Online Appendix for "Subsidies and Time Discounting in New Technology Adoption: Evidence from Solar Photovoltaic Systems"

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I. Data construction

As discussed in the text, the main dataset contains information of all installed PVs across Flanders during 2006–2012. We combine this dataset with various additional datasets on prices, investment tax benefits, electricity prices, GCCs and socio-demographic data at the local market level.

A. *PV installations*

The main dataset comes from VREG, the Flemish regulator of the electricity and gas market. The data records the following three key variables for every new PV installation: the adoption date, the size of the installation and the address of the installation. We aggregate the data to the monthly level, distinguishing between five categories of capacity sizes: 2kW, 4kW, 6kW, 8kW and 10kW. Each category includes all capacity sizes up to the indicated maximum. For example, a capacity size of 6kW refers to all capacity sizes between 4kW and 6kW. To focus on residential solar panels, we exclude all installations with a capacity size larger than 10kW. This is a commonly used cut-off point for distinguishing between residential and non-residential PVs (see e.g. Kwan (2012)). Furthermore, systems of more than 10kW do not qualify from the same public support measures in Flanders.

Our main model aggregates the number of installations to the level of the entire region of Flanders. The extended model considers the highly disaggregate level of the statistical sector, as defined by ADSEI, the Belgian statistical office. The region has 9,182 statistical sectors, with on average 295 households. To organize the data at the level of the statistical sector, we use of a geographic dataset from ADSEI that assigns street addresses of each installation to statistical sectors.

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B. Gross investment price

We obtained price information of PV systems from two independent sources: an internet forum, zonstraal.be, where consumers posted their quotes; and a website, comparemysolar.be, which contains historical data. This resulted in a dataset of 2,659 offers from May 2009 until December 2012. To construct a monthly price index for each of the five capacity size categories (between 2kW and 10kW), we proceeded as follows. For each month and each size category we take the median price per watt, multiplied by the size of the category. If there are less than ten price observations in a given month and category (usually the less popular 8kW and 10kW PVs), we consider the median to be insufficiently accurate. As a price measure for these cases, we use the prediction from a quantile regression model for the median price per watt on monthly fixed effects, capacity fixed effects and capacity interacted with a linear time trend.

To combine the price information with the data on PV installations per month and per size category, we assume there was a time lag of two months between the posted prices and the actual installment. In some months, especially when subsidies would drop in the near future, consumers reported the expected waiting time together with the posted price offer. If such information on the announced waiting time was available, we use this instead of the assumption of a two month time lag.

C. Public support measures

We obtained information of public support measures from various sources.

Investment tax credits

Tax credits fall under the competence of the Belgian Federal government. Information on a doubling of the tax credit ceilings comes from the official document "Programmawet" of 28 December 2006, and announcements on the website of the government agency VEA before and after this publication.[1] Information on spreading tax cuts or splitting bills over multiple years comes from newspaper articles[2] and the Economic Recovery Plan of the Federal Government (March 2009). Details about the abolishment of the tax cut were found on the official website of the finance department of the federal government.[3] Information on the VAT rules also can be found on this website.[4]

We combine this information with the price data to compute the net investment price, as described more formally in the main text section II.A.

[1] Announcements on the doubling of the tax credit ceiling on 6 and 16 December 2006 and information on the increase from 2000 to 2600€ between 1 and 21 March 2007 on VEA's website energiesparen.be. Historic copies from this website are on Internet Archive (https://web.archive.org).

[2] Gazet Van Antwerpen: "Zonnepanelen zijn tot drie keer fiscaal aftrekbaar", 19 Mei 2008; Het Nieuwsblad: "Belastingvoordeel klanten nekt installateurs zonnepanelen", 13 December 2008

[3] http://www.minfin.fgov.be/portail2/nl/current/spokesperson-11-11-30.htm, consulted 14 May 2014.

[4] http://minfin.fgov.be/portail2/nl/themes/dwelling/renovation/vat.htm, consulted 14 May 2014.

Net metering and Green Current Certificates (GCCs)

Information on retail electricity prices comes from Eurostat. These data are half-yearly, and we transform it to monthly data using cubic spline interpolation. We multiply the electricity prices with the expected electricity production to compute the expected electricity cost savings from net metering, as described more formally in the main text section II.A.

Information on the background and start of the GCC policy relating to PVs in 2006 comes from the website of the Flemish energy regulator VREG (www.vreg.be) and from official documents and government information brochures.[5] The price of a GCC was guaranteed for a fixed period, but it was initially expected that GCCs could continue to be sold at the (much lower) market price for the entire life time of the PV system. The renewal of the energy decree in 2012 (Flemish Energy Decree, 30 July 2012) no longer allowed for the possibility to obtain GCCs after the expiration of the fixed period with the guaranteed price. In practice, this does not change much because the life expectancy of PV systems (about 20 years) is close to the fixed period with the guaranteed price.

