Evolution of the electricity market in Germany: Identifying policy implications by an agent-based model*

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Abstract

The diffusion of renewable electricity generating technologies is widely considered as crucial for establishing a sustainable energy system in the future. However, currently the required transition is unlikely to be achieved by market forces alone. For this reason, many countries implement various policy instruments to support this process, also by re-distributing costs related to the policy instruments applied among all electricity consumers. This paper presents a novel history-friendly agent-based study aiming to explore efficiency of different mixes of policy instruments by means of a differential evolution algorithm. Special emphasis of the model is devoted to possibility of small scale renewable electricity generation without any further inputs, but also to storage of this electricity using small scale facilities being actively developed over the last decade. Both combined pose an important instrument to be used by electricity consumers to achieve partial or full autarky from the electricity grid, particularly after accounting for decreasing costs and increasing efficiency of both due to continuous innovation.

Keywords: *agent-based model; differential evolution; electricity storage; energy grid; feed-in tariff; renewable energy;*

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1 Introduction

The diffusion of renewable electricity generating technologies (REGT) is widely seen as a crucial part for establishing a sustainable energy system in the future. However, the current energy system is designed for and locked into the usage of fossil fuels, so that the required transition is unlikely to be achieved by market forces alone. For this reason, many countries have recently implemented different policy instruments to support innovation in and diffusion of REGT (e.g., Grau *et al.*, 2012). Most instruments try to foster innovative activity in REGT by lowering R&D costs for private companies or by performing R&D in public research institutes (del Río and Bleda, 2012); or directly support their diffusion via subsidies. The main goal of these policies is to make electricity from renewable sources competitive (in terms of costs) with fossil fuels inside the electricity grid.

In this diffusion-oriented context, a specific feature of electricity from REGT gains a certain importance, namely the possibility of small scale electricity generation without the need of further inputs. Combined with the possibility of energy storage, this can be used by electricity consumers to become electricity producers themselves or even to achieve partial or full autarky from the electricity grid, in the sense that the consumer can generate and store as much or even more electricity than it consumes in a normal period (Zahedi, 2006). This becomes particularly important as with the decreasing costs and increasing efficiency of both, storage and electricity generation technologies, the necessary investments required to become an electricity producer or to become partially or fully autarkic from the electricity grid fall. The latter can be considered as an unintended side effect of the original policy measures and is a paradigm change in the electricity generation systems of developed countries, which were build around large, fossil electricity generating plants which distributed electricity through complex electricity grids. REGT and storage together provide the possibility of individual electricity supply, which is environmentally friendly and provides an insurance against the rising fossil energy prices.

Another incentive to invest into REGT comes from re-distribution of costs of electricity generated from more expansive renewable sources to cheaper fossil fuels (e.g., Bode and Groscurth, 2006), which raises the consumption price one has to pay for electricity from the grid. By becoming electricity producers themselves, consumers avoid the extra costs and hedge against rising electricity prices in the future. Once more consumers produce electricity or become autarkic and do not demand electricity from the grid anymore, the costs for consumers remaining in the grid increase (since the costs are distributed among fewer people), creating the possibility of a snowball effect. This may put the stability of the grid in question, forcing the policy makers either to change their instruments or risk a collapse of the grid. In the end, if too many consumers already have become autarkic, it may prove necessary to further support consumers to become autarkic.

In this paper we aim to test and compare possible policy instruments and analyse under which combinations of the instruments and market conditions consumers may decide to invest into REGT or even to become autarkic from the grid (and how fast this occurs). Also, different mixes of policy instruments can be compared in terms of how costly the transition of the electricity system is and how high is the probability of a breakdown of the electricity grid.[1]

Since the transition is an out-equilibrium-process (Arthur, 2006), an agent-based sim-

[1] In literature there is no single definition of circumstances, under which grid may break down, and for simplicity we measure the percentage of unstably produced electricity over time, which is penalized by policy maker.

ulation model (ABM) is employed (for a review see, e.g., Tesfatsion and Judd, 2006. ABMs have gained an increasing interest in different fields of economic research thanks to a more realistic representation of agents' behaviour and possibility of an extensive and fast simulation analysis for different effects and parameter settings. In the last years, ABMs have become popular to model transitory processes (see, e.g., Nannen and van den Bergh, 2010 and Safarzynska and van den Bergh, 2013) and also in modeling electricity markets (see, e.g. Sensfuß*et al.*, 2007, Weidlich and Veit, 2008 and Guerci *et al.*, 2010). In addition, there is a large body of literature on the problem of diffusion of eco-innovations (see Cantono and Silverberg, 2009, Bleda and Valente, 2009 and Windrum *et al.*, 2009).

To identify an optimal policy mix, we apply an exercise from optimal control literature (see, e.g., Blueschke-Nikolaeva *et al.*, 2012), where a set of controls is optimised to achieve policy targets as close as possible. Since the search space of possible solutions is infinite (due to the continuous nature of the problem) and not necessarily 'well-behaved' (with non-linearities and multiple local optima), a Differential Evolution algorithm is used.

With this ABM, we aim to answer two main questions. The first one is to illustrate in a history-friendly manner (see, e.g., Malerba *et al.*, 2008; Garavaglia, 2010), which policy instruments played a critical role in the electricity market of Germany in the early 1990s in fostering transition towards the use of electricity generated from REGT. Back then, a low number of large fossil power plants supplied the whole economy with electricity, which was transmitted via the electricity grid. From this situation onwards, we show that policy intervention was necessary to start the transition and is still necessary if the transition shall progress further. For that reason, our model accounts for different policy instruments that were implemented in real life.

A second question we aim to answer is, which possible mix of instruments delivers best outcome (in terms of diffusion reached and grid stability preserved).[2] We compare different mixes of instruments with respect to how steady the transition progresses are and how much REGT technologies are diffused. We purposely underline importance of grid stability, as unstable electricity supply has several adverse effects. The most obvious is the risk of blackouts, which hinder production processes and displeases people used to steady electricity supply (as it is the case in most industrialised countries). Also, unstable electricity supply decreases power quality, which might damage electrical devices (see e.g. Farhoodnea *et al.* (2013) or Liu *et al.* (2011)).

The rest of the paper is organised as follows. In Section 2 we present the basic model together with the relevant theories assumed to be crucial for explaining the evolution of the industry in the last few decades. Necessarily this includes description of alternative policy intervention mechanisms applied in developed countries, and in particularly in Germany. In Section 3 we address the parameter calibration issues of the present ABM, compare its evolution over the 'history-friendly' period with empirical findings and stress stylized facts observed. Section 4 presents a counterfactual analysis exercise, where by means of the Differential Evolution algorithm we try to identify optimal policy mixes for different time periods. Section 5 contains concluding remarks.

[2]Alternatively, the model could be relatively easily adjusted to compromise also along the third dimension, which is policy budget applied, but for this one must declare how to weight cost and benefit of the policy. We leave this extension for further research.

2 Model

This section presents a model meant to serve a consistent but concise representation of routines, relationships and behaviour of economic agents as indicated in available literature. We try to balance between following appreciative theorising making our model empirically oriented and implementing mechanisms closely reconstructing some real world processes (such as merit-order pricing), but keeping our model simple and well-suited for logical explorations helping to understand what factors make the model behave as it does. Clearly, some degree of arbitrariness in that is unavoidable. Our goal is not to provide a 'true' description of the world, but its simplistic interpretation.

In this ABM two connected markets, the market for electricity and the market for electricity generation equipment, are modelled. These markets are populated with three different types of actors, namely electricity consumers, fossil electricity producer and equipment manufacturers. Two technologies for electricity generation are available, fossil fuels and REGT. The heterogeneity inside both technologies (i.e., nuclear, coal and gas for fossil on the one hand, and wind and solar energy on the other hand) is ignored deliberately to reduce complexity of our ABM. Important to note is that under REGT technologies in the current study we solely understand those new technologies which have been experiencing an immense rise in the last two decades providing renewable but unstable energy supply. For that reason, we concentrate on wind and photovoltaic leaving hydro-power and biomass outside the scope of REGTs (assuming the latter two being a part of fossil (stable and established technology) energy supply.[3]

The model is run for T periods, where T is 360. Each period is interpreted as a month in real life, so that the model ends in 2020, while beginning in 1990. For the first twenty years ($T1$=240) then we apply policy interventions in a history-friendly manner as it was done in Germany in 1990-2010, which is described in more detail in Section 3. For the last ten years ($T2$=120), we aim to identify an optimal mix of policy interventions matching best the policy target to reach 26% diffusion of REGT by 2020, which is policy target formulated by German Federal Government (2010).[4] In addition, we compare different scenarios of policy mixes for the total period of thirty years to see, whether one could reach better state of the world having started alternative policy strategies earlier.

2.1 Technologies

For the sake of simplicity, only two technologies for electricity generation are assumed, fossil and renewable. Both technologies are embedded in power generation equipment sold by manufacturers. Innovation in one of them increases efficiency or decreases cost of the technology, but cannot introduce new ones. The only exception is storage technology, which however can only become available by basic research conducted by the state.

Each technology has two independent attributes regarding its cost effectiveness: installation costs and efficiency. Installation costs are the price actors have to pay if they

[3]Hydro-power has long been applied for electricity generation, indicating that the best locations are already in use, limiting the possibility to increase electricity generation from it. Biomass technology, on the other hand, is limited by the availability of soil to grow the plants needed, which conflicts with the needs to feed an ever increasing human population.

[4]Since biomass and hydro-power technologies are not considered in the scope of REGTs and also can hardly increase their share in the electricity market (in 2010 it was around 8.9%) in the next decade for the reasons aforementioned, we assume that photovoltaic and wind alone have to contribute in reaching the target of 35% set by German Government, i.e. increase their share from the current 8.1% to 26%.

want to install the technology. Here it is assumed that manufacturers produce ‘turn-key’ installations, so that other actors do not bear additional costs after purchasing the equipment. Installations are fixed in size, but it is possible to install more than one plant at once, if sufficient space is available and agents possess the sufficient budget. Efficiency determines how much electricity can be generated from one plant (electricity yield per size). Both attributes can be improved by innovation. Installation cost can be further decreased by learning-curve effects (which will be described in detail in Section 2.3).

The fossil technology is assumed to be mature at the starting point of the simulation. Its efficiency is high and the costs per unit of electricity generated are low. However, due to the maturity of the technology, there is little room for further improvements. Since fossil power plants are big (each one generates a high amount of electricity), their number is small compared to the number of consumers. To operate they need fuels, which cannot be stocked and therefore have to be acquired every period.[5] The electricity supply they generate is stable, thereby putting no burden on the stability of the electricity grid.

In difference to the fossil technology, the renewable technology is assumed to be new at the starting point of the simulation, resulting in low efficiency and high cost per unit of electricity generated. REGT plants are small scale of the size which can be installed by majority of households. If a household wants to install more plants (because of, e.g., larger space available) it simply buys more than one plant. REGT do not need additional fuels to run, which means that they can produce at zero marginal costs. However, since there are investment costs present which investors aim to earn back, households want to achieve a positive price when selling electricity, as is explained in Section 2.4.1. An important drawback of electricity generated by REGT is unstable supply, which may put the stability of the electricity grid in question, especially if the share of electricity generated from REGT reaches high levels.

Instability of REGT electricity supply is of two types: short term instability resulting in different amount of electricity produced in different days, hours or even minutes, and mid-term instability, where in different periods of year different amount of sunshine and wind is present. While we explicitly model only the latter one, both are considered as a potential threat for the grid stability. To model the mid term instability of renewable electricity sources, there are periodically times when REGT cannot generate electricity at its full potential. This can be seen as a simple way of modelling the dependence of REGT on weather conditions, which change over the year. Thus, since a period in the model represents a month, there is a cyclical pattern with a length of 12 periods, where the electricity generation from each REGT plant changes each period. After 12 periods, the cycle starts anew:

$$Generation_{i,t} = MaxGeneration_{i,t} \times SeasonValue_t, \tag{1}$$

where electricity consumer i can generate in a specific period t a certain amount of electricity at maximum. $SeasonValue_t$ is a value between 0 and 1,[6] which specifies which share of the maximum generation $MaxGeneration_{i,t}$ can be reached in a specific month. With this assumption, the supply of electricity from REGT is unstable over the year, creating additional demand for fossil plants in some months, while there is excessive supply in other periods.

