Structural Model of Renewable Energy Diffusion:  
The Case of Solar Photovoltaic Panels

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Abstract

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 very few economic/marketing papers addressing the renewable energy topic. To fill this gap, we study the diffusion of renewable energy among consumers. More specifically we investigate what drives the adoption distribution of residential solar PV (Photovoltaic) panels and why different households adopt at different points in time. We use a micromodel to shed light on the underlying adoption mechanisms. We model solar panel adoption as investment problem by households (i.e. electricity producers) in a technology with uncertain payoff. Using the visibility of rooftop solar panels from outside, we incorporate observational learning as the mechanism to reduce the inherent uncertainty in the adoption payoff. We estimate the model using unique individual-level data on the adoption timings of the solar panels in Germany. The estimation of parameters enables us to perform policy experiments on different incentive policy instruments aimed at accelerating the diffusion process. The findings would have relevant implications for policy makers in the renewable energy field.

Key Words: New technology diffusion, Renewable energy, Structural model, Investment uncertainty, Observational learning

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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\textsuperscript{4}.

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 drivers and their interrelated 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 paper we aim to fill the gap in the marketing literature by studying the adoption of renewable energy. We take the consumers’ perspective to study the diffusion of renewable energy among households. More specifically we investigate what drives the distribution of residential solar PV panels and why different households adopt at different points in time. We use a structural model to shed light on the underlying adoption mechanisms. Our model captures the investment aspect of the adoption decisions in an uncertain environment; in other words, we treat households as producers of electricity who decide to invest in solar panels with uncertain payoff. Using the visibility of solar panels from outside, we model observational learning as the mechanism to reduce the inherent uncertainty in the adoption payoff. We estimate the model using unique individual-level data.

\textsuperscript{4} A recent Economist article points to the same phenomenon in the business literature: http://www.economist.com/whichmba/making-climate-change-one’s-business
on the adoption timings of the solar panels in Germany. The parameter estimations enable us to perform policy experiments on the roles that different incentive policy instruments play in accelerating the diffusion process.

2- Literature

Studying the diffusion of solar 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 we briefly discuss the state-of-the-art in each area and their interrelatedness.

Traditionally marketing researchers have been interested in modeling the diffusion of new durable goods. Stemming from the seminal Bass model (Bass (1969)), different aggregate models have been suggested to explain the adoption pattern of the durable goods 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 fail to provide a behavioral explanation of why some individuals are quicker to adopt than others.

With a similar goal but using more fundamental approaches, marketing researchers have tried to use the micromodeling frameworks to study the diffusion process. The pioneering works by Horsky (1990) and Catterjee and Eliashberg (1990) have used the individual level utility maximization as the foundation of the new product diffusion. Unlike
the aggregate diffusion models, these studies incorporate heterogeneity into the diffusion model. Continuing this trend, different 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, which involve quality improvements and price falls over time. Melinkov (2000) and Song and Chintagunta (2003) are among the ones bringing forward-looking behavior to the diffusion models. Although they incorporate consumer heterogeneity (e.g. Song and Chintagunta (2003) consider heterogeneity in preference and price sensitivity), their model is more suitable for aggregate estimation. These models are estimated at the aggregate level and are unable to handle the dynamics in individuals’ behavior, like learning.

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/learning in new technology diffusion is the focus of an extant body of literature. The seminal economic paper by Jensen (1982), and other subsequent papers like McCardle (1985)\(^5\), provided the theoretical models incorporating uncertainty into the diffusion framework. Roberts and Urban (1988) is the first empirical marketing paper that model uncertainty and learning in the adoption of durable goods. The authors utilize individual survey data to estimate the effect of uncertainty in automobile brand choice. Since then, there have been various Bayesian learning papers modeling payoff or quality uncertainty (e.g. Erdem et al. (2005)). These models have mainly used survey data, and have focused on individual learning, where private signals are the source of information.

