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Evaluating the role of social networks in just energy transition

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EVALUATING THE ROLE OF URBAN SOCIAL NETWORKS IN JUST ENERGY TRANSITION

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An electronic version of this thesis is available at http://repository.tudelft.nl/.
The code and data used in the model is available at https://github.com/aarsundaram/Solar-Adoption-Model-ABM

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EXECUTIVE SUMMARY

With over 60% of the world's population estimated to live in cities by 2030 it has never been more important to focus on reducing emissions from the built-environment sector to combat climate change. However, adoption of new technologies to reduce emissions is a complex sociotechnical process. Decisions of households to adopt are not just influenced by economic factors, but also by the type of social networks they are embedded in.

This indicates, there are implications for policy-making if the relation between how social networks influence policy interventions is understood. However this relationship is not clear: literature shows that the same policy while performing effectively in an integrated society can have the opposite, even adverse effect, in a socioeconomically segregated network. Despite comparative studies between networks being performed, there is little insight into a systematic relationship between underlying networks and effectiveness of policy interventions.

This thesis fills this gap in understanding by building an Agent-based Model (ABM) initialised with synthetic household population from a case-study of Albany County, (New York, USA). It uses rooftop solar panel adoptions as the choice of technology for this study. The ABM which is grounded in the Theory of Planned Behaviour (TPB), models social influence using Relative Agreement Theory and models the underlying social network using the concept of 'Circles of Influence' to develop two different social network scenarios in the synthetic population: integrated and segregated networks, in order to study how different policies perform depending on the underlying social network structure they are deployed in. The Key Performance Indicators (KPI) used to measure policy performance in the context of just energy transition are: overall adoption rates, adoption rates of income-groups and cost of policy.

Key results of this study include:

- Financial Incentives such as flat tax-credit schemes for solar panel installations despite rendering cost of panels low, can result in poor adoption rates in a segregated network. This effect is worsened if the size of the income-group is small.
- Flat tax-credit schemes when deployed in integrated networks, performs better (in improving adoption rates across income groups) even if it renders cost of solar panels high, showing the effect of the underlying network on policy performance.
- Policies perform consistently better in integrated networks, revealing the importance of diverse communication channels and more credible information sources in improving adoption rates in segregated networks.
- Policy of seeding influencers or information agents, although costing more does not result in better adoption rates. It recommended to plant credible information sources and adopters in known-circles and personal networks as opposed to mass-communicators.

Given that the most commonly used policy interventions are flat-tax credit schemes, rebates and influencer-seeding, these results deepen the understanding of these policies' performances based on the underlying social network. The outcomes of this study can therefore assist policy-makers in further designing effective energy policy interventions for their locality's social networks to ensure improved adoption rates across income groups, thereby ensuring just energy transition.

In future studies it will be interesting to explore the role credible information sources in encouraging attitude-driven adoption and the impact information policies that tailor to personal networks and known-circles. To further realistically model real-world interactions, studies can infer social networks from existing data sources such as Call Data Records, retweet networks etc.

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ACKNOWLEDGEMENTS

This thesis is the result of a certain kind persistence that I never knew I had but always hoped I would. There were many times in this thesis when the task seemed undoable not just due to computational demands or lack of data front, but also on the personal front. It feels extremely satisfying to behold the final output after this struggle: I'm sure I would look back on this experience with rose-tinted glasses, as is always the case with the past. This statement has been repeated so often it has lost its effect, but I still want to emphasise that this work would not have been possible without my first supervisor Trivik Verma. I learnt to put more trust in my abilities thanks to his unfailing support and mentorship.

My heartfelt thanks to Juliana Goncalves for her excellent advice and thought-provoking questions that forced me to put more thought into how I wrote and presented my work. I also thank my chair Alexander Verbraeck and Amineh Ghorbani for your detailed feedback and support during this process.

This acknowledgement would not be complete without the phrase 'in these pandemic times': considering everything meaningful on the professional front has happened virtually, it will be easy to dismiss this entire experience as something that could have just probably happened in my head. My constant companion through this period: my humble old MacBook Air which I put through quite a lot in the last two years reminded me that this was not all in my head by breaking down 2 days before submitting this document: I visualize my situation as akin to that of Chuck in Castaway mourning for Wilson. For being there in person, I also thank the wonderful friends I made here at Delft without whom the last two years would have been hard to plough through.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

1.1 OVERVIEW

With more than 60% of the world's population expected to live in urban areas by 2030 and general improvement of energy access throughout the world, it is of utmost importance to focus on effective policies to enable energy transition to tackle rising emissions (Nations et al., 2018). Carbon emissions resulting from operational use (heating, cooling of buildings) constitute 28% of the world's total, highlighting the important role that decarbonization of the built-environment plays in reaching climate goals (Anderson et al., 2014). Decarbonizing this sector has been found to be one of the most economical means to mitigate the costs of climate change (World Green Building Council, 2019). Because energy transition involves shifting from conventional fossil-fuel based sources to cleaner energy sources, a transition at the residential level is dependent on adoption of energy-efficient technologies. Be it heating, cooling or lighting, households are expected to make green adoption decisions to enable this transition to occur (Hesselink & Chappin, n.d.). Crucial to improving bottom-up energy transition therefore is the study of new technology adoption (Valente, 2012). An individual's decision to invest and make a shift to a new energy-efficient technology is a complex sociotechnical process and is far from being based on just financial concerns. Barriers to adoption include split incentives, lack of information, adherence to social norms among many others (Hesselink & Chappin, n.d.). Empirical research has shown that perception of innovations and their benefits plays a more important role than economic incentives themselves, with these perceptions directly subject to social influence (Huang et al., 2019). The importance of information in influencing new technology has been established in various studies (Wang et al., 2018),(Li et al., 2019), (Moglia et al., 2018),(Wilson & Dowlatabadi, 2007). Empirical and theoretical research confirm that incorporating social dynamics and network effects in models that serve as policy support instruments will result in successful adoption programs (Valente, 2012),(Pearce & Slade, 2018),(Huang et al., 2019).

However, despite the well-established implications of social network structures on effectiveness of policy design, there exists no systematic understanding if there is a clear relationship that given an underlying social network of an urban space, a certain policy intervention performs better in one type of network as opposed to another (Buskens & Yamaguchi, n.d.),(Anderson et al., 2014). For example it is not clear, if given that an urban space's social network is socioeconomically segregated, a policy that seeds low-income groups performs much better than an information policy. If the urban space is relatively more integrated, is an information policy more effective at increasing adoptions than the more expensive policy alternative of seeding?

The same policy performing better in a socioeconomically integrated society than in a segregated one indicates that not incorporating network structures into policy design can have implications on equitable access to energy-efficient technologies. For example, it has been shown that solar PV adopters tend to be rich, socioeconomically advantaged groups (Brugger & Henry, 2019). Although upfront costs of installing solar PV maybe high and therefore unappealing to low and middle income groups, long-term benefits that come from increased savings, protection against rising electricity prices and reduced emissions can be more useful to such groups. Even with financial assistance such groups can be hesitant to invest in unfamiliar technologies and this is where information from acquaintances and recommendations from known persons who have already adopted the technology can play a big role in helping these groups in making an adoption decision. This is the context within which just transition is discussed the following chapters: designing policies to improve equitable access to energy-efficient, emissions reducing technologies to all socioeconomic groups. In the context of new technology adoption it translates to maximising not just overall adoption rates of the urban space, but also adoption rates of low and middle-income groups.

This research aims to evaluate how effectiveness of policy interventions aiming at improving adoption rates are influenced by the underlying social network structure of the urban space, in the context just energy transition. Using modelling methods, it aims to study the relationship between adoption rates across different socioeconomic groups and the network type that a policy intervention (such as information policies, seeding programs, tax-rebates) is deployed in.

The outcomes of this thesis are twofold: a) Scientific Relevance: to contribute to the body of literature that is systematizing the relationship between network structures and effectiveness of policy interventions in the field of energy-efficient technology adoption and b) Societal Relevance: to result in improved policy support that enables policy-makers to design policy instruments that are tailored to the underlying social networks so as to maximise the reach of energy efficient technologies and strive towards a just energy transition in cities.

1.2 KNOWLEDGE GAP

A survey of literature consisting of studies at the intersection of energy transition policy and information spread through social networks, reveals gaps in understanding of the relationship between the underlying network topology and the effectiveness of different policy interventions.

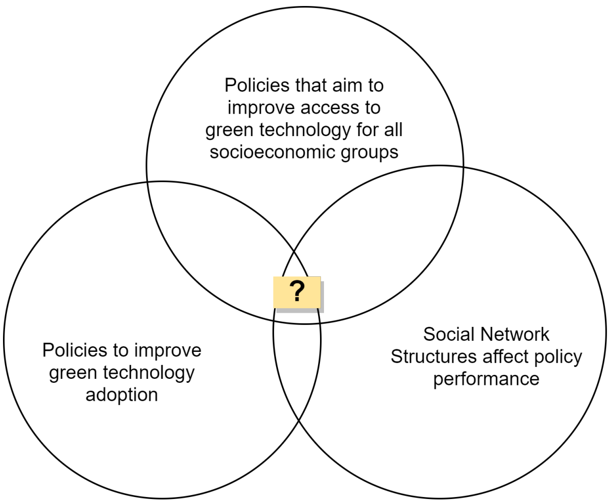

Figure 1.1: Knowledge Gap: there is no systematic understanding of the influence networks have over policy interventions that aim to improve access to green technology in the context of just transition.

Figure 1.1 visualizes the knowledge gap addressed in this thesis visually: it is understood that social networks influence adoption, however there is no systematic understanding how in the context of just transition.Need for Tailoring

Policies to Underlying Network The majority of studies that tested information policy interventions on their social network models highlight the need for policymakers to rethink their information campaigns. Instead of spending resources on unstructured mass campaigns these studies call for designing policy interventions that are tailored to their underlying social network structures, addressing issues such as segregation and clusters in networks. While (Wang et al., 2018) observed the detrimental effects of enhanced communication in scale-free networks as observed in cities and neighbhorhoods connected by social media, (Mittal et al., 2017) see a positive impact of the same policy in a small-world network, suggesting that the same policy can perform well or badly depending on which network structure it is introduced into. (Rasoulkhani et al., 2017) and (Rasoulkhani et al., 2018) conduct studies comparing 5 different network structures and measure their influence over households' decisions to adopt water conservation technologies. They observe that adoption numbers depend on the underlying network, with scale-free structures leading to a significantly lower number of non-adopters in the study area. (Moglia et al., 2018) similarly note a significantly higher adoption rate in scale-free network structures in their study modelling adoption of new technology, namely electric vehicles. (Barbuto et al., n.d.) in their study modelling adoption of new technology, conclude that network structure emerges as the important driver of adoption dynamics. Addressing Energy Justice and Equitable Access to resources (Brugger & Henry, 2019) note that incentive policies that may have worked well in a relatively integrated society, can lead to extremely unjust outcomes within segregated societies. Most studies which addressed adoption of rooftop solar PV, were concerned with keeping in view the need for equitable distribution when designing policy interventions. This is mostly because of different levels of socioeconomic segregation that is observed globally and that adopters of solar photovoltaic systems (solar PV) tend to be from the rich socioeconomically well off groups (Rai & Robinson, 2015). Papers discussing PV poverty alleviation programs like (Li et al., 2019) note how the adoption behavior in reaction to a policy intervention like rebate or information campaign is different in low-income households as compared to high-income. Further evidence to support the different adoption dynamics between low and higher income groups can be found in (Jones & Warren, 2020) which studies adoption of solar home systems in Bangladesh. They find that local community organizations play a significant role in increasing adoption rates in low-income groups.

A survey of the literature reveals that typically studies run along one of two strands: one that discusses the impact of network structures on policy interventions and the other set exploring the different performances policies have on low and high-income groups. Very few studies explicitly study impact of network structures on policy interventions and their consequences on its performance on different socioeconomic groups. As (Brugger et al, 2019) note, if a policy intervention leads to worse outcomes for low-income groups in a segregated network structure, it calls for policy-design that is conscious of the network structure. This study aims to work at this intersection to study how underlying network structure impacts performance of policies that aim to improve adoption rates of energy-efficient technologies in different income groups, thereby ensuring adoption policies bring about just outcomes.

1.3 RESEARCH QUESTIONS

The survey of literature reveals that there indeed is a crucial relationship between the social network and the policy intervention. It is clear that there is a need to tailor policies according to the type of network observed in the community, as the same policy can have less effective and possibly adverse effects in one type of network compared to another. It is revealed that there is no systematic study yet, into what type of policy interventions work for a given network and how it impacts performance for different socioeconomic groups, thereby identifying a crucial knowledge gap. Considering the need to tailor policy interventions to the underlying network type, this study will further focus on studying how the underlying network structure influence effectiveness of policy interventions for enhancing a just energy transition. The results of this study will have implications for policy design and can help design improved adoption programs that make access to new green technologies equitable.

The main research question addressed in the study is the following:

"Given an urban social network into which a policy intervention for enhancing just energy transition has been introduced, what are the effects of the social network's structure on the policy's effectiveness?"

The central research question is quite broad and overarching in its use of terms. It has therefore been broken down into three sub-research questions which together aim to address the central problem.

1.3.1 Sub-Research Questions

Sub-Research Question 1

How can the underlying social network structure and interactions within an urban space be effectively modelled?

This study assumes the existence of an understanding of the underlying social network structure of the locality being studied. This sub-research question therefore addresses the problem of realistically modelling network scenarios that the urban space may contain. This involves realistically simulating interactions between the residents of an urban space. Research has several insights into the basic rules that urban social networks are built around, such as distance decay and homophily. Several studies leverage the concepts of homophily, whereby the likelihood of two agents interacting is higher if they belong to the same socioeconomic group or income group (more colloquially: birds of a feather flock together) (Girvan & Newman, 2002). Research in social networks also shows the importance that distance plays in formation of social ties: people's social groups comprise majorly of geographically proximate connections, with a small number of non-local connections (Rai & Robinson, 2015), (Watts & Strogatz, 1998). Newer studies show that urban communities are shown to be less geographically clustered than they are socially (Herrera-Yagüe et al. (n.d.)).

Aside from using social network principles like homophily and distance decay to model networks, there also exist data-driven methods to model realistic social networks. Such methods leverage rich datasets generated by human activity to estimate how residents of an urban space are connected and how they interact: mobility data, call data records (CDR), Twitter followers and retweet networks, Facebook friends networks and data from other online social networks (OSN). Despite being granular, real-life data, these can pose several issues that the modelling stage: data access at the level of an entire city are rarely available at multiple points in time. Data such as CDRs despite being the closest to using data to observe inter-personal interactions at individual level are riddled with privacy concerns and are proprietary.

This study will synthesize results of social network research, instead of using data-driven methods to infer real-life social networks. This will enable us to model realistic underlying social network scenarios so as to study the effects of network structure in a manner that is also compatible with other model components.

Sub-Research Question 2

How do the characteristics of the underlying social network influence performance of the policy intervention?

This question is closer to answering the crux of the central research question. Answering the previous sub-research question yields the "given" underlying social network of the urban space. This enables us to study under specified network conditions, how different socioeconomic groups make adoption decisions in reaction to policy interventions. As discussed earlier, some studies like (Brugger & Henry, 2019) point toward the direction that policies can perform poorly and sometimes adversely for low-income groups under segregated network conditions. Low-income and disadvantaged socioeconomic communities are revealed to place significantly higher trust in their local community leaders than other groups suggesting a mass information campaign may not be as effective as a policy that seeds influencers for such groups in a segregated society. This study will verify such hypotheticals, by designing experiments so that effects of policy interventions like flat-tax credits, targeted seeding campaigns can be studied under integrated/segregated network scenarios and policy performance can be measured on different income-groups. Therefore the measurement of success of a policy intervention will not just be based on overall adoption rates (of the whole urban space) like most studies, but will also include adoption rates of income-groups.

Sub-Research Question 3

Given the underlying social network, how can policies be designed to ensure a just energy transition?

This will involve synthesising the results from answering the first two research questions, to result in a discussion of policy implications of this work. For a policymaker, given the underlying social network of the urban space they govern, this work will lead towards strategies to design interventions to enable equal access of energy efficient technology across communities (divided economically or geographically).

The research question will be answered using a modelling approach: a data-driven Agent-based Model (ABM) grounded in Theory of Planned Behavior is built, synthetic agents are initialized and network scenarios are modelled. Experiments are designed and implemented on the resultant model, to answer the central research question and thereby evaluate the role of social networks on policy performance in the context of just energy transition. In the following chapters, the ABM is conceptualized, implemented, calibrated, verified, validated and experimented upon. A case-study of rooftop solar panel adoption in the region of Albany County, New York State in the United States of America is chosen for the purpose of initializing the data-driven ABM. Justifications for the choice of technology and geography is elaborated upon in later chapters.

1.3.2 Outline of Thesis

The thesis is outlined as in Figure 1.2: Chapter 2 (Literature Review) outlines previous work in the area of social networks and modelling green technology adoption. Advantages and disadvantages of features of models built by different studies are discussed in the light of building a model to answer research questions of this study. At the end of this chapter an outline of requirements of the model is arrived at. Chapter 3 (Methodology), conceptualization of the ABM is discussed: background to the Theory of Planned behavior, the concept of Circles of Influence in developing the network scenarios is introduced.

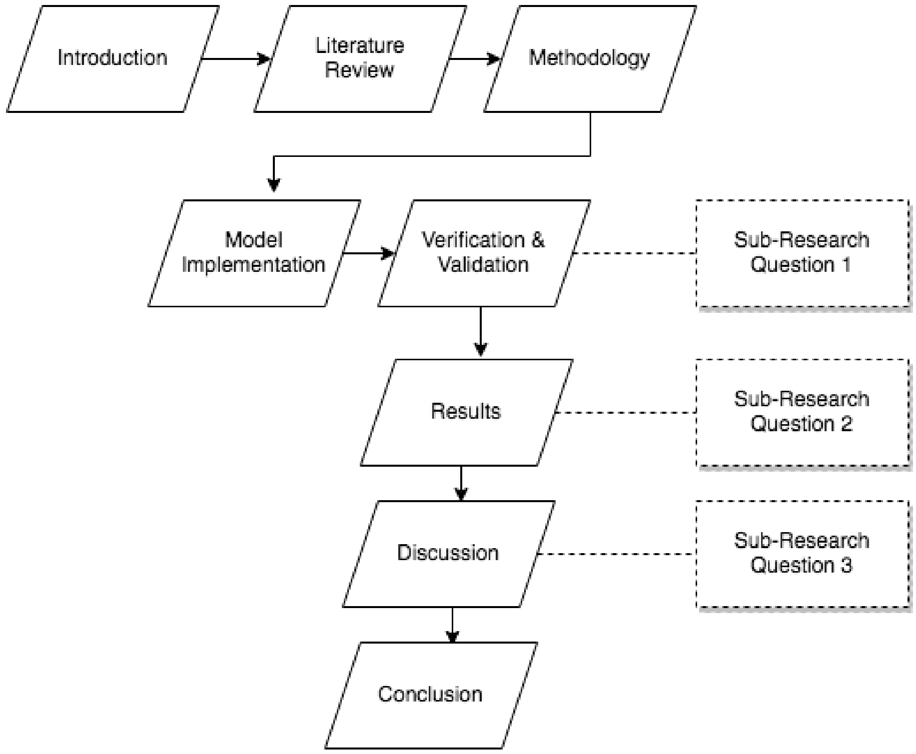

Figure 1.2: Outline of Thesis

Chapter 4 (Model Implementation) details the implementation of the model: how synthetic population was generated, how survey data was used to implement Theory of Planned Behavior and how network interactions are modelled to result in two network scenarios. Experiments are designed so as to answer the research questions listed above. This chapter aims to answer Sub-Research Question-1 whereby the underlying network is realistically modelled. Chapter 5 (Verification and Validation) as the name suggests takes several steps to verify and validate the baseline model that results from the implementation chapter. Chapter 6 (Results) runs the verified and validated model through experiments designed towards the end of Chapter 4 so as to answer Sub-Research Question-2. Chapter 7 (Discussion) puts together the results arrived at in part in the previous chapter and attempts to analyze them in light of application to real-life, in light of the assumptions that were made in the modelling process and how it contributes to existing understanding of the topic in literature. In doing so, it aims to address Sub-Research Question-3 which synthesizes the results of questions 1 and 2 in the context of implications to policy-making. Chapter 8 (Conclusion) revisits the research questions in light of new results, summarises the key findings once again and presents avenues for further research in this field.

2 LITERATURE REVIEW

2.1 BUILDING ON EXISTING STUDIES

The goal of this study is to evaluate the role of social network structures in influencing performance of policy interventions that aim to improve adoption rates of new green technologies across socioeconomic groups to achieve a just transition. Being a modelling study, the model that is built to answer the central research question will require the following features:

- Heterogeneous Agents: agents will have different attitudinal and demographic variables, so as to incorporate the realistic behavior such that not only financial considerations influence adoption decisions, but also social norms, opinions, perceptions of complexity etc.
- Realistic network scenarios: Agents need to be connected to other agents via social networks (which can be a single-level or multi-level network) in a manner that realistically models how agents interact and exchange information in the real-world. Network scenarios need to developed that will enable the modeller to test policy interventions to measure their performance under socioeconomically integrated or segregated network types.
- Decision Rules that incorporate social networks: Agents need to act (adopt or not) via decision rules that more than just aim at financial utility maximization or cost minimization. The decision rule needs to encompass "perceptions" of affordability (instead of purely rational, economic considerations assuming perfect information), the importance that people give to social acceptability of a decision before taking it, social norms/peer-pressure, their own opinions about a product etc.
- Social Influence: the model should include social influence such that interaction between agents holding different perceptions and opinions about the technology should lead to the less decided agent being positively influenced by the more strongly opinionated one. This will lead to attitudes and perceptions evolving over time for the agents depending on their social networks and flow of information.
- Policy Levers: the model should contain decision-rules that are not just dependent on social influence alone, but also include resource availability as an important component. This is because just being positively disposed to the technology may not be enough to make an adoption decision: the agent should also have enough financial resources to be able to invest in the technology. Economies of scale and the technology learning curve will lead to the prices of technologies like solar PV, heat pumps etc., to reduce. The model should include these exogeneous factors into the decision-rules of the agent such that they react to policy interventions.

Several studies exist in current literature that have included one or several of the features above for their respective problem statements. In this chapter, an overview of these models and their features are provided. Advantages and disadvantages of each are discussed in the light of what features will be included in the model that will answer the central research question of this study, thereby building upon existing studies.

2.2 OVERVIEW OF MODELLING APPROACHES

In this section, a brief overview of the evolution of modelling methods in this field is provided.

The area investigating the role of social networks in the adoption of energy-conserving technologies at the residential level can be traced back to some seminal papers that originate in studies of diffusion of innovation and social-psychological foundations of energy-efficiency programs such as (Coltrane et al., 1986),(Everette Rogers, 1995) and (Abrahamse et al., 2007). (Coltrane et al., 1986) is one of the earliest papers that stresses the importance of existing social networks in residential energy conservation. Efforts in literature to study adoption of new energy-conserving and green technologies has however remained relatively disparate from the study of spread of information and influence through social networks up until the last few 3 to 4 years. Especially in the last decade, plenty of new-technology adoption modelling studies have emerged in the context of energy transition using techniques of Agent-based Modelling (ABM). However before the emergence of ABM techniques there were (and still are being used widely in adoption modelling) several modelling approaches that were not agent-based, but equation-based. The overall categories are adapted from a review on studies in innovation diffusion by (H. Zhang & Vorobeychik, 2019) and can be viewed in tabular format in Table 2.1.

Equation-based models were among the earliest approaches, with the most popular one being Bass' S-shaped pattern of aggregation adoption over time of a new technology, where the probability of adoption was modelled to be a linear function of the number of adopters (Bass, 1969). While useful for a theoretical understanding of the problem, the disadvantages of equation-based approaches are that there are no individual agents. Behavior of agents are homogeneous and only observed in the aggregate. Such models also assumed a fully-connected, homogeneous network where everyone interacts with everyone with equal likelihood which is far from reality (H. Zhang & Vorobeychik, 2019).

Economic models followed equation-based models with individual agents being modelled with some attributes that factor in their decision-making. However all agents were assumed to be purely rational and utility maximising, and have full information (Rai & Robinson, 2015) which is far from realistic behavior and ignore important concepts such as perceptions of affordability and complexity which often play a bigger role in decision-making than actual affordability. Spread of social influence through network structures were explored by studies like (Günther et al., 2011) which tests several network structures like Small-world (Watts & Strogatz, 1998) and Scale-free (Barabási & Albert, 1999), generating connections based on geographic proximity and opinion-leadership. Although this study is bracketed under utility-maximisation studies, the utility is not just based on profit-maximisation or cost-minimisation like other studies, but also includes perception of quality, levels of information etc as determinants of adoption behavior. However the choice of what are the determinants of adoptive behavior is not systematic or grounded in theory. This gap was later filled with the introduction of cognitive models that explain decision-making of agents extending beyond purely rational utility-maximising behavior (Moglia et al., 2018).

Cognitive models such as Theory of Planned Behavior (TPB) by (Ajzen, 1991), Theory of Emotional Coherence (TEC) by (Wolf et al., n.d.) and Consumat Model by (Jager et al., n.d.), are increasingly used in combination with Agent-based Modelling to model adoption of new technology. Grounded in socio-psychological theory, with the ability to elicit the required variables via survey data, these models are appealing candidates for integrating into Agent-based models that study influence of social networks in adoption of energy-efficient technology. However a key caveat remains in using these modelling approaches, whereby the manner in which these theories are implemented can greatly influence the outcomes of the model (Muelder & Filatova, 2018)

Statistical Approaches such as Discrete Choice Models (McFadden, 2001), are used widely in studying people's motivations and choices in transport, logistics, environmental and health fields (Haghani et al., n.d.). While these models elicit the weights or importance that people give to different attributes while picking one choice from among others, it does not provide avenues for explicitly modelling their interactions with other people and how that factors into their decision-making.

2.2.1 Two Major Approaches

The studies above can be categorized into two broad approaches: a) Mathematical Models and b) Agent-based Approaches (see Fig 2.1).

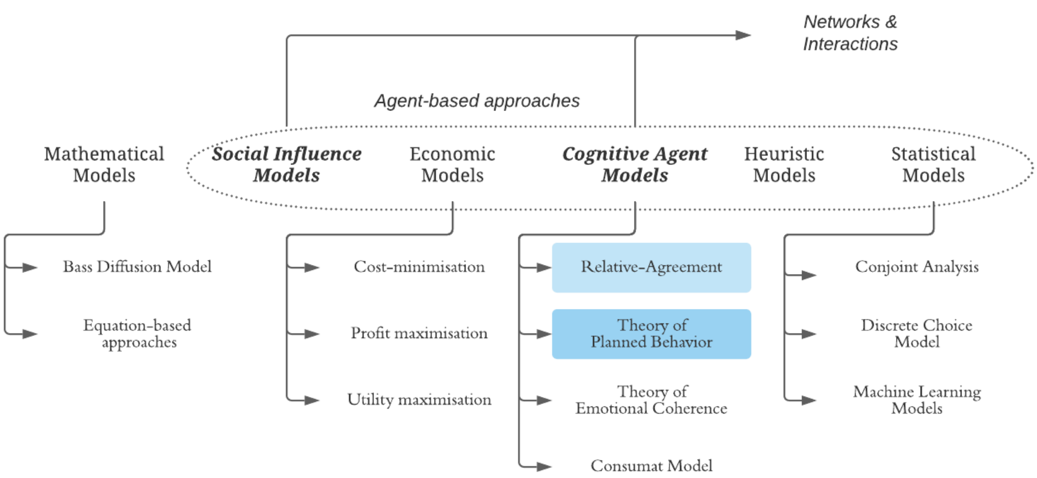

Figure 2.1: Approaches towards modelling innovation diffusion

Equation-based models such as Bass Diffusion Models are categorized as Mathematical models whereas the rest (Economic, Cognitive Agent and Statistic Models) fall under Agent-based approaches. Going forth to determine model features that are best suited to answering this study's central research question, equation-based models do not fit the purpose, as there is no provision to model individual agents with heterogeneous attributes. Agent-based models are a natural fit for this problem statement, whereby agents can be initialized using existing datasets and interactions can be modelled between them to study the effects of social networks. As can be seen in Figure 2.1, Cognitive Models and Utility Maximisation models (under Economic Models) provide the additional advantage of allowing the modeller to not only include non-price factors in decision-making but also connect the agents with a social network such that interactions can be simulated between them. The following section discusses which type of agent-based model will be used among these agent-based approaches.

2.3 AGENT-BASED APPROACHES

The popularity of ABMs in modelling studies have enabled the two previously disparate fields of social networks and energy transition studies to merge and provide opportunities for researchers to introduce more heterogeneity when modelling inter-

Table 2.1: Evolution of Modelling Methods in studying innovation diffusion and adoption of new technologies. Categories used for 'Modelling Method' has been adapted from the review of innovation diffusion studies by (H. Zhang & Vorobeychik, 2019).

