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The Effect of Local and Global Learning on the Cost of Renewable Energy in Developing Countries

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Abstract

High upfront costs are a critical barrier for investments in clean infrastructure technologies in developing countries. This paper uses a case study of Thailand's electricity sector to create realistic estimates for the relative contributions of local and global technological learning to reducing these cost in the future and discusses implications of such learnings for international climate policy. For six renewable electricity technologies, we derive estimates for the share of locally and globally sourced goods and services, and analyze the effects of local and global learning during the implementation of Thailand's renewable energy targets for 2021. Our results suggest that, in aggregate, the largest potential for cost reduction lies in local learning. This finding lends quantitative support to the argument that the conditions enabling local learning, such as a skilled workforce, a stable regulatory framework, and the establishment of sustainable business models, have a more significant impact on cost of renewable energy in developing countries than global technology learning curves. The recent shift of international support under the United Nations Framework Convention on Climate Change towards country-specific technology support is therefore promising. However, our results also show that the relative importance of local and global learning differs significantly between technologies, and is determined by technology and country characteristics. This suggests that international support need to consider both the global perspective and local context and framework conditions in order to reap the full benefits of technological learning across the wide range of clean technologies.

Keywords: Climate policy, Technology transfer, Technological capabilities, Technological learning, Thailand, Renewable energy

Highlights:

- Development of a techno-economic model of Thailand's Alternative Energy Development Plan 2012-2021
- Analysis of the impacts of local and global learning effects on mitigation cost
- Demonstration that the importance of global and local learning varies between clean technologies
- Finding that local learning is significant for wind, PV, biogas and micro hydro, whereas global learning is important for PV and solar thermal
- Discussion of the future role of the international support for clean technologies

1. Introduction

The global climate policy regime needs to significantly accelerate the diffusion of clean technologies to avoid dangerous impacts from climate change (UNFCCC, 2012). In addition to actions taken by the developed world, developing countries are expected to assume greater responsibility by implementing domestic policies that contribute to both domestic economic development and climate change mitigation (Kanie et al., 2010). Indeed many developing countries are already implementing domestic climate legislation, despite the gridlock in international negotiations (Nachmany et al., 2014; REN21, 2013; Townshend et al., 2013). However, high upfront costs remain a critical barrier for large-scale investments in clean technologies, especially in developing countries (IPCC, 2012; Schmidt, 2014). How to accelerate the development and transfer of clean technologies is, therefore, emerging as a central issue in the international climate policy negotiations (Ockwell and Mallett, 2012; Pueyo et al., 2012).

Experience in the industrialized world has shown that cost reductions and performance improvements of new technologies are often closely linked to policies aimed at increased production and deployment (Jänicke, 2012), driven by mechanisms collectively referred to as *technological learning* (Junginger et al., 2010). If successful, the increasing number of mitigation actions taken now by developing countries holds the promise to stimulate innovations and future cost reductions there as well. But technological learning encapsulates a diverse array of purposeful processes that some countries, sectors and organizations manage better than others (Bell and Figueiredo, 2012; van Hoof, 2014). Besides creating financial incentives for investment, one of the key challenges for international climate policy is therefore to actively promote technological capabilities in developing countries and to enable countries to reap the full learning benefits from mitigation investments they make and attract (Benioff et al., 2010; Bhasin, 2013; de Coninck et al., 2008; Ockwell and Mallett, 2012).

Technological learning in developing countries, especially outside the largest emerging economies, follows distinct dynamics (Pueyo et al., 2011). The industries producing clean technologies are increasingly globalized (Gallagher, 2014; Lewis, 2012; Nahm and Steinfeld, 2014). Therefore, in a typical investment project, local firms in developing countries provide only part of the products and services. Learning in this share of the industry value chain is local in nature and driven by local market developments and policies – we will refer to it as *local technological learning* (Morrison et al., 2008; Mytelka, 2000). However, because a substantial share of components is typically sourced from abroad, the economics of local investments are also impacted by technological learning processes in other countries. For example, technological progress by Chinese solar cell producers improves the economics of solar investments around the world. This form of learning is driven more by global markets than by policies in individual countries (Peters et al., 2012). Future investment conditions for clean technologies in developing countries thus depend on a combination of global and local learning processes, which, in turn, depend on domestic and international regulatory, institutional and industrial contexts. Better understanding of the relative importance of the two can improve both domestic and international policy decisions.

Using a quantitative case study, this paper estimates the effect of local and global technological learning on the cost reductions of renewable electricity generation in Thailand. We employ a techno-economic model of the country's electricity sector to project the cost of implementing the country's renewable energy targets for 2021 (Kamolpanus, 2013). We derive estimates for the share of locally and globally sourced goods and services for six renewable electricity technologies and analyze, in different scenarios, the impact of local and global learning effects on the investment cost. Based on the results, we explore implications for the design of international low carbon technology support mechanisms.

The paper makes three main contributions. First, our case study informs the academic debate as well as international negotiations on the post-Kyoto climate policy regime of the United Nations Framework Convention on Climate Change (UNFCCC). In its support for technology development and transfer, the international climate policy regime has recently shifted its attention toward national policies and local technological learning. The analysis presented in this paper enhances the understanding of the merits of this shift, and informs the design and functional specification of the new international technology support mechanisms. Our quantitative approach and the focus on mitigation cost complements existing conceptual and qualitative work on the topic (Benioff et al., 2010; Bhasin, 2013; de Coninck et al., 2008; Ockwell and Mallett, 2012). Furthermore, it contributes to the growing body of literature on the economics of clean energy technology investments in developing countries (e.g., IRENA, 2012a; Schmidt et al., 2012). Finally, our paper is among the first to investigate the impact of local and global learning separately for a specific developing country case.

The next section will introduce the key theoretical constructs used in the analysis (Section 2). Section 3 introduces the case, before section 4 presents the model, the data sources, and the methodology. The results of the case study are presented in Section 5, and their policy implications discussed in Section 6.

2. Local and Global Technological Learning

2.1. Technological Learning in Developing Countries

Technological learning is understood here broadly as the accumulation of technological knowledge and experience, often also referred to as *technological capabilities*, in individuals and organizations (Bell and Figueiredo, 2012). Research on innovation processes has shown that the technological capabilities held by firms comprises not only information codified in capital goods or documents (patents, manuals, etc.), but also includes the tacit knowledge embodied in individual skills and firm routines (Dosi, 1988; Senker, 1995). These elements of knowledge are costly to transfer and therefore highly organization-specific (von Hippel, 1994). This means that removing trade barriers and providing developing countries with intellectual property rights (IPR) and resources for technology imports is not sufficient to enable countries to catch up to the technological frontier (Bell and Pavitt, 1996; Ockwell et al., 2010). Rather, catching up requires building local technological capabilities through the cumulative, costly and time-consuming process of technological learning (Bell, 2010).

Technological capabilities and learning are increasingly being recognized as significant drivers of low carbon development (Byrne et al., 2011; Lema and Lema, 2013; Phillips et al., 2013). The international climate negotiations, too, are taking notice (Ockwell and Mallett, 2012). Improved technological capabilities hold the promise of removing barriers to the diffusion of clean technologies, thereby facilitating further emission reductions in the future (Sandén and Azar, 2005). Besides its effect on mitigation cost, the local build-up of technological capabilities is crucial for local industrial capacity, poverty reduction and economic growth. For many developing countries, investing in climate change mitigation is, for now, only desirable if the government can create opportunities for the local private sector to participate in the value chain of mitigation investments. However, in order to participate in the development and manufacturing of clean technologies, local firms in developing countries need to create the capacity to continuously absorb, adapt and improve new technologies (Bell and Pavitt, 1996).

Climate models increasingly incorporate learning as an endogenous process driven by mitigation investments (Kahouli-Brahmi, 2008; van der Zwaan et al., 2002), but technological learning is not an automatic by-product of investments (Bell and Figueiredo, 2012). Rather, in the analysis of the development of mitigation policies and estimation of future mitigation cost, it is better understood as an *opportunity* that can be only adequately seized when both governments and firms create the necessary conditions. Organizations need to pursue conscious efforts to create the ability, in the form of a skilled workforce and organizational processes, to *absorb* the new knowledge and experience that they generate (Cohen and Levinthal, 1989). Furthermore, organizations innovate and learn through their interaction with users, suppliers, competitors, universities or regulators in *systems of innovation* (Fagerberg et al., 2007; Lundvall et al., 2009). The existence of formal and informal networks, as well as public funding for science and technology, are therefore critical drivers of technological learning. And, last but not least, learned capabilities degenerate rapidly if organizations have a rapid workforce turnover, face an instable regulatory framework, or pursue unsustainable business models.

2.2. Local and Global Learning Effects in Value Chains

Most clean technologies are technological systems consisting of hundreds, or even thousands, of materials, components, and intermediate goods. Furthermore, mitigation investments involve numerous legal, financial, and regulatory services. The collective of technology suppliers and service providers that deliver the materials, components, products and services to deploy technologies we call the technologies' *industry value chain*.

Modern industry value chains are disintegrated and geographically distributed production and service networks. As markets for clean technologies have grown, their supplying industries have also globalized in recent years (e.g., Gallagher, 2014; Lewis, 2012; Nahm and Steinfeld, 2014). Globally traded components and products are often those that can be transported at relatively low cost and have standardized interfaces. (On the extreme end of this spectrum are commodities.) Globally traded services often require highly specialized technological expertise that only very few firms possess. In the wind turbine industry, for example, gearboxes, hubs, generators and bearings are components for which the know-how necessary for design and manufacturing is concentrated in only a few key firms globally. Further, the consulting services needed to make a complex product bankable, or a difficult geography accessible, are often provided by experienced, globally operating firms.

