Do deployment policies pick technologies by (not) picking applications? – A simulation of investment decisions in technologies with multiple applications

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ABSTRACT

The role of deployment policies that aim to foster technological change has grown considerably, especially in the fields of energy and climate. However, recent research has shown that the adoption of deployment policies carries the potential of locking in the technology that is most cost-effective at the point of policy introduction, but may be inefficient in the long term. The present paper contributes to the emerging literature on the role of deployment policies in creating path-dependency and eventually technology lock-in. While previous studies focused on the relationship between lock-in and the technology-specificity of deployment policies, this paper introduces a new factor: the existence of multiple applications for a technology. We argue that this factor is highly relevant for technological lock-in and should be considered by policy makers. To support our argument, we simulate the competition among four stationary battery technologies across energy system applications in an investment simulation model. This simulation shows that the degree of competition among technologies differs strongly across applications, which corresponds with a highly varying lock-in probability. Hence, selecting applications in deployment policies very likely corresponds to selecting technologies. We discuss the implications of these results for policy makers and for the academic debate on deployment policies and technological lock-in and on technology assessment and governance more generally Based on the notion that policies can have different technology-specificity levels, we develop the idea of the application-specificity of policies and provide examples of currently enacted deployment policies that vary in terms of their technology and application specificity.

KEYWORDS: technological lock-in, path-dependency, technology policy, multi-purpose technology, techno-economic model, energy storage

HIGHLIGHTS

- Relates the lock-in debate to literature on multiple applications of technologies
- Suggests how multiple applications can influence the policy effects on lock-in
- Develops a methodology to assess the potential of a lock-in across applications
- Presents evidence of a strong variation of the lock-in probability across applications
- Discusses the implications and develops idea of a policy's application-specificity

1. INTRODUCTION

Technological change is an important lever to address societal challenges such as climate change and energy security. Especially in the fields of energy and climate, the number of deployment policies that target technological change has strongly increased in recent years. Deployment policy instruments – such as standards, taxes, cap-and-trade systems, and fixed-price payment agreements – intervene in markets, and change selection incentives, thereby aiming to diffuse technologies that have not yet been adopted on a large scale because of externalities, higher costs or increased technological uncertainty. However, they also frequently aim to induce technological learning and innovation (del Río González, 2009). While it is relatively clear that stringent deployment policies spur the diffusion of technologies, less research has been conducted analyzing their effect on innovation (Hoppmann et al., 2013). One emerging debate related to the innovative effect of deployment policies centers on the role of those policies in technological lock-in (Safarzynska and van den Bergh, 2010; Azar and Sandén, 2011). Deployment policies often aim to overcome existing lock-ins (e.g., the energy sector's lock-in into greenhouse gas-intensive technologies). A question put forward in that debate is whether these policies create new lock-ins.

Technological lock-in can be understood as a persistent state in which an economy is "trapped" in a specific technology (Unruh, 2000). It corresponds to the lock-out of technologies which might turn out to be superior in the long term, consequently resulting in long-term inefficiencies (del Río González, 2008; Azar and Sandén, 2011). In order to balance short-term and long-term perspectives and avoid major inefficiencies, policy makers should consider technological lock-in when enacting deployment policies (van den Bergh, 2008). However, the best way to avoid technological lock-in is still debated in the literature. In the past, the academic debate mainly centered on the question of whether policies should be technology-neutral or technology-specific. However, recently the debate was taken to the next level by Azar and Sanden (2011), who argue that the dichotomy between technology-neutral and technology-specific policies does not truly exist. Rather, policies can be specific (or neutral) only on a certain technology hierarchy level: while a policy can be "specific" on a certain technology level (e.g., renewable energy), it might still be "neutral" (or "unspecific") on the level below (solar energy). Hence, policy makers have to decide how specific the policy should be, i.e., on what level of the technology hierarchy a policy instrument should intervene.

Our paper builds upon this notion and contributes to the debate on the effect of deployment policies on technological lock-in by introducing another dimension: multiple applications. Thus far the lock-in potential of deployment policies has typically been analyzed assuming different competing technologies in one single application, overlooking the fact that the lock-in effect of deployment policies may differ from application to application. While many technologies can serve in multiple distinct applications (e.g., solar photovoltaics in open space or roof-top applications), this fact has not yet been considered in the lock-in debate, nor in policy design aiming to avoid lock-in. To address this gap, we investigate the role of multiple applications of technologies for the effect of deployment policies on technological lock-in, and we derive implications for policy makers.

Our paper provides three main contributions. First, we revisit the academic debate on path-dependency, lock-in and policy intervention and relate it to the economic literature on multiple applications of technologies (Sandén and Azar, 2005; del Río González, 2008; Hoppmann et al., 2013; Battke and Schmidt, 2015). We then suggest how multiple applications can influence the policy effects on lock-in. Second, to support our theoretical reasoning, we develop a simulation methodology to assess the potential of a lock-in through deployment policies across applications and apply this methodology to four battery technologies in stationary applications. Our results show that the likelihood of investors selecting one technology differs strongly from application to application, which corresponds to strongly varying lock-in potentials across applications and in different technologies. As such, our model enriches the debate on how to calibrate path-dependence models (Vergne, 2013). Third, we discuss the implications of these results for policy makers and for the academic debate on technological path-dependency, lock-in, and policy intervention. Referring to the notion of Azar & Sanden (2011) that policies can have different technology-specificity levels, we develop the idea of the application-specificity of policies. Finally, we discuss how the application specificity of policies relates to the larger debates on path-dependency and public policy (Garud et al., 2010; Pierson, 2010; Vergne, 2013).

The paper is structured as follows. In the theory part (Section 2), we review the literature on deployment policy and lock in and develop our theoretical argument about multiple applications. In Section 3 we describe the scope and methodology to assess the potential of a lock-in through deployment policies through a simulation of investor decisions. Section 4 shows our results, and we discuss their implications for the path-dependency literature and policy makers in Section 5. We conclude the paper in Section 6.

2. THEORY

This section develops the theoretical argument of the paper. Specifically, it derives, in three steps, why and how the fact that some technologies have multiple distinct applications is highly relevant for the debate on deployment policies and technological lock-in. First, the link between deployment policies and lock-in is discussed (2.1). Then the debate on how to avoid lock-in through deployment policies is summarized (2.2). Finally, we contribute to the existing literature by introducing multiple applications of a technology as a new factor in the debate on deployment policies and lock-in (2.3).

2.1 Deployment policies and the potential of technological lock-in

Especially in the energy sector, deployment policies have become increasingly popular in recent years (Peters et al., 2012; Hoppmann et al., 2013). For instance, 109 countries around the world had introduced some form of deployment support mechanism for electricity generated by renewable energy technologies by the end of 2012 (REN21, 2012). Typically, these policies target technologies that have reached a certain maturity level but have not been adopted by the market on a large scale, e.g., due to higher costs or a high degree of technological uncertainty. These policies aim to diffuse the targeted technologies and induce technological learning and innovation by "driving down" the technologies' learning curves and thereby increasing their competitiveness (Sagar and van der Zwaan, 2006; Benthem et al., 2008; Schmidt et al., 2012c). While many analyses focus on the cost effectiveness of different deployment policy instruments (cf., del Río González, 2012; IRENA, 2013a), one debate concerns the question of whether deployment policies can lead to premature technological lock-in.

A lock-in can be understood as a persistent state in which an economy is "trapped" in a specific technology (e.g., internal combustion engines for passenger vehicles) or a specific kind of technological system (e.g., fossil fuel-based centralized electricity system). In such a state this technology or technological system is adopted by the vast majority of users, and alternative technologies have little chance of increasing market shares without exogenous shocks (Unruh, 2000; Vergne and Durand, 2010; van der Vooren et al., 2012). The determinants of a lock-in can be found in path-dependent and self-reinforcing processes (Dosi, 1982; David, 1985; Arthur, 1989, 1994; Krugman, 1991, 1996; Vergne and Durand, 2010), which result from factors both on the technology supply side (economies of scale in production, economies of scope, learning-by-doing, standardization) and on the demand side (decreasing uncertainty, learning-by-using, network externalities, economies of scale in consumption) (Katz and Shapiro, 1985; Arthur, 1989; Sandén and Azar, 2005; van den Bergh, 2008). The concept of path-dependency has been criticized as being applied too loosely (Page, 2006; Vergne and Durand, 2010).[1] However, Arthur (2013) points out that the critique mostly focuses on phenomena where technological innovation potentials through learning-by-doing and -using of the eventually locked-in technology (or rather platform or standard) are limited, e.g. Paul David's (1985) classic case of the QWERTY keyboard (see e.g., Liebowitz and Margolis, 1995; Hossain and Morgan, 2009). The neo-Schumpeterian literature on technological innovation, however, highlights the tremendous importance of feedbacks in the form of learning-by-doing and learning-by-using for innovation (Rosenberg 1994). These self-reinforcing processes are often present in the case of complex modern technologies (David, 1985; Arthur, 1989; David and Rothwell, 1996; Huenteler et al., 2015).[2] Hence, in the case of rather immature (but complex) technologies, early events such as the

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[1] Others have been critical of the absence of the role of agency in the concept of path dependency (Garud et al., 2010). More details on the path-dependency debate can be found in Section 5.

[2] Brian Arthur (2013, p. 1187) also states that the "high-technology sector" is an empirical case that is much better suited than QWERTY to illustrate the importance and validity of path-dependency. Specifically he highlights the role of learning-by-using and the evolutionary (path-dependent) character of technology itself when defending the path-dependency concept against its critics.

introduction of deployment policies can therefore lead to path-dependent self-reinforcing processes and eventually to technological lock-in (Hoppmann et al., 2013). This presents a paradoxical situation, as many deployment policies are enacted in order to serve as 'exogenous shock', helping to overcome existing lock-ins (Unruh, 2002; del Río González, 2008; Rip and Kemp, 1998).[3]

Whether technological lock-in created by deployment policies is problematic depends on two factors. First, the existence of negative societal or environmental impacts related to the production and/or use of a technology; and second, whether the locked-in technology locks out "superior" technologies that have higher learning potentials. Anticipating negative impacts at an early stage can be hard, which results in a dilemma described by Collingridge (1980, p. 19):

> "[A]ttempting to control a technology is difficult and not rarely impossible, because during its early stages, when it can be controlled, not enough can be known about its harmful social consequences to warrant controlling its development; by the time these consequences are apparent, control has become costly and slow."

Locking-out "superior" (i.e., faster learning) technologies can result in long-term inefficiencies (Unruh, 2002; del Río González, 2008; van den Bergh, 2008; Kalkuhl et al., 2012), increasing the economic costs of deployment in the long run (Arthur, 1989; Sandén and Azar, 2005; del Río González, 2008). Using the concept of learning curves (Rubin et al., 2004; Jamasb, 2007), Figure 1 illustrates how a lock-in into Technology A (corresponding to a lock-out of Technology B) may entail long-term inefficiencies due to the lower learning rate of Technology A. Predicting the learning rates of very early stage technologies has proven to be a hard task (for a review of the precision and progress of learning curve techniques, see Taylor and Fujita, 2013), resulting in a similar dilemma as the one described by Collingridge.