Modelling Method	Type	Strengths(S)/Weaknesses(W)	Studies
Mathematical Models	Bass Models	(S) Useful for conceptual understanding of problem. (W) Does not study individual interactions. Assumes fully-connected network. Lack of decision-variables that can be impacted by policy-levers.	(Bass1969) (Hopp, 2004), (Peres et al., 2010)
Economic Models	Cost Minimisation	(W) Agents driven purely by financial considerations	(Faber et al., 2010)
	Profit maximisation	(W) Once again, only financial considerations drive decisions.	(Sorda et al., 2013)
	Utility Maximisation	(S) Scope for including more decision factors thereby introducing heterogeneity. (W) Utility is subjective and some model parameters such as social utility have to be theoretically determined or calibrated.	(Broekhuizen et al., 2011), (Holtz & Pahl-Wostl, 2012), (Günther et al., 2011), (McCoy & Lyons, 2014), (Palm, 2016)
Cognitive Agent Models	Relative Agreement Theory	(S) Allows for social networks to influence individual decision-making. (W) Model parameters governing interactions are theoretical/cannot be empirically derived.	(Deffuant et al., 2002)
	Theory of Planned Behavior (TPB)	(S) Scope for including heterogeneity, with parameters that can be derived from empirical data and surveys. (W) The factors are greatly dependent on the survey questions used to elicit them and the way TPB is implemented (Muelder & Filatova, 2018)	(Kaufmann et al., 2009),(Schwarz & Ernst, 2009),(Sopha et al., 2013), (Rai & Robinson, 2015)
	Theory of Emotional Coherence	(S) Greater scope for including irrational decision-making factors and heterogeneity in agent behavior. (W) Needs survey data specifically designed for building this model.	(Wolf et al., n.d.)
	Consumat Model	(S) There is heterogeneity introduced in the choice of decision-making process, making the process more realistic. (W) Model parameters such as need for satisfaction and uncertainty are difficult to be empirically derived or requires very detailed and representative surveys.	(Jager et al., n.d.),(Schwoon, 2006)
Statistics based models	Discrete Choice Models	(S) Useful to understand the weights attached to attributes of the product and using it, predict choices for new alternatives. (W) Does not include social interactions or social influence explicitly in the choice process	(Train, 2009), (Galán et al., 2009), (Dugundji & Gulyás, 2008), (Tran, 2012)

actions of agents who are connected via social networks.

The abundance of Agent-based modelling studies in the area of modelling adoption of new technology can be attributed to two key advantages: a) Modelling agent heterogeneity and b) Providing for the fine-grained modelling of agent interactions through social-networks. Since 1960s, there have been different approaches aimed at modelling process of diffusion in the field of epidemics, innovation, information spread etc. Specially in the last decade, there has been a spurt in the use of ABMs in modelling technology adoption, especially that of energy-conserving technologies (Rai & Robinson, 2015). ABMs in the area of modelling technology adoption have been approached from two main standpoints: a) Conceptually-driven ABMs and b) Empirically Driven ABMs (H. Zhang & Vorobeychik, 2019). Conceptual ABMs like (Axelrod & Lehman, 1993) and (Epstein, 1999) were exploratory in nature and aimed to understand system behavior under different conditions from a theoretical perspective. Empirically-grounded models on the other hand were data-driven and they were used in the context of providing policy-support. Data-driven ABMs types are the most prevalent in modelling studies today (Kiesling et al., 2012).

2.3.1 Data-Driven vs Classical ABMs

(Axelrod,1993) proposed the KISS principle (Keep it Simple, Stupid) whereby ABMs are used to understand and communicate the problem statement. Using the argument of 'Occam's Razor' the idea is to build a 'toy model' that is simple, easier to implement, verify and analyze than a complex model. These models are conceptual and abstract.

The other school of thought guiding the use of ABMs is that of KIDS (by (Edmonds & Moss, 2006)) which stands for 'Keep it Descriptive and Stupid'. This approaches tries to get as close to modelling the real-life phenomenon as is possible, without regard for the complexity. After approximating the target phenomenon as close as possible, decisions can then be taken as to which parts can be retained and which can be left out. The merits and disadvantages of each approach is debatable; however there is consensus in literature that there needs to be a middle ground between the 'too simplistic' and the 'overly complex' approaches: using data (Hassan et al., 2008).

In Data-driven ABMs (DDABM), data drives simulations as opposed to abstract and theoretical parameter values (such as uniform, triangular or gamma distributions). In Data-driven approaches, empirical data is collected from the target phenomena and is used not just at the simulation phase, but also during initialization and evaluation of the model as is shown in Figure.

The sections below discuss the features offered by the agent-based approaches that most suit this study's problem statement of evaluating social networks and their role in policy performance.

2.3.2 Cognitive Models

The key studies outlined in Figure 2.2 take different approaches to model the underlying social network, agents' decision-rules and social influence models depending upon their research question. For example, the goal of (Rai & Robinson, 2015)'s paper is to produce a predictive model of adoption of rooftop solar for the city of Austin. Therefore, after initializing their agents from survey data and census, they fit the model to historical adoption curves in order to initialize the underlying network parameters.

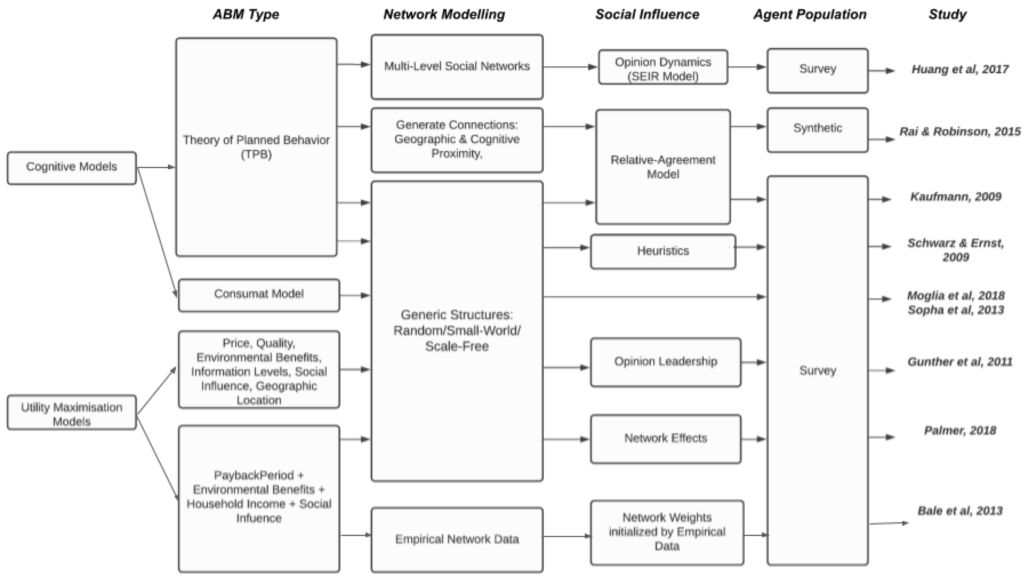

Figure 2.2: Key Empirical Agent-based Modelling Studies in the area of social networks and new technology adoption

(Huang et al., 2017) on the other hand, focus on exploring the role of multi-layer social networks (a physical social network and an online social network) to examine the spread of information through agent networks via Information Agents/Media agents and how this in turn influences adoption decisions. They test out a range of small-world and scale-free networks on the agent population for various scenarios. (Kaufmann et al., 2009)'s model is similar to (Rai & Robinson, 2015), except that their underlying network is a generic small-world network that is calibrated to fit historical adoption curves. (Rai & Robinson, 2015) while also fitting model parameters to the historical curve, however adds the realistic component to their network model whereby links are generated based on the principle of homophily and not randomly. Both papers model social influence based on (Deffuant et al., 2002)'s seminal paper outlining the Relative Agreement Theory.

(Schwarz & Ernst, 2009), while calibrating their agent attributes using Theory of Planned Behavior, use a different method to assign decision-rule for agents. Depending on agent attributes, the agent either chooses a TPB-based decision-rule or it follows a decision-heuristic for adoption. The agent networks, similar to (Kaufmann et al., 2009) are small-world, however with the additional constraints being spatial proximity and lifestyle similarity.

Another approach that tries to realistically model decision-rules of agents is found in (Sopha et al., 2013)'s use of the Consumat Model. In their ABM modelling adoption of heating systems in Norway, the agents randomly choose between 4 decision-rules: repetition, deliberation, imitation, and social comparison. It can be argued when modelling agent decision-making, this approach lends more heterogeneity to agent behavior, as not everyone's actions can be reduced to three attributes as outlined by the Theory of Planned Behavior.

2.3.3 Economic Models: Utility Maximisation

In these type of models agents take decisions that is in the direction of maximising or minimising some chosen attributes such that their utility is maximised or crosses a threshold to signal adoption. In (Günther et al., 2011) each agent is characterized by their product preference, eco-friendliness, their information levels about the product, social influence etc. The knowledge of the product increases via contact with agents, exposure to marketing activities etc. The networks into which agents are initialized range from random, small-world to scale-free. In the case of small-world additional constraints are added where links are drawn between agents that spatially and opinion-wise, proximate. In (Holtz & Pahl-Wostl, 2012), different utility parameters are chosen according to agent-type. The decision for choosing certain utility parameters while leaving out others is however not systematic and is often grounded in expert validation or is very unique to the case-study in question. Therefore extending these models and comparing their results with other case-studies (geographic or technological) is difficult.

2.4 AGENT-BASED MODELS FOR SOLAR ADOPTION

Because this thesis aims to build a model using which the role of social networks on policy performance can be evaluated, the model does not necessarily have the mandate to be used for predictive purposes. That is, its goal is not to predict adoption curves into the future, but rather study how the adoption curves change for different socioeconomic groups if the underlying social network is varied. Although not built for predictive purposes, the resulting model still aims to be used in policy-support: so as to deepen understanding of what type of policies are suitable for which kind of underlying social networks. Therefore, it cannot be a purely theoretical "toy-model" of the KISS school of thought (Keep it Simple, Stupid) by (Axelrod, 1993). The model needs to be grounded in a realistic case-study, initialized with realistic agent population (that have reasonable distributions of age, income and household size combinations). Agents' attitudes towards the green technology in question, their perceptions of affordability also needs to be modelled realistically and need to have a realistic tie to their demographics. By grounding the agent states, decision rules, and environmental variables in real-world empirical patterns, ABMs can gain descriptive (Epstein, 1999), explanatory (Durlauf, 2012) and predictive power (Railsback & Grimm, 2011).

As mentioned in the last section of the Introduction Chapter, a case-study of Albany County in New York State of United States of America is chosen to initialize and deploy the data-driven ABM. The green technology, whose adoption will be studied is rooftop solar photovoltaics (PV). The case-study itself will be elaborated upon in the chapters discussing model implementation. However, in this section, a discussion of studies in area of ABMs and rooftop solar adoption are discussed in the light of choosing features for the model that this thesis will build.

There are a number of studies that use agent-based models to study rooftop solar adoption such as (Borghesi et al., 2013), (Denholm et al., 2009),(Palm, 2017), (Zhao et al., 2011), (H. Zhang et al., n.d.), (Rai & Robinson, 2015) and (Brugger & Henry, 2019). (Denholm et al., 2009) and (Borghesi et al., 2013) build simple-rule based models where agents' decision-making is primarily on price considerations. (Palm, 2017) and (Zhao et al., 2011) on the other hand add heterogeneity to agent behavior by adding behavioral factors into decision-making. The former uses household income and social influence, whereas the latter use survey data and census data to set their model parameters such as household income, word-of-mouth effects etc. (Palm, 2017) calibrate the model to the overall adoption curves, unlike (Zhao et al., 2011). (H. Zhang et al., n.d.) in their ABM study of solar adoption for a Zipcode in San Diego County, USA that uses machine-learning methods to first train a model to predict individual adoption behavior and then use that to forecast adoption trends: their key takeaway being the use of different datasets for calibration and validation.

Their focus is not on the network component, as its characteristics are lost in the calibration component and therefore is not explicitly modelled.

(Rai & Robinson, 2015) build their model grounded in Theory of Planned Behavior, for rooftop solar adoption for predictive purposes for the city of Austin, Texas, USA. They also calibrate network parameters to fit historical adoption curves. However, because their goal is not network inference or network exploration therefore, this modelling choice is justified. Their network component is however modelled according to small-world characteristics, where they use principles of a) homophily, whereby the likelihood of agents belonging to the same income-group have higher chances of interaction and b) distance decay, whereby they ensure these interactions are largely local and are within a realistic radius. They also model social influence by incorporating Deffuant's Relative Agreement Theory. This is a definite improvement over the past studies that try to study the effect of social networks in the context of solar adoption in particular, as they not only use survey-data to implement TPB, but also use synthetic households population, social influence modelling, some network modelling, along with calibration, validation and policy analysis. Although not in solar adoption, another model that also follows similar methods is that of (Kaufmann et al., 2009) which models the adoption of organic farming practices in two EU member states.

(Brugger & Henry, 2019) build theoretical ABMs that model solar adoption in hypothetical social networks, where they study the effectiveness of 3 solar adoption programs (feed-in tariffs, seeding and leasing programs) based on the underlying network. They model two types of networks: integrated and segregated synthetically, whereby it does not build any of the characteristics of real-life social networks such as the community structure or distance decay. The heterogeneity of the agents is very limited: only two types are initialized with either a high propensity to adopt or low. These attributes are understood to be related in someway to demographic and socio-psychological attributes such as income, age, education, political stance etc. Explicitly modelling these attributes are left to future research however and not covered in the modelling process. Two types of social networks are modelled: a)Integrated Networks: where agents are as likely to be connected others of their own type as that of others and b) Segregated Network: where agents are more likely to be connected to connected to agents with similar attributes to theirs. By modelling these two types of networks explicitly, they study how adoption varies with underlying network structure and how this influences the effectiveness of policies that promote adoption of solar technologies. This study throws key insights into the role that network structures play in policy performance: policies that depend on peer-effects need perform badly in segregated networks, cautioning policy-makers to be aware of the underlying network structures when launching an adoption program. The results are however purely theoretical; without clear decision-making rules or agent attributes the model results can be very sensitive to such parameter values and assumptions.

2.5 ADDRESSING THE RESEARCH QUESTION

The choice of the type of model, decision-rules used, types of social networks initialized are determined by the nature and scope of the research questions that the model is built to study. This section synthesises the literature that has been surveyed above and to consider what useful model features will be built upon from existing studies.

The two approaches of Cognitive Models and Utility Maximisation both provide advantages in modelling interactions between agents. As was discussed earlier, in the case of utility maximisation models, the justifications for including or leaving out certain attributes is not systematic and is often tailored to the research question and the case-study in particular. Moreover, the market research that underlies the choice of attributes that are used to calculate utility of agents should be derived from surveys of the population in question. Cognitive models on the other hand provide a more systematic framework which can be used to model agent decision-rules. Given the availability of appropriate survey-data, the model can be quite useful in studying the evolution of the agents' perceptions of the affordability/complexity of the product, how the agents' peers influence their decision-making etc in a manner that is grounded in theory. It is also makes it possible to compare the outcomes of this research with other studies as well. Figure 2.3 summarizes the literature overview process, keeping in mind the relevance of the models to answering the central research question of this study.

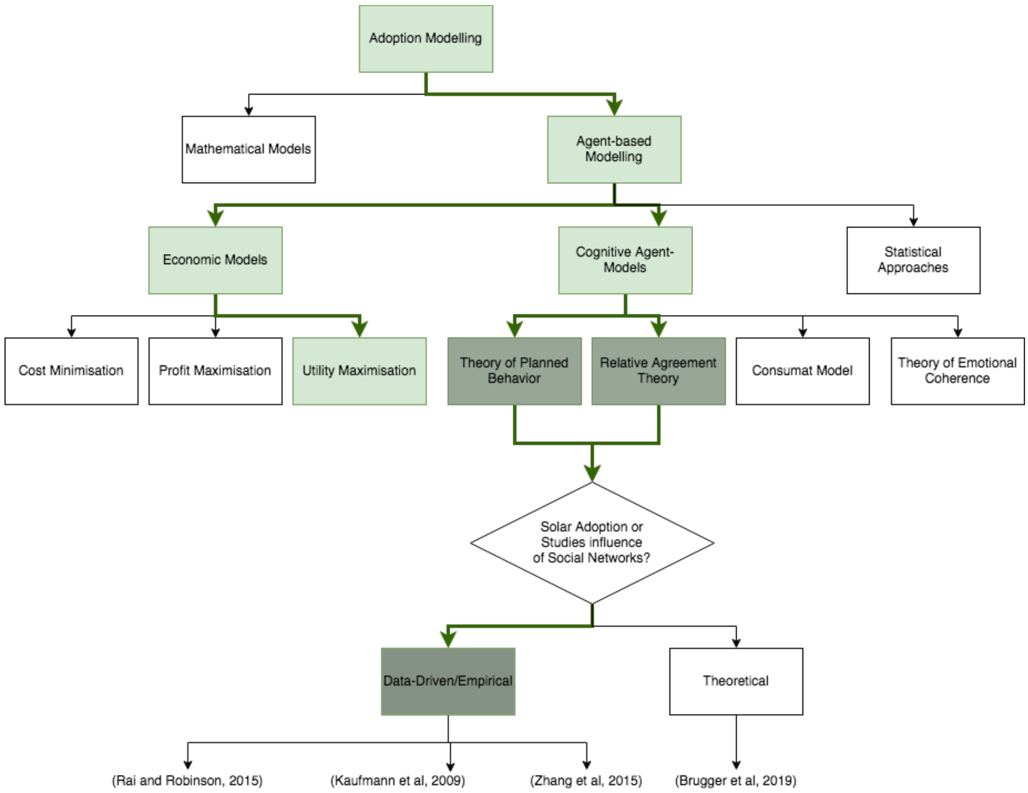

Figure 2.3: Summary of the process of literature overview. Highlighted in green are modelling methods that were preferred in the context of conceptualizing a model for answering this study's central research question

Outlined at the beginning of this chapter were the requirements of the model that will be best suited to answer this study's research questions. Figure 2.3 arrives at four studies that are close in spirit to the goal of this thesis. The following sections will discuss and justify each of the modelling choices made for building this model.

3 | METHODOLOGY

3.1 OVERVIEW

An overview of studies incorporating social networks in adoption modelling reveals important gaps: namely in how social networks are itself modelled and how it influences policy interventions in the context of just energy transition. (Rai & Robinson, 2015) and (Kaufmann et al., 2009) incorporate (a) agent heterogeneity using census data, (b) systematic decision-rules grounded in Theory of Planned Behavior that is initialized for the population via survey data, (c) model social influence and (d) use principles of homophily and distance-decay to model realistic social networks. Although (Zhang et al, 2015) use machine-learning methods to learn and forecast agent behavior (at the micro-level) as well as forecast aggregate trends (at the macro-level such as adoption curves), they do not model networks explicitly and it therefore forms part of the calibration. (Brugger & Henry, 2019) is the only study among those surveyed that finally addresses the gap in understanding how the underlying social network affects efficacy of new technology adoption programs (solar PV specifically). The model is however purely theoretical, with the agents and the networks they interact in, hypothetical. The study's results however open up possibilities of the interesting insights that a more complex ABM that is empirically driven, whose agents have relevant social and demographic attributes and whose social networks are realistically modelled, can provide.

3.1.1 Key Contributions

The key contributions of this study is at the intersection of adoption modelling, realistic modelling of social networks and the measurement of policy performance in the context of a distributively just energy transition. This study models for the first time, a Data-Driven Agent-Based model that is grounded socio-psychologically with the Theory of Planned Behavior with a focus on modelling realistic social networks. This enables the study of network role in influencing performance of policies in light of energy justice: it explores if the network's role in the way the policy pans out, further increases the gap in access to clean energy for some income groups. The key contributions of this study in comparison to four other relevant studies in this field (arrived at via the process followed in Figure 2.3) can be seen in Table 3.1.

Table 3.1: Key Contributions of this study in comparison to relevant studies in the area of Adoption Modelling and study of social network influence over efficiency of policy programs

Model Features	(Kaufmann et al, 2009)	(Rai and Robinson, 2015)	(Zhang et al, 2015)	(Brugger et al, 2019)	This Study
Heterogeneous Agents with non-price attributes included	Yes	Yes	Yes	Very limited	Yes
Decision-rule grounded in Social-psychological theory	Yes	Yes	No	No	Yes
Social Influence is modelled	Yes	Yes	No	No	Yes
Dynamicity in attitudes/perceptions	Yes	Yes	No	No	Yes
Economies of Scale for cost of technology	Yes	Yes	Yes	No	Yes
Social networks modelled realistically	No	Yes	No	Yes	Yes
Impact of Social Network on Policy performance considered	No	No	No	Yes	Yes
Data-driven model	Yes	Yes	Yes	No	Yes
Just Transition/Equitable Access to technology	No	No	No	Yes	Yes

3.1.2 Design of Experiments

To answer sub-research question 2 which explores 'how characteristics of the underlying social network influences performance of the policy intervention', several policy interventions will be tested on the Data-Driven ABM that is built. To explore the effect of the underlying network on the policy interventions, two network scenarios will be generated, in a manner that is conceptually similar to (Brugger & Henry, 2019). The two network scenarios are a) Integrated Network: where the agent is as likely to form a social tie with an agent who shares similar attributes as with an agent who does not and b) Segregated Network: where 'birds of a feather flock together'. Policy interventions that are tested in these two network scenarios are derived from some commonly adopted adoption programs in the case-study region. Because the case-study on which this Data-Driven ABM will be initialized is located in Albany County, New York State (NYS), United States of America (USA), the policy interventions chosen will be those that have been used commonly in New York State:

- Flat vs Income-group based Tax Credits Scheme:
  Residents of the State of the New York (of which Albany County is a part) who opt to install a solar panel on their roof benefit from dual-tax credit schemes. The Federal Tax Credit of 25% and the New York State's Tax Credit of 26% (over and above the federal tax), thereby making a solar adopter in NYS pay only for 49% of their solar panel's cost. This is adopted in this study in two ways: a) Flat Tax Credit structure as is used today, where all those who apply for the credit avail of it irrespective of their income-group background. b) Income-group based Tax Credits: as the name suggests, higher tax credits for applicants from disadvantaged income groups. Although this is not launched in NYS, this study will use this policy-lever to explore if flat-tax-credits unfairly bias the affluent classes to adopt solar PV.

- Increasing or Lowering Tax Credits:
  NYS has plans to decrease support from 26% to 23% by 2022. By increasing and decreasing Tax-Credits (in a flat structure) the effects on different income-groups are examined in a segregated and integrated network. The expected of the role of networks despite the policy-intervention being purely financial is that of attitude-driven and peer-effects driven adoption. Even if the panel costs are a little high for the low-income groups, this policy-intervention experiment will observe if peer-effects (phenomenon by which higher number of peers adopting

increases likelihood of agent adopting as well) can override financial considerations during adoption decision-making.

- Seeding Low and Middle Income-groups:
  Research has established the importance of peer-effect in low-income groups. This strategy in real-life policy-making is at pilot stages deployed in California where low-income households are seeded with solar panels on their roof. Research shows that this can trigger peer-effects via the visibility of panels and also has a positive impact on financial considerations: low-income groups benefit more from financial support. The effect of these programs in adoption rates have been shown to be positive in (H. Zhang et al., n.d.). However the effect on peer-effects by the underlying network is yet to be systematically studied: this policy experiment aims to resolve this gap. Three scenarios are explored a) low-income groups are seeded, b)low and middle income groups are seeded and c) random households are seeded to confirm benefits to low-income groups of targeted seeding.

- Seeding Influencers: While it is acknowledged in research that peer-effects play a very important role in improving adoption rates in low-income communities, this has not been tested by policies that aim to enhance peer-effect by word-of-mouth and increased visibility that comes about when highly-connected and influential individuals are seeded. This has been tested in studies like (Huang et al., 2019) in the context of weatherization adoption: they conclude that seeding influencers and community leaders was important in significantly increasing adoption rates in the locality, in line with (Fuller, 2010). Their local survey confirms this fact, revealing that 59% of residents would turn to their local leaders and experts before making a weatherization decision, especially in low-income groups. This observation is also in line with (Jones & Warren, 2020) who conducted their solar adoption study in low-income groups in Bangladesh and found that community-leaders played a significant role in improving adoptions in these groups. In this study, role of influencers is tested through three methods: a) seeding influencers in low-income groups, b) seeding influencers in low and middle-income groups and finally to confirm benefits of this strategy for the low-income groups, c) seeding random influencers irrespective of their income-group. These three strategies are tested once again in integrated and segregated networks to observe the role of networks.

3.1.3 Choice of Key Performance Indicators

The core concept of this study is to evaluate the role of social networks in influencing effectiveness of policy interventions in the context of just transition (see Sub-Research Question-3). Key performance indicators (KPI) that are used to measure 'policy effectiveness' are therefore framed in this context. Adoption studies generally use aggregated trends such as overall adoption numbers per year [number of agents that have adopted at the time-step] to measure effectiveness of the policy intervention. That is, Policy intervention A is better than B if the overall adoption rates produced under A is higher than B. Some studies like (Brugger & Henry, 2019) use speed of adoption also as a metric to measure effectiveness: how fast is the spread year on year. Because their study too focuses on the distributive justice component of the policy intervention (how well the policy performance for low-income groups as well high-income groups), the study's main KPI is the proportion of adopters who are low-income and high-income. Adoption rates in these groups are compared to assess how successful the policy intervention in its requirement of being distributively just.

Need for evaluating policies in the context of just transition:

The concept of just transition is the subject of much research and public attention today. Climate change being a looming threat, it is essential that there are coordinated efforts between policy, politics, industry and the academia to ensure cutting down of emissions and ensure that this transition doesn't come at the cost of worsening existing living conditions. While just energy transition is framed in different angles, with the Paris Agreement Goals (2015) defining it to be "a just transition of the workforce and the creation of decent work and quality jobs in accordance with nationally defined development priorities" and the International Labor Organization (2015) defining it to be a "well-managed transition to decent work for all, social inclusion and eradication of poverty" (I.E.A. & O.E.C.D., 2014). While the framing of just transition is in the context of job losses in industries that result from phasing out of fossil-fuel based energy sources, the overall connecting theme in most definitions of this term is the need for a "transition to renewables that does not generate new forms of poverty and inequality".

Given widening gaps in access to resources between affluent and disadvantaged communities throughout the world, a strong case can be made for evaluating policies based on their ability to close the gap between richer and poorer households (Brugger & Henry, 2019). Governments worldwide are increasing public expenditure towards stepping up the share of renewables in the energy mix: this amount has grown from USD214 billion in 2014 to about USD300 billion today. With budgets of such scale, there are calls from the academia, international organizations and civil societies for a shift of government goals from being 'target setting' to being directed towards 'distributing the costs and benefits across socioeconomic groups'.

This study therefore uses the term just energy transition in the context of distributive justice as in (Brugger & Henry, 2019), in response to calls in literature to avoid using overall adoption rates as the role criterion for measuring success of policy interventions. In this study a policy performs better in the context of just energy transition, if it improves access to renewables to low-income groups without increasing their financial burden. To implement this quantitatively the following KPIs are used:

- Adoption rates across income-groups: percentage of each income-group's members who are adopters. This gives importance to the proportion of adopters in every income-group as opposed to the total adopters per income group. This ensures that the size of the income-group does not distort the adoption rates.
- Overall adoption rates: to measure overall effectiveness of the policy to allow for comparison of different policy interventions under the two network scenarios.
- Policy Costs: Sometimes two policy interventions may result in similar outcomes. Because design and deployment of policy interventions burden the public exchequer, it is important for the policy-makers to be advised on effective policies that are also cost-effective.

3.2 CONCEPTUAL OVERVIEW

This thesis builds a Data-Driven Agent-Based Model with the following features:

- Agent Decision-Rules: Cognitive Agent-based Model grounded in Theory of Planned Behavior (TPB) (Ajzen, 1991).
- Agent Heterogeneity: In order to realistically examine the effects of different network structures, just using a sample survey population can limit the insights that can be derived from the model. It is more useful if, as in (Rai & Robinson, 2015), a synthetic population is initialized using a combination of survey data

and census data in the case-study region, to generate different network structures and examine their roles. Moreover, this is also justified due to lack of high-resolution, representative survey datasets that are required to derive social networks from empirical data. Due to confidentiality and privacy issues, such datasets are also not available to researchers or the public. The agents are initialized with both a) demographic and b) attitudinal attributes. Demographic variables include variables such as age and income, whereas attitudinal variables involve perception of the technology, agent's opinions about it, perception of affordability and agent's susceptibility to peer influence.

- Multi-level Social Networks via Circles of Influence: This study models the underlying networks realistically so that the networks exhibit characteristics observed in real-world social networks such as homophily and distance-decay. While this is similar to (Rai & Robinson, 2015), this study adopts a multi-level non-physical social network based on income-similarity. This is a unique addition to literature by this study whereby the attribute of a social tie is lent more heterogeneity: not all social connections have the same influence over an agent. This study builds on research that resulted by (Dunbar) whereby an agent is cognitively capable of a maximum of 200 meaningful social connections and that there are multiple levels of influence that members of the social network have over the agent.
- Social Influence: Relative Agreement Theory from (Deffuant et al., 2002) is used to model the evolution of agent's opinions via interactions in their social circles.

A conceptual diagram of the Data-Driven ABM is summarized in the Figure 3.1. The agent based model will be populated with synthetic agents modelled using the population of a chosen geographic region as case-study and agent attributes will be initialized using a combination of survey data and census data, both of which are publicly available. These initialized synthetic agents are then input into an Agent-based model, where they interact with each other. As a result of interactions between agents, their attitudes towards the energy efficient technology, information levels, perception of affordability of the new technology and conformance to social pressure regarding adoption, will evolve over the time period of model run.

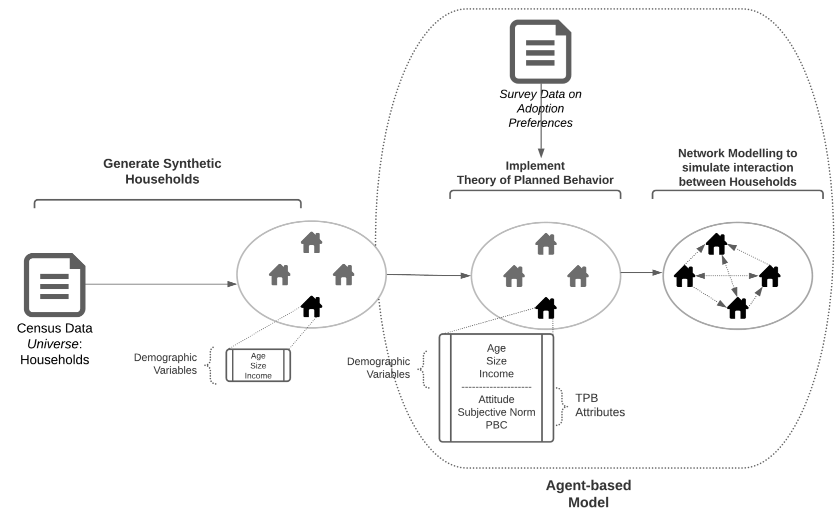

Figure 3.1: Conceptual Overview of how the three models: Theory of Planned Behavior, Agent-based Modelling and Network Modelling integrate to answer the research questions

This multi-method model combining ABM and Network Modelling will help understand how structure of these networks influence an agent's access to information, exposure to opinions, their own perception of affordability of a new energy efficient technology and how all this comes together to influence their likelihood to adopt the technology.