Information on the financial details of the GCC policy comes from the Belgian energy regulator CREG (2010). Announcements of new subsidy policies were gathered from newspapers. The first change in policy was announced in February 2009 (De Standaard, 7 February 2009, p2) for PVs installed from 2010 on. The second change was announced in June 2011 (De Standaard, 6 June 2011, Economie p12) for PVs from July 2011 on. The third change was announced in May 2012 (De Standaard, 26 May 2012) for PVs installed from August 2012 on and the final change was in July 2012 (Degree proposal amending the Energy Decree of 8 May 2009 (6 July 2012) and Energy decree 8 May 2009, changed 30 July 2012) for PVs installed from 2013 on.

Based on the information from these sources, Table A1 provides an overview of the policy support measures during the period 2006–2012 (and the first months of 2013). Figure 1 in the text makes use of this information to express the various subsidies in present value terms.

[5] See the Flemish Energy Decree, changed on 6 July 2012, KB 10 February 1983, changed by the Flemish government on 15 July 2005, 16 June 1998: "Besluit van de Vlaamse Regering tot wijziging van het koninklijk besluit van 10 februari 1983 houdende aanmoedigingsmaatregelen voor het rationeel energieverbruik." The latter also included information about the investment subsidies of which more information was found in a government brochure "Subsidieregeling voor elektriciteit uit zonlicht" (2005).

Table A1—: PV support policy Flanders: 2006-2013/06

Date of investment	**GCC**		**Subsidy**	**Tax cut on investment**	
	Price (EUR)	**Duration (years)**	**Percentage**	**Percentage**	**Ceiling (EUR 1988)**
2006	450	20	10	40	1000
2007	450	20	10	40	2600*
2008	450	20	0	40	2600
2009	450	20	0	40	2600 x 4**
2010	350	20	0	40	2600 x 4**
2011/01-2011/06	330	20	0	40	2600 x 4**
2011/07-2011/09	300	20	0	40	2600 x 4**
2011/10 - 2011/12	270	20	0	40***	2600 x 4***
2012/01 - 2012/03	250	20	0	0	0
2012/04 - 2012/06	230	20	0	0	0
2012/07	210	20	0	0	0
2012/08 - 2012/12	90	10	0	0	0
2013/01-2013/06	21.39****	15	0	0	0

*Announced as 2000 but changed to 2600. New announcement made: 18 March 2007.
** If house > 5years old, the tax cut could be spread over 4 years. Announced March 2009.
*** Contract had to be signed before 28 November 2011. Announced on the same date.
**** Corrected for banding factor

D. *Socio-demographic characteristics*

For the disaggregate model at the local market level we collected socio-demographic information per statistical sector. This data is freely downloadable from the website of ADSEI, the Belgian Statistics Office. We used population data for each statistical sector in 2011 to create the following variables: population density, average house size (number of rooms), average household size, average house age, median income, percentage of homeowners, percentage with a higher education degree and percentage foreign (people who do not have the Belgian nationality). For confidentiality reasons, some variables are not reported when the number of households in the statistical sector is very small. This applies to a small subset of statistical sectors. In these cases, we use the average of the municipality to which the statistical sector belongs.

E. *Exogenous instruments*

Two variables we use do not directly influence the adoption decision of households, but we use them as instruments for endogenous variable that do affect the decision. The first exogenous instrument is the price index for Chinese Crystalline PV modules of "pvxchange" that is available on their website. The prices are per kW so we multiply them by the kW of each category to create $p_{j,t}^{MOD}$. In the discussion on optimal instruments, we also added the oil price as an additional exogenous instrument. The price of crude oil was obtained from Thomson Reuters Datastream. As with other price variables in the model, we correct for inflation by using the HICP.

II. Optimal instruments

We estimate the model using an approximation of Chamberlain's (1987) optimal instruments. While any set of exogenous instruments leads to consistent estimates, more efficient and stable estimates can be found using approximations to optimal instruments. In this section we discuss the optimal instruments in the model that uses only macro data, i.e. ignoring local market heterogeneity. In the next section, which provides details on how we estimate the model when local market data are added, we discuss how we adapt optimal instruments in this case.

Defining the parameter vector $\theta = (\alpha, \beta, \gamma)$, the conditional moment conditions are

$$E\left(e_{j,t}(\theta)|z_{j,t}\right) = 0$$

where

(A1)

$$e_{j,t}(\theta) = \ln\left(S_{j,t}/S_{0,t}\right) - \left(x_{j,t} - \beta x_{1,t+1}\right)\gamma + \alpha\left(p_{j,t}(\beta) - \beta p_{1,t+1}(\beta)\right) - \beta \ln S_{1,t+1}$$

The optimal instrument matrix of Chamberlain (1987) for a single-equation GMM estimator is:

$$\begin{aligned}
g_{jt}(z_{jt}) &= D_{jt}(z_{jt})'\Omega_{jt}^{-1} \\
\text{with } \Omega_{jt} &= E[(e_{j,t})^2|z_{jt}] \\
D_{jt}(z_{jt}) &= \left(E\left[\left.\frac{\partial e_{j,t}(\theta)}{\partial \theta'}\right| z_{jt}\right]\right) \\
&= \left(E\left[\left.\frac{\partial e_{j,t}(\theta)}{\partial \alpha}\right| z_{jt}\right] \qquad E\left[\left.\frac{\partial e_{j,t}(\theta)}{\partial \beta}\right| z_{jt}\right] \qquad E\left[\left.\frac{\partial e_{j,t}(\theta)}{\partial \gamma'}\right| z_{jt}\right]\right)
\end{aligned}$$

In our approximation, we follow Newey (1990) and set $\Omega_{jt} = \Omega$, i.e. we ignore potential heteroscedasticity. Moreover, since Ω is a scalar in the single-equation GMM estimator, we can also replace it by the identity matrix.