\(^5\) We may observe recent papers in operations research literature tackling this problem (e.g. Ulu and Smith (2009)).
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, we have seen different variations of the classic models that make the settings more general (e.g. Rational observational learning in Eyster and Rabin (2011)). Although observational learning has a long history, there are few empirical papers on it. Zhang (2010) is a pioneer in empirically modeling observational learning in marketing literature. The lack of proper individual-level data and difficulty in defining quality perception (i.e. quality is subjective and hard to model) are among the main reasons behind this scarcity. Renewable energy adoption seems to be a suitable context to study the observational learning phenomenon. This is because of the durable nature of the hardware (some of them, like rooftop solar panels, are observable to the outsiders) and the fact that they merely replace a conventional energy source, which makes the problem similar to investment, where the uncertainty is over the payoff (i.e. objective).

Research on sustainability and renewable energy has recently become popular. Renewable energy sources can be considered durable goods since they are one-time adoptions (with long operating life) and experience rapid quality improvements and declines in price. Unlike most of the durable goods studied in the extant literature, they do not bring any additional functionality (utility) to the adopters, but merely replace the conventional non-renewable energy sources. In this sense, the adoption decision can be intuitively viewed as an investment decision (i.e. a producer who decides to invest in a new technology). Since there is no perfect information regarding their performance and cost/benefit before adoption,
uncertainty is an important factor to be considered. Moreover, the role of the government’s incentive policies is prominent, as the government incentivizes the households to adopt by subsidizing the initial fixed cost or by buying back the generated green energy from the households (Feed-In Tariff (FIT)). Thus the adoption payoff of a renewable energy source is contingent on the incentive policy at the time of adoption and the amount of green energy to be generated in future; this makes the investment’s payoff uncertain. In the solar PV panel case, the panels are installed on the roofs and are visible from the outside. Thus it can be assumed that the adoption decisions are observable by others immediately after. This has important implications for the types of information spillover in the solar PV panel market. These features add to the merits of studying the adoption of solar PV panels from the methodological standpoint. Table 1 shows an overview of the micromodels of durable goods adoption in marketing literature. Since we use the same methodological framework, it clarifies our paper’s position.

<table>
<thead>
<tr>
<th>Paper</th>
<th>Context</th>
<th>Level</th>
<th>Data</th>
<th>Uncertainty</th>
<th>Learning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horsky (1990)</td>
<td>Appliances</td>
<td>Aggregate</td>
<td>Sales-Income</td>
<td>Quality</td>
<td>Past sales</td>
</tr>
<tr>
<td>Chatterjee and Eliashberg (1990)</td>
<td>Career counselling software</td>
<td>Individual</td>
<td>Survey (pilot)</td>
<td>Performance</td>
<td>Individual (simulation)</td>
</tr>
<tr>
<td>Song and Chintagunta (2003)</td>
<td>Digital camera</td>
<td>Aggregate</td>
<td>Monthly sales</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Erdem et. al. (2005)</td>
<td>PC</td>
<td>Individual</td>
<td>Survey (Panel)</td>
<td>Quality</td>
<td>Active</td>
</tr>
<tr>
<td>Gordon (2009)</td>
<td>CPU (adoption/replacement)</td>
<td>Aggregate</td>
<td>Sales – Ownership</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Yang and Ching (2013)</td>
<td>ATM cards</td>
<td>Individual</td>
<td>Survey (Panel)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Our model</td>
<td>Solar panels</td>
<td>Individual</td>
<td>Panel</td>
<td>Payoff</td>
<td>Individual - Observational</td>
</tr>
</tbody>
</table>
We have not observed much work on this topic in the marketing literature. Only recently has a new trend has been started to study the adoption of renewable energy from a marketing perspective. 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. The effects show the positive influence of previous adoptions on the decision to adopt (even at the street level). 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 made some 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 studies had to deal with the aggregate nature of the data used for estimation. Moreover, they did not explicitly model the inherent uncertainty and the process through which it gets resolved in the diffusion of renewable energy sources.