3.3 METHODS: A CONCEPTUAL BACKGROUND

This section justifies the models as outlined in the conceptual overview diagram in Figure 3.1.

3.3.1 Theory of Planned Behavior

Agent's adoption decisions are modelled using the Theory of Planned Behavior (TPB), which is a useful analytical framework in social psychology that has been widely applied in several studies on energy efficient technology adoption and people's development of pro-environmental behaviors (Wolske et al., 2017). In summary, the theory states that an agent's intention to perform an action is the result of a rational decision-making process that comprises three attributes:

- a) Attitude: the agent's opinion and predisposition towards performing that action
- b) Subjective Norms: agent's perceived social pressure to perform that action: will her peers be supportive of her decision to perform it? Does she face increasing pressure to perform that action because everyone around her has already performed it?
- c) Perceived Behavior Control (PBC): perception of agent's ability to perform that action.

A visual summary can be viewed in Figure 3.2.

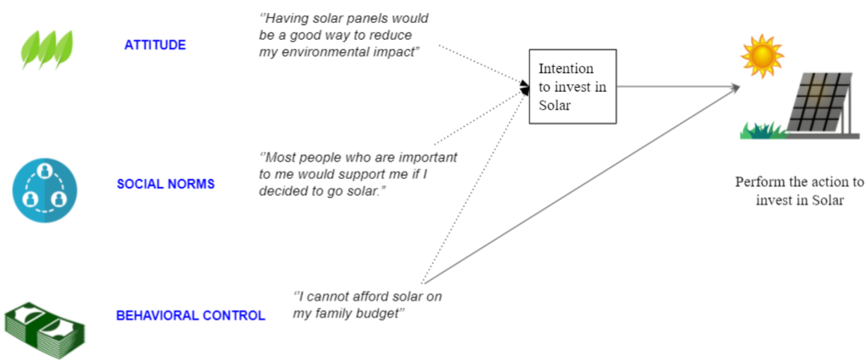

Figure 3.2: Theory of Planned Behavior in the context of Solar PV adoption (An Example)

The behavioral intention (I) to adopt or non-adopt is a likelihood, that is scored according to the formula below, where i is every household agent, a, s, p are attitudes, subjective-norms and PBC respectively and w are the weights.

$$I = w_i^a * a_i + w_i^s * s_i + w_i^p * p_i \tag{3.1}$$

The weights for each of the three attributes are derived from a survey of the population, where questions are designed to elicit the agent's attitude/subjective-norms/PBC and

Intention. Therefore, as is illustrated by Figure 3.2, after the behavioral intention (I) to adopt crosses a threshold conditional on the fact that the agent's PBC also has crossed the required threshold, the agent is ready to adopt or has a very high likelihood of adopting the solar panel.

The 3 TPB attributes independently influence an agent's decision. For examples:

- Case-1 : A person who is positively predisposed to buying a solar and also has a supportive peer network but does not have the finances to invest in one, will not adopt.

- Case-2 : A person financially well-endowed may not choose adopt if they have a negative opinion of the benefits of solar and belong to social circles who are critical of it as well.

- Case-3 : A person has both the finances and the attitude for buying in a solar panel, but has a peer network that is very critical of it, they will be hesitant to make an investment as well.

Despite the availability of other models such as Consumat (Moglia et al., 2018), (Sopha et al., 2013) that try to more realistically depict the randomness with which agent's choose decision-making models themselves, the Theory of Planned Behavior poses a better fit for meeting this problem statement's objectives. Availability of publicly available survey data allows one to elicit TPB-attributes for every agent and therefore initialize a synthetic population with realistic attitudinal distributions. Because TPB is a widely applied framework specially in the area of technology diffusion, it enables one to build upon and compare this model's results with previously established work and add further insights into the role of the network component in adoption. (Rai & Robinson, 2015).

3.3.2 Networks

This component models network interactions as a multi-level social network comprising of physical and non-physical social networks:

- (Physical) Neighborhood Interactions: Social network research shows that links between people comprise majorly of geographically proximate connections, with a minority of non-local connections (Rai & Robinson, 2015),(Watts & Strogatz, 1998), (Schnettler, 2009). Network interactions modelled at this level increase the likelihood of interaction between agents in the same block/neighborhood, with the likelihood of two agents living in geographically disparate regions interacting, smaller. Moreover (Everette Rogers, 1995) shows that demonstration or 'observability' is key to the spread of new technology. Seeing a Solar panel mounted on the roof of the neighbor, puts the possibility in the householder's mind.

- Interactions withing the same economic group: It is said that birds of a feather group together: a fact that is also proven scientifically through the concept of homophily and its importance in community structure (Girvan & Newman, 2002),(McPherson et al., n.d.). Implementing this implies that agents who belong to the same socioeconomic group (income similarity) are given a higher likelihood of interacting with each other in a time-step. While studies such as (Kaufmann et al., 2009), (Günther et al., 2011) and (Rai & Robinson, 2015) also implement this aspect of connections driven by homophily, it does not explain how people attribute different levels of trust to different sources. This is addressed in this study by adding the component of 'Circles of Influence'.

Role of Trust: Circles of Influence

Despite connections being more likely between people of the same socioeconomic group than outside, this method of drawing connections between agents and letting information flow through them is not sufficient to explain how trust and influence plays a role. Research in technology diffusion and adoption shows that the process occurs through existing social networks. Despite information campaigns and other sources, people adopt new technologies only after it's effectiveness is demonstrated through experiences of their friends and acquaintances (Coltrane et al., 1986). Research also shows that effectiveness of a transferred information increases with the credibility of the source of information (Archer et al., 1987). Messages attributed to a highly credible source brings about a greater change in attitude than if it originates from someone who is a not so credible source (Aronson, 1969). Therefore it is suggested in the context of policy design that to make adoption programs effective, strategies need to include using credible and authoritative sources of information that are also personally relevant to people (Coltrane et al., 1986).

Dunbar's number posits that there is a cognitive limit to the number of meaningful and stable relationships one can hold at a particular point in time and this number on an average ranges from 100 to 250 (Lyon et al., 2011). Each person's social network comprises of different 'circles of friendship' upon each of whom have different levels of intimacy and trust is placed (see Figure 3.3).

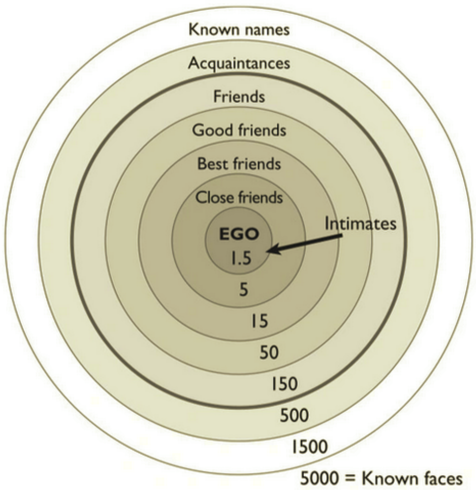

Figure 3.3: Dunbar's Circles of Friends that outlines the typical number of relationships that a person holds in different social circles.

On average people maintain very close relationships with about 5 people in their innermost circle, with 10-15 people in the close friends circle, about 30-35 people who we interact frequently in the context of workplace and other modes of acquaintance and finally about 100 whom we come into contact every now and then (Tamarit et al., 2018).

Quantifying Networks as Integrated or Segregated

Two network scenarios are conceptualized in this study which tries to model an integrated network structure and a segregated network structure. The choice of these two structures, as opposed to the use of other synthetic network structures such as random/scale-free/small-world is based off literature. Research shows that urban social networks have 2 important characteristics: a) they are small-world, b) links between individuals follow two principles of distance decay (increasing distance decreases probability of them forming a connection) and social distance (whereby agents with similar socioeoconomic backgrounds, specially income and racial similarity have a higher probability of establishing ties with each other (Herrera-Yagüe et al., n.d.).

The decision is therefore taken to not develop network scenarios for random or scale-free networks when investigating inter-household and inter-personal social networks in this case-study. Rather, homophily and geographic proximity are assumed to be sources of forming connections. Network homophily is a pattern in which ties are more likely to exist between nodes that are similar to each other; this principle is frequently observed in social relationships. The motivation behind modelling the two network scenarios as integrated and segregated is also because segregation is often encountered in urban areas as a tendency of families to occupy neighborhoods inhabited by families that are similar to theirs (Muller & Peres, 2019).

Literature has several methods proposed to quantify the amount of integration or segregation in the network: Pearson's Correlation Coefficient, H-Index, EI-Homophily Index, Degree Assortativity etc (Anderson et al., 2014). Among these measures, Degree Assortativity is chosen as a global measure of the graph to classify it as integrated or segregated, as it can be calculated using the python package of NetworkX for the resultant social network.

In summary, the proposed multi-level social network model, a person at one particular point in time interacts via two networks: a) Physical network and b) To different people in their social networks in different circles of influence. These circles can overlap as well. The implementation is detailed in the following chapter.

4 MODEL IMPLEMENTATION

The chapter details the implementation of the model conceptualized in the previous chapter and the assumptions made during the same. Model implementation follows the process outlined in Figure.

4.1 CASE-STUDY: ROOFTOP SOLAR IN ALBANY, NY

As discussed earlier, the Data-Driven ABM will be initialized with empirical data pertaining to a case-study. This section introduces the reader to the case study that will be explored by the model henceforth and the justifications for the same.

4.1.1 Choice of Technology: Solar PV

This thesis studies the adoption of residential solar PV: a choice motivated by several reasons. Over the last 10 years, solar has emerged as a serious electricity supply option (Tyagi et al., 2013). It is the fastest growing energy technology globally (Gelman, 2011). Solar PV adopters tend to be rich, economically advantaged groups making this a good case to study implications of policies on just energy transition (Rai & Robinson, 2015). The presence of studies that also study solar adoption using similar methods of TPB and ABMs, allowing the contribution of this thesis to be studied in context of the existing body of literature on the matter.

4.1.2 Choice of Albany

Albany County is located within New York State, USA. Unlike New York City which is very densely populated and comprised primarily of sky-rise buildings, Albany county has a balanced mix of urban, suburban and small-town settlements, making it viable to study rooftop solar. Because survey data that is used to initialize agent attributes for the model are available for only 4 states in the USA: New York, New Jersey, California and Arizona, a choice of case-study within any of these four states should be representative of the state.

4.1.3 Choice of Agent Demographic Attributes

The unit of the ABM, the agent, is that of a household. In Figure 3.1, three demographic attributes are associated with every household, namely that of:

- Age : Age of the householder in whose name the home is owned or being bought.
- Size : Number of people living in the household at the time of survey.
- Income : Reported Income of the householder and all other individuals 15 years old and over in the household, whether they are related to the householder or not.

Figure 4.1: Albany County, New York State

Stepwise Regression to Identify Key attributes of Household

It is acknowledged herewith that the choice of these very attributes to identify an agent is itself influenced by the case-study in question: that of a western demographic (Albany) located in a fully-industrialized country (United States of America) which has a certain system of governance. If this same model were to be built for a small in India for example (where solar energy is slowly picking up as well), several other attributes would have to be taken into account to adequately represent a household for the purposes for decision-making w.r.t to Solar Panel: education level and gender (Harrington et al., 2020).

While conceptualizing this model, several options were considered on what are the set of variables that would finally characterise the agent and it included: stated political stance (ranging from far left to moderate to far right), education levels (ranging from high school and below to graduate and post-graduate degree holders) and gender of the head of the household. To analyse the role that these variables play in explaining the intention of a household to adopt, survey data that recorded respondent's answers to questions that explored their motivations, concerns and experience with adopting (or not adopting) residential solar was analysed. This survey data is publicly made available with the intention to encourage ABM studies that explore the role that social networks play in adoption of new technologies. Using methods such as dummy coding, a step-wise regression model was built where a suite of variables that included education, political stance and gender were taken along with household size, age and income. Variables were added and removed to measure how these variables contributed to explaining the intention of the household to adopt. In this way, the variables of Age, Household Size and Income were finalized.

Education and Political Stance

It was surprising to note that education did not significantly explain intention. But after observing the processes that households typically follow while considering a solar panel in New York it seemed that possessing technical knowledge or an advanced degree did not really help in making a more informed decision about the solar panel. If a person considers adopting a solar panel, their first stop is often in the government website (of that of the county or the state of New York) which has several advanced systems in place to inform residents of the suitability of their roof for solar. The resident need only enter the exact location or locate their roof on a satellite map on the website. The algorithms calculate roof area, expected sunlight that will be received at location and return the expected savings for the user.

Political stance is a variable that was discounted for as an attribute to identify the household. Instead, it is included as part of the 'attitude' component in the model's implementation of the Theory of Planned Behavior. Political view indeed does have a key role to play in ascertaining the predisposition of a household towards the benefits of solar. Sometimes, if the said household does not believe in climate-change in conjunction with their political views / affiliations to certain political parties, they will choose to not adopt even if they do possess adequate financial resources to do so! To account for the strong role such opinions play in determining a household's intention, the variable was retained in another subcomponent of the model.

4.2 SYNTHETIC POPULATION GENERATION

This section gives an overview of how a realistic synthetic population of single-family households can be modelled after population from an area of interest (in the USA) using US American Community Survey of 2015. Year of 2015 is used because the survey was taken for single-family homeowners in 2014-15 time-range. The year 2015 is taken for initializing the population attributes, as the survey data is then used to initialize each agent's attitudes, behavior control variables for TPB is from 2014-15 range.

In this model, three variables are used to characterize each household: Age, Household Size and Household Income. Chapter 3 discusses these choices in detail. Table 4.1 gives the data sources for each, definition of the term and their aggregation levels.

Table 4.1: Census Datasets used to Generate Synthetic Households

Variable	Year	Dataset	Aggregation
Tenure by Household Income in Owner Occupied Households	2015	ACS-5yrs, B25118	Census Tract Level
Tenure by Age of Householder in Owner Occupied Households	2015	ACS-5yrs, B25007	Block Group Level
Tenure by Household Size in Owner Occupied Households	2015	ACS-5yrs, B25009	Block Group Level
Average Electricity Consumption by Area Median Income (AMI) and Building Type	2011-2015	SEEDS-II REPLICA	Census Tract Level

It can be noticed that while age and household size were obtained for owner-occupied households at block-level resolution, household income information for the same category was only at the tract-level (which is higher level of aggregation- for a description of the different administrative divisions in USA, check Appendix- A. Income was therefore dis-aggregated from the tract-level into block-level.

Disaggregating Household Income to Block-Group Level

The process outlined in Figure 4.4 was followed using the datasets from Table 4.1 with the area of interest being Albany County, New York State. It was observed that while Household Size and Age for Owner-Occupied Households were available at a block-group level, Household Income was available only at the census-tract level. Therefore the following steps were taken to disaggregate household income into block-group level.

	<$75k	$75to100k	$100to150k	$150k+	BlockGroup Totals
Tract17, BG-1	?	?	?	?	230
Tract17, BG-2	?	?	?	?	241
Tract17, BG-3	?	?	?	?	157
Tract17, BG-4	?	?	?	?	177
Income Totals	344	97	186	178	805

	<$75k	$75to100k	$100to150k	$150k+	BlockGroup Totals
Tract17, BG-1	98	27	53	50	230
Tract17, BG-2	102	29	55	53	241
Tract17, BG-3	67	18	36	34	157
Tract17, BG-4	75	21	40	39	177
Income Totals	344	97	186	178	805

Figure 4.2: Example for Census Tract-17: Disaggregating Tract Level Data to Block-Group Data

Considering that the totals for the Income Brackets were available for the tract and the total number of households were also available for each Block-Group, the number of households within the block-group for each income bracket were calculated using the number of owner occupied households in the blockgroup weighted by the probability of the income-bracket in the blockgroup. Considering there are no crosstab sample available nor are there datasets of any other aggregation level available, this method was considered satisfactory to get all the datasets to the same aggregation level. Figure 4.2 shows this process for Census Tract 0017 for Albany, which contains 4 Block-Groups within it. This process, done for all census tracts will give a block-group level income dataset. The final output is show in Figure 4.3.

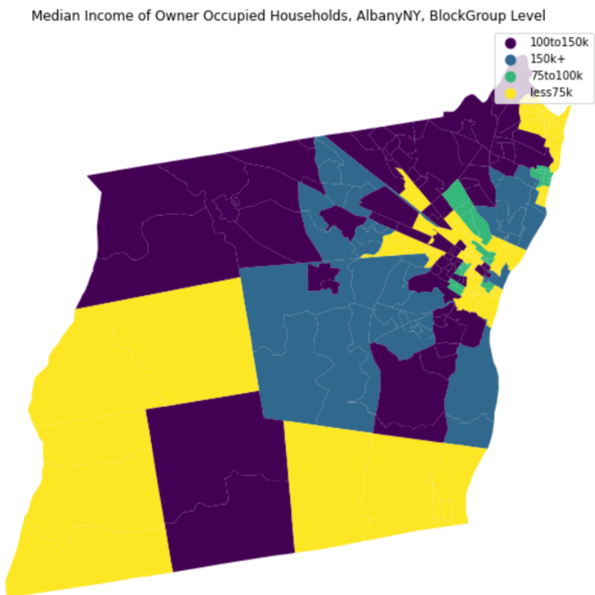

Figure 4.3: Income at Block-Group Level

After getting the three datasets at the same aggregation level, a naive method was then used where marginal distributions for the owner-occupied households for each of the 3 demographic variables (Age, Household Size and Household Income) were generated and multiplied to get the joint-probabilities for each combination. Steps followed at each step are detailed in the Appendix-A. Figure 4.4 outlines the process.

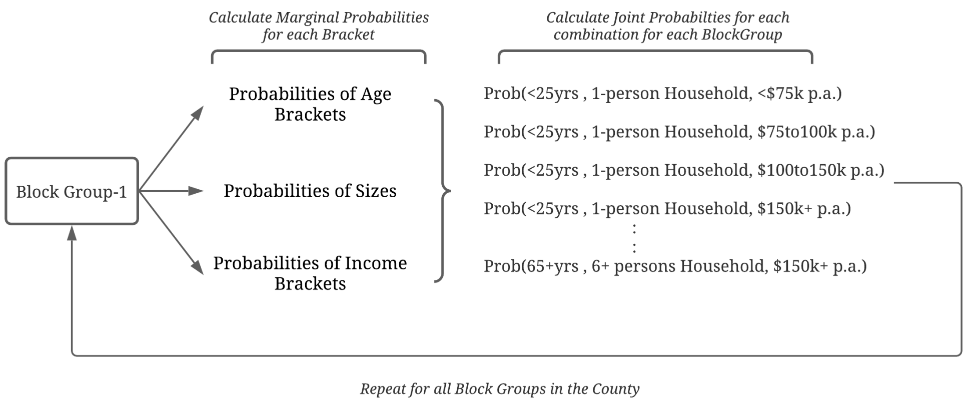

Figure 4.4: Generating Synthetic Households: Naive Method

80,2018 single-family owner-occupied houses were generated for the county of Albany for 2015, with three attributes to identify a household's demography: household age, household size and income.

Verifying Synthetic Population Results

In order to verify if the generated synthetic population of owner-occupied households in Albany County, is valid and is in accordance to the actual census population in 2015, a set of 10 census block groups were randomly sampled and distribution across the three attributes of Householder Age, Householder Income and Household Size are compared with actual distributions provided by census-data.

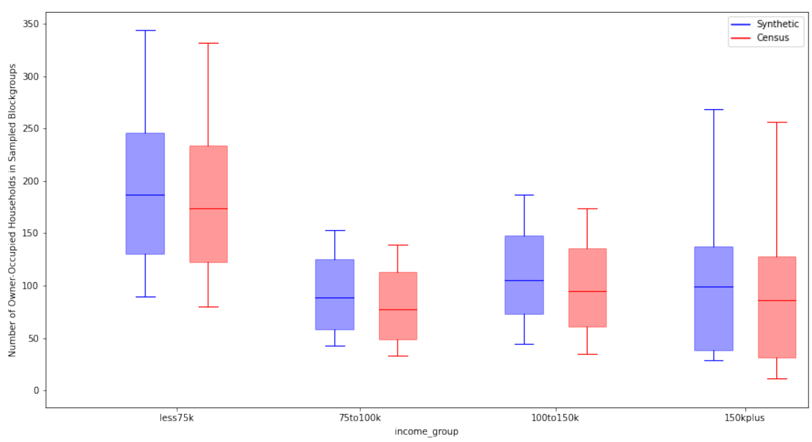

Figure 4.5: Comparing distribution across Household Income brackets in the generated Synthetic Population and Census Data for the Year of 2015

The generated income statistics (seen in Figure 4.5 for synthetic households is comparable to the census distribution within a reasonable margin of difference of +/- 20 households. It is noticed that population-wise, there are many owner-occupied householders belonging to the low-income category of less than USD75,000 per annum. The wide distribution both the high-income and low-income groups suggesting segregation:

there are some blockgroups that have a very high proportion of high-income groups and some block-groups with higher number of low0income groups.

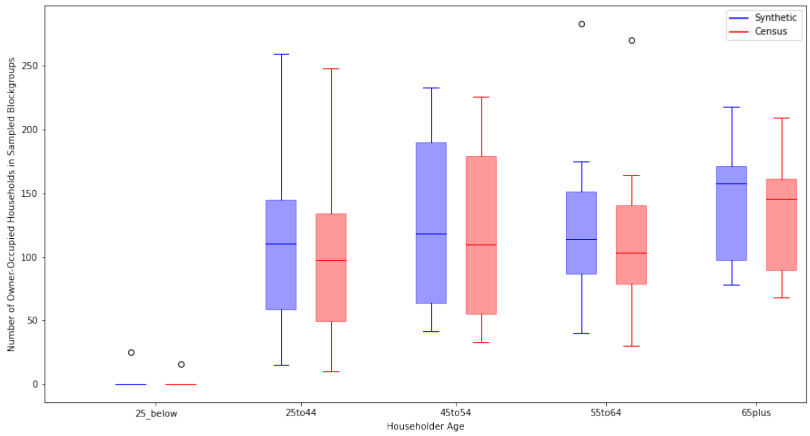

Figure 4.6: Comparing distribution across Household Age brackets in the generated Synthetic Population and Census Data for the Year of 2015

It can be noticed that in the case of household age that except for a few outliers, there are no owner-occupied households where the head of the household is less than 25 years of age, which is justifiable in real-life as well. The wide distribution of the age-bracket 25 to 44 years old is also understandable given the size of the age-group. The distributions of generated synthetic households, like that of household incomes are comparable to the census data.

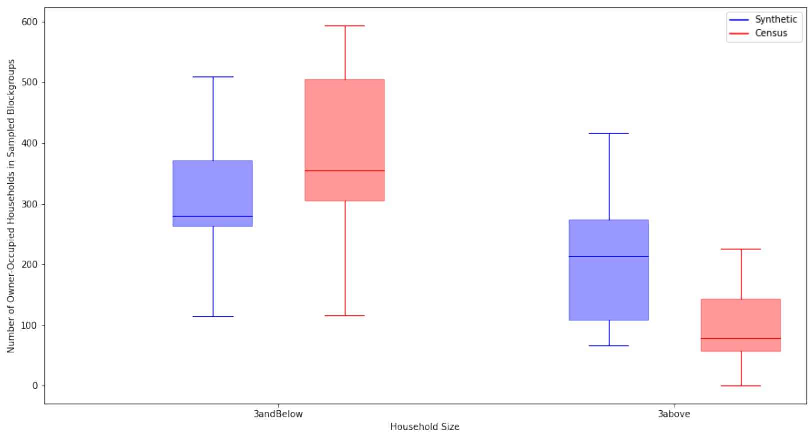

Figure 4.7: Comparing distribution across Household Size brackets in the generated Synthetic Population and Census Data for the Year of 2015

Unlike distributions of household incomes and ages, household sizes of synthetic and census data do not follow the same distributions. The spread of owner-occupied households of size 3 members and below is larger in census data as compared to synthetic datasets. This pattern is reversed in the case of household sizes of greater than 3 members.

In the following section, we proceed to implement the Theory of Planned Behavior where we initialize each of these agents with three attributes: attitude, subjective norms and behavioral control.

4.3 THEORY OF PLANNED BEHAVIOR

This section outlines firstly how publicly available survey data from 2014-15 was used to elicit the three TPB attributes and how it is used to initialize the generated synthetic population. This is followed up in the next section with an explanation of how in the ABM model, these three attributes evolve over time as a result of inter-agent interaction.

4.3.1 Survey Data

The survey data used to elicit the three TPB attributes of Attitude, Subjective Norms(SubNorms) and Perceived Behavioral Control (PBC) are sourced from the publicly available NREL-led "Understanding the Evolution of Customer Motivations and Adoption Barriers in Residential Photovoltaic Markets" SEEDS project (OSTI, 2015). Two of the three survey datasets are used for initializing the TPB-attributes of the agents. Both surveys were fielded for single-family homeowners across the four states of New York, New Jersey, Arizona and California:

- (1) PV General Population Survey: Survey of single-family homeowners who did not have rooftop PV solar at the time of the survey in 2014. This survey is henceforth referred to in this document as "Non-adopter Survey". Demographics of the survey dataset is provided in the Table 4.2 below. The data is much more balanced as compared to the adopters survey below, with more representation from women, lower income groups, of different education levels and ages.
- (2) PV Adopter Survey: This comprises of single family homeowners from the four states, who currently (in 2014) have a solar PV installed in their current home or have signed a contract to do so (less than 1% of the surveyed population belong to this category). Demographics of the adopters' survey are provided in the Table 4.2 below. PV adopters were identified by obtaining sample lists from PV installers willing to share this information; from this contact information, the survey includes those customers who responded to the calls. Therefore representativity of the survey data is not guaranteed, with a definite bias towards respondents from California. Adopters also are mostly high-income, well-educated, male and older than 55 years old.

	Non-Adopters Survey				Adopters Survey			
	Arizona	California	New Jersey	New York	Arizona	California	New Jersey	New York
% Female	62	59	62	56	45	36	25	35
% 55 or older	54	50	50	54	77	61	64	55
% Household income of $100,000 / yr or more	29	37	42	35	31	54	57	62
% Holding 4-year degree or higher	42	43	50	45	64	57	59	56

Table 4.2: Summary Statistics of Survey Datasets

The survey developers intend the use of this survey data primarily for "developing agent-based models of solar adoption with particular attention to social networks".

4.3.2 Calculating Scores for 3 Attributes

The full list of questions used for Adopters and Non-adopters to elicit Attitudes, Subjective Norms and PBC are detailed in Appendix-A. The responses are in the form of a 5-point Likert Scale. These variables are mapped to a score between -1 and 1, maintaining 'positivity'. This means a score towards 1 means the attitude/subjective-norm/PBC supports adoption. Towards -1, it is considered dissuasive for adoption. The different questions are divided into positive and negative Likert variables so that they are maintaining consistency in what the score represents for adoption. The distribution of Attitudes, Subjective Norms and PBC scores across the survey population for Adopters and Non-adopters are show in Figure 4.8 below.

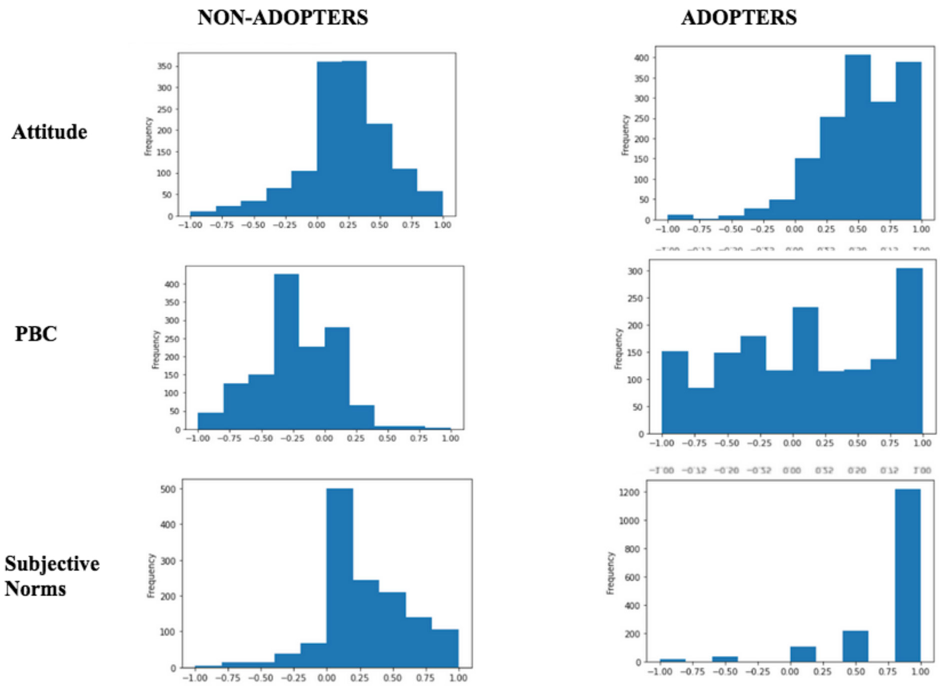

Figure 4.8: Distribution of scored Theory of Planned Behavior (TPB) Attributes for Adopters and Non-adopters

Insights from Survey Data

- Attitudes: The scores for attitude confirm some intuitive expectations: more than 90% of the adopters hold positive attitudes towards solar, whereas majority of the non-adopters seem undecided (with scores distributed around zero).

- Perceived Behavioral Control (PBC): PBC however does not seem too straightforward for the adopters. While the non-adopters profess a behavior control ranging from undecided to completely negative about their ability to invest, Adopters' PBC is much more evenly spread. This discrepancy is understandable: due to the lack of a panel dataset, it is difficult to elicit PBC for an adopter who has already performed the action of purchasing the solar, therefore the responses to the questions that try to elicit "how strong was the agent's belief in their ability to invest in solar" can result in inaccurate responses.

