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The Influence of Financial Benefits and Peer Effects on the Adoption of Residential Rooftop Photovoltaic Systems

Simon Johanning[1, 2], Daniel Abitz[3], Fabian Scheller[4,5] Thomas Bruckner[6]

Abstract

The uptake of residential photovoltaic systems is essential for energy system transformation towards carbon neutrality and decentralization. However, despite numerous campaigns to incentivize their uptake, adoption by residential homeowners is lacking behind. While countless drivers and barriers have been identified, the decision process is not fully understood. To address this gap, we developed an agent-based residential rooftop photovoltaic adoption model called PVact. Our model analyzes the interactions of potential household adopters based on their utility functions and social network, with a focus on the role of monetary evaluation and social pressure in adoption behavior. In this paper, we aim to assess the influence of monetary evaluation and social pressure in an abstract case study based on real-world data from the municipality of Leipzig, Germany. We consider stochastic dynamics through scenario analysis to investigate the influence of these factors on adoption behavior. Our results show that monetary evaluation and social pressure have a significant impact on adoption behavior. Specifically, we find shifting adoption patterns with an increased requirement for monetary returns and higher level of normative pressure required for households to act. Higher resistance against these pressure shows more stochastic variations, more pronounced tipping points and stronger run-away effects.

Keywords: Agent-based Modelling, Photovoltaic Adoption Decisions, Monetary Assessment of Household Photovoltaic, Normative Pressure, Generative Social Sciences

1. Introduction

1.1. Motivation

The uptake of residential photovoltaic systems (PV) is commonly seen as a key element for energy system transformation towards carbon neutrality and decentralization. As a result, extensive research has been conducted to identify the determinants of residential adoption of PV systems, which can significantly accelerate the diffusion process [1, 2]. However, studies have failed to integrate various determinants and to explain the decision-making process behind adoption [3].

Financial considerations are an important driver of residential homeowners‘ adoption of PV systems, as indicated by the consistently positive effects observed in various reviewed studies [4, 1]. These studies show that PV adopters tend to be highly educated and have a high income. Financial benefits have been found to be positively associated with positive attitudes toward PV, intention to adopt PV, and actual PV adoption behavior [5, 6]. However, despite the potential for future revenues, the positive effect was found to be smaller than the negative effect of the initial investment cost [7].

In addition to financial benefits, normative considerations have also been found to be positively related to PV adoption among residential homeowners [1, 8]. There is an indication that spatial peer effects and social networks

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may also play a role [9]. In this context, peer effects on potential PV adopters are seen as a consequence of both the visibility of PV panels (local peer effects) and interpersonal contact about PV (social peer effects) [10].

While financial benefits and peer effects are seen as determinants for residential rooftop PV, their impact varies across studies. Peer effects depend on social circles and proximity. Our analysis focuses on a specific municipal case study, providing a bottom-up approach.

We created the agent-based innovation diffusion model PVact to analyze residential rooftop PV adoption and examine interactions among potential household adopters using utility functions and social networks.

1.2. Research Questions

The objective of this research is to investigate the impact of financial benefits and peer effects on the adoption decision-making of households on rooftop PV systems. This is done by applying the agent-based model PVact [11]. To investigate decision factors, we examine the behavior of agents under monetary and normative influences in isolation within abstract scenarios in a granular municipal context. Thereby, we addresses the following research questions:

- How does monetary evaluation and normative pressure influence the PV adoption behavior of household agents within PVact?
- What model dynamics arise through the introduction of dynamic stochastic elements in the agents' adoption process and how does this impact the diffusion process?

To introduce complexity seen in real-world decision-making, we use stochastic model components that allow for random influences and diffusion dynamics. Through scenario analysis, we derive insights into the influence of monetary evaluation of photovoltaic systems and different degrees of social and local normative pressure. Our findings contribute to the development of effective policies and strategies for promoting renewable energy.

2. Agent-based Model

The agent-based model PVact simulates the diffusion of residential rooftop PV systems, drawing on established theories in social psychology and innovation diffusion [11, 12].[7] The instance represents individual households with socio-demographic and psycho-social identities, as well as their physical living situations based on empirical research ([13, 14]). The physical living situation was derived from building layer and plot data from the city of Leipzig, the EC INSPIRE data set and the LoD 3D building data set of the BKG[8]. It was tied to household purchase power and milieu of the respective addresses by the Microm Socio-Milieu Dataset (see [13] for more information).

PVact incorporates stochastic dynamics by grouping agents with different profiles[9] and incorporating geographical variation[10]. These groups are described through probability distributions which are used for the initialization of each agent. The social network is instantiated randomly with a set *number of ties* for each agent according to their milieu, with the probability to form a link with with agents based on the *affinity*. The psycho-social identities and the social network of the agents were determined through a large-scale German-wide survey conducted in cooperation with the SINUS-Institute[11] as described in [14].

The decision process for adopting PV systems is based on perceived utility, financial performance, and social pressure. A weighted partial utility function is employed to evaluate PV. The adoption is triggered once agents develop sufficient *interest* and the technology is *feasible* for their living situation (i.e. detached or semi-detached houses where the decision authority for the roof lies with the household). *Interest* is generated through *communication* with other agents in their *social network*, and the *interest threshold* is reached once a set level of interest is attained. Inter-agent communication is initiated with set probabilities on a weekly basis[12], with conversation partners being any agent

[7] The code and more information can be found here: `https://github.com/IRPsim/IRPact` and is published under a GPL-3.0 license.
[8] German Federal Agency for Cartography and Geodesy, German: Bundesamt für Karthographie und Geodäsie.
[9] Largely based on groups of like-minded people called the Sinus® milieus.
[10] Through zip-codes and associated spatially distributed buildings.
[11] `https://www.sinus-institut.de/en/sinus-institut`
[12] 20% probability for each agent to initiate communication within this study.

with an established link to the agent. During communication, agent *attitudes*[13] are adjusted and interest is generated depending on the state of the communication partner [14]. Finally, agents have a chance to change their *living situation*, which is proportional to the rate of construction and renovation associated with the case study.

3. Scenario Design

In this study, we systematically investigate the impact of monetary factors and peer pressure on agent decisions, in both stochastic and static settings. We differentiate between social and local peer pressure. Social peer pressure refers to the normative pressure that agents receive directly from their peers in their social network, while local peer pressure refers to the pressure that agents receive from their local surroundings. In the scenarios for the static setting, communication is not a crucial factor since agents adopt as soon as their utility surpasses the threshold. This threshold is based on the assumption that all agents are aware of and interested in PV. In contrast, in the stochastic setting, agents must communicate with their peers in the social network to become interested in the technology.

For investigating the decision factors, we simulate the adoption behavior under different *adoption thresholds*. For normative pressure, we consider social (local) peer pressure as the fraction of adopters among potential adopters in the social network (local surroundings) of the respective agent. For local pressure, we investigate three distances (radius of 100m, 500m and 2.500m around the agent). In our model, potential adopters refer to agents with a *feasible* living situation whose household income exceeds the financial threshold of 38,827.44 Euro per year[15], indicating their capability to take the financial risk.

For monetary benefit we consider two scenarios that vary in their assumptions about rationality and behavioral factors. We use the net present value (NPV) of the PV system as the minimum financial benefit the system has to generate in order to be adopted (defined in equation 1 and visualized in figure 1).

$$NPV(t_0, N_i, A_i) = -I_{0,t_0} + \sum_{t=1}^{t=20} \frac{(FIT_{t_0} \cdot (1 - SC) + RP_{t_0} \cdot (1 + p)^t \cdot SC) \cdot E_t(N_i, A_i)}{(1 + r_{dep,t_0})^t} \tag{1}$$

The first scenario addresses risk aversion, in which households adopt a PV system only if the net present value exceeds a certain positive threshold (called NPV excess threshold, or NET). With additional behavioral assumptions, in the second scenario, households adopt only if the NPV is larger than the weighted average NPV of PV systems in the model scope, up to a certain degree (relative NET, or RNET). With the exception of a NET of 0, we avoid rationality assumptions, as observed adoption patterns have shown that many households didn't even adopt where monetarily the PV systems were very favorable.