For technological learning in globally traded goods and services, global market conditions matter more than *where* their products are finally deployed. If uncertainty about the product's performance is very large, as in the case of carbon capture and storage technology, any demonstration will add to the global knowledge pool (de Coninck et al., 2009). In the case of smaller components, materials, or intermediate goods, producers seldom even interact with end-users, if they know them at all. In the case of services, the global applicability of their experience is the key reason why globally operating producers are selected in the first place. The accumulation of capabilities in firms and industries is therefore more dependent on global, aggregate market trends than on country-specific context factors. We define learning in these goods and services as *global technological learning*, because, in a simplified learning model or experience curve, it would best be predicted by the size of the *global* market.

But value chains are not entirely globalized. To stimulate local private sector participation, many climate-related laws in developing countries contain some form of provision to create a certain level of domestic content. This gives local firms economic advantages over global suppliers. But even without legislative requirements, often local firms provide many steps. This may include large and heavy components that are costly to transport, or factors which are cheaper to make at home; but it is important to note that the drivers underlying these patterns are not affected only by input or transportation cost. The drivers for localization may include the expertise required to deal with idiosyncratic geography, context-specific or fast-changing regulations, or local infrastructure and climate conditions. In a wind power project, for example, towers, blades, and foundations are typically sourced from suppliers not far from the project site, and domestic firms often provide project development, installation, operation, and maintenance services. In developing countries, it is reasonable to assume that local firms are mostly active in their home markets. We will therefore assume that their learning is predominantly local, and refer to technological learning in this part of the value chain as *local technological learning*.

The geographical dispersion of value chains leads to cost and cost trends that differ significantly between components (e.g., Lindman and Söderholm, 2011). Cost trends and learning curves are global whenever global markets exists, while for the locally sourced components trends differ substantially between regions (e.g., Seel et al., 2014). For the latter, local economic, political, and regulatory conditions determine whether or not investments lead to the accumulation of technological capabilities, which in turn are essential to reduce local investment cost. To stimulate progress in this part of the value chain, domestic and international policymakers should focus on strengthening the domestic innovation system. For the global part of the value chain, however, which also affects domestic investment economics, national innovation systems are not very important. Here, policymakers need to work toward international knowledge sharing and standardization activities to strengthen the sectoral innovation system in order to advance low-carbon technologies (de Coninck et al., 2009). They should also strive for the global markets to remain open and try to minimize protectionism to reap the benefits of global technological learning (Lewis, 2014).

3. The Case of Thailand's Electricity Sector

3.1. Case Selection

This paper presents a quantitative case study of Thailand's Alternative Energy Development Plan (DEDE, 2012) for the electricity sector in order to explore the relative importance of local and global learning in developing countries' mitigation efforts. We chose a case study of the electricity sector because it lies at the heart of the climate change challenge as the single largest source of CO_2 emissions among the primary sectors of the world economy (Bazilian et al., 2008). Indeed, the majority of national mitigation policies in developing countries target energy production and consumption in the industrial, energy supply, buildings, and transport sectors (van Tilburg et al., 2013). At the same time, the diversity of technologies in the electricity sector and their globally operating technology providers allows us to model both local and global learning processes.

We chose Thailand as case study for three reasons. First, the country has clear, broad and ambitious targets for renewable energy diffusion which allow us to study the impact of different learning conditions on the cost of an existing policy. Second, the country's government publishes detailed data on energy production and consumption that allow us to model the electricity sector on a single-plant level. Third, the country faces economic and political challenges that make the framework conditions for its energy policy decisions representative of a large number of other middle-income countries. A country of 66.9 million with a GDP per capita at USD 5,210, Thailand has managed to provide its population with almost universal access to electricity (The World Bank, 2014). Like many other middle-income countries, it now faces the challenge of rapidly growing energy consumption, accompanied by growing carbon emissions, import dependency, national security concerns and local resistance to fossil and nuclear power plants. How to assist emerging economies in managing these challenges while simultaneously reducing carbon emissions will be one of the most important questions for international climate policy in the coming decades.

3.2. Trends and Challenges

Primary energy consumption in Thailand has almost tripled from 1990 to 2011, making it the second-largest energy consumer in the Association of Southeast Asian Nations (ASEAN), while subsequently its greenhouse gas (GHG) emissions grew by 177.5% (see Figure 1). The power sector is the largest carbon source, with a share in national emissions that grew from 33% in 1990 to 42% in 2011. By 2035, energy consumption and GHG emissions are expected to roughly double yet again (IEA, 2013a).

Thailand is already a net importer of oil, gas and coal, and is projected to become the most energy import-dependent country among the ASEAN by 2035, with imports estimated to increase to about 90% of consumed oil and gas (IEA, 2013a). Nakawiro et al (2008) estimate that gas and coal import costs will grow from 0.92% of the country's GDP in 2011 to 2.19-2.69% in 2025, depending on the development of fuel prices in the region. The main domestic sources are not without challenges, too, in light of strong local opposition to nuclear power and new coal plants (Greacen and Bijoor, 2007; Pongsoi and Wongwises, 2013).[1]

[1]The first nuclear plant was originally scheduled to come online in 2020, but was postponed to 2026 after the nuclear incidence in Fukushima, Japan, in 2011.

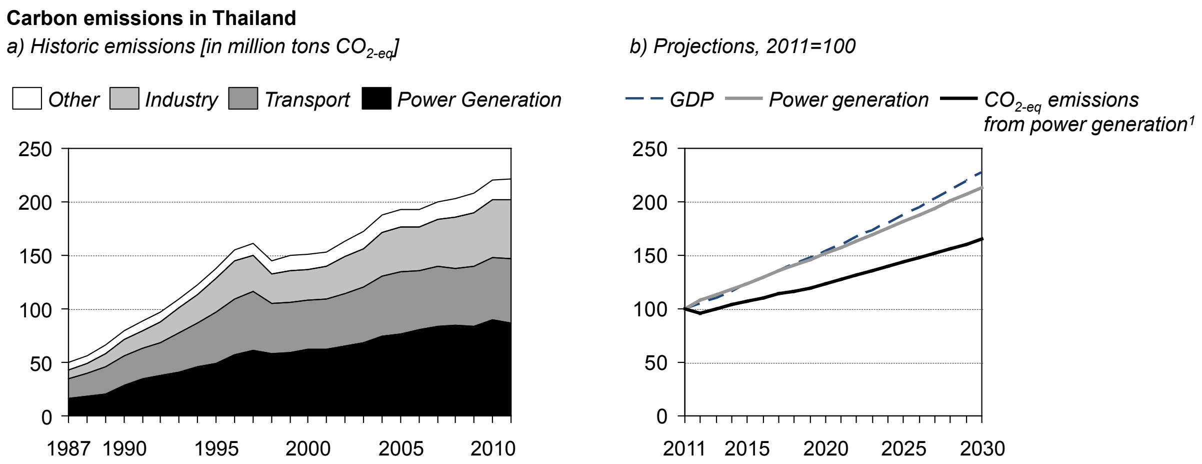

Figure 1: Thailand's carbon emissions by sector (a) and future projections for emissions from the country's power sector (b). [1]CO_2 emissions from power sector do not contain imports. Data from EPPO (2013, 2012a).

As of 2011, the electricity sector is dominated by natural gas (67%), with lignite and hard coal providing together about 20% as well (Figure 2). Besides large hydropower (5%), renewable energy constitutes only a very small part of the electricity mix, mostly in the form of biomass (1.4%) (EPPO, 2012b). The remaining demand is covered by direct electricity imports (6.6%). Electricity generation reached 162 TWh in 2011 and is projected to increase by more than 4% annually (EPPO, 2012b, 2012c). Besides domestic capacity investments, the government plans to meet demand by increasing the share of direct electricity imports from neighboring Malaysia and Laos to 13% in 2030 (Figure 2).

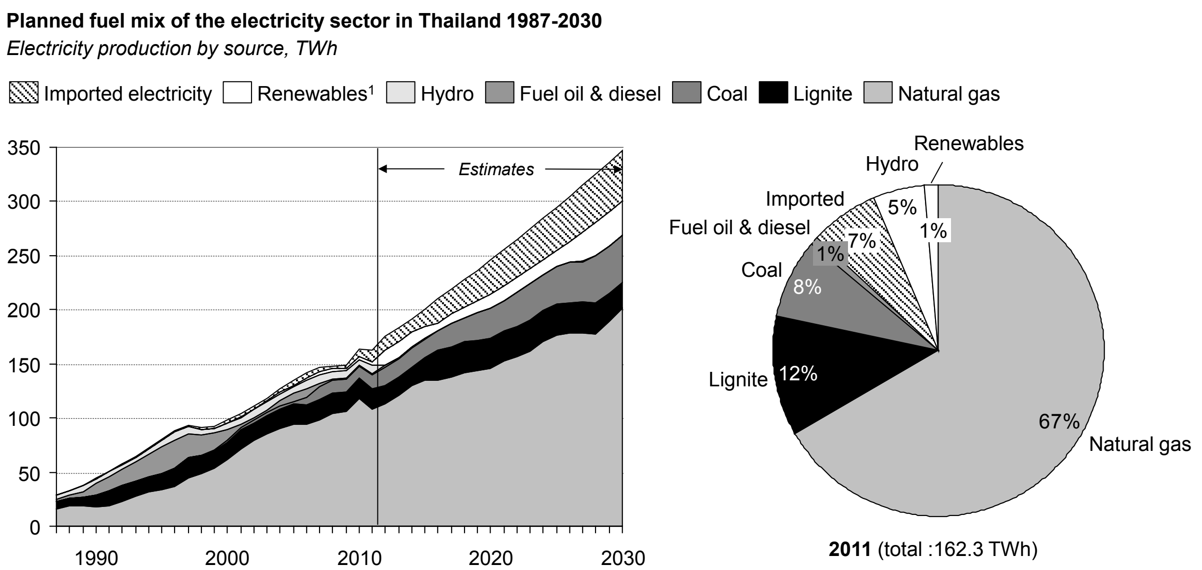

Figure 2: Development of the fuel mix in Thailand's power sector from 1987 to 2030. [1]The renewables wedge contains hydropower after 2011; the share of renewables after 2012 reflects relatively conservative projections of the Power Development Plan. Data from EPPO (2013, 2012a).