- Subjective-Norms: This score shows an encouraging result. A very high number of adopters depended on supportive peer networks and trusted information flowing through their close circles. Meanwhile, majority of the non-adopters seem undecided: this is quite plausible as many of the surveyed respondents may not have had the conversation about solar with their networks, or possibly do not have many contacts who are adopters already.

4.3.3 Survey Data Regression

Dependence on State Variable

Considering that survey data points are available for the four states of New York, New Jersey, Arizona and California, hypothesis testing was performed to see if the states variable significantly explained the TPB attributes that were required for initializing the synthetic households. The hypothesis being: if States did not significantly explain the attributes, more datapoints can be used to initialize the synthetic population. The results of the test summarized in Table 4.4, show that the data points are indeed State agnostic. Since the states are categorical variables, they were dummy-coded.

Adopters		
Constant	-0.2091	Significant
Attitude	1.2295	Significant
SN	-0.0477	Significant
PBC	0.0242	Significant
R-squared	0.589	Significant
Non-adopters		
Constant	-0.5139	Significant
attitude	0.4717	Significant
SN	0.1081	Significant
PBC	0.1409	Significant
R-squared	0.177	Significant

Table 4.3: TPB Weights for Adopters and Non-Adopters

Weights for TPB Attributes

In order to derive the weights for the three TPB attributes found in Equation 3.1, Multiple Linear Regression was performed separately for the non-adopters and adopters' dataset. The Table 4.3 summarizes the weights obtained.

4.3.4 Initializing Synthetic Households with TPB Attributes

Hypothesis Testing

Several approaches were attempted to assign values for Attitudes, Subjective Norms and PBC for synthetic households. Because synthetic households are characterized only by three demographic variables at the time of their generation: Household Age, Household Size and Income, the ideal method would be to build a model that can predict the three TPB variables from the survey data based on the three demographic variables. Therefore, a first check was conducted to ascertain if the three demographic variables of the survey data have predictive power in explaining the Attitudes, Subjective Norms and PBC of the survey population. Considering that Age and Income data are available only in ranges, they were dummy-coded before performing the hypothesis test of predictive power. Table 4.5 summarizes the results for the 2 demographic variables of Income and Age separately on the three TPB attributes:

The results show that income and age separately do not explain the three attribute values well. This could be because a lot of information could have been lost within the brackets. Therefore an alternative method was attempted where values of age and income were uniformly sampled within their brackets to result in numeric values. The hypothesis results still showed that the three TPB attributes could not be explained by the two demographic variables.

Independent	Dependent	T-ratio	R-Squared	Significant?
State	attitude	x1: -0.719 x2: 0.384 x3: 0.041	0.004	no
	subnorms	x1: -0.131 x2: 1.151 x3: 0.195	0.002	no
	pbc	x1: 0.350 x2: -0.428 x3: -1.358	0.006	no
	Age	x1: 0.155 x2: 0.166 x3: 0.121	0.008	no
	Income	x1: 0.375 x2: -4.083 x3: -0.201	0.03	∼

Table 4.4: Testing for data dependence on State variable

Gower's Distance as Similarity Metric

A second approach which involved clustering demographic data to ascertain if TPB attributes within the group were closer to each other as compared to inter-group values. Considering variables are categorical, the following steps was taken:

- Calculating Gower's Distance Matrix
- MultiDimensional Scaling to derive principal components
- K-Means Clustering to derive clusters.

The Figure 4.9 shows that four output clusters that were obtained. This method however showed almost similar distributions both intra-group and inter-group, therefore this approach was abandoned.

Independent	Dependent	T-ratio	R-Squared	Significant?
Age	attitude	x1: -0.542 x2: 0.856 x3: 1.480	0.006	no
	subnorms	x1: 0.042 x2: 0.038 x3: 0.040	0.007	no
	pbc	x1: 0.511 x2: 2.461 x3: 5.345	0.042	no
Income	attitude	x1: -0.327 x2: -0.819 x3: -1.078 x4: -1.066	0.002	no
	subnorms	x1: -1.393 x2: -0.854 x3: -2.036 x4: -1.428	0.005	no
	pbc	x1: 0.493 x2: 1.164 x3: 0.213 x4: -0.557	0.004	no

Table 4.5: Testing Explanatory Power of Demographic Variables on TPB Attributes

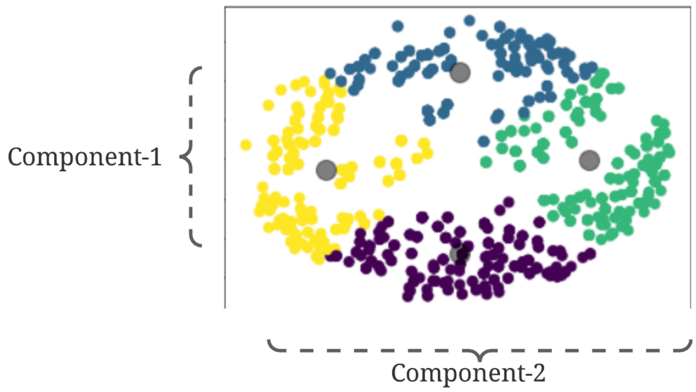

Figure 4.9: Clusters from MDS

The final approach that was finally adopted is that of using Gower's distance as a metric to match two records. Gower's Distance can be used to measure how different two records are. The records may contain combination of logical, categorical, numerical or text data. The distance is always a number between 0 (identical) and 1 (maximally dissimilar). The general form of calculating Gower's Distance is as follows:

$$D_{Gower}(x_1, x_2) = 1 - \left(\frac{1}{p}\sum_{j=1}^{p} s_j(x_1, x_2)\right) \tag{4.1}$$

For every new record of a synthetic household that we want to assign values of the three TPB attributes to, the survey datapoint that is closest (or most similar to) in terms of Gower's Distance to the synthetic household's datapoint is used. This process followed is visualized in Figure 4.10.

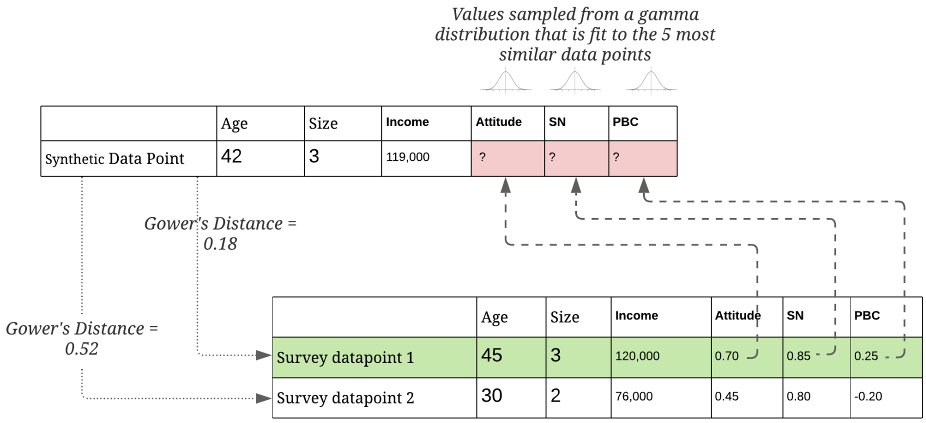

Figure 4.10: Using Gower's Distance to assign TPB values

4.4 AGENT-BASED MODEL

Three aspects of the model have been realized until now:

- Synthetic household population generated for Albany for 2015
- Three decision attributes implemented using Theory of Planned Behavior using survey-data from 2014-15
- The resultant synthetic household population has been initialized with the TPB attributes from the survey data.

In the ABM, these initialized agents will interact with each other via networks, causing these TPB attributes to evolve over time: attitudes and opinions will evolve over time via interaction with more opinionated, experienced friends and acquaintances. Subjective Norms evolve over time as more and more of the agent's acquaintances become adopters. Moreover as years pass solar prices reduce, electricity prices change and the tax incentives vary as well. This makes the agent revise their perceptions of affordability of a solar panel. Figure 4.11 gives an overview of how the TPB attributes evolve over time due to interactions between different agents and consequently drive the adoption behaviors of the agents over time-steps.

4.4.1 Evolution of Attitudes

Attitudes of the agents towards adoption of solar are elicited through questions such as: "Do you believe solar panels can help slow down climate change?", "Do you believe that solar panels are a good way for your household to reduce its environmental impact?" etc. However people's perception of the benefits or difficulties of solar can change upon interaction with people with different opinions.

Relative Agreement Model

Among the various opinion dynamics models available, the most and widely used model for integration with ABMs, is the Relative Agreement Model (RA) that has

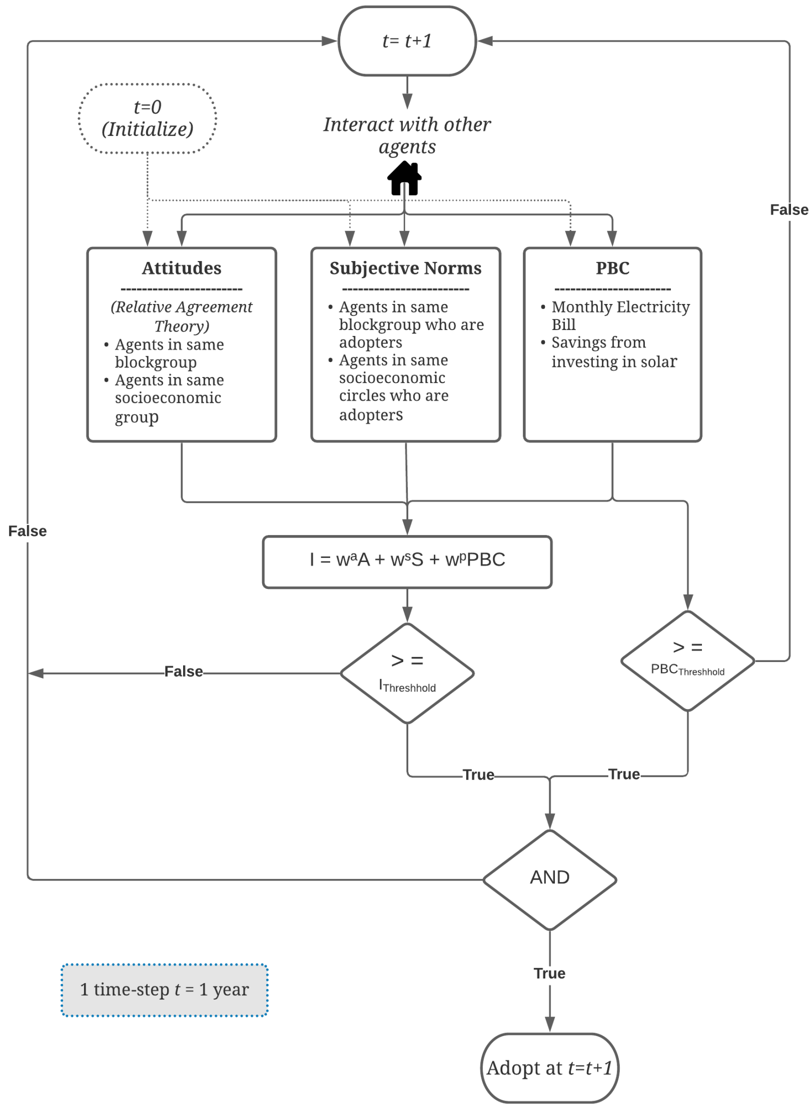

Figure 4.11: Overview of how the three TPB attributes evolve over time for every agent in the ABM

been developed by (Deffuant et al., 2002). While earlier models assigned binary values to agent's opinions, RA has several functions to endow its agents with more nuance and heterogeneity in their interactions with each other, thereby a simulating a more realistic scenario (Zeng et al., 2020). It is therefore used widely in studies that model adoption of green technology (Rai & Robinson, 2015).

The RA model has the following benefits:

- 1.Agents have varying degrees of confidence on their opinions: Two variables describes an agent's opinion: their current opinion and an uncertainty level that describes the confidence that the agent holds on their opinion.
- 2. Assymmetric influence between two agents: it is only the agent who is more confident of her opinion can influence the opinion of a less-confident agent.
- 3. Agents are more likely to be influenced by agents whose opinions are closer to their own. This is plausible in real-life situations as well, where a politically far-right person's opinions is less likely to be influenced positively in any capacity by a far-left person.

In this model, the opinion (attitude) of the agent which is calculated from the survey, is given a certain confidence level depending on how strong their opinion: if they very strongly believe in the benefits of solar (their attitude variable is close to 1), their confidence is close to 1 as well. Similarly, if their attitude is strongly against solar, their confidence will tend towards 1 as well. The confidence/uncertainty levels are mapped as the absolute value of the attitude. The stronger the attitude is on either end of the spectrum, the less uncertain the agent is. This results in a v-shaped map of the agent's attitudes.

$$Uncertainty = 1 - |attitude| \tag{4.2}$$

This is adapted from (Meadows & Cliff, 2012)

4.4.2 Evolution of Subjective Norms

This module captures how the agent is influenced collectively by the virtue of their peers being adopters or not. This is captured in two ways:

- 1. Observability of Solar PV: Research shows that increase in rooftop solar PV in a zipcode positively increases the likelihood of a house in that area to adopt PV as well (Bollinger & Gillingham, 2012).Therefore subjective norms (influence of peer-pressure) increases with increasing presence of adopters in an agent's neighborhood.
- 2. Presence of adopters in social group: More the number of people within an agent's friends circle, the more likely it is for her to consider adopting seriously.

4.4.3 Evolution of PBC

In order to model the realistic scenario where non-adopters reassess their ability to invest in solar in response to several extraneous variables such as: improved Federal Tax Credits (FTC), encouraging subsidies, improved feed-in tariffs, an increase in electricity prices from the utility and finally a decrease in the price of a solar panel itself, the following approach was taken.

Research shows that the perception of affordability of solar is the most cited barrier to adoption, therefore the economic component is used almost exclusively to determine an agent's perceived ability to adopt solar (Rai & Robinson, 2015). At every time-step (of one month each), every agent checks the decision-variables mentioned above, checks her own household's monthly electricity consumption, calculates the estimate payback period to see if it is within tolerable limit.

This is encapsulated by the formulae below. Average electricity consumption data for different income-groups at different census tract locations are available publicly, provided by NREL under the SEEDS-II REPLICA project (Mooney, 2018). This data is focused to the area of interest and the average electricity consumption per month is estimated for the synthetic population generated, using the location and the income bracket information.

$$NetPanelCost = \frac{(AvgElectricityUsepermonth * 12 * AvgPriceperWatt * FederalTaxCredit)}{ProductionRatioofPanel} \tag{4.3}$$

$$AnnualSavings = AnnualElectricityCost - (AnnualSolarProduction * Feed - inTariff) \tag{4.4}$$

$$SimplePaybackPeriod = \frac{NetPanelCost}{AnnualSavings} \tag{4.5}$$

The flowchart in Figure 4.4 illustrates how the Initial PBC is used to estimate the tolerated payback period for the household. Unlike the other two attributes of Attitude and Subjective Norms, PBC of the agent does not change at every time step, but rather it is used to determine the tolerable payback period for the household which is then compared to the payback period they would achieve if they invested in solar that month (at the current prices, tax credits and other incentives). If the payback period of the panel is within their tolerated limit, their PBC switches to 1, which implies they are ready to adopt, if their behavioral intention also crosses threshold limits.

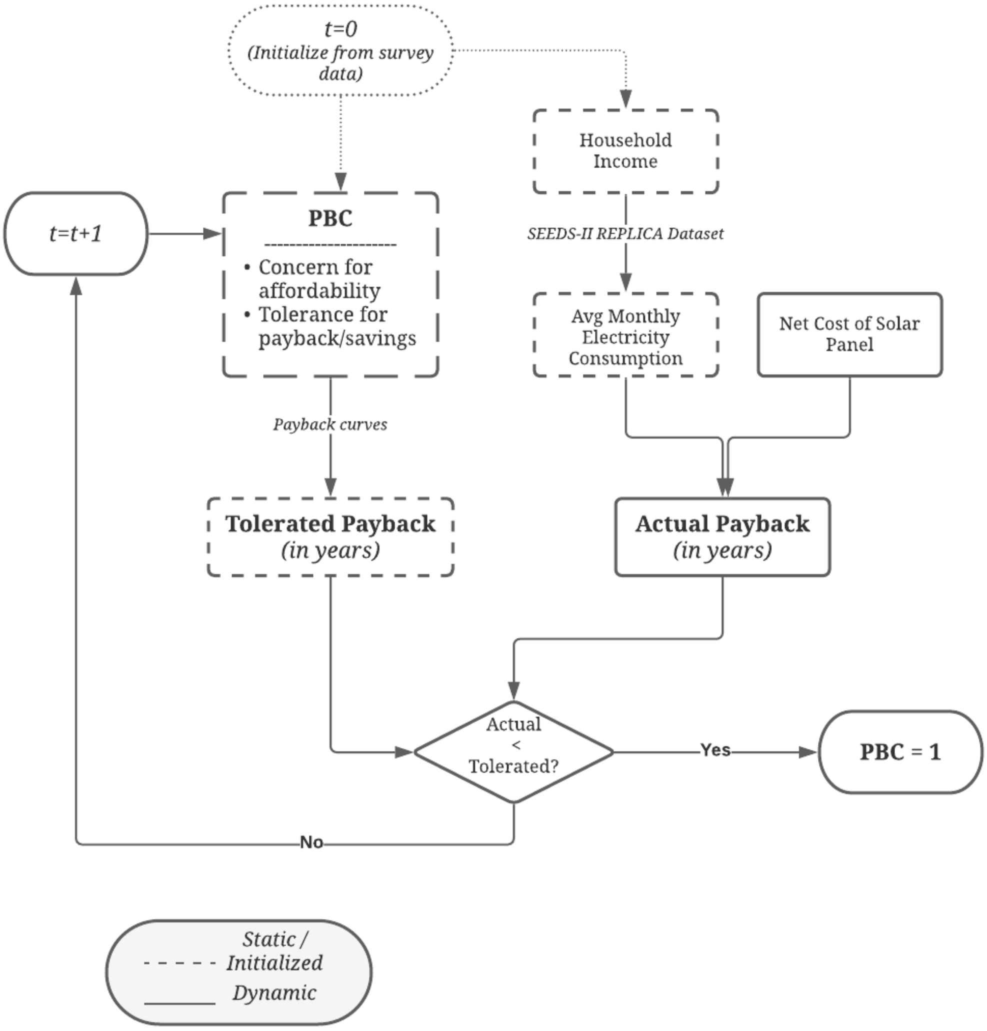

Figure 4.12: Evolution of Perceived Behavioral Control (PBC) through simulation run

4.4.4 Assigning Tolerated Payback Values

As described in Figure 4.12, after initializing PBC values for all households using the similarity metric described above, the *ToleratedPaybackPeriod* for every household calculated from this PBC. A previous study on the same survey dataset conducted, calculated the Payback Curve outlined in Figure 4.13.

At every timestep of a month, the household calculates the actual payback that will be achieved if they invest in solar at the current prices, tax incentives, feed-in tariffs and utility costs. Using the simple payback formula outlined earlier, they will calculate the payback period and compare it with their tolerated period. If they breakeven on their investment earlier, they will have full confidence over their ability to invest/buy the panel if their attitudes and subjective norms are also aligned to the goal of adopting.

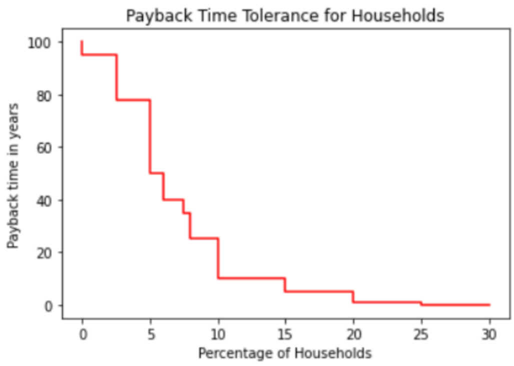

Figure 4.13: Payback Period Tolerances for Survey Data

The mapping from initialized PBC values and the tolerated payback period is based on the curve in Figure 4.13. It gives us the percentage of population that accept different payback periods. 100% of the population accept a payback period of less than 2 years (naturally). Almost no one is willing to tolerate breaking even after 25 years (which is the typical lifespan of a solar panel). The initialized PBC values is elicited from questions that measures a homeowner's tolerance of costs and paybacks. Therefore in a timestep, if the calculated payback of the household 15 years, the curve shows that only 10% of the population is willing to tolerate that period. Therefore only top 10% of the population ranked in terms of their initial PBC will be considered ready to accept this payback period. If the homeowner falls within this 10% of households, they accept the period and switch their PBC to 1. Else, they stick to their perception of affordability assigned to them at t=0 and continue to the next timestep where they re-assess their ability.

4.4.5 Incorporating Policy Levers

An agent who at the beginning of the simulation found solar to be an expensive option given their income will however react to changing solar prices. Effects of the technology learning curve and greater economies of scale have lowered prices of solar and made it a financial viable option (Feldman et al., 2020). This variable is therefore allowed to reflect real-life trends in solar as is shown in Figure 4.14.

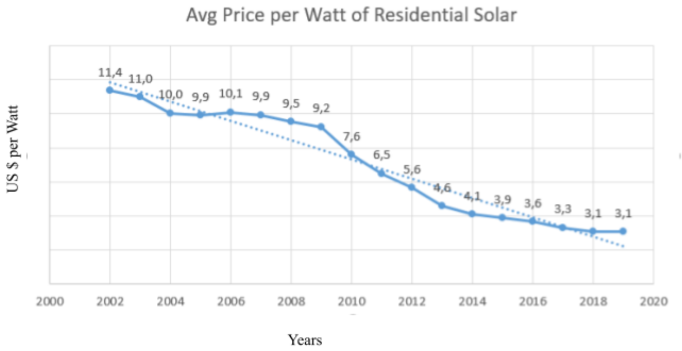

Figure 4.14: Average Price ($) per Watt of Solar PV

Electricity prices fluctuating may also cause the agent the decide to hedge against rising retail prices and decide that despite upfront costs it is better in the long-term to invest in solar. This variable is also incorporated in the model to reflect prices on ground as shown in Figure 4.15.

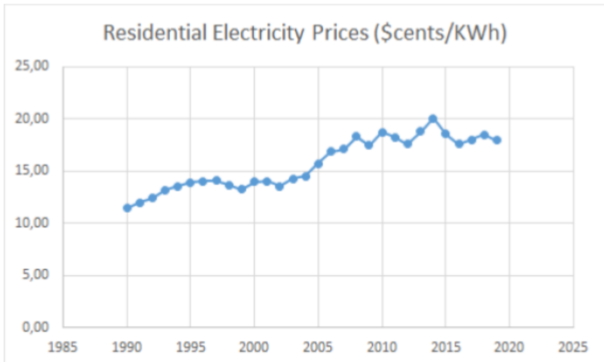

Figure 4.15: Retail Electricity Price (Cents/Watt)

Tax credits and subsidies are regularly implemented to ensure that prices per residential unit are affordable for kick-starting early stage adoption. In New York State, there is a state subsidy of 25% of the upfront cost being included in tax-credits. At the federal level, there is an added tax-credit of upto 26% of the panel cost.

4.5 NETWORK INTERACTIONS

As described in Chapter 3 on conceptualizing the multi-level social network interaction of agents, the agents are made to interact at the physical neighborhood level and then among their circles of influence.

Because data is not available at the neighborhood level, the administrative division of a US census block is taken to represent a block. A census block is the smallest geographic unit used in collecting US Census Data that contains 100% tabulation (data from all households). A census block can correspond to a city block. An oveview of the scale of a census-block in comparison to block-groups (collection of blocks) and census tracts (collection of block-groups) is seen in Figure 4.16.

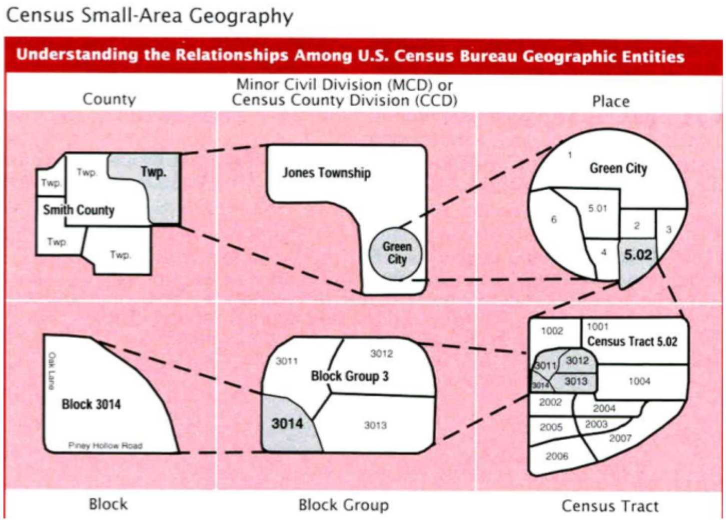

Figure 4.16: Relationships between US Census Geographies (adapted from (US Census, 2010))

4.5.1 Circles of Influence

Although in reality the number of connections in each of these circles are assumed to be higher (see Figure 3.3), a smaller number of connections are taken for the number of people that the agent interacts with in a year, in the context of adopting a solar panel. At the start of the model, these three circles of influence are 'assigned' to every agent. As the model advances, the agent samples from this initial network, to simulate interactions within. This circles-of-influence network does not change with every time-step, only the members the agent interacts with.

- Circle-1 : The close-friends, family and intimates circle. These are the select group of 5 that the agent most frequently interacts with and whom they trust. 5 are sampled to be equally within the same block-group as well as from anywhere within Albany.

- Circle-2 : Workplace friends and good friends. Workplaces are assumed to be geographically nearby, therefore connections are sampled within the census block-group and some within the census-tract. At the start of the run, 50 people are initialized and every time-step the agent interacts with a maximum of 15, which is a realistic assumption to take in the context of discussing solar adoption.

- Circle-3: This includes friends and acquaintances. These friends can be anywhere within Albany and is not restricted to geography. Upto 200 are initialized at the start of the run and the agent interacts with a maximum of 20 ever year as model advances.

Assumption: Who is the householder?

As the reader would have observed, the agent in question is a household, so the question arises: to whom do these circles of influence belong to? In a single-family household, there can be two adult individuals making the decisions in the household, but for the purposes of this model, it assumes that the decision-maker is the head of the household which is stated in the Census.

Intensities of Interaction

To model the evolution of opinions, Relative Agreement Theory (see Chapter 4) is used. When two agents A and B interact, the variable 'mu' which denotes 'Intensity of Interaction' is key to determining how much influence A has over changing the opinion of B and vice-versa. Different intensities of interaction are attributed to these circles of influence as follows:

- Circle-1: Intensity of 0.8
- Circle-2: Intensity of 0.2
- Circle-3: Intensity of 0.1

While there is no literature yet to support these parameter values, the values are set in reference to the default value of 0.2 (which signifies a normal interaction). A sensitivity analysis is performed to measure the effect of this uncertainty on model results.

4.5.2 Two Network Scenarios

Research suggests that information policies when implemented in a society that is socioeconomically integrated (where people have a good likelihood of interacting with members of socioeconomic groups that are different from theirs) performs differently from societies are segregated- where there are closed communities within which people interact. The assumption of a socioeconomic group is based on income similarity, in this model. There was an attempt to include Race/Ethnicity as an attribute to designate socioeconomic group, but the survey data that is used to initialize the TPB attributes does not contain any information on this variable. Therefore, to maintain consistency in the model, the assumption is made to restrict this definition of a socioeconomic group to income similarity alone. To investigate the effect of integrated/segregated networks on adoption rates, two network scenarios are drawn: Integrated and Segregated.

Integrated Scenario

In the integrated scenario, agents are assigned a higher likelihood of establishing social ties with members of other socioeconomic groups. At every time-step of a year an agent interacts with upto 10 neigbhors within its census block. This number is drawn after examining the distribution of number of households in different blocks within Albany. While initializing the circles of influence at the start of the model, there is equal-likelihood of acquaintances being drawn from any of the income-groups. Figure 4.17 shows the network of about 20 agents in the census tract of 14801 in Albany County.

Segregated Scenario

In the segregated scenario, agents are assigned a higher likelihood of establishing social ties with members of the same socioeconomic group as that of the agent. At every time-step of a year an agent interacts with upto 10 neigbhors within its census block of those who belong to the same socioeconomic group as well. This simulate

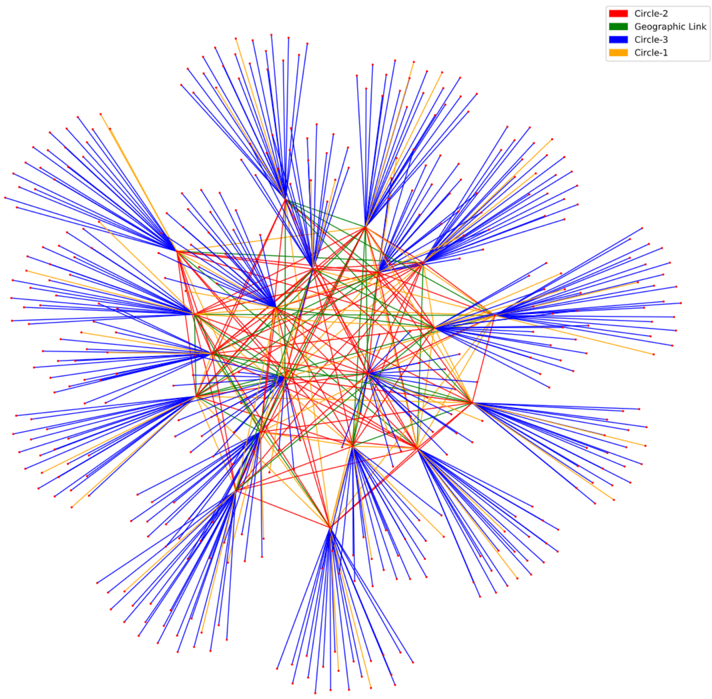

Figure 4.17: Integrated Network Scenario: Census Tract 14801, Albany County, New York

the socioeconomic divide that is often observed in real-life of certain neighborhoods being labelled 'rich white neighborhoods' and 'low-income immigrant areas'. While initializing the circles of influence at the start of the model, there is high likelihood of acquaintances drawing contacts within members of their own income group. The effect this has on the network structure is shown in Figure 4.18

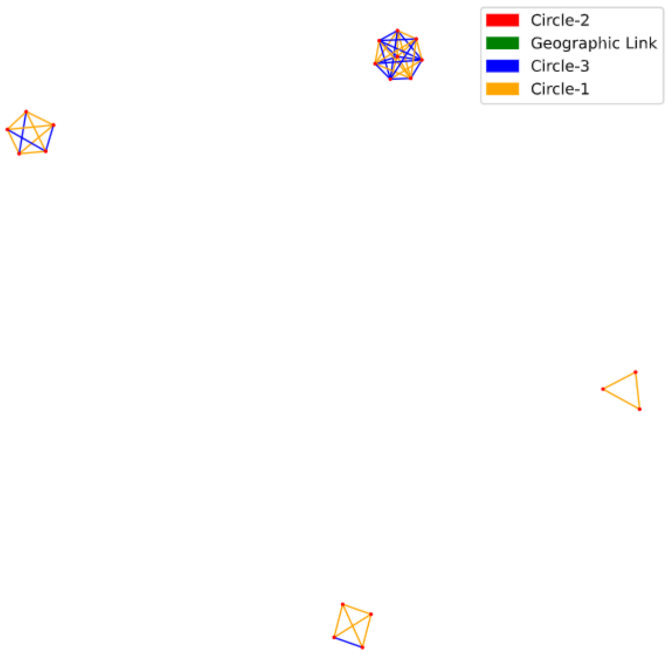

Figure 4.18: Segregated Network Scenario: Census Tract 14801, Albany County, New York

The same 20 households when observing different rules while drawing social ties show such stark difference in how closed their networks suddenly become. Social ties overlap across circles and clusters begin to develop and these networks tend towards clustered small-world network structures.