We now derive the optimal instruments for these various parameters. First, for the linear parameter vector γ we simply have:

(A2)
$$E\left[\left.\frac{\partial e_{j,t}(\theta)}{\partial \gamma'}\right| z_{jt}\right] = -E\left[x_{j,t} - \beta x_{1,t+1}|z_{jt}\right] = -\left(x_{j,t} - \beta x_{1,t+1}\right).$$

The optimal instrument for γ is therefore just a difference term for the exogenous variable $x_{j,t}$, where β is substituted by an estimate $\widehat{\beta}$ in a first stage using non-optimal instruments.

For the other linear parameter α we have

$$E\left[\left.\frac{\partial e_{j,t}(\theta)}{\partial\alpha}\right| z_{jt}\right] = E\left[p_{j,t}(\beta) - \beta p_{1,t+1}(\beta)|z_{jt}\right] = E\left[p_{j,t}(\beta)|z_{jt}\right] - \beta E\left[p_{1,t+1}(\beta)|z_{jt}\right]. \tag{A3}$$

In this expression the conditional expectation of price is

$$\begin{aligned} E\left[p_{j,t}(\beta)|z_{jt}\right] &= E\left[p_{j,t}^{INV}(\beta)|z_{jt}\right] - \rho_t^G(\beta)\, E\left[p_{j,t}^{GCC}|z_{jt}\right] - \rho^E(\beta)\, E\left[p_{j,t}^{EL}|z_{jt}\right] \\ &= E\left[p_{j,t}^{GROSS}|z_{jt}\right] - \sum_{\tau=1}^{4}\beta^{12\tau} E\left[taxcut_{j,t}^{\tau}|z_{jt}\right] \\ &\quad -\rho_t^G(\beta)\, p_{j,t}^{GCC} - \rho^E(\beta)\, E\left[p_t^{EL}|z_{jt}\right] k_j' \end{aligned} \tag{A4}$$

where the capitalization factors $\rho_t^G(\beta)$ and $\rho^E(\beta)$ are defined in (2) and depend on the discount factor β. $p_{j,t}^{EL}$ is the electricity price per MWh, multiplied by $k_j^{'}$, the monthly electricity production of a PV with capacity k_j. The optimal instrument for α thus also depends on β for which we use an estimate $\widehat{\beta}$ in a first stage using non-optimal instruments. In contrast with the optimal instrument for γ, it is now also necessary to compute several conditional expectations, namely for the upfront investment cost of a solar panel, the future tax cuts and the electricity price. The predicted gross investment cost $E\left[\left.p_{j,t}^{GROSS}(\beta)\right| z_{jt}\right]$ is obtained from a constant elasticity model, using a Poisson regression and logarithmic regressors (see Silva and Tenreyro (2006)). Based on this predicted value we can also calculate the predicted future eligible tax cuts $E\left[taxcut_{j,t}^{\tau}|z_{jt}\right]$. The predicted electricity price $E\left[p_t^{EL}|z_{jt}\right]$ is similarly obtained using the oil price as an exogenous regressor. We show the regression results in Tables A2 and A3. Note that any misspecification influences only the optimality of our instrument set and not the consistency of the structural estimates of our model.

Finally, the optimal instrument for the nonlinear parameter β is

$$\begin{aligned} E\left[\left.\frac{\partial e_{j,t}(\theta)}{\partial\beta}\right| z_{jt}\right] &= x_{1,t+1}\gamma - E\left[\ln S_{1,t+1}|\, z_{jt}\right] \\ &\quad +\alpha\left(E\left[\left.\frac{\partial p_{j,t}(\beta)}{\partial\beta}\right| z_{jt}\right] - E\left[p_{1,t+1}(\beta)|\, z_{jt}\right] - E\left[\left.\frac{\partial p_{1,t+1}(\beta)}{\partial\beta}\right| z_{jt}\right]\beta\right). \end{aligned} \tag{A5}$$

