Dynamic discrete choice models: CCP with market shares

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Outline

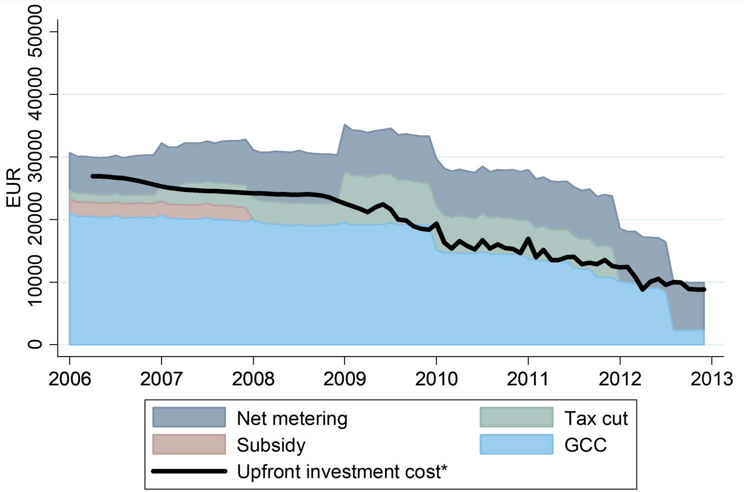
Introduction I

- Paper: De Groote, O. and Verboven, F. "Subsidies and Time Discounting in New Technology Adoption: Evidence from Solar Photovoltaic Systems". American Economic Review 109, no. 6 (June 2019): 2137–72.
- Models the decision of households when and how much to invest in a solar panel
- Main question: what would be the change in government expenditures if subsidization policy mainly reduced investment cost instead of increasing future benefits?
- Also uses CCP but now on aggregate data (+ extension to micro data)
- Similar approach as we saw in static model of Berry (1994)
- Scott (2013) introduces innovation that allows us to make weak assumptions on how agents expect the future to evolve

Costs and benefits of a PV (2006-2012) I

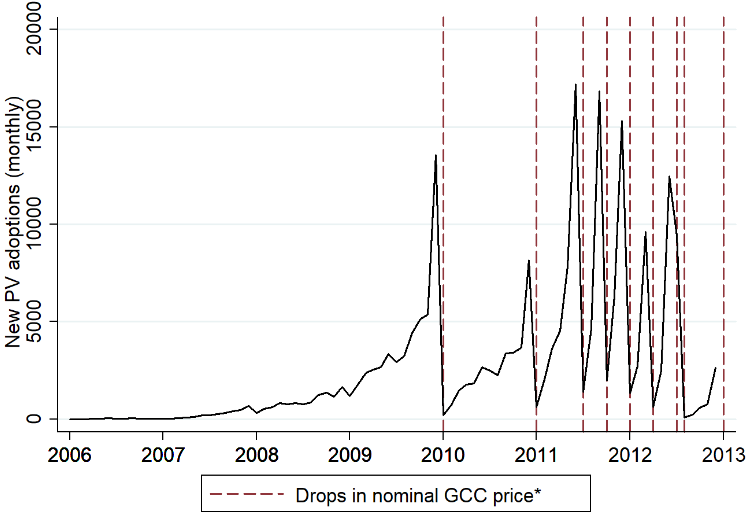
- Upfront investment subsidies and tax cuts
- Future benefits from net metering
  - Electricity bill = electricity price × (consumption-production)
- Future production subsidies: Green Current Certificates (GCCs)
  - Households get a GCC per MWh for fixed number of years (mostly 20)
  - GCCs can be sold to grid operator at a guaranteed price
  - The price guarantee is fixed at the moment of the investment

Costs and benefits of a PV of 4 kW (2006-2012)