[5]The dynamics of the fuel price is described in Section 2.2.2

[6]The specific values are chosen arbitrarily, since they are only used to generate additional variance: 1, 1, 0.9, 0.9, 0.85, 0.8, 0.8, 0.85, 0.9, 0.95, 0.95, 1.

Storage technology is different from the two others in several aspects. First of all, it is not available from the beginning, but has a chance to be 'discovered' at a later point by basic research. Although it does not generate electricity, it is used to store electricity generated from REGT, thereby transforming it into stable energy supply. However, the investment costs of the storage technology have to be added upon the price of electricity from REGT. There are different promising technologies for electricity storage in development, although most were in an premature state at the end of the history-friendly part of the simulation (for an overview, see Hadjipaschalis *et al.*, 2009). A very comprehensive analysis of most possible storage technologies can be found in EASE/EERA (2013). In our model, we only consider small scale electricity storage solutions like fuel cells or batteries (an overview of the different battery solutions is provided by Divya and Østergaard (2009)), for two reasons. First, large scale storage solutions such as pump storage are not decided upon by the actors of our model, but rather by policy maker, making them exogenous to our model. Second, the construction of large scale storage facilities is likely to induce resistance from the population, as can be observed from the discussion about the construction of new pump storage facilities in Germany, as described in Steffen (2011). Therefore, we consider it unlikely that a high number of new large scale storage facilities will be built in near future. Small scale storage solutions, however, are on the verge of becoming profitable (see Colmenar-Santos *et al.*, 2012) and this profitability increases with increasing electricity prices, as shown in Mishra *et al.* (2012). In addition, their installation is a private decision of household owners, which is in line with the assumptions we make about the consumers in our model.

Each investment has a finite life expectancy (see $Life_f$, $Life_r$ and $Life_s$ in Table 1 in Appendix), after which it either has to be replaced at the current investment costs or removed (at zero costs). The life expectancy varies between the different technologies. Fossil power plants, both due to the maturity of the technology and the size of the power plants, are assumed to have a higher life expectancy than REGT and storage technologies.

2.2 Actors

2.2.1 Electricity Consumers

Electricity consumers are the central type of actors. They have a demand for electricity each period, where, for simplicity, it is assumed that the level of demand does not change over time. They can invest into REGT and storage technology, by which they become 'consumer-producers' and generate electricity themselves, which they either consume or sell via the electricity grid. Note that consumers represent households or firms, so that every consumer is independent from the other consumers (only one consumer per household or firm). The number of consumers is set to 1000.

Consumers are heterogeneous in several dimensions. Firstly, they have different income levels. The distribution of income is based on the German income deciles in 1991, which are taken from German Council of Economic Experts (2009).[7] Since the data on income contains ten decile values only, we add additional variance by dividing the consumers into ten groups, one for each income decile value $Decile_k$, where $k = 1, .., 10$, so that 100 consumers share one $Decile_k$. For each group, income is assigned in the following

[7]The values for the income deciles are: 4.1, 5.8, 6.8, 7.7, 8.5, 9.5, 10.6, 12, 14.3, 20.7.

manner:

$$Income_{i,k} \sim \mathcal{N}(5 \times Decile_k, Decile_k). \tag{2}$$

Additionally, no consumer is allowed to have a lower income than 8 to allow all consumers to have sufficient income to pay for electricity at the beginning.

Other attributes of the consumers are assumed to correlate imperfectly with income, for example, the space available to install REGT. REGT needs sufficient space to be installed, which is assumed to be sparse for most consumers.

$$Space_i = \text{floor}\left(\frac{Income_i}{10} - 3 \times X_i\right), \tag{3}$$

where $Space_i$ denotes the amount of space a consumer has available for installing REGT and random component $X \sim \mathcal{N}(2, 1)$ is used to generate additional variance. The $floor(.)$ function (rounding argument downwards) is applied to create non-negative integer values for space distribution (since installation size is one) with a considerable proportion of households with no space available.

Irradiation (electricity yield per space) is additionally used to account for heterogeneity of space in terms of REGT productivity. Given that solar irradiation in Germany is between 0.7 and 1 (see JRC - European Commission (2015)), while for wind it is much more diverse: between 0 and 1, we assume (for simplicity) that it is uniformly distributed between 0.4 and 1:

$$Irradiation_i \sim \mathcal{U}(0.4, 1). \tag{4}$$

Electricity demand is also assumed to be weakly positively correlated with income, as richer consumer can afford higher consumption:

$$Demand_i = \sqrt{Income_i} \times Y_i. \tag{5}$$

where $Y \sim \mathcal{N}(1, 0.2)$. See Figure 10 in Appendix B for visual representation of those distributions.

The demand for electricity of a consumer stays constant over time. However, if a consumer installs REGT and storage technology, she will be able to satisfy at least parts of her own electricity demand by self-production and -consumption. Therefore, the relevant value is the $NetDemand_i$ of a consumer, which is calculated from

$$NetDemand_i = Demand_i - SelfConsumption_i, \tag{6}$$

where $SelfConsumption_i$ is the amount of electricity which a consumer can produce and store herself.

The most important source of heterogeneity among consumers are their preferences. One important preference is for environmental protection, which is bound between 0 and 0.9. This preference is assumed to be imperfectly correlated with income,[8] so that people with high preferences tend to have a higher income. A rich number of empirical studies has shown that wealthier households are willing to pay higher prices for eco-products (e.g. Roe *et al.*, 2001, Wiser, 2007, Diaz-Rainey and Ashton, 2011). Most consumers

[8] Correlation between environmental preferences and income equals 0.1.

have no or only weak preferences for environmental protection. A fraction of consumers (which is a parameter of the simulation and in an default setting equals 5%), however, have very high preferences. These consumers are called 'eco-warriors' (e.g., Williams, 2013). The role of those eco-warriors is important since, on the one hand, due to their high willingness to pay, eco-products sustain at least as niche markets, while on the other hand, those households signal to policy makers importance of ecological goods (e.g., by pointing to the rights of future generations) and actively vote for public intervention. For example, in Germany environmental activists played a key role in supporting the feed-in-tariff (Lauber and Mez, 2004).

The preference values are calculated in the following way:

$$PrefEP_i = \begin{cases} Pref_i^1 \sim \mathcal{N}(0.9, 0.1) & \text{if the consumer is an eco-warrior,} \\ Pref_i^2 \sim \mathcal{N}(-0.2, 0.4) & \text{otherwise.} \end{cases} \tag{7}$$

The values for $Pref^1$ and $Pref^2$ are chosen to ensure values close to 0.9 for eco-warriors and a distribution with many zeros and few intermediate values for other consumers.

This represents the situation in Germany at the beginning of 1990s, where environmental issues were already causing concern for many people (e.g., due to the oil crisis), but very few people invested into REGT (see Jacobsson and Lauber, 2006).

Preference for environmental protection alters the decision on which form of electricity to demand and on whether to invest into REGT. The preference lowers the price consumers subjectively perceive. Even if the objective price for electricity from renewable sources is higher than the one for electricity from fossil fuels, consumers with high preferences may demand the more expensive one. As an additional restriction, consumers want to avoid to spend for electricity a share of their income beyond a certain threshold. The actual share which consumers are ready to spend is a parameter of the simulation, ϕ. In Great Britain, households who spend more than 10% of their income on energy are labeled to live in 'fuel-poverty' (see, e.g., Department of Energy & Climate Change, 2013), which we use as threshold here. If consumers are in danger to pay a higher share of their income, they also consume the objectively cheapest form of electricity.

If consumers demand electricity from REGT (if the subjective price is lower), but there is no supply present in the electricity market, consumers may decide to invest into REGT themselves, becoming 'consumer-producers'. To be able to invest in REGT, sufficient income and space is required. While the space requirement is self-explanatory, the income restriction is mainly present to prevent very poor consumers from investing into REGT. For simplicity, it is assumed that only those consumers can invest into REGT whose income is equal to the price of a REGT plant. Note that, during the simulation, if REGT become cheaper due to innovation and learning, an increasing number of people can afford such investment. As an additional restriction, consumers can only invest once. This means that if the investment is made and REGT are installed, the specific consumer cannot make an investment again until the old plant is removed due to reaching its life expectancy.[9]

Besides preference for environmental protection, there is a preference for autarky. This preference starts to matter only after storage technology becomes available. It can be interpreted as a preference to consume self-generated electricity. This preference can be interpreted as a fear of rising prices of grid-based electricity, as the incentive to self-

[9] This has a convenient feature that efficiency of the plants installed by one consumer is the same.

generate and -consume electricity increases with rising electricity prices. If no storage technology is available, it is assumed for simplicity that no self-generated electricity can be self-consumed. With storage technology, all self-generated electricity which is stored can be self-consumed and the electricity supply from REGT becomes stable. Again, like in the case of preferences for environmental protection, this preference decreases the subjective price of storage equipment, making it subjectively more attractive to consumers with high preferences. The extent of the preference is correlated with the electricity demand per income,[10] as a high level of electricity demand per income increases the effect of changing electricity prices:

$$PrefAutarky_i \sim \mathcal{N}\left(\frac{Demand_i}{Income_i} - \frac{\sum_{i=1}^{N}\frac{Demand_i}{Income_i}}{N}, 0.3\right). \tag{8}$$

Here, $PrefAutarky_i$ is calculated from a normal distribution, where the mean of the demand per income is subtracted from the individual value to ensure that a sufficient number of consumers have very small (or zero) preference values, since we assume high preference values for autarky to be an exception. Illustration on the distribution of those two preferences is provided in Figure 11 in Appendix B.

2.2.2 Fossil Electricity Producers

Producers generate electricity using fossil power plants and sell it to electricity consumers via the electricity grid. For simplicity, each producer operates only one power plant (therefore, the terms fossil producer and fossil power plant are used as synonyms). For the same reason, the producers cannot invest into REGT or storage technology. Producers are assumed to be profit oriented, which means that they aim to avoid losses from operating their power plants. The central variable which indicates if losses are made is the 'up-time' of a power plant. The up-time is the share of the maximum electricity generation capacity a plant is able to feed-in (therefore, up-time is a number between 0 and 1). A power plant generates losses if the up-time is lower than a certain threshold γ, which is a parameter of the simulation. This simplified rule ensures that those fossil power plants generating electricity at lower cost (and in reality making profits) will feed-in most of their electricity supply and stay in the market longer, while those with relatively higher cost, may have to exit the market first. The rule has a convenient feature of not making specific assumptions on how past profits can be accumulated to finance future performance.

The conditions for a power plant to run (to be inside the market) are described in Section 2.4.1. The number of fossil power plants is low compared to the number of consumers. To be precise, the number of fossil producers is hundred times smaller than the number of consumers. The size of power plants is determined at the beginning of the simulation in a way to guarantee that the entire demand is satisfied by the fossil power.[11]

[10] This correlation equals 0.25 in our model.

[11] Note that power plants will not shut down permanently prior to hitting their life expectancy, as there are no maintenance costs if the plant is not running. However, a low up-time will discourage replacement investment once the power plant reaches its life expectancy. A power plant that reaches its life expectancy is shut down permanently and has to be replaced, if supply shall remain constant. New power plants have to earn back their investment costs, which is unlikely if the power plant does not sell a sufficient amount of electricity.

The cost of each power plant consists of capital cost and fuel cost:

$$CostFossil_{p,t} = CapitalCost_p + FuelCost_{p,t}, \tag{9}$$

where $p = 1, ..., P$, with P as the maximum number of fossil producers on the market. The capital cost reflects the income needed to earn back the installation costs:[12]

$$CapitalCost_p = \frac{InstallCost_{f,t}}{Life_f \times 12}, \tag{10}$$

where $InstallCost_{f,t}$ denotes the cost of installing a fossil plant. Since the cost is distributed over the lifetime of the plant, it is divided by $Life_f$. Also, since electricity is sold on a monthly basis, we also divide it by 12. The fuel costs are calculated from:

$$FuelCost_{p,t} = FuelPrice_t / Efficiency_{f,t}, \tag{11}$$

where $Efficiency_{f,t}$ denotes the efficiency level of the plant, while $FuelPrice_t$ denotes the price of the fossil fuels which have to be acquired every period. Note that, while $CapitalCost_p$ and $Efficiency_{f,t}$ are determined when the plant is installed and are constant over time,[13] The $FuelPrice_t$ changes every year (every 12 periods). In the history-friendly part, we approximate the $FuelPrice_t$ by taking the oil price for German consumers, as reported by the German Statistical Office (Destatis (2015)). For simplicity, how normalise the initial price value to one and adjust all other prices accordingly. Outside the history-friendly part, we assume a slowly increasing time trend for fuel prices:

$$FuelPrice_t = FuelPrice_{t-1} \times F, \text{ where } F \sim \mathcal{N}(1.04, 0.01). \tag{12}$$

Therefore, $CostFossil_{p,t}$ changes over time, but due to the fixed cost effect of $CapitalCost_p$ not as strongly as the price of fossil fuels.