In the above expression the expected value of the derivative of price with respect to β is

$$E\left[\left.\frac{\partial p_{j,t}(\beta)}{\partial\beta}\right| z_{jt}\right] = -\sum_{\tau=1}^{4} 12\tau\beta^{12\tau-1}E\left[taxcut_{j,t}^{\tau}|z_{jt}\right] - \frac{\partial\rho_t^G(\beta)}{\partial\beta}p_{j,t}^{GCC} - \frac{\partial\rho^E(\beta)}{\partial\beta}E\left[p_t^{EL}|z_{jt}\right]k_j'$$

where the derivatives with respect to the capitalization factors $\rho_t^G(\beta)$ and $\rho^E(\beta)$ are easily computed from (2) and (3). The optimal instrument for β therefore depends on all parameters $\theta = (\alpha, \beta, \gamma)$, for which we obtain a consistent first stage estimate using non-optimal instruments. There is also an additional expectation term for the CCP term, i.e. the log of the predicted next period market share of alternative 1, $E[\ln S_{1,t+1}|z_{jt}]$. We obtain this from a linear regression on several variables, similar to the prediction of the first stage of an IV regression, as shown in Table A4. Note that by using future values of exogenous instruments, we assume that these variables are not correlated with the demand shock or prediction error at time t. Therefore, they must be known at time t. Since we are using only one and two month leads, we believe this is a reasonable assumption as new policies were announced several months ahead (see Appendix I).

To summarize, our final estimation procedure takes the following steps:

- Estimate a GMM model with instruments $p_{j,t}^{MOD}, p_{j,t}^{GCC}$ and $x_{j,t}$ to obtain an initial consistent estimate of α, β and γ
- Compute the conditional expectations for the investment price, the electricity price and the CCP term using the regression models
- Estimate the GMM model again, but now using the approximation of optimal instruments, as given by (A2), (A3) and (A5), after substituting (A4) and the initial consistent estimates of α, β and γ.

Table A2—: Estimation results for electricity price

Variables	$E\left[p_t^{EL} \mid z_{jt}\right]$
Log of oil price	0.183
	(0.018)
Constant	4.599
	(0.073)
Observations	44

Poisson regression model of exponential conditional mean
Standard errors in parentheses, clustered within time period

Table A3—: Estimation results for PV investment price

Variables	$E\left[p_{j,t}^{GROSS} \mid z_{jt}\right]$
Log of PV module price x kW	0.499
	(0.063)
4kW	0.202
	(0.021)
6kW	0.310
	(0.031)
8kW	0.400
	(0.039)
10kW	0.468
	(0.045)
Log of GCC benefits	0.112
	(0.058)
Constant	4.631
	(0.316)
Observations	220

Poisson regression model of exponential conditional mean
Standard errors in parentheses, clustered within time period

Table A4—: Estimation results for CCP correction term

Variables	$E\left[\ln s_{1,t+1} \vert z_{jt}\right]$
PV module price x 4kW in t+1	-0.001
	(0.001)
PV module price x 4kW in t+2	0.001
	(0.001)
GCC benefits of 4kW in t+1	0.116
	(0.019)
GCC benefits of 4kW in t+2	-0.054
	(0.019)
Oil price x 4 kW in t+1	0.006
	(0.009)
Oil price x 4 kW in t+2	0.003
	(0.008)
Constant	-12.995
	(2.485)
Observations	44

OLS regression model of linear conditional mean
Standard errors in parentheses, clustered within time period

III. Estimation of model with local market heterogeneity

Section II.D in the main text specified the model with local market heterogeneity. We estimate this model using a GMM estimator that combines macro and micro-moments at the local market level. This is in the spirit of the static discrete choice literature, as in Petrin (2002) and Berry, Levinsohn and Pakes (2004), and applied to local market data in Nurski and Verboven (2016).

First, we explain how one could proceed when the discount factor β is known, i.e. does not need to be estimated. In this case it is possible to estimate the impact of local market heterogeneity and of the mean utility determinants in two separate steps. Second, we explain how to proceed if the discount factor β is not known, i.e. needs to be estimated. This also includes a discussion of how we implement optimal instruments and some final estimation details.

A. Estimation when the discount factor β is known

Step 1. Maximum likelihood estimation including fixed effects $\widetilde{\delta}_{j,t}$

In this step we construct the likelihood function of observing the local market adoption data, and we maximize this likelihood function with respect to the parameters, including a large set of alternative/time fixed effects $\widetilde{\delta}_{j,t}$, defined below. We first make use of the Hotz-Miller inversion to obtain an expression for $v_{i,0,t}$ that is parallel to that of (10) in the main text:

$$v_{i,0,t} = \beta \left(v_{i,1,t+1} - \ln s_{m,1,t+1} - \eta_t \right). \tag{A6}$$

Note that this assumes that a household's prediction error is common across local markets, i.e. $\eta_t \equiv \overline{V}_{m,t+1} - E_t \overline{V}_{m,t+1}$. We then use the expressions for the conditional values $v_{i,j,t}$ and $v_{i,0,t}$, as given by (15) and (A6), to write the choice probabilities as:

$$\begin{aligned} s_{m,j,t}\left(\widetilde{\delta}, \Lambda\right) &= \frac{\exp(v_{i,j,t})}{\sum_{j'=0}^{J} \exp(v_{i,j',t} - v_{i,0,t})} \\ &= \frac{\exp(v_{i,j,t} - v_{i,0,t})}{1 + \sum_{j'=1}^{J} \exp(v_{i,j',t} - v_{i,0,t})} \\ &= \frac{\exp(\widetilde{\delta}_{j,t} + \widetilde{w}_{j,t}\lambda_m + \beta \ln \widehat{s}_{m,1,t+1})}{1 + \sum_{j'=1}^{J} \exp(\widetilde{\delta}_{j',t} + \widetilde{w}_{j',t}\lambda_m + \beta \ln \widehat{s}_{m,1,t+1})} \end{aligned} \tag{A7}$$

