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Research Article

Equity of Incentives: Agent-Based Explorations of How Social Networks Influence the Efficacy of Programs to Promote Solar Adoption

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Agent-based models are used to explore how social networks influence the effectiveness of governmental programs to promote the adoption of solar photovoltaics (solar PV) by residential households. This paper examines how a common characteristic of social networks, known as network segregation, can dampen the indirect benefits of solar incentive programs that arise from peer effects. Peer effects cause an agent to be more likely to adopt a technology if they are socially connected to other adopters. Due to network segregation, programs that target relatively affluent agents can generate rapid increases in overall adoption levels but at the cost of increasing disparities in access to solar technology between rich and poor communities. These dynamics are explored through theoretical agent-based models of solar adoption within hypothetical social systems. The effectiveness of three types of solar incentive programs, the feed-in tariff, leasing programs, and seeding programs, is explored. Even though these programs promote rapid adoption in the short term, results demonstrate that network segregation can create serious distributional justice problems in the long term for some programs. The distributional justice effects are particularly severe with the feed-in tariff. Overall, this paper provides an illustration of how agent-based models may be used to evaluate and experiment with policy interventions in a virtual space, which enhances the scientific basis of policymaking.

1. Introduction

This paper uses agent-based models (ABM) to evaluate the effectiveness of public policies to promote the adoption of alternative energy technologies by residential households. Of particular interest is the adoption of rooftop solar photovoltaics (PV), or solar panels, which convert sunlight falling on one's rooftop into electricity. Solar PV is one example of a decentralized energy technology with great potential for reducing a given region's dependence on fossil fuels and can therefore contribute positively to sustainability [1]. At the same time, solar PV has a long way to go. Even in markets where rooftop solar is prevalent, such as in Germany and in California, USA, overall market penetration is relatively small [2, 3]. For individuals, solar PV systems represent large investments and carry with them risk and uncertainty. It is in reducing these risks and up-front costs that incentives to install residential solar systems can help promote more widespread adoption and commensurate decarbonization of energy systems.

These considerations underscore the need for public policies that incentivize more widespread interest and adoption of solar PV. While incentive programs come in many shapes and sizes, the essential logic of an incentive program is that it will reduce barriers to adoption for direct recipients of a program benefit, such as those agents that receive tax credits or other subsidies for installing solar PV. Incentive programs also create indirect benefits through peer effects—a phenomenon whereby the adoption behavior of agents increases the probability that other agents in the system will adopt (see, e.g., the diffusion model by [4]). Peer effects work through a variety of mechanisms, such as the exertion of social influence on nonadopters (e.g., [5, 6]) and the provision of new information about the true costs and benefits of solar through active communication with solar adopters (e.g., [7–9]).

Thus beneficiaries of governmental incentive programs can, through their adoption behavior, increase the probability that other actors in the system will also adopt. At the same time, however, peer effects are naturally limited to a certain group of people around an adopter. Certain incentive programs may perform well in terms of promoting greater distributional energy justice through supporting PV adoption specifically by low-income households, thus increasing the number of social multipliers who put the peer effect into action within this group. Other incentives systematically target more affluent households and thus might increase injustice by spurring a peer effect in a group with less need for a given technology.

In this way, public policies meant to promote solar adoption may create inequalities in the adoption of solar between disparate social groups. These potential inequities are ignored in most formal evaluation of energy policy, which tends to focus on the overall penetration of solar PV, that is, the aggregate number of people who have adopted in a given region. And yet, understanding inequality in access to renewable energy is a crucial research need ([10]; [11, 179]; [12, 435]). This is important in part because solar PV technology carries more than just environmental benefits. Solar PV can also create significant cost savings for households, helping them to be less vulnerable to energy rate increases and fluctuations in availability. Depending on local policies, rooftop solar can even create a revenue stream for households as they sell surplus electricity back to the energy utility. However, these benefits accrue in the long term and becoming a PV adopter generally requires substantial capital investments and financial risk. This makes it difficult for households with modest incomes to enjoy the long-term benefits of solar, potentially creating inequities where the solar PV is exclusively available to wealthy house holds.

1.1. The Need for a Complexity Science Approach to Policy Evaluation. In order to design better public policy for solar PV, it is necessary to evaluate the efficacy of different policy choices given the complex social systems in which these policies unfold, particularly in terms of the degree to which they avoid (or exacerbate) inequities in access to a given technology. Classic tools of policy evaluation are poorly suited for this task. Classic tools tend to extrapolate future scenarios based on past behaviors, assume relatively homogenous and rational agents, and focus on aggregate trends. These approaches largely ignore the complexity that arises through the interplay of individual decision-makers and focus instead of the decisions of a hypothetical "central planner" (see, e.g., [13]).

The use of a network science perspective allows us to study complex system processes through the explicit representation of relations between actors, such as pathways or the interdependence of decision-making. In recent years, a vast body of literature has emerged on diffusion processes in complex networks [14, 15], such as the spread of epidemics [16] or information [17]. We build on this research and extend it to the evaluation of policies that aim to promote a certain technology adoption behavior, explicitly taking into account the interdependencies between decision-makers and the complex social networks in which they are embedded. The peer network influences studied here are nested within the larger study of economic networks, which are themselves an important approach for complex systems analysis (see Emmert-Streib et al., 2018, for a comprehensive review). For tractability, we focus on the purely social influences by which potential adopters learn about the benefits and costs of solar energy. Of course, potential adopters are embedded in a complex economic network of organizations providing adoption incentives and banks providing the capital for necessary upfront investments.

Consequentially, this paper applies a complexity science perspective by explicitly accounting for the diffusion of adoption behavior in complex networks in the evaluation of solar policies, particularly in terms of equity outcomes. One useful tool in the complexity science toolkit is the agent-based model (ABM), which is increasingly recognized as a promising approach to evaluate the effectiveness of public policies where costs and benefits accrue from complex social behaviors. Theoretical ABMs can examine the nonlinear dynamics of solar PV adoption which arise from the behaviors of interconnected, heterogeneous agents, as we see in the real world where solar PV adoption decisions are made. By focusing on the individual decision-maker rather than aggregate trends, ABMs allow for an explicit representation of agents' adaptive capacity [18]. ABMs are increasingly used to develop a more robust understanding of energy demand and the ex-ante evaluation of renewable energy policies [19].

1.2. Roadmap of This Paper. This paper uses a series of theoretical, computational ABMs to compare and evaluate three distinct types of real-world solar incentive programs: the feed-in tariff, leasing programs, and seeding of underserved communities. Of particular interest is the effectiveness of these incentive programs in terms of (i) the overall speed of solar PV adoption in a social system and (ii) the access to solar PV that is afforded to different groups, particularly high- and low-income agents. This second evaluative criterion is a crucial component of the distributional justice issues discussed above. These inequities may be underestimated if an analyst assumes that social networks allow for the positive, indirect benefits of incentive programs to spill over to less affluent communities that face high barriers to solar adoption. In reality, social network structures may inhibit these processes and dampen the indirect benefits of solar incentive programs. In other words, program effectiveness is likely conditional on how social networks are structured within a given market.

Our model compares the effectiveness of incentive programs in terms of aggregate adoption as well as energy justice as called for by Sovacool [10, 2] and illustrates the degree to which the structure of actual social networks—particularly the degree of segregation observed within networks—is likely to change the relative effectiveness of different policy instruments. Understanding the mechanisms behind the interplay of different network structures and policy instruments is crucial for a transfer of policies from a context with a rather integrated society (such as Germany or California) to a context with a more segregated society (as might be the case in developing countries).

This paper turns next to a discussion of the benefits generated by solar incentive policies, with a particular focus on the indirect benefits derived from peer effects. We discuss how network segregation may create distributional justice concerns in that certain segments of society will accrue disproportionate benefits. We then turn to a focused discussion of the particular types of incentive programs represented in our ABM, as well as expectations based on network theory regarding program effectiveness based on varying degrees of network segregation. The structure of the ABM is discussed afterwards—this is a theoretical model in which agents in a hypothetical social system are randomly exposed to incentive programs and make subsequent adoption decisions. We conclude with an analysis and summary of the results, as well as a discussion of policy implications of this research.

2. Solar Adoption Incentives and the Role of Social Networks

Solar PV adoption dynamics are ultimately the result of decisions made by individuals and households. As with other types of high-cost, emerging technologies, these are not simple decisions [20, 21]. Many factors play into adoption decisions, such as peoples' financial means, peer-group behavior, and attitudes towards green and new technologies (e.g., [6, 173]).

Solar incentive programs seek to intervene in these individual decision-making processes by reducing the various barriers to adoption, whether this means making solar PV more affordable, less uncertain, or more socially desirable. Most programs focus on reducing financial barriers and perceived risks associated with solar. Perceived risk can be decreased through information provision—providing trustworthy information about the true costs and benefits of adopting solar PV. Perceived risk can also be reduced by guaranteeing a reasonable amortization period (e.g., through guaranteed feed-in-tariffs as used, e.g., in Germany and discussed in more detail below). Incentives may decrease financial barriers in two ways: by decreasing the upfront investment costs for purchase and installation of the PV (e.g., through convenient loans or leasing contracts) and by increasing the long-term profitability of a solar system [20, p. 74].

