n. Now the trade-off between benefits and costs of differentiation disappears: the model predicts that the cost will be minimized when the planner chooses the smallest possible number of technologies for period 1, $n = 1$. In other words, when the uncertainty on the value of the learning rate is ignored, the model biases the projection on the optimal level of RES differentiation downward.

We stress again that the sole purpose of this subssection was to illustrate the predictions of proposition 1 in the most tractable way possible. The results of the simulation presented in figure 3 and in table 1 show that a higher level of uncertainty regarding the learning rate should incentivize a higher differentiation of RES in the energy mix. However, it is important to keep in mind that this simulation ignores the other benefits of an increase in differentiation, such as complementarity between intermittent RES.

3.4 The exogenous technological shocks

In this section we will explore the effect of an alternative form of uncertainty: instead of uncertainty in the learning-by-doing, we will allow the costs of the technology installed to be hit by an exogenous shock, such as a change in material prices or scientific discoveries and technological inventions that are independent of the learning-by-doing process. As indicated in figure 2, we will distinguish between two types of shocks. The first type can take place before the government selects the supported technologies for period 1. In effect, this shock will determine the heterogeneity of technologies at the moment of the planner taking the decision in period 1. Larger variance of shocks should be therefore interpreted simply as an increase in technological heterogeneity. The second type of shock takes place after the selection, and thus remains random at the moment of auction design. In effect, this shock will be a source of uncertainty faced by the planner at period 1. We will examine each of these shocks in the separate subsections.

The reason why we distinguish between these two types of shocks is to highlight the fundamentally different consequences of these two types of shocks for the effects of differentiation at period 1. While the presence of type I, i.e. the presence of heterogeneity, will increase the costs of differentiation, the presence of type II, i.e. the presence of uncertainty, implies that the differentiation brings benefits.

The separation of the costs and benefits will be helpful for understanding the implication of introducing exogenous shocks in more complicated models. In contrast to our simple two-period model, large energy system models and integrated assessment models include a large number of subsequent periods. Translating our results into predictions of these models imply that an exogenous shock at time t+1 will be of type II from the perspective of period t and of type I from the perspective of period t. In plain language, a shock which causes uncertainty from the perspective of period t also causes heterogeneity from the perspective of period t+1. Combining this with our result, this implies that exogenous technological shocks will increase the benefits of differentiation at time t as well as generate costs of differentiation at time t+1. The introduction of the distinction between type I and type II will allow us to disentangle these two effects.

In addition to the discussion of the costs and benefits of differentiation, in the following two subsections we will discuss how the effects depend on the feasibility of learning-by-doing. We will demonstrate that while the shock of type I always increases the costs of differentiaiton, the consuquences of the presence of type II will depend on whether or not the technologies may experience learning-by-doing. If yes, then the presence of type II will imply that differentiation brings benefits in terms of lower energy costs in the future. If not, even when type II shock is present differentiation brings no benefits. These results can be summarized with a policy recommendation: large and frequent exogenous shocks on technological costs imply that countries that do not have a chance to experience learning-by-doing should limit differentiation and choose the technologies which are cheapest at a given point in time.

3.4.1 The exogenous shocks of type I - before the choice of technologies for period 1.

We start by evaluating the effects of diversification in the presence of exogenous shocks of type I. In this subsection we assume that there are no exogenous shocks in period 2. We also assume that the learning rate is constant and known to the planner at the moment of taking the decision in period 1. Consequently the planner in period 1 does not face any uncertainty. However, the exogenous shock in type I generates heterogeneity, which has to be faced by the planner.

The consequences of this heterogeneity are straightforward. Since there is no uncertainty, the planner knows already in period 1 which technology will win the race and be selected in period 2. This implies that the diversification has no effect on the costs of electricity in period 2. On the other hand when, due to type I shocks, the costs of technology vary significantly, the diversification must imply a support for technologies which are far from being the leading (least costly) technology. The difference in the costs between technologies then constitutes the costs of diversification.

This logic is summarized by the following proposition and formally derived with the proof below.

Proposition 2

The presence of technological heterogeneity caused by the exogenous shocks of type I (the shocks before the choice of technologies in period 1) increases the costs of differentiation

Proof

The evaluation of the expected costs of energy in the period 2 when there is no uncertainty becomes trivial:

$$E\left(z|\Delta_{i1}\right) = \max_{i\in N}\left\{e^{-\eta_{i1}-\Delta_{i1}\gamma}\right\}$$

Since the technology with the lowest cost in the second period always belongs to the set N, the expression above does not depend on the size of set N.