where we define $\widetilde{\delta}_{j,t} \equiv \delta_{j,t} - \beta(\delta_{1,t+1} - \eta_t)$ and $\widetilde{w}_{j,t} \equiv w_{j,t} - \beta w_{1,t+1}$, and $\widehat{s}_{m,1,t+1}$ is a predicted value of the next period choice probability of $j = 1$, discussed in the next paragraph. The current choice probabilities $s_{m,j,t}\left(\widetilde{\delta}, \Lambda\right)$ are thus a function of the alternative/time fixed effects $\widetilde{\delta}_{j,t}$ (collected in the vector $\widetilde{\delta}$) and of the local market interaction effects λ_m (collected in the parameter matrix Λ).

Note that the right hand side of (A7) also depends on a predicted value of the next period probabilities $\widehat{s}_{m,1,t+1}$, which are treated as data from a first-stage estimation. In contrast to the model with only aggregate data, we no longer accurately observe the CCP correction term $\ln s_{m,1,t+1}$ directly due to the small number of households in each statistical sector m. In many local markets adoption rates are zero, so that the CCP correction term would be undefined. We therefore use a first-stage prediction of the CCP correction term, $\widehat{s}_{m,1,t+1}$, based on a flexible logit. We include local market fixed effects, capacity fixed effects for each time period, capacity-specific effects for each demographic, and capacity-time-specific effects for the demographics that enter the price parameter. We then use the parameters of this model to calculate the predicted market shares for $j = 1$ in every time period and use the predictions in $t + 1$ in the conditional value functions at time t.

The maximization problem of the log likelihood function is then

$$\max_{\widetilde{\delta},\Lambda} \ln L(\widetilde{\delta},\Lambda) = \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{j=0}^{J} q_{m,j,t} \ln s_{m,j,t}(\widetilde{\delta},\Lambda)$$

where $q_{m,j,t}$ is the observed number of households in local market m that adopt $(j = 1, ...J)$ or choose not to adopt $(j = 0)$ at period t. This is similar to a maximum likelihood estimator that sums over individual data but since $\ln s_{m,j,t}(\widetilde{\delta},\Lambda)$ is identical for each household in market m, we can multiply it by the number of households that make each choice. Note that this contains a potentially large number of parameters, because of the set of alternative/time fixed effects $\widetilde{\delta}_{j,t}$ $(J \times T)$, but also a large number of parameters in Λ due to the inclusion of local market fixed effects.

Step 2. Instrumental variables regression of $\widetilde{\delta}_{j,t}$

The second step is an instrumental variable regression of the estimated fixed effects $\widetilde{\delta}_{j,t} \equiv \delta_{j,t} - \beta(\delta_{1,t+1} - \eta_t)$ after substituting the expressions of $\delta_{j,t}$ and $\delta_{1,t+1}$ based on (1). This gives the regression

$$\text{(A8)} \qquad \widetilde{\delta}_{j,t} = (x_{j,t} - \beta x_{1,t+1})\,\gamma - \alpha\,(p_{j,t} - \beta p_{1,t+1}) + e_{j,t} \text{ for } j = 1, ...J$$

where $e_{j,t}$ was already defined before for the aggregate model as $e_{j,t} \equiv \xi_{j,t} - \beta(\xi_{1,t+1} - \eta_t)$. The IV regression then imposes the following moment conditions

$$E\,(z_{j,t}e_{j,t}) = 0$$

Hence, this regression is very similar to the aggregate model. In the disaggregate model the dependent variable consists of the estimated fixed effects $\widetilde{\delta}_{j,t}$ from the first step, while in the aggregate model the dependent variable, including the correction term, was $\ln(S_{j,t}/S_{0,t}) - \beta \ln S_{1,t+1}$. Price is given by (2), based on the imposed value of β, and the instruments are the same as the ones used before in the aggregate model (though one can reduce the number of instruments, since the discount factor is treated as known).

Simultaneous GMM

Given the known discount factor β, this two-step approach yields consistent estimates of all parameters, but in the second step standard errors need to be corrected because the $\widetilde{\delta}_{j,t}$ are estimated values. Alternatively, this model can be estimated at once using a GMM estimator that combines the scores of the likelihood function of the first step (micro-moments), with the moment condition that is imposed by the IV regression of the second step (macro-moment). The stacked vector of sample moment conditions is then

$$g(\widetilde{\delta}, \Lambda, \alpha, \gamma) = \begin{pmatrix} \partial \ln L(\widetilde{\delta}, \Lambda)/\partial(\widetilde{\delta}, \Lambda) \\ \sum_{t=1}^{T} \sum_{j=1}^{J} z_{j,t} e_{j,t} \left(\widetilde{\delta}, \alpha, \gamma\right) \end{pmatrix}$$