3.3. Targets and Support for Renewable Energy

In recent years, electricity sector planning initiatives have begun to consider renewable energy as a potential remedy for some of the problems the country faces. Thailand has no official renewable energy law at this point but several comprehensive long-term energy plans (Tongsopit and Greacen, 2013). The two most important are the Power Development Plan by the Energy Policy and Planning

Office (EPPO, 2012c) and the Alternative Energy Development Plan (AEDP) by the Department of Alternative Energy Development and Efficiency (DEDE, 2012; Kamolpanus, 2013), both under the Ministry of Energy. The AEDP, updated in 2013, is aiming to increase the renewable energy in the power sector to 14 GW by 2021, or 24% of the total capacity (compare with Figure 2). As shown in Figure 3, the largest part of this capacity is projected to come from biomass (4.8 GW), followed by biogas (3.6 GW), solar power (3 GW), wind power (1.8 GW) and micro hydro (324 MW).[2] The largest relative increase is targeted for biogas (17-fold) and wind energy (15-fold). It is notable that large hydro is not part of the AEDP. For simplification, we therefore use the term 'renewable electricity' in this paper to refer to non-large-hydro renewable electricity technologies.

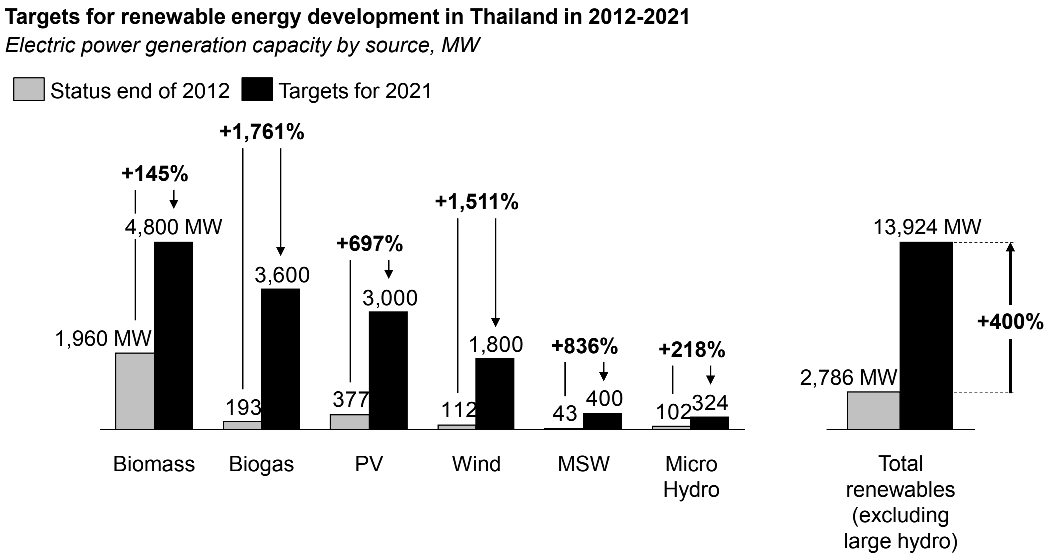

Figure 3: Targets for renewable electricity under Thailand's Alternative Energy Development Plan (DEDE, 2012). Data for 2012 are from DEDE (2013); updated targets for 2021 from Kamolpanus (2013).

In addition to public research, tax incentives, venture capital and investment grants, the primary government policy to induce renewable energy investments is currently a feed-in tariff premium scheme, referred to as 'FIT adder' (DEDE, 2012; Tongsopit and Greacen, 2013). The FIT adder program provides a purchase guarantee under which fixed premiums, which differ by technology, capacity and project location, are paid on top of a base tariff that is determined by the utility's avoided cost. Originally implemented in 2007, the official objectives of the FIT adder policy included enhanced levels of renewable energy generation; private sector involvement; economic growth and rural development; diversification of the fuel mix; local pollution reduction and utilizing agricultural wastes; as well as local equipment manufacturing and thus reduced international equipment imports (Tongsopit and Greacen, 2013). In 2010, Thailand's government announced plans to transform the FIT adder into a fixed FIT, but has done it so far only for rooftop solar PV (Kamolpanus, 2013). There is no local content requirement in Thailand's renewable electricity support policies, but import duties create incentives to source locally (Beerepoot et al., 2013).[3]

[2] The targets include another 400 MW of municipal waste incineration plants.
[3] These import duties were not considered in our analysis.

3.4. Local and Global Learning in Renewable Energy in Thailand

As developed in Section 2, modern clean technology value chains feature significant local and global value creation. To illustrate how the local and global aspects of the value chain play out in Thailand, the value chain of a typical project in the electricity sector in Thailand is shown in Figure 4. Displayed is a value chain of a solar PV project, including the primary value chain, from material and component suppliers, up to the grid operator, and secondary activities such as universities, consultancies or legal services. For one specific project, a 9.5 MW solar PV project in Mae Chan in Chiang Rai province developed in 2013, we identified the most likely countries of origin for each value chain step. In the depicted case the project operator, the grid operator, the construction company, one of the two project developers, (probably) legal and financial services, and the regulator are local, while no core hardware components were manufactured in Thailand. The modules are manufactured by a Norwegian company in Singapore, while the inverters are made by a Swiss-Swedish company, most likely in Estonia. The leading production equipment suppliers, material suppliers and research institutes are located in Europe, the United States and Australia, thus it is almost certain that all these countries/continents are also represented in the value chain. The economics of the final project are determined by progress by all these actors in a concurrence of local and global learning effects, which calls for policy support that strengthens learning conditions locally and globally to facilitate overall technological progress.

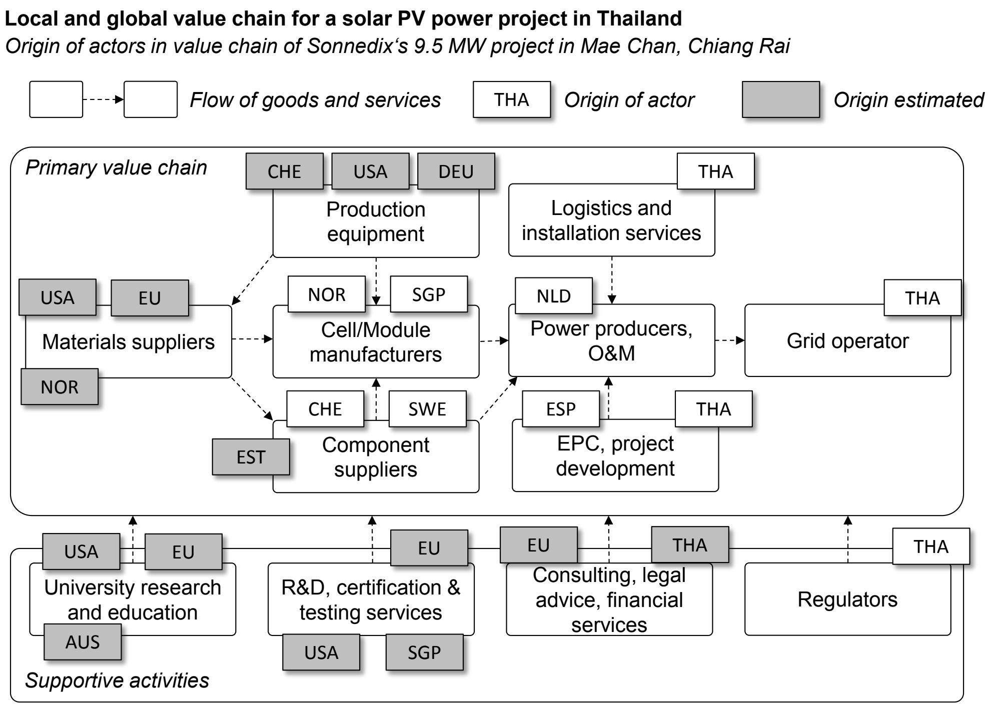

Figure 4: Value chain for an exemplary solar PV project in Thailand. Country codes as defined by UN Statistics Division; EU stands for European Union. Company identification from news sources.

4. Materials and Methods

4.1. General model framework

We developed a model of Thailand's electricity sector and used different scenarios to estimate the effects of technological learning on the cost of achieving the Alternative Energy Development Plan (AEDP) targets. We chose a bottom-up, techno-economic model (Berglund and Söderholm, 2006) because it allows us to study the effects of cost dynamics on the technology-level on the aggregate cost of renewable energy policies (Kahouli-Brahmi, 2008). To model the effects of learning on the cost of technologies, we chose the learning curve approach because it enables us to treat local and global effects separately (Hayward and Graham, 2013). We focused on six renewable energy technologies under the AEDP: biomass, biogas, micro hydro, on-shore wind, solar PV, and concentrating solar power (CSP).