2.2.3 Equipment Manufacturers

Manufacturers produce the equipment necessary for electricity generation and storage. For simplicity, there is only one manufacturer present for each technology. This simplification is made for two reasons: modeling a number of manufacturers per technology would also require competitive and cooperative structures among these manufacturers, which would increase the complexity of the model with little explanatory power added. On the other hand, if manufacturers could sell more than one technology, it would be necessary to create a decision mechanism in which technology R&D is done.[14]

There is little heterogeneity in the structure of the individual manufacturers. One difference comes from how much equipment a manufacturer has sold in the past (which is linked to how long it was operating in the market). The fossil producer is assumed to

[12] The period in which the producers try to earn back the money invested is assumed to be equal to the life expectancy of the power plant, and that the costs are distributed equally among the lifetime, so that the capital costs do not change over time.

[13] Since the power plants are installed at different times (at the beginning of the simulation, the age of the power plants present is heterogeneous) and manufacturer of fossil plants experiences (although small) learning effects from their production (more on this in Section2.3), there is small heterogeneity in investment costs and efficiency levels, resulting in slightly heterogeneous prices.

[14] If the simple rule of 'R&D expenditure equals share of turnover' would be chosen (i.e. routine-based decision), there would be no difference from assuming independent manufacturers for each technology.

have been in the market for a long time even at the beginning of the simulation, which means that it had a long time to improve its technology via innovation and learning (more details on this in Section 2.3). The manufacturer for REGT enters the market right at the beginning of the simulation, while the storage manufacturer only enters after storage technology becomes available.

Based on the demand faced in the past, each manufacturer adjusts her production capacity. This production capacity is flexible in the sense it can be adjusted if the demand for installation exceeds the production capacity and is cut back if demand is too low for several consecutive periods. This approach was inspired by the neo-Austrian capital theory (see Faber and Proops, 1991). The number of past periods considered when deciding upon capacity change S and the extent to which production capacity can be changed are parameters of the simulation. In default, it is assumed that manufacturers change their production capacity according to the mean difference between demand for installations and production capacity over the last five periods:

$$CapacityChange_{m,t} = \sum_{\iota=1}^{S} \frac{DemandPlant_{m,t-\iota} - Capacity_{m,t-\iota}}{S}, \tag{13}$$

where $DemandPlant_{m,t}$ depicts the number of installations actors demand from manufacturer of technology m in period t. In contrast, $Capacity_{m,t}$ depicts the production capacity of manufacturer of technology m in period t. With this, manufacturers are assumed to have adaptive expectations. The maximum increase (Inc) and decrease (Dec) in production capacity per period is symmetric, meaning that capacity can be at best doubled and in the worst case halved.

2.3 Innovation

Innovation and learning are an important part of the model since they can alter the competitiveness of different technologies by making them cheaper or more efficient.[15] Innovative activity can in this model make the technology more efficient. While there are of course pure cost saving innovation, they are incorporated into the learning curve. As long as any amount of money is invested into R&D, there is innovation activity. The innovative step is then calculated based on how much is invested:

$$Efficiency_{m,t} = Efficiency_{m,t-1} + \max(Z_{m,t}, 0), \tag{14}$$

where $Z \sim \mathcal{N}(\frac{log_{10}(Invest_{m,t})/2*0.01}{Efficiency_{m,t-1}}, \frac{log_{10}(Invest_{m,t})/10*0.01}{Efficiency_{m,t-1}})$ and $Invest_{m,t} = shareRD \times SoldPeriod_{m,t} \times InstallCost_{m,t}$. The variable $shareRD$ depicts how much of their turnover manufacturers invest into R&D, which is 5% in an ordinary simulation run. The formula is chosen in a way that higher the efficiency level prior to the innovation, the smaller the innovative step is on average. This implies that it becomes increasingly difficult to improve a technology. As innovative activity cannot make technology worse (since in such a case the old technology would be used instead), only $Z \geq 0$ are allowed.

The source of cost reductions in installation costs of a technology are learning effects (e.g., van der Zwaan, 2003). In this model, learning effects are based on the cumulative number of installations sold by a manufacturer. If the number of plants sold increases,

[15]The initial value for installation costs and efficiency can be found in Table 1 in Appendix A.

the installation costs decrease. The effect of the number of plants sold in one period is:

$$InstallCost_{m,t} = InstallCost_{m,t-1} \times LearnRate^{log_2\left(\frac{SoldPeriod_{m,t}+StockSold_{m,t}}{StockSold_{m,t}}\right)}. \qquad (15)$$

Here, the parameter $LearnRate$ determines how fast costs decrease. For an ordinary simulation run, it is set to 0.87, which means that every time the overall number of plants sold $StockSold_{m,t}$ doubles, installation costs decrease by 13%.[16] Note that this equation is the same for all manufacturers, regardless of technology. The only difference is in the number of plants assumed to be sold prior the simulation starts. As fossil power plants are a mature technology, it is assumed that a very high number of plants is sold prior to the simulation, which makes further learning very slow. In contrast, only few REGT installations and storage installations have been sold (a positive number is needed to avoid division by zero in equation (15), allowing for strong learning effects. For an ordinary simulation run, it is assumed that this starting value is equal to 2 for both REGT and storage, while being equal to 250 for fossil plants.

2.4 Markets

The general structure of the markets can be observed in Figure 1. The two markets are connected, as the outcome of the market for electricity determines demand in the market for electricity generation equipment, while the installation of fossil power plants, REGT or storage technology alters the conditions in the electricity market. In the following, both markets are described in detail.

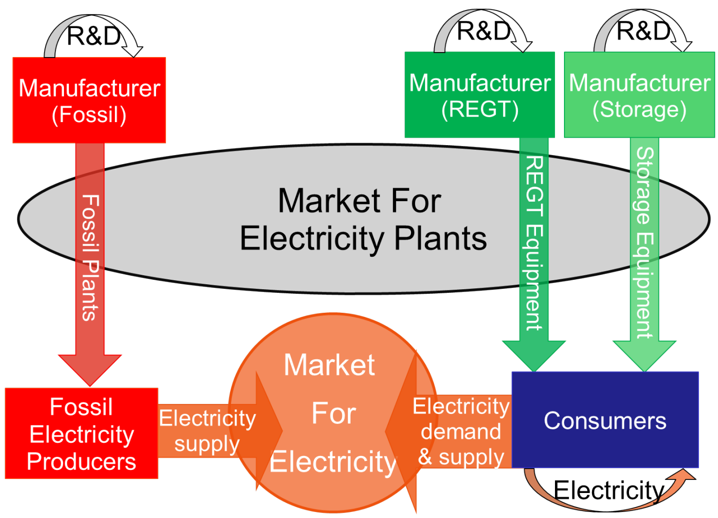

Figure 1: Markets for Electricity and Electricity Generation Equipment

[16]In reality, the learning rate is different for each individual technology and there is disagreement about the extent of the learning effect, as can be observed from the meta-study Lindman and Söderholm, 2012 for wind turbines. 13% is slightly below the average learning rate named for wind and PV combined (for PV, see Candelisea *et al.*, 2013). However, since we look at the complete costs of a REGT installation (technology + installation), we have to assume a lower learning rate, since not all cost components decrease as fast as the technology cost.

2.4.1 Market for Electricity

In the market for electricity two types of actors are present: fossil electricity producers and consumers. Producers generate electricity using fossil power plants and sell it to the consumers via the electricity grid. As the ABM is modeled to represent the electricity market of an industrialised country, it is assumed that sufficient grid capacity is available at the beginning of simulation. Overall electricity demand is assumed to be stable.

Electricity can be generated both by fossil producers and by consumers who invested into REGT (becoming consumer-producers). Which one is demanded by the consumers depends on relative prices and consumer preferences. Consumers always want to purchase the form of electricity which is subjectively cheapest.

In order to allow consumer-producers to get their investment costs back, heterogeneous prices in the electricity market are allowed. These prices are individual for each 'consumer-producer' and are determined in the moment when the REGT is installed:[17]

$$ElecPriceREGT_i = \frac{InstallCost_{r,t}}{Efficiency_{r,t} \times Life_r \times 12}. \tag{16}$$

The desired electricity price $ElecPriceREGT_i$ is set in a way that the 'consumer-producer' will be able to earn her investments back, if she is able to sell all the electricity she produces. The value $InstallCost_{r,t}/Efficiency_{r,t}$ denotes the technological characteristics of the plant installed. The costs are distributed over the lifetime of the plant, therefore this value is divided by $Life_r$ (in years). Also, since the consumer can sell electricity every month, we divide it again by 12. In the case that a consumer-producer is not able to sell all her electricity to other consumers, she will feed-in the remaining electricity into the general grid at the price which equals the cost of the cheapest fossil producer.[18]

This can be understood as consumers forming contracts among each other individually, allowing for different conditions compared to the general market. Using this mechanism, consumers with high preferences can pay higher electricity prices for the form of electricity they prefer. The consumers who want to purchase electricity from REGT can 'see' if there is supply available, so there is no uncertainty for them. If the consumer-producers are unable to sell all the electricity they generate to other consumers, they feed-in their electricity at a price which equals the cost of the cheapest fossil producer.

The market for electricity is progressed in the following order. At first the 'consumer-producers' (if there are any present) try to sell their electricity. Other consumers buy this electricity if the following two conditions are fulfilled:

1. $ElecPrice_t > ElecPriceREGT_i \times (1 - PrefEP_i)$,
2. $\frac{\phi Income_i}{12} > ElecPriceREGT_j \times NetDemand_i + (ElecPriceREGT_i + CostStorage_i) \times SelfConsumption_i$.

Here $ElecPrice_t$ is the electricity price consumers have to pay when buying electricity

[17]Since installation costs are distributed equally among the lifetime of the REGT installations, the desired price stays constant over time.

[18]This assumption is made to ensure that the consumer-producers can feed-in all their electricity instead of loosing it and making large losses.

from the grid,[19] while the cost of storage per unit of electricity is calculated from:

$$CostStorage_i = \frac{InstallCost_{s,t}}{Efficiency_{s,t} \times Life_s \times 12}, \tag{17}$$

which is analogous to the calculation of the desired electricity price in (16).

In sum, consumers buying (potentially more expansive) REGT electricity, do not spend more than threshold ϕ of their income both on that electricity and on the electricity they already produce themselves.[20] The remaining demand is satisfied by the fossil electricity producers. The 'general' market price for electricity $ElecPriceMarket_t$ is determined by a merit-order (e.g., Sensfuß*et al.*, 2008). This means that the electricity producers feed-in their electricity according to their cost in ascending order. $ElecPriceMarket_t$ is equal to the $CostFossil_{p,t}$ of the producers with the highest price who can feed-in any amount of electricity. Power plants with costs below the electricity price run the entire time, resulting in an up-time value equal one for this period. The power plants which produce at costs equal to the electricity price (the power plants which feed-in last), might not face sufficient demand to run the entire time. Therefore, their up-time is determined by how much residual electricity demand they face compared to the maximum amount of electricity they could generate.

On $ElecPriceMarket_t$ a markup is added if there are policy instruments in place, as described in Section 2.5:

$$ElecPrice_t = ElecPriceMarket_t + MarkupPolicy_t. \tag{18}$$

Here, $MarkupPolicy_t$ denotes the cost of all policy instruments applied, calculated on a monthly basis and divided by the $NetDemand_i$ in the electricity grid. With this notation, the price of each unit of electricity bought from the grid is increased by the same markup. Electricity generated from 'consumer-producers', which is directly sold to another consumer on a bilateral basis, is not increased by $MarkupPolicy_t$, as we assume that the policy maker does not increase the cost disadvantage of electricity from REGT further. Consumers who do not buy electricity directly from 'consumer-producers', or are able to satisfy their demand by self-production and - consumption, have to pay $ElecPrice_t$ for the electricity they consume, even if the total expenses result in a higher share than ϕ of their income.[21]

2.4.2 Market for Electricity Generation Equipment

In this market, all three actor types are present. The manufacturers sell their individual equipment to fossil producer and consumers who want to invest into REGT or storage technology.