We build on micromodels of durable goods adoption to study the adoption of solar panels by households. We incorporate the investment nature of adoption, the uncertainty in adoption payoff, and the visibility of adoptions as the distinguishing features of our durable goods adoption model. This dissertation introduces a general micromodel of renewable energy based on individual level data. Furthermore, we contribute to the durable goods literature by customizing an individual level model suitable for uncertain investment scenarios and accounting for cross-individual information spillover. The specific context and
the unique individual level solar PV adoption dataset allow us to avoid the limitations faced in the extant micromodel durable goods diffusion literature.

The following sections elaborate on the proposed model and the dataset. They are then followed by a discussion of the estimation procedure and results.

### 3- Model

The utility of adopting solar panels for consumer $i$ at time $t$ is a function of benefits $Q_{it}$ and cost $p_{it}$ of adopting solar energy. We use a general indirect utility specification, derived from a class of direct utility called Cross-Product Repackaging Utility, as follows:

$$U_{it} = \theta_t Q_{it} - p_{it}$$

where $\theta_t$ is the propensity to benefits (importance measure), which is individual-specific. Since we have a rich demographic data set at the street level, we can define $\theta_t$ to be the function of observed demographics.

The benefits term $Q_{it}$ is defined as the average payoff $\overline{PV}_{it}$ (i.e. the net present value of the revenues from selling the solar-generated electricity to the grid based on the federal Feed-In Tariff rate) subject to the perception quality $q_{it}$ (i.e. the perception of the solar panel’s payoff which is assumed to be between zero and one).

$$U_{it} = \theta_t \overline{PV}_{it}(q_{it}) - p_{it}$$

Households are uncertain of the true value of $q_{it}$ (we name it $q$) and only have probabilistic

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6 The utility of not adopting $U_{ai}$ is normalized to be zero (i.e. status quo).

7 It has been used in the marketing literature (e.g. Mehta et al. 2008).
belief of its distribution. Initially (at t=0), we assume that all households have a common belief about its distribution:

\[ q_{it}(t = 0) \sim N(\omega_0, \sigma_0^2) \]

where \( \omega_0 \) is the initial belief of the expected value of \( q_{it} \) and \( \sigma_0^2 \) is the initial level of uncertainty. To accommodate the heterogeneity of the beliefs, we assume that households receive a private signal regarding the true value of quality at t=1 (i.e. household-specific information which captures the information each household receives on the viability of the solar technology). We assume the signals follow normal distribution around the true quality:

\[ \lambda^i_1 \sim N(q, \sigma_s^2) \]

where \( q \) is the true quality and \( \sigma_s^2 \) is the noise associated with the signal. The private signals received by each household are:

\[ \lambda^1_1, \lambda^2_1, \lambda^3_1, \ldots, \lambda^i_1, \ldots \]

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

\[ \omega^i_1 = \frac{\lambda^i_1 + \omega_0}{\frac{1}{\sigma_s^2} + \frac{1}{\sigma_0^2}} \quad \text{and} \quad \sigma^i_1 = \frac{1}{\frac{1}{\sigma_s^2} + \frac{1}{\sigma_0^2}} \]

where \( \omega^i_1 \) is the posterior belief of the true quality and \( \sigma^i_1 \) is the posterior variance of the belief. Acting on the posterior belief, each household decides whether to adopt the solar panel.

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8 Unknown mean but known variance.
9 For the ease of estimation \( \omega_0 \) is assumed to be zero and \( \sigma_0^2 \) is set to be 1. We have estimated \( \omega_0 \) in a trial estimation and the value turned out to be almost zero.
10 Each household only observes his signal and not others’; otherwise it could know the distribution of signals and thus the true quality.
or not. We assume the households to be risk neutral (i.e. maximizing expected value) which means:

\[
\begin{align*}
\text{adopt if: } & \theta_i \frac{PV_{t1}}{v_{i1}} \omega_{i1} - p_{i1} \geq 0 \Rightarrow \omega_{i1} \geq \frac{p_{i1}}{\theta_i \frac{PV_{t1}}{v_{i1}}} \\
\text{don't adopt: otherwise}
\end{align*}
\]

7

Given the random nature of \( \omega_{i1} \) (normally distributed), the probability of adoption by consumer \( i \) (from others’ perspective) would be:

\[
\text{Prob(adoption by consumer } i \text{) } = 1 - \text{CDF} \left( \frac{p_{i1}}{\theta_i \frac{PV_{t1}}{v_{i1}}} \right)
\]