4.6 EXPERIMENTAL SETUP

The following policy scenarios were designed to test the model under two network structures: integrated and segregated.

Table 4.6: Experimental Setup

Scenario Number	Description	Parameters
1	Tax Credits of 46%	Panel Cost=54% of Net Panel Cost
2	[Baseline] Tax Credits of 51%	Panel Cost=49% of Net Panel Cost
3	Tax Credits of 56%	Panel Cost=44% of Net Panel Cost
4	Tax Credits based on Income-Group	less75k (low income): Tax Credits= 56% 75to100k (middle income): Tax Credits= 51% 100to150k (high income): Tax Credits= 46% 150kplus (high income): Tax Credits= 46%
5	Seeding Low Income Groups	[0.1%,1%,2%] of members of Income-Group less75k
6	Seeding Low & Middle Income Group	[0.1%,1%,2%] of members of Income-Group less75k and 75to100k
7	Seeding Random Influencers	[0.1%,1%,2%] of top influencers in network
8	Seeding Low Income Group Influencers	[0.1%,1%,2%] of top influencers low income group network
9	Seeding Low & Middle Income Group Influencers	[0.1%,1%,2%] of top influencers low and middle income group network
10	Seeding Random Households	[0.1%,1%,2%] of households in network

5 VERIFICATION AND VALIDATION

5.1 BASELINE RUN

The model was calibrated for the baseline adoption curve of Tax Credits of 51% using the process shown in Figure 5.1.

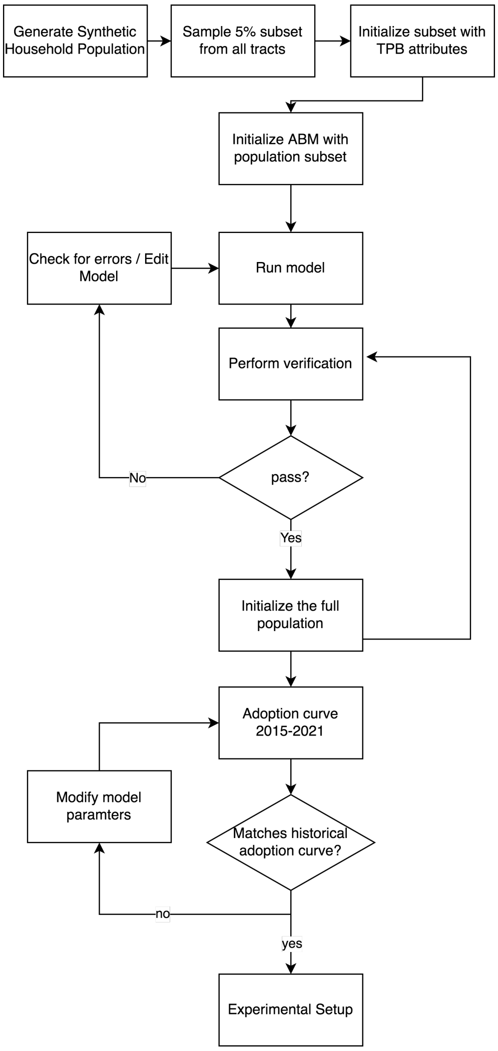

Figure 5.1: Verification, Validation and Calibration process was conducted in an iterative manner

The baseline results seen in Figure 5.2 and Figure 5.3 is run for one random seed and basic insights from it are described. The baseline policy reveals some important information about the underlying network of Albany: the adoption curves in relation to the actual adoption rates suggest that the underlying network of Albany tends towards a segregated social network with more intra-group communication as opposed to inter-group. Once again, the enhanced performance of the policy in an integrated network as compared to a segregated network justifies the fact that tax incentives alone do not a play key role in encouraging households to adopt.

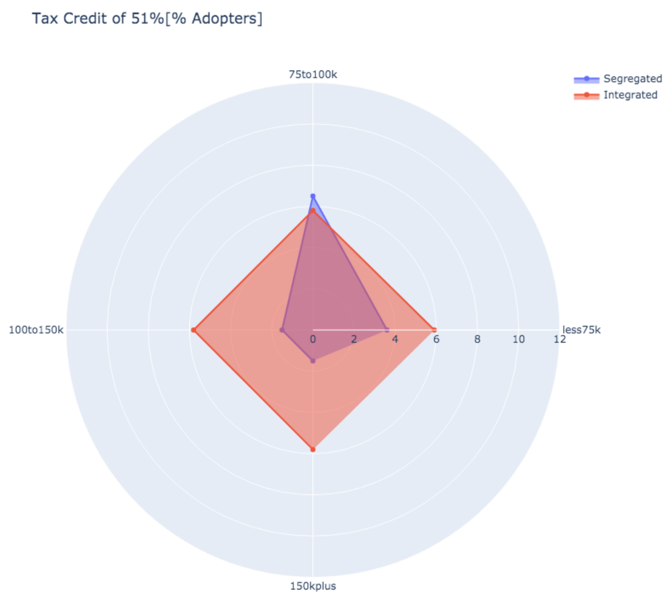

Figure 5.2: Percentage of income-group population that are adopters under baseline scenario with tax credits of 51%

This policy has a balanced performance across the 4 income-groups in the integrated scenario (of 6% adopters), whereas in the segregated scenario its a different case: the policy performs poorly in the high income-groups as compared to the low and middle-income. The low-income group, despite being double the population of the other 3, still has a low group-adoption rate. This policy however fares well in the middle income-group.

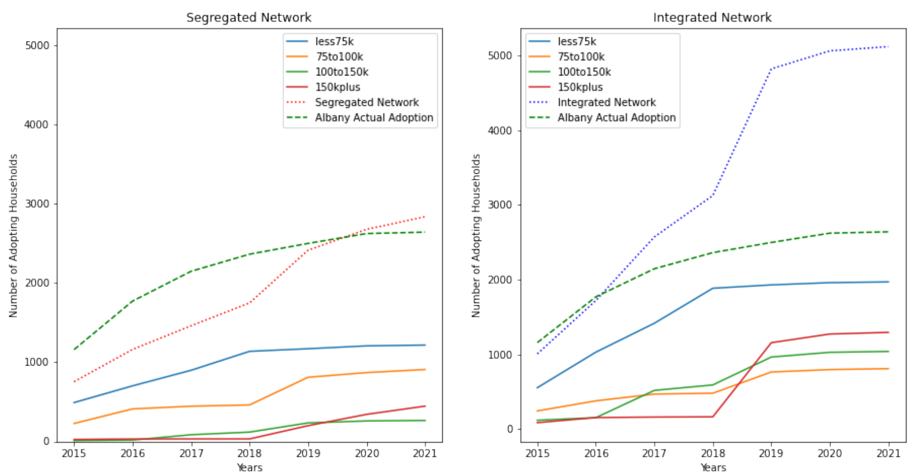

Figure 5.3: Time-series plot of income-group population that are adopters under the baseline scenario with tax credits of 51%

This weakens the hypothesis that financial incentives alone have a strong role to play in gathering adopters: if that were the case, the high-income groups would have increased rates on account of affordability alone. However that is not the case, suggesting that in the segregated network the increased inter-group communication has benefited the more populated income groups of low and middle incomes. The segregated network in combination with a smaller population, can cause the policy to perform poorly in such groups.

5.1.1 Sensitivity Analysis: One Factor at a time (OFAT)

Sensitivity Analysis is a common approach used to understand model behavior. Although there are many standardised methodologies for performing Sensitivity Analysis in literature such as (Saltelli et al., 2004), (Hamby, 1994), (Thiele et al., 2014), these methods are not always suitable for ABMs because of the following reasons ((Windrum et al., 2007),(Macal & North, 2010):

- Existence of micro-level encompassing individual behavior of agents as well as emergent properties whereby these individual behaviors aggregate to macro-level outcomes.
- As a result of these emergent properties the link between input and output is non-linear.
- Properties of ABMs such as path dependency, tipping points can change over time.

As ABMs are used increasingly in policy-support and in recent years for predicting/forecasting consequences of policies, these models are expected to be empirically grounded (D. Zhang & Guo, 2014). In the use of empirically grounded ABMs, reliability is identified with their ability to replicate, represent and predict the behavior of the target phenomenon that is being modelled. This measure of reliability in modelling studies is confirmed through Validation.

With more studies using empirically grounded ABMs, there is growing research in also standardising verification and validation of computational social science models, specifically ABMs. Some key studies are (Garcia et al, 2007), (Rand & Rust, 2011). From the many methodologies suggested in literature (Cariboni et al., 2007), (ten Broeke et al., 2016) to effectively understand and verify the robustness of an ABM, the approach of One Factor at a Time (OFAT) is used in this study.

OFAT methodology involves running the baseline model by varying one parameter at a time while keeping every other parameter constant (to the baseline values). This method is useful because it can be used to understand in isolation the effect of this parameter on the KPIs. This can reveal if the model is particularly sensitive to a particular parameter (identification of tipping points) and thereby improve understanding of how the model functions. Traditionally, this method calculates sensitivity measures in partial derivatives format and involves several runs. Due to limitations in the availability of computational resources, this model currently is run through a limited set of parameters values. Because the traditional partial derivative method requires very small step sizes and a large number of replications, this study does not compute these partial derivatives and instead confirms results via visual inspection.

The parameters that are varied on the baseline is listed in Table 5.1.

Table 5.1: Model parameters and range for sensitivity analysis using OFAT methodology

Parameter	Baseline Value	Range for OFAT
Tax-Credits (%)	51%	[46%, 51%, 56%]
Random-Seed	123	10 random-seeds
Interaction Intensity (unitless)	0.2	[0.1, 0.2, 0.3, 0.4]
Intention threshold (unitless)	0.80	[0.60, 0.70, 0.80, 0.90]
Sampling percentage (%)	0.1%	[0.1%, 1%, 2%]

5.1.2 Random Seed Analysis

Due to the model being computationally expensive and limited resource availability, the baseline model was run for 10 random-seed replications for the two network scenarios of Integrated and Segregated each. The outcomes of the runs are shown in Figure 5.4

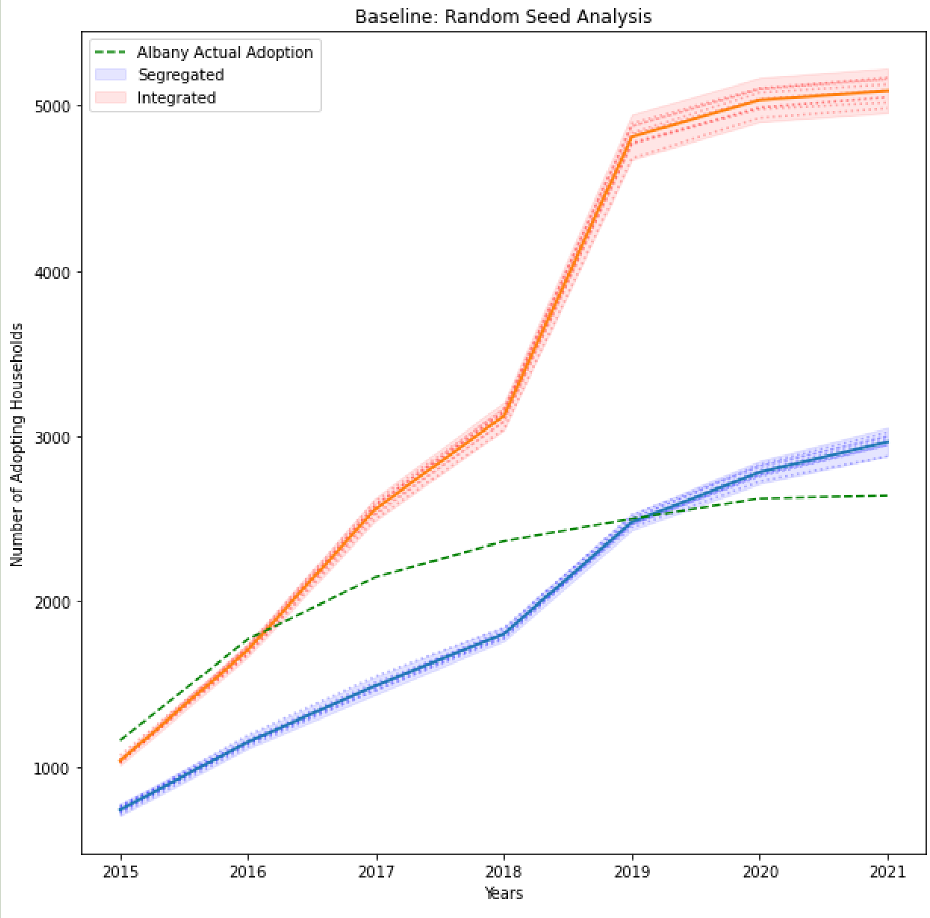

Figure 5.4: Results of 10 model replications run under different random seeds for integrated and segregated networks.

Table 5.2: Confidence Intervals of 10 replications of the Integrated Network Scenario

Year	Mean	Standard Deviation	ci95_hi	ci95_lo
2015	1034.8	13.851394	1043.892	1025.885
2016	1705.0	20.211383	1718.137	1691.863
2017	2561.0	34.874776	2583.669	2538.331
2018	3120.7	42.248603	3148.239	3093.316
2019	4808.1	68.127536	4852.394	4763.828
2020	5032.1	66.491436	5075.331	4988.892
2021	5088.1	66.998964	5131.660	5044.562

Table 5.3: Confidence Intervals of 10 replications of the Segregated Network Scenario

Year	Mean	Standard Deviation	ci95_hi	ci95_lo
2015	739.2	18.109236	750.993	727.451
2016	1149.7	19.658190	1162.556	1137.000
2017	1491.2	26.682287	1508.566	1473.879
2018	1802.8	21.549040	1816.896	1788.882
2019	2479.3	24.622145	2495.338	2463.329
2020	2780.4	34.702706	2803.001	2757.888
2021	2964.7	43.010981	2992.735	2936.821

The resulting tables 5.2 and 5.3 show the confidence intervals that another model run with a different random seed can lie within. The ranges are different for integrated and segregated scenarios, with the latter showing smaller confidence intervals. The integrated network scenario's range of values widens with increasing time-step with its behavior becoming more uncertain. However, because the purposes of this model is not intended for predictive purposes but instead intends to serve as a model that reasonably emulates the target phenomena (adoption curves of Albany County between 2015 and 2021) so that different network scenarios and policy interventions can be tested on it this range of variation (+/-60 households) is deemed acceptable to proceed. It is acknowledged that more number of model runs (more number of samples) can lead towards the true mean. However, due to long waiting times for model-runs and limited computational resources this approximation was made to continue towards policy analysis.

6 MODEL RESULTS

In this section, results of different experiments that were designed in Chapter 4 under Table 4.6 is visualized and some preliminary insights are described. For re-iterative purposes, a flowchart of the experiments conducted is presented in Figure 6.1

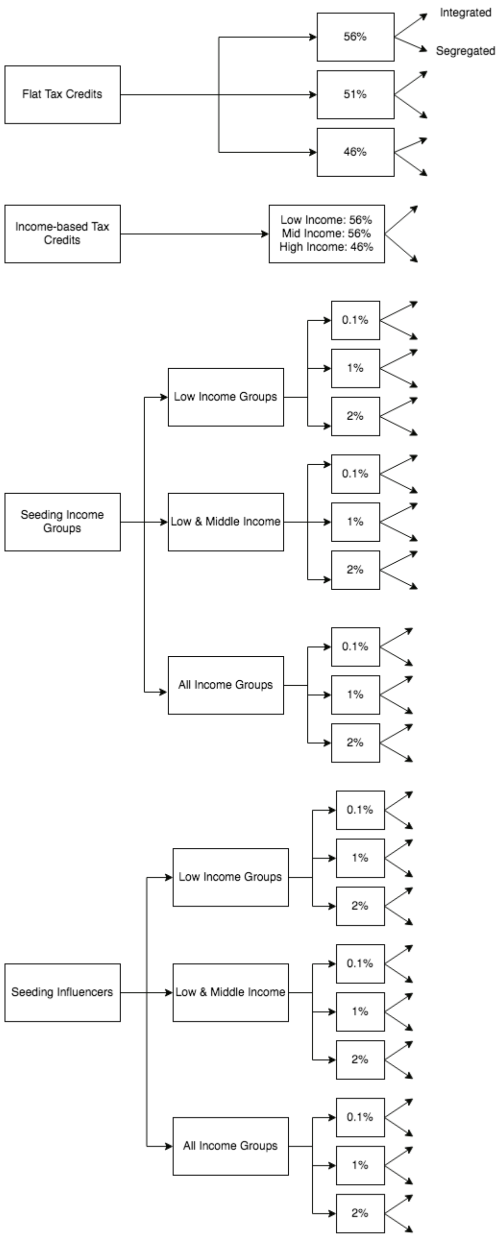

Figure 6.1: A Flowchart outlining all the experiments conducted. Scenarios involving Seeding Influencers and Income Groups are experimented with three different sampling percentages of 0.1%, 1% and 2% of the income group populations.

6.1 FLAT TAX CREDITS

6.1.1 Tax Credits of 46%

Studies that work at the intersection of social networks and adoption modelling often build on the claim that financial subsidies alone are not enough to result in successful adoption campaigns. It is also claims that the same policy can perform differently if launched in an integrated network as opposed to a segregated network. To observe these effects, a flat tax credit scheme is studied. As of today, the total tax credits that are offered in Albany irrespective of your financial background, to a solar PV panel purchases is 51% (26 from Federal Tax Credits and 25 from New York State). By 2023, the government plans to revoke this 26% tax rebate completely.

In this scenario, the adopter pays 54% of the net panel cost. Figure6.4 shows the overall adoption rates in the integrated and the segregated network across time, along with the adoption rates across income-groups.

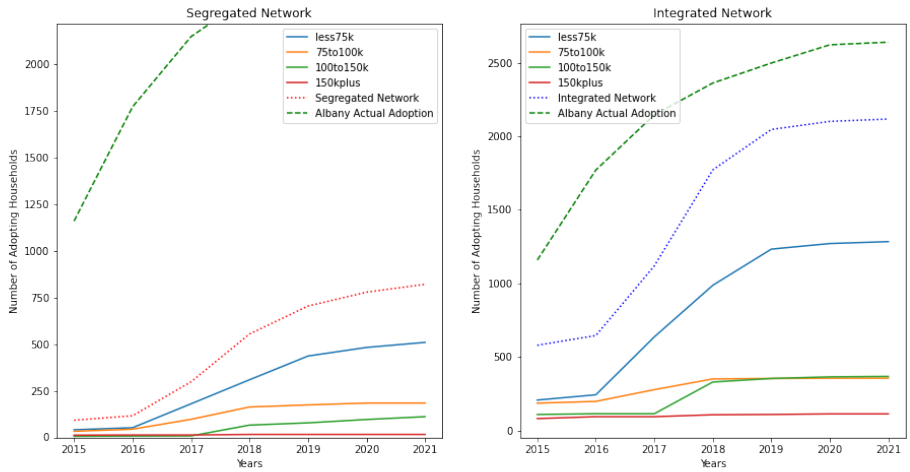

Figure 6.2: Adoption Rates across time and across income groups for integrated and segregated networks respectively in Scenario 1 where tax-credits are 46%

The baseline tax credits provided in Albany along with federal tax credits is 51%. The tax credits when lowered by 5% to 46% results in adoption curves below baseline for both Integrated and Segregated network scenarios. To have a better look at how this policy pans out for the different income groups, a radar plot (see Figure 6.3) was made.

From Figure 6.3 it can be observed that there is not much difference in the percentages of adopters of each income group within a network scenario, but in comparing the networks, this policy performs better in the integrated network. Despite the higher costs borne upfront by the consumer, the higher percentage of adopters within an income-group is that of the low-income group of 'less75k' whether its an integrated or a segregated network. The key take-away from this policy is that despite the same tax subsidy being applied, the network itself has a big role to play suggesting that attitude-driven adoptions which arises due to information exchange between trusted sources and increased communication has a significant effect upon the adoption rate.

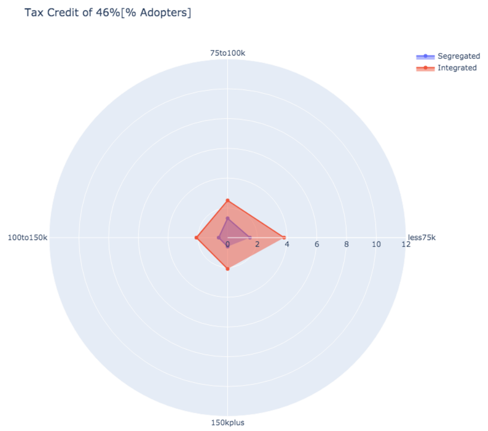

Figure 6.3: Percentage of income-group population that are adopters with tax credits of 46%, under segregated and integrated network scenarios

6.1.2 Tax Credits of 56%

This is a 5% increase over the baseline policy. It is expected that with increased tax credits, the actual cost of panel borne by the household reduces, thereby an increase in the number of adoptions with this price incentive is expected. Figure 6.4 confirms this expectation, as the policy performs better in comparison to the two lower tax-credit values of 46% and the baseline of 51% across both integrated and segregated networks for all years.

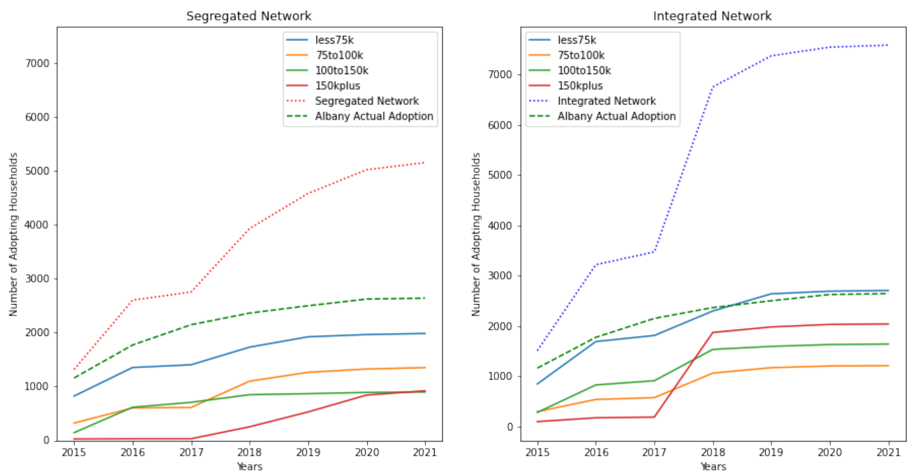

Figure 6.4: Adoption Rates across time and across income groups for integrated and segregated networks respectively in the scenario where tax-credits are 56%

The radar plot Figure 6.5 tells a positive story of the performance of the policy across income groups. In the integrated network the policy sees a lower adoption rate in the low-income group of 'less75k' compared to the others. Whereas in the segregated network, the policy once again sees (albeit slightly) better performance in the low and middle income groups as compared to high-income suggesting the positive role of diverse information sources and attitude-driven adoptions. The policy is line with the previous tax scenarios in seeing a better performance in an integrated network as compared to a segregated one.

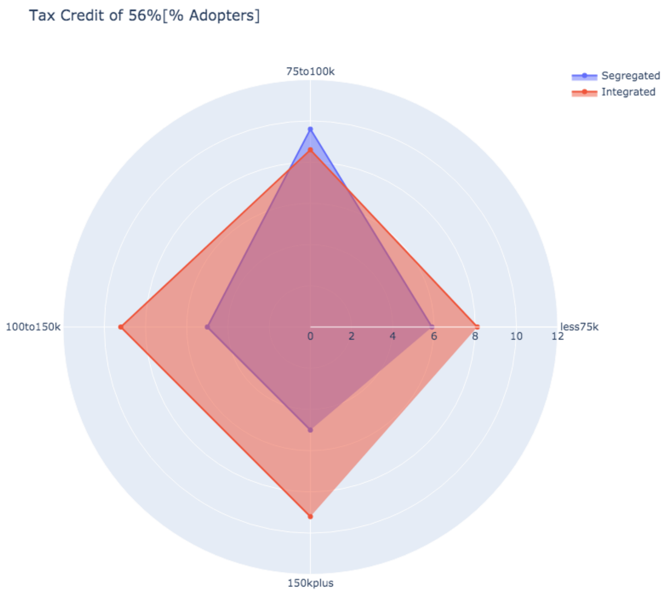

Figure 6.5: Percentage of income-group population that are adopters with tax credits of 56%,under segregated and integrated network scenarios

6.2 INCOME-BASED TAX CREDITS

In this policy scenario, tax incentives targeted income-groups instead of a flat-tax policy. The following tax-credits are given to each income-group.

Table 6.1: Tax-Credit values for income groups in the scenario where tax-credits are tailored to income groups

Income Group	Tax-Credits
Less than USD75k per annum	56%
USD75k to 100k per annum	56%
USD100k to 150k per annum	51%
More than USD150k per annum	46%

This policy, performs exceedingly well in the low-income group but also sees a significant drop in performance in the high-income groups specially in the segregated network which is justified by the higher prices for the latter. The better performance of the integrated network in comparison to the segregated network of this policy, also suggests the role of trusted information sources: in the segregated network scenario, the higher prices result in lower number of adopters and as the information sources function only within the group, attitudes become stagnant.

Attitude-driven adoption fails when the financial incentives do not change within a closed segregated network. This however changes in the integrated scenario: despite there being lower number of adopters within the high-income group alone, there are more diverse information sources (experienced adopters from other groups) whereby attitude-driven adoption is once again kick-started even though the tax itself remains same.

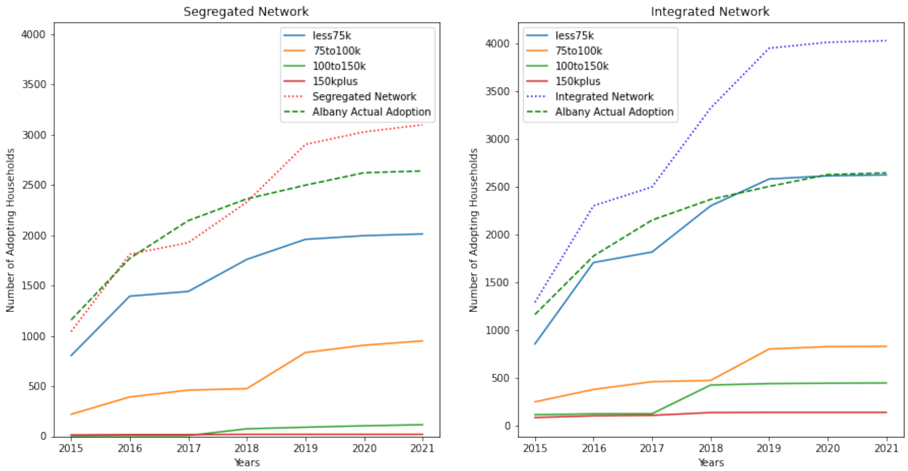

Figure 6.6: Adoption Rates across time and across income groups for integrated and segregated networks respectively in the scenario where tax-credits are tailored to the income. For the tax-credits allotted to each income group, see Table 6.1

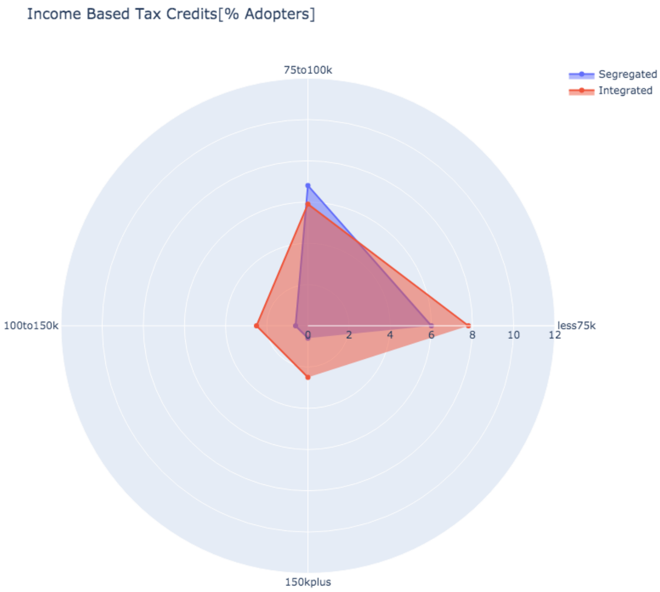

Figure 6.7: Percentage of income-group population that are adopters under scenario where tax-credits are tailored to the income. Analyzed under segregated and integrated network scenarios

6.3 SEEDING BASED ON INCOME

6.3.1 Seeding Low-Income Groups

In this policy scenario, households belonging to the low-income group are seeded with a solar PV system that meets their energy needs, with the aim of increase the number of early-adopters and trigger network-effects.