The decision of consumer to invest into REGT and storage technology is based on a number of factors. For REGT, consumers will only invest if they would buy electricity generated from REGT based on the current technology. Therefore, the decision rule

[19] Note that $ElecPriceREGT_j$ can be different for each 'consumer-producer', so that it is possible that some can sell their electricity at their desired price level while some cannot.

[20] The cost of storage is included as no household can self-consume without installing storage capacity.

[21] Thus, the threshold ϕ is effective only when consumers choose between the two alternatives and tend to select a more expansive one. If however, these consumers lack funds to pay even for objectively cheapest electricity, then they can spend more than this threshold. The number of consumers who have to pay more than $Income_i \times \phi$ is recorded, as it is likely what a policy maker aims to avoid.

to invest is the same as the decision rule to consume electricity generated from other 'consumer-producers' in Section 2.4.1. However, there are two additional restrictions. First, a consumer will not invest if all of her electricity demand was satisfied by electricity generated from REGT by other 'consumer-producers', so $NetDemand_i > 0$ must hold.[22] Second, the consumer must have sufficient funds to purchase at least one REGT installation, $Income_i > InstallCost_{r,t}$.

For storage technology, the decision process is similar. The consumers will invest if the following three conditions are fulfilled:

1. $ElecPrice_t > ElecPriceREGT_i \times (1 - PrefEP_i) + CostStorage_i \times (1 - PrefAutarky_i)$,
2. $\frac{\phi Income_i}{12} > ElecPriceREGT_i \times NetDemand_i + (ElecPriceREGT_i + CostStorage_i) \times SelfConsumption_i$,
3. $NumberOfStoragePlantsInstalled_i \times Efficiency_{s,i} < NumberOfREGTPlantsInstalled_i \times Efficiency_{r,i}$

The rules stated, thus, ensure that i) the household i finds that the cost of self-produced electricity subjectively cheaper than the current one from the grid; ii) the household also can finance the additional consumption of the self-produced REGT electricity not surpassing its threshold of income; iii) the number and efficiency of storage plants already installed does not yet cover the amount of electricity (maximally) produced by REGT plants installed.

Manufacturers always sell up-to-date equipment at current prices, so there is no stock. Everything which is sold in one period is also produced in this period. Also, since it is assumed that manufacturers only start producing after they face demand, there is no risk of unsold products.

2.5 Policy Intervention

Policy intervention plays a central role in this model. Historically, policy intervention was needed (Jacobsson and Lauber, 2006) to initiate and foster the transition towards the usage of electricity generated from REGT. Even though there is a number of 'eco-warriors' present in the model which invest into REGT, their influence alone is not sufficient to induce innovation and learning to an extent that would make a general transition possible. Therefore, at some point the policy maker may decide to intervene and support the diffusion of REGTs.

We assume that the policy maker has the aim to foster the transition towards electricity from REGT. In particular, we use a policy target of 26% diffusion of REGT by 2020. This aim is fixed, so that there are no changes due to political elections or other changes in government. Apart from this main goal, policy maker aims to preserve the stability of the electricity grid. In the model, stability is measured as the share of unstable electricity supply inside the electricity grid. The policy maker is willing to keep stability of electricity supply high, which conflicts with the goal of increasing the share of electricity from REGT.[23] Also, the transition should be as steady as possible and achieved with possibly

[22] If all of her demand was satisfied, she will assume that a sufficient amount of renewable electricity is present in the market and will not act.

[23] The only exception is when the REGT electricity is sufficiently supported by the storage capacities of consumers. In that case, REGT becomes automatically stable.

lower public support.[24]

To limit the choice options, the policy maker can only apply a pre-specified collection of policy instruments (either separately or as a mix). A mix of different policy instruments is sometimes considered to be more efficient than single instruments with the same commitment level (Rogge and Reichardt, 2013), so that fewer resources have to be spent to achieve the same result. The costs of these instruments are laid as a surcharge upon the electricity price for electricity distributed via the electricity grid. This means, the costs are distributed among the consumers who buy electricity from the grid (see equation 18).

Most of the policy instruments can be applied to all technologies present in the ABM. However, since the fossil technology is already mature and supplies the whole market at the beginning of the simulation, there is no policy support for it.[25]

Public R&D

The most basic form of policy intervention is research performed by public actors. This research can be either basic or applied. Basic research in this model has the sole purpose of making storage technology available. Without basic research, there is no chance the storage technology will appear (see Section 2.1). Applied research performed by the state works in the same way as private research, as described in Section 2.3, but is conducted separately. The policy maker can choose in every period t the amount of money invested in technology m.[26] Results of public R&D in terms of technology advances both in cost and efficiency improvements are assumed to be transferred to technology producers at no cost.

R&D Subsidies

Instead of performing R&D in the public sector, another policy option is financing private R&D. This policy instrument simply adds funds for research to the respective manufacturers, which is added upon the share of turnover which those manufacturers invest. The sum available for innovative activities changes to:

$$InvestSub_{m,t} = Invest_{m,t} + StateFunds_{m,t} \tag{19}$$

where $StateFunds_{m,t}$ is the sum of money the state provides for R&D for a specific technology.

REGT Installation Subsidies

There are several diffusion-oriented policy instruments possible. The most straightforward is to subsidise the installation cost of REGT or storage technology, which increases the incentive for consumers to install them. In the model, this policy instrument is modeled to decrease the price a consumer has to pay for buying from the specific manufacturer

[24] In the present version we keep budget fixed maximizing diffusion and stability. However, with little reconfiguration one could compromise along all three dimensions.

[25] Of course, in reality there is a lot of institutional support and subsidies for fossil power plants. However, to simplify the search for an optimal policy mix, currently all the policy instruments are aimed at improving REGT and storage technology.

[26] Public R&D on storage technology can only be applied when the basic research was already successful and storage technology is available.

by a certain percentage. Note that the cost of the manufacturer does not change, so that income of the manufacturer per plant sold remains unchanged:

$$PInstall_{m,t} = InstallCost_{m,t} \times (1 - SubInstall_{m,t}). \tag{20}$$

Here $PInstall_{m,t}$ is the price for a consumer, while $InstallCost_{m,t}$ is the price at which the manufacturer is selling. The variable $SubInstall_{m,t}$ determines the percentage of the installation cost which is covered by the state. $SubInstall_{m,t}$ is depended on the cost and efficiency of technology m in time t, since both variables can easily be observed by the governement. THe actual value is computed from:

$$SubInstall_{m,t} = min(S_{m,t}, 0.9), \tag{21}$$

where $S_{m,t} \sim \mathcal{N}\left(\frac{InstallCost_{m,t}}{Efficiency_{m,t}} \times \frac{1}{InstallCost_{m,0}}, \frac{InstallCost_{m,t}}{Efficiency_{m,t}} \times \frac{1}{InstallCost_{m,0}}/10\right)$. The government here tries to keep to subsidy level stable in relation to the decreasing prices, since it has to offer less subsidies if the technology becomes cheaper and more effective.

Feed-in Tariff

In the case of Germany, the most important policy instrument was a feed-in tariff (FIT) (see Jacobsson and Lauber, 2006). FIT guarantees the feed-in of electricity generated from REGT at a fixed price. This takes most of the uncertainty away that comes with the investment into REGT, namely if there are consumers willing to purchase electricity from REGT at a sufficiently high price. The decision to invest into REGT becomes a simple decision based on net-present value, as both cost of installation and expected income from the installation are now known.[27] Since the installation costs are covered by the FIT, the 'consumer-producers' do not need a positive electricity price anymore and feed-in electricity into the market at marginal costs, which are zero, crowding out electricity from fossil power plants. Another side consequence of FIT is that it reduces the incentive to self-consume electricity from REGT, if FIT granted is higher than the price of electricity consumers have to pay.

The height of FIT is calculated in the following way:

$$FIT = \frac{InstallCost_{r,t}}{Efficiency_{r,t} \times Life_r \times 12 \times mean(Irradiation)}. \tag{22}$$

Here, FIT denotes the amount of money consumer-producers gets per unit of electricity fed-in. FIT is dependent on the installation cost $InstallCost_{r,t}$ the 'consumer-producer' has to pay per installation and the efficiency of the installation $Efficiency_{r,t}$. Also, FIT is granted over the entire lifetime of the REGT installation, $Life_r$, and paid on a monthly level (hence it has to be divided by 12 in the end). To avoid all consumers from being able to take the FIT, it is divided by the mean irradiation of consumers, which means that only people living in locations which are suitable for REGT will be able to benefit from the FIT. Since the extent of the FIT is calculated from the the mean irradiation, consumers enjoying irradiation above average can benefit from FIT. Thus, the policy intervention creates an additional source of inequality among the consumers.

Furthermore, further policy instruments could be implemented (see Appendix C for

[27]Note that this policy instrument greatly reduces the importance of preferences for environmental protection, since now even people with low preferences might have an incentive to invest into REGT.

details), but as their calibration becomes increasingly complex while justification of their relevance in the past is rather questionable, we leave their inclusion for further research.

2.6 Ordering of the Simulation Model

In the ABM, the following consequence of simulation steps is adopted:

1. Set all exogenous parameters.
2. Allocate randomly preferences to consumers, size and age to fossil plants.
3. In each time period (month) do the following:
   - Sell electricity to consumers (consumers buy from subjectively cheapest producer).
4. At the end of each year do the following:
   - Electricity producers and consumers (future consumer-producers) buy new plants from manufacturers if necessary.
   - Equipment manufacturers invest in R&D accordingly experiencing innovation and learning effects.
   - Policy maker updates her policy intervention.
5. After a pre-specified number of periods T stop the ABM and display results on:
   - diffusion of REGT,
   - instability of electricity production,
   - income/losses generated by consumers from investing into REGT technologies,
   - electricity prices.

3 Robustness Analysis and Empirical Verification

In this section, tests with alternative parameter settings are performed to calibrate the model. Calibration is particularly important as not all parameters can be constructed from historical data. While there is information about, e.g., income structure or the speed of learning, other parameter values are unknown. This is for example the distribution of preferences, where some assumptions have to be made (as discussed in Section 2.2.1). In those cases we follow Malerba *et al.*, 2008 and other history-friendly models in not attempting detailed calibration of *all* parameters: 'Because most parameters fall into groups within a particular mechanism in the model, common-sense guidance is available for choosing plausible orders of magnitude'.

The model has been calibrated with the parameter settings presented in Table A in Appendix. The parameters were chosen to represent the conditions of an industrialised country (in particular, Germany) in the 1990s. The parameters for fossil producers are set that every consumer can afford to satisfy her electricity demand at the beginning of the simulation without spending more than $\phi\%$ of her income on electricity. This is partly due to the high efficiency of fossil plant, but also due to the low initial price for fossil fuels. The initial values for price and efficiency of REGT, as well as the preferences of consumers, are chosen in a way to allow consumers with high preferences to install REGT, but make it unattractive for others.[28] The technological characteristics, however, can be improved substantially making electricity from REGT attractive for most consumers and replicating the progress of the REGT technology in the last two decades. Due to the parameters chosen for innovation and learning, it is very unlikely that REGTs overcome their cost-disadvantage without governmental support. The figures on space available (for consumers) and its irradiation is calibrated to make possible all demand for electricity from consumers to be satisfied from REGT sources, if there are substantial improvements in the efficiency of REGT.[29]

With the set of parameters chosen, there is no meaningful diffusion of REGT without public support, as can be observed from Figure 2. The only investment into REGT-installations (bottom right chart) is from the 'eco-warriors', but their number is not sufficient to induce adequate learning effects or innovation to improve REGT to a level where it can compete with fossil power plants, even though there are some improvements in efficiency of the REGT installation and a significant drop in prices, caused by early learning effects. [30] Therefore, the share of electricity generated from REGT stagnates at below 1% (top left chart).

