STRUCTURAL MODEL OF RENEWABLE ENERGY DIFFUSION: THE CASE OF SOLAR PHOTOVOLTAIC PANELS

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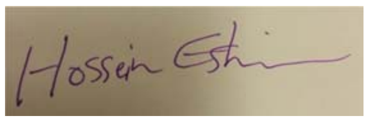
DECLARATION

I hereby declare that this thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.



Hossein Eslami Dizeje

4 February, 2015

To my mother.

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SUMMARY

Sustainability has become a hot issue globally and renewable energy sources are among the most important themes of sustainability research. Despite this trend, there are a few marketing papers addressing the renewable energy topic. To fill this gap, I study the diffusion of solar photovoltaic (PV) panels among households. More specifically I investigate why different households adopt at different points in time and how uncertainty affects their decisions. I use micromodeling approach to shed light on the underlying adoption mechanisms. I model solar panel adoption by forward looking households (or electricity producers in this context) as an investment decision in a technology with uncertain payoff. Using the visibility of rooftop solar PV panels from outside, I incorporate observational learning as the mechanism for information spillover across time and across households. I estimate the model using a unique household-level data set on the adoption timings of the solar PV panels in Germany. The estimation of parameters enables me to perform counterfactual policy experiments on the incentive instruments aimed at accelerating the diffusion process. I demonstrate that by leveraging the observational learning phenomenon, policy makers can adjust the timing of the incentive policies in order to maximize the diffusion of solar PV panels. The proposed framework can be adapted to other sustainable technologies and to different geographical contexts.

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1- INTRODUCTION

Sustainability has become a hot issue globally, and renewable energy sources are among the most important topics of sustainability research. During the past two decades there has been a big movement among different countries to support the adoption of renewable energy on a small scale (i.e. among households). This might result in the creation of a huge potential market for renewable energy sources which would ultimately replace conventional energy sources. Despite the importance and significance of this trend, the adoption of renewable energy has not been sufficiently studied in the marketing literature[1].

Looking at the diffusion pattern of solar PV (Photovoltaic) panels, it is important to understand why different households adopt at different points in time. Investigating the adoption dynamics can help answering this research question. The insights generated when applied to the policy experiments can have important implications for policy makers in the renewable energy field.

In this dissertation I aim to fill the gap in the marketing literature by studying the adoption of renewable energy. I take the consumers' perspective to study the diffusion of solar photovoltaic (PV) panels among households. More specifically I investigate what drives the temporal distribution of residential solar PV panels and why different households adopt at different points in time[2]. My structural model captures the investment aspect of the

[1] A recent Economist article points to the same phenomenon in the business literature: http://www.economist.com/whichmba/making-climate-change-one's-business

[2] Since our data set only covers the households who have adopted solar panels, the focus of our study is on the adoption timing decisions (i.e. adoption now or delay) rather than the adoption decision per se. Most of the diffusion models take the similar position.

adoption decisions in an uncertain environment; in other words, I treat households as forward-looking producers of electricity who decide to invest in solar PV panels with uncertain payoff. Using the visibility of solar panels from outside, I model observational learning as the mechanism to reduce the inherent uncertainty in the adoption payoff. I estimate the model using a unique individual-level data on the adoption timings of the solar panels in Germany. The estimation of parameters enables me to perform policy experiments on the role of incentive policy instruments in accelerating the diffusion process.

2- LITERATURE

Studying the diffusion of solar PV panels is both important and complex. It crosses over different streams of research in economics and marketing. These broad areas include new technology diffusion models, durable goods adoption models, learning models, and renewable energy policy. In this section I briefly discuss the relevant literature in each area and their interrelatedness.

2-1- Diffusion models of new products

Traditionally marketing researchers have been interested in modeling the diffusion of new products. Stemming from the seminal Bass model, Bass (1969), different aggregate models have been suggested to explain the adoption pattern of the new products as the function of the previous adopters, innovativeness of the adopters, and marketing variables (e.g. Generalized Bass model of Bass et. al. (1994)). While these models could forecast the adoption pattern well, the lack of theoretical foundations and their aggregate approach make them unsuitable for explaining the underlying mechanisms behind the diffusion pattern. Aggregate diffusion models assume that the population is homogenous and that only stochastic forces affect the spread of adoption timings. Thus they may not capture the underlying behaviors by heterogeneous customers such as learning. As such, they may not be very suitable for policy experiments.

2-2- Micromodels of Durable Goods Adoption

With the goal shedding more lights on the adoption process, marketing researchers have tried to use the micromodeling frameworks. The early theoretical works by Horsky (1990) and Catterjee and Eliashberg (1990) have built individual-level utility maximization as the foundation of the new product diffusion. In Horsky (1990), the diffusion curve is generated from individuals' utility maximization over the household's production function of all the commodities. It is then aggregated by assuming that the income follows extreme value distribution across the population. He incorporates uncertainty while not using the conventional Bayesian learning framework. By estimating an aggregate model, he shows that both income heterogeneity and uncertainty can affect the diffusion pattern. Chatterjee and Eliashberg (1990) propose a utility maximization framework allowing for heterogeneity in the preferences and beliefs of adopters. Their model incorporates the Bayesian learning mechanism with risk aversion to construct different aggregate diffusion curves. They demonstrate via a pilot survey-based estimation procedure that utility maximization and learning are important in affecting the aggregate diffusion pattern. Their model may not be easily applicable to estimating the typical individual-level adoption data used in the literature.

Continuing this trend, several structural models have been proposed in the literature ever since, to provide deeper insights into the durable goods diffusion process. Forward-looking behavior is an important aspect in the adoption of durable goods where quality improves and price falls over time. Melinkov (2000) and Song and Chintagunta (2003) are among the earliest papers bringing forward-looking behavior to the micromodels of diffusion. Melinkov (2000) proposes a dynamic model of computer printer adoption incorporating the expectation over the future quality. The setting is an optimal stopping problem for when to buy (e.g. hazard model) decisions. The estimation is done on aggregate sales data of the U.S. computer printer market. He shows that forward-looking is an important aspect in estimating micromodels of new durable products. Song and Chintagunta (2003)'s model is similar except for the built-in heterogeneity for both price and preference parameters. They estimate the model using aggregate data on the digital camera category in the U.S. market. Their model can generate flexible aggregate diffusion patterns incorporating heterogeneity and forward-looking. Despite having the micromodeling foundation, these two models are tailored for aggregate-level estimation. In other words, these models are estimated at the aggregate level and are unable to capture the dynamics in individuals' behavior, like learning and information spillover. Thus they may not provide the best means for policy experiments in markets where uncertainty and learning play salient roles.

Another interesting paper to note is Yang and Ching (2013). They study the adoption of ATM cards by building a micromodel with dynamic usage optimization and static adoption decision. They benefit from a rich individual level data plus the cash withdrawal patterns before and after adoption. In their model, heterogeneity comes from age which affects the life horizon of individuals and therefore the total discounted adoption benefits they get. They are able to demonstrate why elderly have lower adoption rates. Their model does not incorporate any form of uncertainty into the adoption decisions.

2-3- Learning Models

In adopting products or services, there are usually uncertainties involved. They may be quality uncertainty (either because of quality variation or match uncertainty), actual cost uncertainty (uncertainty regarding the cost and benefits over the long term), and usage uncertainty (over subscribing to mobile phone plans). Modeling uncertainty and learning in new technology diffusion is the focus of an extant body of literature. The early decision-theoretic paper by Jensen (1982), and subsequent papers like McCardle (1985)[3], have proposed individual-level new technology adoption models incorporating uncertainty into the diffusion framework. While these models do a good job in behaviorally explaining the diffusion curve, they are ill-suited for empirical applications.

Roberts and Urban (1988) is among the first empirical papers in marketing that model uncertainty and learning in the adoption of durable

[3] Some recent papers in operations research literature have started tackling this problem (e.g. Ulu and Smith (2009)).

goods. The authors propose a model and utilize individual-level survey data to estimate the effect of attribute uncertainty on automobile brand choice decisions. Since then, there have been proposed various Bayesian learning papers modeling quality uncertainty (e.g. Erdem et al. (2005) utilize panel surveys to study the active information searching in choosing between different brands of personal computers). Since there is no repeat purchase, these models have mainly used survey data and have focused on individual learning, where private signals are the source of information.

In a similar vein, observational learning models study the setting where observing the adoption decisions of others is the source of information. Since actions reflect underlying beliefs, they give the attentive observer the ability to infer those beliefs via private signals. Thus the public will gradually converge in their actions (right or wrong) such that individuals neglect their private signals and only look at the predecessors actions. This phenomenon is called “Information Cascade”. The seminal theoretical papers in this field are Banerjee (1992) and Bikhchandani et al. (1992). So far, different variations of the classic observational learning models have emerged in the literature with the goal of making the settings more general (e.g. Rational observational learning introduced in Eyster and Rabin (2011)).

There have been a few empirical papers in economic journals on the adoption of durable goods in the presence of observational and social learning. Grinblatt et.al (2008) is among the early papers studying the role of social learning in the adoption of automobiles[4]. It leverages the unique data of the

[4] It is to be noted that automobiles are not conventionally considered as a new technology.

location of individual households and their purchase decisions in Finland. Individual-level choice model with the car purchases in the near proximity as the independent variable of interest. It establishes that the purchase history of the close neighbors affects the purchase of automobile by the focal consumer[5] while does not tackle the process behind this phenomenon. The other interesting paper to be mentioned is Conley and Udry (2010) that studies the impact of social learning on the adoption of new agricultural technology. It utilizes a unique dataset of the pineapple farmers in Ghana and their adoption of new fertilizers. The data allows the researchers to define the information reference groups of each farmer and to establish the sequence of information one receives on the performance of fertilizers used by peers. By assuming that the focal farmer can observe the performance of new technologies by others, the setting resembles information sharing (where one observes the outcome and the reasons behind it) as compared to observational learning (in which one doesn't know the reasons behind adoption).