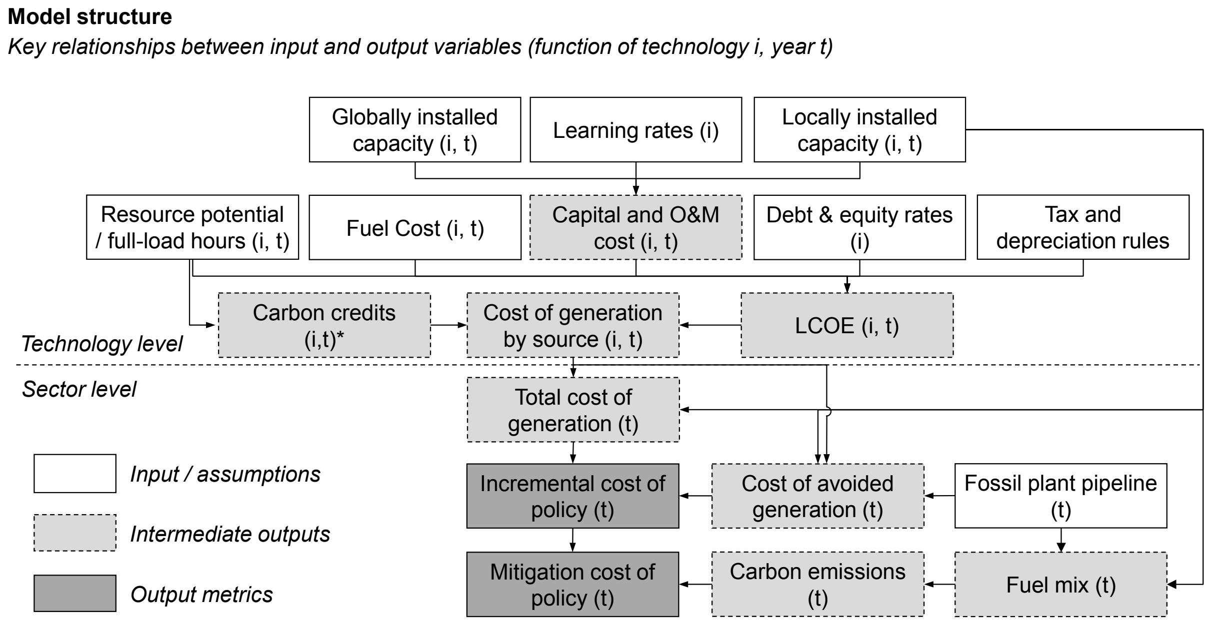

Figure 5: Relationships between key input and output metrics in the techno-economic model; the upper half of the graphic shows variables calculated on the technology-level; the lower half shows variables calculated for the entire electricity sector/policy.

The overall structure of the model with its key variables and relationships is depicted in Figure 5. Calculating the cost of renewable electricity is a well-established process in renewable energy policy analysis (Burtraw et al., 2012). The cost of the avoided electricity, however, even though at least equally important, are often neglected (Schmidt et al., 2012). To obtain the cost of avoided electricity and the avoided greenhouse gas emissions, we compared different scenarios for diffusion of renewable energy with a hypothetical scenario without any renewables diffusion. Based on this comparison, the model provides two main outcome metrics, shown in dark grey in Figure 5, to assess the policy support needed to achieve Thailand's renewable electricity targets: the *incremental policy cost* and the *mitigation cost*, both stated as net present value.[4] The former is a proxy for marginal

[4] The incremental costs and the mitigation costs are discounted to the year 2012 with the yield of 40-year Thai government bonds, which reflects the refinancing cost of the Thai government over the period of the assumed feed-in Tariff payments.

social cost (Palmer and Burtraw, 2005), while the latter allows comparisons between different mitigation measures and carbon prices.

How the scenarios deviate from the non-renewables scenario is calculated on the sectoral level. The incremental costs represent the difference between the total cost of renewable electricity and the total cost of avoided electricity (Schmidt et al., 2012). The mitigation costs are calculated based on the total carbon emission reductions from the AEDP and the incremental cost:

$$(i)\ Incremental\ policy\ cost = \ Cost\ of\ renewable\ electricity - Cost\ of\ avoided\ electricity\ [in\ USD\ or\ \frac{USD}{MWh}]$$

$$(ii)\ Mitigation\ cost = \frac{Incremental\ cost}{Avoided\ greenhouse\ gas\ emissions}\ [\frac{USD}{tCO_2}]$$

For each of the renewable and fossil technologies in the sector we calculated the cost of electricity generation for each year of the considered period. The cost of renewable electricity and the cost of avoided electricity were then aggregated from the technology-level calculations. The cost of renewable electricity was aggregated over the renewable technologies under the AEDP in 2013-2021 (details in Section 4.2). The cost of avoided electricity was aggregated over the 9 main fossil technologies from 2013, when the electricity is displaced, to 2040, when the last renewable plant goes offline. How we calculated the avoided cost and avoided emissions is explained in detail in Appendix A.

4.2. Cost of Renewable Electricity Generation

4.2.1. Generated Electricity

The electricity generated by each source of renewable electricity is a function of the diffusion path and the plant utilization. Since the AEDP does not contain interim targets, we modeled the diffusion of the six considered technologies as a linear increase in installed capacity. The split between PV and CSP in the (undifferentiated) total solar target is assumed as a relation of 9 (PV) to 1 (CSP). All renewable electricity is assumed to be fed into the grid (no curtailment), so the plant utilization is a mere function of the resource potential. In the case of micro hydro, biogas and biomass, for which significant domestic experience exists, we took the capacity values from domestic academic sources (Delivand et al., 2011; Pattanapongchai and Limmeechokchai, 2011a; Promjiraprawat and Limmeechokchai, 2012). For wind, solar PV and CSP we estimated the capacity factors based on resource information from the IRENA global atlas (3Tier layer; IRENA, 2014).

4.2.2. Cost Per Unit of Generated Electricity

To model the cost of electricity, we assumed that the government supports each technology with an inflation-adjusted, fixed feed-in tariff (FIT). A 20-year lifetime for all investments in 2013-2021 implies FIT payments in the period 2012-2040. The FIT rates for each technology are assumed to exactly reflect, at any point in time, the technology's levelized cost of electricity (LCOE) (Waissbein et al., 2013):

$$LCOE_{i,t} = \frac{SE * INV_i + \sum_{\tau=0}^{T} \frac{OPEX_{i,t} + CD_{i,t} - TR * (OPEX_{i,t} + IE_{i,t} + DP_{i,t})}{(1+ROE)^{\tau}}}{(1-TR) * \sum_{\tau=0}^{T} \frac{P_{i,t} * CF_{i,t} * 8760h}{(1+ROE)^{\tau}}}$$

An equity investor perspective was adopted by modeling the cash flows generated for every technology on a single plant basis (Dinica, 2006). The determinants of the LCOE of a technology *i* in year *t* are thus the share of equity (SE), the total investment cost (INV), the operational expenses (OPEX), including operation, maintenance and fuel cost, and the cost of debt (CD), which includes the interest expenses and capital payments of the debt-financed investment share in a fixed-rate, 10-year loan. A fixed corporate tax rate (TR) was assumed to apply to all income minus OPEX, interest expenses (IE) and annual depreciation (DP). The annual revenues from electricity generation are determined from the net electric capacity (P) and the time- and technology-specific capacity factor (CF; see below). ROE is the after-tax return on equity that an investor requires taking into account the risk-free rate as well as political, market and technology risks in the designated location. For system integration cost of variable renewable energy technologies (PV, CSP and wind), we considered an additional average of 0.0115 USD/kWh to account for balancing and grid integration cost (IEA, 2008). Table 3 and Table 6 in the appendix provide an overview over the input parameters for renewable energy technologies and key sector-wide assumptions used in our model.

4.2.3. Local and Global Learning

The cost of renewable electricity is assumed to decrease over time as technological capabilities accumulate in the industry (compare Section 2). In particular, the initial investment cost and the fixed O&M cost of technology *I* were modeled as a function of local and global cumulative installations (Y_{local} and Y_{global}), learning rates and diffusion over time:

$$(iii)\ INV_{i,t} = \alpha_{i,local} * INV_{i,t-1} * \left(\frac{Y_{i,local,t-1}}{Y_{i,local,t-2}}\right)^{\frac{ln(1-LR_{i,local})}{\ln 2}} + \alpha_{i,global} * INV_{i,t-1} * \left(\frac{Y_{i,global,t-1}}{Y_{i,global,t-2}}\right)^{\frac{ln(1-LR_{i,global})}{\ln 2}} \quad [\frac{USD}{kW}]$$

$$(iv)\ O\&M\ cost_{i,t} = \beta_i * INV_{i,t}\ [\frac{USD}{kWh}]$$

To separate the effects of local and global technological learning, we split up the investment cost into locally and globally sourced components ($\alpha i_{,local}$ and $\alpha_{i,global}$). The learning rate LR, too, is differentiated for local and global learning ($LR_{,local}$ and $LR_{,global}$) (Hayward and Graham, 2013).

The cost structures of different renewable technologies were taken from the literature (sources listed in Table 1). The estimates for the share and type of locally sourced components are based on a survey of news reports on renewable energy projects implemented in Thailand and interviews with local renewable energy investors. In the news report analysis, we coded the companies and main components involved renewable projects in Thailand (such as the Mae Chan PV project shown in Figure 4) according to the type of service or component they provided and the location of business (domestic / international)[5]. The interviews were used to verify the findings about the general patterns of locally sourced components. The information on typical sourcing strategies was then linked to the technology-specific cost structure data to obtain estimates of local and foreign cost shares, to which we applied local and global learning rates obtained from the literature (see Table 1).

[5] We considered local manufacturing as local sourcing, even when it is the result of foreign direct investment.