8

In the conventional learning models like Erdem and Keane (1996), it is assumed that there would be incoming signals in the subsequent periods (e.g. each time a consumer experiences a product) and in each period consumers update their beliefs according to (6) and make adoption decisions according to (7). In our model, there is no chance of product experience before adoption. On the other hand, unless we have data on the new information acquisition by households in the subsequent periods (e.g. the number of solar PV related articles published in the general newspapers and magazines can be a proxy for this), there are no further private signals. On the other hand, since households can observe the adoption behavior of other households in their neighborhood (here we use street segment vicinity as the neighborhood), they can infer the true quality from this mere observation. We do not observe between-households communication in our adoption data (as in word of mouth, where consumers reveal their private signals to each other), and thus can only incorporate observational learning (i.e. inferring private signals from observing the actions of others). This observation is a source of probabilistic inference.
We assume that the adoption decisions are observable by everyone in the neighborhood. Not knowing the reasoning behind the adoption of others, household i is assumed to have a prior belief about the proportion of households in its neighborhood that would adopt. This prior belief is assumed following beta distribution\(^1\):

\[ (Adoption\ Proportion\ Belief|t = 1) \sim Beta(\alpha_1, \beta_1) \]

For tractability, we use the adoption proportion of different neighborhoods before \(t=1\) to exogenously define priors \(\alpha_1\) and \(\beta_1\) (i.e. we equate the historic proportion to the mean of the Beta distribution \(\frac{\alpha_1}{\alpha_1 + \beta_1}\) and choose them accordingly).

At the end of period 1, the decisions of all households in a single neighborhood \(j\) become realized (in total \(N_{1j}\) adoptions out of \(M_{1j}\) market potential for households in neighborhood \(j\); we drop index \(j\) for ease of exposition). Observing this, household i updates its belief regarding the adoption proportion in its neighborhood.

\[ (Adoption\ Proportion\ Belief|t=1,M_1,N_1) \sim Beta(\alpha_1 + N_1, \beta_1 + M_1 - N_1) \]  
with mean \(\hat{p}_1 = \frac{\alpha_1 + N_1}{\alpha_1 + \beta_1 + M_1} \]

Since the neighborhoods are not isolated from each other, the focal household also observes the decision of others in the region. To incorporate cross-neighborhood observations into our model, we need to adjust for the physical distance (or demographics similarity) between neighborhoods. As with Yang and Allenby (2003) we define the distance-adjusted weights and multiply them to the respective adoption proportions of each neighborhood at a time. For the physical distance, we consider the Euclidian distance between each of the two neighborhoods (their centers) with the following transformation:

\(^1\) Beta distribution is chosen for its range (between 0 and 1) that matches the proportion and also is conjugacy with Bernoulli/Binomial observations (i.e. adoption proportion observations).
\[ W_{ij}^{\text{physical distance}} = \frac{1}{d(i,j)} \]  

Where \( d(i,j) \) is the distance between neighborhoods \( i \) and \( j \). In the distance matrix \( W \), we set diagonal elements to zero. We normalize the \( W \) matrix such that sum of the elements of each row becomes one. We then need to multiply the adoption proportions of all the neighborhoods to the rows of the \( W \) matrix to obtain the distance adjusted adoption proportion for each household (the same goes for all the households in a neighborhood). The final adoption proportion is the summation of mean value from (10) and the distance-adjusted proportion:

\[ \text{proportion}^i_1 = \frac{\alpha_i + N_i}{\alpha_i + \beta_i + M_i} + \sum_{j=1}^I W_{ij} \times \text{proportion}^i_1 \text{ where } \sum_{j=1}^I W_{ij} = 1 \]  

There is a direct relationship between quality perception (\( \omega_1^i \)) and the adoption decision as shown in (7). The reverse is also true; by observing the adoption decisions of others one can infer the quality perception behind those decisions (though probabilistically). This relationship is shown in Figure 1:

**Figure 1 – Relationship between adoption proportion and perceived quality**
The signal noise (4) and the posterior uncertainty (6) is known and common knowledge. Thus, by knowing the adoption proportion from (12), we can solve for the corresponding mean quality perception:

$$\hat{\omega}_i = -\left(\sigma_i^2\right) * \text{InverseCDF}(1 - \text{proportion}_1) + \frac{p_{i1}}{\theta_i \overline{PV}_{t1}}$$  \hspace{1cm} (13)

Similar to $t=1$, household $i$ combines its prior belief with this new piece of information to arrive at the posterior belief.

$$\omega_{2i} = \frac{\omega_{1i}^2 \sigma_i^2}{\sigma_i^2 + 1} \quad \text{and} \quad \sigma_{2i}^2 = \frac{1}{\frac{1}{\sigma_i^2} + \frac{1}{\sigma_i^2}}$$ \hspace{1cm} (14)

We can see from (14) that the effect of observing others’ behavior has been incorporated into the learning model. Moreover, the posterior signals are consumer specific (at neighborhood level). These add to the realism of the model.

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

$$\begin{cases} \text{adopt if:} & \theta_i \overline{PV}_{t2} \omega_{2i} - p_{i2} \geq 0 \Rightarrow \omega_{2i} \geq \frac{p_{i2}}{\theta_i \overline{PV}_{t2}} \\ \text{don’t adopt: otherwise} \end{cases}$$ \hspace{1cm} (15)

The same process repeats for those households who have not adopted till time $t$.

Having this adoption setting, we can construct the likelihood function for household $i$ as follows:

$$\text{Likelihood}_i = \prod_{t=1}^{T} \left( \text{Prob}\left( \omega_t^i \geq \frac{p_{it}}{\theta_i \overline{PV}_{tt}} \right) * \text{Adoption}_{i,t} + \text{Prob}\left( \omega_t^i \leq \frac{p_{it}}{\theta_i \overline{PV}_{tt}} \right) * \text{Non-Adoption}_{i,t} \right)$$ \hspace{1cm} (16)
Where Adoption_{i,t} and Non_Adoption_{i,t} are dummy variables for adoption and not adoption respectively; their sum is 1 at each time. Multiplying the likelihood of each household, we will have the total likelihood, which is used to estimate the model parameters \((q, \sigma^2, \theta_1, \theta_2, \theta_3, \theta_4)\) using Simulated Maximum Likelihood Estimation.

4- Data

We utilize a unique dataset on adoption timings of the residential solar PV panel adopters in Germany. The sizes of the residential solar panel systems are equal to or less than 10 KWp\(^{12}\). The data covers 9 years, from 2002-2010, and we consider each year as a discrete time unit. In total there are over 11000 adopters. Table 1 shows the distribution of adoptions across the years:

<table>
<thead>
<tr>
<th>Year</th>
<th>Adoptions</th>
<th>Average Panel Size</th>
<th>Price (€/1KWp)</th>
<th>Feed in Tariff (€/KWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>584</td>
<td>6.09</td>
<td>5100</td>
<td>0.48</td>
</tr>
<tr>
<td>2003</td>
<td>563</td>
<td>6.18</td>
<td>4900</td>
<td>0.46</td>
</tr>
<tr>
<td>2004</td>
<td>923</td>
<td>6.24</td>
<td>5800</td>
<td>0.574</td>
</tr>
<tr>
<td>2005</td>
<td>1276</td>
<td>6.31</td>
<td>5400</td>
<td>0.54</td>
</tr>
<tr>
<td>2006</td>
<td>844</td>
<td>6.35</td>
<td>5100</td>
<td>0.52</td>
</tr>
<tr>
<td>2007</td>
<td>884</td>
<td>6.41</td>
<td>4400</td>
<td>0.49</td>
</tr>
<tr>
<td>2008</td>
<td>1488</td>
<td>6.47</td>
<td>4260</td>
<td>0.46</td>
</tr>
<tr>
<td>2009</td>
<td>2082</td>
<td>6.54</td>
<td>3500</td>
<td>0.43</td>
</tr>
<tr>
<td>2010</td>
<td>2402</td>
<td>6.51</td>
<td>2800</td>
<td>0.39</td>
</tr>
</tbody>
</table>

\(^{12}\) The conventional definition of residential solar PV installations.
As can be seen from Table 1, the average size of the installed panels increases over time. On the other hand, as with other new technologies, the price decreases over time, as does the subsidy (in the form of FIT). The following figure shows the trend of the number of adoptions in each year contrasted against the net present value (NPV) of solar PV panels\textsuperscript{13}.