Regarding the first period, the unit energy cost is given by $\sum_{i\in N}\omega_i e^{-\eta_{i1}}$, where $\omega_i = \frac{\Delta_{i1}}{\sum_k \Delta_{k1}}$. The benefit of an additional technology in the set N is given by

$$\sum_{i\in N}\omega_i e^{-\eta_{i1}} - \left(\sum_{i\neq j}\omega_i e^{-\eta_{i1}} + \omega_j \min_{i\in S}\left(e^{-\eta_{i1}}\right)\right) =$$

$$= \omega_j\left(e^{-\eta_{j1}} - e^{\min(-\eta_{i1})}\right) < 0$$

The condition implies that replacing one technology with the the technology which is characterized by the smallest possible cost will always lower the unit cost of the planner.

If there are no idiosyncratic shocks of type 1, i.e. if $\eta_{1i} = \eta_1$, then the expression above is equal to zero, i.e. there are no benefits to be derived from differentiation.

3.4.2 The exogenous shocks of type II - before the choice of technologies for period 1.

In the last subsection we examined the role of the exogenous shock in the second period. The randomness of the realization of the shock captures the uncertainty about the future costs of technologies which is faced by the central planner in period 1 and which does not originate from the uncertainty of the learning-by-doing process. The shock can be interpreted as an unexpected technological breakthrough that happens regardless of the current demand for technology, or an unexpected change in the material costs, which can have an asymetric effect on the costs of various renewable technologies.

The model predicts that the presence of such shocks increase the benefits of differentiation when the learning rate is positive (and not random). When learning is not possible, i.e. when the current demand for technology has no effect on the costs in the future, then the differentiation will bring no benefits.

The prediction has important policy implications. For example, it suggests that there is no reason to differentiate the technologies in the peripheral economies which cannot influence the costs of the frontier technologies. On the other hand, the possibility of shocks to future costs should encourage the countries at the technological frontier, which have significant learning potential, to diversify their portfolio of supported technologies even when the learning rate is constant or predictable.

The intuition behind the result is not immediate and requires careful explanation. We outline the logic behind the results in the subsequent paragraphs and conclude by restating the formal proposition and its formal proof.

First, note that since an exogenous shock of type II takes place only in the second period, it does not affect the costs of electricity in the first period. Consequently, its presence cannot affect the costs and benefits of differentiation in the first period. Therefore, as in the case of the uncertainty due to learning, it is sufficient to examine the effects of differentiation for the costs of electricity in the second period.

Next, consider a given technology which does not belong to the set of supported technologies. In the presence of type II shocks there is some non-zero probability that this technology will receive a large exogenous shock and become the winner in period 2. In this scenario, the winning technology could not benefit from the learning-by-doing, while the learning of the supported technologies was wasted. Conversely, if all technologies receive support, then in all possible scenarios the winning technology can benefit from the learning-by-doing process. Note that models that do not allow for the uncertainty of technological shocks are unable to capture this mechanism and therefore bias the benefits of differentiation downward.

We summarize the result in the following proposition:

Proposition 3

When learning-by-doing is not feasible then the presence of exogenous shocks of type II (shocks after learning-by-doing but before the final choice of technologies in period 2) has no effect on the benefits from differentiation.

When learning-by-doing is feasible, then the uncertainty due to the presence of an exogenous shock of type II increases the benefit of differentiation.

Proof

As explained in the text the presence of the random shock in period 2 has no effect on the benefits or costs of differentiation in period 1.

In period 2, the cost of electricity is characterized by the cdf function, $F(z)$, which can be derived as follows:

$$\begin{aligned} 1 - F(z) &= \prod_{i \in N} P\left(e^{-\eta_{1i} - \eta_{2i} - \gamma\Delta_{i1}} > z\right) \prod_{i \in S} P\left(e^{-\eta_{1i} - \eta_{2i}} > z\right) \\ &= \prod_{i \in N} P\left(\eta_{2i} < -\ln\left(z e^{\eta_{1i} + \gamma\Delta_{1i}}\right)\right) \prod_{i \in S} P\left(\eta_{2i} < -\ln\left(z e^{\eta_{1i}}\right)\right) \end{aligned}$$

$$= \prod_{i \in N} H\left(-\ln\left(ze^{\eta_{1i}+\gamma\Delta_{1i}}\right)\right) \prod_{i \in S} H\left(-\ln\left(ze^{\eta_{1i}}\right)\right)$$