In the initial specification, our model used high but realistic estimates for the local share, as presented in Table 1. For all six considered renewable technologies, we assumed that grid connection, EPC (engineering, procurement and construction) and heavy, bulky components are sourced locally, while the core of the electro-mechanical conversion system is sourced globally. This rule leads to very different local shares: from 43% in the case of PV up to 87% for micro hydro. To assess the sensitivity to these assumptions, a second set of model specifications (see section 4.3) uses more pessimistic estimates for local private sector participation (values given in Table 5 in the appendix). A third set of model specifications assumes a cost markup of 20% for all local components in wind, solar PV and CSP, which are relatively new technologies in Thailand.

Table 1: Split between locally and globally sourced components by technology

Technology	*Locally sourced parts*	*Globally sourced parts*	*Cost split local/global*	*Learning rate local/global)*
Wind	Grid connection; engineering; procurement & construction; foundation; rotor blades; tower	Nacelle (including electrical machinery, power electronics & control system)	67%/33%[a]	11.3/4.3[e]
PV	Grid connection; engineering; procurement & construction; balance of system excluding inverter	PV modules; inverter	43%/57%[b]	17/20[e]
CSP (solar tower)[f]	Grid connection; engineering; procurement & construction; solar field	Power block; heat transfer fluid cycle	67%/33%[b]	14.6/14.6[e]
Biomass (anaerobic digestion)[f]	Grid connection; engineering, procurement & construction; fuel shredder; boiler; heat exchanger; piping	Steam turbine and electric generator (prime mover); flue gas and water treatment	75%/25%[c]	5/5[d]
Biogas	Grid connection; engineering, procurement & construction; fuel handling; balance of system; 75% of converter system	Gas engine (prime mover); 25% of converter system	78%/22%[d]	5/5[d]
Micro hydro	Grid connection; engineering, procurement & construction; 50% of electro-mechanical equipment	50% of electro-mechanical equipment	87%/13%[c]	5/5[d]

[a]IRENA (2012b); [b]NREL (2012); [c]Delivand et al. (2011); [d]Mott McDonald (2011); [e]Hayward & Graham (2013); [f]For both CSP and biomass a range of technological options exists, of which we chose one each to simplify the model; we chose anaerobic digestion because it is the dominant technology in Thailand (JIE, 2008), and solar tower because it represents 43% of the global near-term project pipeline (Hering, 2012).

4.3. Model Specification and Scenarios

Different model specifications were created to evaluate the learning effects, to gauge the impact of key assumptions, and to compare learning effects to other policy priority areas (see Table 2). Models A-L were specified to investigate the impacts of local and global learning. The first four, A-D, assume the local shares estimated in Table 1 and only differ by the learning rates. Model A assumes no learning at all (learning rates set to zero) and serves as base-case scenario, while model B and C estimate the separate effects of local and global learning, respectively, and model D estimates the full joint effect of local and global learning. Models E, F, G and H follow the specifications of models A-D, but use a more conservative estimate of the share of local components (values are given in Table 5 in the Appendix). The models I, J, K and L, too, mirror models A-D, but account for the uncertainty about the initial cost of locally produced components by assuming a markup of 20%[6] on all local components in wind, solar PV and concentrating solar power. Finally, model GL assumes that no components are locally sourced and global learning opportunities are fully exploited.

[6] The mark-up of 20% is within the range of mark-ups implicitly assumed in policies such as Turkey's Renewable Energy Law 2010 (IEA and IRENA, 2013).

The last two models, CARBON and FINANCE, were specified to allow a comparison of the magnitude of learning effects to those of other suggested policy priority areas for international support. In model CARBON, we assumed a global carbon price of USD 15 to reflect a reinvigorated global carbon market from which renewables projects can raise additional financing. Model FINANCE assumes that both debt and equity cost are reduced by one percentage point to estimate the impact of improving financing conditions through policies that reduce investor risks.

Table 2: Model description and specification; all models assume local diffusion of renewable technologies according to AEDP targets and global diffusion according to predictions in IEA (2013b)[a].

Model	*Description*	*Implementation*	*Purpose*
A or base-case	AEDP targets implemented, but neither local nor global diffusion leads to learning	Learning rates LR_{local} and LR_{global} set to 0	Estimate cost without learning
B	Same as A, but local industry realizes learning opportunities from diffusion	LR_{local} >0; LR_{global} =0	Estimate effects of local learning
C	Same as A, but global industry realizes learning opportunities from diffusion	LR_{local} =0; LR_{global} >0	Estimate effects of global learning
D	Same as A, both local and global industries realize learning opportunities from diffusion	LR_{local} and LR_{global}>0	Estimate full effects of learning
E, F, G, H	Same as A-D, but lower share of local components	Reduced local share; values in Table 5 in the Appendix	Estimate sensitivity to share of local cost; account for variance between projects
I, J, K, L	Same as A-D, but cost markup for local components technologies that are new to Thailand	20% cost markup for local components in wind, PV, CSP	Estimate sensitivity to initial local component cost; account for uncertainty about initial cost
GL	Same as C, but no local content	No local content; LR_{global} >0	Evaluate value of local component sourcing
CARBON	Same as A, but renewables projects benefit from carbon credit sales	LR_{local} =0; LR_{global} =0; carbon price USD 15 for 10 years; credits generated according to methodology of Clean Development Mechanism	Compare learning effects to impact of a functioning global carbon market
FINANCE	Same as A, but renewables projects benefit reduced financing cost	LR_{local} =0; LR_{global} =0; the investor's expected rate of return and the lending rate for renewables are reduced by 1%-point	Compare learning effects to impact of derisking activities

[a]Local installation data for 2012 from DEDE (2013); global installations in 2011 for solar, CSP and wind from IEA (2013b); for biomass and biogas from IRENA (2012c); and for micro hydro from IRENA (2012d).

5. Results

5.1. Impact on the Electricity Mix

Our model predicts that, if the AEDP targets are achieved, Thailand will increase its share of non-large-hydro renewables in the electricity sector from 6 to 24%, as shown in Figure 6. Biomass (47%) and biogas (36%) are responsible for most of this increase, given their high capacity increases and high plant utilization. Solar PV and wind contribute 8% and 7%, respectively, while CSP and micro hydro each produce 1%.

Increasing by a total of over 11 GW, the diffusion of renewable energy reduces the pressure to install new conventional power plants. The construction of some coal power plants will be delayed – the capacity in 2021 is 800 MW lower with the AEDP targets implemented – but the most significant effect is on natural gas. In 2021, the installed capacity is 3,600 MW lower than in the case without additional renewable capacity; this leads to a drop of natural gas in the fuel mix from 59 to 46% (see Figure 6b). If all construction delays caused by the diffusion of renewables in the modeled period

2013-2040 are aggregated and stated in MW-years (MWa), natural gas power plants are delayed by 62,250 MWa; coal power plants by 8,850 MWa; nuclear by 8,000 MWa and diesel plants by 1,250 MWa. In terms of displaced electricity, too, natural gas is affected most (654 TWh in 2013-2040), followed by coal (145 TWh), nuclear (90 TWh), lignite (61 TWh) and diesel (5 TWh). In total, our model estimates that the AEDP targets avoid a total of 956 TWh of conventional electricity and 455.7 million tons of CO_2.

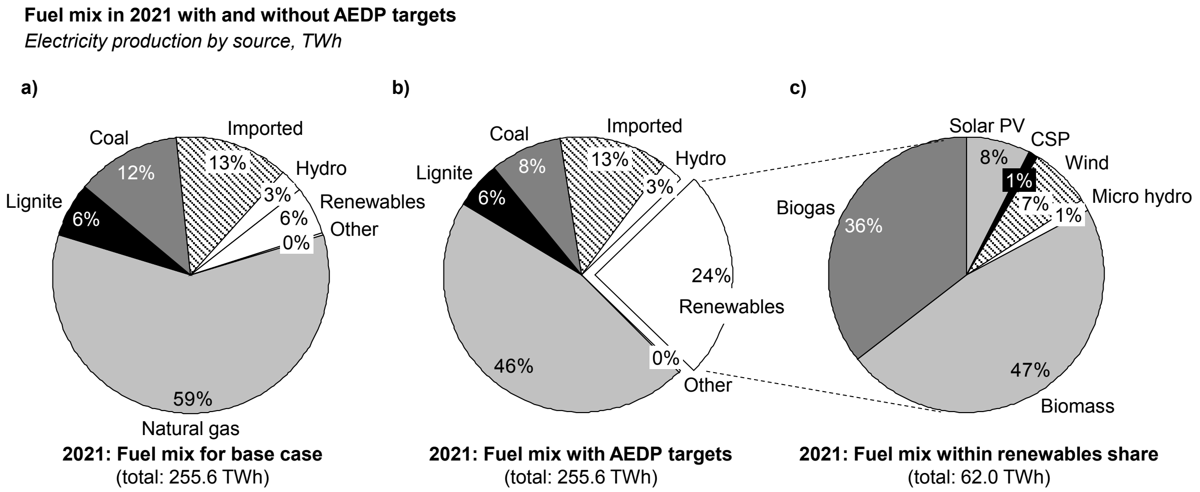

Figure 6: Impact of the AEDP targets on the fuel mix in the electricity sector in 2021

5.2. Incremental Policy Cost and Effects of Learning

Since we are assuming fixed feed-in tariff payments over a 20-year lifetime for each installation, the cost of the increase in renewable electricity is spread over the period 2013-2040. The annual payments increase linearly with the capacity additions in 2013-2021 to a maximum of almost USD 5bn per year, staying flat until the first added plants retire in 2032 and then dropping to zero (as shown in Figure 7). The savings from avoided conventional electricity production follow a similar path, with small variations between years caused by the delay of large fossil plants.