To generate a history-friendly simulation run which can serve as a basis for our optimal policy mix identification, we run the first 20 years of our simulation with a predefined set of policy interventions and the values presented in Table A in Appendix. For the policy interventions, we try to mimic the order in which different policy instruments were applied (see, e.g. Cantner *et al.* (2014) : public R&D and R&D subsidies are present over the whole period, with increasing amounts of money invested over time. Investment incentives are introduced periodically (since they were usually subsidy programs with a finite time frame) with varying amount of money invested. However, the subsidy per REGT installation decreases over time, as the decreasing cost and increasing efficiency of the plants lower the subsidy necessary to induce consumers to invest (this consequently leads to more installations supported with the same governmental investment). Since the first German FIT (Electricity Feed-in Law – 'Stromeinspeisegesetz') was introduced already in 1991 (see, e.g., Jacobsson and Lauber, 2006 and Cantner *et al.*, 2014), FIT is active all the time in our model. However, the first FIT provided sufficient incentives only for some technologies. More effective FIT was introduced in 2000, the Renewable Energy Sources Act ('Erneuerbare Energien Gesetz', EEG), which provided sufficient incentives for most REGT. We try to replicate this evolution by choosing very small sums which can be spent on FIT in the first years, but then strongly increasing the amount of money so that an increasing number of consumers can apply for FIT over time.[31] To summarize, the amount of funds invested to support REGT and storage technologies increase over time, particularly after an effective FIT is introduced in 2000.

[28]This reflects the lack of cost competitiveness of REGT compared to fossil fuels, especially at the beginning of the simulation (in 1990).

[29]The REGT technology has to be improved by about 80% so that the complete demand can be satisfied from REGT-installations.

[30]Due to the low initial number of installed plants chosen, even low production numbers will allow manufacturers to achieve strong learning effects.

[31]Note that the money which can be spent on policy intervention is pre-specified for each period. By changing these values, the focus of the policy mix can be shifted between different instruments.

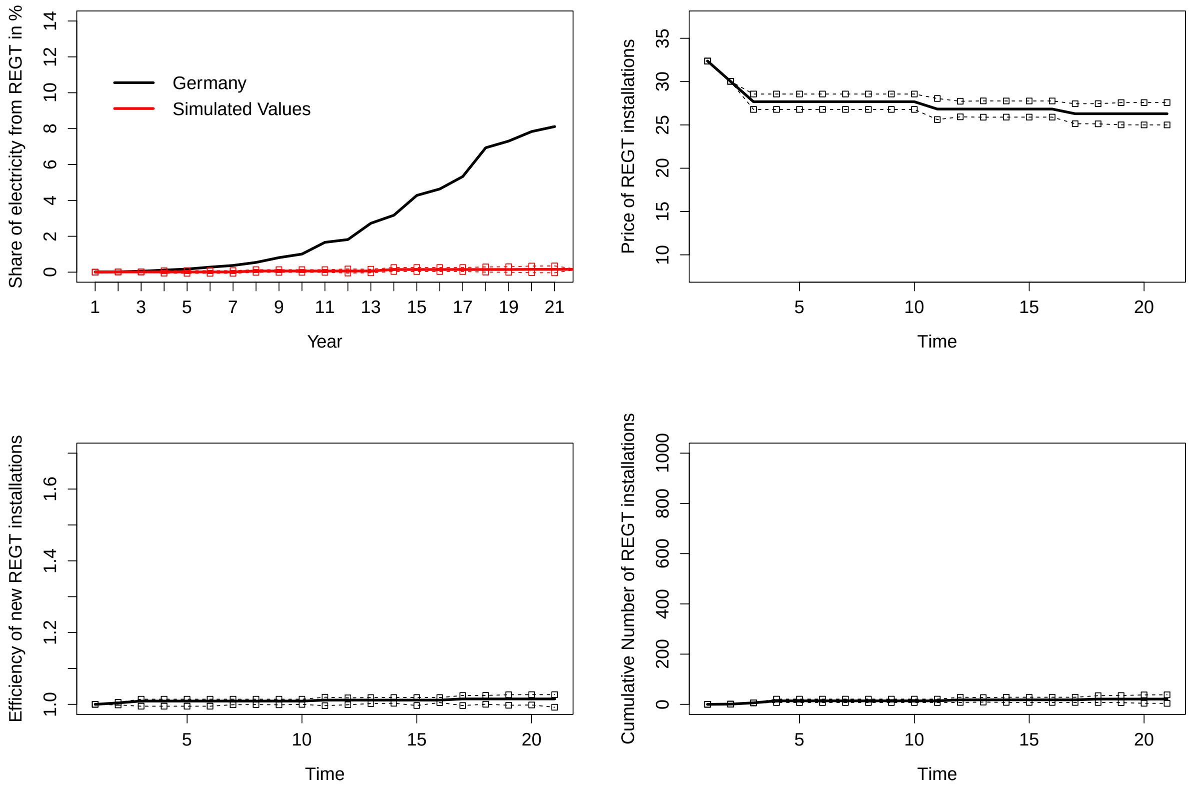

Figure 2: Characteristics of REGT evolution without policy support

Note: In all charts the median run +/- two standard deviations are presented.

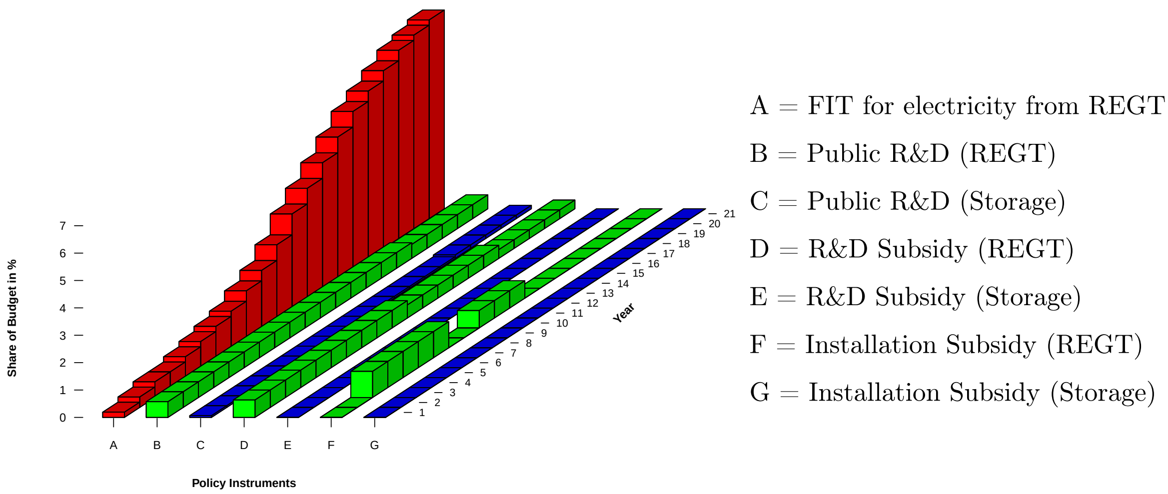

Figure 3: Policy Mix for History-Friendly Runs

We take as a basis the simulation run which produces the median share of renewable electricity in the electricity market over 101 replications.[32] This share is 8.3%, which is nearly identical to the actual value for Germany in 2010 (according to the German Federal Minstry for the Environment and Nuclear Safety (2012)). The development over time is very similar, as can be observed from the top left plot in Figure 4.[33]

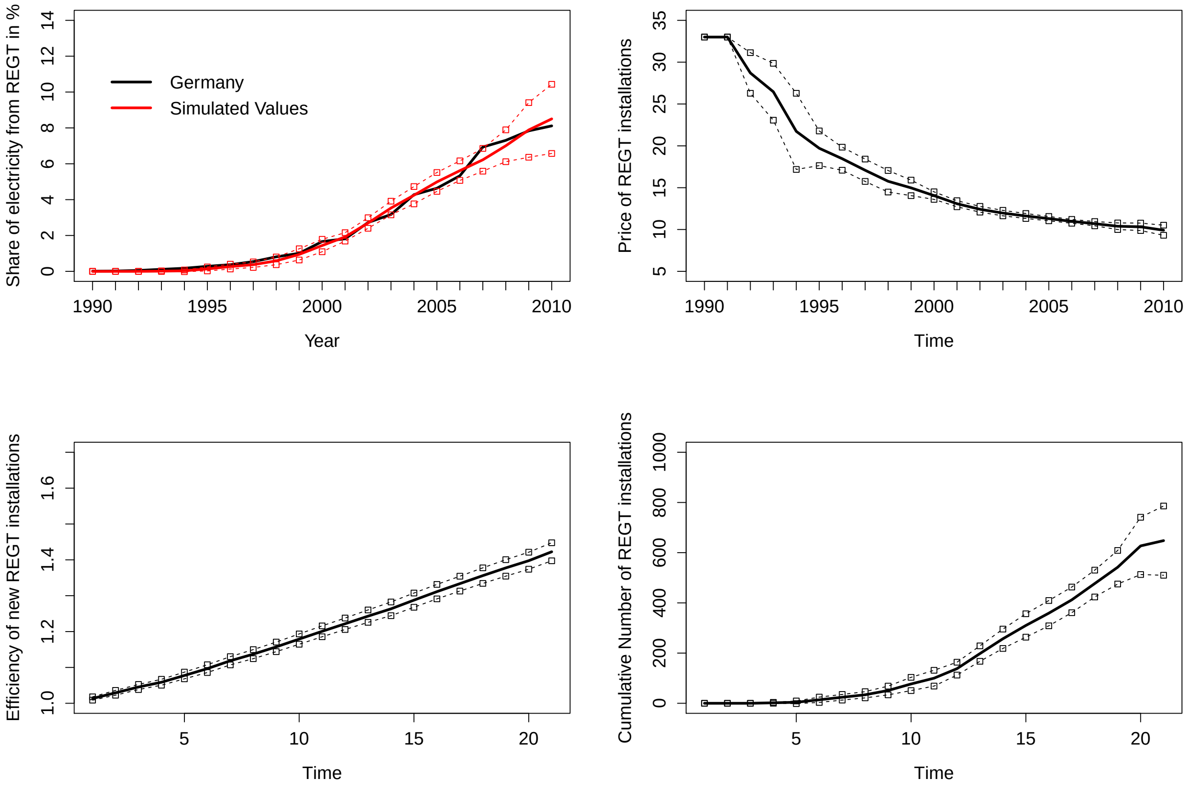

Figure 4: Characteristics of REGT evolution with HF policy support

Note: In all charts the median run +/- two standard deviations are presented.

Since this 'history-friendly' simulation run serves as a basis for optimal policy mix identification by DE, it is useful to show some developments and final values at $t = 240$ (at the end of 20 years period, $T1$). As can be observed from the bottom right chart in Figure 4, the number of REGT installations increases steadily, closely correlated with the share of electricity generated from REGT. This fact is hardly surprising, since the electricity must be generated from the installations. The technical reason for the close correlation can be observed from the bottom left chart in Figure 4: the efficiency (electricity generated per REGT installation) increases over time, by about 40% in 20 years.

The variance between single runs in the top charts of Figure 4 spurs mainly from the stochastic nature of efficiency improvements. More improvements here mean that less REGT plants have to be installed to generate a certain amount of electricity, which influences the profitability of single plants and therefore the cost-competitiveness of REGT in comparison to fossil fuels. The price of REGT installation decreases over time by nearly

[32]It is not possible to take mean results of all 101 runs since we need an individual simulation result as input into the differential evolution and not averaged values . Another advantage of the median is its robustness to outliers, which is also an asset for our modeling exercise.

[33]The correlation between our simulation results and the German time-line is 0.98529.

65%, so that the cost per unit of electricity generated is reduced by about 80% (i.e. combined effect from efficiency and cost improvement), which is more than a substantial decrease.

Storage technology was introduced in the simulation by public R&D in 2003. However, due to still high costs of REGT, only 4 consumers installed a storage facility. Nearly all improvement to the technology was from public R&D, which increased efficiency by about 6%. The cost of storage technology decreased by about 20%, due to the very strong initial learning effects. However, since there is large room for further improvement, storage can become important in the near future (in the period 2011-2020, where we attempt to identify an optimal policy mix).

The number of consumers who have invested into REGT is quite high. Out of 1000 consumers, 148 did invest into REGT, but 91 of these consumers did not use all their space available due to the income constraint. If they have to replace their installations after 20 years, they will probably use more space due to the reduced price of REGT. Out of the 181 consumers who have already installed REGT, 110 were granted a FIT, which means that only 38 consumers did invest without the incentive of the FIT. However, some of them could have invested due to an investment subsidy which reduced prices. While most 'eco-warriors' invested (42 out of 50), 16 of them accepted the FIT. In addition, 7 'eco-warriors' also used a subsidy to install REGT. Since at least some 'eco-warriors' would also have invested without the FIT, it is possible that the existence of FIT is crowding-out voluntary investment. However, as can be observed from Figure 5, the oldest installations were accepting the FIT. Only after some time 'eco-warriors' started investing on their own and did so for most of the history-friendly run, as lowering prices allowed poorer 'eco-warriors' to invest as well. This indicates that the existence of a high FIT is crowding out other reasons to invest, since even consumers who would invest on their own are better off if they accept FIT (as they have no uncertainty about how much electricity they can sell). However, this is inefficient, since the policy maker grants a FIT to consumers who would also have invested without it.