The net present value of the PV system $NPV(t_0, N_i, A_i)$ at time t_0 for rooftop angle N_i and orientation A_i is modeled as the cumulative monetary advantage of the investment. This is achieved by subtracting the investment cost I_{0,t_0} at adoption time t_0 from the discounted sum of generated feed-in remuneration[16] $\sum_{t=0}^{t=20}(FIT_{t_0} \cdot (1 - SC) \cdot E_t) \cdot (1 + r_{dep,t_0})^{-t}$ and avoided energy purchased cost as in equation 2 [17]:

$$\sum_{t=0}^{t=20}(RP_{t_0} \cdot (1 + p)^t \cdot SC) \cdot (1 + r_{dep,t_0})^{-t} \tag{2}$$

, with r_{dep,t_0} as the reference interest rate for a savings deposit at time t_0[18]. The amount of electricity generated in year t is given by $E_t(N_i, A_i)$ as expressed in equation 3:

$$E_t(N_i, A_i) = H^t_{solar_i}(N_i) \cdot V(A_i) \cdot \eta_{t_0} \cdot (1 - D)^t \cdot PR_{t_0} \tag{3}$$

[13] While attitudes play no role within the context of this study, this information is added for completeness.
[14] Within this study agents receive 5 *interest points* from *adopters*, 2 from agents that are *interested* themselves and 1 from other agents.
[15] As determined by [14] for the city of Leipzig, Germany.
[16] With feed-in tariff FIT_{t_0} for each kWh of generated electricity (E_t) for the year t that was not self-consumed $(1 - SC)$.
[17] With the exponentially increasing electricity cost $RP_{t_0} \cdot (1 + p)^t$ for the share of self-consumed energy $SC \cdot E_t$.
[18] For the period between 2008 and 2019 set to 2%.

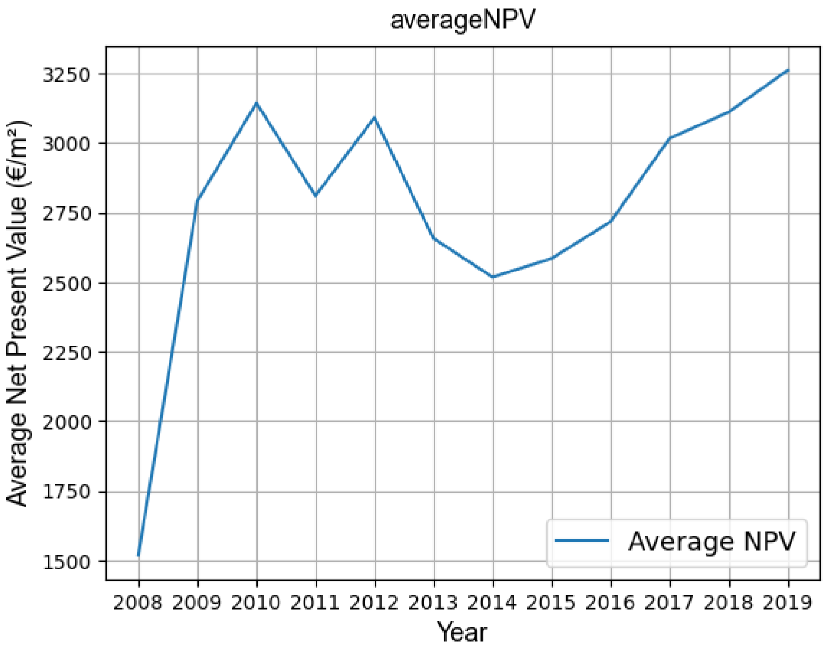


Figure 1: Visualization of the average Net Present Value over time for all roofs within the case study in the respective simulation year.

The amount of energy E_t (in kWh) generated per 1kWhp for a PV system of an agent a_i with rooftop angle N_i and orientation A_i is expressed as the product of the average annual global irradiation[19] with rooftop angle N_i, corrected by the loss for rooftop orientation $V(A_i)$, the efficiency of the module at time of adoption η_{t_0}, degradation[20] and the performance ratio PR_{t_0}.

To achieve more realistic results and introduce further heterogeneity, we enrich the scenarios in the stochastic cases by introducing agent communication and knowledge propagation. In this case, agents consider adopting the technology only after they reach a critical level of interest by communicating with other agents. At each time step, agents seek communication partners with a small probability depending on their social milieu and communicativity. Agents accumulate interest points depending on the state of their communication partner. Agents receive 1 interest point for communicating with uninterested agents, 2 points for communication with interested agents and 5 points for communication with an adopter. Once the agent reaches a critical interest threshold, they enter the decision phase, where we evaluate their utility in the same way as in the static case.

4. Simulation Results

This section presents key results of a range of simulation runs with the described scenarios[21]. For this, the scenario-adjusted model was empirically sampled with a parameter grid that was refined where qualitatively varying model behavior was observed. For these parameter regions, finer grids were used to determine where model behavior changed qualitatively. Where phase transitions or critical points were suspected, parameters were repetitively adjusted to get as close as possible to the parameter of interest, resulting in high-precision values within the result section. The precision of these values should not be interpreted to be of exact practical relevance but are valid only within the scope of these scenarios and in conjunction with system parameterizations where a qualitative model change occurs.

[19] As expressed in kWh per $6m^2$ area with inclination N_i at south orientation based on monthly values of the years 2010-2016 in the municipality of Leipzig.

[20] Set at $0.5\%/year$ for the model.

[21] For simulation results see `https://www.researchgate.net/publication/370658672_The_Influence_of_Financial_Benefits_and_Peer_Effects_on_the_Adoption_of_Residential_Rooftop_Photovoltaic_Systems`.