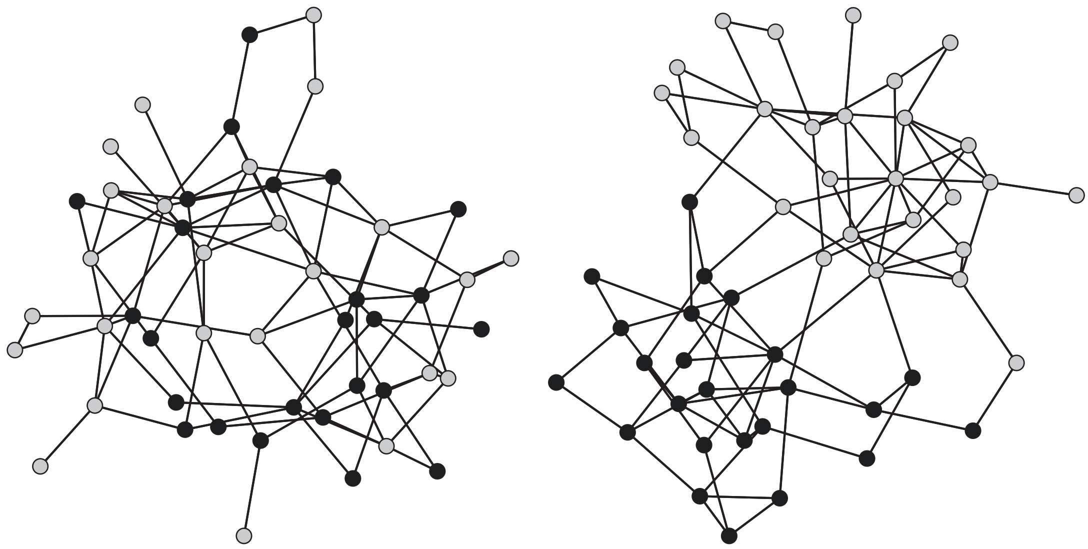
As noted above, these direct benefits of solar incentive programs are complemented by the indirect benefit of making solar PV a more viable or attractive option for potential adopters. It is these indirect benefits—realized through several possible mechanisms—through which a bulk of the benefit of solar incentive programs are likely realized. These mechanisms include, for instance, lowering costs as more individuals adopt. Increasing demand for solar PVs followed by more competitors on the supply side leads to more efficient ways of production and decreasing prices [23]. Of central interest in this paper, however, is the peer effect, where the adoption of solar by a substantial number of early adopters makes it more likely that agents in the (geographical or social) neighborhood adopt solar PV. A number of mechanisms underlie the peer effect, such as increased information provision through one's social network, the creation of social pressures to reduce one's environmental impact, or the showing-off of investments in new technologies. Solar adopters who are well integrated in the network may act as social multipliers by distributing information and being positive role models. For designing just and effective incentives, it is necessary to consider the role that the peer effect and network structures play within the diffusion process of environmental-friendly technologies.

2.1. Networks and Indirect Benefits of Solar Incentive Programs. The idea that social networks enhance the indirect benefits of solar incentive programs is not new; indeed, there is a growing body of research on the interdependencies of environmental consumption decisions by individuals and households. This has been studied in the literature alternatively as peer effects [5, 9, 24], social influence [6, 7], and diffusion of innovations [25–27], all of which underscore the same fundamental lesson that the behavior of any particular agent is determined in part by the behaviors of those they are socially close to.

Varied notions of "closeness" matter for peer effects, such as spatial proximity (e.g., one might tend to adopt the behaviors that are prevalent in the community) or informal social relations (e.g., one might adopt the behaviors of their friends). Whatever the case may be, social closeness may be represented in social systems using the concept of social networks [28, 29]. A network is simply a generic representation of how agents in social systems—commonly referred to as the *nodes*, which may represent individuals, households, formal organizations, or any discrete decision-maker—are related to one another through *linkages*, which represent socially important relationships such as information sharing, friendship, or proximity.

There is a vast literature in the emerging field of network science that seeks to understand how individual behaviors are correlated with one's position in a network [30, 31]. Most relevant to the idea of the peer effect are diffusion models of networks. Generally speaking, these models examine how network nodes adopt the attributes of their neighbors and how certain structures influence the speed with which a particular attribute spreads throughout the network (see [26] for a current overview). These models are applicable to a wide range of phenomena, such as the spread of disease over space and time (see, e.g., [32, 33]), the reaching of a consensus within groups [34, 35], or the adoption of environmental technologies including rooftop solar [5, 36, 37].

The primary characteristic of a network that increases diffusion speeds (and therefore the effectiveness of peer effects) is the closeness of agents within the network [38]. "Closeness" refers to the average distance between any two pairs of network nodes and is related to how many steps



(a) Integrated network (b) Segregated network

Figure 1: Illustrative network structures. *Note: networks generated using ABMs of random network formation in R* [22].

it takes to reach a given node by starting at any particular node. Even relatively slight changes in network structure can dramatically influence the closeness of nodes. For instance, only a few random rewires of a lattice-type network can dramatically increase the overall closeness of nodes and thus increase potential diffusion speed [39, 40].

In this paper, we focus on two particular types of network structures: "integrated" and "segregated" networks (Figure 1, Panels (a) and (b), resp.). In these networks, network actors have a group membership represented by the shading of the nodes. Integrated networks are those where actors are as likely to be connected to actors of their own type as to actors of another type. For diffusion processes in an integrated network, it should make no difference to which group the first adopters belong. In a segregated network, however, actors with the same attributes are much more likely to be connected than actors with different attributes. For instance, actors might be divided along economic characteristics or in terms of attitudes towards new technologies. In the case of segregated networks, diffusion is fastest among the group of the early adopters. However, overcoming the gap between the two groups—and thus achieving widespread adoption—will be much more difficult. Again, the position of the early adopters will be crucial: if the early adopters are brokers between the two groups overcoming the gap will happen much faster than if the early adopters are at the periphery of the network.

The speed of diffusion processes in varying types of network structures should be an important consideration when designing policies to promote technology adoption—otherwise one cannot realistically estimate peer effects. In this paper, we explicitly model the process in integrated and segregated networks and study how diffusion processes differ with network structure and how the efficacy of incentive programs is conditional on these structures.

3. Theoretical Expectations: Distributional Equity and the Problem of Network Segregation

Governmental goals are mostly set towards reaching certain target percentages of, for instance, renewable energies relative to overall energy production (for the German case, see [41]) or towards the achievement of absolute goals, such as the 100,000 Roof Program for solar PV or the recent example of subsidies for hybrid and electric vehicles in Germany [42]. This means that the success of incentive programs is measured primarily according to their influence on overall adoption rates [43–45]. However, in a world where large gaps between affluent and poorer households are observed, one could argue that an aim of public spending and public policies should lie in minimizing this gap. Over the last decades, public spending towards supporting renewable energies has substantially increased worldwide and is expected to grow further, from an estimated USD 214 billion in 2014 to USD 300 billion by 2020 ([46, p. 5]; [47]). Calls are getting louder that this vast amount of public spending cannot be one-dimensionally directed towards increasing, for example, the share of renewable energies. Instead, "the distribution of the costs and the benefits of these subsidies across socioeconomic groups"—and thus the question of social equity in policy design—must be taken into account ([46, p. 5]; [48, p. 263]; [49, 50]). Therefore, overall adoption rates should not be the only evaluative criterion for policy investment incentives, but the effect of the policy on social equity has to be taken into account when deciding for suitable policies to support renewable energies and other measures towards an energy transition [48, p. 255].

As noted above, one's choice to adopt solar PV is dependent on a given actor's position in a social network. Thus the ability of a given agent to influence the decisions of

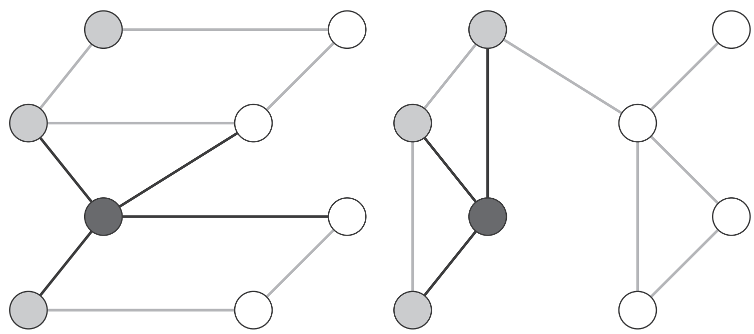


Figure 2: Possible influence relations of an adopter.

others is likely dependent on the level of segregation in the network. Figure 2 illustrates this schematically. In Figure 2(a), a technology adopter (the shaded agent) is embedded in an integrated network, in the sense that the adopter is connected to similar agents (circles) about as often as to dissimilar agents (triangles). Thus, the adopter influences both groups (circles and triangles) equally through the peer effect. In many real-world scenarios, however, we observe that adopters have networks that are segregated in the sense that connections exist primarily among agents with similar attributes [51–53]. Attributes that might be relevant in this context include the level of education, the awareness of environmental problems, the willingness to pay for sustainable technology, and overall financial means [8, p. 344]. This scenario of agents embedded in segregated networks is depicted in Figure 2(b). In this case, peer effects lead to an increased probability of adoption within the group of the first adopters [48, p. 263], while the probability of the members of the other group is not affected at a large scale. In our application, types of actors reflect an actor's individual propensity to adopt solar PV. This propensity may be dependent upon characteristics such as the affluence and environmental beliefs of an actor, among other factors [6].