In this paper we focus on two policy strategies to deal with the dilemmas discussed in literature. The first strategy is to maintain a certain level of technological diversity. This diversity level can be targeted in the short- or mid-term in order to better anticipate potential negative impacts and compare learning potentials as these properties will become more obvious over time. However, diversity should arguably also be maintained in the long run: technological diversity is one of the main prerequisites of an economy resilient enough to adapt to unexpected shocks (Stirling, 2007, 2010; Kharrazi et al., 2013), which can be external or related to the use of the technology. Maintaining or even increasing

[3] The arguably most prominent examples of technology-deployment policies are instruments targeting renewable energy technologies. These instruments mostly aim at overcoming the power sector's lock-in into fossil fuel- powered technologies and the related negative externalities in the form of carbon emissions contributing to anthropogenic climate change. The two countries that introduced deployment policies for renewables at an early phase, at large scale, and in a continuous manner, Denmark and Germany, are now experiencing transitional dynamics of their electricity sectors, suggesting a successful escaping from the fossil fuel lock-in in the mid-term future. This is e.g. indicated by the loss in stock market capitalization of the utility corporations holding large fossil fuel-based assets (The Economist, 2013).

technological diversity can thus be understood as an “investment” justifying policy interventions in order to increase the long-run efficiency and resilience of an economy (van den Bergh, 2008; Stirling, 2010). Deployment policies that support this strategy should therefore induce market demand for various technological alternatives.

The alternative strategy is to improve the knowledge base through technology assessments (TA) to “search for unanticipated secondary consequences of an innovation derived from applied science or empirical developments” (Huddle, 1972). Over the past decades various forms of TA have been developed. The trend in TA is towards involving relevant stakeholders or even integrating the scientists and engineers who develop the technology (Berloznik and van Langenhove, 1998; Kemp et al., 1998) and a plethora of methodologies is now available in TA (Tran and Daim, 2008). In addition, the methods to anticipate learning have been further developed. Hence, TA can be helpful in avoiding lock-ins into problematic technologies through deployment policies. Deployment policies that support this strategy have to be designed in a way that they lead to investments in the selected technology or at least avoid investments in problematic technologies.

For both strategies it is essential to understand the probabilities of locking-in (or -out) certain technologies by means of differently designed deployment policies. While evolutionary dynamics play an important role in lock-in processes (Etzkowitz and Leydesdorff, 2000; Safarzyńska et al., 2012), very early adoption preferences of users can already determine lock-in (David, 1985; Arthur, 1989). The likelihood that users will adopt one specific technology corresponds to the degree of competition between a technology and its rival technologies. Consequently, the degree of competition among technologies, once the deployment policy is introduced and intervenes in the market, is an important predictor of lock-in potential. Note that thus far research on deployment policies and lock-in typically assumes one single market for rival technologies. We will introduce the aspect that technologies can compete on different markets in Section 2.3. A low degree of competition is very likely to result in a high market share for one technology. Consequently, this technology is likely to profit most from the self-reinforcing processes described above, whereas its rival technologies will benefit less (Arthur, 1989, 1996). While a technology’s dimensions of merit and consequently users’ selection criteria differ across sectors, technologies and user groups, the technology costs are always an important criterion (Abernathy and Clark, 1985; Anderson and Tushman, 1990). Assuming technological substitutability, i.e., different technologies providing highly comparable performance, functionalities and qualities, the degree of competition is strongly correlated with the initial (lifecycle) cost differential of technologies, especially if these technologies are new and hardly deployed (del Río González, 2008).[4] Figure 1 shows that a high cost differential between two technologies at the point

[4] Depending on the industry or market type (e.g., business-to-business or business-to-consumer type markets), costs can refer to the lifecycle costs or to the purchase price of a technology/product (Ferrin and Plank, 2002).

the deployment policy is introduced increases the likelihood that users will respond to the policy by adopting technology A only, thereby driving the technology down its learning curve. Meanwhile Technology B is scarcely adopted and consequently locked out, resulting in a long-term inefficiency of the deployment policy.

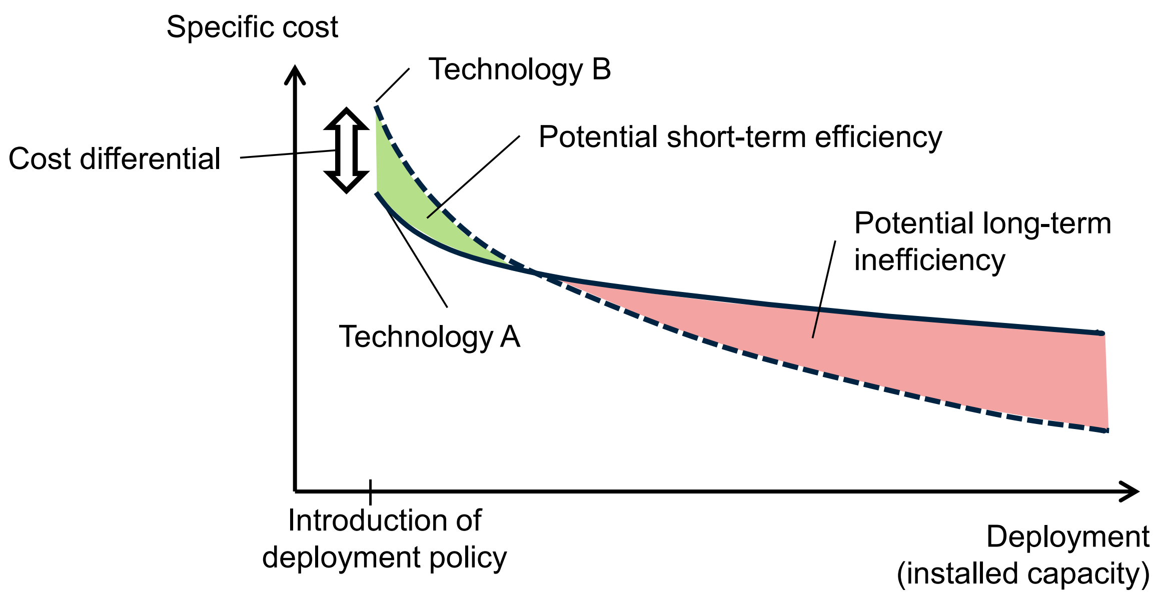

Figure 1 – Technological competition and lock-out of superior technology

2.2 Technology-neutral or technology-specific deployment policies?

While most scholars agree that policy makers should consider potential lock-in effects when designing deployment policies, they debate which policy designs are more likely to result in or avoid technological lock-in. One strand of literature emphasizes the need for *technology-neutral* instruments, i.e., instruments "encouraging all efforts that achieve specified objectives without focusing on a particular approach" (Jaffe et al., 2005, p. 171). Proponents of technology-neutral instruments argue that policy makers should avoid selecting single technologies to be supported – especially given their bad track record of 'picking the winner' (Krugman, 1996). Aghion et al. (2009, p. 688) note that in the view of many economists "bureaucrats are assumed to have no independent sources of expert knowledge" and to act on the basis of political considerations rather than market signals. Hence, scholars favoring technology-neutral policies recommend letting several technologies compete against one another under market conditions, which assures the most efficient way of re-allocating resources (Aldy and Stavins, 2011). In cases where deployment policy intervention is justified, these scholars typically recommend implementing economy-wide price instruments that affect all technologies in a given area by altering market selection mechanisms (e.g., through a carbon tax or a cap-and-trade scheme) (Metcalf, 2009).

On the opposite side, supporters of *technology-specific* policies argue that it is exactly technology-neutral policy instruments that result in the early lock-out of promising technologies. Similar to a market environment in which buyers typically select the *currently* (or at least in the short-term) most competitive technology, the technology that is most competitive once a new deployment policy is introduced will benefit most from that technology-neutral policy. In simpler terms, technology-neutral policies drive down the learning curve only of the *currently* most competitive technology (Aghion et al., 2009; Junginger et al., 2010). In this case, the policy maker does not directly select a technology; rather, the implementation of a supposedly neutral deployment policy results in an indirect selection of a technology as the market mechanism favors one technology, reversing the neutrality of the policy support (Azar and Sandén, 2011).[5] Consequently, this line of argument proposes a set of (complementary) technology-specific instruments to avoid (premature) technological lock-in (van der Zwaan et al., 2002; Sandén and Azar, 2005; del Río González, 2008; Vogt-Schilb and Hallegatte, 2014). A number of empirical analyses (e.g., Suurs and Hekkert, 2009; Rogge et al., 2010; Schmidt et al., 2012c; Polzin et al., 2015), papers based on formal models (Benthem et al., 2008; del Rio Gonzáles, 2008; Lehmann, 2015), as well as institutional bodies (e.g., the International Energy Agency) also support the rationale for complementing technology-neutral with technology-specific policy instruments.

Recently, Azar and Sanden (2011, p. 137) argued that the "debate about whether […] policies should be technology specific becomes rather meaningless, and should be replaced by a discussion about *how* technology specific the policies should be." Their argument asserts that the contrast between technologically neutral and specific policies does not truly exist. Rather, policies can be specific (or neutral) only on a certain *technology hierarchy level*: a policy that is "specific" on a certain technology level might still be "neutral" (or rather "unspecific") on the hierarchy level below. To illustrate their argument, they offer the example of feed-in tariff specificity: a feed-in tariff for renewable electricity is less specific than one for solar electricity, which in turn is less specific than one for solar photovoltaic (PV), which again is less specific than a tariff for thin-film solar PV, a specific sub-technology. Thus, policy makers do not have to decide between technology-neutral and technology-specific instruments. Rather, they have to decide *how* specific the policy should be, or in other words, on which technological "hierarchy" the policy should intervene. Using power generation as an example, Figure 2 gives an exemplary illustration of technology hierarchy levels and provides examples of technologies (PV and batteries as defined on the technology level) as well as of deployment policies on each level. Note that the definition of hierarchy levels is not prescribed.[6]

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5 Aghion, David and Foray (2009) argue that the common assertion that governments are worse than the private sector at picking "winners" lacks empirical evidence.

6 In this paper we follow the definition used in policy and policy literature, where RPS address technological fields (renewable energy technologies for power generation; or energy storage technologies) whereas feed-in tariffs address

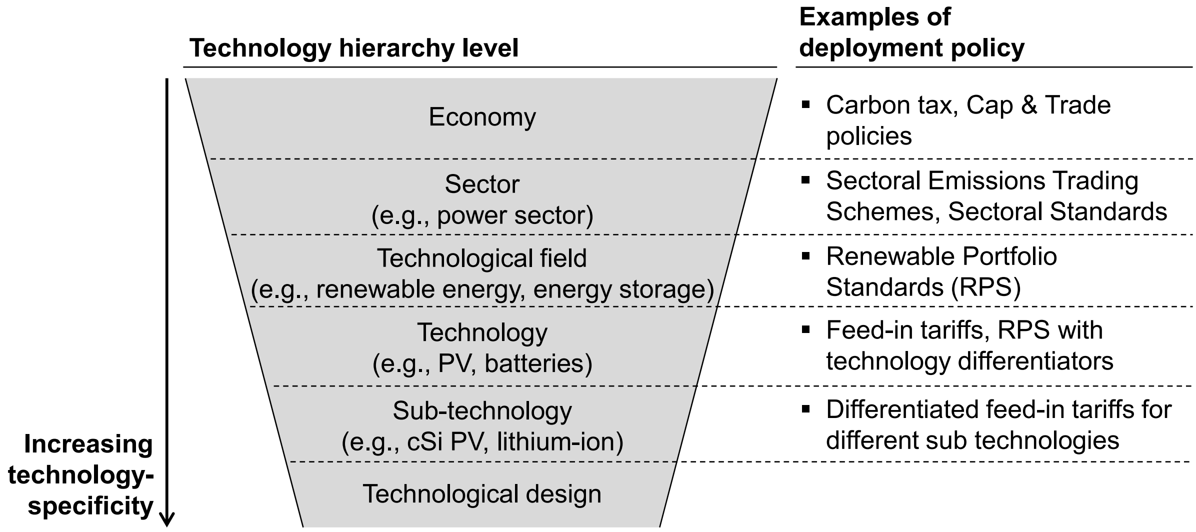

Figure 2 – Technology-specificity, technology hierarchy levels and examples of deployment policies – adapted from Winskel et al. (2013)

In case the degree of competition among technologies is low at the technology hierarchy level on which policy intervenes, markets are expected to select the leading technology/ies on that very hierarchy level. This theoretical assumption is supported by the following empirical evidence: In the US, Renewable Portfolio Standards (RPS), which mandate a power generator to produce a certain amount of electricity from (new) renewable energy sources, are in widespread use. As RPS mostly do not differentiate between renewable technologies, these policies resulted in the adoption of almost exclusively wind – 94% from 1998 to 2009 (Wiser et al., 2010)) – the cheapest renewable technology in that period of time.[7] By contrast, the German Feed-in Tariff (FiT), which is enacted at a more specific technology level and provides different support to different technologies (Reiche and Bechberger, 2004), resulted in a more diverse portfolio of technologies: 58% wind, 26% solar PV, and 13% bioenergy (see ZSW-BW, 2013). Thus, where the degree of competition among technologies is low at a certain technology hierarchy level, increasing the specificity of deployment policies can help to avoid premature lock-in.