4.1. Static Scenarios

4.1.1. Net Present Value Excess Threshold (ss1)

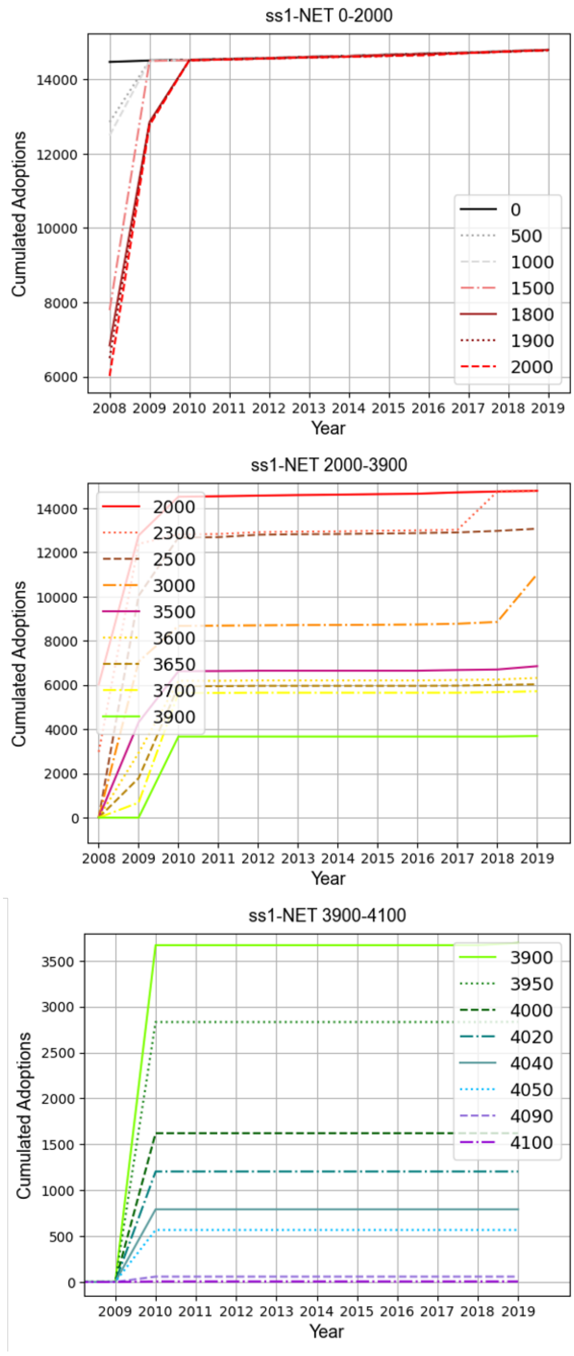


Figure 2: Cumulated adoptions for increasing monetary intervals of the Net Present Value Excess Threshold (NET) of the PV system (with NET between 0 € and 2,000 € (top), 2,000 € and 3,900 € (middle) and 3,900 € and 4,100 € (bottom)) for the simulation years 2008 – 2019 (scenario ss1).

For the influence of the financial benefit of PV systems, we tested a range of NETs, as shown in figure 2. As expected, the overall number of adopters decreased steadily with increasing thresholds. However, the temporal patterns of adoption shift over time as well. While the number of adopters over the whole simulation remain constant up to 2,300 €, more and more agents wait until 2009 to adopt since their individual NPV only turn beneficial then (see figure 1).[22] This pattern continued with increasing thresholds, shifting adoption to 2010 around 3,600 € NET. With a requirement of 3,900 € NET, adoption concentrates entirely on 2010, gradually decreasing with increasing NET requirement until 4,100 € beyond which no adoption is seen.

4.1.2. Relative Net Present Value Excess Threshold (ss2)

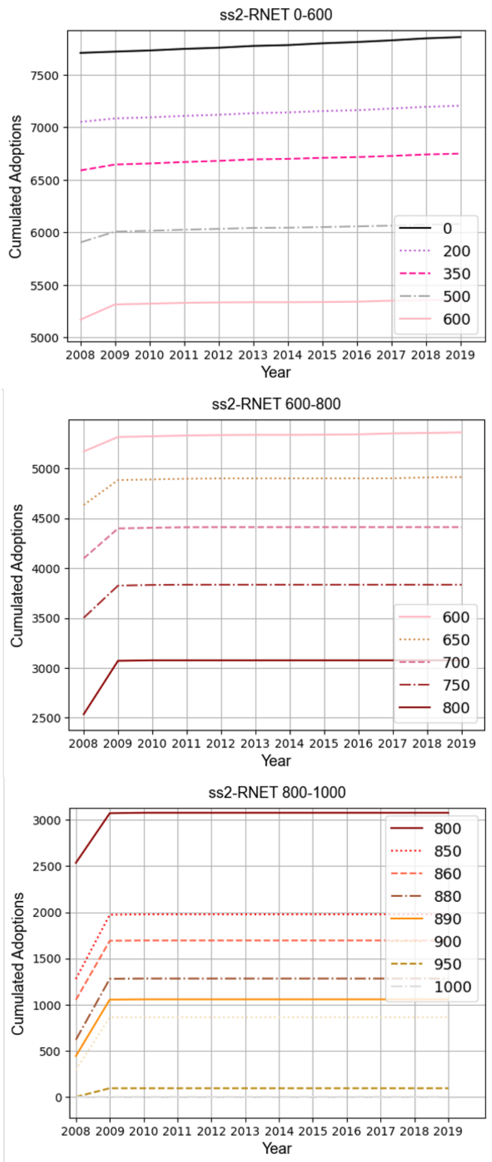


Figure 3: Cumulated adoptions for increasing monetary intervals of the Relative Net Present Value Excess Threshold (RNET) of the PV system (with RNET between 0 € and 600 € (top), 600 € and 800 € (middle) and 800 € and 1,000 € (bottom)) for the simulation years 2008 – 2019 (scenario ss2).

[22]In every year, agents check whether their own NPV exceeds the given threshold.

In this scenario (shown in figure 3), agents only adopt when the difference between their NPV and other agents reaches or exceeds the RNET. As with ss1, increasing RNET sees a decrease of the number of adopters over time, but with a less pronounced shift to later simulation years. With increasing RNET requirements, adoptions concentrate in 2008 and 2009 almost entirely (up to 900 € RNET), and no adoptions are seen beyond 900 € RNET.

4.1.3. Social Pressure (ss3)

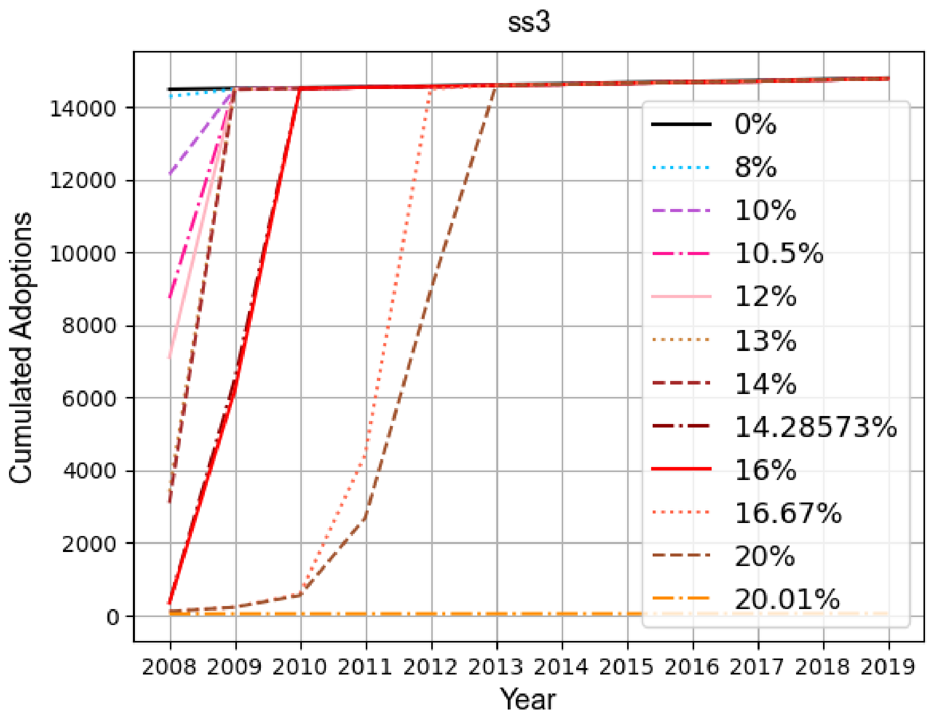


Figure 4: Cumulated adoptions for different thresholds of required adopters within the social network of the agent for the simulation years 2008 – 2019 (scenario ss3).

In ss3 adoption behavior depends on the fraction of adopters in the social network. As seen in figure 4, up a value of 13%, ss3 sees diffusion within the first year, after which it increasingly shifts to the second year. At 14.29%, we see a transition to adoption in the 2nd and 3rd year. A critical point is reached at 16.67%, where adoption shifts to the 5th simulation year. Beyond 20%, the system drastically changes, where the total number of adoptions throughout the simulation falls off drastically.

4.1.4. Local Pressure Small Radius (ss4)

As shown in figure 5 on the next page, local pressure with a small radius (100 meters) shows strong adoption behavior up to 3% required adopters in the area. In addition to a steep decline, a shift of the adoption pattern to later years is seen beyond this. Around and adoption threshold of 7%, adoption patterns concentrate on later years and smear out increasingly. After an adoption threshold of 9%, adoption falls off steeply until no adoption is seen beyond 30%.