![Figure 2 – Number of Adopters and NPV of solar PV over time](image)

As can be seen from the graph, the changes in NPV do not perfectly coincide with the changes in the number of adopters. Thus other factors such as heterogeneity and learning play a role in the diffusion process.

For each household in our data, we know the neighborhood (a unit similar to the street). We plotted the spatial pattern of adoption over time to see if the adoption centers are fixed or not. As can be seen from Figure 3, the adoption centers (a different color is used for each year) are shifting over time. This suggests the important role of heterogeneity in the diffusion process.

\textsuperscript{13} The NPV is calculated for 1KWP unit. We assumed the life of the solar system to be 20 years and average annual electricity output of the system to be 750 KWh per 1KWP. The discount rate of .95 is assumed.
To this end we further supplement the adoption timing data with the demographics information of the households at the neighborhood level (11000 households spread across the 7000 neighborhoods). Table 3 shows the summary statistics for the demographics data used in our analysis.

Table 3– Demographics Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average net income (€/10000)</td>
<td>.34</td>
<td>.16</td>
</tr>
<tr>
<td>Proportion of married families with children</td>
<td>.38</td>
<td>.19</td>
</tr>
<tr>
<td>Proportion of married families without children</td>
<td>.36</td>
<td>.18</td>
</tr>
<tr>
<td>Proportion of single households</td>
<td>.26</td>
<td>.18</td>
</tr>
<tr>
<td>Proportion of residential building</td>
<td>.74</td>
<td>.17</td>
</tr>
<tr>
<td>Proportion of commercial buildings</td>
<td>.26</td>
<td>.17</td>
</tr>
<tr>
<td>Proportion of Organic life-style households</td>
<td>.06</td>
<td>.051</td>
</tr>
</tbody>
</table>
Having the demographics with variation across the households in different regions allows us to incorporate the heterogeneity across neighborhoods into the adoption model, which is essential to our observational learning framework.

5- Results

We have estimated the model using individual-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, we needed to use simulation-based estimation methods. Thus we used the Simulated Maximum Likelihood Estimator for this purpose. Given the richness of the data, number of observations, and complexity of the model, each round of estimation took a few days to converge using the Gauss Optimum package.

We assumed that each household observed the adoptions in the previous periods across the region. To account for the difference in observational signal across the neighborhoods, we used physical distance as the weight factor (i.e. the effect of observation is stronger for nearer neighborhoods). The estimation results for the whole sample, using distance-adjusted weights for observational learning and observed heterogeneity\(^{14}\) for \(\theta_i\), are given in Table 4.

\[^{14}\theta_i = \theta + \theta_1 \text{AverageIncome}_i + \theta_2 \text{PercentageOfFamiliesWithChildren}_i + \theta_3 \text{PercentageOfFamiliesWithoutChildren}_i + \theta_4 \text{PercentageOfResidentialBuildings}_i\]
Table 4 – Estimation Results (Distance-Adjusted Observation)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>True Quality ($q$)$^{15}$</td>
<td>0.47*</td>
<td>0.005</td>
</tr>
<tr>
<td>Signal Noise ($\sigma_X^2$)</td>
<td>0.00*</td>
<td>0.005</td>
</tr>
<tr>
<td>Average Theta ($\theta$)</td>
<td>-149.8*</td>
<td>0.52</td>
</tr>
<tr>
<td>Average Income ($\theta_1$)</td>
<td>-21.08*</td>
<td>0.29</td>
</tr>
<tr>
<td>Percentage of Families with Children ($\theta_2$)</td>
<td>2.92*</td>
<td>0.21</td>
</tr>
<tr>
<td>Percentage of Families without Children ($\theta_3$)</td>
<td>20.61*</td>
<td>3.89</td>
</tr>
<tr>
<td>Percentage of Residential Buildings ($\theta_4$)</td>
<td>-1.44</td>
<td>1.35</td>
</tr>
</tbody>
</table>