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individual technologies (PV, Wind for power generation; or batteries for energy storage). Alternatively one could define technologies based on their underlying industry supply chain. Different types of PV (cSi or thin film) or batteries (Li-ion or lead-acid) would then be defined as technologies and not – as in our case – as sub-technologies. The alternative definition does, however, not change the argument of this paper, as long as the technologies on one level are (close to perfect) substitutes.

[7] Hydro, which has typically had lower costs than wind, is typically excluded from RPS. The 6% non-wind new renewables mostly occurred under RPS schemes featuring technology differentiators (Lewis and Wiser, 2007; Wiser et al., 2010) and are therefore specific on a technology level (compare Figure 2).

In more abstract terms, depending on the competition among technologies on different hierarchy levels, the technology- specificity of policy can determine the probability of lock-in. To understand that probability, it is consequently important to consider the competition among technologies across different levels when designing or enacting deployment policies. However, to further develop the debate and improve policy advice, we challenge an assumption in the literature: lock-in studies (at least implicitly) assume that technologies typically compete in only one defined market and that, depending on the hierarchy level, policy makers intervene in that very market.

2.3 Multi-purpose technologies and lock-in

While the debate on deployment policies and lock-in has advanced in recent years, scholars have typically analyzed different substitutable technologies in one single application. However, often technologies can serve multiple applications and consequently compete on different markets, a fact that has not been considered in the debate around deployment policy design and lock-in. In the following, we enhance the debate to include technologies with multiple distinct applications (i.e., multi-purpose technologies – MPTs).

Economic growth literature emphasizes that an important aspect for differentiating technologies is the number of use cases in an economy (see e.g., David 1990). Some technologies are typically employed for one single purpose (e.g., a laptop charging adapter) by mainly one user group, while so-called "general-purpose technologies" (e.g., the microprocessor) exhibit an almost infinite number of use cases across the economy (Lipsey et al., 1998). Situated between single-purpose and general-purpose, a multi-purpose technology (MPT) can be defined as a "technology that has several distinct, economically relevant applications" (Battke and Schmidt, 2015, p. 336). In contrast to general-purpose technologies, MPTs lack (i) the potential for a pervasive use across a virtually unlimited number of applications and (ii) the technological complementarities creating economy–wide spillovers (Bresnahan and Trajtenberg, 1995; Lipsey et al., 1998; Battke and Schmidt, 2015). Typical examples of MPTs are x-ray machines, lasers, bio-gasification and batteries (Lipsey et al., 1998; Holm-Nielsen et al., 2009; Battke and Schmidt, 2015).

The key characteristic of an MPT is the existence of multiple, economically relevant applications, where an application is defined as a specific source of value creation for a specific user group (Dolata, 2009; Battke and Schmidt, 2015). Thus, an MPT can be understood as a technology that has the potential to create economic value in different ways and for different users. As the applications of MPTs differ in terms of users, value drivers and competing technologies, each application can be conceptualized as a separate niche market in which a technology can develop (Nill and Kemp, 2009). Thus, for MPTs, policy makers can decide which market to intervene in by implementing application-specific deployment policies.

An example of a policy that supports different applications is the German feed-in tariff (FiT) for solar PV. While the PV deployment policy that preceded the FiT (the "100,000 roofs program") was limited to roof-top installations, the FiT, which was introduced for PV in 2003, was no longer limited to roof-tops but also included support for open space installations. Of the approximately EUR 7.3 bn that Germany spent on the FiT subsidy for solar PV in 2011 alone, about EUR 0.8 bn (11%) were given to open-space installations (Prognos and Belectric, 2012). From a sub-technology lock-out perspective, the inclusion of open-space applications in the FiT had important effects. Roof-top and open-space PV are two different applications according to the above definition, as they feature very different user groups: building owners on one hand and energy investors on the other (Dewald and Truffer, 2011). In the roof-top application, crystalline silicon (cSi) PV was more competitive than its rival sub-technology thin-film PV. Consequently cSi dominated the roof-top market and remains dominant. By contrast, thin-film PV was (and still is) cost competitive with cSi in the open space application.[8] The FiT for open-space applications helped thin-film PV to gain market share and thereby reduce its cost due to learning-by-doing and learning–by-using (BSW, 2006; Hoppmann et al., 2013).[9] In this way, the FiT helped to avoid locking out thin-film PV simply by including open-space applications.[10] While the German policy makers did not deliberately include open-space applications in the FiT to avoid locking out thin-film technology, the decision had a clear effect on the global thin-film industry, especially as Germany represented the most important global market for solar PV during those years (Peters et al., 2012; IRENA, 2013b). In 2005, the US-based company First Solar, the world's leading thin-film PV cell manufacturer, generated 100% of its net sales in Germany, and even in 2011 it was still 23% (First Solar, 2006, 2011).

This example shows how the degree of competition among a set of technologies at the point the deployment policy is introduced can differ strongly from application to application. Consequently, the lock-in risk of deployment policies differs across applications. Enacting a specific application-based deployment policy can result in the market selecting – i.e., locking-in – one technology if the degree of competition among technologies is low in that application. Conversely, enacting deployment policies for various applications reduces the lock-in potential. Alternatively, enacting one policy for an application with a high degree of competition among technologies also reduces a policy's lock-in potential. Hence, in order to base policy design on quantitative information, policy makers need to

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8 Thin-film exhibits lower cost per watt installed, which makes it more cost competitive in large-scale applications (Peters et al., 2011) However, it also has a lower cell efficiency, which lowers its competitiveness in roof-top applications where space is constrained and soft costs (i.e., those beyond the PV module) are more important than the module costs (Seel et al., 2014).

9 Thin-film PV reached a market share of about 8% in Germany, which is equivalent to an estimated 50% market share within open space installations in Germany (ARGE, 2008; First Solar, 2011; Prognos and Belectric, 2012; BDEW, 2013).

10 As of 2010, the global market share of thin-film was around 13% compared to 86% for cSi (Hoppmann et al., 2013).

know the degree of competition of technological alternatives for MPTs not only across different hierarchical levels, but also in different applications. In the following we use the case of four different battery technologies in stationary applications and develop a methodology to assess the initial degree of competition among those batteries.

3. Case selection and Methodology

This section gives an overview of the methodology employed to assess the competition among technologies. The aim of the modelling analysis is to assess rival technologies' *initial* competitiveness (i.e., when a policy is designed) across applications by simulating the number of investors who would select a particular technology in a particular application. In our model, we assume that investors decide on the expected lifecycle cost of a technology. At the same time, our model considers that each investors has different assumptions about technical and market parameters, all affecting the lifecycle cost (using Monte-Carlo simulation). The methodology section proceeds in three steps and start by motivating stationary batteries as a case example (3.1). Then, we describe how the degree of competition among technologies can be assessed using a simulation of investor decisions based on lifecycle cost (3.3).[11]

3.1 Case example: Stationary batteries as multi-purpose technology

While in the previous section we mostly referred to renewable power generation technologies, such as wind turbines or PV and its various sub-technologies, we now employ the case of stationary batteries to show how the degree of competition among technologies varies across different applications. Stationary batteries store electricity using electrochemical principles and have multiple distinct economically relevant applications in the economy. They are thus are a primary example of a multi-purpose technology (MPT). They have different sources of value generation (e.g., *Power Reliability, Power Quality,* or *Arbitrage)* and they can be employed by different users (e.g., end-consumers, industrials, utilities, network operators), creating multiple distinct applications (for a detailed description of these applications, see Appendix B). Consequently, stationary batteries are well suited to exemplify the varying degree of competition across applications.

Three additional arguments support the focus on stationary batteries. First, knowledge spillovers between different battery technologies are limited (Battke et al., 2016). Strong knowledge spillovers represent positive externalities that can decrease the lock-in created by a deployment policy, as rival technologies would profit from learning in the most favored technology. Second, the analysis of

[11] Note that we apply a static modeling approach, focusing on the initial degree of competition only. Another simplification is that in our simulation, investors decide purely based on lifecycle cost. While we are aware of the limitations of these approaches, our intention is to support our theoretical argument in a first approximation.

deployment policies for stationary batteries is highly relevant given recent efforts by policy makers to support these technologies. As the high costs of stationary batteries currently inhibit the large-scale deployment of these technologies, deployment support policies have started to be introduced in several countries in order to foster innovation and diffusion of stationary batteries (Borden and Schill, 2013). Third, the power sector, to which stationary battery technologies belong, is especially prone to lock-ins. Electricity is a homogeneous good and thus technologies used for storing electricity are typically highly substitutable (Kalkuhl et al., 2012). Given the high degree of substitutability, no niche markets for specific technologies exist, underlining the potential of a lock-in where one technology is the most cost competitive. Moreover, the power system is characterized by long investment cycles, high upfront capital costs, network externalities and economies of scale, increasing the potential of lock-ins (Unruh, 2000, 2002; Schmidt et al., 2012b).[12]

Specifically, we assess the degree of competition among the four battery technologies lead-acid, lithium-ion, sodium-sulfur and vanadium redox flow batteries.[13] These four battery technologies were chosen since they are typically seen as the technologies with the highest potential for grid-connected electricity storage (Proser, 2011; Sauer et al., 2011).

3.2 Assessment of the degree of competition among technologies

A first assessment of the competitiveness of batteries in different applications is to compare their levelized lifecycle cost, i.e., the discounted lifecycle cost per discounted service provided over the entire lifecycle. Appendix A describes how this is done in the case of batteries. The technology with the lowest levelized lifecycle cost in a certain application can be assumed to be most attractive for investors. However, while comparing the lifecycle cost might give a first impression of the relative competitiveness of technologies, it does not assess to what extent specific technologies would be picked by investors at the point of potential policy introduction. However, this extent is pivotal for assessing the degree of competition among technologies and thus the potential of a technological lock-in. To estimate the extent to which each technology is picked in each application, we therefore simulate investment decisions by independent investors. In particular, we calculate the initial degree of competition based on a simulation of 10,000 independent investors who each decide in which technology to invest depending on their assessment of the lifecycle cost of the four battery technologies. Based on the investors' decisions and thus on the expected initial market shares, the *Technological competition coefficient (TCC)* summarizes the degree of competition among technologies. The remainder of this section describes the investor-based model (3.2.1), introduces the

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12 The high likelihood of a lock-in in various segments of the power system is reflected in the multiple scientific studies investigating this phenomenon across technologies. Lock-ins have been described and discussed in the literature for fossil power generation technologies (Islas, 1999), nuclear reactor types (Cowan, 1990), and renewable power generation technologies (Menanteau, 2000; Hoppmann et al., 2013).