4.1.5. Local Pressure Medium Radius (ss5)

Local pressure with a medium radius (500 meters) shows similar behavior to the one noted above, with a much stronger decline of adoption (see figure 6). The number of adoptions in the first year already declines at a threshold of around 1.6%, with an increasing shift to later years around 1.92%, with overall adoption staying constant. Beyond 4.76% the system sees a phase transition to the third year, switching around $\frac{1}{3}$ of the overall adoptions to this year. This trend gradually grows up to 5.3% until adoptions in every year fall off until they reach a low level of adoptions around 10.733%, leaving no adoptions around 15%.

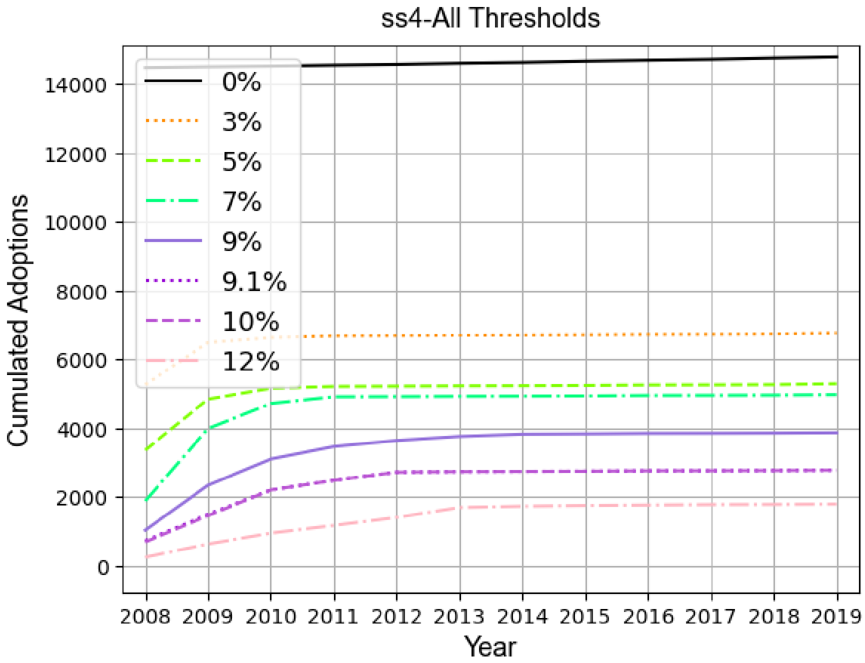
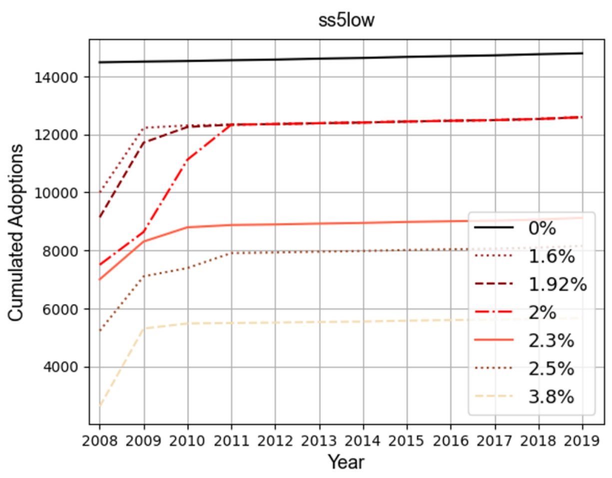


Figure 5: Cumulated adoptions for different thresholds of required adopters within a 100 meter radius of the agent for the simulation years 2008 – 2019 (scenario ss4).



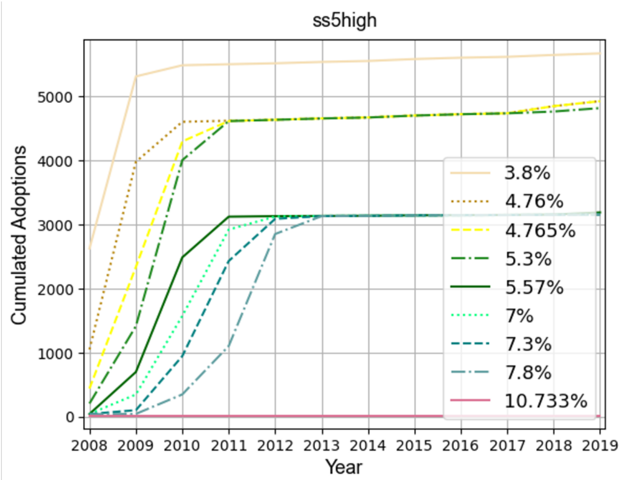


Figure 6: Cumulated adoptions for different thresholds of required adopters within a 500 meter radius of the agent with thresholds between 0 and 3.8% (left) and 3.8 and 10.733% (right) for the simulation years 2008 – 2019 (scenario ss5).

4.1.6. Local Pressure Large Radius (ss6)

Local pressure with a large radius (2,500 meters) shows very drastic and binary behavior, as is seen in figure 7. Adoptions are heavily concentrated on the first year up to a critical threshold just above 1.4% after which the adoption pattern radically collapses and no adoption occurs whatsoever.

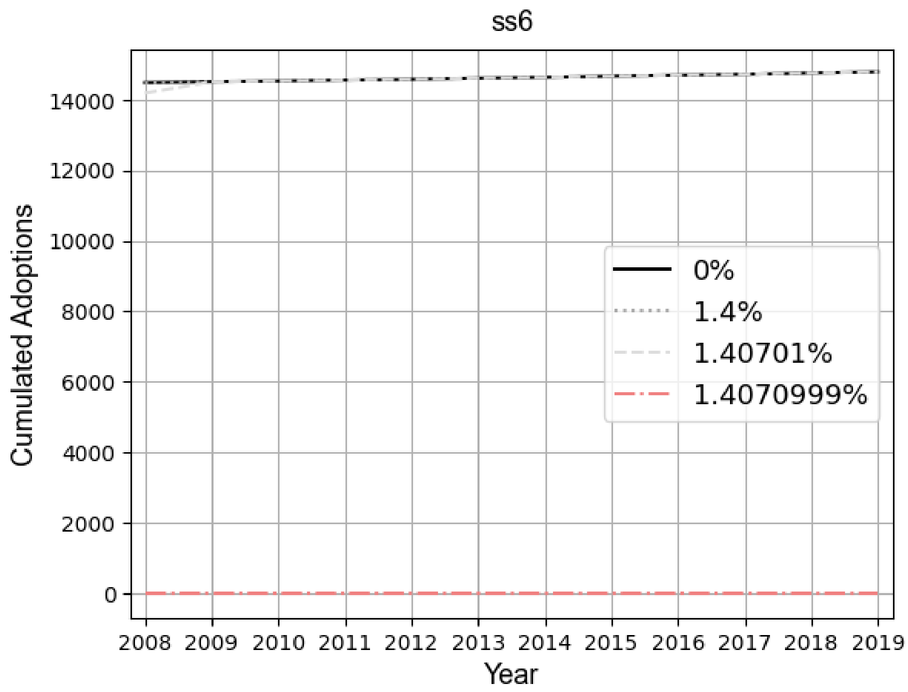


Figure 7: Yearly adoptions for different thresholds of required adopters within a 2,500 meter radius of the agent for the simulation years 2008 – 2019 (scenario ss6).

4.1.7. Discussion of Static Scenarios

In addition to declining overall adoptions beyond certain critical points, the simulations exhibit regions of stability that are often marked by critical points where adoption behavior shifts to later years. These critical points mark parameter regions where system dynamic shift rapidly and where interesting things happen within the system.