Figure 1(a) depicts an integrated social network in which links between actors of the same type are as likely as links between actors of different types. Diffusion can flow unhindered from one actor (type) to another. In an integrated network, peer effects can counteract initial differences in adoption propensities if a low-propensity actor is connected to many high-propensity actors who already adopted PV; this will drastically increase its own probability to adopt. In a segregated network, on the other hand, links between actors of the same type are much more likely than links between actors of different types (see Figure 1(b)). Thus, in a segregated network, peer effects cannot enhance the diffusion of positive environmental consumption equally throughout the whole network. Low-propensity actors are mainly influenced by other low-propensity actors, which will hinder diffusion among them. Without any incentives, we thus expect adoption curves of low- and high-propensity actors to be closer together in integrated than in segregated networks–where adoption curves depict the percentage of adopters within a given group over time.

In this way, network segregation can slow the diffusion of positive behaviors in social systems. Segregation limits peer effects between unlike actors, and therefore incentives targeted to affluent actors will not benefit less affluent actors in the long run because sufficient connections between the two groups are missing. A careful evaluation of incentives and their intended and unintended outcomes is needed to set diffusion processes in motion which lead to more, instead of less, energy justice. Our evaluation of equity outcomes of renewable energy subsidies can bring us one step further to answering one of the research questions proposed by Sovacool [10, p. 22]: "Which energy [...] systems help reduce poverty and meet development goals and which ones exacerbate inequality and concentrate wealth?"

3.1. What Incentives Work and When? Various forms of supporting PV installations through incentives are already practiced in numerous contexts; incentives include the feed-in-tariff (e.g., in Germany), leasing programs (e.g., in California) and pilot projects of seeding solar to poorer communities (also in California). While the outcome of increasing overall adoption rates can easily be measured, other effects of incentive programs remain mostly unknown, for example, the questions of who is benefitting from this kind of incentive in the short and the long run. Modelling the processes of solar adoption allows us to analyze the effect of the varying incentives on the adoption dynamics, which include uptake of installations as well as equity between different societal groups. In the following, the three forms of incentives applied in this work will be briefly summarized.

Feed-In Tariff. The feed-in tariff guarantees adopters a long-term fixed rate for every kWh fed into the grid from renewable energies, with solar PV systems being the most feasible option for private households. Through this long-term guarantee, the financial risk of adopting is substantially reduced and the large investment will pay off much faster than without the incentive. This incentive primarily targets actors with the financial means to make the initial investment in solar. This is because the economic benefits of the feed-in tariff are for long term, and the upfront investment is not necessarily made any easier.

The first country to implement a feed-in tariff was USA with its Public Utility Regulatory Policies Act (PURPA) in 1978. (Pub.L. 95–617, 92 Stat. 3117, enacted on November 9, 1978.) In 1991, a feed-in tariff was enacted in Germany, the *Act on the Sale of Electricity to the Grid* [54]. This act had a far-reaching impact on the development of PV installations in Germany. Since then feed-in tariff policies have spread worldwide and are by now world-leading instruments to support renewable energies [55, p. 19]. In the year 2007, 46 jurisdictions worldwide have implemented a feed-in tariff. Beside numerous western countries and jurisdictions such as Switzerland (1991), Italy (1992), Denmark (1993), Spain, and Greece (1994), also quite a number of countries from the global south have implemented a feed-in tariff, such as India (1993), Sri Lanka (1997), and Algeria and Indonesia (2002) to name the first among them [56]. As multiple studies have shown that the implementation of the feed-in tariff in Germany led to a fast uptake of renewable energies in general and solar energy in particular (see, e.g., [57]), this in turn led to decreasing prices for the PV technology making the technology more cost-efficient [58, 59]. By targeting the actors that are most likely to adopt (high-probability agents), we expect that a faster overall uptake of installations will be observable (as compared to no incentives).

However, Welsch and Kühling [6] show that in Germany higher-income households are more likely to invest in solar. This trend is consistent with the feed-in tariff, which makes the adoption of solar a profitable investment for affluent actors. Jenkins et al. [11, 176] thus argue that the German feed-in tariff is an example of a program that promotes energy injustice because it leads to higher energy prices in general in order to refinance the promised fixed feed-in rate for renewable energy producers ([48, p. 263]; [60]). People that are interested in investing, but do not own their home or do not have the initial money to invest, cannot participate in the transition. However, in the long run, they have to bear the burden of rising energy costs due to the guaranteed feed-in, without having had the chance to participate in the beginning ([61, p. 3882]; [11, p. 176]). This phenomenon of feed-in tariffs on energy inequity was analyzed by researchers in a wide variety of contexts, such as in Australia, California, and UK [46], Denmark, Germany, Cyprus, and Spain [62], and Thailand [63]. Based on these observations, we argue in the following that the high and upper middle-income class is disproportionally benefitting from the feed-in tariff, while low-income households are unlikely to benefit from this incentive. Because of missing links to social multipliers, we expect this effect to be more critical in societies with a major income gap and high segregation, having crucial implications for the distributional energy justice of this incentive [11, p. 176]. To evaluate these distributional justice issues, we will examine the adoption dynamics of high- and low-probability actors separately. In integrated networks, we expect that the difference between the dynamics of the two actor groups will not increase significantly through the feed-in tariff (as compared to no incentive in integrated networks). In segregated networks, however, we expect that the difference in adoption dynamics between high- and low-probability actors increases significantly through the feed-in tariff (as compared to no incentive in segregated networks).

Leasing. This form of incentivizing solar adoptions is based on a third-party ownership. Third parties own and operate PV on private households or small industrial buildings. Through the leasing agreement, upfront costs for installing solar are extremely reduced or even eliminated. Economic benefits occur from the first month and not after a long amortization period. Leasing programs are widely present in USA (see, e.g., [37]) and are currently becoming more visible in Europe. Drury et al. [64] as well as Rai and Sigrin [36] are able to show that leasing options are increasing the demand and widening the range of potential adopters through making PV available for less wealthy agents as well. Leasing programs are thus expected to lead to a faster overall uptake of installations (as compared to no incentives). Wealthier agents (particularly those who are risk-averse) will benefit from this type of incentive as well. The leasing program thus targets both high- and low-probability actors. Therefore, we expect the differences in adoption dynamics between high- and low-probability actors to stay stable with leasing programs in integrated as well as in segregated networks (as compared to no incentive in the respective network). These expectations will be tested with the model introduced in the next section. The same dynamic is expected to occur with incentivizing solar adoption through low-interest loans [63, p. 266].

Seeding Less Affluent Communities. Using this strategy, free or low-cost PV systems are given out to a selected number of qualified agents in low-income communities. This has a doubled positive effect on adoption rates: first, strong financial support is especially important for low-income households to support their investment [20, p. 85]; second, it is increasing the visibility of PVs, spurring peer effects within those communities [8, p. 340] (see above on the importance of peer effects in low-income communities). Currently, this form of support is in pilot status only. For example, pilot projects have been implemented in California under the Greenhouse Gas Reduction Fund in collaboration with the Oakland-based nonprofit organization *Grid Alternatives*. The project is partly financed by California's cap and trade program and aims at supporting low-income families through free PVs. The peer effects of this project are not yet monitored. In an agent-based model, Zhang et al. [65] show extremely positive effects of seeding for overall adoption rates. Therefore, seeding programs are expected to lead to a faster overall uptake of installations in our models as well (as compared to no incentives). Since the seeding program is only targeting low-income actors, it drastically increases the probability that these agents will adopt solar. Especially in segregated networks, it will be of major importance to spur peer effects in currently underserved communities. We therefore expect that seeding programs positively affect the adoption dynamics in segregated networks by decreasing the differences between high- and low-probability actors (as compared to no incentive in segregated networks). In integrated networks, however, the difference in adoption dynamics is not expected

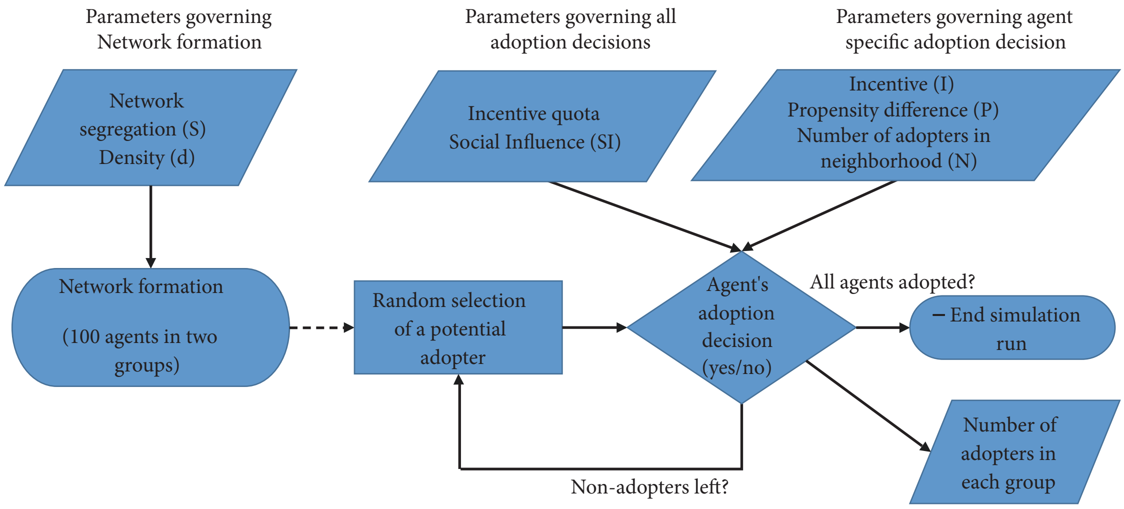


Figure 3: Model overview of one simulation run.

to change significantly with seeding programs (as compared to no incentive in integrated networks).