From the results in Table 4, we can see that the true quality is significant and is 0.47. This means that households scale down the average payoff to almost half of its value. Signal noise is also significant and is low$^{16}$. The payoff coefficient’s mean is significant and negative; in other words, households attach more importance to the price than the future payoff in adoption decisions. Average income decreases the propensity to the average payoff; this means that households with higher income attach more weight to the payoff compared with the price of the solar panels which is intuitive. Compared with the singles, the families are more sensitive to the average payoff of the panels.

Physical distance may not be the only determinant for the households engaging in conformity in adoption decisions. If a neighborhood is far away but like-minded, its choices will still influence yours. Demographic variables have been used in the marketing literature (Yang and Allenby (2003)) to adjust for the similarity of individuals. To test this hypothesis, we have constructed the distance based on two demographic measures.

Average income in the neighborhood and percentage of the neighborhood following an

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$^{15}$ For ease of estimation, this coefficient is constrained to be between 0 and 1.

$^{16}$ This might be due to having one initial signal in our setting.
organic lifestyle (a segmentation scheme available in our demographics data) are the two measures we have utilized. Table 5 shows the estimation results using income as the similarity measure.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>True Quality ((q))</td>
<td>0.48*</td>
<td>0.006</td>
</tr>
<tr>
<td>Signal Noise (\sigma^2_i)</td>
<td>0.00*</td>
<td>0.013</td>
</tr>
<tr>
<td>Average Theta (\bar{\theta})</td>
<td>-164.3*</td>
<td>0.625</td>
</tr>
<tr>
<td>Average Income (\theta_1)</td>
<td>-25.1*</td>
<td>4.44</td>
</tr>
<tr>
<td>Percentage of Families with Children (\theta_2)</td>
<td>1.79</td>
<td>0.92</td>
</tr>
<tr>
<td>Percentage of Families without Children (\theta_3)</td>
<td>23.04*</td>
<td>2.05</td>
</tr>
<tr>
<td>Percentage of Residential Buildings (\theta_4)</td>
<td>-4.25*</td>
<td>1.54</td>
</tr>
</tbody>
</table>

As can be seen from the results, true quality is almost the same as the distance-adjusted model. For the rest of the coefficients, the signs are similar to the physical distance model while the magnitudes are different. The major difference is the significance of the residential building percentage (compared with commercial buildings). We examine more closely the estimation results based on lifestyle similarity in Table 6.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>True Quality ((q))</td>
<td>0.46*</td>
<td>0.006</td>
</tr>
<tr>
<td>Signal Noise (\sigma^2_i)</td>
<td>0.00*</td>
<td>0.006</td>
</tr>
<tr>
<td>Average Theta (\bar{\theta})</td>
<td>-151.93*</td>
<td>5.32</td>
</tr>
<tr>
<td>Average Income (\theta_1)</td>
<td>-22.43*</td>
<td>6.12</td>
</tr>
<tr>
<td>Percentage of Families with Children (\theta_2)</td>
<td>5.24</td>
<td>7.46</td>
</tr>
<tr>
<td>Percentage of Families without Children (\theta_3)</td>
<td>21.99*</td>
<td>7.85</td>
</tr>
</tbody>
</table>
As can be seen from Table 6, the estimates are similar to the distance model in terms of the signs, while their magnitudes are different. Contrasting the estimates in Tables 4-6, we can see that the demographics play a role in observational learning, and households take into account the similarity of the target neighborhoods while learning from their behavior.

The estimates shown in Tables 4-6 show the true quality and signal noise values but do not reveal the process of observational learning. To better understand the learning mechanism, we need to look at the belief evolution of households in different neighborhoods and contrast it with the aggregate adoption levels they observe. For this purpose, we have selected individual households, and plotted the quality belief at each time versus the number of adoptions they observed in the previous period.