It has taken some time for the marketing research scholars to study this established phenomenon. Zhang (2010) is a recent interesting paper with empirical model of observational learning. She studies the acceptance of kidneys for transplant in the U.S. market. In her paper, the perceived quality of kidney is influenced by number of refusals earlier in the waiting list. She uses a unique individual-level data of the sequence of decisions by patients in different queues allowing a clear formulation of observational learning. She assumes that each patient knows the preferences of its peers in the waiting list and thus shows that earlier rejections negatively affect the quality perception

[5] In this sense it is similar to Bollinger and Gillingham (2010) while their model is at the aggregate-level.

for the focal patient. The unique setting (i.e. where learning is only from the past non-adopters) and the assumptions taken (i.e. one knows the preference distribution of others) make it difficult for the adoption model to be applied to the typical new products. There have been attempts to use novel settings to study the social influence on the adoption of durable goods. Narayan et. Al. (2011) construct a conjoint experiment to investigate the peer influence on the adoption of E-book readers and mobile phones. Contrary to the conventional models where learning is on quality or other product attributes, they show that social learning can also affect the attribute weights. In general the lack of proper individual-level data (i.e. to allow for a clean construction of observational learning) and difficulty in defining quality perception (i.e. quality is subjective and hard to model in most contexts) are among the main reasons that we have not seen substantial similar models for the adoption of durable goods.

Table 1 shows an overview of the micromodelds of durable goods adoption in marketing literature. Since I use the same methodological framework, it helps clarifying my thesis's position in terms of the methodology and data.

Table 1 - Micromodels of Durable Goods Adoption

Model	Context	Individual Level	Panel Data	Forward Looking	Individual Learning	Observational Learning
Roberts and Urban (1988)	Automobile models	✓			✓	
Horsky (1990)	Appliances				✓	
Chatterjee and Eliashberg (1990)	Career counselling software	✓			✓	
Song and Chintagunta (2003)	Digital camera			✓		
Erdem et. al. (2005)	PC	✓	✓ *	✓	✓	
Gordon (2009)	CPU (Adoption/Replacement)			✓		
Heutel and Muehlegger (2010)	Hybrid vehicle			✓	✓	
Yang and Ching (2013)	ATM cards	✓	✓	✓		
My model	Solar PV panels (Investment)	✓	✓	✓	✓	✓

* They have used a survey in which respondents were asked explicitly how they search and gather information.

2-4- Diffusion models of sustainable technologies

Only recently a new trend has been started to study the adoption of renewable energy from a marketing perspective. Somehow similar to the topic of this thesis, Bollinger and Gillingham (2010) look at the significance of peer influence in the spatial diffusion of solar panels in California. They use an aggregate hazard model at street level and focus on a quasi-experimental approach to identify the peer effects. They could show the positive influence of previous adoptions on the decision to adopt at the street level which results in clustering. While they control for neighborhood demographics, time trend, and cumulative number of installations, they do not structurally construct the adoption utility. The reduced form of the model can show the peer effects on adoption but not the mechanism through which it works[6] and therefor it can't be used for policy experiments.

Heutel and Muehlegger (2010) use an individual-level model to study the consumer learning phenomenon in hybrid vehicle adoption. They focus on model-specific quality learning using aggregate sales data (they had to make assumptions to handle learning with aggregate data). They show that model-specific learning is effective and can be either positive or negative. Shriver (2010) uses a full structural model of both demand and supply in a two-sided market setting (the automobile as the platform for consumers and fuel retailers) to study the role of network effects on ethanol fuel adoption. He uses zip code-level data to estimate the demand parameters in a BLP-style model (as in Berry et al. (1995)). He shows that the network effect of the ethanol retailer positively affects the adoption of ethanol-compatible vehicles. All these

[6] They have mentioned this as a "prime topic for future research".

studies had to deal with the aggregate nature of the data used for estimation. The aggregate estimation doesn't allow the proper heterogeneity incorporation which may results in biased estimates. Moreover, it doesn't allow to explicitly modeling the uncertainty and the process through which it gets resolved during the diffusion process.

2-5- Solar PV case

Solar PV panels can be considered durable goods since they are one-time adoptions (with long operating life) and they experience rapid improvement in performance and decline in price over time. As in the case of durable goods, consumers form expectation about the trends of price and performance before they decide to adopt or wait depending option value of waiting. This makes it necessary to incorporate the dynamics of forward-looking behavior into the adoption model.

Unlike most of the durable goods studied in the extant literature, solar PV panels do not bring any additional functionality (utility) to the adopters, but merely replace the conventional non-renewable electricity sources. Under the Feed-in Tariff scheme[7], the electricity generated by solar panels will be fed into the grid at a rate higher than the one household buys conventional electricity from the grid[8]. Thus the adoption decision can be intuitively viewed

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[7] Among the incentive policies used by the policy makers around the world, Feed-in Tariff (FIT) has gained more attention especially in the case of solar PV panels. This is contract based with long horizon in European countries (e.g. 20 years fixed Feed-In Tariff contract in Germany). Please refer to the Appendix 1 for the brief introduction and historical account on the Feed-in Tariff policy in Germany.

[8] Here we assume that the electricity consumption would be the same regardless of adopting solar panels. In this case, the adopters pay for the fixed cost of the solar

as an investment decision (i.e. households acts as electricity producers who decide to invest in a new technology).

In this setting, there would be no perfect information regarding the actual electricity output of the installed solar panel in future (i.e. it can be a function of weather and many other factors) and thus the payoff of the investment beforehand. As the result, uncertainty is an important factor to be accounted for. Specifically in the case of rooftop solar PV panels, the panels are installed on the roofs and can be visible from the outside. Therefor it can be safely assumed that the adoption decisions are observable by others immediately after installation. This makes the adoption of solar panels a suitable context to study the role of observational learning on the durable goods adoption. This can have important implications for the types of information spillover in the solar PV panel market.

The above mentioned features add to the merits of studying the adoption of solar PV panels from the methodological standpoint. I build on micromodels of durable goods adoption to study the adoption of solar panels by forward-looking households. I incorporate the investment nature of adoption, the option value of waiting, the uncertainty of the adoption payoff, and the visibility of adoptions as the distinguishing features of my model. I contribute to the durable goods literature by customizing a dynamic individual level model suitable for uncertain investment scenarios and accounting for cross-individual information spillover. The specific context and the unique

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system and will receive stream of revenues by feeding the generated electricity to the grid in the future.

individual level solar PV adoption dataset allow us to avoid the limitations faced in the extant diffusion literature.

In the following sections I elaborate on the proposed model and the dataset used. I will then continue by discussing of the estimation procedure and the results.

3- MODEL

The utility of adopting solar panels for household i at time t is a function of benefits Q_{it} and cost p_{it} of investing in solar energy. I use a general indirect utility specification:

$$U_{it} = \alpha_i + \theta_i(Q_{it} - p_{it}) + \varepsilon_{it} \tag{1}$$

ε_{it} is IID an additive random shock to the utility which follows the standard normal distribution. α_i is the base utility of adoption (it is a function of neighborhood-level demographics), θ_i is the propensity to the net financial benefits derived from adopting the solar panel (it is a function of neighborhood-level demographics), Q_{it} is the potential benefits of adoption which is basically equals the average payoff $\overline{PV_{it}}$ of investment[9]. However, since solar PV panel is a new technology and the future income stream (i.e. the stream of revenues from selling the solar-generated electricity to the grid

[9] I assume the life of the solar panel to be 20 years and the average annual electricity yield of the panel to be 1000 KWh per 1KWp (to be multiplied by FIT of the installation year). The discount rate of 0.95 is assumed for calculating the payoff of the income stream in the next 20 years.

based on the federal Feed-In Tariff rate over the life of the panels)[10] depends on many unknown factors at the point of adoption (weather in the long run, quality of the panel in the long run, etc.), the households will have some uncertainty as to if they will fully receive the benefits or not. I call this uncertainty as 'belief about investment payoff', q_{it}, which is assumed to be between zero and one[11]. Therefore, I modify equation (1) as follows:

$$U_{it} = \alpha_i + \theta_i(\overline{PV_{it}} q_{it} - p_{it}) + \varepsilon_{it} \quad (2)$$

In the extant marketing literature, consumers are usually considered to be forward looking with respect to the adoption of the new technology. The utility of not adopting at time t, U_{0t}, is the value[12] that household i would get if he forgoes adopting now but keeps the option of adoption in the future periods. Since one does not have the perfect information about the future market, household i forms expectation over the value she gets in the next period. Therefore we have:

$$U_{it0} = \beta * E(V_{it+1}|S_{it}) \quad (3)$$

where $E(V_{it+1}|S_{it})$ is the expectation of the value function in t+1 given the current state[13] S_{it} and β is the discount factor.

[10] I can also make the payoff net of the risk-free interests from investing P_{it} in bank deposits. I have run trial estimation and found that it doesn't improve the estimates much.
[11] This uncertainty is different from the discount rate that one may use. Discount rate is known to the investor while the belief about the investment payoff is a function of the information one has prior to the investment.
[12] In the dynamic programing context, value (or value function) captures the utility one gains if he acts optimally given the state of the world.
[13] In the dynamic programing context, state (or state variables) encapsulates all the information one needs to know about the state of the world at time t.

I further assume that initially all the households have a common knowledge about the realization of investment payoff, q_{it}, although no one would know the true payoff. Each places faith on her belief. The initial belief for household i is:

$$q_{it}(t = 0) \sim N(\omega_0, \sigma_0^2) \qquad (4)$$

where ω_0 is the mean of initial belief and σ_0^2 is its standard deviation[14].