4.2. Dynamic Scenarios

The dynamic scenarios investigate the systems' behavior with the introduction of communication and delayed diffusion (through interest propagation) beyond the shifts noted above. Agents accumulate interest through communication with one another based on their adoption state (uninterested, interested and adopter). When a certain value is reached (the so-called *interest threshold*), the agents test for adoption. The focus here is on model behavior under different interest thresholds. For adoption thresholds, characteristics values derived above are used.

4.2.1. Net Present Value (ds1)

For investigating interest propagation in combination with NET, four core NET values (0, 2,300, 3,600 and 3,900 €) were chosen (see figure 8). For an NET of 0 € (positive NPV), adoptions progressively shift to later years with increasing threshold due to the propagation of interest. Overall, this sees a temporal delay without much change in the total number of adoptions over the simulation time frame. With a NET of 2,300 €, the pattern starts out differently with numerous adoptions in 2018 even without the diffusion of interest. Increasing interest threshold further delays adoptions and spreads it out. At a NET of 3,600 €, communication barely changes the adoption pattern up to a threshold of 55, where it shifts to later years. This is also seen with a NET of 3,900 €, which similarly concentrates on 2010, but shifts to later years; in contrast to the system behavior of other cases, overall adoption drops off significantly for higher interest thresholds as much adoption is delayed close to the end of the simulation and interest dynamics don't have time to unfold.

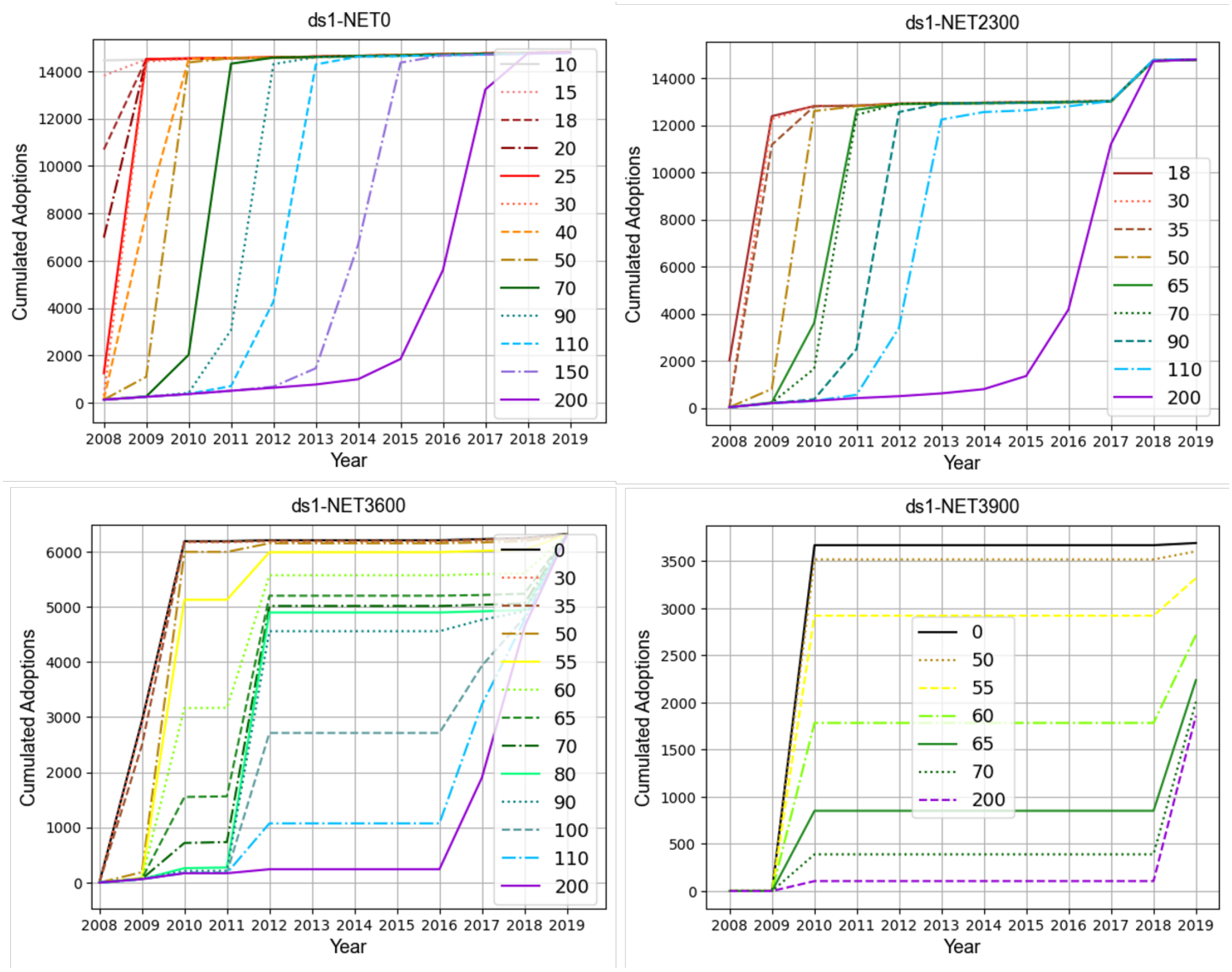


Figure 8: Cumulated adoptions for varying interest threshold for characteristic NET values (0€ (top left), 2.300€ (top right), 3.600€ (bottom left) and 3.900€ (bottom right) for the simulation years 2008 – 2019 (scenario ds1).

4.2.2. Relative Net Present Value (ds2)

For the RNET, interesting behavior is seen for RNET $\in \{0, 350, 650, 880\}$ € (figure 9 for more details). Overall, increasing interest threshold leads to delayed adoption and temporal shifts. The lower thresholds (0 and 350 €) are barely impacted beyond temporal delay; for higher thresholds (650 and 880 €), the total adoption falls off steeply with higher interest thresholds.

In addition to the bulk of adoption being delayed to a later simulation year, we see less pronounced adoption peaks for lower thresholds and more spread over adjacent years. Similar behavior can be seen for an RNET of 650 € with a strong drop for higher interest thresholds after which adoption patterns do not take off as in cases with a lower RNET or interest requirement. For the high RNET requirement (880 €), adoption can only be seen in the beginning of the simulation (years 2008 – 2010), with decreasing adoption.