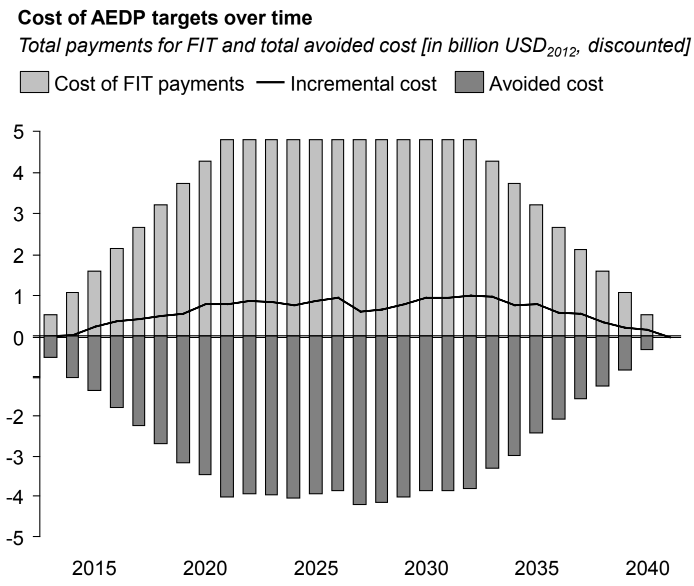

Figure 7: Payments for renewable electricity under the AEDP and avoided fossil electricity over time

The total cost of reaching the AEDP targets as well as the model's two main outcome metrics, the (discounted) incremental policy cost and the carbon mitigation cost, are depicted in Figure 8 for the different learning scenarios. For the base case, the FIT payments supporting the renewable energy installations add up to a total of USD $74.75bn in 2013-2040, while the cost of the avoided conventional electricity reach an aggregate of $61.43bn over the same period. The remaining, incremental policy cost is thus $13.3bn, which corresponds to a mitigation cost of $29.2 per ton of CO_2.[7]

By exploiting the local and global learning effects, this incremental policy cost can be reduced significantly. If both learning effects are fully exploited in the standard specification of the model (model D), the incremental policy cost drops by about 80% to $2.6bn. If most components are sourced globally (model H), the effect is less strong, but the cost is still reduced by $8.8bn (66%) to $4.5bn. Through learning, the incremental cost falls below the original base-case cost to $4bn, even if initial cost is assumed to include a 20% markup for local components. The models CARBON and FINANCE, not shown in Figure 8, help put the learning effects in perspective: A $15 carbon price would reduce incremental cost from $13.3bn to $7.52bn, while a reduction of one percentage point in the weighted cost of capital would reduce it to $9.88bn.

Across all models, the effect of local learning outweighs that of global learning. Figure 8 shows the results for incremental and mitigation cost of all 12 different learning scenarios. If a high share of local sourcing is assumed (models B-D), local learning can reduce the incremental cost by $6.7bn, while global learning can further decrease them by $3bn. This strong effect of local learning is robust across all considered model specifications. In the models that assume a low local component share (E-H), local and global learning reduces the incremental cost by 36% and 31%, or $4.7bn and $4.1bn, respectively. When a mark-up of 20% is considered (models I-L), local learning shaves 47% ($8.5bn) off the incremental cost, while local learning reduces them by 19% ($3bn).

[7] If distributed as a surcharge on the electricity bill, these incremental cost would peak at about c$0.3 per kWh in 2020, or about 3% of the average retail electricity price (Ruangrong, 2012).

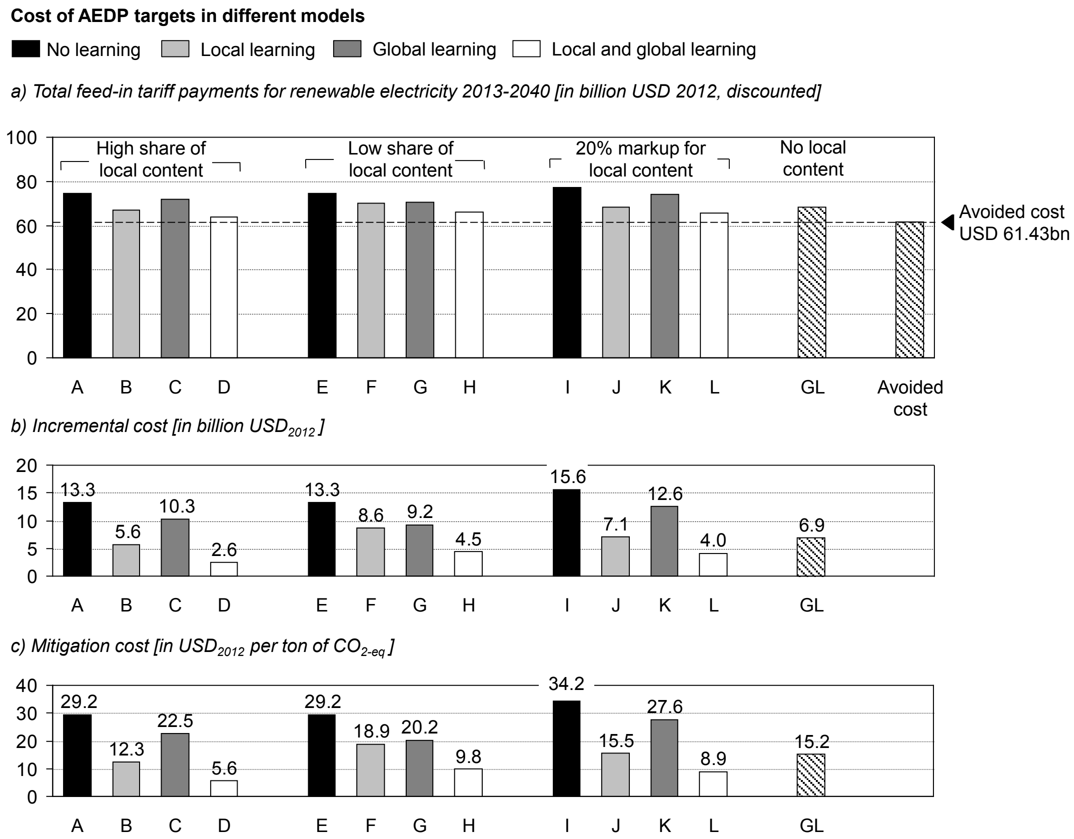

Figure 8: Total cost of supporting the AEDP targets in 2021 in different learning scenarios

Another important finding is that strong local private sector participation, represented in the models by a high share of local components, can reduce mitigation cost beyond the reductions possible under a purely global value chain. This can be seen when comparing model GL with models D, H and L – the incremental cost in all three models are significantly lower than in GL. Indeed, the effect of local learning alone exceeds the total learning effect in GL in all but model F, the model with a low share of local content.

5.2.1. Differences Between Technologies

The effects seen on the global level are more nuanced when looking at the effects by technology. Figure 9 shows the LCOE of all technologies in 2021 for different scenarios. It can be seen that, overall, the learning effect is strongest for CSP (-54%) and PV (-43%) and weakest for micro hydro (-8%) and biomass (-3%). Similar differences are visible for the relative importance of local and global learning. The effect of local learning is much stronger for CSP, with 41% and 13% reduction, respectively, whereas global learning is more relevant for PV (25% compared to 18%). Local learning also outweighs global learning for wind, biogas and micro hydro. However, in biomass, both are not very significant.

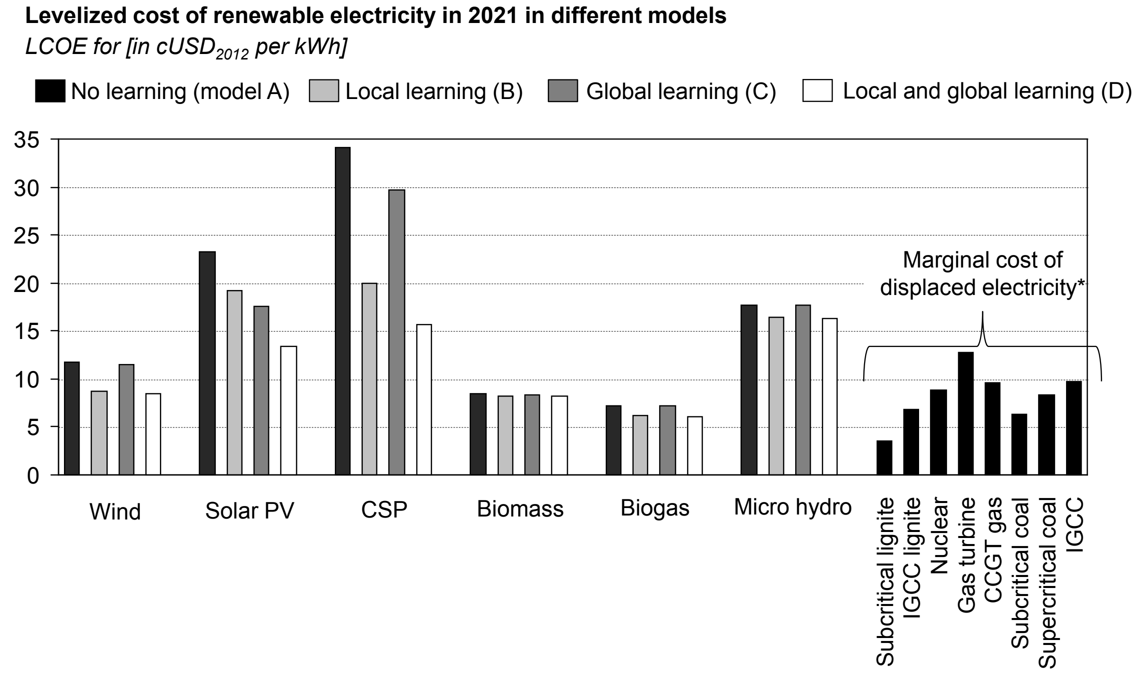

Figure 9: Effect of technological learning on the levelized cost of different renewable energy technologies in 2021. *The presented cost for fossil fuel electricity represents marginal cost of newly built power plants; the fuel cost reflect import prices of coal, diesel and natural gas (see Table 4 in the attachment).