Companies marketing the product would be contacting the potential customers through mass media, direct mails and telephones and trying to convince customers on the product quality or the potential income stream in the solar PV case using scientific reports that support their claims. I assume that the signals received by the individual households follow normal distribution around the true q (unknown to the households):

$$\lambda_1^i \sim N(q, \sigma_s^2) \qquad (5)$$

where q is the true realization (between 0 and 1) of investment payoff and σ_s^2 is the noise associated with the signal. The private signals received by each household are[15]:

$$\lambda_1^1,\ \lambda_1^2,\ \lambda_1^3, \dots, \lambda_1^i, \dots \qquad (6)$$

Combining the initial common belief with the private signal, each household updates its belief in a Bayesian fashion as follows:

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[14] In the learning models literature, for the ease of estimation, usually ω_0 is assumed to be zero and σ_0^2 is set to be 1. I have estimated ω_0 in trial estimation and the value turned out to be almost zero.

[15] Each household only observes her signal and not others' signals; otherwise they could get to know the distribution of signals and thereby the true quality.

$$\omega_1^{i} = \frac{\frac{\lambda_1^{i}}{\sigma_s^2}+\frac{\omega_0}{\sigma_0^2}}{\frac{1}{\sigma_s^2}+\frac{1}{\sigma_0^2}} \quad \text{and} \quad \sigma_1^2 = \frac{1}{\frac{1}{\sigma_s^2}+\frac{1}{\sigma_0^2}} \qquad (7)$$

where ω_1^{i} is the posterior belief of the true realization and σ_1^{i2} is the posterior variance of the belief. Acting on the posterior belief, each household decides whether to adopt the solar panel or not. I assume the households to be risk neutral (i.e. maximizing expected value) which means:

$$\begin{cases} \text{Adopt if: } \alpha_i + \theta_i\left(\overline{PV_{i1}}\omega_1^{i} - p_{i1}\right) + \varepsilon_{i1} \geq \beta * E(V_{i2}|S_{i1}) \\ \\ \text{Wait if: Otherwise} \end{cases} \qquad (8)$$

Given the normality assumption for the random shock, the probability of adoption by household i at t=1 would be[16]:

$$1 - \text{CDF}\left(-\alpha_i + \theta_i * p_{i1} - \theta_i\,\overline{PV_{i1}}\omega_1^{i} + \beta * E(V_{i2}|S_{i1})\right) \qquad (9)$$

In the conventional learning models like Erdem and Keane (1996), it is assumed that there would be incoming signals in the subsequent periods (i.e. each time a consumer experiences a product) and in each period consumers update their beliefs according to (7) and make adoption decisions according to (8). Since my model is about the adoption of a new durable product, there will be no such product experience signal to influence the beliefs (i.e. my model is different from the conventional Bayesian learning models in a sense).

Further, I assume that no new information is made available by the companies or acquired by the households in the subsequent periods, in effect implying that there are no more private signals after the initial period.

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[16] Each household knows its utility with certainty. From outsider's point of view (e.g. neighbors), it is a random variable.

However, an important aspect of deciding to adopt a new technology is learning from others. In the solar PV case, households can observe the adoption of rooftop solar panels by other households in the neighborhood and use that information to infer about the investment payoff. Although I do not have data on the actual word of mouth (i.e. consumers share their private signals to each other), the mere observation of other households' adoption in the same neighborhood can reveal something about the investment payoff. I hence incorporate observational learning (i.e. inferring private signals from observing the actions of others) in my proposed model. This observation is a source of probabilistic inference because the observed number of adoptions in the neighborhood is just one of many possible outcomes and the focal household may never know the reasoning behind the adoptions by others. Further, as long as the household has not adopted the product, she would keep updating her belief every period via observation. I model this process as follows.

Representing the neighborhood[17] as consisting of homogenous consumers, the average household's utility of adoption at time t in neighborhood k is given by:

$$\alpha_k + \theta_k\left(\overline{PV_{kt}}\gamma_{kt} - p_{kt}\right) + \varepsilon_{kt} \qquad (10)$$

This is very similar to equation (2) but operates at the average household at the neighborhood level[18]. The average household is expected to adopt if the utility

[17] I use street segment vicinity as the neighborhood where each street has a unique code.
[18] α_k and θ_k are the same for all since they are function of neighborhood demographics. $\overline{PV_{kt}}$ and p_{kt} are calculated based on the average panel size in the neighborhood.

of adopting is greater than zero. Here γ_{kt} [19] is the mean belief across the neighborhood k in time t while the standard deviation is assumed to be σ_t^2. The standard deviation is same as that of the quality signal received from the company (i.e. as in (5)) for the reason that the market level belief will be reflecting the underlying uncertainty of the signal generating source. Since a household observes the fraction of households adopting the solar PV panels in its neighborhood out of those who have not adopted yet, she can make an inference. Using (9) and by using the probability of adoption and acceptance rate in neighborhood k interchangeably, we'll have[20]:

$$\gamma_{kt} = \left(\left(InverseCDF\left(\widehat{AcceptanceRate}_{k,t-1}\right) - \alpha_k + \theta_k * \mathrm{p}_{\mathrm{kt-1}}\right)\right) \Big/ \theta_k * \overline{PV_{kt-1}} \tag{11}$$

This defines the payoff inference a household in neighborhood k will be getting by observing others' adoption decisions. This will be same for all the households in neighborhood k[21].

Note that since at t=1 (before realization of the adoption decisions in each neighborhood) there was no observation. To initialize the process I assume that the household i has a prior belief about the proportion of households in its

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[19] The mean belief, γ_{kt}, is time variant and captures the belief at the neighborhood level about the investment payoff. In other words, γ_{kt} is what one infers about the investment payoff by observing the adoption pattern at neighborhood k at time t.
[20] The proof is given in Appendix 3.
[21] Note that γ_{kt} is the inference taking place in time t by observing the adoption pattern in the neighborhood in t-1.

neighborhood that would adopt (i.e. acceptance rate). This prior belief is assumed to stem from a beta distribution[22]:

$$(Acceptance\ Rate\ Belief_1 | No\ Observation) \sim Beta(\mathrm{A}_1\ , \mathrm{B}_1) \qquad (12)$$

For tractability, I assume that households don't have any knowledge (i.e. ignorance) of the proportion of adopters beforehand which can be modeled by choosing (1,1) as priors for A_1 and B_1[23].

At the end of period one, the decisions of all households in the neighborhood k become realized (in total N_{1k} adoptions out of M_{1k} households in neighborhood k). Observing this, household i updates its belief regarding the acceptance rate in its neighborhood.

$$\left(Acceptance\ Rate\ Belief_1 | M_{1k}, N_{1k}\right) \sim Beta(\alpha_1 + \mathrm{N}_{1k}\ , \beta_1 + \mathrm{M}_{1k} - \mathrm{N}_{1k}) \qquad (13)$$

As noted above (equation 11), there is a one to one correspondence between the acceptance rate and the quality inference. Thus household *i* combines her prior belief with this new signal from the market (mean quality inference from observation as in 11) to arrive at her posterior belief in t=2 and afterwards.

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[22] Beta distribution is chosen for its range (between 0 and 1) which makes it suitable for the proportion (i.e. acceptance rate) and also its conjugacy with Bernoulli/Binomial observations (i.e. adoption proportion observations).

[23] Alternatively, I can use the adoption proportion in different neighborhoods before t=1 to exogenously define the priors A_1 and B_1 (i.e. I need to equate the historic proportion to the mean of the Beta distribution $\frac{\mathrm{A}_1}{\mathrm{A}_1+\mathrm{B}_1}$ and solve for them accordingly).

$$\omega_2^{\mathrm{i}} = \frac{\frac{\gamma_{k2}}{\sigma_S^2}+\frac{\omega_1^i}{\sigma_1^2}}{\frac{1}{\sigma_S^2}+\frac{1}{\sigma_1^2}} \quad \text{and} \quad \sigma_2^{2\mathrm{i}} = \frac{1}{\frac{1}{\sigma_S^2}+\frac{1}{\sigma_1^2}} \tag{14}$$

It can be seen from (14) that the effect of observing others' behavior (at the neighborhood level) has been incorporated into the learning model.

Given the posterior belief, household *i* decides to adopt or not depends on:

$$\begin{cases} \text{adopt if: } \alpha_i + \theta_i\left(\overline{PV_{\imath 2}}\omega_2^{\mathrm{i}} - \mathrm{p_{i2}}\right) + \varepsilon_{i2} \geq \beta * \mathrm{E}(V_{i3}|S_{i2}) \\ \\ don't adopt: otherwise \end{cases} \tag{15}$$

Those households who have not adopted till time *t* would go through the same process.

I need to solve for the value function before I can proceed with the likelihood function. The adoption decision depends on the price and payoff of investment (observable states) as well as the belief about the quality and the random shock (unobservable states). For the new technologies, the price falls down dramatically over time and usually consumers form rational expectation over the price in future before deciding to adopt or not. This makes the dynamic problem non-stationary (or time dependent). The adoption of solar panels is a one-time investment (i.e. if you adopt the solar panel there is a little chance you repeat the same adoption in the near future) which makes the dynamic problem similar to the optimal stopping problems. Therefor I can cast the solar panel adoption into the finite horizon optimal stopping problem. Following the extant literature on this methodology (e.g. Pakes (1986), Eckstein and Wolpin (1989)), I solve for the value function at each time and for each household using the backward induction algorithm starting from the terminal period T[24]. I assume that each household forms rational expectation over price and payoff given all the historic data points up to t (this makes the expectations time specific which seems intuitive). Moreover, I assume that the future quality belief (ω_t^i) is expected to be the same given the unobserved nature of it. Lastly, I use the conditional independence assumption for random shocks to make the individual-level backward induction algorithm tractable.