These adoption dynamics—and the role of governmental interventions in managing the tradeoff between speed and equality of adoption across communities—are the focus of the agent-based model described in the following section.

4. Model Overview

These theoretical expectations are explored through an agent-based model that examines adoption dynamics over time in a hypothetical social system, given variation in the underlying social network structures and incentive in place. This model was coded in R and is an advancement of the model previously developed and explored by Henry and Brugger [66]. The predecessor model included many of the components explained in detail below but laid its focus on the effect that the strategies of firms (when targeting their potential customers) would have on the adoption dynamics, by being a gatekeeper to adoption possibilities without altering the actual adoption decisions. Advancing the previous model, the current version allows explicitly modelling the effect of policy interventions (here through various incentives) on the adoption probabilities of the different types of individual agents and thereby on the overall adoption dynamics.

As noted above, we study peer effects by modelling the social network connecting actors, and that enables and constrains social influence. Figures 1(a) and 1(b) show two illustrative networks in which agents are visualized as circular nodes, with their color representing the fact that they belong to one of two groups, differentiated through socioeconomic attributes that influence the probability of adoption. The links between those nodes represent the relations between them, such as information exchange or proximity, through which peer effects and social influence can unfold. Therefore, agents that are connected to other agents that have already adopted solar are assumed to have a higher probability of adopting solar themselves, compared to agents who are not connected to adopters.

Figure 1(a) shows an integrated network, where links between actors of different types are as likely as links between actors of the same type. This represents a network where actors build their relations entirely independent of their own and of the other agents' group membership. Contrasting this network, Figure 1(b) visualizes a segregated network in which the realization of a relation is highly dependent on whether two agents belong to the same group. In this network structure, agents within one group are much more likely to be influenced by other agents within their own group. How strong this effect is depends on the level of segregation, which is governed by the segregation model parameter (see below). As Henry and Brugger [66] note, this representation of the network may capture various types of social closeness which determine the ability of one agent to influence another, such as spatial proximity, shared participation in social venues, or friendships. Many such real-world networks exhibit segregation.

Figure 3 gives a graphical overview of a model run. In the first step of every model run, a network of 100 agents is formed. The agents are randomly assigned to one of two groups. Links between those agents are built based on the network segregation parameter (S) and the density (d). Following this network formation, in each time step, one potential adopter is selected at random. This agent then makes an adoption decision based on parameters, which are fixed for the whole simulation run (the incentive quota and the social influence parameter, SI) and on parameters that are actor-specific (incentive, I, and propensity difference, P) or even time-step-specific (number of adopters in the neighborhood, N). After each time step, the number of adopters in each group is reported. The random selection of a potential adopter and the following adoption decision is repeated until all agents are adopters. In the following

Table 1: Model scenarios: overview over determining parameters.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8
Incentive	No incentive	Feed-In	Leasing	Seeding	No incentive	Feed-In	Leasing	Seeding
Segregation	Low (S=0)	Low (S=0)	Low (S=0)	Low (S=0)	High (S=0.75)	High (S=0.75)	High (S=0.75)	High (S=0.75)
Density	**0.05**	**0.05**	**0.05**	**0.05**	**0.05**	**0.05**	**0.05**	**0.05**
Incentive quota	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**
Propensity difference	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**
Social influence	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**

With these eight scenarios we can study the diffusion processes under the four possible incentive parameters (no incentive, feed-in, leasing, and seeding) in highly segregated (segregation high, S=0.75) and in integrated (segregation low, S=0) networks. Keeping all other (bold font) parameters constant over all simulations allows us to single out the effects of the different incentives and segregation on the diffusion processes.

section, the model parameters and the decision are explained in greater detail.

4.1. Synopsis of Model Parameters. This model examines the effect of various policy incentives within networks with different structures. The different network structures are governed by the *network segregation* parameter. Three additional key characteristics are defined and controlled for in the model, *incentive quota*, *social influence*, and *propensity difference*, all of which are introduced in the following. All of these characteristics stay constant within one model run but may vary across runs.

Network segregation is captured by parameter S, reflecting the degree to which linkages tend to exist among actors with a similar propensity for technology adoption. For the purpose of this study, the segregation parameter was chosen to be either 0 or 0.75. A value of zero leads to an integrated network (see Figure 1(a)), meaning that agents are as likely to form links with those that are within the same group as to those that are in the other group. In contrast, if S=0.75, the network is highly segregated (see Figure 1(b)) and within-group links are much more likely to be realized than links between agents of different types. In the setup of this model, the link formation is solely governed by this segregation parameter S and the density d of the network. Links between actors of the same type are assumed to occur with probability $d + (S * d)$. On the other hand, links between actors from different groups are assumed to occur with probability $d - (S * d)$. Therefore, with a segregation parameter of 0.75, links between similar agents are seven times as likely to be realized as links between different types of agents (8.75% and 1.25%, resp., displayed in Figure 1(b)). As discussed below, other values might be reasonable as well; however, a clear distinction between the two observed network structures is crucial.

Incentive quota is a model parameter regulating how many incentives are given out. This variable ranges between 0 and 1, where 0 means that no incentives are given out and 1 means that all adoptions are supported by incentives. For the analysis of this paper, we studied an incentive quota of 0.3, which means that adoption decisions are made under the knowledge of the incentives until 30% of the agents have adopted. This quota reflects the governmental course of incentivizing the starting phase of the new technology rather than aiming at supporting all agents to adopt.

Social influence is a parameter determining the strength of the peer effect by which an agent's adoption probability increases as a function of the number of adopters they are connected to. This parameter (SI) takes a value from 0 to 1, inclusive, where 0 indicates that agents are not at all influenced by the adoption of other agents they are connected to, but the strength of this influence increases as SI goes towards 1. In the current model, we simulate a constant strong social influence of $SI = 1$.

Propensity difference is a model parameter (P) that allows differentiating the baseline adoption probability of actors that are part of two different groups. The baseline adoption probability captures an agent's probability to adopt when no neighbors have adopted yet and no incentives are in place. In the current model, we differentiate between two groups, the "high" and "low" propensity agents. We assume a propensity difference parameter of $P = 0.6$, giving a baseline adoption probability for low-propensity agents of 5% and a baseline probability of 8.8% for high-propensity agents.

The model setup consists of three initial steps: (1) the creation of 100 agents, (2) their assignment to one of two groups (either with a high or a low baseline propensity to adopt the technology), and (3) the formation of the network. The segregation parameter and a fixed density of 0.05 govern the network formation. A density of 0.05 means that 5% of all possible relations are realized in the network. The density of the network reflects the overall intensity of social interaction within the network (e.g., how often do people speak about the adoption of solar and how often do they observe that other people have already adopted).

In order to compare a reasonable number of different scenarios, identify only the effect of the parameters that are of major interest within the context of this paper, only the segregation parameter (high versus low), and the type of incentives (no incentive, feed-in, seeding, and leasing) across model runs, leading to eight distinct scenarios as summarized in Table 1.

4.2. Model Dynamics. After the model is set up, an iterative process is started, which consists of two stochastic processes: first, one potential adopter (i.e., any agent that has not yet adopted) is selected at random and, second, the chosen agent makes his adoption decision. In the following, both processes are explained in detail.

Table 2: Incentive parameter values $\boldsymbol{I}(\boldsymbol{r_i}, \boldsymbol{z})$ by incentive program and agent type

	Poorer households ($\boldsymbol{r_i} = 0$)	Richer households ($\boldsymbol{r_i} = 1$)
Feed-In tariff ($\boldsymbol{z}$ =1)	$\boldsymbol{I_{0,1}} = 1$	$\boldsymbol{I_{1,1}} = 1.5$
Leasing ($\boldsymbol{z} = 2$)	$\boldsymbol{I_{0,2}} = 1.25$	$\boldsymbol{I_{1,2}} = 1.25$
Seeding ($\boldsymbol{z} = 3$)	$\boldsymbol{I_{0,3}} = 1.5$	$\boldsymbol{I_{1,3}} = 1$

Random Agent Selection. Each time step starts with the selection of a potential adopter. Therefore, from all current nonadopters, one agent is chosen uniformly at random. This gives every nonadopter the same probability of being selected as all other nonadopters. Mathematically, the probability $Pr_R(i,t)$ that the ith nonadopting agent is selected at time t is therefore given by

$$Pr_R(i,t) = \frac{1}{Q_t}, \tag{1}$$

where Q_t represents the number of agents at time t who have still not adopted the technology. In each time step, exactly one agent is chosen, who will then make an adoption decision.