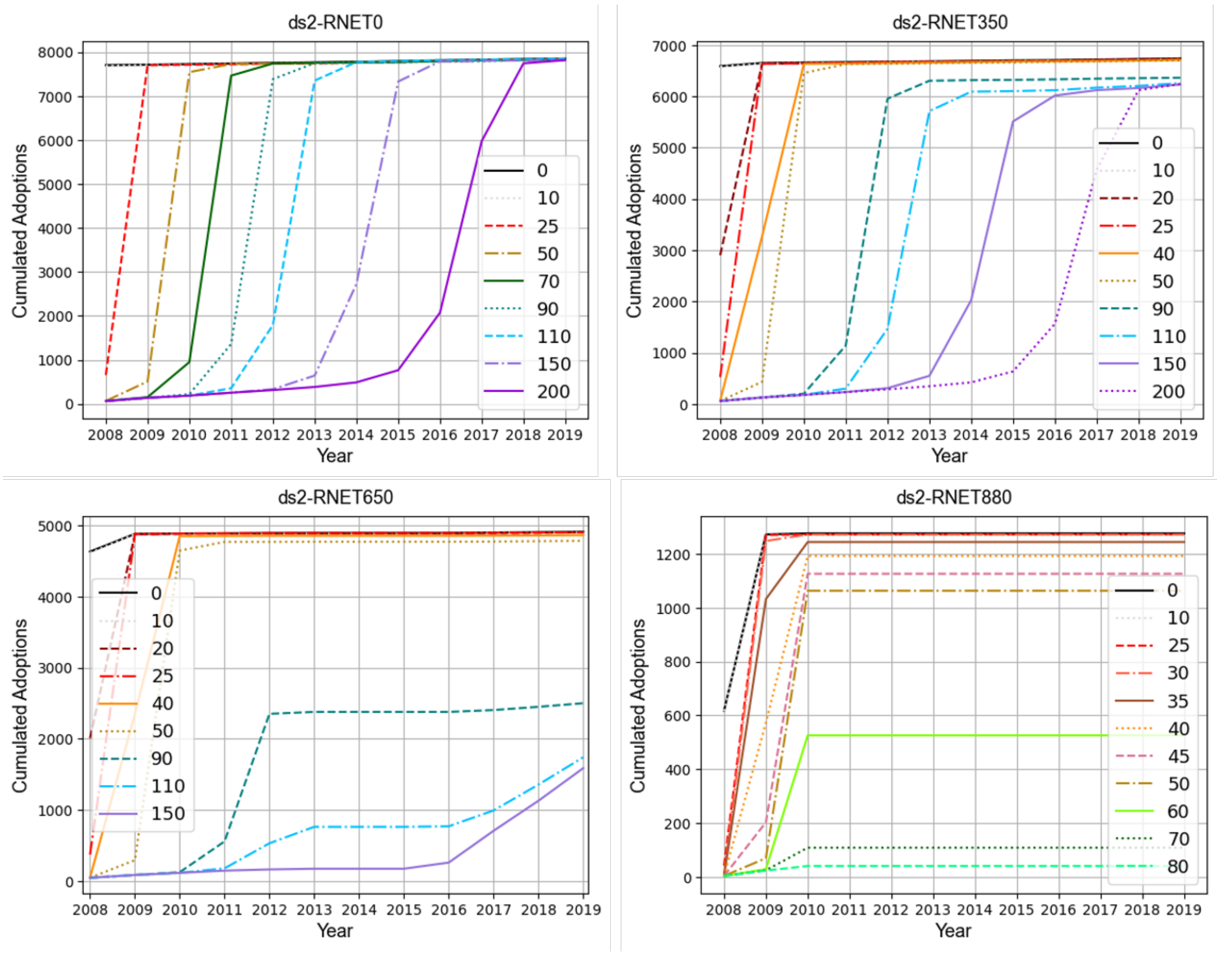


Figure 9: Cumulated adoptions for varying interest threshold for characteristic RNET values (0€ (top left), 350€ (top right), 650€ (bottom left) and 880€ (bottom right) for the simulation years 2008 – 2019 (scenario ds2).

4.2.3. Social Pressure (ds3)

Adding interest propagation to the requirement of a minimum number of adopters in the agents' social network changes the temporal patterns of adoption but (with the exception of a high interest threshold of 14.3%) does not impact the total adoption, as is seen in figure 10.

Overall it can be seen that the introduction of interest accumulation to the system further shifts adoption to later times than the single threshold has by itself. Different values for the adoption threshold below the critical value where

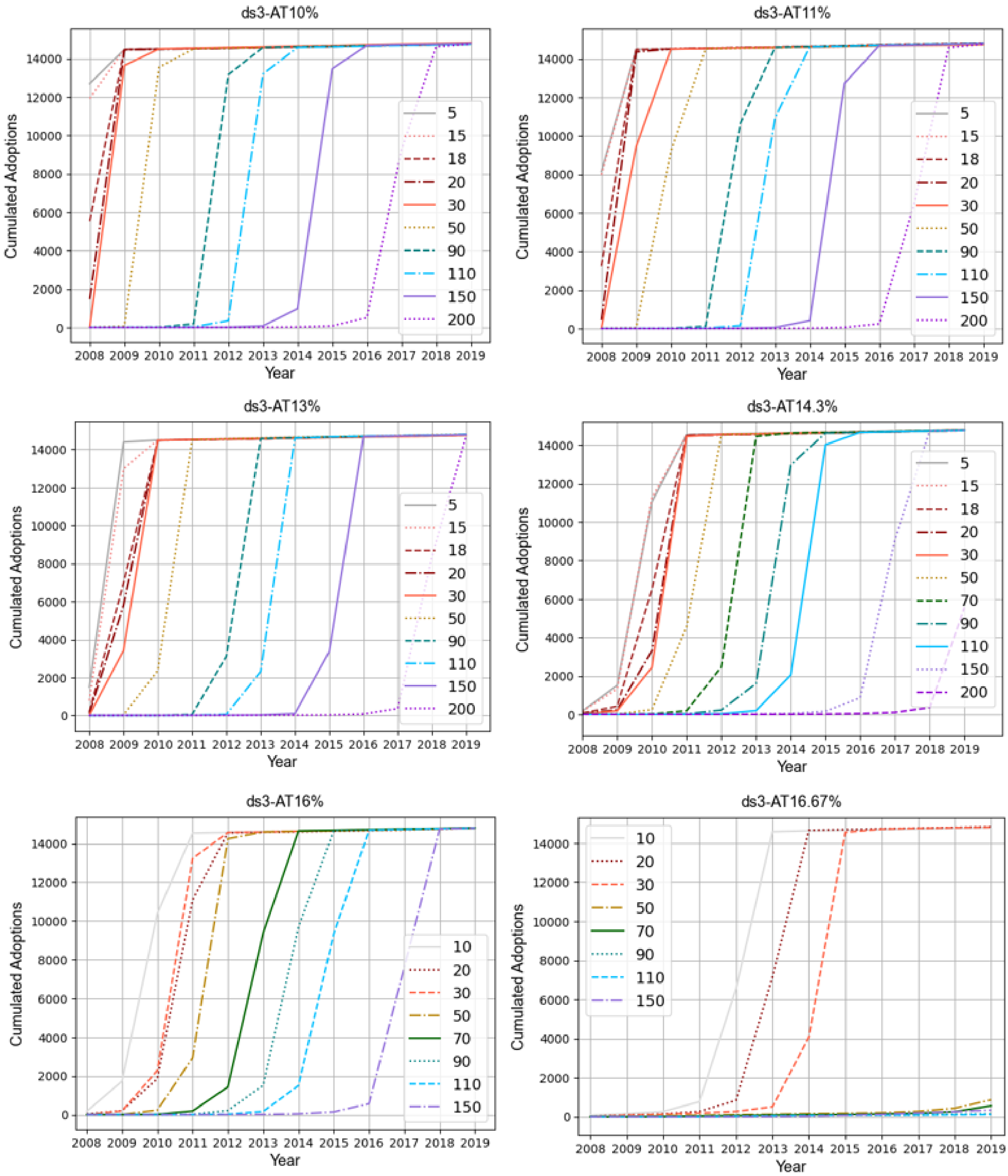


Figure 10: Cumulated adoptions for varying interest thresholds for the required proportion of adopters in the agents' social network (10% (top left), 11% (top right), 13% (middle left), 14.3% (middle right), 16% (bottom left) and 16.67% (bottom right) for the simulation years 2008 – 2019 (scenario ds3).

cumulated adoptions fall off lead to a delayed onset of adoption which is further exacerbated with the introduction of interest dynamics. The stochastical variety between runs was particularly high in this scenario, in particular for high interest thresholds.

4.2.4. *Local Pressure Small Radius (ds4)*

Scenario ss4 showed qualitatively different behavior in four parameter regions, which are further investigated in ds4[23], as plotted in figure 11. With the exception of stochastic variation between individual runs, overall adoption is stable between different interest thresholds of the same adoption threshold.

The concentrated adoption in early years with AT 1% gradually shifts to later years, with minor spreading to years adjacent to the take-off effect. The more spread out adoption seen in ss4 for AT 7% shows similarly shifts, making it more balanced and spread out than in the first case. This behavior is even more pronounced with an AT of 9.3%, which distributes the bulk of adoption over four simulation years, showing the gradual local diffusion in combination with the delaying effect of the requirement to grow interest. Qualitatively the same behavior is seen at an adoption threshold of 12%, albeit with lower overall adoption rates.