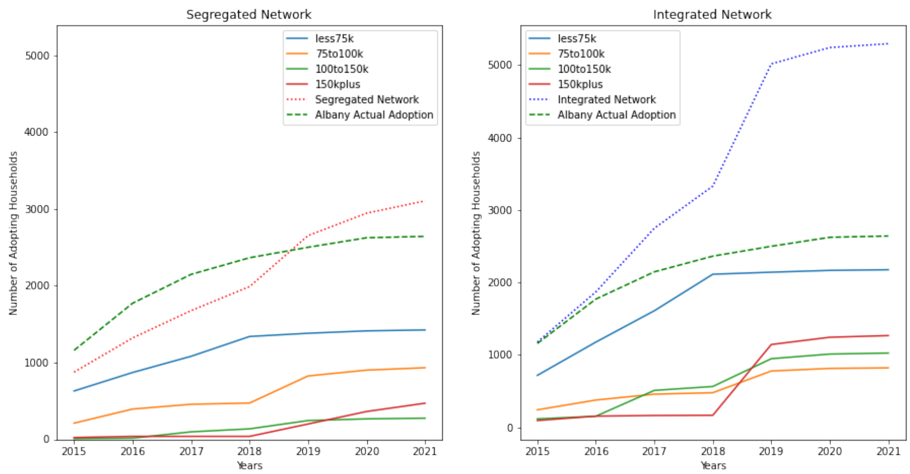

Figure 6.8: Adoption Rates across time and across income groups for integrated and segregated networks respectively in the scenario where households belonging to low-income group of 'less75k' are seeded. Sampling percentage = 0.1%

Different sampling-percentages are employed to test the sensitivity of the policy-performance across income-groups to this parameter. The radar plot in Figure6.9 shows that this policy performs better in an integrated network on all three sampling percentages. Across income groups, this policy favors the low and middle-income group in both integrated and segregated scenarios. High-income groups are favored by the policy in the integrated network scenario particularly, while the performance is quite poor in the segregated scenario.

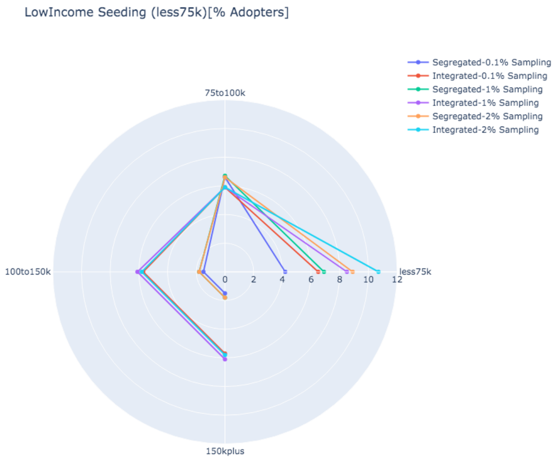

Figure 6.9: Percentage of income-group population that are adopters under the scenario where low income group (less than USD75K per annum) are seeded with solar PV.

6.3.2 Seeding Low and Middle-Income Groups

In comparison to the policy where only low-income groups are seeded, this addition of middle-income groups (the income category of 75to100k) to the seeding program does not result in any significant improvement to overall adoption rates as can be observed in Figure 6.10. The adoption rates however improve with increased initial sampling percentages, as can be observed in Figure 6.11.

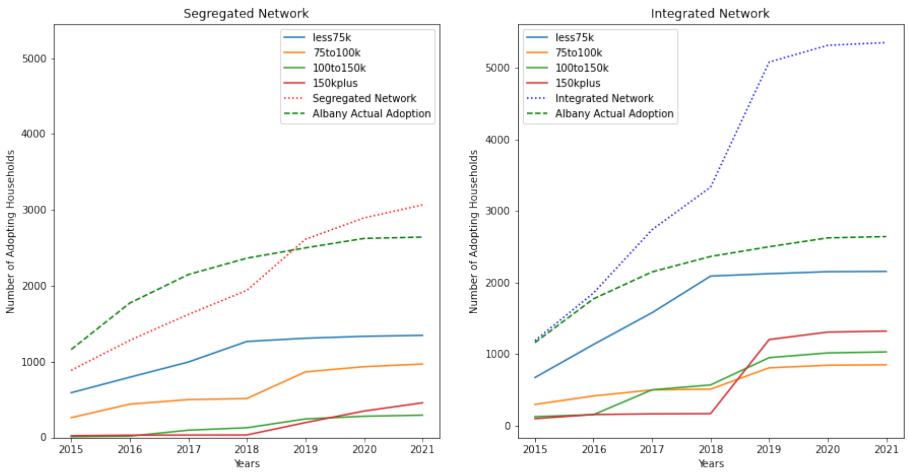

Figure 6.10: Percentage of income-group population that are adopters under Scenario 3b where households belonging to low and middle-income groups are seeded. Sampling percentage = 0.1%

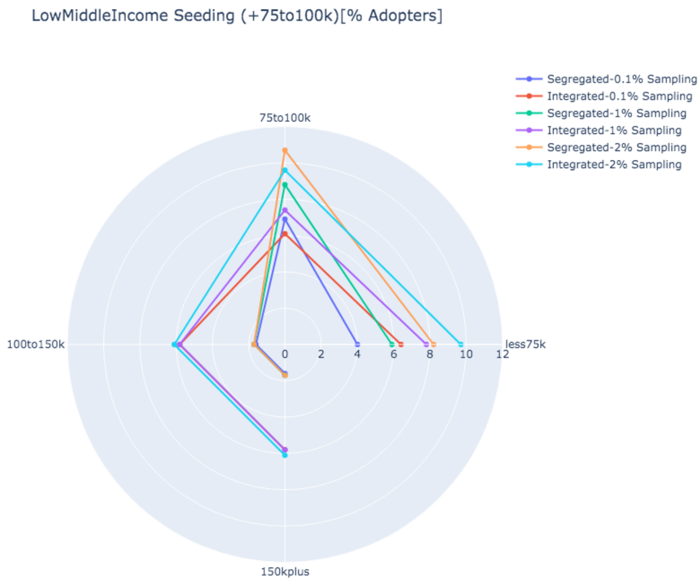

Figure 6.11: Percentage of income-group population that are adopters under the scenario where low income groups (those belonging to the income category of less75k) are seeded with solar PV systems that meets their energy needs.

6.4 SEEDING INFLUENCERS

In this policy, influencers are identified in both integrated and segregated networks and are seeded either a)randomly without regard to which income-group they cater to, b)if they belong to low-income groups and c)if they belong to low or middle-income groups with different sampling percentages (top 0.1%, top 1% and top 2%). The results of policy-performance across different income groups is visualized in Figure 6.12.

6.4.1 Seeding Influencers irrespective of Income Group

It can be seen that the number of seeds initialized has a key role to play on how well this policy performs compared to one where a random household is seeded (see Figure 6.12) in the income-group (not necessarily an influencer). When the top 0.1% points of influencers are seeded, the policy performs poorly in a segregated-network compared to all the previous policies (tax incentives and seeding non-influencers). This is not the case in the integrated network highlighting the overriding effect of diverse communication channels in spread of information.

6.4.2 Seeding Influencers in Low-Income Groups

There is a marked improvement in the performance of this policy on low-income groups in both segregated as well as integrated networks, with its performance on middle and high-income groups remaining relatively the same. This is an expected response to a policy that targets low-income groups.

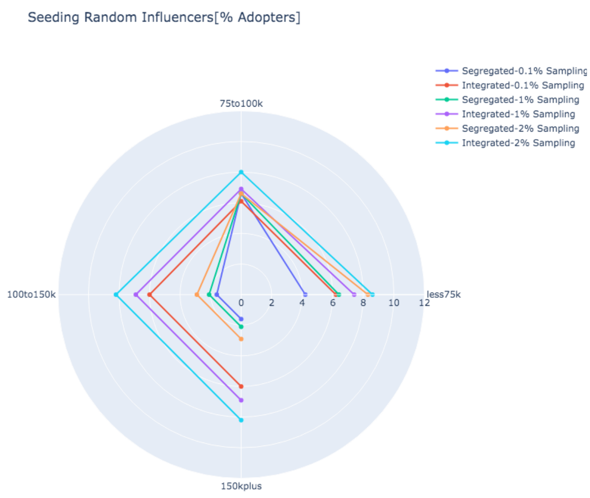

Figure 6.12: Seeding Random Influencers

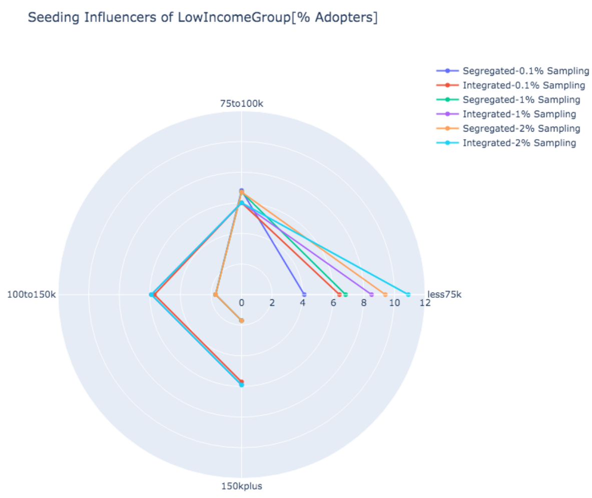

Figure 6.13: Seeding Infuencers in Low-Income Groups

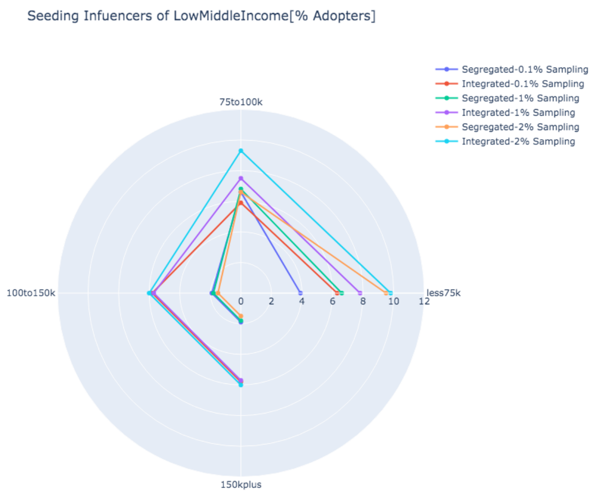

Figure 6.14: Seeding Influencers in Low-Middle-Income Groups

6.4.3 Seeding Low and Middle Income Groups

This policy's performance improves upon the group adoption rates in the middle-income group in both network scenarios while retaining performance across the other income groups.

A key observation can be made when comparing the performance of a policy that seeds influencers in an income group to a policy that seeds a random household (regardless of level of influence) in an income-group: influencers are not necessarily effective in transferring information across different groups or dispersing information within a group. This is noticeable because at the maximum, the integrated policy that seeds low and middle-income can reach a maximum of 9% group adoption rate, which the Scenario 4 (tax credits tailored to income groups) achieves. The trade-offs with respect to policy-costs will be dealt with later. This fact throws light into a potential reason for influencers not being effective enough: role of trust. If influencers are mass communicators and belong mostly to the agents' third circles (outer-most circle in the circles of influence model, with less intimate relationship with the agent), their influence is far lesser compared to the influence that people within the first circle have over agent's attitudes. That could be the reason why despite influencers having high degree centrality or betweennes-centrality, do not automatically kick-start attitude-driven adoptions.

6.5 SEEDING RANDOM HOUSEHOLDS

This policy is an extension of the policy seeding income-groups; here households are seeded randomly irrespective of income group or influence-level essentially to check if these two aspects have any significant role to play at all, in the overall and group adoption outcomes.

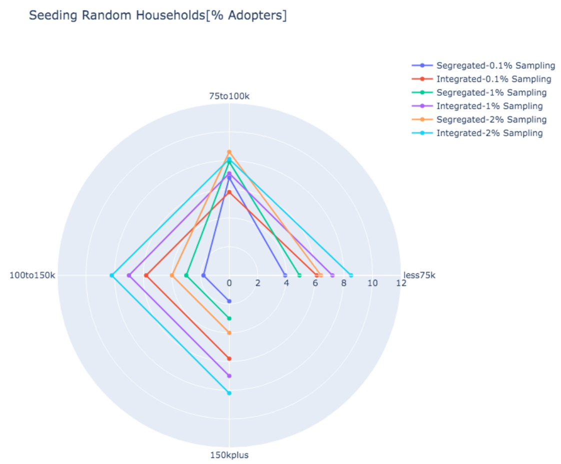

Figure 6.15: Percentage of income-group population that are adopters under Scenario 10

This policy performs very similar to the random influencer-seeding scenario further hinting strongly at the role that trust plays in the ensuring effectiveness of information transfer by influencers.

The scenario results have revealed some interesting insights into the function of trust in information circles, the relationship between population of the income-group and the nature of the underlying network in influencing the group adoption-rates and finally the increased importance of attitude-driven adoptions compared to financial incentive-based adoption. The tradeoffs between these policies can however be more effectively compared when looked at in the light of policy-costs that are required in implementing each of these policies. The results of these scenarios will be summarized in this aspect in the next concluding chapter.

7 DISCUSSION

7.1 MEASURE OF POLICY PERFORMANCE ACROSS KPIS

7.1.1 Adoption Rates per Income Group

Ten policy scenarios were generated under two different network scenarios each, with three sampling percentages for those scenarios that involved seeding households (see Figure 6.1). At this juncture, the model results can answer several important questions regarding the role of the network in determining the policy performance. It has been mentioned in Section 3.1.3 that three KPIs were used to measure the effectiveness of a policy namely: adoption rates per income group, overall adoption rates and policy costs. In this section, the effect of network structure on the first KPI of adoption-rates per income group is studied. Results are visually summarized in Figure 7.1.

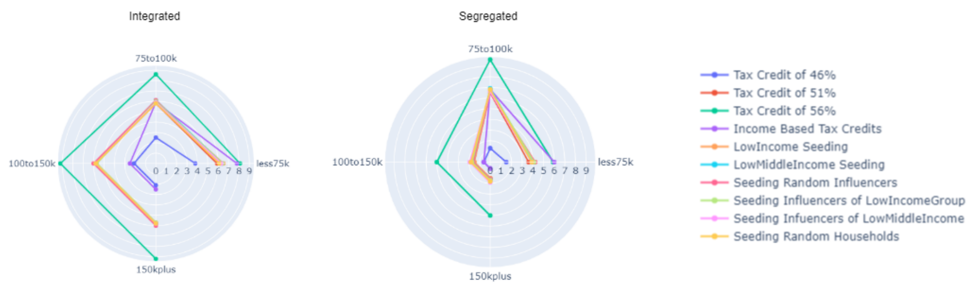

Figure 7.1: Policy Performance as a measure of percentage adopters in each income-group shown as comparison between segregated and integrated network scenarios

Financial policies lie at the extremes of performance for all the income groups, with the best performing being flat-tax credits of 56% across both integrated and segregated. For the low-income group of 'less75k', income-based tax policies work equally well, compared to flat-tax credits of 56%: this is understandable as the implications of this policy for the group remain the same (in both cases, this income bracket get 56% tax credits). With regards to income-based tax credits, the other groups do not benefit from it as much as the low-income group, with the the seeding policies performing consistently better for the high-income groups of '100to150k' and '150kplus'. For the middle-income group of '75to100k' it appears that none of the policies except for the flat-tax credits cause any significant improvement or decline in their adoption rates: neither the income group seeding nor influencer seeding show a clear improvement over the baseline policy. This remains the case for the two high-income groups as well. In order to explore the effects of seeding further, plots are produced to compare different sampling percentages used for seeding policies.

Effects of Sampling Percentages

Policy outcomes of three sampling percentages: 0.1, 1 and 2 percentage points were used for both segregated and integrated network scenarios and compared in Figures 7.2 (for segregated) and 7.3 (for integrated)

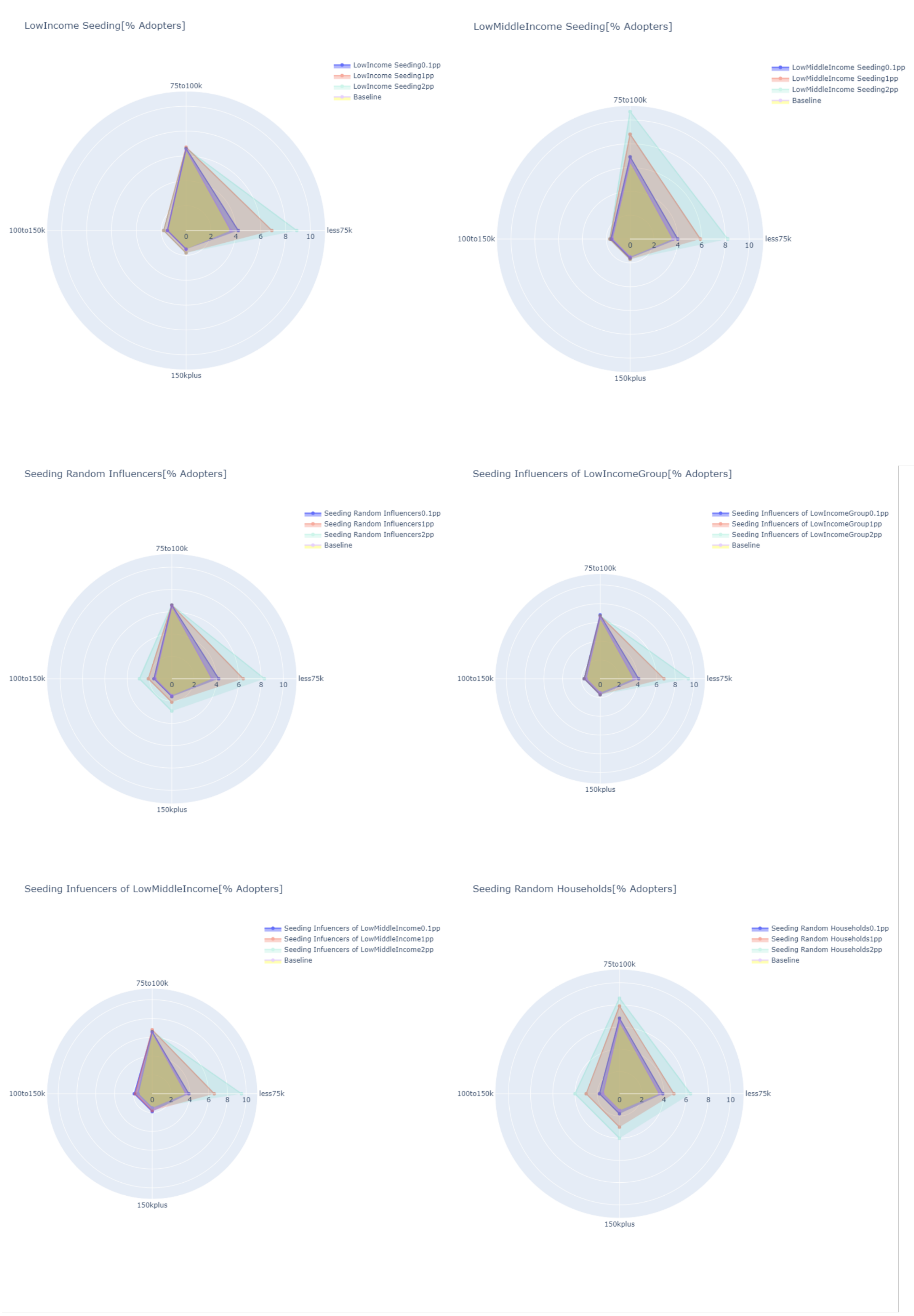

Figure 7.2: Comparing the effects of Sampling Percentages for different policy-interventions within the segregated network scenario. Note that 0.1pp implies 0.1 percentage points of the target group is sampled.

- Random Seeding versus Influencer Seeding in Segregated Networks

  Results in Figure 7.2 reveal interesting results. The effects of seeding influencers emerges only as the sampling percentage increases: at 0.1 and 1 percentage points, there is little to no difference in the adoption rates of the low-income group (less75k). However at a sampling percentage of 2pp, there is more than a percentage point increase in adoption rates. This indifference of adoption rates to policy of seeding an influencer versus a random member of the income group suggests the more important role of trusted messengers of information as compared to mass communicators who have good reach (number of connections) but belong to the outer-most circle in the circles of influence model.

  This effect is particularly noticeable in the policy seeding low and middle groups. There is significant difference in performance of random seeding of members of the low and middle income group versus seeding influencers from the same, with the former achieving very good adoption rates for the middle-income group. The little to no difference between seeding influencers of low-middle groups and seeding influencers of low-income groups alone suggests that randomness of sampling within this group can play a role in why performance is biased towards low-income group. The larger network size of the low-income group compared to the middle-income group can cause more influencers being sampled from the former group. The middle-income group sees performance improved over the baseline only in two policy-interventions: a) low and middle income seeding and b) Seeding of Random Households. The income group that benefits most from seeding policies (whether targeting influencers or income-groups) is the low-income group of 'less75k'. If the goal is to use a policy that improves upon the adoption rates of all income groups simultaneously in a segregated network the following policies are good candidates: a) Seeding Random Households in each census tract and b) Flat Tax Credits of 56%.

- Random Seeding versus Influencer Seeding in Integrated Networks

  In this sub-section, results from Figure 7.3 are analyzed. Sampling percentages for all policy interventions show marked improvement over the baseline in the integrated network scenario for all income groups except for middle-income group of '75to100k'. The middle-income group benefits the most from both Low-Middle Income Random Seeding as well as influencer seeding. This is in contrast to the segregated scenario where seeding influencers in low-middle income group did not show any improvement in adoption rates for the middle-income group. In the context of policy design to improve outcomes across the table for all income-groups the following policies are good candidates for an integrated network: a) Seeding Random Households in each census tract, b) Seeding Random Influencers in income-groups and c) Flat Tax Credits of 56%.

  Comparing effects of sampling percentages on seeding policies for integrated and segregated network scenarios results in an important insight about the role of geography, trust and network-size in improving adoption rates.

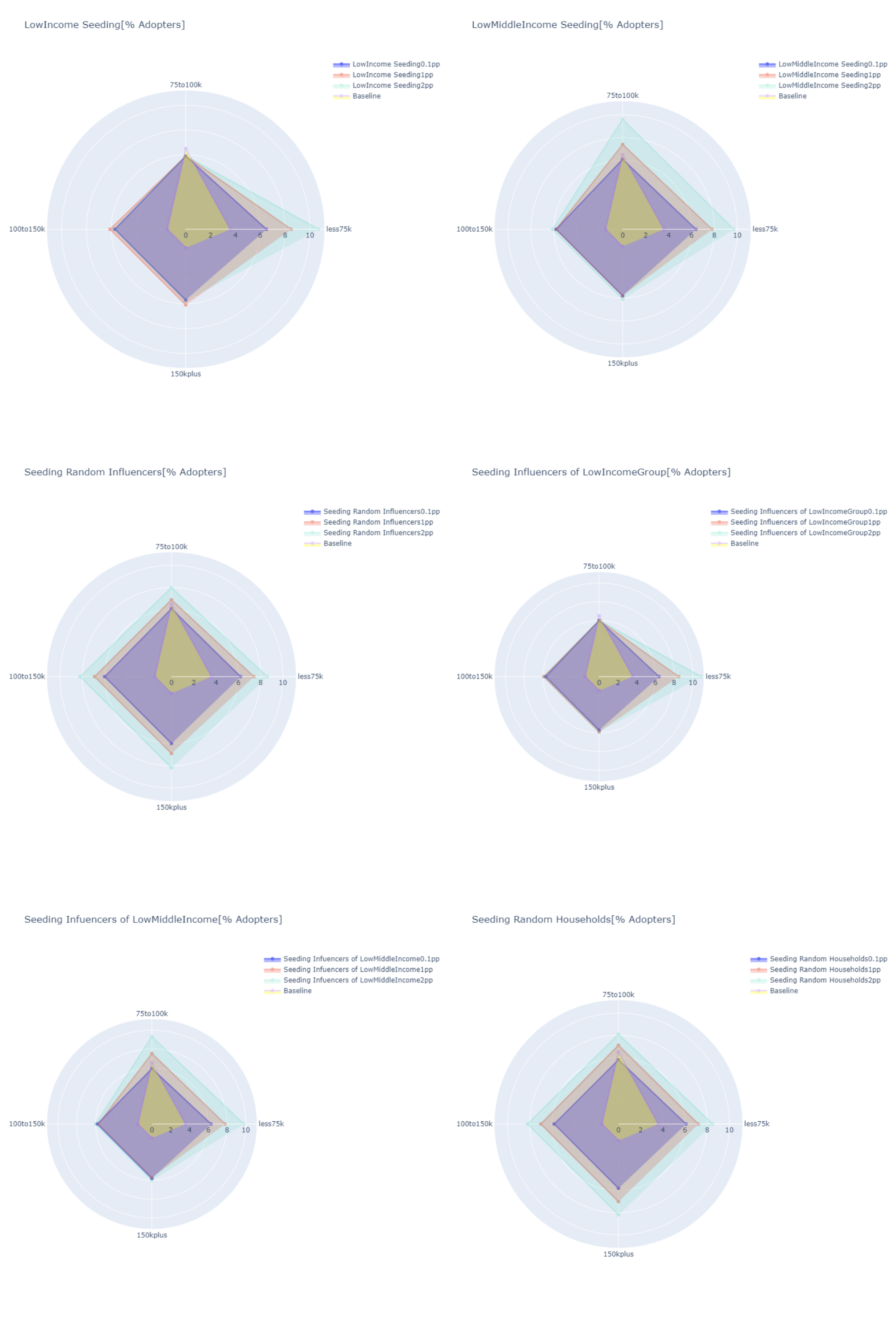

Figure 7.3: Comparing the effects of Sampling Percentages for different policy-interventions within the Integrated network scenario. Note that 0.1pp implies 0.1 percentage points of the target group is sampled.

7.1.2 Overall Adoption Rates

Overall adoption goals that are set by governments as targets are often from a utilitarian perspective, where policies aim to benefit (and increase utility) as many people as possible, rather than catering to close socioeconomic divide. Most studies also use Overall Adoption goals are the prime metric to judge policy effectiveness. From the perspective of this KPI, Scenario-3 (see Table 7.1) achieves the highest overall adoption rate, with the least overall rates brought about by Scenario 1 (which is the lowest flat-tax-credit bracket). However as is observed from Figure 7.1, 7.2 and 7.3 where adoption rates of different income-groups were observed under different policies and network scenarios, it is clear that the redistribution of adoption numbers within these income groups is driven by seeding policies as opposed to financial policies.

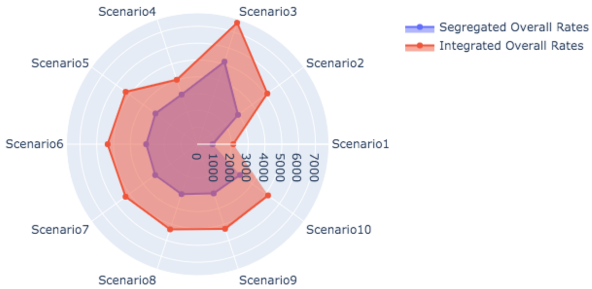

Figure 7.4: Overall Adoption Rates of Scenarios

Table 7.1 provides a reference for the scenario numbers used in Figures 7.5, 7.6, 7.4 and 7.7.

Table 7.1: Reference for scenario numbers used in Figures

Scenario Number	Description
Scenario 1	Flat Tax 46%
Scenario 2	Flat Tax 51%
Scenario 3	Flat Tax 56%
Scenario 4	Income-based Tax Credits (see Table 6.1)
Scenario 5	Seeding Low Income Group (less75k)
Scenario 6	Seeding Low and Middle Income Group (less75k and 75to100k)
Scenario 7	Seeding Influencers (irrespective of income-group)
Scenario 8	Seeding Influencers of Low Income Group (less75k)
Scenario 9	Seeding Influencers of Low and Middle Income Group (less75k and 75to100k)
Scenario 10	Seeding Random Households (irrespective of income group)

Analyzing results through the utilitarian metric of Overall Adoption rates brings to light an important observation: sensitivity of the metric to the financial policies. All the other policies involving seeding income-groups and influencers have overall adoption rates that are comparable to the baseline, with significant changes (improvement or decline) of overall rates coming about only in Scenario 1 and Scenario 3 when the flat-tax rates are decreased and increased by 5 percentage points from the baseline respectively.

7.1.3 Policy Trade-offs

Several policies achieve similar performances within a given network structure thereby raising the question of what is most preferable to the policymaker to deploy. If a policy performs significantly better than others (across 1 KPI or multiple), what are the tradeoffs in terms of resources that were required to achieve it? To answer these questions, it is necessary to evaluate the policy performance not just in terms of Overall Adoption rates and Income-Group Adoption rates, but also in terms of policy costs.

Policy costs are calculated by summing up the costs that are reimbursed by the government as tax-incentives to adopters. This involves calculating the system size that is bought by the adopter and the costs for it being calculated at that year's price-per-watt of solar and retail electricity rates. In policies that involve seeding, the full net cost of the panel is included. This is calculated for all the policies and the parallel plot Figure 7.5 visualizes how the policy costs relate to the scenario deployed, the resultant overall adoption rates, the type of network it is deployed in and the group adoption rates.