Agent Adoption Decisions. The agent that has been selected makes a stochastic decision of whether or not they adopt the technology. The probability hereby varies depending on group membership, type of incentive, and importance of social influence. The probability $A(i,t)$ of the potential adopter i to adopt at time step t is therefore governed by the following logistic function:

$$A(i,t) = \frac{\boldsymbol{I_{r_i,s}}}{1 + e^{-(-2.944 + P*r_i + SI*N_{i,t})}}, \tag{2}$$

where r_i indicates the group membership of agent i and is coded as one if the agent is member of the high-propensity group and zero if the agent is a member of the low-propensity group. P and SI are the propensity difference and social influence parameters described above, and $N_{i,t}$ represents the number of adopters the ith agent is connected to at time t. (In some few cases, this can lead to $A(i,t) > 1$; in that case, the probability is redefined to $A(i,t) = 1$.)

Moreover $\boldsymbol{I_{r_i,z}}$ is introduced to model incentive programs. The incentive parameter $\boldsymbol{I_{r_i,z}}$ is contingent on the group that the actor belongs to (r_i) and the incentive (z) in place. If the agent i is profiting from the given incentive, it will increase its probability to adopt ($\boldsymbol{I_{r_i,z}} > 1$). However, if a policy incentive is not targeting the group that i belongs to, the probability function will stay the same as without any incentive ($\boldsymbol{I_{r_i,z}} = 1$); Table 2 shows the respective values for $\boldsymbol{I_{r_i,z}}$. Critical for the idea of the simulation are the relative values of $\boldsymbol{I_{r_i,z}}$ for each incentive—the relationship between the parameter $\boldsymbol{I_{0,z}}$ for the low-propensity and $\boldsymbol{I_{1,z}}$ for the high-propensity agents—rather than their absolute values. This approach is comparable to classical game theoretical models—like the Prisoners Dilemma—in which not the actual payout values matter but rather their relative structure (see, e.g., [67, p. 4f].). However, actual values are necessary for following the decision-making within the game and in our case for simulating decision-making processes.

The feed-in tariff (incentive: $z = 1$), which is most beneficial to the high-propensity group (as explained above), does not alter the probability function of the members of the low-propensity group ($r_i = 0 \Longrightarrow \boldsymbol{I_{0,1}} = 1$) but does have an impact on the probability function of the high-propensity group ($r_i = 1 \Longrightarrow \boldsymbol{I_{1,1}} = 1.5$). In this way, the incentive parameter is chosen such that it increases any given probability, which is dependent on propensity difference and the social influence parameter as well as the number of connected agents that have already adopted, for high-propensity actors by 50%.

The seeding incentive (incentive: $z = 3$) targets the low-propensity group by giving out free PVs to poorer households, thus increasing the probability function to adopt. Again the incentive parameter increases any given probability, which is dependent on propensity difference and the social influence parameter as well as the number of connected agents that have already adopted, by 50% ($r_i = 0 \Longrightarrow \boldsymbol{I_{0,3}} = 1.5$), while keeping the probability function of the high-propensity group unaltered ($r_i = 1 \Longrightarrow \boldsymbol{I_{1,3}} = 1$).

Under the possibility to lease PVs to private households (incentive $z = 2$), the members of the high- as well as low-propensity groups can benefit, because it gives actors of both groups the chance to avoid high upfront investments and long-term benefits through the installation. However, long-term benefits are not expected to be as high as with the other two incentives (for the targeted group). Thus the incentives through leasing options are expected to have a positive influence on the adoption probability functions of both groups but not as high as when targeted directly. This is reflected in the applied incentive parameter ($r_i = 0 \Longrightarrow \boldsymbol{I_{0,2}} = 1.25$ & $r_i = 1 \Longrightarrow \boldsymbol{I_{1,2}} = 1.25$), which increases any given adoption probability for actors of both groups by 25%.

Three additional points about the behavior of this adoption probability function are needed. First, the constant coefficient of -2.944 on the logistic function ensures a minimum probability of adoption of 5% for all agents, no matter their propensity or social connections. The minimum probability that an agent i will adopt is a situation where i has low propensity (i.e., $r_i = 0$) and the agent is not linked to any adopters (i.e., $N_{i,t} = 0$). Thus, a constant coefficient of -2.944 fixes this minimum probability of adoption at approximately 0.05 or 5%. We conjecture that the value of this coefficient will not alter adoption trends other than speeding up or slowing down the overall process. Varying this constant will only speed up or slow down the model and should not fundamentally change the underlying dynamics.

Second, the propensity difference parameter P captures the marginal difference in adoption probability between low- and high-propensity agents. Since P may not be larger than one, a high-propensity agent will be no more than three times as likely to adopt as a low-propensity agent, controlling for other factors. Following the preceding point about minimum adoption probabilities, this means that a low-propensity agent will have a minimum adoption probability of 5%, and

Table 3: Effect of incentive programs on speed of adoption: integrated versus segregated social networks.

	DV = avg. wait time (smaller values signify faster adoption speeds)	
	Model 1: Integrated networks	**Model 2: Segregated networks**
Program dummy variables		
Feed-in tariffs used?	-0.415 * * *	-0.394 * * *
Leasing program used?	-0.366 * * *	-0.413 * * *
Seeding program used?	-0.282 * * *	-0.362 * * *
Constant coefficient	3.328 * * *	3.411 * * *
N	7,428 simulations	7,408 simulations
R^2	0.029	0.030

Note: the table reports results of OLS regression models with average wait time as the dependent variable. For dummy variable effects, the simulation with no incentive programs is the left-out category. * * * $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

if P=1, then a high-propensity agent will have a minimum adoption probability of 15%.

Third, this function assumes that the effect of being connected to an adopter is larger when adoption probability is low. Thus, the connections to adopters have a larger influence on potential adoption for low-propensity agents than for high-propensity agents. This difference increases with larger values of P. This is an artifact of the logistic model being used here and is in line with current findings (see, e.g., [5, 14f.]) that show that peer effects play a more important role for adoption decisions in low-income households.

5. Results

The following results are drawn from running 3,500 simulations with the three incentive programs described above. Approximately 25% of these simulations were run assuming no incentives to establish a baseline for comparison. In another 25% of simulations, the feed-in tariff was modelled, supporting the higher-propensity (wealthier) group, 25% of simulations implemented leasing possibilities favoring both groups equally, and the last 25% of simulations explore the influence of the seeding program to poorer households on the adoption dynamics. The models were not run for a certain amount of time steps but rather until all agents have adopted the technology (i.e., until complete saturation was reached). Since the number of time steps necessary varied between the various model runs, the results are analyzed dependent on the percentage of adopters rather than on time steps. Through this uniform exploration of the results, we are able to analyze how adoption dynamics differ based on the various policy incentives in place and based on the two analyzed network structures.

5.1. Influence of Policy Incentives on Saturation Times. The influence of model parameters, including the existence of certain incentive programs, on adoption dynamics is explored through two regression models summarized in Table 3. Using the individual simulation run as the unit of analysis, these models predict two evaluative criteria—average wait times (Model 1) and differences in average wait times (Model 2)—as a function of model parameters specified at model setup. These evaluative criteria are measures of the speed of adoption and the equity of adoption dynamics between low- and high-propensity groups, respectively.

More specifically, *average wait time* is defined as the number of time steps required for 100% of agents to adopt divided by the number of agents in the system. This measures the average number of time steps that one must wait before any given agent in a system adopts. Average wait time is thus a measure of the overall speed of adoption within a given system but ignores *who* is adopting. Higher values indicate slower adoption speeds (worse outcomes), whereas smaller values indicate faster adoption speeds (better outcomes).

The variable *difference in average wait time* is defined as the average wait time among low-propensity agents minus the average wait time among high-propensity agents. In other words, this is a measure of the degree to which one group lags behind the other in terms of average adoption trends. Large positive values of this variable mean that the high-propensity group becomes saturated much more quickly than the low-propensity group, thus indicating lower equity (i.e., a worse outcome). Values close to zero indicate that high- and low-propensity groups become saturated at approximately the same rate.

These regression models allow us to distill the enormous amount of data generated by our computational simulations into a relatively small set of average trends that emerge across simulations. By integrating the incentive program dummy variables into the model, we are able to examine the degree to which each program influences our evaluative criteria on average, controlling for other stochastic model parameters. In both models, the left-out categories are simulations without any incentive program.

In both models, we see that all programs appear to have a positive effect on overall speed of adoption. This is to be expected because, as noted above, speed of adoption does not account for the distribution of adoption behaviors over space or within a network. In other words, any incentive program yields significantly better outcomes than no incentive program.