The score $\partial \ln L(\widetilde{\delta}, \Lambda)/\partial(\widetilde{\delta}, \Lambda)$ has an intuitive expression for the demographic parameters and the fixed effects:

$$\begin{aligned} \frac{\partial \ln L(\widetilde{\delta}, \Lambda)}{\partial \widetilde{\delta}_{j,t}} &= \sum_{m=1}^{M} N_{m,t} \left(\frac{q_{m,j,t}}{N_{m,t}} - s_{m,j,t}(\widetilde{\delta}, \Lambda) \right) \\ \frac{\partial \ln L(\widetilde{\delta}, \Lambda)}{\partial \lambda^h} &= \sum_{t=1}^{T} \sum_{m=1}^{M} N_{m,t} \sum_{j=1}^{J} \left(\frac{q_{m,j,t}}{N_{m,t}} - s_{m,j,t}(\widetilde{\delta}, \Lambda) \right) \widetilde{w}_{j,t} D_m^h \end{aligned}$$

where D_m^h is demographic characteristic h in the vector D_m and λ^h is a $K \times 1$ vector for demographic characteristic h (one of the columns in Λ). The scores $\partial \ln L(\widetilde{\delta}, \Lambda)/\partial \widetilde{\delta}_{j,t}$ (for each j and t) are essentially conditions that the observed country-level market shares should be equal to the predicted country-level market shares. The scores $\partial \ln L(\widetilde{\delta}, \Lambda)/\partial \lambda^h$ (for each demographic h) are moment conditions that the observed sales-weighted demographic interactions should be equal the model's predictions. Since we include dummy variables for each local market in the flow utility of a PV, it essentially also introduces a moment condition that matches the total number of adoptions at the end of the sample predicted by the model with that observed in the data. The GMM estimator minimizes $g'Wg$ with respect to the parameters, where W is the weighting matrix.

B. *Estimating the discount factor* β

When β is known, a two-step procedure is possible because no parameter estimated in the second step, enters the estimation in the first step. If β also has to be estimated, this is no longer the case. The discount factor enters the local market shares directly as the coefficient in front of the CCP term (see (A7)), but also implicitly in the interaction effects of demographic variables with the price variable. We therefore proceed with joint estimation. The stacked vector of sample moment conditions then also depends on the discount factor

$$g(\widetilde{\delta},\Lambda,\alpha,\beta,\gamma)=\begin{pmatrix}\partial\ln L(\widetilde{\delta},\Lambda,\beta)/\partial(\widetilde{\delta},\Lambda)\\ \sum_{j,t}z_{j,t}e_{j,t}\left(\widetilde{\delta},\alpha,\beta,\gamma\right)\end{pmatrix}$$

Similar to the aggregate model, we now also need an extra instrument in $z_{j,t}$ to identify the discount factor.

Optimal instruments

We again make use of the approximation to optimal instruments we discussed in Appendix II. However, due to the variation of the CCP correction term across local markets, the error term, and therefore also the optimal set of instruments, is different. From (A8) it follows that the error term is now

$$e_{j,t}(\widetilde{\delta},\alpha,\beta,\gamma)=\widetilde{\delta}_{j,t}-\left(x_{j,t}-\beta x_{1,t+1}\right)\gamma+\alpha\left(p_{j,t}(\beta)-\beta p_{1,t+1}(\beta)\right) \tag{A9}$$

Notice the difference with (A1): $\widetilde{\delta}_{j,t}$ has replaced $\ln\left(S_{j,t}/S_{0,t}\right)-\beta\ln S_{1,t+1}$.Therefore the derivative of the discount factor no longer depends on the CCP so that (A10) replaces (A5) in the construction of the optimal instrument vector:

$$\begin{aligned}E\left[\left.\frac{\partial e_{j,t}(\widetilde{\delta},\alpha,\beta,\gamma)}{\partial\beta}\right|z_{jt}\right] &= x_{1,t+1}\gamma\\ &+\alpha\left(E\left[\left.\frac{\partial p_{j,t}(\beta)}{\partial\beta}\right|z_{jt}\right]-E\left[p_{1,t+1}(\beta)\right|z_{jt}\right]-E\left[\left.\frac{\partial p_{1,t+1}(\beta)}{\partial\beta}\right|z_{jt}\right]\beta\right).\end{aligned} \tag{A10}$$

Estimation details

Our main specification includes a full set of local market fixed effects in Λ. We then exclude the local markets where adoption never occurred, because with the local market fixed effects these markets do not add any information to the likelihood function which we use to construct the micro-moments of the model. To reduce the number of fixed effects and speed up the estimation procedure, we use a random sample of 50 percent. We also estimated an alternative specification with all local markets, but with a reduced number of 308 fixed effects at the municipality level and with household characteristics interacted with the constant. This gave similar results to the specification with a full set of local market fixed effects.

To correct for the fact that within a local market observations are not independent over time, we cluster the moments in the calculation of the covariance matrix. We also cluster the macro moments within time periods.