13 Dunn (2011) provides a description of battery technologies.

TCC (3.2.2) and develops a way to assess the degree of competition across multiple applications beyond the four applications described above (3.2.3).

3.2.1 Investment simulation model

In order to calculate the initial degree of competition among technologies, we apply an investment simulation model (compare Eager et al., 2012). Specifically, we use the Monte-Carlo simulation applied above to model the investment decisions in the four battery technologies of 10,000 independent investors (each run representing one investor decision) in four steps. First, as battery input parameters currently exhibit a high degree of uncertainty, it is assumed that different investors estimate different input values for the main technical parameters of batteries (round trip efficiency, calendrical life and cycle life).[14] For new complex technologies, it is hard to estimate ex-ante long-term efficiencies and lifetimes. This is especially true in the case of batteries which are strongly affected by degradation (Ebner et al., 2013) but also applies to other technologies, such as early solar PV technology (Jordan and Kurzt, 2013). Investors' estimates regarding the (future) performance of the technologies along these three dimensions differ substantially due to varying technological expertise and risk preference (see Battke et al, 2013). A fourth source of variation concerns the energy capacity cost, i.e., the energy-specific initial investment cost. The variation here stems from sources such as varying asymmetries in bargaining procedures or economies of scale. The model incorporates all four sources of variation using random distributions for each parameter (compare 3.2). The random distributions were constructed from typical real-world battery industry estimates for the respective input parameters and are based on Battke et al. (2013). Second, using these input values, each investor (represented by one run in the Monte-Carlo analysis) calculates the lifecycle cost of *each of the four battery technologies* in a techno-economic assessment for a given application (cf. section 3.2). Third, we assume that each investor invests in the technology that exhibits (from her point of view) the lowest lifecycle cost.[15] Finally, the model observes and stores the investment decisions of each investor in order to forecast the expected initial market shares of technologies and thus the degree of competition among technologies across applications (cf. section 3.3.2).

3.2.2 An indicator to assess the degree of competition among technologies

In order to assess the degree of competition among technologies, the investment decisions by each investor (calculated as described in 3.3.1) are compared. Based on the notion that the degree of competition can be understood as the inverse probability that the market selects one specific

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14 The remaining deterministic input values are described in Appendix B.

15 Although besides lifecycle cost and technical performance additional decision criteria exist for investment in technologies (e.g., security, historic investment decisions), several interviews with project developers and investors indicated that the lifecycle costs are highly relevant for investment decisions in stationary batteries.

technology (cf. section 2.2), we introduce the *Technological Competition Coefficient (TCC)*. The TCC represents the share of investors who deviate from the investment decisions of the majority of investors for a given application (cf. Formula 2).[16] In other words, the *TCC* describes the combined market share of those technologies that are outcompeted by the (on average) most cost competitive technology. A low *TCC* indicates a high lock-in probability, as almost all investors initially choose that very technology. In contrast, a high *TCC* indicates that investment flows are distributed more evenly across two or more technologies, resulting in a low lock-in probability.[17]

$$TCC = \frac{Investorsdeviating}{Totalinvestors} = \sum_{i=2nd}^{N} Expectedinitialmarketshare_i \qquad (2)$$

TCC: Technological competition coefficient
$\#_{\text{Investors deviating}}$: Number of investors who deviate from the investment decisions of the majority of investors
$\#_{\text{Investors}}$: Total number of investors
N: Number of technological options, sorted by cost competitiveness
2^{nd}: Second most cost competitive technological option

In contrast to alternative calculation methods to assess the variation of values (e.g., the variance, standard deviation or the mean deviation), the focus of the *TCC* is on the competition *at the top*, i.e., the competition of the leading technology or technologies. This makes the *TCC* a relevant metric for the risk of technological lock-in, as only those technologies that are most attractive for investors have a chance to diffuse in the market. This assumes that the learning feedbacks that a (sub-) technology receives do not differ substantially between applications. This is a fair assumption in the case of battery technologies, where application-specific knowledge is rather peripheral apart from the material selection, which defines the sub-technology (Battke et al., 2016). For instance, in a case in which three out of four technologies are in close competition, with similar costs and service characteristics, while the fourth technology is significantly more attractive for investors, a low variance (or standard deviation) would result. In this case, a variance-based metric would indicate a low lock-in probability as the majority of technologies are in close competition, although the real probability is high. In contrast, the *TCC* would identify the high lock-in probability correctly as the large majority of investors would select the same technology and thus only this technology would be deployed.

[16] In the following, the term "majority" refers also to a "simple majority" situation, i.e., a situation in which the largest group of investors selecting a specific technology represents less than 50% of all investors.

[17] The TCC can take values in the interval of [0; (N-1)/N[where N denotes the number of technological options.

3.2.3 Holistic assessment of the degree of competition in the "application landscape"

While section 3.2 described the methodology to assess the relative performance of stationary batteries in specific applications, this section describes how the competition among technologies can be investigated holistically.

The focus on a selected number of specific applications in the previous sections is useful to outline the methodology and highlight the notion of varying degrees of competition across applications. However, both policy makers and practitioners need a more comprehensive assessment in order to make well-informed decisions. As the technical parameters defining an application all span across ranges and as additional applications may exist, we assess competition among technologies across *all possible* applications, i.e., independently from individual applications.[18] This also helps, for instance, to understand whether minor changes of the technical requirements of the application might alter the competitive situation within this application.

Therefore, we depict the degree of competition in a two-dimensional matrix ("the application landscape"), covering all possible stationary battery applications, spanned by the factors that impact the relative competitiveness of technologies most: discharge duration and cycle frequency.[19] Essentially, these two factors describe how big the battery needs to be (i.e., investment costs) and how often it has to run (i.e., the operating and replacement costs). To assess the degree of competition among technologies for each spot in the application landscape, the model iterates the simulation of the decisions of the investors (cf. section 3.3.1) and the calculation of TCC for each possible combination of discharge duration and cycle frequency.[20] As a result, the application landscape depicts the degree of competition among technologies holistically, i.e., for all possible applications. As the TCC is most sensitive to the two parameters that form the basis of the landscape, our procedure can also be regarded as sensitivity analysis of variations in the application parameters. It is important to note that all four analyzed technologies can be applied across this landscape from a technical standpoint, and that the installation of all four technologies takes place across almost the entire landscape – mostly driven by differently designed deployment policies (for data on the global stationary storage deployment, see US DOE, 2014 and Malhotra et al., 2016).

[18] For instance, although an assumption of a discharge duration of four hours in the application *Increase of Self-consumption* is often made, a range from two to six hours is typically described as reasonable (EPRI, 2010; Nair and Garimella, 2010; Battke et al., 2013).

[19] A sensitivity analysis of the LCOEC across technologies and applications showed that discharge duration and cycle frequency are the application parameters with the highest impact on LCOEC.

[20] A constant discount rate of 8% and an electricity price of 50 EUR / MWh are assumed throughout the application landscape. With a resolution of 30,000 combinations of discharge duration and cycle frequency in the application landscape, the model calculates in total 1.2 billion technology assessments (4 technologies, 10,000 actors, 30,000 applications).

4. RESULTS

This section presents the simulation results in two steps. First, the levelized lifecycle costs as well as the assessment of the degree of competition (in terms of *TCC*) for the four specific applications are presented (section 4.1). Second, the relative performance and degree of competition among technologies are shown in the applications landscape, i.e., for all possible applications (section 4.2).

4.1 Costs of and competition among technologies in specific applications

Table 1 shows the mean lifecycle costs and its standard deviation as well as the distribution of investment decisions (i.e., the expected market shares) and the degree of competition among technologies. (For a graphic presentation of the cost distributions, see Appendix E).

With respect to the relative performance of the technologies in terms of mean lifecycle cost, Table 1 shows that different technologies are most cost competitive in different applications. For instance, lead-acid is the most cost competitive technology in *End-consumer Power Reliability,* while lithium-ion leads in *Support of Voltage Regulation*, and sodium-sulfur exhibits the lowest mean lifecycle cost in *Wholesale Arbitrage* and *End-consumer Arbitrage*. This implies that depending on the application in which the diffusion of stationary batteries is enabled – either through market mechanisms or through the intervention of policy makers – different technologies are likely to prevail.

However, as the exact lifecycle costs are uncertain (cf. the standard deviation in Table 1), different investors may invest in different technologies for a given application.[21] The expected initial market shares shown in Table 1 reflect the resulting investment decisions; the *TCC* aggregates them in a single coefficient indicating the degree of competition within an application. The simulation results presented in Table 1 underline to what extent the degree of competition among technologies can vary across applications. For instance, in *End-consumer Power-Reliability* the vast majority of investors (99.4%) would select lead-acid batteries. This would result in a high probability of a deployment policy-induced lock-in of the lead-acid technology indicated by *TCC* of 0.6%. By contrast, in *End-consumer Arbitrage* only 47.8% of the investors chose the most cost competitive technology (sodium-sulfur), while 35.3% invest in vanadium redox flow, 9.9% in lithium-ion and 7.0% in lead-acid. Thus, in this application, several technologies would co-exist and compete in the market, reducing the probability of a technological lock-in resulting from deployment policy.

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[21] It is assumed that investors lack perfect information about the distribution of the mean lifecycle cost (in that case, they would select a technology based on the mean lifecycle cost resulting in a 100% market share for the average most cost competitive technology in each application).

Table 1 – Levelized lifecycle costs, market share and technological competition across applications[a]

Application	*Technology*	*Mean lifecycle cost [EUR/kW-yr]*	*Standard deviation*	*Expected initial market share[b]*	*Technological competition coefficient (TCC)*
End-consumer Power Reliability	Lead-acid	79 €	10 €	99.4%	**0.6%**
	Lithium-ion	190 €	55 €	0.1%	
	Sodium-sulfur	118 €	11 €	0.4%	
	Vanadium redox flow	154 €	26 €	0.1%	
Support of Voltage Regulation	Lead-acid	73 €	9 €	22.2%	**24.5%**
	Lithium-ion	61 €	14 €	75.5%	
	Sodium-sulfur	80 €	3 €	2.3%	
	Vanadium redox flow	95 €	6 €	0.0%	
Wholesale Arbitrage	Lead-acid	711 €	213 €	18.1%	**31.5%**
	Lithium-ion	1,338 €	451 €	0.4%	
	Sodium-sulfur	527 €	83 €	68.5%	
	Vanadium redox flow	756 €	203 €	13.0%	
End-consumer Arbitrage	Lead-acid	455 €	131 €	7.0%	**52.2%**
	Lithium-ion	491 €	191 €	9.9%	
	Sodium-sulfur	314 €	40 €	47.8%	
	Vanadium redox flow	333 €	64 €	35.3%	

[a] Most cost competitive technology underlined for each application
[b] Distribution of investment decisions

As the applications of stationary batteries are not limited to the four exemplary ones shown in Table 1, the next section displays the degree of competition among technologies in the application landscape, i.e., across all possible applications.

4.2.1 Leading technologies and competition among technologies in the application landscape

In order to assess the competition among technologies holistically, we simulated the distribution of investment decisions in battery technologies for each spot in the application landscape (cf. section 3.3.3). Figure 3 shows the results of this simulation and indicates the leading technology (in terms of cost competitiveness), the locations of several prominent applications, and the probability of a lock-in across the application landscape that is induced by a deployment policy.[22] The present section briefly discusses the leading technologies across the application landscape before shifting the focus to the degree of competition among technologies.