By comparing Models 1 and 2, however, we can see that the effectiveness of programs depends on the degree of segregation observed in the networks. While the feed-in tariff seems to generate the fastest saturation times in integrated networks (Model 1), leasing programs appear to

TABLE 4: Effect of incentive programs on distributional equity: integrated versus segregated social networks.

	DV = difference in avg. wait time (smaller values signify greater equity)	
	Model 1: Integrated networks	**Model 2: Segregated networks**
Program dummy variables		
Feed-in tariffs used?	0.008 ∗	0.024 ∗ ∗ ∗
Leasing program used?	0.007	0.006
Seeding program used?	0.003	-0.011 ∗
Constant coefficient	0.037	0.056 ∗ ∗ ∗
N	7,428 simulations	7,408 simulations
R^2	0.001	0.007

Note: the table reports results of OLS regression model with difference in average wait time (distributional equity) as the dependent variable. For dummy variable effects, the simulation with no incentive programs is the left-out category. ∗ ∗ ∗ $p < 0.001$; ∗∗ $p < 0.01$; ∗ $p < 0.05$.

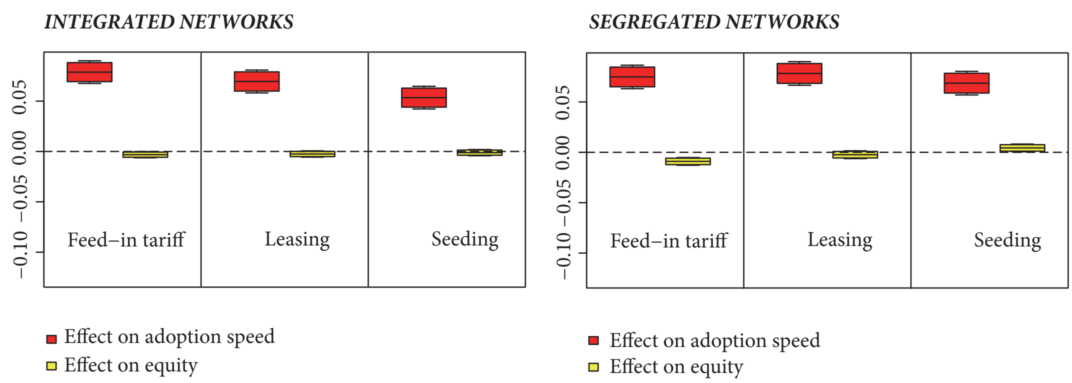


FIGURE 4: Graphical depiction of program outcomes, speed of adoption versus equity in segregated versus integrated networks.

support faster overall adoption speeds in segregated networks (Model 2).

Evaluating these programs in terms of equity gives yet another picture of program effectiveness. Table 4 summarizes the potential differences in program outcomes in terms of equity of adoption trends. Indeed, seeding programs appear to be the only type of incentive that significantly increases equity in terms of realizing a lower gap in the average number of adopters within high- and low-propensity groups.

Figure 4 offers a graphical depiction of these results. The program effect coefficients were reestimated using a measure of equity and adoption speed that is (1) normalized to fall in a range from 0 to 1, such that the effects of programs are comparable across models and (2) adjusted such that larger values indicate better outcomes and smaller values indicate worse outcomes. Red bars indicate the estimated effect of each program on adoption speeds, while yellow bars indicate the effect on equity. Colored regions indicate a 90% confidence interval for each coefficient estimate, while the outside bars delineate a 95% confidence interval. As seen also in Table 4, only seeding programs have a positive effect on both evaluative criteria when we assume segregated networks. Leasing has a positive effect on adoption speeds and no discernible effect on equity, whereas the feed-in tariff appears to promote *greater* inequalities.

5.2. Characterizing Adoption Dynamics. While these regression models provide useful insights into average trends, they also hide much of the richness of adoption dynamics—that is, the process by which adoption behaviors spread throughout the system over time. Figure 5 provides a descriptive illustration of these dynamics. Each panel of this figure illustrates trends realized across all simulation runs; bars in these figures represent the distribution of the proportion of agents that have adopted at different stages of the process, among high-propensity agents (white bars) and low-propensity agents (green bars). For any given simulation, the "stage" of process is defined as the number of time steps that have elapsed as a proportion of the overall saturation time. Thus, a simulation that takes 1,000 time steps for all agents to adopt is at the 10% mark at 100 time steps; however, a simulation that takes only 500 time steps for all agents to adopt is at the 20% mark at 100 time steps. Viewing adoption trends in this way allows us to focus on the overall shape of adoption curves controlling for the variation in overall saturation times (as seen in Table 3, Model 1).

The trends seen in these figures support the results of the models presented in Table 4. Feed-in tariffs produce much larger inequalities between high- (white) and low- (green) propensity groups, especially later in the process, than we see in any other scenario. Seeding policies tend to

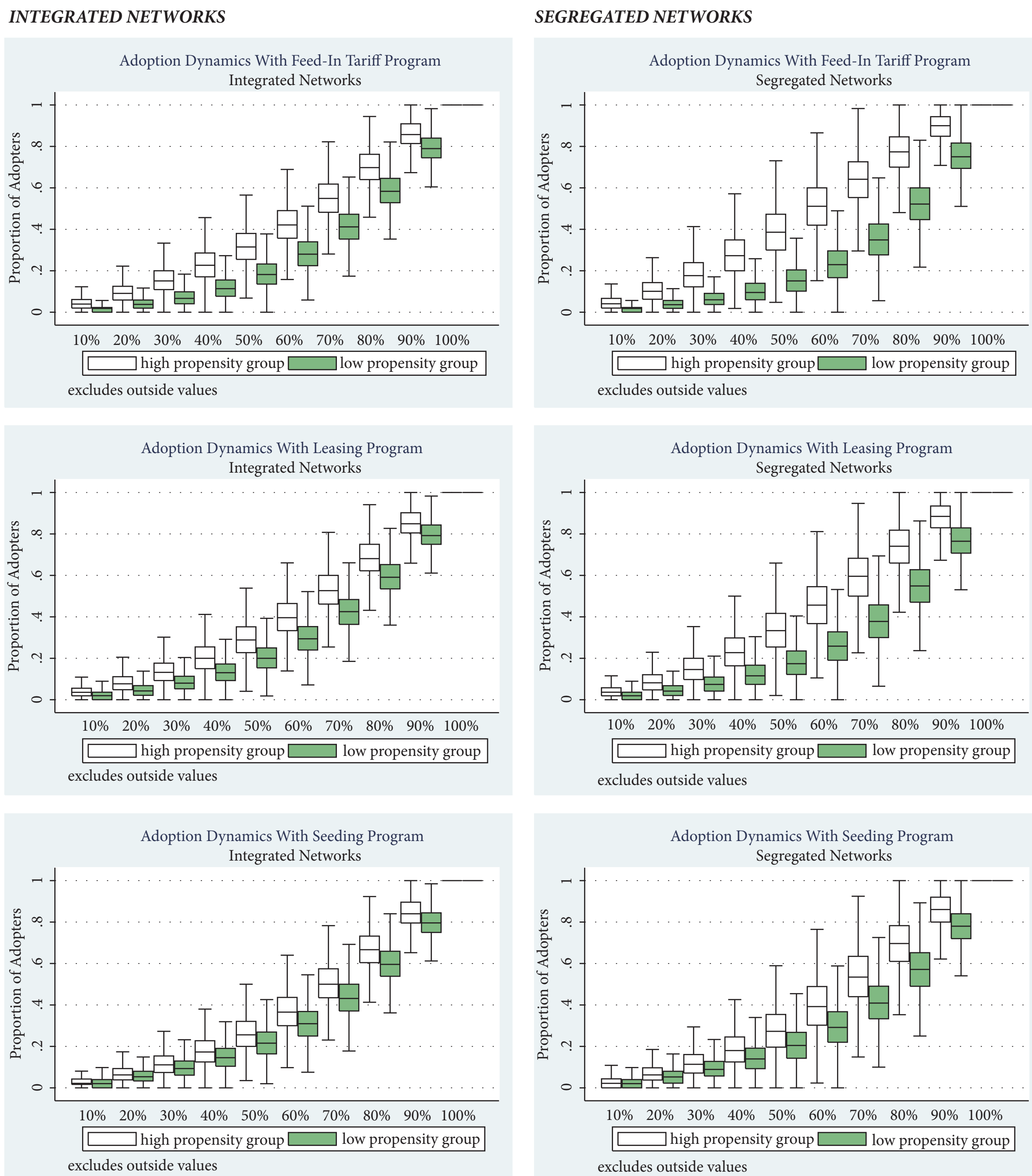


FIGURE 5: Realized adoption dynamics under various incentive programs.

have very narrow gaps between groups over time, although disparities to tend to increase later in the process as the incentive programs are phased out of more of the simulations. Finally, leasing programs do not appear to alter the shape of adoption curves for either group over and above the no-incentive scenario.

6. Conclusion

This agent-based model allows us to evaluate the effects of various types of (simplified) incentives in a virtual space, accounting for different societal structures. The results demonstrate that underlying network structures of a society have an important effect on the effectiveness of policy incentives.