Now suppose that the planner considers whether to add an economy j to the pool of auctioned technologies. Let $p1$ denote the policy with Δ^{p1} such that $\Delta_j = 0$ and $p2$ denote the policy with Δ^{p2} such that $\Delta_j > 0$. For the first policy, the expression above becomes

$$1 - F\left(z|\Delta^{p1}\right) = \prod_{i \in N^{p1}} H\left(-\ln\left(ze^{\eta_{1i}+\gamma\Delta_{1i}}\right)\right) \prod_{i \in S^{p2}} H\left(-\ln\left(ze^{\eta_{1i}}\right)\right) H\left(-\ln\left(ze^{\eta_{1j}}\right)\right)$$

and for the second policy it becomes:

$$1 - F\left(z|\Delta^{p2}\right) = \prod_{i \in N^{p1}} H\left(-\ln\left(ze^{\eta_{1i}+\gamma\Delta_{1i}}\right)\right) \prod_{i \in S^{p2}} H\left(-\ln\left(ze^{\eta_{1i}}\right)\right) H\left(-\ln\left(ze^{\eta_{1j}+\gamma\Delta_{1j}}\right)\right)$$

Since H must be an increasing function, and since $\Delta_{1j} > 0$, if $\gamma > 0$, then $F\left(z|\Delta^{p2}\right) > F\left(z|\Delta^{p1}\right)$ at least for some $z > 0$. If $\gamma = 0$ then $F\left(z|\Delta^{p2}\right) = F\left(z|\Delta^{p1}\right)$. Thus, as in the proof of proposition 1,

$E\left(z\left|\Delta^{p2}\right.\right) < E\left(z\left|\Delta^{p1}\right.\right)$ if $\gamma > 0$ and $E\left(z\left|\Delta^{p2}\right.\right) = E\left(z\left|\Delta^{p1}\right.\right)$ if $\gamma = 0$.

When there is no uncertainty $E_n = \max\left(A_i e^{\gamma\Delta_i}\right)$, which does not depend on the number of varieties, that is there will be no benefit of differentiation.

QED

Importantly, when Δ_{i1} is endogenized, then the total effect of differentiation (which includes the negative effect through a deacrease in Δ_{i1}) depends on the shape of the distribution, H. Since the endogeneity of Δ_{i1} is already captured in the energy models, we leave the exploration of this case for future research involving the use of these models.

4 Summary

In public policies there is a consensus that the market itself does not provide the desirable level of energy from RES, therefore there is a need for public intervention in that area. In recent years, policies of support for RES deployment show a visible shift from systems based on feed-in-tarrifs, feed-in-premiums or quota obligations to systems based on auctioning. In the auction system the support is given to those investors who offer the most competitive bid (lowest price) for a certain amount of energy produced from renewables.

Previous experience of the auctioning system suggests that the crucial determinant of an auction's effectiveness is its optimal design. There is a set of design options related to supply and demand specification, the process of selecting winners and contract characteristics, which ultimately determine whether the auction is successful. However, there is no one-size-fits-all auction design, and in every case it has to be adapted to specific country conditions.

One of the most important auction design options is technological diversity. On the one hand, technology-neutral auctions lead to maximum cost-efficiency and high competition, but almost entirely exclude less mature technologies from the system of support. On the other hand, technology-specific auctions ensure diversification of the energy mix, but bring the risk of too low competition and overcompensation. Therefore the choice between technology-neutral and technology-specific auctions represents a significant challenge for public policies.

The aim of this article was to answer the question of whether governments should support development of a wide range of different RES, or instead focus on supporting a select few? We show that the answer depends on the nautre of uncertainty associated with the progress (future costs) of RES technologies. We divide this uncertainty into two types – uncertainty about the magnitude of the learning-by-doing effect, as well as uncertainty about the possibility of future technological shocks (random and exogenous to the capacity of specific technology installed).

Our model shows that in the presence of uncertainty on the learning rate, the more technologies that are supported, the lower is the expected cost of the winning technology. Because of uncertainty about the learning-by-doing effect, supporting a wide range of technologies gives a higher probability that there would appear another, cheaper technology. Therefore the uncertainty on the learning rates increases the benefits of differentiation.

We find also that the presence of exogenous technological shocks (independent from the learning-by-doing process) increases the costs of differentiation in the first period. The decision to support a wide range of technologies instead of supporting only the cheapest technology at a given moment generates costs, which equates to the surplus of the price of each technology over the price of the cheapest one. However, this may be beneficial in the next period, as it results in higher probability that the development of the cheapest technology after the technological shock will not be neglected. Therefore the uncertainty about the technological shocks increases the benefits of differentiation in the second period.

Our findings may have some implications for policymakers. The countries with potentially large learning rates, e.g. countries which are at the technological frontier or close to the frontier, should rather increase differentiation in order to derive benefits from the learning-by-doing effect. Contrary to that, the peripheral countries, which rely less on the learning-by-doing process (and more on the adoption of ready technologies from other countries), should rather limit differentiation and concentrate on supporting only a select few (cheapest) technologies. This is because making the decisions over the level of support for each technology after technological shocks rather than before technological shocks would prevent these countries from bearing the costs of differentiation.

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