Having solved for the value function in (15), I can construct the likelihood function for household *i* as follows:

$$Likelihood_i = \prod_{t=1}^{T}\Big(\Big[1 - \mathrm{CDF}\,\Big(-\alpha_i + \theta_i * \mathrm{p}_{\mathrm{it}} - \theta_i\,\overline{PV_{it}}\omega_t^i + \beta * \mathrm{E}(V_{it+1}|S_{it})\Big)\Big] * Adoption_{i,t} + \Big[\mathrm{CDF}\,\Big(-\alpha_i + \theta_i * \mathrm{p}_{\mathrm{it}} - \theta_i\,\overline{PV_{it}}\omega_t^i + \beta * \mathrm{E}(V_{it+1}|S_{it})\Big)\Big] * Non\_Adoption_{i,t}\Big) \qquad (16)$$

Where 1-CDF(…) is the probability of adoption given in (9) and therefor CDF(…) is probability of not adopting. $Adoption_{i,t}$ and $Non\_Adoption_{i,t}$ (i.e. adopt later) are dummy variables for adoption and not adoption respectively; their sum is 1 at each time.

I take the log of the $Likelihood_i$ to get $logLikelihood_i$. This way the product term in (16) (i.e. $\prod_{t=1}^{T}$ ...) will become the summation (i.e. $\sum_{t=1}^{nT}$ ...) which is easier to handle. By summing over the log likelihood of each household, I will have the total log likelihood. Minimizing the total log likelihood, I can

[24] We assume T to be 10 years ahead of time t. Given the rapid changes in the solar photovoltaic technology, having a very far terminal period would make little sense.

estimate the model parameters $(q, \sigma_s^2, \alpha, \theta)$[25] using Simulated Maximum Likelihood Estimation.

4- DATA

I utilize a unique dataset on adoption timings of the residential solar PV panels in Germany. The sizes of the residential solar panel systems are equal to or less than 10 KWp[26]. The data covers nine years, from 2002-2010, and I consider each year as a discrete time unit. In total there are over 11000 adopters. Table 2 shows the distribution of adoptions as well as market statistics across the nine years[27]:

Table 2 – Annual Adoptions Statistics

Year	**Adoptions**	**Average Panel Size**	**Price (€/1KWp)**	**Feed in Tariff (€/KWh)**
2002	584	6.09	5100	0.48
2003	563	6.18	4900	0.46
2004	923	6.24	5800	0.574
2005	1276	6.31	5400	0.54
2006	844	6.35	5100	0.52
2007	884	6.41	4400	0.49

[25] q, σ_s^2 are not shown in the likelihood function but they are the essential part of the process generating ω_t^i as in (6), (7), and (14). They are treated as parameters and get estimated. Also to be noted that I assume $\beta = 0.95$, $\omega_0 = 0$, and $\sigma_0^2 = 1$ due to the lack of data for identification; this is a common practice in the marketing literature.

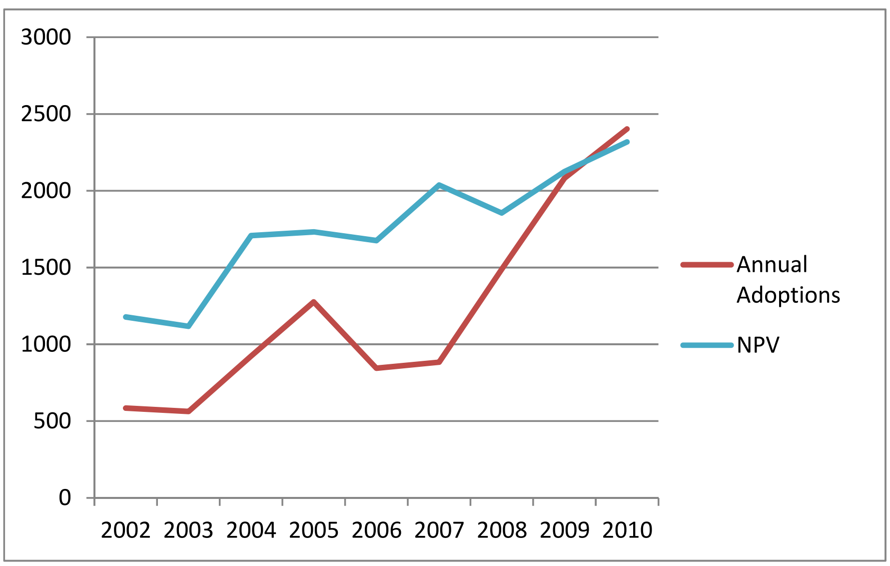
[26] This is the conventional definition of residential solar PV installations.

[27] The number of adoption and the average panel sizes in each year are calculated from the adoption dataset. The values of price and Feed-in Tariff are taken from the public solar PV market data in Germany; they are controlled for inflation.

2008	1488	6.47	4260	0.46
2009	2082	6.54	3500	0.43
2010	2402	6.51	2800	0.39

As can be seen from Table 2, the average size of the installed panels increases over time. On the other hand, as with other new technologies, the price decreases substantially over time. Having the information on price and Feed in Tariff rate, we can calculate the net present value (NPV) of investing in 1KWp solar PV panel from 2002 to 2010[28]. The following figure shows the trend of the number of solar panel adoptions in each year contrasted against the calculated NPV of the corresponding investment at each year.

Figure 1 - Number of Adopters vs NPV of Investing Solar PV over Time

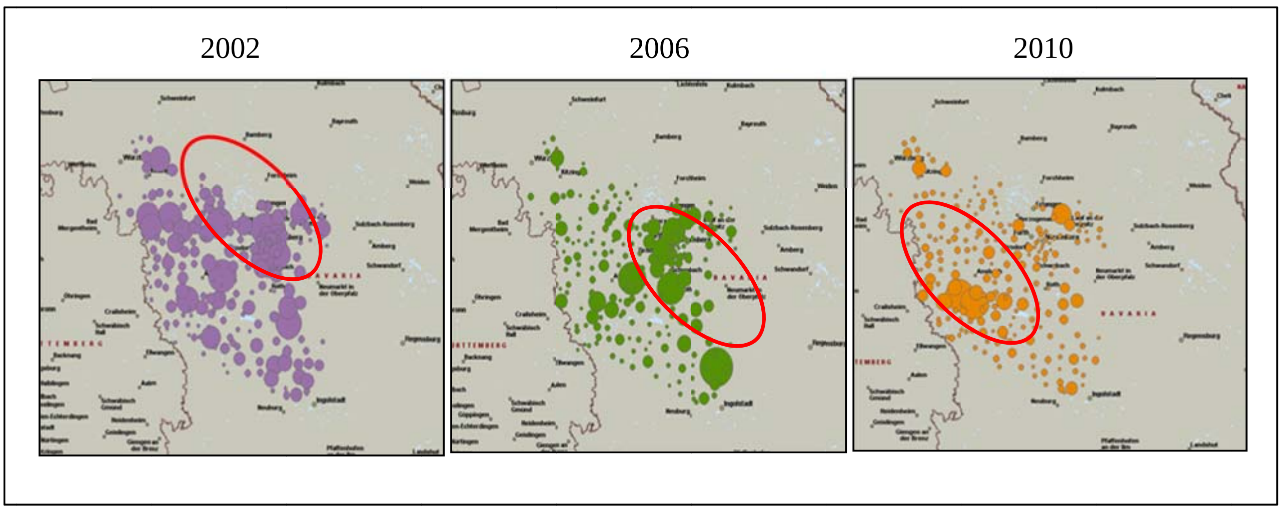


[28] The NPV is calculated for 1KWp unit. We assume the life of the solar panel to be 20 years and the average annual electricity yield of the panel to be 1000 KWh per 1KWp. The discount rate of 0.95 is assumed.

By looking at figure 1, we can see that the changes in NPV do not perfectly show the changes in the number of adopters. Thus on top of the return on investment, other factors such as heterogeneity and uncertainty in the beliefs about the investment return could possibly play role in the diffusion process.

For each household in my data, I know its neighborhood (a unit similar to streets in size). I have plotted the spatial pattern of adoptions over time to see if the adoption centers are fixed or moving.

Figure 2 - Centers of Solar PV Adoptions across Time



From figure 2 we can see that the adoption clusters are being formed over time which can be regarded as an evidence of social learning. I have tested this evidence further by running a simple binary logit model of adoption. The results of the model are given in Appendix 4. These model-free evidences coupled with the findings in the literature (e.g. Bollinger and Gillingham (2010) have shown that peer effects have positive influence on adoption of solar PV panels), tell us that social learning is playing role in adoption of solar PV panels and thus it should be incorporated into the model.

Furthermore we can see form figure 2 that the adoption centers[29] are shifting over time. This suggests that the demographics of early and late adopters are not necessarily similar and thus it might be important to account for the observed heterogeneity in modeling the diffusion process. To this end, I further supplement the adoption timings data with the rich demographics information of the households at the neighborhood level (there are 7338 neighborhoods in my sample). For each neighborhood I know the average income, proportion of singles and married (with and without children), proportion of residential and commercial buildings. Moreover using consumer lifestyle segmentation, I augment the neighborhood demographics with the percentage of households with different lifestyle[30]. Table 3 shows the summary statistics and definition of the demographic variables used in my analysis.