IV. Additional results for robustness checks

A. Alternative terminal actions for CCP approach

Table A5—: Robustness: terminal action

	Terminal action: 2kW		Terminal action: 4kW (used in paper)		Terminal action: 6kW	
Price sensitivity in 10^3 EUR ($-\alpha$)	-0.351	(0.113)	-0.470	(0.098)	-0.513	(0.102)
Monthly discount factor (β)	0.9870	(0.0032)	0.9884	(0.0025)	0.9906	(0.0016)
Annual interest rate in percent ($r \equiv \beta^{-12} - 1$)	16.99	(4.68)	15.09	(3.43)	11.94	(2.10)
Control variables (γ)						
Alternative-specific constant						
Common constant	-0.983	(15.425)	-1.423	(16.38)	-4.575	(19.325)
2kW	-2.111	(0.457)	-1.828	(0.562)	-1.199	(0.531)
6kW	-0.193	(0.484)	-0.513	(0.595)	-1.162	(0.565)
8kW	-1.847	(0.942)	-2.453	(1.158)	-3.742	(1.097)
10kW	-1.747	(1.372)	-2.605	(1.684)	-4.507	(1.592)
Hansen's J (p-value)	Exactly identified		Exactly identified		Exactly identified	
Obs. macro moments (JxTx terminal choices)	220 x 1		220 x 1		220 x 1	
Obs. micro moments (MxJxT)	0		0		0	
	Terminal action: 8kW		**Terminal action: 10kW**		**Terminal action: All (joint estimation)**	
Price sensitivity in 10^3 EUR ($-\alpha$)	-0.542	(0.112)	-0.505	(0.111)	-0.422	(0.046)
Monthly discount factor (β)	0.9885	(0.0018)	0.9882	(0.0020)	0.9873	(0.0007)
Annual interest rate ($r \equiv \beta^{-12} - 1$)	14.85%	(2.46%)	15.27%	(2.81%)	16.62%	(1.03%)
Control variables (γ)						
Alternative-specific constant						
Common constant	-2.599	(16.429)	-1.270	(18.673)	-10.158	(11.278)
2kW	-1.734	(0.416)	-1.832	(0.429)	-2.044	(0.129)
6kW	-0.628	(0.432)	-0.518	(0.448)	-0.282	(0.136)
8kW	-2.663	(0.849)	-2.453	(0.879)	-2.022	(0.262)
10kW	-2.890	(1.246)	-2.591	(1.288)	-1.990	(0.399)
Hansen's J (p-value)	Exactly identified		Exactly identified		31.726 (p= 0.2858)	
Obs. macro moments (JxTx terminal choices)	220 x 1		220 x 1		220 x 5	
Obs. micro moments (MxJxT)	0		0		0	

Notes: Standard errors clustered within 44 time periods. Instruments are approximations of optimal instruments (Chamberlain, 1987). Standard errors of r obtained via delta method.

B. Heterogeneous discount factor

This section first explains how we extend our model of local market heterogeneity to incorporate heterogeneity in the discount factor. Next, we present the empirical results.

Approach

With a local market-specific discount factor β_m, the predicted local market shares are given by the following generalization of (A7):

$$s_{m,j,t} = \frac{\exp(\widetilde{\delta}_{m,j,t} + \widetilde{w}_{j,t}\lambda_m + \beta_m \ln \widehat{s}_{m,1,t+1})}{1 + \sum_{j'=1}^{J} \exp(\widetilde{\delta}_{m,j',t} + \widetilde{w}_{j',t}\lambda_m + \beta_m \ln \widehat{s}_{m,1,t+1})} \tag{A11}$$

where

(A12)

$$\widetilde{\delta}_{m,j,t} = (x_{j,t} - \beta_m x_{1,t+1})\gamma - \alpha_m(p_{j,t}(\beta_m) - \beta_m p_{1,t+1}(\beta_m)) + \xi_{j,t} \underbrace{- \beta_m \left(\xi_{1,t+1} - \eta_t\right)}_{\widetilde{\tau}_{m,t}}.$$

Note that we explicitly write a local market specific price coefficient α_m, therefore $\widetilde{w}_{j,t}$ no longer contains interactions with the price variable. Suppose the discount factor is the following function of $H \times 1$ vector of household characteristics D_m:

$$\begin{aligned} \beta_m &= g\left(\beta_0 + \kappa_\beta D_m\right) \\ &= \frac{\exp(\beta_0 + \kappa_\beta D_m)}{1 + \exp(\beta_0 + \kappa_\beta D_m)}, \end{aligned}$$

where κ_β are parameters measuring how the discount factor varies with household characteristics. This allows for a very flexible specification of β_m and ensures that $\beta_m \in (0, 1)$, even with continuous variables in D_m.

Apart from the non-linearity through which β_m enters (also through the term $p_{j,t}(\beta_m)$), the key issue relates to the term $\widetilde{\tau}_{m,t}$ entering (A12). This term contains interactions between the market-specific discount factor β_m and the expectational error η_t. One approach would be to discretize the vector of household characteristics D_m to D possible realizations or "demographic groups", $d = 1, \dots, D$. One can then absorb the $\widetilde{\tau}_{m,t}$ with fixed effects by period t and group d, allowing us to also control for expectational errors $\eta_t(d)$ by period t and group d.