6. Discussion

6.1. How to Tap Local Learning Potentials?

The climate policy regime that emerges for the post-2020 period foresees that developing countries will pursue domestic policies that deliver on both climate and development objectives. In the view of national governments, local private sector participation in the value chains of low carbon investments holds the promise of creating employment and growth opportunities. At the same time, as our model results suggest, it can help to reduce the long-term cost of emissions mitigation. The process linking these two objectives is *local technological learning.* Our calculations imply that local learning can reduce the cost of renewable electricity to the point where they are very close to competitiveness with fossil fuels. But how can developing countries realize the learning opportunities that our model predicts are possible? And how can the international institutional framework assist developing countries in this agenda?

Our case study of Thailand's electricity sector highlights that the cost reduction opportunities from local learning depend on three interlinked factors: the (cumulative) local installations at the beginning of the analyzed period, which can be understood as proxy for the maturity of the domestic industry; the average share of locally sourced components; and the rate of local learning in the different technologies.

First and foremost, the potential for future cost reductions from technological learning is determined by the (cumulative) size of the existing domestic market. The projected learning potentials in our model are highest for technologies that are new to Thailand, such as solar PV and CSP, while mature industries, such as biomass, exhibit limited opportunities to radically alter the cost structure of future investments.

The share of local components, the second factor, depends crucially on the *availability* of local components, which in turn depends on the amount of prior local investment in building up production capacity by firms along the industry chain. Any such investment will hinge on a credible, long-term market perspective (Pueyo et al., 2011). But besides their availability, the share of locally sourced components also depends on their *competitiveness*. Research has presented ample evidence that the competitiveness of local firms is the result not only of factor cost, or hardware imports, but also their stock of technological capabilities (Bell and Figueiredo, 2012). Without the necessary capabilities – i.e., if the initial markup is too high – local firms might never be able to enter the virtuous cycle of learning and new investments. Even if the investment comes from foreign firms, it will require complementary local capabilities to be “absorbed” effectively (Bell, 2010). Local technological capabilities depend on domestic private and public investments, in the form of a skilled workforce, local science and technology infrastructure, as well as firm networks and coordinating actors. International factors, such as the conditions for access to state-of-the-art technology, also play an important role for the local private sector to produce competitive products and services.

Lastly, the third and most important factor in our model that determines the potential for learning to reduce cost compared to the base case is the *rate of learning*. If the learning opportunities are not seized, a large share of locally sourced components does not yield any benefit in terms of mitigation cost. Indeed, if there is a positive markup, it might actually be counterproductive, at least from a cost perspective. The extent to which industries can reap the benefits of learning is determined by the opportunities to *create* new knowledge from experience, but also by the processes that govern the dissemination, utilization and retention of the created knowledge (Bell and Albu, 1999). These processes can be shaped and enhanced by domestic governments and international support mechanisms.

6.2. Implications for Domestic Policy

Our results suggest that the governments of developing countries should pursue any investments in low carbon infrastructure with the explicit target of seizing the opportunity to build up local technological capabilities. First and foremost, whether low carbon investments can promote learning is determined by the nature of the policies that attract this investment. Experience in developed countries has shown that technological capabilities can best be created under stable and predictable market conditions (IRENA, 2013). Developing countries can create such conditions domestically through long-term targets and stable regulatory frameworks, as well as a clear allocation of responsibilities in the public sector. Options to promote industry-wide learning through efforts targeted at the dissemination, utilization and retention of created knowledge include investments in collaborative research programs that accompany and monitor infrastructure technology; public institutions for testing and certifying technology; requirements for beneficiaries of government support to publish non-sensitive information on cost and performance of the technologies; and the creation of government-led platforms for knowledge exchange.

Apart from the need for efforts targeted at learning, the case study also suggests that policies to subsidize early local private sector participation can be a good investment. By lowering entry barriers in the beginning, public support can create conditions that enable learning, which, in the long term, lowers overall cost beyond what would have been possible with purely foreign suppliers. But such a policy needs to be designed with a clear target and procedure to review and eventually phase out support. Furthermore, direct subsidies for local sourcing of specific components carry the risk of wasting public resources on subsidizing the production of components that are too costly, or too complex, to yield any local learning effects. Nevertheless, if they are focused on technologies and components for which technical expertise is available (or attainable), and if they are linked to efforts to build technological capabilities, our model suggests that local content policies can deliver on both development and cost reduction objectives (see also Johnson, 2013).

6.3. Implications for International Technology Support Mechanisms

In its support for technology development and transfer, the international climate policy regime has recently shifted attention from global agreements toward country-specific support, and from the transfer of hardware to the build-up of local technological capabilities. Most notably, the Technology Mechanism (TM) was created under the UNFCCC in 2011 to determine "technology needs […] based on national circumstances and priorities", and to "accelerate action consistent with international obligations, at different stages of the technology cycle, including research and development, demonstration, deployment, diffusion and transfer of technology in support of action on mitigation and adaptation" (UNFCCC, 2011, p. 18-19). By emphasizing local and global aspects of technology development, innovation, and knowledge networks, the TM's functions clearly go beyond the 'one-size-fits-all' approach of the mechanisms under the Kyoto Protocol, but also beyond the purely country-centered practice of technology needs assessments supported by the United Nations. However, given the range of initiatives that institutions such as the TM could potentially support means that there is a need for analysis to inform the design and priority setting of these institutions. The analysis presented in this paper provides implications for the allocation of resources between global and local support.

Our results suggest technology characteristics, such as novelty and the share of simple, heavy and country-specific components, determine the relevance of local learning in concert with country characteristics, such as the existence of domestic industry in similar sectors and the size of the already existing market for the considered technology. These case-specific differences suggest that the TM should ideally integrate global and local perspectives. In cases where local learning is crucial, the TM should assist countries by strengthening the local innovation system, e.g., by identifying technology needs and priorities; by supporting the design of policies and regulations; by providing training and capacity building; through efforts to provide developing countries with access to IPR; or through the creation of local actor networks. In cases where global learning is very important, the TM should strengthen the global, sectoral innovation systems through the creation of global technology roadmaps; the promotion of global technology standards; the coordination of policies across countries and regions; the creation of global, technology-centered networks; or the coordination of institutional linkages between the TM and other global and regional institutions (such as the World Trade Organization, the Green Climate Fund, or the Global Environmental Facility). Overall, our case study suggests that the recent emphasis on *local* capabilities is promising. However, since resources are necessarily limited, the TM should pursue these different activities with priorities reflecting country characteristics and technology-specific value chain structures.

6.4. Limitations

A quantitative case study such as the one presented in this paper has a number of inherent limitations that constrain the validity and applicability of our findings. We see three main factors that need to be highlighted here. First, we are not aware of any other attempt to differentiate local and global learning in a techno-economic model for a developing country. Our projections for the potential of local learning are therefore limited by the availability of empirically grounded, cross-industry estimates for local component shares, cost mark-ups and local learning rates.[8] To obtain more accurate estimates than those presented here, further research is needed to better understand the cost structure and cost dynamics of renewable energy projects in developing countries. A second limitation concerns the model's output metrics. Government decisions should be made based on cost-benefit calculations. Our paper provided only estimates for possible cost reductions – the benefits side – while neglecting the cost of policies to realize and support local learning processes. Public research programs, testing and certification institutions, and international support for policy design and capacity building all come at a cost. In order to provide estimates for the *leverage* of these public investments, i.e., how many cost reductions can be realized at what cost, further data and analysis is necessary. This is particularly important when comparing different policy options. Lastly, by modeling technological capabilities as production cost, and modeling technological learning as cost reductions through a logarithmic function of only installations, our model grossly simplified what is, in reality, a set of extremely complex and distributed processes with multiple qualitative and quantitative dimensions. It can thus only function as a small piece in the broader set of analyses on technological learning that aims to support the design of domestic and international climate policy.

7. Conclusion

This paper presented a case study of Thailand's electricity sector in order to estimate the effects of local and global technological learning on the cost of renewable energy technologies in developing countries. Our model results suggest (i) that technological learning can, in the near future, reduce the cost of renewable electricity in emerging economies to a level that is close to competitiveness with fossil fuels; (ii) the major potential for cost reductions through learning lies in the build-up of *local* technological capabilities; and (iii) the relative importance of local and global learning, while clear in aggregate terms, differs significantly between technologies. This finding lends quantitative support to the argument that the conditions enabling local learning, such as a skilled workforce, a stable regulatory framework, and the establishment of sustainable business models, have a more significant impact on the cost of renewable energy in developing countries than global technology learning curves. The recent shift of international support under the UNFCCC toward the strengthening of local innovation systems is therefore promising. However, our results also suggests that international support must not disregard the global innovation system perspective in order to reap the full benefits of technological learning across the wide range of clean technologies. These insights are particularly relevant for the ongoing design and functional specification of mechanisms for technology support under the post-Kyoto climate policy regime of the UNFCCC. Here, our quantitative approach and the focus on mitigation cost complements existing qualitative and conceptual work on the topic. Further qualitative research should explore in more detail the economics of renewable energy projects in developing countries, and the effectiveness of different policy options to promote technological learning in and across the developed world. Additional quantitative research should investigate the leverage of different policy options, in particular the relative merit of options targeted at learning, de-risking and global pricing of carbon emissions.