Table 3 - Demographics Summary Statistics

Variable	**Explanation**	**Mean**	**Standard Deviation**
Average net income (€/10000)	Average monthly income	0.34	0.16
Proportion of married families with children		0.38	0.19
Proportion of married families		0.36	0.18

[29] A different color is used for the adoptions in each year while the size of circles shows the density of adoptions in each location.
[30] These include the percentage of households in each neighborhood belonging to a segment with different values, behavior and interests. The segmentation scheme is developed by GfK.

without children			
Proportion of single households*		0.26	0.18
Proportion of residential building		0.74	0.17
Proportion of commercial buildings*		0.26	0.17
Proportion of Settled*	Looking for peace and harmony	0.16	0.06
Proportion of Homebodies	Looking for material security	0.22	0.05
Proportion of Dreamers	Looking for happiness	0.08	0.05
Proportion of Adventurers	Following passion	0.13	0.05
Proportion of Open-minded	Balancing self-actualization, social responsibility and pleasure	0.11	0.05
Proportion of Organics	Searching for sustainability and self-actualization	0.06	0.05
Proportion of Rational/Realists	Valuing hard work and responsibility	0.12	0.05
Proportion of Demanding	Balancing responsibilities and pleasure	0.12	0.06

* Chosen as the base group in analysis.

Having the rich demographics information of the households allows us to incorporate the heterogeneity across neighborhoods into the adoption model, which is shown to be important in studying the diffusion of new products.

5- RESULTS

5-1- Full Structural Model

As households in my model are forward-looking, I needed to solve for the value functions before being able to derive the adoption probabilities and substitute them into the likelihood function. I formulate a finite-horizon dynamic programing problem[31] with 10 years ahead as the terminal stage. The corresponding values were calculated for each household at each time. The conventional discount factor of 0.95 was used for the backward induction algorithm. The exact details of the procedure used are given in the Appendix 2.

I have estimated the model using household-level adoption data over the period of 2002-2010, supplemented with the demographics data at the neighborhood level. As the model incorporates individual and observational learning, I needed to use simulation-based estimation methods. The random draws were taken from the normal and beta distributions and supplemented into the model to generate the evolution of beliefs about the adoption payoff for each household across time. I used the Simulated Maximum Likelihood Estimator. I have used a bunch of demographics variables to capture the heterogeneity among the households. For θ (i.e. propensity to the adoption payoff), I have chosen the demographics which may influence the importance of adoption in lieu of the financial payoff. Average income and the socio-behavioral attributes (i.e. lifestyle segments in my study) seem to be suitable alternatives. For α (i.e. General perception of the solar technology), I have chosen another set of demographics which are mostly related to the neighborhood characteristics. Percentage of single and married (with and without children) households as well as the percentage of residential and commercial buildings in the neighborhood were chosen. Given the richness of the data, the number of observations, and the complexity of the model (i.e.

[31] It's to be contrasted with the stationary infinite-horizon dynamic programing problems, where a common value is calculated for all individuals irrespective of the time.

individual-level, forward-looking, observed heterogeneity for α and θ[32], uncertainty, observational learning), each round of estimation took a few days to converge using the Gauss Optimum package. The estimation results for the structural model are given in Table 4.

Table 4 - Estimation Results (Full Structural Model)

Parameter	Estimate	Standard Error
Average Alpha ($\bar{\alpha}$)	-0.21*	0.03
Percentage of Families with Children (α_1)	0.00	0.04
Percentage of Families without Children (α_2)	0.06	0.04
Percentage of Residential Buildings (α_3)	-0.16*	0.04
True Quality (q)	0.26*	0.00
Signal Noise (σ_s^2)	2.53*	0.22
Average Theta ($\bar{\theta}$)	2.47	7.19
Average Income (θ_1)	6.72*	2.78
Percentage of Homebodies (θ_2)	49.23*	9.98
Percentage of Dreamers (θ_3)	42.31*	7.91
Percentage of Adventurers (θ_4)	47.81*	7.25
Percentage of Open-minded (θ_5)	45.11*	7.17
Percentage of Organics (θ_6)	36.92*	9.61
Percentage of Rationales (θ_7)	42.37*	9.04
Percentage of Demanding (θ_8)	54.45*	9.91
Log Likelihood	-27068.42	
AIC	54233.09	

[32] $\theta_i = \bar{\theta} + \theta_1 AverageIncome_i + \theta_2 PercentageOfHomebodies_i + \theta_3 PercentageOfDreamer_{i+} \theta_4 PercentageOfAdventurers_i + \theta_5 PercentageOfOpenMinded_i + \theta_6 PercentageOfOrganics_i + \theta_7 PercentageOfRational_i + \theta_8 PercentageOfDemanding_i$
$\alpha_i = \bar{\alpha} + \alpha_1 PercentageOfFamiliesWithChildren_i + \alpha_2 PercentageOfFamiliesWithoutChildren_{i+} \alpha_3 PercentageOfResidential\ Buildings_i$

From the results in Table 4, we can see that the true quality is significant and is 0.26. This means that households scale down the average payoff to almost a quarter of its value in their own beliefs; thus for a new technology such as solar PV panels the payoff information given by marketers can be scaled down significantly. Signal noise is also significant and is high. This shows the diversity of initial beliefs over the payoff of solar PV panels among the population; it makes sense for a new technology where the perceptions are heterogeneous initially.

$\bar{\alpha}$ is negative and significant which means that on average households have negative view on the performance of solar panels; this can be true for all the new technologies in their initial diffusion phases. This can also be interpreted as on average households having low environmental or sustainability concerns as opposed to the economic concerns. α_1 and α_2 are insignificant which means that Compared to the singles, the families don't have much different attitudes to the solar PV technology. α_3 is negative and significant. In other words, households in the neighborhoods with more residential buildings (in contrast to the areas with higher commercial buildings) have lower perception on the solar technology or have lower sustainability concerns. This might be explained by looking deeper at the distinction between these two types of urban settings in Germany (i.e. the difference between demographic profiles like their income or education).

$\bar{\theta}$, the intercept for the propensity to the net investment payoff, is positive but insignificant. θ_1, the effect of income on the propensity to the investment payoff is positive and significant; it means that households with higher income attach more weight to the net payoff. This might be attributed to the higher education of the households with higher income. Looking at it differently, if the net payoff is positive households with higher income may adopt earlier and if the payoff is negative they may delay the adoption.

Looking at the coefficients of lifestyle segments[33], $\theta_2$to θ_8, we can see all of the coefficients have positive and significant values. Since I have chosen "settled" as the base lifestyle variable, we can say that compared to the settled segment the rest attach more weight to the net payoff of the solar panel investment. Looking deeper into at the coefficients, we can see that the Demanding segment has the highest propensity to the payoff while the Organics have the lowest and all other segments are falling somewhere in between. In the initial stages of product definition where the price is high and thus the NPV of investment is negative, the Organics are more likely to adopt. In other words, early adopters of solar PV technology are mostly among those with Organics lifestyle or similar ones like Open-Minded and Dreamers. Once the price goes down and the NPV of the investment increases sufficiently, we'll see more adoptions form other segments depending on their profile. The Demanding households tend to be among those adopting later (i.e. the late adopters are mostly from the Demanding segments). The coefficient estimates seems to be in line with the diffusion literature and the definition of different lifestyle segments.

[33] The definition of the lifestyle segments are given in table 3.

5-2- Reduced-From Model (No Uncertainty and No Forward Looking)

Modeling the adoption decisions without incorporating the payoff uncertainty and forward looking behavior, would result in biased estimates. This could eventually lead to inaccurate recommendations to the policy makers. To check this, I have estimated a benchmark adoption model without forward looking and payoff uncertainty (i.e. $\mathrm{Q_{it}}$ was set to 1 in equation 1). Table 5 shows the estimates:

Table 5 - Estimation Results (Reduced-Form Model)

Parameter	Estimate	Standard Error
Average Alpha ($\bar{\alpha}$)	-1.45*	0.03
Percentage of Families with Children (α_1)	0.01	0.04
Percentage of Families without Children (α_2)	0.01	0.04
Percentage of Residential Buildings (α_3)	-0.09*	0.04
Average Theta ($\bar{\theta}$)	66.93*	8.04*
Average Income (θ_1)	3.19	3.14
Percentage of Homebodies (θ_2)	-30.97*	10.84
Percentage of Dreamers (θ_3)	-22.17*	8.66
Percentage of Adventurers (θ_4)	-25.94*	9.50
Percentage of Open-minded (θ_5)	-7.58	11.05
Percentage of Organics (θ_6)	-15.01	10.15
Percentage of Rational (θ_7)	-18.05	9.47
Percentage of Demanding (θ_8)	-23.88	12.24
Log Likelihood	- 29391.69	
AIC	58809.38	

Looking at the estimation results of the reduced-form model with no uncertainty and forward looking, and comparing them to those of the full structural model in Table 4, we can see that there are significant changes in sign and magnitude of the coefficients. The magnitude of $\bar{\alpha}$ is almost eight time of the same variable in table 4. The magnitude of the $\bar{\theta}$ in the benchmark model is almost thirty times that of the full model. On the other hand, the effect of income on θ is insignificant. Moreover, we can see that the sign of lifestyle segments is negative, which is opposite the full structural model. These drastic changes in θ may be the result of omitting the uncertain element, Q_{it} , from the equation.

Looking at the fit of the two models, we see that the full structural model outperforms the reduced-form model both in terms of log likelihood and AIC. This is due to the fact that uncertainty plays a significant role in adoption of new technologies and specifically in the case of solar PV panels. Thus it's important to properly incorporate learning mechanisms (both individual and social) into the micromodels of new technology adoption.

5-3- Learning (Evolution of Beliefs)

I have structurally incorporated the observational learning mechanism into the diffusion framework. While the estimated parameters in Tables 4 show the significance of the true quality and signal noise, we can't see how observational learning works by looking at the estimates. To inform the policy decisions, we may need to look at the evolution of households' beliefs (of the investment payoff[34]) over time in different regions. To demonstrate the power of my proposed framework in explaining the underlying adoption mechanisms,

[34] Having the parameters estimated, the beliefs are constructed for each household over time.