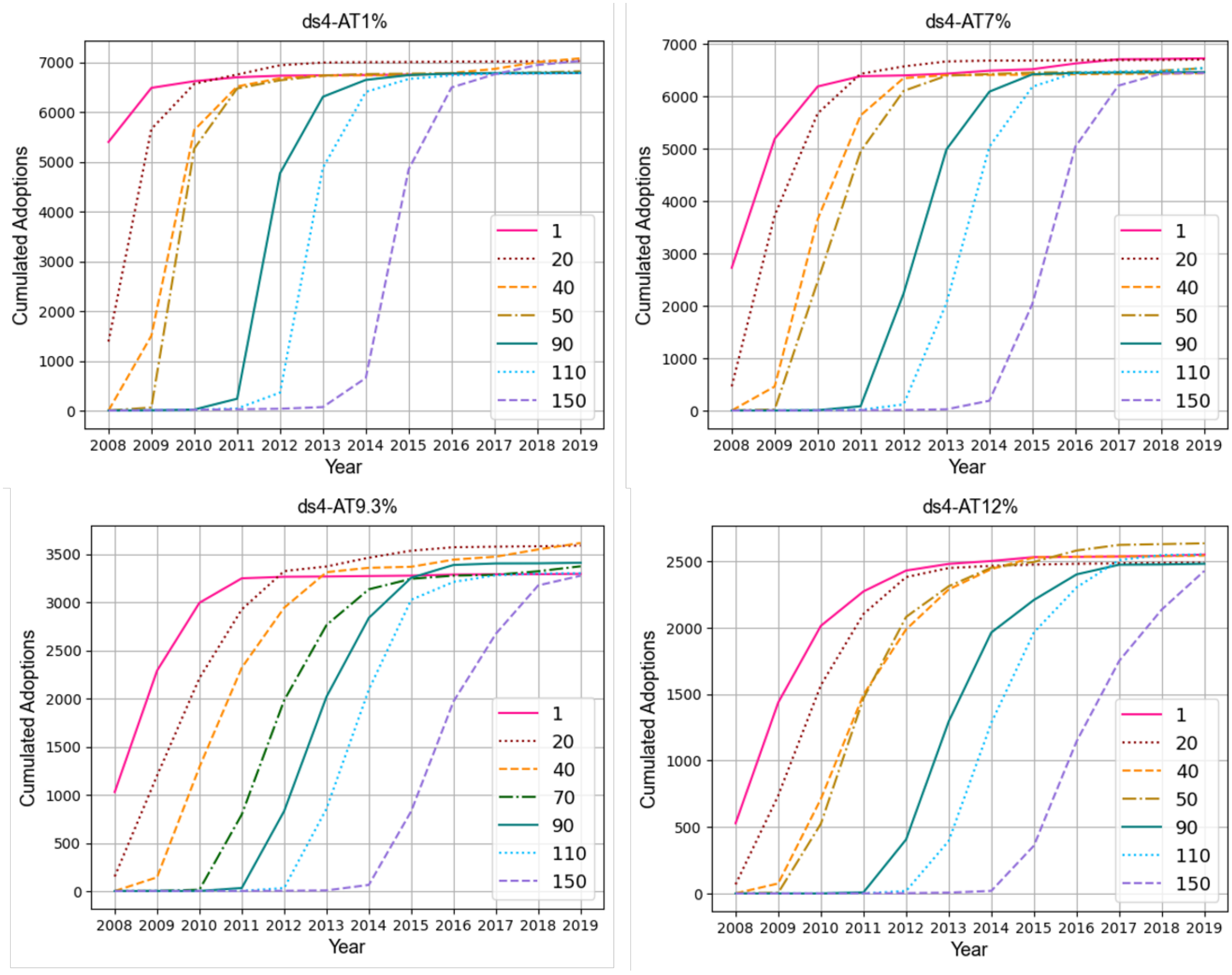


Figure 11: Cumulated adoptions for varying interest threshold for the required proportion of adopters in a 100m radius (1% (top left), 7% (top right), 9.3% (bottom left) and 12% (bottom right) for the simulation years 2008 – 2019 (scenario ds4).

[23] Exemplary adoption thresholds (AT) of 1%, 7%, 9.3% and 12%.

4.2.5. *Local Pressure Medium Radius (ds5)*

Similar effects can be seen with a larger local radius, although less pronounced (see figure 12 for details). For four thresholds that showed interesting behavior in the static case[24], increasing interest thresholds lead to a delayed response in adoption behavior. While for the lower adoption threshold the adoption is more concentrated within a year (with some spread around the peak uptake), higher adoption thresholds show a bulk of adoption that is more concentrated in two adjacent years, slowing the adoption uptake to some extend. Additionally, for the higher adoption thresholds, this shows a much slower uptake even with low interest threshold. As in ds3, significant stochastic variation was seen, leading to some runs inconsistent with one another.

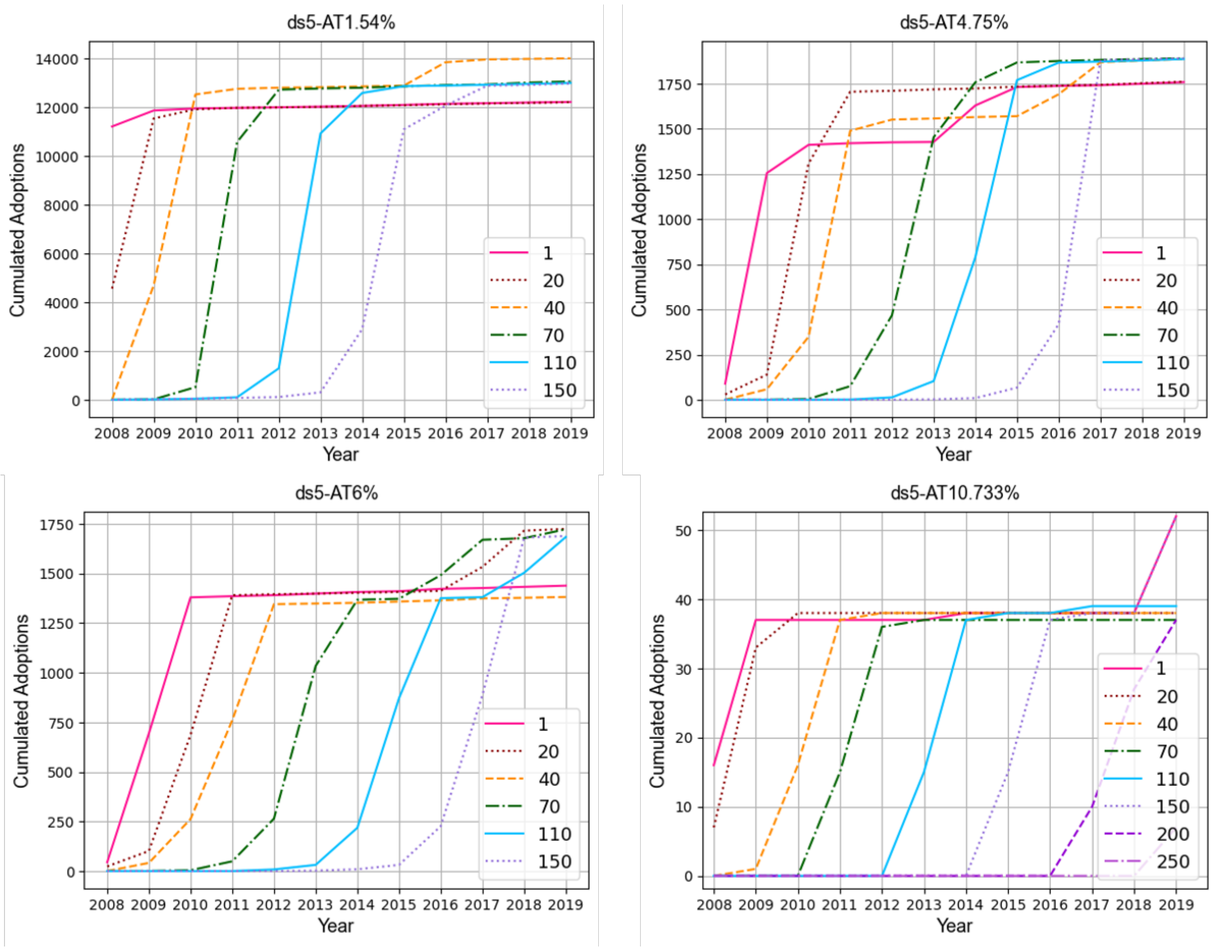


Figure 12: Cumulated adoptions for varying interest threshold thresholds for the required proportion of adopters in a 500m radius (1.54% (top left), 4.75% (top right), 6% (bottom left) and 10.733% (bottom right) for the simulation years 2008 – 2019 (scenario ds5).