The leading technology is defined as the technology that is on average perceived of as most cost competitive, i.e., as the investment decision of the majority of investors. Figure 3 indicates that each

[22] Each point represents a combination of a specific discharge duration and cycle frequency, thus representing a generic application for stationary batteries. These are the two key requirements defining an application. We added the four specific applications (ref. Table 1) in the landscape, as indicated by the letters A-D.

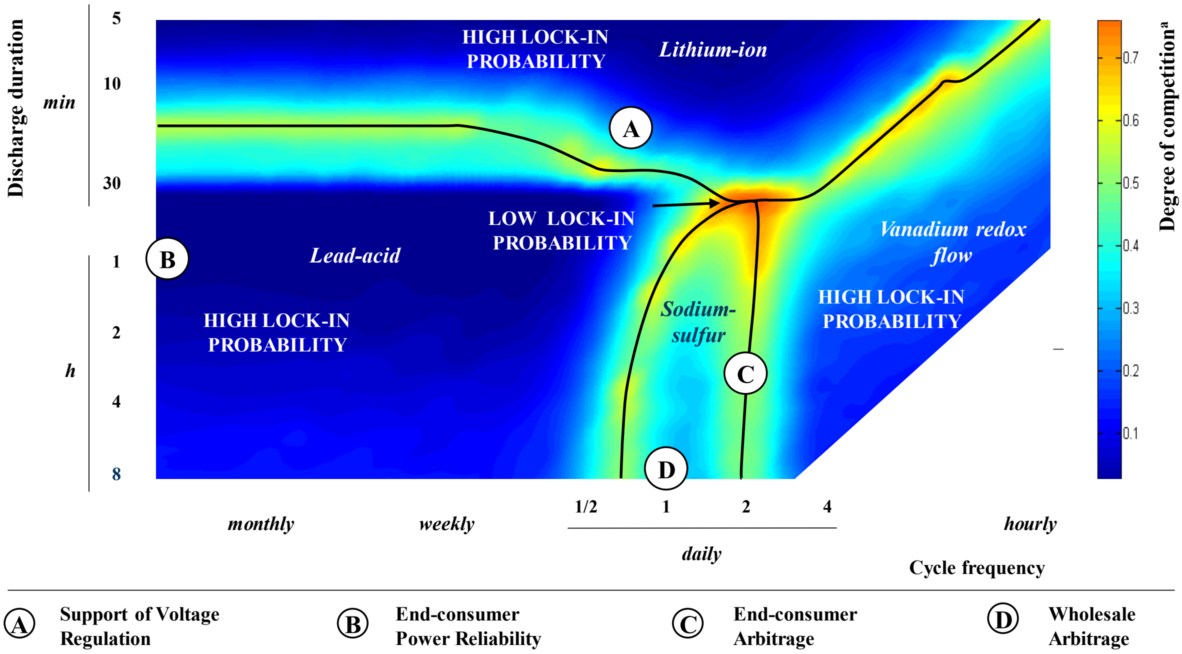
battery technology has its “sweet area” in the application landscape: each battery technology is the primary investment choice of investors for a specific range of combinations of discharge duration and cycle frequency. Specifically, given relatively low investment costs along with a short cycle life, lead-acid has a comparative advantage for rarely used applications. With increasing scale and cycle frequency, the advantage shifts to sodium-sulfur, and with further increasing cycle frequency, it shifts further to vanadium redox flow. Lithium-ion excels in all applications with a high power-to-energy ratio (i.e., with rather short discharge durations).

Figure 3 also depicts the degree of competition among the four battery technologies using a color scale (warmer colors representing a higher degree of competition). Appendix F displays the same information across three dimensions in order to better visualize the slope of the degree of competition.

The main result shown in Figure 3 is the strong variation of the degree of competition across the application landscape. While in some areas, one technology is very likely to be selected by users, other areas are marked by close technological competition. Naturally, the degree of competition increases towards the border between two areas where different technologies are the primary choice of investors. Thus, while lithium-ion, lead-acid and vanadium redox flow have areas where they enjoy a clear lead with almost no competition (dark blue), sodium-sulfur faces strong competition almost everywhere due to its position in the center of the landscape. The area with the highest competition, in which up to 70% of investors deviate from the majority investment decision, is rather small and close to the center of the landscape and exhibits steep slopes (compare Appendix F).

Figure 3 can be related to the results shown in Table 1. While *End-consumer Power Reliability (B)* is located in a dark blue area indicating a low degree of competition, Figure 3 depicts a moderate degree of competition for *Support of Voltage Regulation (A)* and for *Wholesale Arbitrage (D)*. Finally, *End-consumer Arbitrage (C)* is located in the green-marked area indicating a higher degree of competition.

To give an example of how this result can be interpreted from a policy maker perspective, we focus on application (A), *support of voltage regulation*. A policy focusing on this application would mostly result in the adoption of Li-ion technology. If other applications experience low (business-as-usual) diffusion rates, only Li-ion would benefit from learning feedbacks and therefore the potential of locking in this technology is high. Of course, the lock-in potential depends on all technologies' learning rates relative to one another. Yet, in cases where the learning rate is not well known (such as in the case of sodium-sulfur and Vanadium redox flow) but one can expect learning feedback from production and use – which is typically the case in complex technologies such as batteries (Huenteler et al., 2015) – analyzing the initial degree of competition is a good first estimate for policy makers.



[a] Share of actors who deviate from the majority investment decision (Technological competition coefficient (TCC))

Figure 3 – Degree of competition among battery technologies in the application landscape

5. Discussion

The results presented in the previous section underline the relevance of the application perspective for deployment policies and technological lock-in.

This application perspective has been ignored thus far in the academic debate and in policy design, despite its large potential impact on technological lock-in. Our simulation of investors' decisions shows that the degree of competition among a set of technologies can differ strongly across applications.[23] While some applications exhibit a fierce competition among several technologies, one technology may enjoy a clear lead in another application. In yet another application, a different technology can clearly lead. This corresponds to strongly varying lock-in probabilities across applications and among different technologies. In other words, selecting an application (or application level) is likely to result in selecting a technology. But also being application "agnostic" can result in (the markets) selecting a technology. This has implications for policy makers as well as for the literature on path-dependency and technological lock-in. The key policy implication is that enacting an application-specific deployment policy without considering the degree of competition between

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[23] Our study is limited to battery technologies in stationary applications. Nevertheless, we are confident that major differences in competition across applications can be found for many multi-purpose technologies, where deployment policy intervention is currently in place or may possibly be enacted in the future (compare the solar PV example given in Section 2.3).

technologies bears the risk of *unintentionally* locking in a certain technology if this technology is currently the most cost competitive in the selected application.[24] In order to avoid this "randomness" (more below on the question of whether these events are random or not) policy makers should consequently incorporate the degree of competition among technologies and across applications in their decisions, especially with respect to the scale of support policies for clean energy technologies (REN21, 2012). They should incorporate this consideration in either of the two policy strategies discussed above: maintaining technological diversity, or actively selecting a technology based on ex-ante technology assessment. The implications of our study for each strategy are discussed in the following sections and also feed into the general debate on path-dependency and technology policy as highlighted in the subsequent sections. In these sections we will also highlight implications for future research.

5.1 Designing deployment policies to maintain technological diversity

The first policy strategy we discussed in Section 2.1 is to maintain a certain level of technological diversity at least over a period of time. This would allow a better assessment of learning potentials and negative societal consequences. An additional argument for maintaining technology diversity is that low technological diversity limits the possibility for inter-technology knowledge spillovers and positive effects from "recombinant innovation" (van den Bergh, 2008; van der Vooren et al., 2012).[25] If the policy maker is informed about the degree of competition among technologies across applications, what options are available to maintain technological diversity? One option is to target an application that exhibits a sufficient degree of competition among technologies (if such an application exists). In this case, policy makers can ensure that several technologies have the chance to develop and diffuse in the market and thus minimize the probability of a lock-in. Another option is to implement a set of deployment policies that each target a specific application: By supporting several applications in which different technologies each have a high probability of being selected by users, policy makers can avoid premature lock-in. However, they have to be aware that with an increasing number of deployment policies, the complexity and administrative burden of the policies also increases.

Yet, policy makers have a third option: adapting the specificity of a policy. Azar and Sanden (2011) point out that policy makers can decide how technology-specific a deployment policy should be. Similarly, in the case of multi-purpose technologies, policy makers can also decide on how application-specific a deployment policy should be. Consequently, policy makers aiming to maintain

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[24] Note that in case of MPTs a lock-in can result in additional inefficiencies: Depending on the market size and growth that an application-specific deployment policy triggers, the potentially resulting technological lock-in can affect other applications. 'In case the market-favored technology learns relatively quickly, its costs can be reduced to an extent that it outperforms the technology originally leading in other applications that are not supported.

[25] Combining knowledge from distinct technologies in a new technology or in new settings is recognized as a main driver of innovation (Gilfillan, 1935; Usher, 1954; Arthur, 2009).

or reach a desired level of technology diversity are faced with choosing the specificity level of the deployment policy along two dimensions: a technology and an application dimension.

Figure 4 depicts the decision space for policy makers schematically. In order to make the concept of the decision space more illustrative, Figure 4 features five currently enacted deployment policy instruments affecting stationary electricity storage. Each policy instrument has a different combination of technology-application-specificity. The figure shows that in general, policy makers can decide independently on the specificity of deployment policies with respect to technologies and applications covered. For instance, an (I) economy-wide carbon tax benefits all technologies in an economy that have a relatively low level of emissions, independent of any application. A (III) loan guarantee for clean energy technologies is more specific with respect to the technologies covered, whereas a (II) pay-for-performance regulation for specific energy technologies employed in spinning reserve is additionally more specific with respect to the application covered.[26] A (V) deployment policy that is restricted to one sub-technology (e.g., lithium-ion batteries) is the most specific example on the technology dimension.

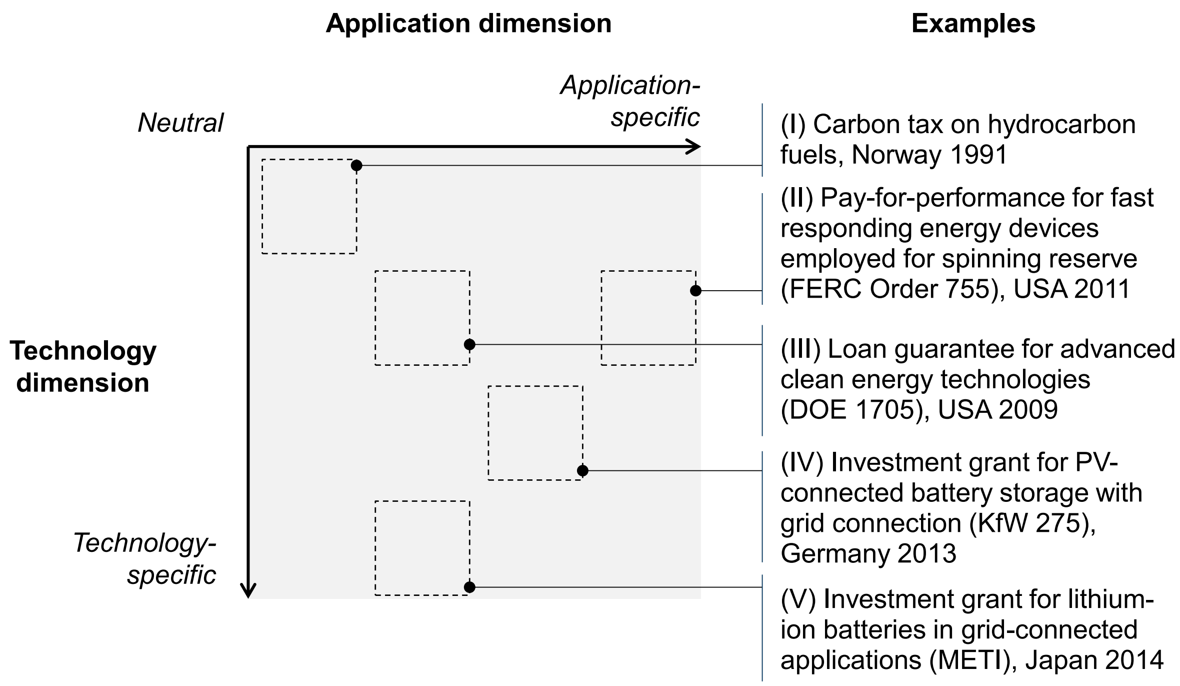

Figure 4 – Decision space for deployment policies[27]

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26 Spinning reserve is a specific form of *Area & Frequency Regulation* which is described in Appendix A.