I have selected few individual households and have plotted their payoff beliefs (ω_t^i) at each time against the number of adoptions they observe in their neighborhood.

Figure 3 - Evolution of Belief (Constant/Declining Case)

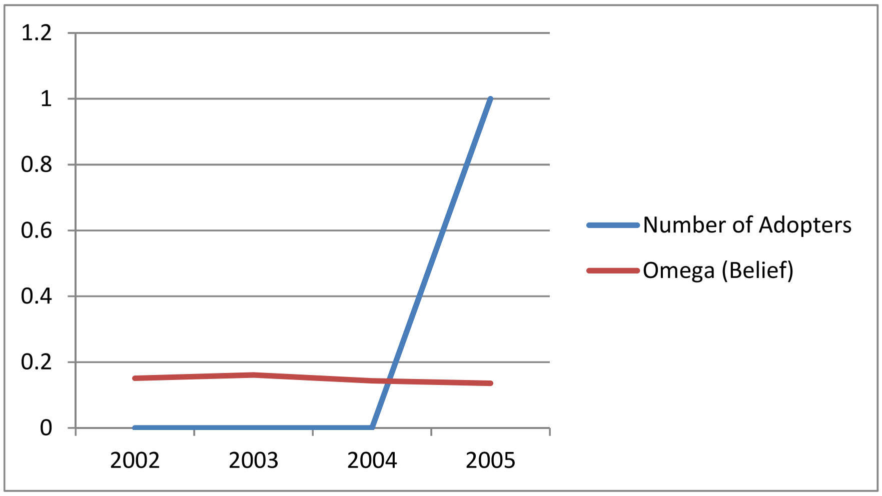


Figure 3 shows the belief evolution for a sampled household across time. We can see that its belief decreases gradually as time goes by, since the number of adoptions it observes over time is zero from 2002 to 2004.

Figure 4 - Evolution of Belief (Increasing Case)

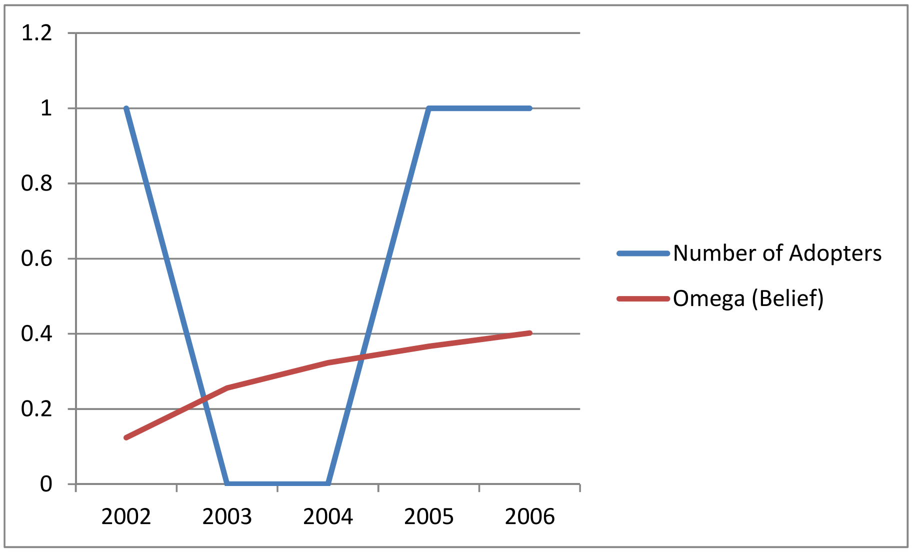


Figure 4 shows that the belief increases over time when a household observes the adoption decisions by its neighbors along the way. In this figure, there is one adoption in 2002 and the next ones take place in 2005 and 2006. Therefore we can see that the belief increases by more than two times from the 2002 to 2006.

Figures 3 and 4 depict the importance of accounting for observational learning in order to be able to explain the evolution of beliefs and consequently adoption decisions of households in different neighborhoods across time. This is indeed an important factor in explaining why some households adopt earlier than the others in contexts where the choices are observable by others. The in-depth insights generated can support designing incentive policies to cater to the heterogeneous population.

5-4- Policy Experiments

Having estimated the structural parameters of the adoption model, I am able to run policy experiments. This allows me to investigate the effect of governmental incentive policies on the adoption of the solar PV panels. Moreover I can also investigate the impact of the information spillover in the diffusion process and to demonstrate how it can benefit the policy makers.

5-4-1- Seeding

Seeding is an established marketing strategy in which marketers give trial samples of the new product to a group of consumers in order to trigger the diffusion process via social learning. This strategy has been documented in the literature long time back (e.g. Arndt (1967)) and has been revisited over time (e.g. Libai (2005)). Seeding strategy can be of special interest to the policy makers for the solar PV market where uncertainty and observational learning play role.

I run a simple seeding policy experiment in which the government is giving away a free solar panel to each neighborhood in 2002. In total, 7338 additional solar PV installations[35] take place in this scenario. I then investigate the incremental number of installations, due to observational learning, from 2003 to 2010 as the result of such incentive scheme.

To show this, I need to re-run the full structural model with the additional 7338 adoptions (equally spread across neighborhoods) in 2002. Then the estimates were contrasted to the status quo policy to calculate the incremental installations in each year[36]. The results are shown in Table 6.

Table 6 - Policy Experiment 1: Seeding One Solar PV Panel in Each Neighborhood

Year	Incremental Adoptions (Compared to Status Quo)
2002	7338

[35] There are 7338 distinct neighborhoods in my dataset and with a free solar panel to each neighborhood, there would be additional 7338 adoptions in 2002.
[36] We assume that the seeding is an exogenous process and thus doesn't affect the forward looking behavior of the dynamic model.

2003	31
2004	46
2005	46
2006	35
2007	29
2008	18
2009	8
2010	2
Total	**7338** (in 2002) **+ 215** (from 2003-2010)

From Table 6, we can see that the seeding policy has resulted in 7338 additional solar PV panel installations in 2002 directly. More interestingly, due to the observational learning across different neighborhoods, there were additional installations after 2002. Adding up incremental adoptions from 2003 to 2010, the total adds up to 215 which can be attributed to the observational learning. The cost of running this seeding policy would be roughly around 227 million Euros[37].

5-4-2- Subsidy

Subsidizing the price of the solar PV panels for early adopters is a popular incentive policy practiced among the policy makers globally. The objective is to make the solar PV technology more affordable such that more people adopt it in early stages and help kicking off the diffusion faster.

[37] It is calculated based on the average panel size in 2002 (6.08 KWp) and the average cost of the panels in 2002 (5100Euros/KWp).

To demonstrate how this scheme works, I run an experiment in which the government subsidizes 50 percent of the cost of solar PV panels for adopters in 2002. As the results, based on the utility in (8), there would be 1501 additional adoptions in 2002 across the neighborhoods. Similar to what was done in the previous experiment, I can also show the incremental number of adoptions in post 2002 as the results of the one shot policy change in 2002. The results are shown in Table 7.

Table 7- Policy Experiment 2: Subsidizing 50 Percent the Installation Cost of Solar Panels in 2002

Year	**Incremental Adoptions (Compared to Status Quo)**
2002	1501
2003	5
2004	8
2005	9
2006	7
2007	6
2008	5
2009	3
2010	2
Total	**1501** (in 2002) **+ 45** (from 2003-2010)

From Table 7, we can see that the subsidy policy has resulted in 45 additional adoptions from 2003 to 2010 which can be attributed to the observational learning in the neighborhoods. The cost of running this subsidy policy would be roughly around 32 million Euros.

5-4-3- Feed-in Tariff

Apart from the price of solar PV panels, Feed-in Tariff rate is an important aspect which affects the investment return through the future revenues from selling solar generated electricity to the grid. From this angel, FIT rate can be a policy instrument itself. European policy makers in the renewable energy field have leveraged the FIT rate over the past two decades in order to adjust the diffusion of renewable energy especially the solar PV. There are still hot debates among European Economists and Environmentalist on the right FIT rate.

To demonstrate how this scheme works, I run an experiment in which the government increases the FIT rate by 100% for the adopters of solar PV panels in 2002. Consequently there would be 432 additional adoptions in 2002 across the neighborhoods just because of the new FIT rate. I can also demonstrate the effect of observational learning through the incremental number of installations post 2002. The results are shown in Table 8.

Table 8- Policy Experiment 3: Increasing the FIT rate for the adopters of Solar Panels in 2002

Year	Incremental Adoptions (Compared to Status Quo)
2002	432
2003	1
2004	3
2005	3
2006	2

2007	1
2008	1
2009	1
2010	1
Total	**432** (in 2002) **+ 13** (from 2003-2010)

From Table 8, we can see that the subsidy policy has only resulted in 13 additional adoptions from 2003 to 2010. The cost of running this subsidy policy would be roughly around 38 million Euros.

By comparing the subsidy and FIT as the two common incentive policy instruments, we can see that subsidizing the price of solar PV panels in early years is far more effective and less costly at the same time. This can be due to the asymmetric roles of investment cost and return on the adoption decisions. Coupled with uncertainty, this can be an interesting area for further investigation in the future research. Moreover it seems that subsidy is also more efficient than the seeding policy. But this needs to be further investigated as per different seeding policies (e.g. giving free samples to all neighborhoods or only to the targeted ones).

This section also highlights the importance of the information spill over through observational learning on the diffusion pattern. Thus it would be important for the policy makers in the renewable energy market to measure the impact of observational learning and to leverage it in determining the timing of introducing the incentive policies. As shown in the three policy experiments, this can have substantial financial implications for the policy makers in the solar energy field.