4.2.6. *Local Pressure Large Radius (ds6)*

The adoption patterns for local pressure within a large spatial radius, as visualized in figure 13, shows a very binary picture. Different adoption thresholds have little impact on the overall behavior and the system shows concentrated adoption peaks (often one to two years) that shift to later simulation years with increasing threshold. Higher thresholds increase the spread to other years, albeit to a small amount. This scenario sees even larger stochastic deviations than ds3 and ds5, as in the same parameterization adoption took off only in some runs. Due to the large radius, these cases determined the overall adoption behavior.

[24] 1.54%, 4.75%, 6% and 10.733%.

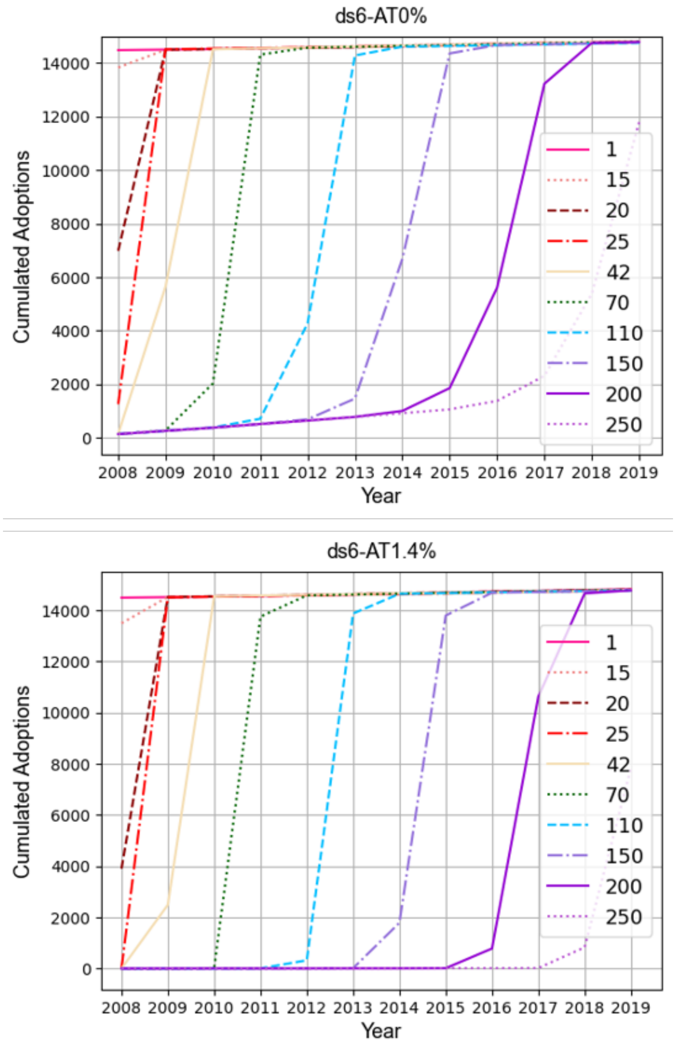


Figure 13: Cumulated adoptions for varying interest threshold for the required proportion of adopters in a 2,500m radius (0% (top), and 1.4% (bottom) for the simulation years 2008 – 2019 (scenario ds6).

4.2.7. Discussion of Dynamic Scenarios

While the general behavior of the introduction of interest propagation (delayed onset, spreading out adoption and lower adoption levels for high interest thresholds) was no surprise, the investigation showed additional critical points where run-away effects occurred and gave insight into model robustness at different parameter levels. Additionally, it identified parameter regions where stochastic behavior made overall model behavior hard to predict and indicated where interesting model behavior can be expected.

5. Concluding Discussion

The adoption of PV systems has become an increasingly important goal for policymakers seeking to promote sustainable energy use. In order to guide these efforts, simulation studies can provide important insights into the factors that influence the adoption of PV systems, and the effectiveness of various policy interventions.

The present study explored several scenarios to investigate the impacts of financial benefits, (relative) NPV, social pressure, and local pressure on the adoption of PV systems. The results reveal important insights that could guide policy implications for increasing the adoption of PV systems as well as guiding deeper inquiries, in particular with respect to critical points and model robustness.

The scenarios on normative pressure showed that the adoption patterns were predictable and concentrated for low thresholds, but changed drastically beyond these points, shifting to different years and becoming less reliable. They feature run-away effects, tipping points and exhibited a high level of stochasticity, particularly when being close to tipping points of the system. For local pressure, this was particularly seen with contingencies in local pockets of adoption. Policymakers could incentivize community groups formation to increase social pressure on adoption; for local pressure they could target local communities with a higher adoption rate to create concentrated areas of adopters.

The scenarios on monetary evaluation showed shifting adoption patterns to years with high (relative) NPV. This suggest that policies that incentivizing a higher financial return could encourage adoption for agents that require a higher net benefit. For RNET, policymakers could consider policies that compare the NPV of the PV system to others to incentivize adoption and create social pressure for adoption.

From a policy view, policymakers should consider a combination of financial incentives, social and local pressure policies to encourage adoption. Policies could be designed to create long-term plans, incentivize community groups, and target specific communities to encourage concentrated adoption.

While helpful for tools and methods, this research should not be seen to directly give policy recommendations or to show real-life dynamics that can be related to observed past dynamics. Rather it exemplifies the qualitative dynamics that play a role in adoption decisions driven by monetary factors and normative pressures while interest propagation is taken into account. PVact is capable of producing dynamics, tipping points and runaway effects. This provides a starting point for a more in-depth investigation on other factors involved.

5.1. Limitations & Future Work

This investigation was limited by the constraints of a conference paper, requiring a narrow focus on a limited set of decision factors. Large stochastic variation, especially in scenarios with large local radius, posed additional limitations. More thorough analysis of tipping points and stochastically sensitive parameters of was out of scope, despite examining over 650 parameter combinations.

The model's unrealistic behavior at the start of the simulation, due to limited opportunity for coordination and interaction between the agents, caused a significant initial bump in adoption. While prediction, coordination optimization through learning or a realistic diffusion process was not the aim of the model, this is an important point to consider.

Due to data availability, the study only analyzed pre-pandemic years, missing potential psycho-social effects and energy market disturbances. A new survey is planned to gather current data and update the model for a post-pandemic situation that reflects the energy crisis starting in 2022.

The study investigated individual effects within a complex web of behavioral, cognitive, social, attitudinal and socio-economic factors. Social pressure and NPV and sensitivity to these factors are likely to vary across the population. Investigating them in isolation merely suggests potential dynamics and research questions.

Future research aims to explore the interplay of monetary and social factors, household attitudes, and address stochasticity more systematically and thoroughly.

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