[8] For example, we were only able to obtain differentiated estimates for local and global learning rates for wind and solar PV, and for both cases the numbers are from developed country analyses.

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Appendix A: Cost of Avoided Electricity

Fuel Mix in the Electricity Sector

Thailand's electricity sector is partly vertically integrated and dominated by state-owned enterprises (Wisuttisak, 2012). The Electricity Generation Authority of Thailand (EGAT) is the transmission system operator and directly operates around 50% of the generation assets and, as their largest shareholder, controls the two largest independent power producers. Furthermore, the wholesale market is not liberalized. Decisions over new power plant investments are therefore still made based on long-term integrated plans, rather than purely based on market signals, and plant utilization is based on long-term allocations rather than marginal cost of generation.

Our model of the fuel mix aims to reflect this decision-making process. We took the power plant pipeline from the Power Development Plan from June 2012 (EPPO, 2012a) and assumed that all hydropower, combined-heat-and-power, and contracted import capacity comes online as planned. Additional power plants were assumed to be built, in the sequence determined by the plan, whenever dependable capacity exceeds peak demand by less than 15%, or total expected demand exceeds expected generation, based on historic capacity factors, exceeds more than 5%. This approach is similar to the one adopted by domestic researchers (Sangarasri-Greacen and Greacen, 2012). The dependable capacity equals the total capacity adjusted by factors that aim to reflect the fact that not all build capacity can be expected to be available in the moment of peak demand, because of maintenance, failures, or intermittent generation.[9] The fuel mix was then calculated, on a yearly basis, from historic capacity factors, marginally adjusted for the dispatchable plant fleet to exactly meet yearly demand. "Dispatchable" refers here to the plants that are ramped up and down to balance demand, i.e., the full fleet excluding renewables, contracted import capacity (lignite and hydro), municipal solid waste and (heat-led) cogeneration.

Avoided Electricity

To model the effect of renewable energy diffusion on conventional electricity generation, we compared the hypothetical scenario without renewable energy diffusion to the case of full implementation of the AEDP targets. The total avoided electricity we then calculated by aggregating the differences between total generation in 2012-2041 with and without AEDP targets for each of the dispatchable technologies (generation from non-dispatachable technologies is not affected by the AEDP).

Modeling the marginal cost of avoided electricity required one more step of differentiation. The impact of renewable capacity installations can be twofold: plant utilization of dispatchable power plants can be reduced or the construction of new power plants postponed. Our model accounted for these two effects by dividing the total avoided electricity into build and operating margins. For all displaced electricity the cost of electricity was calculated based on the LCOE approach presented in section 4.2.2. However, in the case of reduced plant utilization, the operating margin, we assumed the marginal cost of electricity to contain only the variable cost (O&M and fuel). The displaced

[9] The factors are taken from Sangarasri-Greacen and Greacen (2012) and listed in Table 3.

electricity from postponed power plants, the build margin, contains all fixed and variable cost.[10] Table 4 summarizes the input assumptions for all conventional technologies.

Appendix B: Model Input Assumptions

Table 3: Input assumptions for renewable energy technologies (values for 2012; $=USD$_{2012}$)

	Size (MW)	*Lifetime [a]*	*Investment [$/kW]*	*O&M fix [$/kWa]*	*O&M variable [$/MWh]*	*Fuel cost [$/MWh]*	*Efficiency [%]*	*Capacity factor [%]*	*Dependable capacity [%]*	*Carbon credits* [kCO2e/MWh]*
Wind	10	20	1,980[a]	60[a]	0[a]	-	-	31.8[e]	9[f]	555.4[h]
PV	10	20	2,830[a]	50[a]	0[a]	-	-	19.8[e]	20[f]	555.4[h]
CSP	5	20	4,910[a]	50[a]	0[a]	-	-	21.5[e]	70[g]	555.4[h]
Biomass	10	20	2,157[b]	0[b]	10.4[b]	41.2[b]	19.8%[b]	69[b]	55[g]	511.3[h]
Biogas	1	20	2,554[c]	116[c]	0[c]	10[c]	31%[c]	70[c]	21[g]	511.3[h]
Micro hydro	1	20	2,800[d]	112[d]	0[d]	-	-	29[i]	40[g]	511.3[h]

[a]NREL (2012); [b]Delivand et al. (2011); [c]Pattanapongchai and Limmeechokchai (2011); [d]IRENA (2012e); [e]calculated based on data from the IRENA Global Atlas (3Tier; 2014); [f]Naksrisuk and Audomvongseree (2013); [g]Sangarasri-Greacen and Greacen (2012); [h]Munchareon et al. (2010); [i]Promjiraprawat and Limmeechokchai (2012) other data are own assumptions and calculations; *used for calculation of generated carbon credits; data from the Thailand Greenhouse Gas Management Organization (Muncharoen et al., 2010), which calculates the avoided carbon emissions of renewable projects in Thailand based on CDM methodology. The CDM methodology distinguishes between intermittent (solar and wind) and non-intermittent technologies (biomass, biogas and micro-hydro)- Because they need back-up power, intermittent sources are assumed to not much affect the decision about new fossil-fuelled power plants. The electricity they avoid therefore comes mostly from existing power plants (75% to 25%), while non-intermittent sources are assumed to avoid a larger amount of newly built fossil-fuelled power capacity (50% to 50%). Since the new power plants have lower emissions than the existing plant fleet, the intermittent sources end up avoiding slightly more carbon emissions than the non-intermittent sources.

Table 4: Input assumptions for dispatchable fossil fuel technologies (values for 2012; $=USD$_{2012}$)

	Lifetime [a]	*Investment [$/kW]*	*O&M fixed [$/kWa]*	*O&M variable [$/MWh]*	*Fuel efficiency [%]*	*Fuel cost* [$/kWh]*	*Capacity factor [%]*	*Carbon emissions [tCO2e/MWh]*
Subcritic. lignite	30	1,125[a]	38.91[b]	11.02[b]	35[b]	0.005[d]	90	1,159[b]
IGCC lignite	30	2,830[c]	50[c]	7.9[c]	46[c]	0.005[d]	90	882
Adv. nuclear	40	5,429[c]	91.65[c]	2.1[c]	33[c]	0.003[d]	90	21[b]
Gas turbine	**	**	7.21[c]	15.28[c]	31.4[c]	0.052[e]	30	631[b]
CCGT	30	1,006[c]	15.1[c]	3.21[c]	54[c]	0.052[e]	60	404[b]
Subcritic. coal	**	**	38[b]	0.04[b]	36[b]	0.015[f]	90	973[b]
Supercrit. coal	30	2,934[c]	31.18[d]	4.7[d]	39[c]	0.015[f]	90	782[b]
IGCC coal	30	3,784[c]	51.39[c]	8.45[c]	39[c]	0.015[f]	90	782[b]
Diesel turbine	**	**	12[a]	28.6[a]	22[a]	0.061[d]	30	808[b]

CCGT: combined cycle gas turbine; IGCC: integrated gasification combined cycle; [a]Pattanapongchai and Limmeechokchai (2011); [b]Promjiraprawat and Limmeechokchai (2012); [c]DOE/EIA (2013); [d]EPPO (2012d);[e]price for natural gas is for imports from Myanmar, from PTIT (2012) [f]IEA (2013c); *Fuel price trends from IEA (2013c); **Not needed because no new power plants in the pipeline

[10] This procedure was also employed by Schmidt et al. (2012) and is related to the rules employed to calculate avoided carbon emissions in the Clean Development Mechanisms under the UNFCCC.

Table 5: Split between locally and globally sourced components by technology in models E-H, representing a low share of local components

Technology	*Locally sourced parts*	*Globally sourced parts*	*Cost split local/global*	*Learning rate local/global*
Wind	Grid connection; engineering; procurement & construction	Nacelle (including electrical machinery, power electronics & control system); foundation; rotor blades; tower	36/64[a]	11.3/4.3[d]
PV	Grid connection; engineering; procurement & construction	PV modules; inverter; balance of system	36/64[b]	17/20[d]
CSP	Grid connection; engineering; procurement & construction	Power block; heat transfer fluid cycle; solar field	23/77[b]	14.6/14.6[d]
Biomass	Grid connection; engineering, procurement & construction; fuel shredder; piping	Steam turbine and electric generator (prime mover); flue gas and water treatment; boiler; heat exchanger	37/63[c]	5/5[c]
Biogas	Grid connection; engineering, procurement & construction; fuel handling	Gas engine (prime mover); converter system; electrical system	48/52[c]	5/5[c]
Micro hydro	Grid connection; engineering, procurement & construction	Electro-mechanical equipment	77/23[c]	5/5[c]

[a]IRENA (2012c); [b]NREL (2012); [c]Mott McDonald (2011); [d]Hayward & Graham (2013)

Table 6: Sectoral assumptions in the model

Factor	*Assumption*	*Source*
Currency	USD 2012 in real terms	---
Exchange rate	1 USD = 31.5 Thai Baht	The World Bank
Inflation	2.5%	Bank of Thailand
Equity/debt spilt	30/70	Current practice
Return on equity	11.2% real	UNFCCC (2010)
Lending rate	6.7% nominal	Ondraczek et al. (2013)
Loan tenor	Half of investment lifetime	Waissbein et al. (2013)
Tax rate	30%	Current practice
Depreciation	Linear, max 5% p.a., min book value 5%	Current practice
Discounting of public expenditures	Equals 40-year bond yield of 4.43 %	Thai Bond Market Association, http://www.thaibma.or.th/yieldcurve/YieldTTM.aspx,; assessed on 4/3/2014