To make better use of the rich and continuous variables in D_m we also follow an alternative approach. Let the term $\widetilde{\tau}_{m,t}$ be given by the following function of household characteristics

$$\widetilde{\tau}_t\left(D_m\right) \equiv -g\left(\beta_0 + \kappa_\beta D_m\right)\left(\xi_{1,t+1} - \eta_t\left(D_m\right)\right)$$

where $\eta_t(D_m)$ is a differentiable function of D_m, reflecting an expectational error that may vary across markets by demographics. We approximate $\widetilde{\tau}_t(D_m)$ using the following first-order Taylor expansion for $\widetilde{\tau}_t(D_m)$ around the mean of D_m, which we normalize to 0:

$$\widetilde{\tau}_t(D_m) \approx -g(\beta_0)\left(\xi_{1,t+1} - \eta_t(0)\right) + \nabla\widetilde{\tau}_t(0) D_m,$$

where $\nabla\widetilde{\tau}_t(0)$ is the $1 \times H$ gradient for each t at $D_m = 0$. A typical element of $\nabla\widetilde{\tau}_t(0)$ is $\nabla\widetilde{\tau}_t^h$, yielding t-specific parameters to be estimated as interactions with each of the demographics D_m^h. The main benefit of this Taylor expansion is that $\widetilde{\tau}_t(D_m)$ now depends linearly on D_m in each time period.

We add the following scores as micro-moments to identify the discount factor parameters κ_β^h (elements of κ_β) and the parameters $\nabla\widetilde{\tau}_t^h$:

$$\begin{aligned}
\frac{\partial \ln L}{\partial \kappa_\beta^h} &= \sum_{t=1}^{T}\sum_{m=1}^{M} N_{m,t}\sum_{j=1}^{J}\left(\frac{q_{m,j,t}}{N_{m,t}} - s_{m,j,t}(\widetilde{\delta},\Lambda)\right)\frac{\partial \Upsilon_{m,j,t}}{\partial \beta_m} g'\left(\beta_0 + \kappa_\beta D_m\right) D_m^h \\
\frac{\partial \ln L}{\partial \nabla\widetilde{\tau}_t^h} &= \sum_{m=1}^{M} N_{m,t}\sum_{j=1}^{J}\left(\frac{q_{m,j,t}}{N_{m,t}} - s_{m,j,t}(\widetilde{\delta},\Lambda)\right) D_m^h,
\end{aligned}$$

where $\Upsilon_{m,j,t}\left(\beta_m\right)$ is the differenced value function that enters the choice probabilities (A11).

Findings

Table A6 shows the empirical results. We allow for a very flexible specification in which the valuation of price, capacity and the discount factor depends on all demographics.[6] This flexible specification mainly aims to document the role of heterogeneity in the discount factor, as summarized in Figure 5 and the corresponding discussion in the main text. The coefficients themselves are difficult to interpret on a stand-alone basis, because we include a large set of demographics in all valuation terms, which show multicollinearity and may also capture other location characteristics. For example, homeowners tend to have a higher discount factor. Households with a higher income tend to have a lower discount factor, perhaps because they have better investment opportunities or because the home ownership variable also captures the impact of wealth.

[6] We also considered a specification where we do not rely on the Taylor approximation but instead discretize the vector of household characteristics into eight groups according to below/above average income, percentage foreigners and population density. The resulting distribution of the implicit interest rate is discrete but otherwise comparable to our more flexible approach, with most mass at 14.7% and 90% of households has a rate between 12.8% and 15.2%.

Table A6—: Empirical results with heterogeneous discount factor

	Interactions with capacity difference		Price sensitivity in 10^3 EUR ($-\alpha$)		Index of monthly discount factor (κ_β)	
Effect at mean of demographics			-0.487	(0.105)	4.468	(0.223)
Pop. density (10^4 inhab / mš)	-0.738	(0.076)	-0.077	(0.030)	0.010	(0.052)
Average house size	0.108	(0.033)	-0.034	(0.018)	-0.058	(0.033)
Average household size	-0.157	(0.094)	-0.118	(0.028)	0.157	(0.066)
Average house age (decades)	-0.014	(0.013)	-0.004	(0.006)	0.016	(0.011)
Median income (10^4 EUR)	0.187	(0.085)	0.097	(0.024)	-0.173	(0.064)
Percentage homeowners	-0.973	(0.224)	-0.178	(0.062)	0.632	(0.185)
Percentage higher education	-0.027	(0.175)	0.020	(0.085)	-0.038	(0.146)
Percentage foreign	-0.126	(0.153)	0.172	(0.107)	0.456	(0.193)
Alternative-specific constants				YES		
Local market fixed effects				YES		
Local market expectational errors				YES		
Obs. macro moments (JxT)				220		
Obs. micro moments (MxJxT)				935,440		

Notes: Demographic variables demeaned. Standard errors are clustered accross alternatives within 44 time periods. For the micro moments at the local market level we additionally cluster across time periods within each of the 4252 local markets. Instruments are approximations of optimal instruments (Chamberlain, 1987).

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