Our results suggest that policy incentives designed to support primarily high-propensity agents might not be the best or even correct way to induce diffusion throughout a segregated network. In segregated networks, peer effects are dampened by missing societal links between more and less affluent actors. Thus, policy incentives that specifically target actors that are more affluent may further increase energy inequality. This is an important finding for policy-makers thinking about transferring existing incentives, for example, best practices examples, from other contexts to their own. An incentive that might have worked well in a relatively integrated society can lead to extremely unjust outcomes within segregated societies.

This underscores a need for more reliable measures of the segregation of a society, so that policy programs can be crafted accordingly to enhance peer effects in a way that diffusion spreads throughout the whole social system. Introducing programs that will properly seed underserved communities could be one way to enhance distributional justice. These findings are, of course, not limited to the adoption of solar PV but within any policy domain where governments try to foster diffusion processes through policy interventions. Furthermore, these results can help to inform more complex (agent-based) models, which try to map the effect of policy incentives. They emphasize that peer effects cannot be reduced to simple diffusion models but that models considering social effects need to take more realistic network structures into account.

6.1. Limitations of this Work. The aim of this theoretical model is to study the effect of network structures on diffusion processes and the equity between two groups in this process. Naturally, such a theoretical model comes with a number of limitations. First, for simplification reasons, the model only considers two different types of actors. Those types have to be understood as a compilation of attributes, such as level of income, level of education, or level of environmental concern or geographical proximity, many of which are known to correlate in real life. The important point is that actors with similar attributes are either more likely to be connected to, and thus to influence, each other (in a segregated network) or equally likely to be connected to each other than to actors with different attributes (in an integrated network). Within the scope of this model, no explicit decomposition in the different attributes and their influence on the diffusion of the adoption of solar PV is modelled. Following this level of abstraction, costs of solar PV are also not explicitly modelled but are implicitly taken into account in the baseline propensity to adopt.

Second, it may seem that the results of the model are sensitive to the particular choice of incentive parameters. Two parameters are chosen for each incentive, which determine how the incentive affects the adoption behaviour of actors in the high- and low-propensity group. The key issue is how the assumed parameters influence the direction in which a certain policy will influence the adoption probability in each of the groups. While the magnitude of these parameters influences the speed of adoption, it is not expected to change the adoption patterns. Furthermore, conclusions are not drawn based on findings that directly depend on the setting of these parameters but are drawn from the comparison between adoption dynamics in the two network structures, given the same incentive parameters. Therefore, we do not test the results for varying parameters.

Third, the two types of networks studied here have to be understood as stylized network types, representing the two extremes in which either no barriers or high barriers for relations between two actor types exist. Future work should expand this work by studying diffusion processes in larger networks with underlying real-world network structures, such as networks enxhibiting community structure.

Fourth, in order to reach an analysable number of model parameter combinations, a very limited number of settings for each model parameter had to be selected. Therefore, exemplary settings were chosen, which allowed the contrasting of the process with two distinct network structures while keeping the other conditions (such as density and social influence) constant. However, previous work suggests that the network density plays a crucial role in diffusion (e.g., [68]). Therefore, it would be interesting to explore in future work, whether changing densities and changing social influence parameters have similar effects on the diffusion in integrated and segregated networks.

6.2. Applied Implications of This Work. Despite the theoretical focus of the model, its findings prove to be relevant in actual policy design. Especially, but not only, in segregated societies, public policy-makers are well advised to consider equity effects of the policies they propose. Policies supporting renewable energies can go a long way in empowering poorer households and communities if they are targeted in the right way. The findings in this work show that multiple incentives are suited to realize the targeted outcome of increasing the share of solar PV adopters but that not all incentives have the additional effect of benefiting poorer households and communities. It has to be taken into account that in some contexts it will be most beneficial to aim for a fast diffusion, for example, because this might drive the prices down and would thus allow that a technology could also be adopted by less affluent actors in the long run. However, this kind of long-term positive effects is not always given. This work unveils that equity effects can differ widely for different policies and within different societal structures. It would thus be fruitful if the assessment of how societal structures and social influence could speed up or dampen the diffusion process of the benefits of certain incentives would be part of policy evaluation.

Data Availability

As these are computational simulations, interested readers may run simulations on their own to replicate the findings. All data used will be published at the author's website, and all codes will be made available for replication of models (run in R).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] T. Dietz, G. T. Gardner, J. Gilligan, P. C. Stern, and M. P. Vandenbergh, "Household actions can provide a behavioral

wedge to rapidly reduce US carbon emissions," *Proceedings of the National Acadamy of Sciences of the United States of America*, vol. 106, no. 44, pp. 18452–18456, 2009.

[2] Fraunhofer ISE., *Aktuelle Fakten zur Photovoltaik in Deutschland [Current Data on Photovoltaics in Germany]*, Fraunhofer ISE, Freiburg, Germany, 2015.

[3] G. Selby, "Branding at the U.S. census bureau: A case study," *Social Marketing Quarterly*, vol. 6, no. 3, pp. 121–123, 2000.

[4] F. Bass, "A new product growth model for consumer durables," *Management Science*, vol. 15, pp. 215–227, 1969.

[5] B. Bollinger and K. Gillingham, "Peer effects in the diffusion of solar photovoltaic panels," *Marketing Science*, vol. 31, no. 6, pp. 900–912, 2012.

[6] H. Welsch and J. Kühling, "Determinants of pro-environmental consumption: The role of reference groups and routine behavior," *Ecological Economics, The DPSIR framework for Biodiversity Assessment*, vol. 69, no. 1, pp. 166–176, 2009.

[7] M. J. Eppstein, D. K. Grover, J. S. Marshall, and D. M. Rizzo, "An agent-based model to study market penetration of plug-in hybrid electric vehicles," *Energy Policy*, vol. 39, pp. 3789–3802, 2011.

[8] T. Islam, "Household level innovation diffusion model of photovoltaic (PV) solar cells from stated preference data," *Energy Policy*, vol. 65, pp. 340–350, 2014.

[9] D. Noll, C. Dawes, and V. Rai, *Community Organizations and Active Peer Effects in the Adoption of Residential Solar PV (SSRN Scholarly Paper No. ID 2305790)*, Social Science Research Network, Rochester, NY, USA.

[10] B. K. Sovacool, "What are we doing here? Analyzing fifteen years of energy scholarship and proposing a social science research agenda," *Energy Research & Social Science*, vol. 1, pp. 1–29, 2014.

[11] K. Jenkins, D. McCauley, R. Heffron, H. Stephan, and R. Rehner, "Energy justice: A conceptual review," *Energy Research & Social Science*, vol. 11, pp. 174–182, 2016.

[12] R. J. Heffron and D. McCauley, "Achieving sustainable supply chains through energy justice," *Applied Energy*, vol. 123, pp. 435–437, 2014.

[13] J. S. Lansing, "Complex adaptive systems," *Annual Review of Anthropology*, vol. 32, pp. 183–204, 2003.

[14] C. Li, L. Wang, S. Sun, and C. Xia, "Identification of influential spreaders based on classified neighbors in real-world complex networks," *Applied Mathematics and Computation*, vol. 320, pp. 512–523, 2018.

[15] R. Pastor-Satorras, C. Castellano, P. Van Mieghem, and A. Vespignani, "Epidemic processes in complex networks," *Reviews of Modern Physics*, vol. 87, no. 3, pp. 925–979, 2015.

[16] C. Zheng, C. Xia, Q. Guo, and M. Dehmer, "Interplay between SIR-based disease spreading and awareness diffusion on multiplex networks," *Journal of Parallel and Distributed Computing*, vol. 115, pp. 20–28, 2018.

[17] M. Jalili and M. Perc, "Information cascades in complex networks," *Journal of Complex Networks*, vol. 5, no. 5, pp. 665–693, 2017.

[18] R. Axelrod, "Advancing the Art of Simulation in the Social Sciences," in *Simulating Social Phenomena, Lecture Notes in Economics and Mathematical Systems*, D. R. Conte, P. D. R. Hegselmann, and P. D. P. Terna, Eds., pp. 21–40, Springer, Berlin, Heidelberg, Germany, 1997.

[19] V. Rai and A. D. Henry, "Agent-based modelling of consumer energy choices," *Nature Climate Change*, vol. 6, no. 6, pp. 556–562, 2016.

[20] I. Kastner and P. C. Stern, "Examining the decision-making processes behind household energy investments: A review," *Energy Research & Social Science*, vol. 10, pp. 72–89, 2015.

[21] V. Trommsdorff and T. Teichert, *Konsumentenverhalten [Consumer Behavior]*, Kohlhammer, Stuttgart, Germany, 2011.

[22] R Core Team., *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria, 2016.

[23] EuPD Research., *Photovoltaik-Preismonitor Deutschland - German PV ModulePriceMonitor 2013 (No. EX0091- 059-2-3- 01–1)*, vol. No. EX0091, Bundesverband Solarwirtschaft e.V. (BSW-Solar), 2013.