27 FERC stands for U.S. Federal Energy Regulatory Commission; DOE stands for U.S. Department of Energy; KfW stands for the German Kreditanstalt für Wiederaufbau (Reconstruction Credit Institute); METI stands for Japanese Ministry of Economy, Trade and Industry. The U.S. Department of Energy (DOE) loan program 1705 is also more application-specific than a carbon tax because the granting of a loan is “subject to various conditions” (Borden and Schill, 2013, p. 9).

When deciding on the specificity of deployment policies, policy makers need to be aware of the fact that the more neutral a deployment policy is, the higher the likelihood that users pick applications and respective technologies based on short-term competitiveness. In case the degree of competition is too low, policy makers can increase the specificity of a policy on the technology and/or the application dimension. The more specific the policy program becomes, the more specifically the policy maker must select the number and type of technologies and applications to target. The option to shift between application-specificity levels is also illustrated by the example of the German support policies for PV for roof-top and open-space applications (cf. section 2.3). While the initial policy was limited to the roof-top application and therefore very specific, the subsequent FiT was less application-specific and thus included open-space applications. However, in 2004, a differentiated FiT for open-space applications was introduced (with tariffs set about 30% lower than for roof-top applications, to reflect the lower costs of open-space applications stemming from such factors as economies of scale) (Bundesgesetzblatt, 2003). In this way, the German policy maker moved back to a more application-specific policy, while supporting two different applications of a single technology in parallel.[28]

The market size and growth that is created through the deployment policy is also relevant for maintaining diversity. The potential of a technology to realize improvements in cost and performance, e.g., through learning-by-doing and learning-by-using, is a function of its deployment and thus increases with the market size.[29]. Technological diversity should be considered as a continuum, not as a binary indicator. Consequently, policy makers need not choose between diversity and lock-in; rather, they have to decide on the "optimal" level of technological diversity and the associated costs they have to incur to achieve it (David and Rothwell, 1996, p. 196). In the words of van den Bergh (2008, p. 566): "[…] an optimal investment decision really comes down to identifying the optimal level of diversity rather than choosing a particular option." Hence, in order to select a technology-application-specificity level, the degree of competition needs to correspond with the desired technological diversity. To maintain this desired diversity level in the long-run, policy makers need to monitor competitiveness levels and eventually intervene or readjust existing interventions over a longer period. Often, technologies that are not reached through deployment policies are not fully lost but survive in niches (Hoppmann et al., 2013). However, whether they will be able to compete on mass markets is questionable and depends in part on how far the competing technology or technologies are driven down the learning curve. Finally, in addition to deployment policies, policy makers have the option to

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28 In addition, this FiT differentiation by application was not driven by lock-in but by pure policy cost reduction considerations. Hence, it can be seen as a rather "random" event in the early history of the two sub-technologies.

29 If a deployment policy targets a specific technology but this only leads to limited diffusion of the technology because the resulting market size is too small, the technology will not be able to drive down the learning curve. If at the same time a competing technology (e.g., in a different application) exhibits a much higher diffusion through another deployment policy, the lock-in danger persists despite the fact that the policy maker targeted several technologies through application-specific deployment policies in parallel.

implement R&D support policies in order to maintain technological diversity. Recent papers (e.g., Jaffe et al., 2005; Taylor, 2008; Peters et al., 2012; Hoppmann et al., 2013) argue that over the past decades, policy makers have focused too narrowly on deployment policies and have neglected R&D support. They stress the importance of a policy mix that combines deployment policies with supply-side policies. Regarding R&D support policies, the debate on how technology-neutral (basic) or specific (applied research) the support should be is much older (Bush, 1952; Martin, 2012). But, similarly to deployment policies, they can be more or less technology-specific (Azar and Sandén, 2011). At least with regard to applied research, the application dimension seems relevant, as the name ‘applied research’ implies. Supporting applied research for one specific application (e.g., a battery for a submarine) may produce a very different technological outcome than supporting another application (e.g., a stationary power back-up). Tailoring a mix of deployment and R&D support policies to avoid lock-in is possible, but admittedly a complicated task.

5.2 The role of applications in purposefully selecting technologies

Of course, preserving technological diversity comes at a cost. In addition to the short-term inefficiency, keeping several technological options can result in high uncertainty in the innovation system, potentially scaring away innovators and investors (Marcus and Kaufman, 1986). This in turn might undermine the original intention of deployment policies, namely to overcome existing lock-ins into technologies with negative societal consequences. To avoid this situation, an alternative solution is to purposely select a technology or a few technologies (cf. Section 2.1). In order to minimize unintended consequences of these new technologies, ex-ante technology assessments (TA) aim at building in foresight into social choice (Kemp et al., 1998). Besides analyzing the full range of potential externalities, TA can also help estimate learning potentials (and thereby long-term inefficiencies of technological choice). Our finding that applications matter for path-dependency also has implications for TA: focusing on individual applications (that mostly drive the rationale of the deployment policy) and leaving aside the implications of technology choice for other applications in which the focus-technology can also be used can lead to an unintended consequence in the form of a lock-out of a technology in that other application. Hence, considering the potential role of the assessed technologies in applications other than the focal ones should be part of TA.

Diving deeper into the process of TA, Garud and Ahlstrom (1997) highlight that assessing technologies is by no means an objective, but rather a highly socio-cognitive process. Specifically, they differentiate technology ‘insiders’ – the developers of technology – and ‘outsiders’ – the sponsors and regulators of technologies. While insiders have a rather local focus and narrow assessment criteria, outsiders’ focus is more global and their assessment criteria broader. The interaction points between insiders and outsiders are instrumental, as “insiders actively influence the emerging assessment approaches that outsiders adopt as basis for their selection cycle” at these points (Garud and Ahlstrom, 1997, p. 45). Following this logic, the authors argue (p. 46) that providing fora “wherein different constituencies can come together to discuss and debate their different points of view” and thereby increase chances that the “most appropriate technology evolves over time.” Our findings that different technological alternatives can outcompete their competitor technologies in different applications imply that arguments put forward by technology insiders on the applications of technologies could be used as “hidden” arguments pushing the technology (as this technology might be leading in the application). To avoid this, constituents around all relevant applications for the respective TA (with preferably no technology bias) should be part of these discussion fora. While technology insiders are likely to focus on technology scenarios, constituents around applications – ‘application insiders’ as it were – are more likely to think about application scenarios. Bringing them together can show compatibilities and incompatibilities between these scenarios, improving the (socially constructed) TA.

Once a TA results in the selection of a preferred technology, deployment policies can be designed specifically targeting this technology. For the design of such selective deployment policy as well, the decision space regarding the technology-application specificity developed above can be helpful. Ensuring that the deployment policy leads to the selection of the preferred technology does not necessarily have to be achieved via a technology-specific policy but can also work by targeting a specific application (or a specific application specificity level) in which this technology clearly outcompetes its rival technologies (which might be more feasible from a political economy perspective – see Section 5.3). Even if the technology is clearly targeted by the policy (by being technology specific), targeting applications with a lower gap to profitability can lead to a lowering of the public cost of the deployment policy (Battke and Schmidt, 2015).

5.3 Implications for the larger debate on path-dependency and public policy

Besides providing these policy implications, our paper contributes to the broader literature on path-dependency, lock-in, and the role of policy in steering technological change. In this literature, heated debates can be observed, e.g., on whether policy makers or markets are better (or worse) at picking winners, or on whether the emergence of the QWERTY keyboard really is a case of path-dependency resulting in sub-optimal outcomes.[30] Our paper does not resolve these conflicts; rather, by highlighting that applications matter for path-dependency, we expose a dimension of complexity of path-dependency that has thus far been mostly overlooked.

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[30] For instance, Liebowitz and Margolis (1995) argue that the QWERTY case can be seen as a second-degree path dependency, where the sub-optimality only is relevant at later points in time and not at the point of the emergence of the technology. Kay (2013) goes even further, arguing that the QWERTY keyboard does not seem to be a sub-optimal solution compared to its alternatives.

Here, we do not want to engage in the debate on QWERTY. Deployment policies that carry the potential of inducing technological lock-in typically target complex technologies.[31] Their economies of increasing returns are – unlike those of a standard like QWERTY – largely driven by learning-by-doing and -using which themselves entail many contingencies (Arthur, 2013). (The learning argument is in fact the underlying argument for installing deployment policies in the first place.) Our findings suggest that a "contingent" design of an intervening policy can unintentionally lock-in a technology. The contingency we highlight is that of the application specificity and selection. Whether such lock-in would be sub-optimal is a different question. Here, we also subscribe to Arthur's (2013) argument that lock-in and sub-optimality are two related but separate issues: whether a lock-in leads to inferior outcomes is not given but depends on the criterion applied (e.g., the time frames), which differ across various actors.

This leads us to the role of actors and their agency in the path-dependency debate. Garud and Karnoe (2001) and Garud et al. (2010) have argued that agency is present in all relevant aspects of path-dependency: the definition of starting conditions, the "contingent" events, and the self-reinforcing processes. Based on this notion, they propose the concept of path-creation, in which agency "is distributed and emergent through relational processes that constitute phenomena" (Garud et al, 2010, p. 760). Our paper also has implications for this agency-perspective. Agency around different applications can differ substantially. Relating agency to the decision space shown in Figure 4, it can be assumed that the *technology dimension* mostly affects technology *suppliers'* interests, increasing the likelihood for agency or advocacy from suppliers (Jacobsson and Lauber, 2006; Torvanger and Meadowcroft, 2011). In contrast, the *application dimension* mainly affects *users'* interests, making user advocacy more likely (both from end-users – who are also voters – and business users, who can be quite powerful politically). The presence of a technology-producing industry in a country can strongly influence the political dynamics around the technology dimension (it is probably not a coincidence that Japan specifically supports Li-ion batteries through a deployment policy as shown in Figure 4). Other than technology suppliers, technology users are always found within the country enacting a deployment policy, which implies different political dynamics along the two dimensions. Thus, the strength of agency around different applications (and at different levels) is likely shape policy in a way that eventually leads to path-dependency (or rather path-creation). Future research should analyze the role of supplier *and* user agency in policy design and how it might eventually lead to path-dependency.

Whether agency leads to policy change also depends on whether it is well received in the political arena, bringing us finally to the politics of technology policy. Politics is also not free from path- (or

[31] Note that the complexity does not necessarily have to lie in the complexity of the technological design but can also reside in the complexity of the underlying production processes, as arguably the case in PV (see Huenteler et al., 2015)

past- or outcome-) dependency (Pierson, 2000; Page, 2006); in other words history matters in politics. Windows of opportunity might only open for short times (Sabatier, 1998). Hence, the political feasibility of targeting specific technologies (or technology levels) typically differs over time (and from country to country). The same can be true for applications. The windows of opportunity might be closed for some applications but open for others, e.g., because their regulation falls under the jurisdiction of different government branches (with different political economies attached). Our finding that application specificity and selection matters for technology selection also has a strategic implication in politics: If technology selection is not feasible, selecting applications (or the respective level) might lead to the same result (while keeping the policy "technology neutral"). The extent to which this strategy is already being implemented should be analyzed in future research.