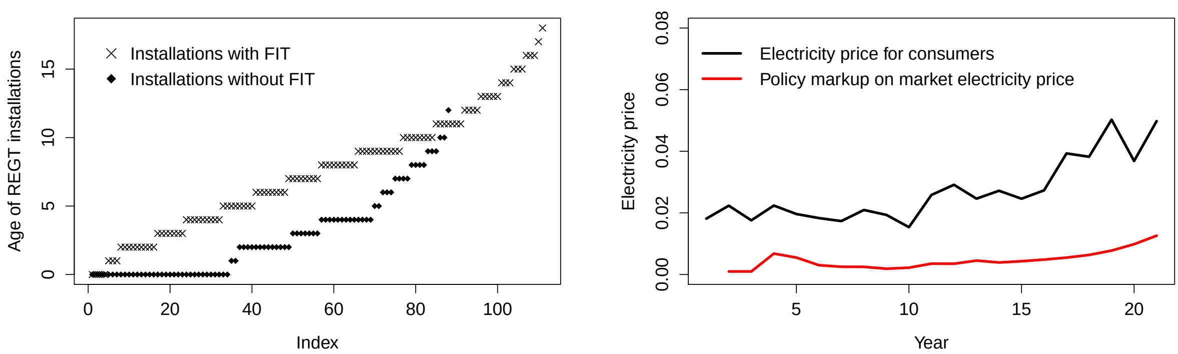

Figure 5: Technological characteristics of new REGT installations

The electricity price from the grid (consumers have to pay for) increases over time, as can be observed from the right chart of Figure 5. However, the reason for this increase is mainly caused by the increase in prices for fossil fuels, which increase by factor four throughout the simulation. The price effect of public action is low in the first half of the simulation (with the exception of a very strong subsidy programm in the beginning), but increases steadily in the second half. At the end, it accounts for about one fifth of the electricity price and is expected to remain high due to the long term character of FIT subsidy (FIT being granted over the entire lifetime of REGT installations, Section 2.5. As a consequence, the policy instruments already being applied will affect the REGT diffusion in the near future (2011-2020) making installations of renewable technologies even more attractive.

Figure 6 shows that, averaged over the whole time period of the history-friendly run, only poor consumers with relatively high electricity demand become 'energy poor' (left chart). Together with the right chart illustrating cost of policy intervention compared to income, it becomes clear that poorest households have to pay disproportionally more for the public support of renewable technologies. The main reason for this is that low income households have less means and space to install REGT and storage facilities. As a consequence, staying dependent from the electricity grid and receiving less support in terms of installation subsidies and FIT, those consumers are most vulnerable to the electricity price dynamics observed.

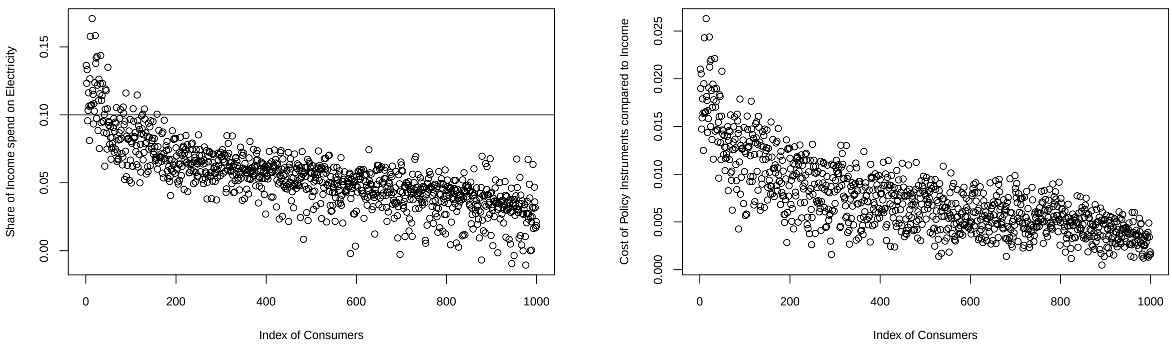

Figure 6: Income Spend on electricity

Note: Consumers in this figure are ordered in ascending order by their income.

Another purpose of numerical experiments is sensitivity analysis. Here, the purpose is to find out how robust the simulation results are to changes in parameters. The model results are sensitive especially towards changes in the initial values concerning costs and efficiency. Also, the extent to which innovation and learning can reduce costs and efficiency over time have a strong impact on the results. This is, however, not surprising as the decisions of consumers in this model are based on the comparison of electricity costs from REGT and electricity from fossil fuels. Any substantial change in these values is therefore expected to change results.

4 Counterfactual Analysis by Differential Evolution

In this section we take a challenge in 'looking further ahead' instead of only in the 'rearview mirror' as has been put by Garavaglia (2010). A necessary limitation of the counterfactual (i.e. 'what if') analysis provided below is that it provides sufficient (in the structure of the present model) but not necessary condition for a certain outcome. Therefore, results shall be considered with caution. Nevertheless, we believe that this is an important and very promising direction of research, particularly in the line of history-friendly modelling literature, fostering the discussion on the normative role of simulation modelling in economics.

To identify an optimal policy mix we apply an exercise from the optimal control literature (see, e.g., Blueschke-Nikolaeva *et al.*, 2012), where a set of controls is optimised to achieve the states as close as possible to policy targets. An important difference is that since we fix the overall budget of policy interventions[34]. Therefore, the controls themselves do not contribute to an objective function value,[35] but only the corresponding states achieved. The states in our study are of two types only: the difference between the targeted and reached level of REGTs on the market and a penalty added in case the energy grid's stability becomes vulnerable (the latter is made large and increasing over optimisation process[36] – here $\frac{g}{Gmax}$ captures a multiplier increasing in every next DE generation g from 1 to $Gmax$– to prohibit the model to approach that option).

Another difference to optimal control literature consists in taking for diffusion only the final year of simulation into account in evaluating the objective function, i.e. diffusion may be slow or fast, but the policy maker is interested in the final outcome only.[37] For stability, in contrast, it is natural to consider the average stability of electricity sold on the market over the entire period of consideration. The objective function than looks as follows:

$$\min(J) = (\ Diffusion^{Target} -\ Diffusion^{Actual}) - \frac{g}{Gmax}\log\left(Stability\right) \tag{23}$$

where $Diffusion^{Target}$ is the target set by policy maker for the system at the final period $T2$ (i.e. 26% diffusion of the REGT technology), while $Diffusion^{Actual}$ is the level of the REGT diffusion achieved, respectively. Thus, in our case a positive deviation from the target value is penalised, while a negative deviation (i.e. an 'over-achievement') reduces the value of the objective function, as the policy makers are even more successful with their policy intervention then expected. $\log\left(Stability\right)$ represents the penalty on grid instability, which is measured as a logarithm of the average (over all periods under consideration) percentage of electricity produced either out of fossil sources or supported by sufficient storage capacity.[38]

To optimise the function a Differential Evolution (DE) algorithm, initially proposed by Storn and Price (1997), is used. The choice in favour of a so-called heuristic optimisation method is due to i) large flexibility in terms of formulating our ABM and its main objective function with no essential assumptions about the optimisation model (for more details

[34]In particular, the yearly budget for the last ten years is taken close to the value observed in the last year of the history-friendly part (i.e. 2010) (thus, we assume that in the future the overall sum of support should not increase further). For the period of 30 years we consider the sum of the history-friendly budget and the one we fix for the last ten years, thus ensuring comparability between the exercises in terms of the total budget spent on REGT support. The overall extent of governmental support for the history-friendly run and the DE is shown in Table A in Appendix .

[35]Though it is interesting later to relax this assumption and allow the model to compromise along the three dimensions: diffusion, stability and budget, – spending more (less) on the diffusion of REGTs depending on the additional benefit (loss) achieved. A challenging question in this respect becomes a cost-benefit analysis for the current model.

[36]Increasing the penalty over DE simulation allows for a more extensive search over possible solutions and still ensures that the final result satisfies the constraint (see Savin and Winker, 2012 for an example).

[37]A possible extension may consist in setting intermediate targets for diffusion like, e.g., 15% by 2015, 20% by 2018 and finally 26% by 2020. Results on this will follow in due course.

[38]It is easy to see that objective function is falling in $Diffusion^{Actual}$ with constant marginal return for each additional percent of electricity produced by means of REGTs, while J is also falling in $Stability$ with the difference that of diminishing marginal returns, i.e the more stable situation we have, the less every additional percent of unstable electricity supply is penalized.

read Gilli and Schumann (forthcoming)) and ii) not necessarily 'well-behaved' search space of our problem (with non-linearities and multiple local optima), where classical methods are inappropriate. Since computing power has increased dramatically over the last decades, it is also not a problem of time to optimise our ABM by DE.[39]

DE is a population-based optimisation technique for continuous objective functions and only few tuning parameters to initialise Blueschke *et al.* (2013). In short, starting with an initial population of random solutions (line 2 in Algorithm 1), DE updates this population by linear combination (line 7) and crossover (line 9) of four different solution vectors into one, and selects the fittest solutions among the original and the updated population. This continues until some stopping criterion is met.More specifically, DE starts with a randomly initialised set of candidate solutions $P^{(1)}_{j,t,i}$ ($j = 1, ..., K$; $t = 1, ..., T^{DE}$, $i = 1, ..., p$) of the $K \times T^{DE} \times p$ size, where $K \times T^{DE}$ is the dimension of a single candidate solution, with K being the number of control variables (policy intervention options in our case) and T^{DE} – the size of the planning horizon (10 or 30 years), and p is the population size. Based on the tuning exercise described in (Blueschke *et al.*, 2013, p. 825-826), shrinkage parameter F and crossover rate CR are set both equal to 0.5. A detailed discussion on how DE can be applied and tuned for optimal control problems is provided in Blueschke *et al.* (2013).

As for the DE stopping criterion, this has to: i) ensure that DE population of solutions converges to an optimum (local or global); ii) signal DE to stop once the convergence is observed. Again, in line with Blueschke *et al.* (2013), we set an upper limit on the number of DE generations to be performed within one restart (G^{max} equal to 1000), but at the same time control for convergence within the population by looking on the candidates' objective values. In particular, DE algorithm stops if 50% of solutions in the population reach a deviation less then 10^{-9} from the best solution available. In addition, if for 100 periods more than 50% of solutions in the population do not improve, the algorithm also stops. Since our model contains stochastic components, one must repeat the model evaluation for each candidate solution certain number of times (ten in our case) and use their median value (more on advantages of using the least median objective value is written in Savin and Blueschke (2013)).

Algorithm 1 Pseudocode for Differential Evolution

1: Initialize parameters K, T^{DE}, p, F and CR
2: Randomly initialize $P^{(1)}_{j,t,i}$, $j = 1, \cdots, K$; $t = 1, \cdots, T^{DE}$; $i = 1, \cdots, p$
3: **while** the stopping criterion is not met **do**
4:     $P^{(0)} = P^{(1)}$
5:     **for** $i = 1$ to p **do**
6:         Generate $r_1, r_2, r_3 \in 1, \cdots, p$, $r_1 \neq r_2 \neq r_3 \neq i$
7:         Compute $P^{(v)}_{.,.,i} = P^{(0)}_{.,.,r_1} + F \times (P^{(0)}_{.,.,r_2}$ - $P^{(0)}_{.,.,r_3})$
8:         **for** $j = 1$ to K and $t = 1$ to T^{DE} **do**
9:             **if** $u < CR$ **then** $P^{(n)}_{j,t,i} = P^{(v)}_{j,t,i}$ **else** $P^{(n)}_{j,t,i} = P^{(0)}_{j,t,i}$
10:         **end for**
11:         **if** $J(P^{(n)}_{.,.,i}) < J(P^{(0)}_{.,.,i})$ **then** $P^{(1)}_{.,.,i} = P^{(n)}_{.,.,i}$ **else** $P^{(1)}_{.,.,i} = P^{(0)}_{.,.,i}$
12:     **end for**
13: **end while**

[39]Our ABM is written in R. A single restart of the ABM for the parameter setting stated requires from 6 to 10 seconds using R 3.1.1 and Pentium IV 3.3 GHz (depending on the policy mix applied).