Figure 4 shows mean belief evolution for one household across 4 years. We can see that the belief becomes smaller gradually across the time, since the number of installations in previous periods is small (except for the jump at the end).
In Figure 5 the abrupt adoption spike in the neighborhood prevents the belief from decreasing over time. We can see that the downward trend of the quality belief has become slower after observing the past adoptions, and remains almost flat because of the big spike.

Figure 6 shows the belief increase over time because of one adoption, but in a smaller neighborhood. These figures show the importance of accounting for observational learning to
be able to explain the belief evolution among households in different neighborhoods. This is indeed a reason behind the fact that some households adopt earlier than the others.

Modeling the adoption decisions without incorporating the payoff uncertainty, would result in biased estimates. This could eventually lead to inaccurate recommendations to the policy makers. To check this, we have estimated a solar panel adoption model without uncertainty as the benchmark. Table 7 shows the estimates:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Theta ($\bar{\theta}$)</td>
<td>-49.86*</td>
<td>1.87</td>
</tr>
<tr>
<td>Average Income ($\theta_1$)</td>
<td>-7.21*</td>
<td>2.305</td>
</tr>
<tr>
<td>Percentage of Families with Children ($\theta_2$)</td>
<td>0.94</td>
<td>2.48</td>
</tr>
<tr>
<td>Percentage of Families without Children ($\theta_3$)</td>
<td>6.14*</td>
<td>2.61</td>
</tr>
<tr>
<td>Percentage of Residential Buildings ($\theta_4$)</td>
<td>-3.77</td>
<td>2.55</td>
</tr>
</tbody>
</table>

Looking at the estimation results of the benchmark model (no uncertainty) and comparing them to those of Table 4, we can see that there is a significant change in magnitude of the effects despite no change in the signs. The magnitude of the $\bar{\theta}$ is one third of that of the main model. Moreover, we can see that the effects of demographics are much lower in the benchmark model compared to the complete model. From these observations we can say that not accounting for payoff uncertainty in the model of renewable energy adoption can result in significant underestimation of the weight of investment payoff. This highlights the importance of properly modeling the learning mechanisms (both individual and social) in studying the adoption of renewable energy sources in specific and durable goods in general.
6- Conclusion and Future Directions

In this paper we studied the adoption of solar PV panels by households. We used a micromodel to shed light on the underlying adoption mechanisms and to explain why some households adopt earlier than others. We modeled solar panel adoption as an investment problem by households (electricity producers) in a technology with uncertain payoff. Using the visibility of rooftop solar panels from outside, we incorporate observational learning as the main mechanism to reduce the inherent uncertainty in adoption payoff. We estimated the model using an individual-level data of the solar panel adopters in Germany augmented by demographics data at street level. We showed that uncertainty plays a major role in adopting solar panels and not incorporating a proper learning framework to the adoption of solar panels would result in biased results. We also contributed to durable goods adoption literature by developing a micromodel of investment decisions (it shares the basic features of durable goods) with uncertain payoff incorporating individual and social learning.

Having estimated the parameters of the adoption model, we will be able to run policy experiments. This allows us to investigate the effect of different governmental incentive policies on the adoption timings of the households. More specifically we want to measure and compare the impact of price subsidy (decreasing the price for adopters), Feed-in Tariff (increasing the Feed-in Tariff rate), and free solar panels on initial adopters in different neighborhoods (leveraging on the observational learning) as policy instruments of the federal government. For each option, we can compare the incremental adoptions with the status quo model, taking into account the extra budget requirements. The results could provide important insights to the policy makers in the renewable energy field.

Another extension to the current model would be the incorporation of the forward-looking behavior by the households. As with other durable goods, expecting price to fall is an
important aspect of the market. Moreover, the subsidies from the government are also changing, and household can form belief regarding their evolution over time. Incorporating these two factors into the decision making, some households may delay their adoption given their belief about the future. It would be interesting to model that behavior and to see if the insights are in line with the static model or not.

7- References


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