In case a policy is enacted, this policy (and its underlying politics) and technology interact: if there is positive feedback between policy and technology, a policy-technology-path can emerge (Hoppmann et al., 2014). Given the potential role of applications for technology paths and policy paths, one can expect a major role for applications in the emergence (or creation) of these policy-technology-paths. Future research should specifically analyze the role of applications in the emergence of such paths.

This brings us to our final point. One of the main critiques of the quasi-evolutionary path-dependency literature is that it mostly draws from case studies which do not allow verification of path-dependency as the counterfactual cannot be analyzed (Vergne and Durand, 2010;Vergne 2013). Alternative solutions have been proposed by Vergne (2013), each having different strengths and drawbacks. One of the proposed solutions is computer simulations which contain random elements. Existing contributions (see e.g., Zott 2003, or Zeppini and van den Bergh, 2011) typically model abstract cases without using real-world data to 'calibrate' the models, limiting their ability to detect real-world path-dependent sequences (Vergne, 2013). Our paper offers a first step towards 'calibration,' as it approximates the initial conditions in a probabilistic way using real-world input data. We also contribute to the methodological gap by introducing a new indicator for competitiveness among technologies tailored towards analyzing path-dependency and lock-in (by focusing on the probability of one technology outcompeting its competitors in the market place). Future research could use this indicator and simulate different 'random' events (in the form of different deployment policy designs) and analyze how these condition develop over time, using approximations for the mechanisms underlying the increasing returns which are also calibrated (e.g., learning curves). While these models would help improve our understanding of path-dependency and particularly the role of policy in creating or avoiding lock-in, the contingencies involved in innovation are impossible to model. Nevertheless, such simulations could be used as a tool to rule out some of the (many) potential unintended consequences involved when policy aims to steer technological change.

6. CONCLUSION

The main objective of this paper was to contribute to the ongoing academic and policy debates on path-dependency and deployment policies. While previous studies have focused on the relationship between technological lock-in and the specificity of deployment policies, this paper introduced a new factor: the existence of multiple applications of a technology. Based on a review of the literature on deployment policies and lock-in, and supported by simulation of investors' investment decisions, the relevance of this factor was derived. We then discussed potential policy options and implications. Policy makers aiming to maintain or reach a desired level of technology diversity are faced with choosing the specificity level of the deployment policy along two dimensions: technology and application. Policy makers relying on technology assessments should make sure that 'application insiders' are considered in these assessments. Finally, we discuss our findings in light of the larger debate on path-dependency and technology policy and the underlying politics. We argue that the application perspective also matters in path-creation, political dynamics, as well as the co-evolution of policy and technology. To our knowledge, our paper is the first in the literature on technological lock-in to investigate the role of multiple applications. As such it offers only a first step and is not free of limitations. In the discussion section, we have therefore highlighted several avenues for future research.

APPENDIX

Appendix A – Levelized lifecycle costs calculation

In order to compare the costs of the four battery technologies, which in our model represent the investors' decision criterion, and thus shed light on the batteries' relative competitiveness, we calculate their lifecycle costs in terms of Levelized Costs of Electric Capacity (LCOEC). As different technologies exhibit different investment costs, operating costs, efficiencies and lifetimes, a comparison on a fair basis needs to incorporate both costs and performance characteristics. By putting the total annualized costs of a technology (investment costs and operating costs) that occur during its lifetime in relation to the installed electric capacity (in kW-yr), the LCOEC are an appropriate indicator to compare different energy technologies (EPRI, 2010; Madlener and Latz, 2013).[32]

$$LCOEC = \frac{\sum_{t=0}^{T} (CAPEX_t + OPEX_t)/(1+r)^t}{\frac{kW_{year} * 1 - (1+r)^{-T}}{r}}$$

LCOEC: Levelized costs of electric capacity [EUR/kW-yr]
CAPEX: Investment costs [EUR]
OPEX: Operation & maintenance costs [EUR]
kW_year: Installed electric capacity [kW-yr]
r: Discount rate [%]
T: System lifetime [years]
t: year

The LCOEC of the four battery technologies are calculated in two steps. First, depending on the parameters that characterize each application (required power rating and discharge duration) and on the technology parameters (roundtrip efficiency and maximum depth-of-discharge), the required energy capacity of the battery installation is calculated. In order to achieve the energy rating of the application (i.e., required discharge duration at nominal power), the size of the battery system is increased, accounting for electricity losses and limitations in the depth-of-discharge (i.e., the maximum energy to be withdrawn from the battery as a share of the total energy capacity of the battery). The following formula is used:

$$EC_B = \frac{ER_A^{req}}{\eta_{el} * DOD}$$

EC_B: Energy capacity of battery [kWh]
ER_A^{req}: Required energy rating by application [kWh]
η_{el}: Roundtrip efficiency (electric) [%]
DOD: Depth-of-discharge [%]

[32] In other words, the LCOEC describe the average annual costs of owning and operating a 1 kW stationary battery employed in a specific application accounting for investment costs, financing costs, operating costs, replacement costs, lifetime and efficiency.

The size of the battery is important as it affects investment and operation costs (Battke et al., 2013). A larger battery results in larger CAPEX and OPEX. Besides size, the discharge duration and frequency also affect the energy amount cycled through the battery per energy capacity of the battery, which in turn impacts on lifetime and OPEX. Second, we employ the LCOEC using the Monte Carlo simulation technique with 10,000 runs in order to account for the high degree of uncertainty present in the main battery input parameters (Hanna et al., 1998; Steward et al., 2009).[33] Specifically, the LCOEC are calculated using the stochastic technology input parameters *energy capacity costs*, *roundtrip efficiency, calendrical life* and *cycle life* as well as the deterministic input parameters power conversion system costs, balance-of-plant costs, and operations & maintenance costs. Note that the LCOEC of all four analyzed technologies are much more sensitive to the stochastically modelled variables than to the deterministically modelled ones. The Monte-Carlo analysis therefore can be regarded as a variance-based sensitivity check. An overview of the input values can be found in Appendix C.

We calculate the LCOEC of the battery technologies for the four applications *End-consumer Power Reliability, Support of Voltage Regulation, Wholesale Arbitrage,* and *End-consumer Arbitrage.* These four applications were chosen as they represent key applications in the stationary energy system and are targeted by planned or existing deployment policies. The four applications are described in Appendix B, and their technical parameters can be found in Appendix D.

[33] Monte Carlo simulation is a numerical method to solve mathematical problems (Jacoboni and Reggiani, 1983). By repeatedly calculating the LCOEC with different sets of input values drawn from random distributions, the Monte Carlo simulation can account for the uncertainty present in input parameters. PERT (Program Evaluation and Review Technique) distributions are assumed for the stochastic variables.

Appendix B

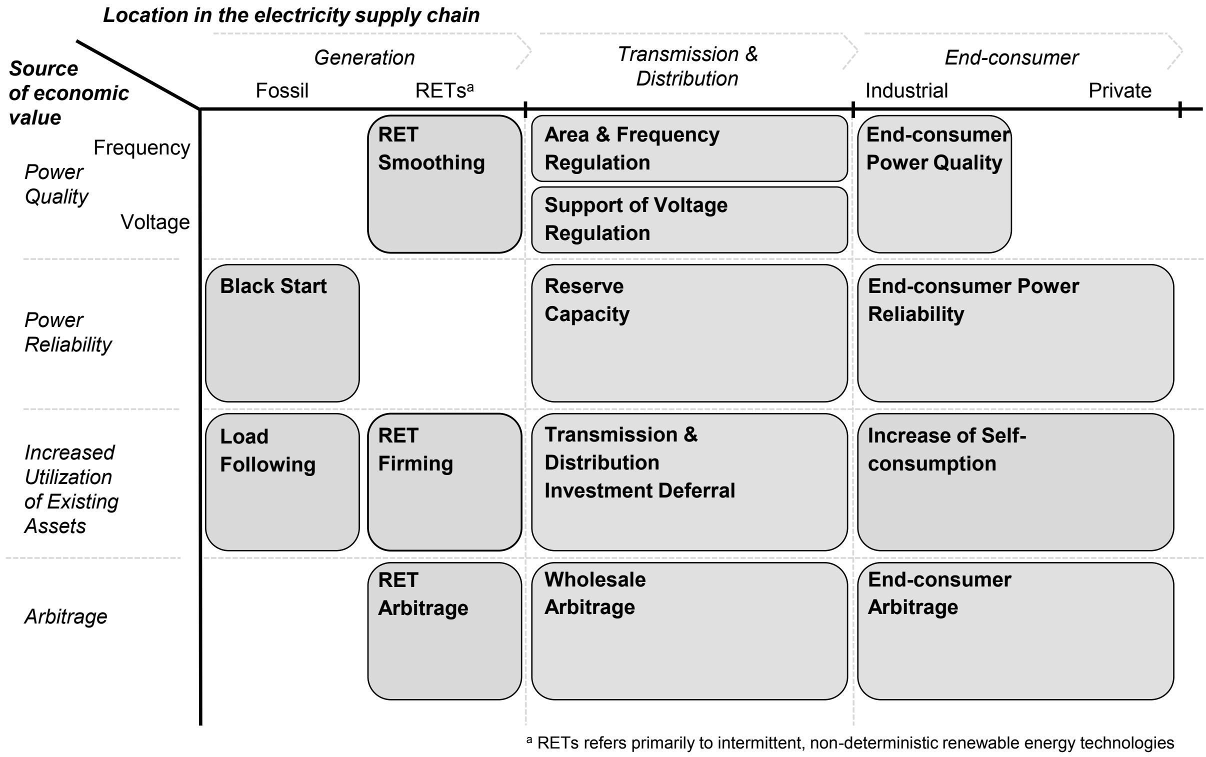

Figure B.1 – Applications of stationary batteries (Battke and Schmidt, 2015)[34]

Power Quality applications compensate electrical disturbances and anomalies in order to maintain a power system's performance at its optimal level (Lemaire et al., 2011). Consequently, these applications create economic value by ensuring power supply without deviations from the optimal frequency and voltage level. On the *Generation* level, SES devices can enable RETs to deliver electricity without any voltage sacks or harmonic distortions (*RET Smoothing*). On the *Transmission & Distribution* level, SES can be employed to maintain grid frequency at the required level (*Area & Frequency Regulation*) or to support the voltage level by providing flicker compensation and reactive power control in combination with additional electrical equipment as, for example, flexible AC transmission systems (*Voltage Regulation*). SES can also provide these services exclusively to specific end-consumers that have high requirements for power quality as, for instance, high-precision manufacturing (*End-consumer Power Quality*).

Power Reliability applications create economic value by helping guarantee an uninterrupted power supply. As most power generation plants require electricity to start, *Black Start* is one highly relevant SES application on the *Generation* level. In *Reserve Capacity* SES can help mitigate long-term

[34] By depicting 14 applications in the power system across a matrix of *source of economic value* and *location in the electricity supply chain,* Appendix A exemplifies the multi-purpose character of stationary batteries. Each application has a different combination of value creation and customer group.

imbalances of power supply and demand on the *Transmission & Distribution* level[35]. *End-consumer Power Reliability* assures uninterrupted power supply exclusively for customers facing very high costs in case of a black out (e.g., data centers, hospitals).