We run the DE algorithm taking the history-friendly run presented in Section 3 as basis. Here, of special importance is the policy mix applied. Assuming that the government keeps its promises, a FIT introduced in former periods limits the autonomy of decision in later periods. For the policy mix candidate solutions used in our DE algorithm, we have to make sure that sufficient money is allocated on paying for the 'old' installations which were installed with FIT. This reduces the funds which can be allocated towards other policy instruments (or used for new installations with FIT).

4.1 10 Year Differential Evolution

As can be observed from Figure 7, the policy mix fund by differential evolution is dominated by FIT. However, this high level of FIT was predetermined by the 'history-friendly' part of the simulation and is decreasing as fast as the promise of paying FIT over a period of 20 years allows. No new FIT are granted. This strongly points in the direction of the FIT being too high before, so money could have been spend more efficiently on other instruments.

Over the course of ten years, budget is spend rather evenly among the different policy instruments (with the obvious exception of FIT). There is, however, a slight advantage for storage technology, which is interesting since it shows a switch in priority of the policy maker in the model (in the 'history-friendly' part, there was very little spend on storage). The temporal distribution of the non-FIT instruments shows a slight bias towards to beginning, which means that it seems optimal to spend the budget early on, given that technology costs have already decreased substantially in the 'history-friendly' period.

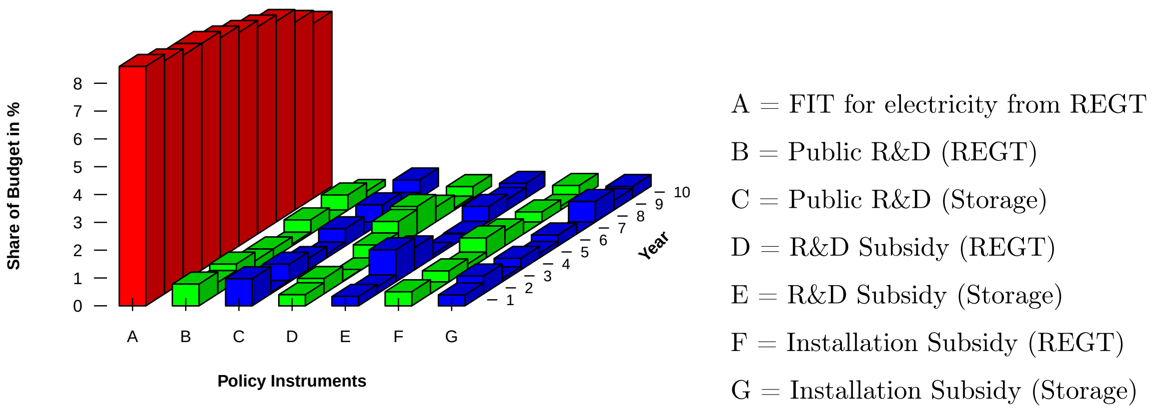

Figure 7: Policy Mix derived from 10 years DE runs

The diffusion of REGT continuous in a nearly linear manner and reaches about 19% in the last year, meaning that the government is not able to reach its diffusion goal of 26% diffusion with the given budget and policy mix combination.[40] The price of REGT decreases by 20% over the course of ten year (compared to the value at the end of the history friendly run), while efficiency increases by 20 percentage points and is now 60% higher than in the beginning of the history friendly runs. All in all, 234 consumers

[40]Note that there are no Graphics presented here since the developments are nearly linear and the paper already includes a high number of Figures.

installed REGT installation, which is very close to 25% of the population and an increase by 58% compared to the end of the 'history-friendly' run.

90.5% of all electricity produced is considered stable. Here, most of the stable electricity still comes from the fossil plants. However, the number of consumers who have installed a storage facility is with 131 quite high. This means that more than half of all consumers who invested into REGT also have installed a storage solution. However, only 8 consumers did install a sufficient amount of REGT installations AND storage facilities to completely cover their electricity demand (allowing them to become autarkic of the electricity grid most of the time). The cost of the storage technology decreased by about 50% compared to the end of the 'history-friendly' runs, while the efficiency increased by about 20 percentage points.

4.2 30 Year Differential Evolution

In contrast the the 10 year differential evolution runs, the 30 year runs are not based on the 'history-friendly' part and therefore start in 1990. It is immediately observable from Figure 8 that the FIT has much less dominating in the policy mix, which allows the policy maker to shift around budget more freely. However, at the end of the time frame, there is huge investment into FIT, which will be discussed below. There is strong initial investment into basic R&D for storage, which helps to make it available early on. After this, support for storage is mostly realised through installation subsidies (which is the policy instrument with most budget, except for FIT). Therefore, policy regarding both technologies show a focus on demand-side policies especially in the later years, while in the beginning a relatively higher amount is invested into R&D.

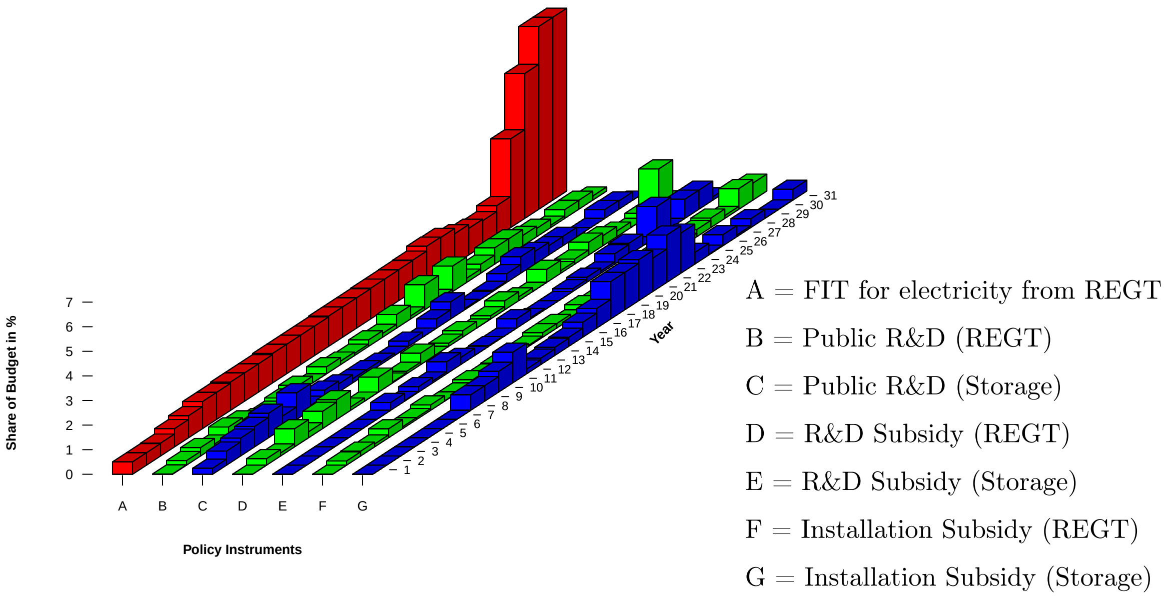

Figure 8: Policy Mix derived from 10 years DE runs

The Figure 9 shows the development of several policy indicators over time. As can be observed from the top left graph, the diffusion of REGT is weaker over a long time period compared to the actual German values. However, towards the end of the simulation, there is a sudden rise in diffusion. In the end 375 consumers did install REGT, which is a much higher number than in the 10 years case. The price of REGT decreases by 75% over the time period, while the efficiency of the technology increases by 55%. All in all, the system costs (price and efficiency combined) decreased by 85%, which is not much more than what was achieved in the 'history-friendly' runs already. The reason for this finding is the learning effect, which becomes weaker the more installations are already sold. Since we assume only a domestic market here, we do not consider the learning effect acquired elsewhere. Including these would be a valuable extension of the model, however, we would have to make strong assumptions about the behaviour of the foreign markets.

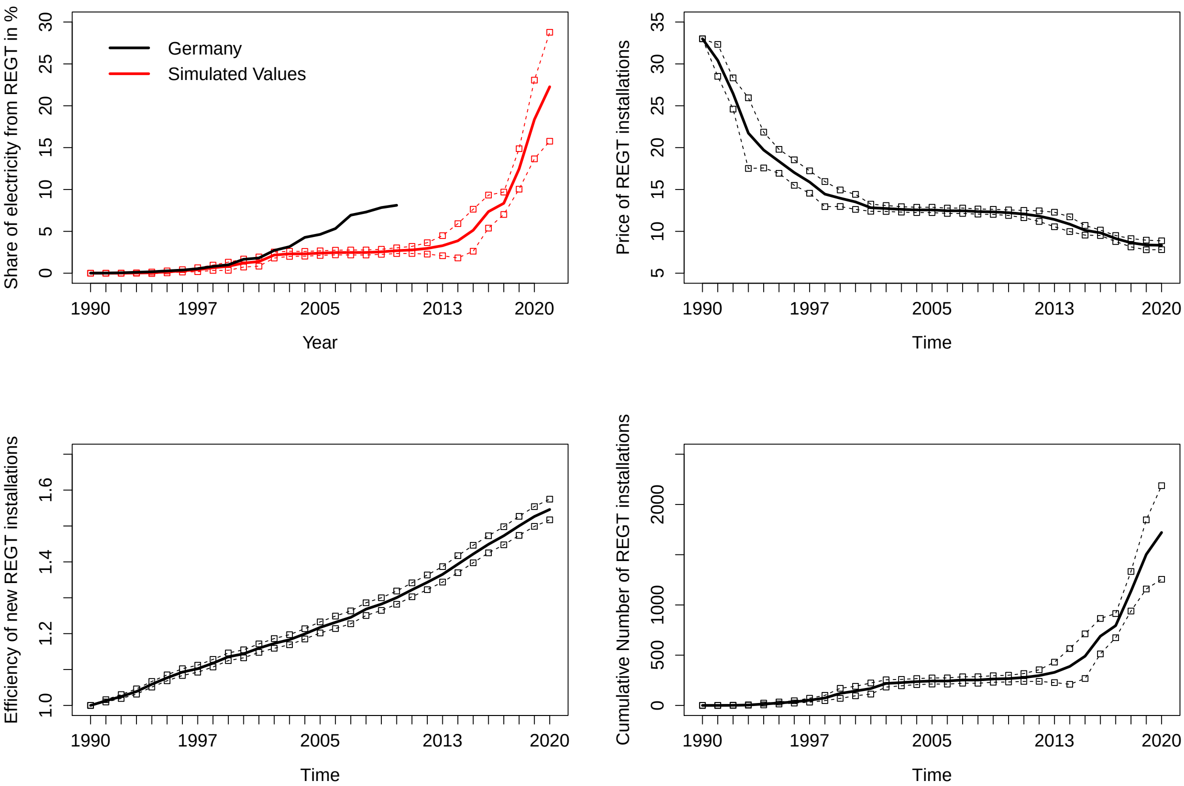

Figure 9: Characteristics of REGT evolution with optimal policy support

Note: In all charts the median run +/- two standard deviations are presented.

The high final rate of diffusion can be attributed to the strong increase in FIT at the end and several period of high installation subsidy for REGT (which is not clearly visible in Figure 8, since installation subsidy for storage is also high in these periods). This seems to be an optimal solution since the strong demand-side support occurs in a period where the technology has already evolved for some time (based on R&D and weaker demand-side support), which increases the amount of REGT the government can support with a given level of policy support. However, this strategy is only optimal since we take the diffusion at the end of the simulation as an indicator. If we would consider intermediate values, the result would likely be different. However, even if the results are better than for the 10 years run based on the 'history-friendly' results, the actual policy goal of 26% diffusion is still not met. Here, the median result is 22.5% compared to 19%

above.

The same can be said about storage technology. The share of stable electricity is much higher for the optimal policy mix over 30 years (96%), compared to the 10 years case. As was the case for REGT, also for storage the diffusion is fastest towards the end of the observed period. 189 consumers did install storage facilities. In relation to the number of consumers who installed REGT this is close to the result for the 10 year runs, but here each consumer on average bought more storage facilities. Also, the number of people who are autarkic from the grid is 20 for this run, which is 2.5 times more than in the case above. The price of storage facilities decreased by about 2/3, while the efficiency increased by 30%, making the technological development slower than in the case of REGT. However, since REGT benefit from the FIT, while the storage technology has no similar supporting instrument, this was to be expected.