6- CONCLUSION

In this paper I studied the adoption of solar PV panels by households. I used a micromodel to shed light on the underlying adoption mechanisms and to explain why some households adopt earlier than others. I modeled solar panel adoption as investment problem by forward-looking households (or electricity producers so to say) in a technology with uncertain payoff. Using the visibility of rooftop solar panels from outside, I incorporated observational learning as the main mechanism to reduce the inherent uncertainty in adoption payoff. I estimated the model using household-level data of the solar panel adoptions in Germany augmented with the demographics data at neighborhood-level. I showed that uncertainty plays an important role in explaining the diffusion of solar panels. Moreover, not incorporating a proper social learning framework to the diffusion models of solar PV panels (and to the new technologies in general) would result in biased results.

I contribute to the durable goods adoption literature by casting the new technology adoption as a micromodel of investment with uncertain payoff incorporating heterogeneity, forward looking, and individual/observational learning. I demonstrated the strength of the proposed structural model in showing the evolution of beliefs for each household over time and thus explaining the underlying adoption mechanism. These could not be achieved by the aggregate diffusion models (even by the earlier micromodels in the literature discussed). The parsimony of the proposed framework makes it adaptable to other new technology contexts with minor modification.

Estimating the parameters of the structural adoption model has allowed me to run policy experiments to show the effect of governmental incentive instruments on the diffusion. I was interested to show how seeding, subsidy, and FIT instruments work as incentive policies. I tried to demonstrate that observational learning can be leverage in designing the incentive policies. Moreover, the timing and the breadth of implementation for such policies can be improved using my proposed model.

The implementation of incentive policies to boost the diffusion of solar PV panels can put a heavy financial burden on governments. Germany has become a case of success and is currently number one globally in terms of the share of solar energy. Despite this, German government has received lots of criticisms for the amount of money it has allocated to the renewable energy incentive policies including its generous federal-level Feed-in Tariff rates. Adding to the debate, other countries like Spain have followed the German way and ended up unable to pay the huge tariff deficit to the solar PV adopters[38]. Therefore it's becoming imperative for the policy makers to be able to understand the effect of incentive policies on diffusion pattern beforehand so that they design the policies sound and spend the tax payers' money wisely. Looking at the ambitious targets set by big emerging economies like India and the early debates around it can underline the

[38] You may refer to the Economist's article: http://www.economist.com/news/business/21582018-sustainable-energy-meets-unsustainable-costs-cost-del-sol

implications of diligence in making such policy decisions[39]. The proposed model in this thesis may be of special interest to the policy makers in the solar PV market. The framework presented can be adapted to various sustainable technologies in different political contexts.

However, this thesis has several limitations. Firstly, the data used didn't cover the household-level information for the non-adopters. All the households in my data ultimately have adopted the solar PV panels in the course of my study. Thus my estimates can be interpreted as the timing of adoption (i.e. adopt now or delay) rather than the broader decision to adopt or not. This is a common problem with most of the aggregate and even micromodels of adoption. Secondly, I did not have access to the electricity usage data of the households in my data set. This prevents me from looking at the difference of the electricity bill before and after adoption of solar PV panels which is an interesting research problem itself. Thirdly, the demographics data used were at neighborhood-level. Having finer demographic measures at household-level would add to the power of the estimates and might bring in new insights. Having finer data on measures such as political affiliation of the households and their past adoption of other green initiatives would add to the identification power of the estimates and to the richness of the insights. Finally, I had to assume that all the households in the market were aware of the benefits of the solar PV technology and their initial perceptions were similar. The awareness and perceptions can be affected by many factors including the local and federal advertisement campaigns for solar

[39] You may refer to the article:
http://www.livemint.com/Politics/lXzGQMT3ilOBUs1kM5Jg6N/Narendra-Modis-solar-boom-closer-as-German-model-mulled.html

PV technology. This can bring another layer of heterogeneity to the model and can further improve the estimation power.

APPENDIX

1- Feed-in Tariff Policy in Germany

Feed-in Tariff (FIT) is a subsidy policy under which utilities or grid operators are obliged to accept and remunerate the feed-in of green electricity at a predetermined rate. The electricity may be produced by households or firms. Different tariff rates are typically set for different renewable energy technologies to compensate for their lack of cost effectiveness (i.e. their higher cost compared to conventional energy sources). The first form of feed-in tariff was implemented in the USA in 1978 following the energy crisis.

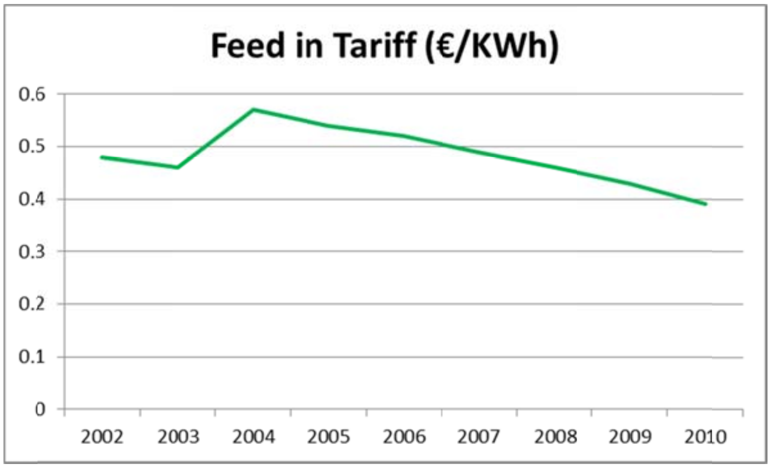
Germany has gone through different phases in which different incentive policies have been implemented to support the adoption of solar panels.

In 1990s, 1000 Roofs Program (a joint federal-state program) was implemented to assess the potential of solar PV. It was targeted for the below 5 KWp capacities and subsidized 70% of investment cost with an upper limit of DM 27000 per KWp. This policy ended in 1995 with 4000 adoptions.

Later on, Feed-In Law (StrEG) introduced which mandated the purchase of solar energy by utilities at 90% of average electricity price. It was supported by all parties while being objected by the utility companies.

In 1998, the Green Party entered the ruling coalition in federal government and at the same time the Germany energy market was liberalized. The incentive policy in place currently was incepted in 2000. Renewable Energy Act (EEG) was passed in April 2000 which guaranteed a fixed feed-in tariff for 20 years. It was planned to have 5% decrease annually in the Feed-in rate starting from 50 Eurocents/kWh. EEG was opposed by the utility industry. This rate changed over time in contrast to the plan. For instance in January 2004, the amendment to EEG increased the FIT for rooftop PVs to 57.4 Eurocents/kWh from 45 Eurocents/KWh. It was the outcome of a joint effort by solar industry, parts of Red/Green government, and environmental NGOs. The following graph shows the changes in Feed-in Tariff rate from 2002 to 2010:

Figure 5 – Changes in Feed-in Tariff in the German Market



Germany has been involved in FIT policy aggressively over the past 3 decades and it is considered the most successful example of adopting FIT around the world in terms of increasing green electricity shares. In overall, German policies are considered to be successful in increasing the share of renewable energy. For instance, Germany has exceeded its Kyoto Protocol target in 2007. Many European nations (e.g. France, Italy, and Spain) have followed the German way afterwards. Despite these facts, it is regularly being criticized for the economic burden it has put on the German economy and whether there could have been better ways of achieving environmental targets.

2- Dynamic Programming Problem

The adoption of solar panels is a one-time investment decision facing the households which makes the dynamic setting similar to the optimal stopping problems. Therefor I can cast the solar panel adoption into the finite horizon optimal stopping problem (i.e. the problem stops once each household adopts). The mathematical representation of the investment decision for household *i* at time *t* is as follows:

$$\begin{cases} \text{Adopt if (stop): } \alpha_i + \theta_i\left(\overline{PV_{it}}\omega_t^i - p_{it}\right) + \varepsilon_{it} \geq \beta * E(V_{it+1}|S_{it}) \\ \text{Wait if: } \qquad \alpha_i + \theta_i\left(\overline{PV_{it}}\omega_t^i - p_{it}\right) + \varepsilon_{it} \leq \beta * E(V_{it+1}|S_{it}) \end{cases}$$

(A1)

To solve the problem, I need to solve for the expected value function $E(V_{it+1}|S_{it})$ (i.e. expected value of delaying the adoption). The value function is maximum utility one can gain if he takes optimal decisions in the future (i.e. the option value waiting in the investment problems). It is a function of the current state S_{it}. I have four state variables in my model; two observable variables (p_{it}, $\overline{PV_{it}}$) and two unobservable variables (ω_t^i, ε_{it}). I need to know how each state variable evolves over time in order to get the expectation of the value function. For tractability, I assume that the belief over the payoff (ω_t^i) remains the same as one looks into the future (one can't predict the behavior of others perfectly to know how it will affect his own belief). In other words, each household keeps its status quo belief when it considers how the world will look like in the future. As in extant dynamic models literature, I assume that the random shocks (ε_{it}) are IID and independent from other state variables. In other words, I use the conditional independence assumption in the literature.