[24] J. Axsen, D. C. Mountain, and M. Jaccard, "Combining stated and revealed choice research to simulate the neighbor effect: The case of hybrid-electric vehicles," *Resource and Energy Economics*, vol. 31, no. 3, pp. 221–238, 2009.

[25] M. C. Claudy, C. Michelsen, and A. O'Driscoll, "The diffusion of microgeneration technologies - assessing the influence of perceived product characteristics on home owners' willingness to pay," *Energy Policy*, vol. 39, no. 3, pp. 1459–1469, 2011.

[26] D. McCoy and S. Lyons, "Consumer preferences and the influence of networks in electric vehicle diffusion: An agent-based microsimulation in Ireland," *Energy Research & Social Science*, vol. 3, pp. 89–101, 2014.

[27] J. Zhao, E. Mazhari, N. Celik, and Y.-J. Son, "Hybrid agent-based simulation for policy evaluation of solar power generation systems," *Simulation Modelling Practice and Theory*, vol. 19, no. 10, pp. 2189–2205, 2011.

[28] M. O. Jackson, *Social and Economic Networks*, Princeton University Press, Princeton, NJ, USA, 2008.

[29] S. Wasserman and K. Faust, *Social Network Analysis: Methods and Applications*, Cambridge University Press, Cambridge, England, 1994.

[30] A. D. Henry and B. Vollan, "Networks and the challenge of sustainable development," *Annual Review of Environment and Resources*, vol. 39, pp. 583–610, 2014.

[31] M. E. J. Newman, "The structure and function of complex networks," *SIAM Review*, vol. 45, no. 2, pp. 167–256, 2003.

[32] M. Altmann, B. C. Wee, K. Willard, D. Peterson, and L. C. Gatewood, "Network analytic methods for epidemiological risk assessment," *Statistics in Medicine*, vol. 13, no. 1, pp. 53–60, 1994.

[33] M. D. Shirley and S. P. Rushton, "The impacts of network topology on disease spread," *Ecological Complexity*, vol. 2, no. 3, pp. 287–299, 2005.

[34] M. H. DeGroot, "Reaching a Consensus," *Journal of the American Statistical Association*, vol. 69, no. 345, pp. 118–121, 1974.

[35] N. E. Friedkin and E. C. Johnsen, *Social Influence Network Theory: A Sociological Examination of Small Group Dynamics*, vol. 33 of *Structural Analysis in the Social Sciences*, Cambridge University Press, Cambridge, UK, 2011.

[36] V. Rai and B. Sigrin, "Diffusion of environmentally-friendly energy technologies: Buy versus lease differences in residential PV markets," *Environmental Research Letters*, vol. 8, article 014022, no. 1, 2013.

[37] L. Strupeit and A. Palm, "Overcoming barriers to renewable energy diffusion: Business models for customer-sited solar photovoltaics in Japan, Germany and the United States," *Journal of Cleaner Production*, vol. 123, pp. 124–136, 2016.

[38] A. Banerjee, A. G. Chandrasekhar, E. Duflo, and M. O. Jackson, "The Diffusion of Microfinance," *Science*, vol. 341, no. 6144, pp. 1236498-1236498, 2013.

[39] P. Erdös and A. Rényi, "On the evolution of random graphs," *Publications of the Mathematical Institute of the Hungarian Academy of Sciences*, vol. 5, pp. 17–61, 1960.

[40] D. J. Watts and S. H. Strogatz, "Collective dynamics of "small-world" networks," *Nature*, vol. 393, no. 6684, pp. 440–442, 1998.

[41] BMWi and BMU., *First Monitoring Report - "Energy of the future."*, Bonifatius GmbH, Paderborn, Germany, 2012.

[42] BMWi., *Rahmenbedingungen und Anreize für Elektrofahrzeuge und Ladeinfrastruktur [WWW Document]*, 2016, http://www.bmwi.de/DE/Themen/Industrie/Elektromobiltaet/rahmenbedingungen-und-anreize-fuer-elektrofahrzeuge.html.

[43] M. Bechberger and D. Reiche, "Renewable energy policy in Germany: Pioneering and exemplary regulations," *Energy for Sustainable Development*, vol. 8, no. 1, pp. 47–57, 2004.

[44] S. Jacobsson and V. Lauber, "The politics and policy of energy system transformation—explaining the German diffusion of renewable energy technology," *Energy Policy, Renewable Energy Policies in the European UnionRenewable Energy Policies in the European Union*, vol. 34, no. 3, pp. 256–276, 2006.

[45] BMWi., *Energie der Zukunft - Vierter Monitoring-Bericht. Bonifatius GmbH*, Bonifatius GmbH, Paderborn, Germany, 2015.

[46] H. Granqvist and D. Grover, "Distributive fairness in paying for clean energy infrastructure," *Ecological Economics*, vol. 126, pp. 87–97, 2016.

[47] IEA and OECD., *World Energy Investment Outlook*, OECD (Organisation for Economic Co-operation and Development), Paris, France, 2014.

[48] D. Grover and B. Daniels, "Social equity issues in the distribution of feed-in tariff policy benefits: A cross sectional analysis from England and Wales using spatial census and policy data," *Energy Policy*, vol. 106, pp. 255–265, 2017.

[49] A. Macintosh, *The Australian Government's solar PV rebate program (Policy Brief No. 21)*, vol. 21, The Australian Institute, 2010.

[50] R. J. Procter, "Fixed-Cost Recovery, Renewables Adoption and Rate Fairness," *The Electricity Journal*, vol. 27, no. 5, pp. 42–53, 2014.

[51] L. C. Freeman, "Segregation in social networks," *Sociological Methods & Research*, vol. 6, no. 4, pp. 411–429, 1978.

[52] A. D. Henry, P. Pralat, and C.-Q. Zhang, "Emergence of segregation in evolving social networks," *Proceedings of the National Acadamy of Sciences of the United States of America*, vol. 108, no. 21, pp. 8605–8610, 2011.

[53] T. C. Shelling, "Dynamic models of segregation," *Journal of Mathematical Sociology*, vol. 1, pp. 143–186, 1971.

[54] BGBl., *Gesetz über die Einspeisung von Strom aus erneuerbaren Energien in das öffentliche Netz (Stromeinspeisungsgesetz)*, 1991.

[55] N. Martin and J. Rice, "Solar Feed-In Tariffs: Examining fair and reasonable retail rates using cost avoidance estimates," *Energy Policy*, vol. 112, pp. 19–28, 2018.

[56] REN21., *Renewables 2007 Global Status Report. REN21, Paris & Washington,DC*, 2008.

[57] S. Chowdhury, U. Sumita, A. Islam, and I. Bedja, "Importance of policy for energy system transformation: Diffusion of PV technology in Japan and Germany," *Energy Policy*, vol. 68, pp. 285–293, 2014.

[58] A. J. Schaffer and S. Brun, "Beyond the sun—Socioeconomic drivers of the adoption of small-scale photovoltaic installations in Germany," *Energy Research & Social Science*, vol. 10, pp. 220–227, 2015.

[59] C. Schelly, "Transitioning to renewable sources of electricity: motivations, policy and potential," in *Controversies in Science and Technology: From Sustainability to Surveillance*, D. L. Kleinman, K. A. Cloud-Hansen, and J. Handelsman, Eds., pp. 62–72, Oxford University Press, New York, NY, USA, 2014.

[60] N. Martin and J. Rice, "The solar photovoltaic feed-in tariff scheme in New South Wales, Australia," *Energy Policy*, vol. 61, pp. 697–706, 2013.

[61] BT- Drs., *Stenografischer Bericht. 40. Sitzung (BT-Plenarprotokoll No. 17/40)*, Deutscher Bundestag, Berlin, Germany, 2010.

[62] A. Pyrgou, A. Kylili, and P. A. Fokaides, "The future of the feed-in Tariff (FiT) scheme in europe: The case of photovoltaics," *Energy Policy*, vol. 95, pp. 94–102, 2016.

[63] T. Tantisattayakul and P. Kanchanapiya, "Financial measures for promoting residential rooftop photovoltaics under a feed-in tariff framework in Thailand," *Energy Policy*, vol. 109, pp. 260–269, 2017.

[64] E. Drury, M. Miller, C. M. Macal et al., "The transformation of southern California's residential photovoltaics market through third-party ownership," *Energy Policy*, vol. 42, pp. 681–690, 2012.

[65] H. Zhang, Y. Vorobeychik, J. Letchford, and K. Lakkaraju, "Predicting rooftop solar adoption using agent-based modeling," in *Proceedings of the 2014 AAAI Fall Symposium Series*, 2014.

[66] A. D. Henry and H. Brugger, "Agent-Based explorations of environmental consumption in segregated networks," in *Social Systems Engineering: The Design of Complexity, Computational and Quantitative Social Science*, C. García-Díaz and C. Olaya, Eds., John Wiley & Sons, 2017.

[67] R. Axelrod, "Effective Choice in the Prisoner's Dilemma," *Journal of Conflict Resolution*, vol. 24, no. 1, pp. 3–25, 1980.

[68] D. J. Watts, "A simple model of global cascades on random networks," *Proceedings of the National Acadamy of Sciences of the United States of America*, vol. 99, no. 9, pp. 5766–5771, 2002.

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