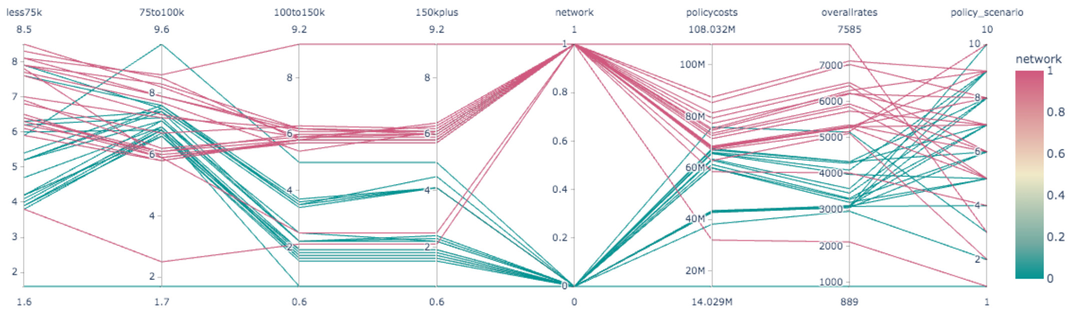

Figure 7.5: Comparing Policy trade-offs across two other KPIs of policy costs and overall adoption rates. Here, network labels are 1:integrated and 0: segregated. The goal of this figure is to show how policy costs differ for the network structures.

According to expectation, as the number of adopters increases the policy costs increase accordingly, making policies launched in integrated networks to be more expensive across the board, compared to segregated networks. The overall adoption rates are also consistently higher for policies deployed in integrated networks, except for the cases where tax-incentives were high. For example, despite observing that the policy of Seeding Random Influencers does not perform any better than Seeding random individuals (who are not necessarily influencers), we look to the policy costs (see Figure 7.6) to observe that seeding households within a census tract (Scenario 10) costs USD67 Million to the tax-payers while achieving similar overall rates and group-adoption rates via Influencer-Seeding (Scenario 7), costs the taxpayer USD68 Million.

Therefore, if the policymaker were to look for a cost-effective strategy that maximises both overall adoption rate as well improving low-income adoption rates in their segregated network, she would opt for the policy intervention that tailors tax credits according to income-group (Scenario 4) (comparing Figures 7.6 and 7.7. The trade-off being that while Scenario-4 performs well on the egalitarian front, improving adoption rates for low-income groups, it has the lowest performance in the overall adoption rates (Figure 7.4). If a policymaker were trying to maximise overall adoption targets with minimum cost, any of the seeding policies achieve the required effect.

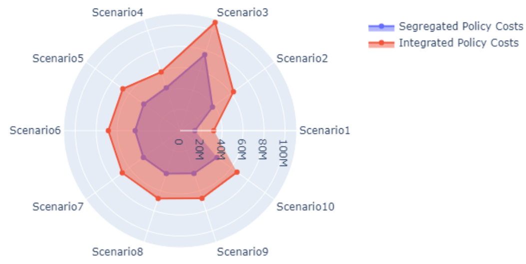

Figure 7.6: Policy Costs of Different Scenarios. See Table 7.1 for legend

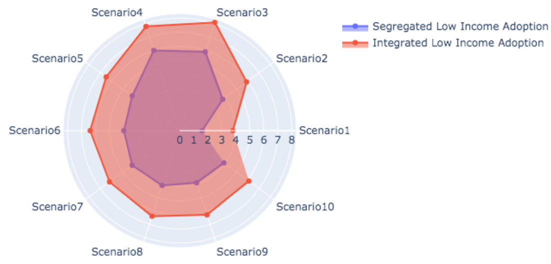

Figure 7.7: Low Income Adoption Rate of Scenarios. See Table 7.1 for legend

7.2 KEY TAKEAWAYS

Several key insights can be observed from this study evaluating the role of underlying social networks in influencing adoption rates in the context of just energy transition.

Structure of the underlying network plays key role

Structure of the underlying network, as a measure of being an integrated or segregated network consistently influences overall as well as group adoption rates. This is revealed in scenarios where flat-tax incentives across income-groups are applied (Scenario 1,2,3): despite high upfront costs that have to be borne by the consumer, low-income groups show high group adoption rates due to attitude-driven adoptions. When the financial component remains constant, attitudes are the only component of the decision-making structure that evolves over time. Information is exchanged between acquaintances and when these acquaintances are adopters who also share an intimate relationship with the adopter, the change in attitude that positively impacts adoption is greater. This is especially revealed when integrated and segregated scenarios are compared: high-income groups which are smaller in size/population see policies perform very poorly in their group as the segregated network causes information to circulate only within this group and therefore (ceterus paribus) attitude stagnates over time and adoption numbers are low.

Another key aspect of the network structure that plays a role is the number of group members. This is reflected in the fact that all policies perform consistently well (as compared to adoption rates of other income-groups) in the middle-income group of '75to100k' which is similar in population to the low-income group. The reason being: when the tax-incentives are low for this group, the attitude-driven adoption sustains performance and when tax-incentives are also in favor, this group's adoption rate far exceeds all the other three groups. This once again highlights the importance of inducing attitude-driven adoptions by planting credible sources of information in personal networks.

Importance of diverse communication channels

In segregated networks information circulates primarily within the group, which in the absence of tax incentives or low number of group members and lack of adopters in known circles can result in stagnation of adoptions within the group. This can be combated by seeding income-groups at block-level (a smaller geographic unit) as opposed to at a census-tract level, thereby increasing the chances of increasing adopters in people's known-circles. Efforts such as 'Solar parties' can be encouraged where adopters host members of the neighborhood to share their experience of installing a solar panel (such parties are popular in USA and Europe).

Role of Trust

Scenarios 7, 8, 9 reveal the importance of credible sources of information. It is not necessarily the case that influencers who are bridges or highly-connected individuals are effective in disseminating information. If influencers are mass-communicators dealing mainly in one-sided communication and belong mostly to the agents' third circles (outer-most circle in the circles of influence model, with no intimate relationship with the agent), their influence is far lesser compared to the influence that people within the first circle have over agent's attitudes. This result is in line with (Abrahamse et al., 2005), (Valente, 2012) and (Brugger & Henry, 2019) that stress the importance of policy-makers to ensure tailored information campaigns that increase number of credible sources of information. This can be done by redefining the role of influencers (high number of connections) or information agents (bridges between networks) from that of popular online social networks) to personal networks at a more local level (in a municipality or block level).

Role of Geography

This result could apply exclusively to the choice of technology in this case-study, due to the observability component of solar PV. (H. Zhang et al., n.d.) reveal that the likelihood of a household adopting solar PV in a zip-code area is higher with the presence of another adopter nearby. That, the prospective adopter can be persuaded to adopt by the presence of a solar panel in a neighbor's roof is posited to be one of the reasons why seeding households randomly within the census block shows similar performance in adoption rates across income-groups as that of the policy seeding influencers in the integrated scenario. In the segregated network scenario, this random household seeding has a slightly better performance in comparison to influencer seeding: this could be attributed to sampling bias where the larger size of the low-income group could have led to increased likelihood of sampling influencers from this group.

Financial Policies increase numbers whereas Seeding Policies redistribute numbers

This is an important observation that originates from analysing the results from the two lenses of utilitarian and egalitarian metrics. Flat-tax policies are instrumental in increasing the overall adoption rates, whereas seeding policies are instrumental in redistributing the number of adopters within the income-groups with policies such as low-income seeding and low-income influencer seeding particularly target improving adoption-rates of the 'less75k' group. While increased sampling percentage values in seeding policies also plays a role in improving overall numbers, the unreasonably high policy costs (in the range of more than 10 billion USD), these expensive seeding programs that increase the adoption rates only marginally are not considered in this discussion. For the numbers behind the figures, see Appendix.

7.3 ROLE OF ASSUMPTIONS IN MODEL RESULTS

The Agent-based model, which aims to simulate the behaviors that lead to adoption of rooftop solar for about 80,000 synthetic single-family owner-occupied households in Albany is based on several assumptions.

7.3.1 Modelling Agent Behavior

Limitation of Theory of Planned Behavior

Despite the claims of modelling heterogeneity in agent behavior (which is a definite step up from the earlier equation-based Bass Models), there is a great amount of homogenization that arises from the way decision-rules are modelled for the agent: everyone is assumed to be influenced primarily by three attributes of attitude, subjective norms and perceived behavioral control. There have been several criticisms to the use of TPB including excessive emphasis on rational reasoning and decision-making, disregarding people's responses to unconscious biases and subliminal messaging (including political advertisement) (Sniehotta et al., n.d.). The paper also highlight TPB's limited predictive validity: that not everyone who crosses a certain threshold will actually perform the behavior. The static nature of TPB is also reflected in the fact the attribute weights are initialized at the start of the model and do not update later. This model also initializes households and their TPB weights for 2015. While the attributes evolve dynamically in this model, the weights attached to each do not change.

Implementation of Theory of Planned Behavior

- Differences in Architecture:
  TPB is a socio-psychological theory that outlines the behavioral factors that guide agents'decisions: modellers incorporating this qualitative theory into their quantitative, empirical data-driven ABMs involves interpreting what kind of data can be used to elicit these behavioral factors. As a result interpretation of this theory by modellers and its operationalization results in different model formalizations of this single theory (Park & Barabási, 2007). (Muelder & Filatova, 2018) in their paper discussing the implications of these different formalizations on model outcomes, consider three basic architectures that most implementations of TPB follow. This model's architecture of TPB implementation is similar (not exactly the same) to (Rai & Robinson, 2015) where income is used to gather electricity consumption information which in turn is used to calculate actual payback. This actual payback value is compared with the perceived payback threshold and determines whether or not the agent possesses enough Perceived Behavioral Control (PBC) in order to make an adoption decision. Some other methods to implement this include having income thresholds (that are empirically derived or assumed) or thresholds for utility. (Muelder & Filatova, 2018) report that this difference in architecture can result in diffusion rates from 58% to 91% holding other aspects of the model constant.

- Duration of the simulation:
  The number of time-steps for which the model is run is also a modeller's choice. For example, (Muelder & Filatova, 2018) run (Rai & Robinson, 2015)'s model for 30 timesteps each accounting for half-a-year. The model is this thesis has every time-step equivalent to 1 year. The difference is very subjective: this model's choice of timestep is due to the granularity of the datasets involved in its construction. The exogeneous factors that vary such as price of solar PV, electricity prices all vary annually, therefore making 1 year the smallest unit of change. The output for (Rai & Robinson, 2015)'s model stabilizes with no increase in adopters after about 6 time-steps into the model, whereas this model in on an upward trajectory for all its policy scenarios and does not show signs of flattening. It is not clear how different granularity of data and consequently the timestep, can influence this adoption rate.

- Factors:
  The type of questions that were used in eliciting the TPB factors depends on the survey that is taken. A different choice of questions that are used to quantify a

factor will change eventually lead to changing weights that is used to calculate the intention, which influences adoption decisions. For example, it was identified early on that the ambiguity of values representing an adopters' PBC was due to the fact that there were no questions in the survey questionnaire that explicitly asked the adopter how strongly they felt about their ability to have taken the decision to adopt. Therefore other proxy measures were used to elicit this variable. If however the survey data had been a panel dataset, this could have led to sharper PBC values that differentiated the adopter and non-adopter clearly, resulting in lesser/more adopters being initialized in the first timestep, thereby influencing the trajectory of the adoption curves itself.

7.3.2 Static Population

While this was a modelling choice made at the beginning to keep the number of exogeneous dynamic variables within a scope so as to study the effects of policy interventions and network structures in isolation, this is still an assumption worth noting to highlight the model scope. This is because perception of affordability is allowed to vary in the model, as the agent compares their own tolerated payback to the actual payback of the panel and revises this perception. But in real-life, a rise in income can also be a factor that influences perception of affordability; this is however not incorporated.

7.3.3 Its all sunshine and hay

A crucial assumption made is that the azimuth angle is 180 degrees for all rooftops taken into account, that is all rooftops face south when the Annual-Solar-Production value is calculated. In reality, not all households face the south (see Figure 7.8, nor do they get shade-free exposure to the sun.

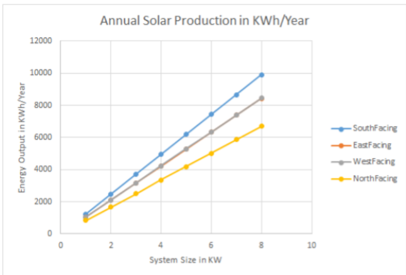

Figure 7.8: Annual Solar Production of a typical household in Albany based on Azimuth Angle

This will mean different system-size calculations, however requires a granular dataset that provides the rooftop and orientations of all houses in Albany. Even if that were provided, it requires a mapping of the synthetic households to the actual houses which is out of the scope of this study, given the limited attributes that are used to generate synthetic households.

An assumption is also made that efficiency of solar panels remain the same even though the price of solar panels are modelled realistically. However this assumption does not affect the calculations significantly, as the typical quotes that household usually get from online sources such as PV Watts calculator or other solar installers usually contain similar assumptions. The aim is to model perception of affordability and therefore the emphasis is not on accuracy of price of the solar panel that is bought.

In summary, there are different sources of uncertainty involved in the design of this model and the quality of the data underlying its construction: Structural and Parameteric Uncertainty and is summarized in Table 7.2

Table 7.2: Sources of Uncertainty in the model

Uncertainty	Parameter	Range
Structural Uncertainty	Implementation of TPB	Adoption Rates can differ between 50% to 90%
	Circles of Influence Model	Number of People in Circle 2: 15 to 30, Circle 3: 50 to 100
Parametric Uncertainty	Adoption Threshold (no units)	0.75 to 0.99
	Interaction Intensity (no units)	0.1 to 0.8 (Calibrated, no basis in theory)
	Annual Solar Production in KWh/Hr	6500 to 10,000 KWh/Hr

7.4 IMPLICATIONS FOR LITERATURE

This study adds a key insight into the academic discourse concerning the role of social networks in technology adoption: the role of small network size in widening the gap in segregated networks. Despite the presence of supportive financial instruments and the ability to invest, policies perform poorly in high income groups due to their small network size and stagnation of information. Holding financial incentives constant, it is seen that attitude-driven adoption that comes about a result of interaction with other agents in social circles and observing neighbors install solar PV plays a bigger role in getting agents to adopt.

Several studies call for policymakers to incentivise influencers, information agents, community leaders such as (Huang et al., 2019), (Brugger & Henry, 2019), (Moglia et al., 2018). However this study shows that simply seeding influencers (highly connected as well as connectors of different clusters) does not improve adoption rates significantly. Seeding households has a better outcome in the case of integrated networks: this is an unexpected result, which could be due to the nature of the case-study itself. Solar PV has a strong observability component whereby agents can see the panel mounted on a neighbor's roof and be persuaded to consider adopting a panel. Therefore a policy that is modelled to seed agents in every geographical unit (a census block in this case) brings about a better adoption rate, rather than just seeding influencers (where geography is ignored). Therefore, this result cannot be directly compared to other studies which do not study solar PV and therefore do not include the observability component. However this has implications for policy design, as is discussed in the following section.

The role of trust in driving attitude-based adoptions indicates that future models should extend policy interventions to explicitly test the circles of influence model. Although introduced in this study, policy interventions have not leveraged the features of this model: the results can be studied by exploring the relationship between an agent's likelihood to adopt and the number of adopters in her social circles. How many adopters in her close social network is required to convince her to adopt? Or do experts in the outer circle have more influence over the adoption as opposed to the opinion of an unexperienced but close friend? This study, with its implementation of the circles of influence, opens avenues to further study the role of trust in adoption decisions, as was called upon literature by (Brugger & Henry, 2019).

7.5 IMPLICATIONS FOR POLICY DESIGN

7.5.1 Egalitarian versus Utilitarian Metrics

This study finds that depending on the policy agenda, the role of the network can be undervalued without consequences. If a policy maker aims to hit utilitarian targets such as overall adoption rates, flat-tax policies (which are the status quo) work very well to significantly increase these numbers (while also coming at the cost of burdening the exchequer). However if egalitarian outcomes are considered, seeding policies and disseminating trusted information is far more important. For example from an egalitarian perspective a policy-maker can prefer a policy that tailors tax-incentives to income groups, which improves adoption rates of low-income groups. However this policy performs very poorly on the Overall Adoption Rates front if the underlying network were integrated. On the other hand, if the underlying network was segregated the policy performs similar to others on this KPI, while still improving performance for low-income groups. Depending on the policy-agenda therefore, the policy-maker can make a different decision: sticking to the status-quo with financial policies and ensure hitting overall targets, or increase the budget to cater to increase support for economically disadvantaged groups.

7.5.2 Leveraging Observability

This study shows the importance of visibility and therefore geography of policies that try to improve solar PV adoption. Policy-makers instead of expending resources on identifying and seeding influencers, can focus on ensuring that solar PVs are distributed geographically to enhance its visibility. Solar 'parties' are recommended in neighborhoods to encourage discussions between prospective adopters and those who have already adopted. Policy-makers should consider referral programs and tailored information campaigns that open lines of communication on this topic between members of close social circles.

8 CONCLUSION

8.1 REVISITING RESEARCH QUESTIONS

Several sub-research questions were posed at the start of this study and are revisited in the light of new results.

8.1.1 Sub-Research Question 1

How can the underlying social network structure and interactions within an urban space be effectively modelled?

The goal of this was to model a realistic social network that effectively captures how people react differently to different sources of information depending on how they related to the source. Studies that was cited in the related work section, mainly modelled social networks by the principle of homophily and geographic proximity or varied synthetic network structures from random to small-world connections. In such networks, people do differentiate between the sources once they are connected them and absorb the information they receive equally. This means, the attitude change the agent experience from information on solar panel they received from a random person they met 1 year back weighed equally to a close family member recommending them a solar panel based on their experience. To avoid these erroneous assumptions, the Circles of Influence model was developed to allow for the agent to place different levels of trust. This, in combination with Deffuant's Relative Agreement Theory (Deffuant et al., 2002) whereby people with similar opinion ranges are influenced by each other and an strongly opinionated person influences someone on-the-fence, along with geographic and homophilic principles, ensured that the network realistically captured social network interactions in the synthetic population of Albany.

8.1.2 Sub-Research Question 2

How do the characteristics of the underlying social network influence performance of the policy intervention?

Two network scenarios of integrated and segregated were designed based on the principles of homophily and distance-decay and several policy scenarios were designed to test their performance on integrated and segregated networks. It revealed that policies that aimed at improving overall adoption rates performed better in integrated networks than segregated. However, when trying to improve adoption rates in a given network across particular income groups, certain policies were preferred but it traded-off on cost of policy, or came at the cost of poor policy performance in other income-groups. It is also revealed that flat-tax structures performed poorly for income-groups of small network size in segregated networks and run the risk of stagnation of adoption curves in the absence of information-based interventions. In integrated networks, despite lower-tax incentives attitude-driven adoption can far out-perform group adoption rates for lower tax structures in segregated networks, therefore lending credibility to the importance of network structure in influencing policy intervention.

8.1.3 Sub-Research Question 3

Given the underlying social network, how can policies be designed so that they can overcome socioeconomic inequalities present in the networks to ensure a just energy transition?

Based on the results of this study, whereby a just transition was conceptualized from an egalitarian concept of justice and operationalized as improved adoption rates across income-groups, it can be concluded that policy-makers have to be conscious of their underlying network structures when deploying policies for improving adoption rates across income-groups. Flat-tax structures despite being keeping cost of solar panels low may not improve adoption rates of high-income groups in segregated networks whereas in integrated networks even lower tax-credits can enhance adoption in low-income groups. Seeding programs should not target mass-communicators as influencers, but should ensure credible sources of information are planted in personal networks through more grass-root initiatives such as neighborhood-level solar parties and seeding information agents in personal networks. While flat-tax credits work well for improving overall adoption rates, they perform poorly from the perspective of just transition, where egalitarian measures of policy evaluation are employed. Seeding policies perform better at improving adoption rates of low-income groups, and these policies perform better when they include they are distributed geographically and observability is increased.

8.2 EXTENDING THIS WORK

The results of this model encourages expanding on the use of circles of influence model to test effectiveness of policy intervention. Given the importance of credible information sources on encouraging attitude-driven adoption, scenarios can be evaluated based on number of times that different household agents interact with members in the known-circles versus with members in the third circle and the number of adopters in each circle. This will deepen the understanding how trust and influence-levels related to adoption decisions at the individual level.

This work can use techniques such as spatial autocorrelation to study the results of the model spatially: how does the introduction of seeded agents within a locality influence the likelihood of adoption of other residents in the area. Spatial influence of the local and non-local social ties can be explored. While the multi-level social networks that have been modelled are primarily real-life networks and physical networks, it is undeniable that online social networks have an equally important role to play in dissemination of information (positive or negative), specially in informing the agent of a product's quality. This model can be improved with an addition to the multi-level network of online social networks. In realistically modelling social networks, efforts can be made to infer real-life social social networks from data-sets such as Call Data Records, Twitter retweet networks and so on, to infer personal networks.

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A APPENDIX-A

Appendix-A contains supplementary data and steps for Chapter ?? and 3

A.1 US STANDARD CENSUS HIERARCHY

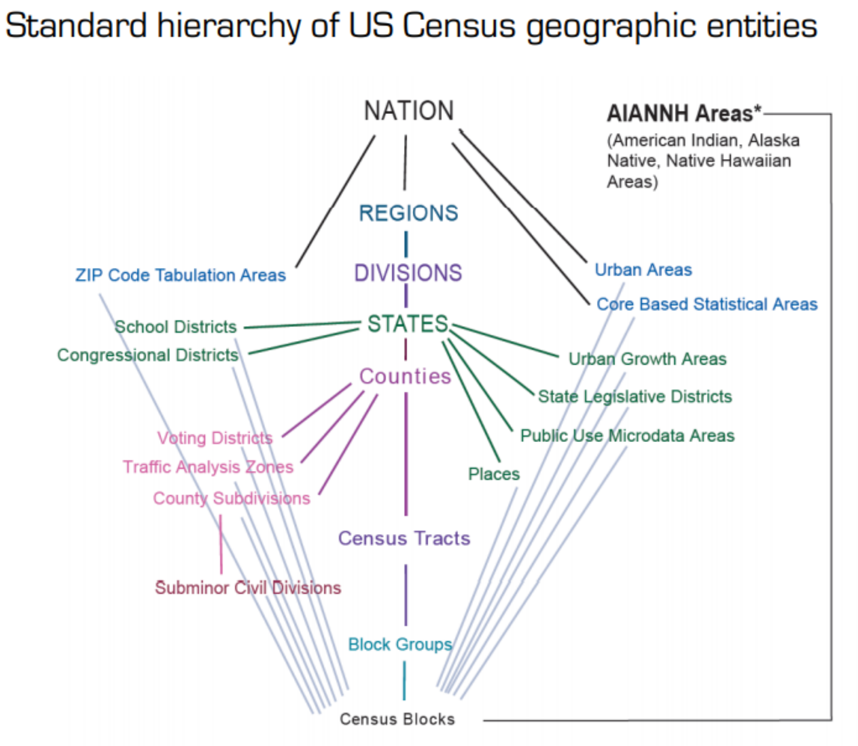

Figure A.1: USA Census Administrative Divisions

A.2 SURVEY DATA

Two survey datasets: Adopters and Non-adopters were used to calculate weights for the 3 TPB-variables Attitude (A), Subjective Norms (SN) and Perceived Behavioral Control (PBC) separately for each.

While the variables did not contain null-values, demographic information contained considerable number of null-values, specially in Income category. So as to preserve as many data points as possible, null-values and undisclosed values were replaced with the median of the datasets. Age was also corrected similarly.

For Household-Size, relationship between income and household-size age and household-size was explored. The rationale being, younger respondents will most likely have household-sizes that are 2 (a couple) or 1 (single). The aim is to use one of the two variables as predictors for filling in the null-values contained in household-size data.

The output of household-size data is binary: if 0, then household size is less than 3 and if 1, the size is 3 or more. The independent variables are age and income which are categorical. Dummy coding and Logistic Regression models are used to check predictive power.

A.2.1 Scoring Variables

While the main text referred to the example of calculating PBC such that the variables captured similar concepts across adopters and non-adopters, here another example is presented for subjective norms. For non-adopters:

- SN1 : People who are important to me would be in favor of installing solar panels.
- SN-2: My family members would be opposed to getting solar panels.
- SN-3: Most people who are important to me would support me if I decided to go solar.

Whereas for adopters, the following questions were asked to enable respondents to retrospect:

- SN-2 : My family members were not convinced with going solar.

Considering availability of data, SN-2 is chosen for adopters. Whereas SN-2 and SN-3 are chosen for non-adopters.

Table A.1: Non-adopters Scoring Table

Status	Column Name	Question	Rating	Score
Intention	DV7	I plan to contact a solar installation company within the next 6 months to discuss installing solar at my home.	1: strongly disagree 5: Strongly agree	1: -1 2: -0.5 3: 0 4: +0.5 5: +1
Propensity to communicate	CIJM1	Before buying a new brand, I usually ask someone who has experience with the brand for advice.	1: Not at all like me 5: Extremely like me	
	CIJM2	Before buying, I often ask acquaintances about their experiences with product or service	1: Not at all like me 5: Extremely like me	
Social Influence	CIJM3	When considering a new product or service, I usually trust the opinions of friends who have used the product or service.	1: Not at all like me 5: Extremely like me	
Opinions	E2	Climate change is a serious problem for society.	1: strongly disagree 5: Strongly agree	
	BTE7	Using solar could protect my family from electricity blackouts.	1: strongly disagree 5: Strongly agree	
	BB1	If more households get solar panels, environmental quality will improve.	1: strongly disagree 5: Strongly agree	
	BB2	Solar panels help slow down climate change.	1: strongly disagree 5: Strongly agree	
	BB3	Having solar panels would be a good way to reduce my environmental impact.	1: strongly disagree 5: Strongly agree	
	BTE8	Using solar will help protect my family from rising electricity prices in the future.	1: strongly disagree 5: Strongly agree	
	BE10	Using solar would save me money.	1: strongly disagree 5: Strongly agree	
	Co3	Having solar panels on my home would help meet my family's needs.	1: strongly disagree 5: Strongly agree	
	BE13	Installing solar provides a great return on a family's investment.	1: strongly disagree 5: Strongly agree	
	BTE9	Installing solar panels is a risky thing for a household to do.	1: strongly disagree 5: Strongly agree	1: +1 2: +0.5 3: 0 4: -0.5 5: -1
PBC	PBC7	I may not be in my home long enough to get the benefits of investing in solar.	1: strongly disagree 5: Strongly agree	
	PBC3	Solar panels are still very expensive, even with government incentives.	1: strongly disagree 5: Strongly agree	
	PBC5	I can't afford solar on my family budget.	1: strongly disagree 5: Strongly agree	
	PBC9	The process of getting solar installed is a hassle.	1: strongly disagree 5: Strongly agree	
Social Norm	SN1	People who are important to me would be in favor of installing solar panels.	1: strongly disagree 5: Strongly agree	
	SN4	My family members would be opposed to getting solar panels.	1: strongly disagree 5: Strongly agree	
	SN5	Most people who are important to me would support me if I decided to go solar.	1: strongly disagree 5: Strongly agree	
Personal Norms	PN1, PN2	I feel a personal obligation to do my part to move the country to a renewable energy future. I feel a personal obligation to do my part to prevent climate change.	1: strongly disagree 5: Strongly agree	

Table A.2: Adopters Scoring Table

Status	Column Name	Question	Scoring
Intention	RECONSIDER	In the next few years, how likely are you to reconsider solar?	
Propensity to communicate	CIJM1	Before buying a new brand, I usually ask someone who has experience with the brand for advice.	1: Not at all like me 5: Extremely like me
	CIJM2	Before buying, I often ask acquaintances about their experiences with product or service	1: Not at all like me 5: Extremely like me
Social Influence	CIJM3	When considering a new product or service, I usually trust the opinions of friends who have used the product or service.	1: Not at all like me 5: Extremely like me
Opinions	E2	Climate change is a serious problem for society.	1: strongly disagree 5: Strongly agree
	BTE7	Using solar could protect my family from electricity blackouts.	1: strongly disagree 5: Strongly agree
	BB1	If more households get solar panels, environmental quality will improve.	1: strongly disagree 5: Strongly agree
	BB2	Solar panels help slow down climate change.	1: strongly disagree 5: Strongly agree
	BB3	Having solar panels would be a good way to reduce my environmental impact.	1: strongly disagree 5: Strongly agree
	BTE8	Using solar will help protect my family from rising electricity prices in the future.	1: strongly disagree 5: Strongly agree
	BE10	Using solar would save me money.	1: strongly disagree 5: Strongly agree
	Co3	Having solar panels on my home would help meet my family's needs.	1: strongly disagree 5: Strongly agree
	BE13	Installing solar provides a great return on a family's investment.	1: strongly disagree 5: Strongly agree
	BTE9	Installing solar panels is a risky thing for a household to do.	1: strongly disagree 5: Strongly agree
PBC	PBC7	I may not be in my home long enough to get the benefits of investing in solar.	1: strongly disagree 5: Strongly agree
	PBC3	Solar panels are still very expensive, even with government incentives.	1: strongly disagree 5: Strongly agree
	PBC5	I can't afford solar on my family budget.	1: strongly disagree 5: Strongly agree
	CONCERN1	Was affordability a concern?	1: Not at all 5: Extremely
	PBC9	The process of getting solar installed is a hassle.	1: strongly disagree 5: Strongly agree
	SN1	People who are important to me would be in favor of installing solar panels.	1: strongly disagree 5: Strongly agree
Social Norm	INFLNC_OTH_MULT1	Others R knew with solar while considering - Knowing them made you more inclined to get solar panels	1: None of them 2: Some of them 3: All of them 98: Don't know
	INFLNC_OTH_ONE1	One other R knew with solar while considering - Knowing them made you more inclined to get solar panels	0: No 1: Yes
	INFLNC_OTH_MULT2	Others R knew with solar while considering - Knowing them made you less inclined to get solar panels	1: None of them 2: Some of them 3: All of them 98: Don't know
	INFLNC_OTH_ONE2	One other R knew with solar while considering - Knowing them made you less inclined to get solar panels	0: No 1: Yes
	SN4	My family members would be opposed to getting solar panels.	1: strongly disagree 5: Strongly agree
	INFLNC_OTH_MULT6	Others R knew with solar while considering - They were important to your own decision to get solar panels	1: None of them 2: Some of them 3: All of them 98: Don't know
	INFLNC_OTH_ONE6	One other R knew with solar while considering - They were important to your own decision to get solar panels	0: No 1: Yes
	SN5	Most people who are important to me would support me if I decided to go solar.	1: strongly disagree 5: Strongly agree
Personal Norms	PN1, PN2	I feel a personal obligation to do my part to move the country to a renewable energy future. I feel a personal obligation to do my part to prevent climate change.	1: strongly disagree 5: Strongly agree
Household Size	PEOPLE_TOT_3PLUS	3 or more adults or children live in the house	0: False 1: True
Propensity to communicate	CIJM2	Before buying, I often ask acquaintances about their experiences with product or service	1: Not at all like me 5: Extremely like me
Suitability	DIFFICULTY6	Suitability of your home site	1: None/Not at all applicable 5: A great deal

B APPENDIX-B

Appendix-B contains supplementary data and steps for Chapter 4

B.1 SOLAR PRODUCTION DATA

Calculated from PV-Watts Calculator for Albany, NY.