Increased Utilization of Existing Assets applications create economic value by improving the use and value of existing generation or transmission capacity and thereby avoiding or deferring additional investments. In combination with a conventional generation unit, an SES device can balance fluctuations in demand while the generation unit runs in its optimal load at maximum efficiency (*Load Following*). Together with SES, intermittent renewables can provide dispatchable energy (*RET Firming*)[36]. While in *Load Following* the economic value is generated from the gain in efficiency of the conventional generation unit, the economic value in *RET Firming* results from compliance with regulations or from reduced need for investment in generation capacity. An SES installed at a grid transmission bottleneck can be employed to shave transmission peaks and thus defer investment in additional transmission capacities (*T&D Investment Deferral*). End-consumers with generation capacity (e.g., photovoltaics) can increase the amount of self-consumed energy by adding SES (*Increase of Self-consumption*). This application creates value for the operator by replacing power purchase from the grid.

Arbitrage applications use price differentials to create economic value for the SES operator. *RET Arbitrage* stores energy produced from intermittent renewables in order to sell it when the power prices are high. *Wholesale Arbitrage* buys energy at the power markets at low prices and sells it again when prices peak. *End-consumer Arbitrage* uses prices differentials in electricity contracts. For example, utilities offer contracts for private consumers with different prices for electricity consumption during the day and at night. Moreover, industrial companies often have combined contracts, invoicing the electricity consumed and the yearly maximum power provided separately. An SES used to shave consumption peaks can lower the latter cost component considerably.

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[35] While *Area & Frequency Regulation* refers to very short-term imbalances in demand and supply (similar to spinning reserve or primary frequency regulation), *Reserve Capacity* refers to imbalances of longer durations (similar to non-spinning reserve, minute reserve or cold reserve).

[36] In island grids such as those in Hawaii operators of large wind and photovoltaic power generation capacity are required to deploy large energy storage facilities in order to meet the reliability provisions imposed by power purchasing agreements (IHS Emerging Energy Research LLC, 2011).

Appendix C

Table C.1 – Input data and assumptions for battery technologies

Technology[a]	*Primary (stochastic) parameters*					*Secondary (deterministic) parameters*		
		Energy capacity costs	*Roundtrip efficiency*	*Calendrical life*	*Cycle life*	*Power conversion system costs*	*Balance-of-plant costs*	*Operation & maintenance costs*
	Value	[EUR/kWh]	[%]	[years]	[# of cycles]	[EUR/kW]	[EUR/kW]	[EUR/kW p.a.]
	Low	102	80	5	500			
Lead-acid	Most likely	171	82	8,5	1250	172	70	22
	High	354	90	15	2000			
	Low	356	85	5	1000			
Lithium-ion	Most likely	844	90	11,5	10250	125	0	19
	High	2034	95	15	30000			
	Low	178	71	5	2500			
Sodium-sulfur	Most likely	256	81	8,5	3333	171	53	45
	High	400	90	15	5000			
	Low	110	70	5	10000			
Vanadium redox flow	Most likely	298	75	9,5	13000	271	63	43
	High	809	80	10	15000			
Distributional assumption		PERT	PERT	PERT	PERT	n/a	n/a	n/a

[a] All costs are inflation adjusted to 2011 EUR. Since a high-power application such as Area & Frequency Regulation requires a slightly different cell layout for lead-acid and lithium-ion batteries, input costs parameters of lead-acid (lithium-ion) for Area & Frequency Regulation were adapted in the following way: Energy capacity costs +100% (+0%), Power conversion system costs +43% (+14%), Operations & maintenance costs -34% (-60%), Balance-of-plant costs -100% (-100%) (Schoenung and Hassenzahl, 2003). All other data and assumptions are based on Battke et al. (2013).

Appendix D

Table D.1 – Overview of technical parameters of applications[37]

	Required power rating	*Required energy rating*	*Discharge duration*	*Cycle frequency*	*Electricity price*	*Discount rate*
	[MW]	[MWh]	[h]	[# cycles / year]	[EUR/ MWh)	[%]
End-consumer Power Reliability (commercial scale)	0.1	0.1	1	0.5	100	8%
Support of Voltage Regulation	1	0.25	0.25	250	50	8%
Wholesale Arbitrage	100	800	8	365	50	8%
End-consumer Arbitrage (commercial scale)	0.1	0.25	2.5	730	100	8%

All applications are evaluated assuming the context of the German power market.
Sources: (Akhil et al., 1997; Butler et al., 2002; ESMAP, 2007; Merz, 2008; Eyer and Corey, 2010; Lemaire et al., 2011; Sauer et al., 2011; Krause, 2012; Battke and Schmidt, 2015; Battke et al., 2013)

37 "Required power rating" refers to the maximum power (in watts [W]) a battery has to deliver. "Discharge duration" refers to the maximum time a stationary battery needs to be able to discharge continuously. "Cycle frequency" refers to the number of discharge cycles within a given time frame (e.g., one cycle per day). "Electricity price" refers to the average price of electricity (in EUR/Wh) the operator has to pay for charging the stationary battery. "Discount rate" is the interest rate (in percent) the operator applies to investments in the stationary battery.

Appendix E

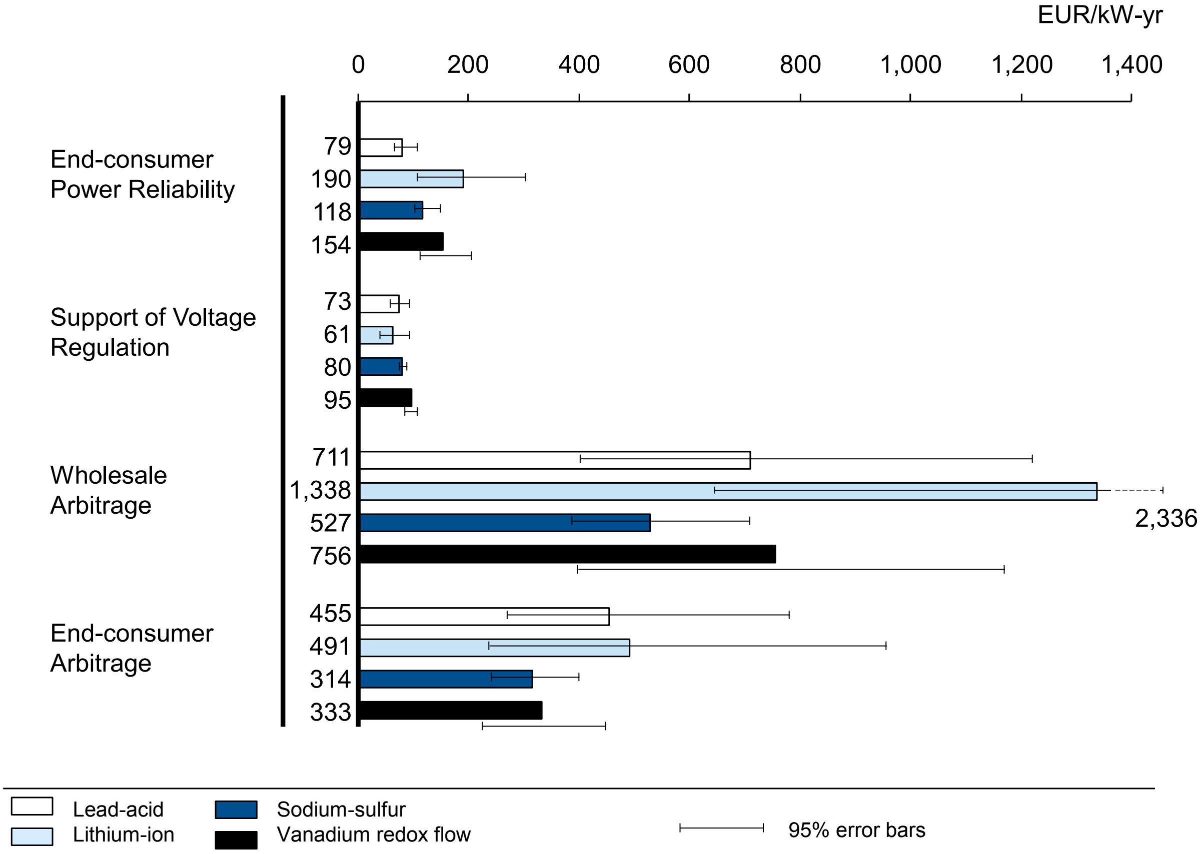

Figure E.1 – Levelized costs of electric capacity (LCOEC) of battery technologies across applications[38]

[38] Appendix D depicts the probabilistic LCOEC of the four battery technologies in four specific applications. The lengths of the colored bars as well as numerical values left of the bars indicate the mean LCOEC. The impact of the uncertainty in the main input parameters of stationary batteries is represented by the black 95% error bars. The degree of competition among technologies in different applications is indicated by the overlap of the 95% error bars. The more the errors bars of the average most cost competitive technology overlap with those of the other technologies, the more investors deviate from the majority decision, resulting in a lower lock-in risk.

Appendix F

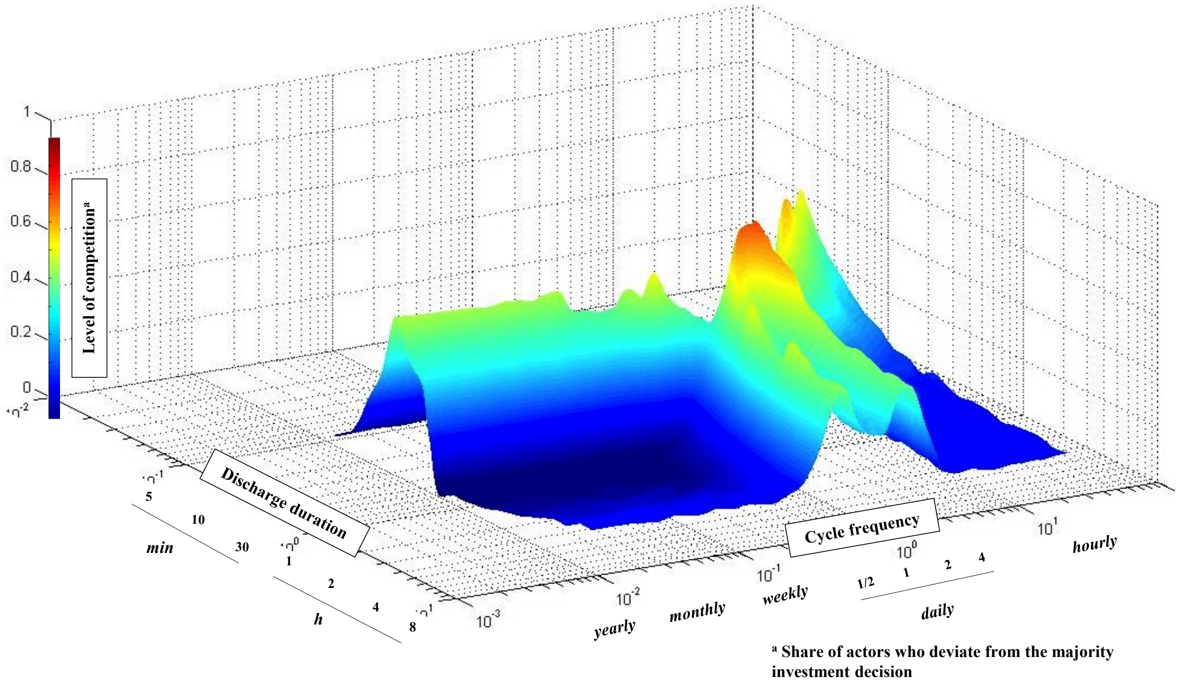

Figure F.1 – Degree of competition among battery technologies in the application landscape (3D)

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