I assume that each household at each time forms rational expectation over price ($\mathrm{p_{it}}$) and average payoff ($\overline{PV_{\iota t}}$) given all the historic data points up to *t* (this looks as if instead of the two state variables, I have time as the single state which makes the estimation much easier). This makes sense intuitively as we usually use the observed values from the past to construct our belief for the future. This also brings another dimension of temporal heterogeneity to the model. Therefore, I have used the observed price and payoff values by the households up to time *t* to extrapolate the future trends for them using time series regression. The data covers 2000 to 2010 (I have augmented the historic data from 2000 and 2001 to my data set) and I have extrapolated 10-year ahead of the state variables at each *t* (e.g. 2003-2012 for t=2002 and 2004-2013 for t=2003 , and so on) . Table 9 shows the estimates:

Table 9 - Expectation over Observable State Variables ($\mathbf{p}_{\mathbf{it}}$, $\overline{\boldsymbol{PV}_{\boldsymbol{it}}}$) for 10 years Ahead

	2002		2003		2004		2005		2006		2007		2008		2009		2010	
	Price	**Payoff**	**Price**	**Payoff**	**Price**	**Payoff**	**Price**	**Payoff**	**Price**	**Payoff**	**Price**	**Payoff**	**Price**	**Payoff**	**Price**	**Payoff**	**Price**	**Payoff**
2000	7000	6673.35	7000	6673.35	7000	6673.35	7000	6673.35	7000	6673.35	7000	6673.35	7000	6673.35	7000	6673.35	7000	6673.35
2001	6500	6673.35	6500	6673.35	6500	6673.35	6500	6673.35	6500	6673.35	6500	6673.35	6500	6673.35	6500	6673.35	6500	6673.35
2002	5100	6280.8	5100	6280.8	5100	6280.8	5100	6280.8	5100	6280.8	5100	6280.8	5100	6280.8	5100	6280.8	5100	6280.8
2003	4300	6166.667	4900	6019.1	4900	6019.1	4900	6019.1	4900	6019.1	4900	6019.1	4900	6019.1	4900	6019.1	4900	6019.1
2004	3350	5970.4	3950	5821.477	5800	7510.79	5800	7510.79	5800	7510.79	5800	7510.79	5800	7510.79	5800	7510.79	5800	7510.79
2005	2400	5774.133	3180	5585.947	4660	6936.98	5400	7135.251	5400	7135.251	5400	7135.251	5400	7135.251	5400	7135.251	5400	7135.251
2006	1450	5577.867	2410	5350.416	4260	7039.043	4752.784	7171.069	5100	6778.488	5100	6778.488	5100	6778.488	5100	6778.488	5100	6778.488
2007	500	5381.6	1640	5114.885	3860	7141.105	4458.498	7301.359	4656.899	7075.964	4400	6439.56	4400	6439.56	4400	6439.56	4400	6439.56
2008	-450	5185.333	870	4879.355	3460	7243.168	4164.212	7431.648	4399.756	7164.149	4272.332	6845.195	4260	6117.591	4260	6117.591	4260	6117.591
2009	-1400	4989.067	100	4643.824	3060	7345.231	3869.926	7561.937	4142.613	7252.335	3993.761	6880.244	3988.403	6557.601	3500	5626.55	3500	5626.55
2010	-2350	4792.8	-670	4408.293	2660	7447.293	3575.64	7692.227	3885.47	7340.52	3715.19	6915.293	3709.07	6544.053	3514.11	6172.667	2800	5120.161
2011	-3300	4596.533	-1440	4172.763	2260	7549.356	3281.354	7822.516	3628.327	7428.705	3436.619	6950.343	3429.737	6530.505	3208.171	6108.333	2947.296	5726.325
2012	-4250	4400.267	-2210	3937.232	1860	7651.419	2987.068	7952.805	3371.184	7516.891	3158.048	6985.392	3150.404	6516.957	2902.232	6044	2608.932	5614.197
2013			-2980	3701.701	1460	7753.481	2692.782	8083.095	3114.041	7605.076	2879.477	7020.441	2871.071	6503.409	2596.293	5979.667	2270.568	5502.069
2014					1060	7855.544	2398.496	8213.384	2856.898	7693.261	2600.906	7055.491	2591.738	6489.861	2290.354	5915.333	1932.204	5389.941
2015							2104.21	8343.673	2599.755	7781.447	2322.335	7090.54	2312.405	6476.313	1984.415	5851	1593.84	5277.813
2016									2342.612	7869.632	2043.764	7125.589	2033.072	6462.765	1678.476	5786.667	1255.476	5165.685
2017											1765.193	7160.639	1753.739	6449.217	1372.537	5722.333	917.112	5053.557
2018													1474.406	6435.669	1066.598	5658	578.748	4941.429
2019															760.659	5593.667	240.384	4829.301
2020																	-97.98	4717.173

Notes The red colored years are for the states after the data points in the forward looking model.
The yellow shaded values are the forecasts while the non-shaded ones are actual values of the states observed by the households.

The conventional algorithm to solve the finite horizon dynamic programing problem is backward induction. In this algorithm, a terminal stage is assumed when the problem can't go beyond then. In my setting, T=t+10 is assumed to be the terminal stage. I start from the terminal point:

$$\begin{cases} \text{Adopt}: & \mathrm{U_{iT}} = \alpha_i + \theta_i\left(\overline{PV_{\iota T}}\omega_{\mathrm{T}}^{\mathrm{i}} - \mathrm{p_{iT}}\right) + \varepsilon_{iT} \\ \text{Don't adopt}: & \mathrm{U_{iT}} = \varepsilon_{i0T} \end{cases} \tag{A2}$$

The optimal decision would results in the expected value function for T=t+10:

$$E(V_{iT}|S_{iT-1}) = \max_{adopt,don't}\ \mathrm{E}\{\alpha_i + \theta_i\left(\overline{PV_{\iota T}}\omega_{\mathrm{T}}^{\mathrm{i}} - \mathrm{p_{iT}}\right) + \varepsilon_{iT}\ , \varepsilon_{i0T}\} \tag{A3}$$

Going backward one period, we have:

$$\begin{cases} \text{Adopt}: & \mathrm{U_{iT-1}} = \alpha_i + \theta_i\left(\overline{PV_{\iota T-1}}\omega_{\mathrm{T-1}}^{\mathrm{i}} - \mathrm{p_{iT-1}}\right) + \varepsilon_{iT-1} \\ \text{Don't adopt}: & \mathrm{U_{iT-1}} = \beta * E(V_{iT}|S_{iT-1}) \end{cases} \tag{A4}$$

Which can be solved similarly to have the $\mathrm{E(V_{iT-1}|S_{iT-2})}$.I repeat the same procedure 10 times to ultimately solve for the expected value function in t+1, $\mathrm{E(V_{it+1}|S_{it})}$, which is needed to calculate the adoption probability in time t as in equation (9).

3- Inference from Observation

In neighborhood k, the average household's utility of adoption at time t is given by:

$$\alpha_k + \theta_k\left(\overline{PV_{kt}}\gamma_{kt} - p_{kt}\right) + \varepsilon_{kt} \tag{A5}$$

Where γ_{kt} is the mean belief across the neighborhood k in time t and is what one infers about the investment payoff by observing the adoption pattern at neighborhood k at time t. Given the normality assumption for the random shock, the probability of adoption by an average household in neighborhood k would be[40]:

$$1 - \mathrm{CDF}\,(-\alpha_k + \theta_k * p_{k1} - \theta_k\,\overline{PV_{kt}}\gamma_{kt}) \tag{A6}$$

In this equation, the assumption is that by knowing γ_{kt} we can solve for the probability of adoption for neighborhood k at time t. On the other hand from the Frequentist approach to probability, we may substitute probability with the ratio (i.e. proportion of households adopted or acceptance rate in neighborhood k at time t).

The reverse is also true; by observing the acceptance rate in neighborhood k at time t , $Accep\widehat{tance}Rate_{kt}$, one knows the probability of adoption at the neighborhood level. We equate the acceptance rate to (A6):

$$Accep\widehat{tance}Rate_{kt} = 1 - \mathrm{CDF}\,(-\alpha_k + \theta_k * p_{k1} - \theta_k\,\overline{PV_{kt}}\gamma_{kt}) \tag{A7}$$

Since Normal is a symmetric distribution, we can have:

$$Accep\widehat{tance}Rate_{kt} = \mathrm{CDF}\,(\alpha_k - \theta_k * p_{k1} + \theta_k\,\overline{PV_{kt}}\gamma_{kt}) \tag{A8}$$

We can take inverse Normal CDF of the both sides:

$$InverseCDF\left(Accep\widehat{tance}Rate_{k,t}\right) = \alpha_k - \theta_k * p_{k1} + \theta_k\,\overline{PV_{kt}}\gamma_{kt} \tag{A9}$$

[40] For tractability, we don't incorporate value function into the average neighborhood belief.

By using (A9), she can solve for the mean belief:

$$\gamma_{kt} = \left(\left(InverseCDF\left(Accep\widehat{tance}Rate_{k,t}\right) - \alpha_k + \theta_k * \mathrm{p_{kt}}\right)\right) \Big/ \theta_k * \overline{PV_{kt}}$$

(A10)

4- Social Learning Evidence

By looking at Figure 2 we could see that some adoption clusters were being formed over time. This means that previous solar PV installations may have positive impact on the probability new installations as can be seen from the spatial pattern of adoptions. To further test this, and before estimating the full model, I have used a simple binary logit model of adoption as follows:

$$Adoption\_Probability_{it} = \frac{exp(a*Price_t + b*FIT_t + c*Installations_{t-1} + d*cum\_installations_{t-1})}{1 + exp(a*Price_t + b*FIT_t + c*Installations_{t-1} + d*cum\_installations_{t-1})}$$

(A11)

Where the left hand side measures the probability of adoption by household i at time t as a function of price of the solar PV panels, Feed-in Tariff, number of installations in the last period, and cumulative number of installations. The parameters to be estimated are a, b, c, and d respectively. I use data from 2004 to 2007 (around 8000 installations) to estimate the model. The estimation results are shown in Table 10:

Table 10 - Estimation Results (Binary Logit Model of Adoption)

Parameter	**Estimate**	**Standard Error**
a	-.973*	.004
b	.191*	.005
c	.231*	.003
d	.016*	.000

From Table 10 we can see that all of the coefficients are significant. The coefficient for price, a, is negative and the coefficient for FIT, b, is positive as expected. Related to learning, we can see that the coefficient for cumulative installations is positive even after controlling for the installations in the previous period. This shows that the main effect (i.e. effect of past adoptions) for social learning is positive and significant.

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