B.1.1 Monthly Solar Production Azimuth Angle= 180

Table B.1: Monthly Solar Production for Azimuth Angle of 180 for Albany

System Size	month	AC electricity produced	Total Solar Production
1	1	70	
	2	85	
	3	118	
	4	122	
	5	129	
	6	133	
	7	142	
	8	127	
	9	109	
	10	84	
	11	64	
	12	55	1238
2	1	140	
	2	170	
	3	235	
	4	244	
	5	258	
	6	267	
	7	284	
	8	253	
	9	219	
	10	168	
	11	128	
	12	109	2475
3	1	210	
	2	256	
	3	353	
	4	366	
	5	387	
	6	400	
	7	425	
	8	380	
	9	328	

Table B.1 continued from previous page

	10	252	
	11	193	
	12	164	3714
4	1	281	
	2	341	
	3	471	
	4	488	
	5	516	
	6	533	
	7	567	
	8	507	
	9	438	
	10	336	
	11	257	
	12	219	4954
5	1	351	
	2	426	
	3	588	
	4	610	
	5	644	
	6	667	
	7	709	
	8	634	
	9	547	
	10	419	
	11	321	
	12	273	6189
6	1	421	
	2	511	
	3	706	
	4	732	
	5	773	
	6	800	
	7	851	
	8	760	
	9	657	
	10	503	
	11	385	
	12	328	7427
7	1	491	
	2	596	
	3	824	
	4	854	
	5	902	
	6	933	
	7	993	
	8	887	
	9	766	
	10	587	
	11	449	
	12	383	8665
8	1	561	
	2	682	

Table B.1 continued from previous page

	3	941	
	4	976	
	5	1031	
	6	1066	
	7	1135	
	8	1014	
	9	876	
	10	671	
	11	514	
	12	437	9904

B.1.2 Annual Solar Production: All Angles

Table B.2: Annual Solar Production Values for all four azimuth angles, Albany

System Size	SouthFacing	EastFacing	WestFacing	NorthFacing
1	1238	1055	1056	837
2	2475	2110	2113	1674
3	3714	3165	3169	2511
4	4954	4220	4225	3348
5	6189	5275	5282	4186
6	7427	6331	6338	5023
7	8665	7386	7394	5860
8	9904	8441	8451	6697

B.2 PV INSTALLED PRICE TRENDS OVER TIME

Table B.3: PV Installed Price Trends (Historical)

Year	Residential				Small Non-Residential				Large Non-Residential			
	Median	20th Percentile	80th Percentile	Percentile Band	Median	20th Percentile	80th Percentile	Percentile Band	Median	20th Percentile	80th Percentile	Percentile Band
1998	-	-	-	-	-	-	-	-	-	-	-	-
1999	8.8	5.9	14.0	8.2	-	-	-	-	-	-	-	-
2000	12.3	7.4	14.4	7.0	-	-	-	-	-	-	-	-
2001	11.9	10.3	14.9	4.6	-	-	-	-	-	-	-	-
2002	12.2	10.5	14.4	4.0	11.4	10.2	13.9	3.7	-	-	-	-
2003	10.8	9.5	12.5	2.9	11.0	9.7	12.9	3.2	-	-	-	-
2004	10.1	8.8	11.4	2.5	10.0	9.0	11.6	2.6	9.3	8.3	10.1	1.8
2005	9.7	8.6	10.7	2.0	9.9	8.7	11.0	2.3	8.8	7.7	9.7	2.0
2006	9.8	8.8	10.8	2.0	10.1	8.6	12.6	4.0	8.6	7.7	9.4	1.7
2007	9.9	8.9	10.9	2.0	9.9	8.9	11.3	2.4	8.5	7.2	9.9	2.6
2008	9.5	8.5	10.6	2.0	9.5	8.5	10.8	2.3	8.4	7.2	9.8	2.5
2009	9.0	7.9	10.2	2.4	9.2	7.9	10.6	2.7	8.0	6.4	9.2	2.8
2010	7.6	6.5	9.1	2.6	7.6	6.2	9.3	3.1	6.4	5.5	7.7	2.2
2011	6.8	5.7	8.4	2.6	6.5	5.4	8.0	2.6	5.5	4.7	6.9	2.2
2012	5.7	4.7	7.5	2.8	5.6	4.6	7.2	2.5	5.0	4.0	6.6	2.7
2013	4.9	4.0	6.1	2.1	4.6	3.7	5.9	2.2	4.0	3.1	5.8	2.7
2014	4.5	3.8	5.6	1.8	4.1	3.4	5.3	1.9	3.3	2.6	4.6	2.0
2015	4.4	3.8	5.4	1.6	3.9	3.2	4.9	1.6	3.0	2.3	3.9	1.6
2016	4.2	3.6	5.2	1.6	3.6	3.0	4.5	1.6	2.7	2.2	3.8	1.6
2017	4.0	3.3	4.9	1.6	3.3	2.6	4.3	1.7	2.6	2.0	3.5	1.5
2018	3.8	3.1	4.6	1.5	3.1	2.5	4.0	1.5	2.4	1.8	3.3	1.5
2019	3.8	3.1	4.5	1.4	3.1	2.4	4.2	1.8	2.3	1.8	3.1	1.4

Table B.4: New York State Electricity Prices (Historical). Sourced from [https://www.eia.gov/electricity/data/state/]

Year	State	Industry Sector Category	Residential	Commercial	Industrial	Transportation	Other	Total
2019	NY	Total Electric Industry	17.94	14.06	5.61	12.28	NA	14.34
2018	NY	Total Electric Industry	18.52	14.50	6.02	12.14	NA	14.83
2017	NY	Total Electric Industry	18.03	14.75	5.92	12.67	NA	14.74
2016	NY	Total Electric Industry	17.58	14.45	6.03	12.05	NA	14.47
2015	NY	Total Electric Industry	18.54	15.31	6.31	12.95	NA	15.28
2014	NY	Total Electric Industry	20.07	16.12	6.58	13.82	NA	16.25
2013	NY	Total Electric Industry	18.79	15.35	6.58	13.65	NA	15.44
2012	NY	Total Electric Industry	17.62	15.06	6.70	14.20	NA	15.15
2011	NY	Total Electric Industry	18.26	15.81	7.83	13.45	NA	15.89
2010	NY	Total Electric Industry	18.74	16.31	8.79	13.74	NA	16.41
2009	NY	Total Electric Industry	17.50	15.48	8.37	13.13	NA	15.44
2008	NY	Total Electric Industry	18.31	16.79	9.39	12.64	NA	16.47
2007	NY	Total Electric Industry	17.10	15.92	8.71	10.96	NA	15.22
2006	NY	Total Electric Industry	16.89	15.51	9.39	11.94	NA	15.27
2005	NY	Total Electric Industry	15.72	14.36	8.23	11.39	NA	13.95
2004	NY	Total Electric Industry	14.54	12.98	7.04	7.92	NA	12.55
2003	NY	Total Electric Industry	14.31	12.93	7.14	9.38	NA	12.44
2002	NY	Total Electric Industry	13.55	12.33	5.18	NA	8.68	11.16
2001	NY	Total Electric Industry	14.04	12.87	5.56	NA	8.77	11.55
2000	NY	Total Electric Industry	13.97	12.65	5.37	NA	8.99	11.38
1999	NY	Total Electric Industry	13.23	10.11	4.74	NA	8.74	9.95
1998	NY	Total Electric Industry	13.66	11.63	4.95	NA	8.85	10.71
1997	NY	Total Electric Industry	14.12	12.13	5.20	NA	9.17	11.13
1996	NY	Total Electric Industry	14.04	12.08	5.62	NA	9.13	11.13
1995	NY	Total Electric Industry	13.90	11.92	5.79	NA	9.07	11.06

C APPENDIX-C

Appendix-C contains supplementary data and steps for Chapter 5 and 6

C.1 SENSITIVITY ANALYSIS

Sensitivity Analysis according to the OFAT technique was conducted as per parameter values listed in Table 5.1.

C.1.1 Sensitivity to Interaction Intensity

Interaction Intensity is a variable used in the implementation of Deffuant's Relative Agreement Theory and it controls the influence that an agent has over the other interacting agent in changing their opinions or their uncertainty with respect to that opinion. It is posited that with increased influence, there is stronger attitude-driven adoption and therefore the adoption numbers are expected to increase. As per results in Figure C.1, this expectation is confirmed.

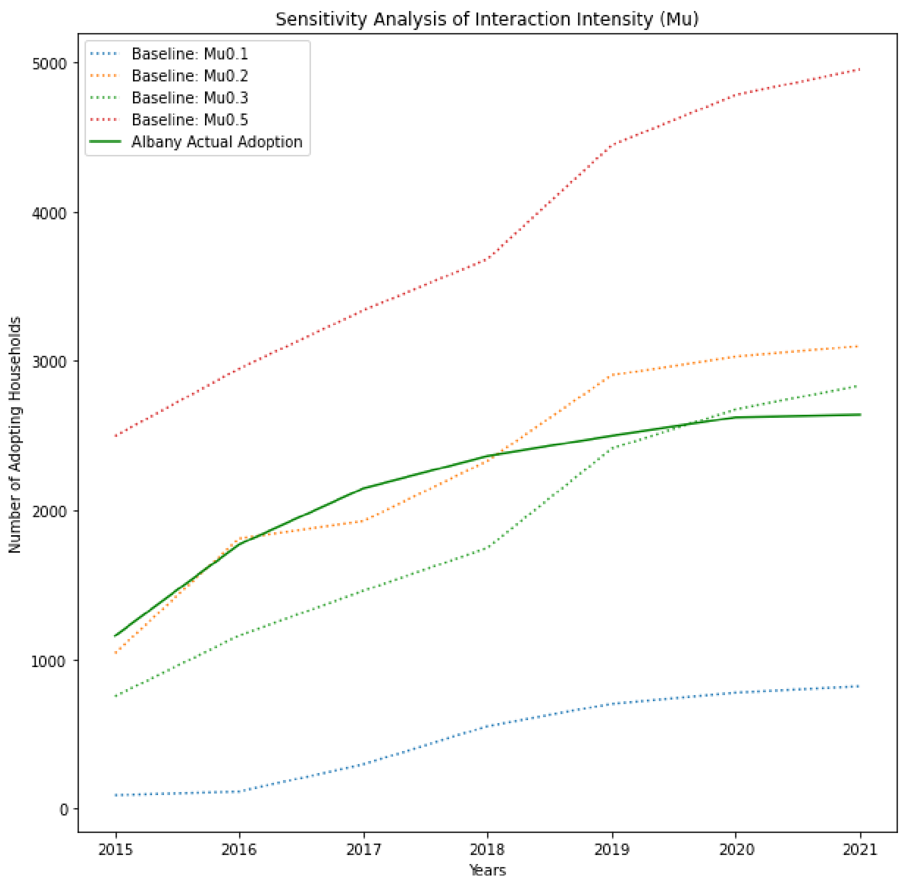

Figure C.1: Sensitivity of Baseline model to Interaction Intensity

C.1.2 Sensitivity to Intention Threshold

According to the Theory of Planned Behavior, Intention is the main predictor of adoption decisions: higher the intention, higher is likelihood that the agent makes a positive adoption decision. This intention is calculated by a weighted sum of three decision factors: a)attitude, b)subjective norms and c) perceived behavioral control. The weights are derived via Linear Regression from survey data and the values of these three factors are results of scoring from survey questions. In order to determine if an adoption decision is made, an intention threshold is used. Some studies derive this intention threshold from survey data itself while some studies use this to calibrate the model. In this study, the intention threshold is part of the calibration process. The Figure C.2 shows the results of the baseline model's sensitivity to this threshold.

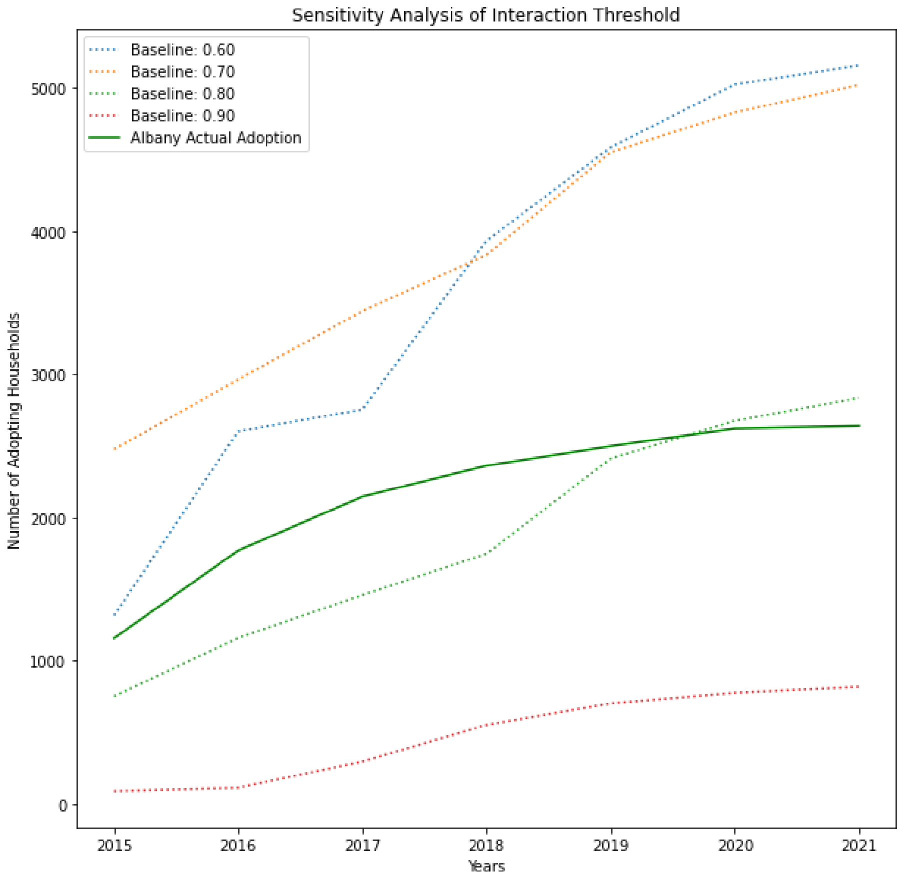

Figure C.2: Sensitivity of Baseline model to Intention Threshold

Lower the threshold, greater are the number of agents that show an intention that leads them to adopt. Figure C.2 confirms this expectation as with decreasing thresholds, the number of adopters increases.

C.1.3 Sensitivity to Sampling Percentages

Sampling percentage is the number of agents belonging to the target group that is seeded with solar PV at the start of the model run. Greater the number of initial seeded agents it is expected that peer-effects kick-in and increase adoption rates. This behavior will confirm that attitude-driven adoption mechanisms work successfully in the model. Figure C.3 confirms this expectation; the results are that of seeding low-income households model and the adoption curve increases with increased sampling percentages.

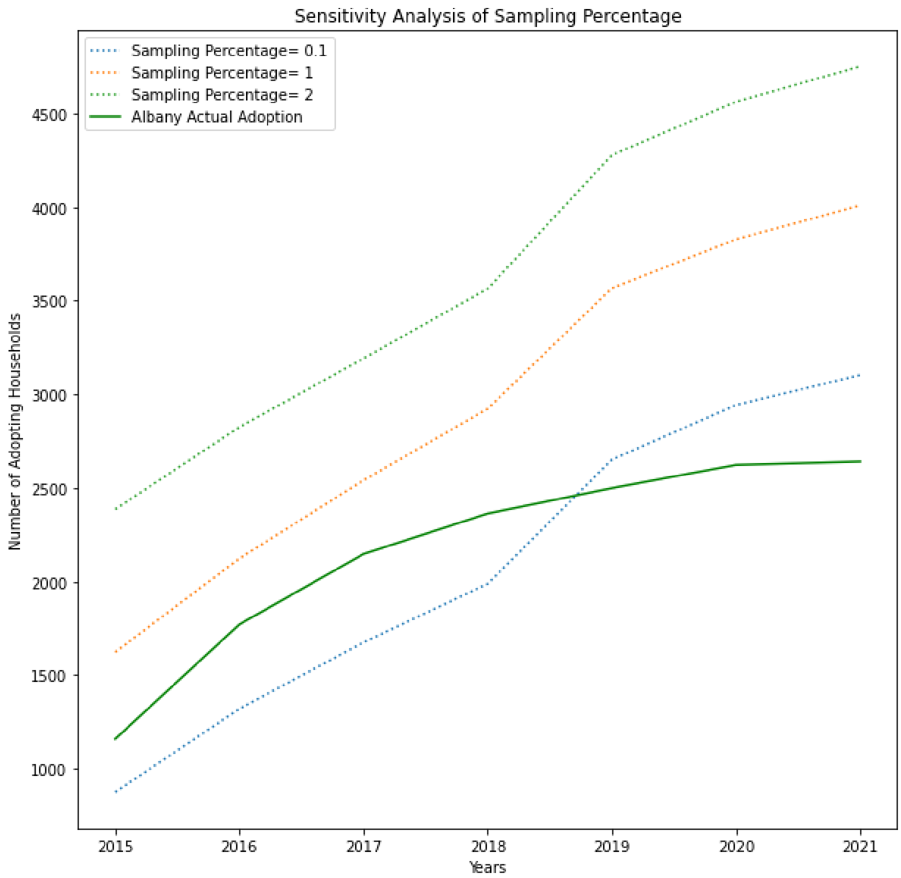

Figure C.3: Sensitivity of Baseline model to Sampling Percentages

C.2 MODEL RESULTS

To test the effects of policies and analyse how how it diffuses in an integrated network as compared to a segregated network, several policy-interventions are modelled. In this section, data with respect to the KPIs and the final adoption numbers are presented in tabular form. Policies are also compared with one another.

C.2.1 Policy Costs

Policy costs for all scenarios are listed herewith for integrated and segregated networks.

Table C.1: Policy Costs for all scenarios in USD ($)

scenario	integrated	segregated
S1_tax46	67678820	27981274
S1_tax51	125691418	72796059
S1_tax56	206061825	144619790
S2_main	115254132	83178077
S3_3a	18182783136	11432563926
S3_3a_1pp	1,45918E+11	99219950678
S3_3a_2pp	3,12085E+11	2,19948E+11
S3_3b	18417139552	11423889008
S3_3b_1pp	1,4302E+11	99525752386
S3_3b_2pp	3,28133E+11	2,38691E+11
S4_4a	18312603808	11545203799
S4_4a_1pp	1,50489E+11	1,01245E+11
S4_4a_2pp	177058008	2,37134E+11
S4_4b	18235268332	11423241103
S4_4b_1pp	1,46043E+11	1,01117E+11
S4_4b_2pp	169047179	2,34291E+11
S4_4c	18160638777	11447323650
S4_4c_1pp	1,44711E+11	98770900915
S4_4c_2pp	171529753	2,3281E+11
S5_5_0.1pp	17959068051	11573861605
S5_5_1pp	1,48846E+11	1,00041E+11
S5_5_2pp	3,32131E+11	2,38026E+11

Considering that the numbers for sampling percentages greater than 0.1 percentage points reach billions of USD, these policies were used primarily to explore the role of trusted messengers and not included in policy cost considerations. Table describes the policies used.

C.2.2 Adoption rates

Table C.2 documents the numbers that were obtained for each of the income groups for each of the policies implemented. 0 stands for segregated network structure and 1 for integrated.

C.2.3 Discussing Flat Tax Rebates

Studies that work at the intersection of social networks and adoption modelling often build on the claim that financial subsidies alone are not enough to result in successful adoption campaigns. It is also claimed that the same policy can perform differently if launched in an integrated network as opposed to a segregated network. To observe

Table C.2: Adoption Rates for each income-group for all policies and network structures. 0: segregated network and 1: integrated network

scenario	overallrates	less75k	75to100k	100to150k	150kplus	network	policy_scenario
S1_tax46	820	1.5	1.3	0.6	0.6	0	1
S1_tax51	2835	3.6	6.5	1.5	1.5	0	2
S1_tax56	5156	5.9	9.6	5.0	5.0	0	3
S2_main	3100	6.0	6.8	0.6	0.6	0	4
S3_3a	3103	4.2	6.6	1.5	1.5	0	5
S3_3a_1pp	4009	6.9	6.7	1.8	1.8	0	5
S3_3a_2pp	4752	8.9	6.6	1.8	1.8	0	5
S3_3b	3065	4.0	6.9	1.6	1.6	0	6
S3_3b_1pp	3980	5.9	8.8	1.7	1.7	0	6
S3_3b_2pp	5019	8.2	10.7	1.7	1.7	0	6
S4_4a	3122	4.2	6.6	1.6	1.6	0	7
S4_4a_1pp	4053	6.4	6.6	2.1	2.1	0	7
S4_4a_2pp	4912	8.3	6.6	2.9	2.9	0	7
S4_4b	3115	4.1	6.8	1.7	1.7	0	8
S4_4b_1pp	3987	6.8	6.7	1.7	1.7	0	8
S4_4b_2pp	4895	9.4	6.7	1.7	1.7	0	8
S4_4c	3071	3.9	6.6	1.9	1.9	0	9
S4_4c_1pp	3970	6.6	6.8	1.8	1.8	0	9
S4_4c_2pp	4855	9.5	6.6	1.5	1.5	0	9
S5_5_0.1pp	3109	3.9	6.8	1.8	1.8	0	10
S5_5_1pp	3911	4.9	7.9	3.0	3.0	0	10
S5_5_2pp	4953	6.4	8.6	4.0	4.0	0	10
S1_tax46	2118	3.8	2.5	2.1	2.1	1	1
S1_tax51	5119	5.9	5.8	5.8	5.8	1	2
S1_tax56	7585	8.1	8.6	9.2	9.2	1	3
S2_main	4024	7.8	5.9	2.5	2.5	1	4
S3_3a	5293	6.5	5.9	5.7	5.7	1	5
S3_3a_1pp	6086	8.5	5.9	6.1	6.1	1	5
S3_3a_2pp	6768	10.7	5.9	5.8	5.8	1	5
S3_3b	5352	6.4	6.1	5.8	5.8	1	6
S3_3b_1pp	5936	7.8	7.4	5.8	5.8	1	6
S3_3b_2pp	7111	9.7	9.6	6.1	6.1	1	6
S4_4a	5298	6.2	6.1	6.0	6.0	1	7
S4_4a_1pp	6152	7.4	6.9	6.9	6.9	1	7
S4_4a_2pp	7093	8.6	8.0	8.2	8.2	1	7
S4_4b	5314	6.4	6.0	5.7	5.7	1	8
S4_4b_1pp	6023	8.5	6.0	5.9	5.9	1	8
S4_4b_2pp	6892	10.9	6.0	5.9	5.9	1	8
S4_4c	5279	6.3	5.9	5.8	5.8	1	9
S4_4c_1pp	5949	7.8	7.5	5.7	5.7	1	9
S4_4c_2pp	6961	9.8	9.3	6.0	6.0	1	9
S5_5_0.1pp	5171	6.1	5.8	5.8	5.8	1	10
S5_5_1pp	6127	7.2	7.1	7.0	7.0	1	10
S5_5_2pp	7056	8.5	8.1	8.2	8.2	1	10

these effects, a flat tax credit scheme is studied. As of today, the total tax credits that are offered in Albany irrespective of your financial background, to a solar PV panel purchases is 51% (26 from Federal Tax Credits and 25 from New York State). By 2023, the government plans to revoke this 26% tax rebate completely. In this model, 3 tax-credit structures are studied.

Figure C.4 shows a summary of the three tax-structures.

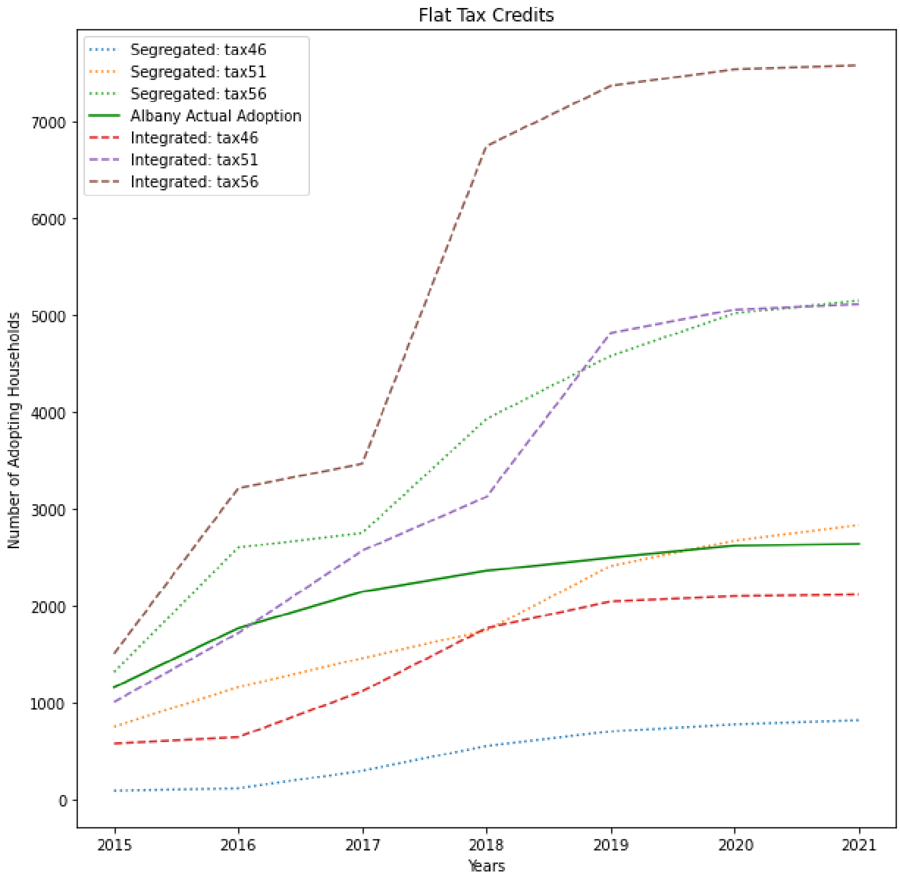

Figure C.4: Flat Tax Credit Structures

Although the percentage of adoptions drop to 2% in the segregated scenario, surprisingly, the percentage adopters in income groups comes about to be higher in the low-income groups. While it was expected that when the cost became high only the few high income groups would gather the financial resources to adopt, it speaks of the reverse. It has to be kept in view that the difference in percentages are very small, but the scales exaggerate the difference. It can be argued that because the population of 'less75k' and '75to100k' groups are much higher in comparison to the high-income groups, the potential for attitude-based changes and the decrease in solar prices are the years pass, could have enabled the low-income groups to adopt as well.

It can be noted however that overall adoption rates remain higher for the integrated network, as opposed to the segregated network scenario for all the rebate structures, highlighting the importance that information exchange and attitude-driven changes to intention can have in adoption.

Figure C.5 shows a comparison of flat-tax policies with tailored income-based tax credits.

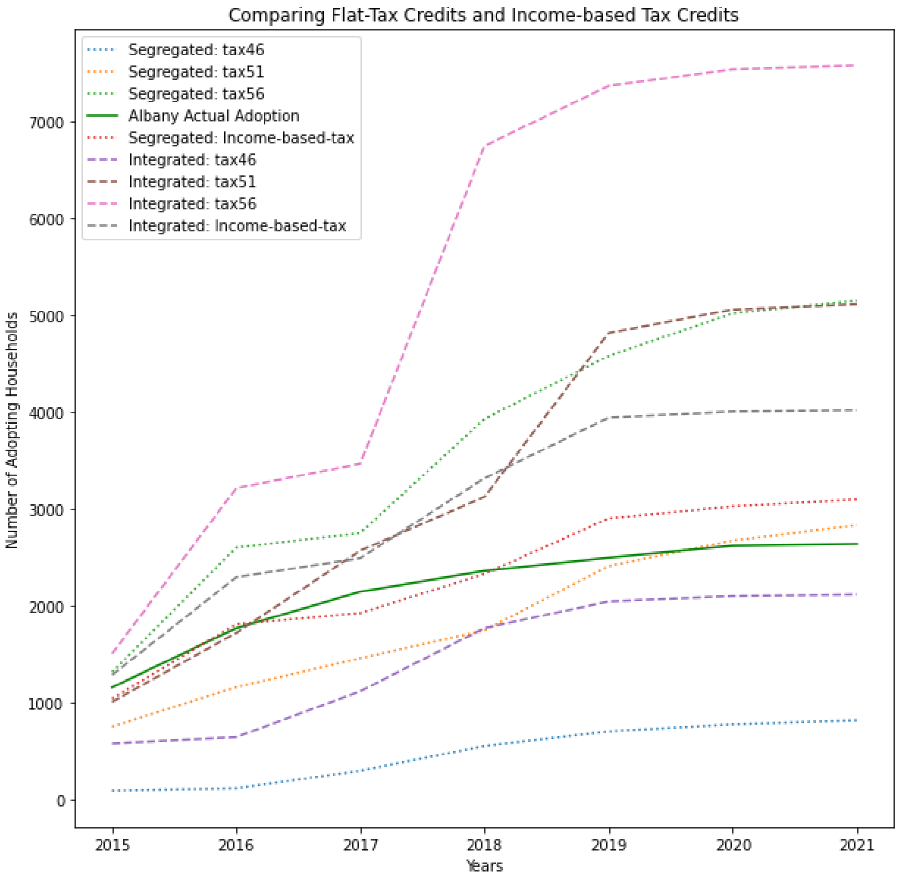

Figure C.5: Comparing Flat Tax Credit Structures with income-based