5 Conclusion

This ABM models development of the electricity market in Germany over the past 20 years with an outlook for the next ten years. Its aim is to analyse the conditions under which a transition towards a sustainable electricity can be achieved efficiently. The transition is based on diffusion of two different technologies, renewable electricity generation technology and storage technology. Since both are characterised by high costs and low efficiency at the beginning of simulation, policy intervention is necessary to start the transition (as it is shown in the simulations run without policy support in Section 3). Without policy intervention, the diffusion process stops after some time, since all consumers who would invest at current prices and efficiency levels have done so, leaving no market for the manufacturer of REGT equipment.

Using a set of policy interventions which share important features of the policy mix applied in Germany over the last 20 years, we are able to generate simulation runs with similar diffusion levels as observed in Germany in 1990-2010. We take the run which produces the median diffusion level of 101 restarts as a basis for our differential evolution approach, in which we simulate the next 10 years. From these history-friendly experiments, we can take several insights. First of all, the introduction of a FIT is a very effective way of inducing the diffusion of REGT. However, this comes at relatively high costs and is inflexible over time. In particular, since FIT is granted for 20 years, it is not possible to reduce spending on FIT in the short run, at least not without breaking the promise given by policy maker to respective households. Introducing a FIT creates some path dependency inside the policy mix, as future spending has to take into account the funds already promised for FIT in former periods. In addition, the FIT (and to some extent also REGT installation subsidies) is crowding-out voluntary investment into REGT installations, since even people which would invest without incentives are better off accepting FIT or the subsidy (or both).

The counterfactual analysis also shows that it is possible to identify a policy mix over 30 years of DE which is superior to the 10 years DE based on the results of the 'history-friendly' run. This indicates that, if only the results at the very end of the time frame are considered, the historical policy mix of Germany introduced too strong demand-side instruments too early on. While they did produce impressive diffusion rates, it would have been more cost efficient to introduce them later, when the technology was more evolved and the same amount of money could have bought more diffusion. Of course, this is at odds with the goal to bring greenhouse emissions down as fast a possible, since most greenhouse gases accumulate over time in the atmosphere, which makes an early diffusion desirable. Also, from an international perspective, it creates interesting and adverse incentives. If it is assumed that imitation of a technology is cheap (or if the technology can be bought by the cheapest producer without restrictions), each country has an incentive to postpone its own investment into the diffusion of REGT and storage technology as long as possible, to benefit from the improvements based on the investments made by others. This is likely to lead to an under-investment in the technology and a too low rate of diffusion to tackle the international climate problems.

From this, some insights about policy making can be gained. First of all, it is important to define binding intermediate goals, to ensure a steady diffusion of new technologies and to avoid adverse incentives. In addition, the policy maker should avoid to fix large shares of its budget over a long period of time, since it loses its ability to react to changes in the situation (e.g., the emergence of a new technology). Both goals may conflict in some cases. Last but not least, a policy mix regarding the long-term diffusion of a new technology should be based on a as broad as possible political consensus. Otherwise, a government which is in fear of losing an election against competitors who follow different policy goals regarding the technology, might be tempted to create precedents by using policy instruments which bind the policy maker over a long period of time to 'conserve' its political will in this field. This, however, comes at the cost of less flexibility and denies later governments the chance to react to new situations.

In none of our (median) scenarios the policy makers were able to fulfil the goals they set themselves for 2020. This can have various reasons: One possible reason is that we disallowed budget increases after the 'history-friendly' period, assuming that the policy maker wants to avoid further cost increases, which could jeopardise the political support for REGT from the electorate. Our results would then simply mean that the budget has again to be expended to reach the diffusion and stability goals of the policy maker. Another possiblity is that we set the wrong goal. While we are only looking at PV and Wind technologies here, there are of course over renewable sources. It is possible that the policy maker would invest more in these technologies, thereby reducing the diffusion target for PV and Wind.

There are several reasonable direction to develop further our work. One limitation of our model as of now is that preferences are fixed, which is an unrealistic assumption, given the long time period under consideration. Therefore, a preference changing mechanism, e.g. due to consumer interaction, would add some explanatory power, especially if the 'eco-warriors' are able to convince other consumers. Also, we make the assumption that all consumers interact with each other with the same probability, which is again unlikely. Therefore, a spatial representation of consumers would contribute to our model. Ideally this should be implemented through a certain network structure, in which single consumers are only connected to a limited number of other consumers. However, this would increase the computational demand of our model greatly. A more suitable option would be to introduce a regional structure, where each consumer is assigned to a specific region. Consumers who belong to the same region have a higher chance of interacting with each other. Also, this would allow us to study the effect of REGT on the electricity grid better, since one could assume that certain transmission capacity is necessary to transfer electricity between the regions, which is interesting because the irradiation and wind power being unevenly distributed inside most countries. This should allow us to look at regional effects of REGT and storage technology as well. However, as mentioned earlier, these extensions are left for further research.

Appendices

A Analytical description of the simulation model

Table 1: Parameters used

	Description	Symbol	Value
General parameters	Number of consumers	N	1000
	Share of 'eco-warriors'	δ	0.05
	Number of fossil producers	P	10
	Number of manufacturers	M	3
	Number of periods (months)	T	240
	Number of periods considered by manufacturers for capacity change	S	5
	Maximum production capacity increase per period	Inc	1
	Maximum production capacity decrease per period	Dec	0.5
	Average percentage of GDP per year government support in history-friendly run (240 periods)	$Support$	0.75
	Average percentage of GDP per year government support in DE (120 Periods)	$Support_DE$	1.53
	Average percentage of GDP per year government support in DE (360 Periods)	$Support_DE$	0.95
Electricity market	Life expectation of fossil power plants (years)	$Life_f$	40
	Life expectation of REGT (years)	$Life_r$	20
	Life expectation of storage technology (years)	$Life_s$	20
	Maximum percentage of income to be spent on electricity	ϕ	0.1
	Minimal uptime of fossil plants	γ	0.7
	Initial value for fuel price	$FuelPrice_t$	1
Innovation	Parameter for learning effects	$LearnRate$	0.87
	Share of manufacturer's turnover invested into R&D	$shareRD$	5%
	Initial value for number of sold REGT installations	$StockSold_{r,t}$	2
	Initial value for number of sold storage installations	$StockSold_{s,t}$	2
	Initial value for number of sold fossil plants	$StockSold_{f,t}$	250
	Initial value for installation cost of REGT	$InstallCost_{r,t}$	33
	Initial value for installation cost of storage technology	$InstallCost_{s,t}$	33
	Initial value for installation cost of fossil plants	$InstallCost_{f,t}$	200
	Initial value for efficiency of REGT	$Efficiency_{r,t}$	1
	Initial value for efficiency of storage technology	$Efficiency_{s,t}$	1
	Initial value for efficiency of fossil technology	$Efficiency_{f,t}$	100

B Graphical illustration on initial conditions used and results obtained

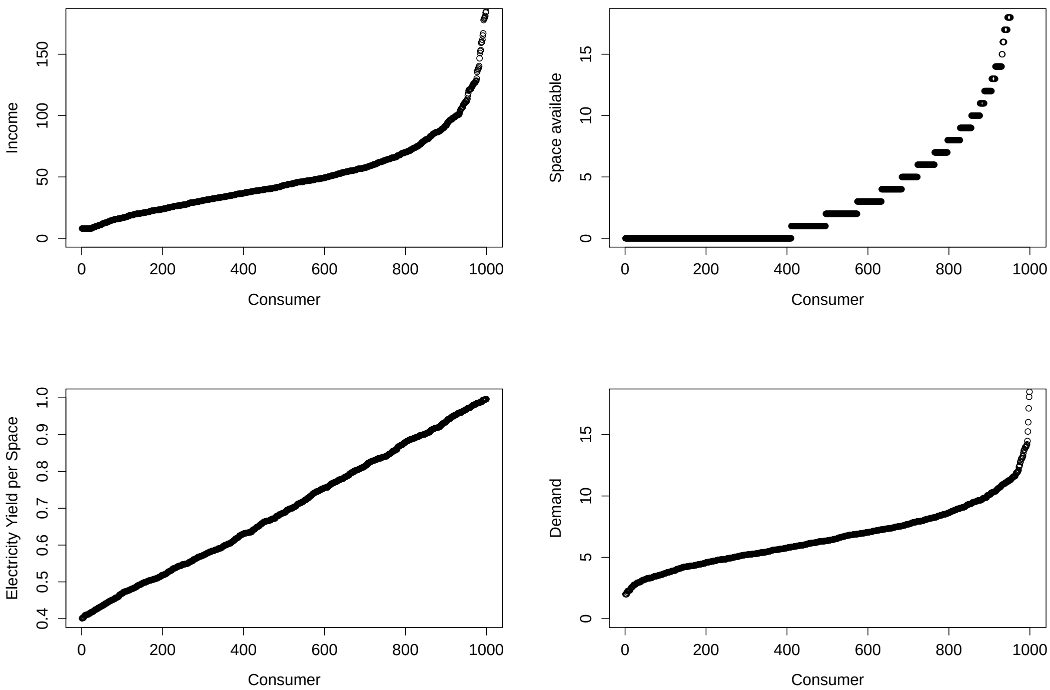

Figure 10: Income, space, irradiation and demand distributions of consumers

Note: On the x-axis consumers are always ordered in ascending order for the corresponding variable on the y-axis. Hence, consumers with, e.g., highest income are not the ones with highest preference for REGT.

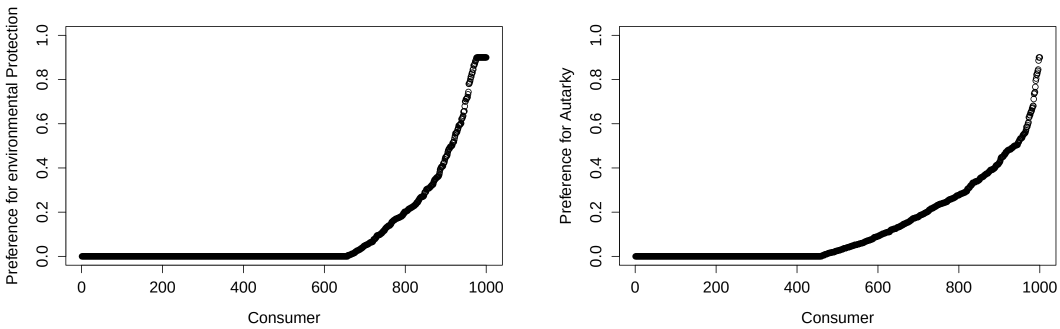

Figure 11: Consumer preferences for REGT and storage technologies

Note: On the x-axis consumers are always ordered in ascending order for the corresponding variable on the y-axis. Hence, consumers with, e.g., highest income are not the ones with highest preference for REGT.

C Possible Extensions of Policy Instruments

Here we describe several alternative policy instruments which can be introduced in the present ABM. So far we do not include them in further analysis mainly due to difficulties in calibrating some of these instruments.

Carbon Tax

This policy instrument can influence the working conditions of fossil power plants by increasing the production costs of these plants by a certain percentage. This can be seen as a tax upon carbon emissions or the effect of a trading system for carbon certificates. This policy instrument has the advantage that it creates income for the state instead of costs. In the model, this policy instrument increases the cost of fossil fuel by a certain amount, so that the price of fossil fuels becomes:

$$PFosPol_t = PFos_t + CarbonTax_t, \tag{24}$$

where $PFos_t$ is the price of fossil fuel without tax and $CarbonTax_t$ is the increase of fossil fuel price induced by policy intervention.

Reserve Subsidy

One policy instrument specifically designed to support fossil power plants is a subsidy for power plants being in reserve. This policy instrument may be used if the stable electricity supply from fossil power plants is required, but competitive pressure from REGT would not allow investment due to low up-time. In this case, the state may pay fossil producers a subsidy for building reserve power plants, which can run in times where stability is low or the supply of electricity is insufficient. The subsidy offsets the expected losses from low up-time, thereby creating an incentive for fossil producers to replace plants which reach their life expectancy.

Commercial Campaign

A subtle policy instrument is the state trying to change the preferences of the consumers. In the ABM, this may be modeled as a sort of information campaign, which has on average positive influence on preferences. However, there is also a chance of it reducing preferences, as consumers might become aware of the downsides of electricity from REGT (e.g., unstable supply). Therefore, the effect of an information campaign on the preference for environmental protection of consumer i is:

$$PrefEP_{i,t} = PrefEP_{i,t-1} + Y, \tag{25}$$

where $Y \sim N(0.03, 0.05)$. Note that preferences cannot become higher than 0.9 or lower than 0.

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