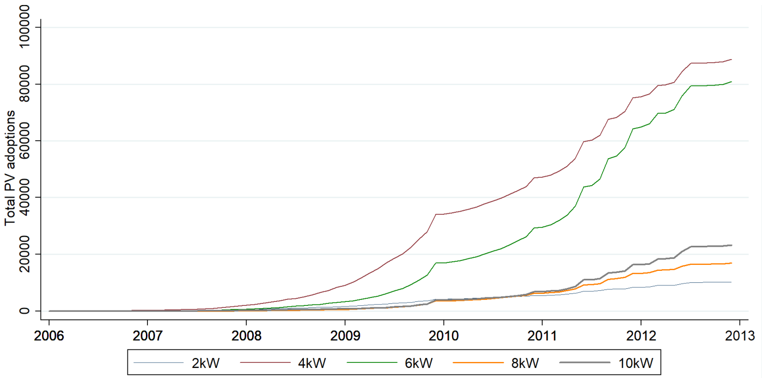
Upfront investment cost*: predicted values using German price index EUPD before May 2009
Real interest rate used to calculate present values = 3%

Evolution of new PV adoption and drops in GCC price



* GCC price corrected for banding factor when installed after 2012

Evolution of total PV adoption by capacity



Model I

- Note: I am deviating from the paper here to keep things simple and stay closer to Grigolon et al. (2018) (will show connection later)
- Each month t, every household that has not yet adopted a PV decides to either:
  - Don't adopt ($j = 0$)
  - Adopt 2kw, 4kw, 6kw, 8kw or 10kw: ($j = 1, ..., 5$)
- Conditional value function of adoption (net of ε_{ijt}) in model with only aggregate data

$$v_{i,j,t} = \delta_{j,t} = x_{j,t}\gamma - \alpha p_{jt} + \alpha\theta b_{jt} + \xi_{jt}$$

- x are observed characteristics (here just choice-specific constants)

Model II

- ξ_{jt} is a demand shock (see lecture on static models)
- p_{jt} is the investment cost
- b_{jt} is the present value of investment benefits
- Conditional value of not adopting ($j = 0$):

$$\delta_{0,t} = u_{0,t} + \beta E_t \overline{V}_{t+1}$$

- with $\overline{V}_{t+1} = 0.577 + \ln \sum_{j=0}^{J} \exp\left(\delta_{j,t+1}\right)$.

Model III

- We follow important insight of Scott (2013), instead of specifying households expectations of the future ($E_t \overline{V}_{t+1}$), we define a prediction error

$$\eta_t \equiv \overline{V}_{t+1} - E_t \overline{V}_{t+1}$$

  and use realizations of the future instead. In estimation, we can treat η_t in a similar way as the demand shocks ξ_{jt}, we don't need to know them, we simply need instruments that are not correlated with them.
- Normalize $u_{0,t} + 0.577\beta = 0$ such that

$$\delta_{0,t} = \beta \left(\ln \sum_{j=0}^{J} \exp\left(\delta_{j,t+1}\right) - \eta_t \right).$$

Model IV

- Now we apply CCP using $j = 1$ as a terminal action
- Because we use realized value functions and not expected value functions, the CCP is simply the market share:

$$S_{1,t+1} = \frac{\exp\left(\delta_{1,t+1}\right)}{\sum_{j=0}^{J} \exp\left(\delta_{j,t+1}\right)}$$

$$ln \sum_{j=0}^{J} \exp\left(\delta_{j,t+1}\right) = \delta_{1,t+1} - lnS_{1,t+1}$$

- Substituting back into the mean utility of not adopting:

$$\delta_{0,t} = \beta\left(\delta_{1,t+1} - \ln S_{1,t+1} - \eta_t\right)$$

Model V

- Now we do the same as in Berry (1994), it still holds that

$$\ln S_{j,t}/S_{0,t} = \delta_{j,t} - \delta_{0,t}$$

- Because

$$S_{j,t} = \frac{\exp\left(\delta_{j,t}\right)}{\sum_{j'=0}^{J} \exp\left(\delta_{j',t}\right)}$$

and

$$S_{0,t} = \frac{\exp\left(\delta_{0,t}\right)}{\sum_{j'=0}^{J} \exp\left(\delta_{j',t}\right)}$$

- But the mean utilities look different now

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

where $e_{j,t} \equiv \xi_{j,t} - \beta(\xi_{1,t+1} - \eta_t)$

Model VI

- Fix β and estimate using 2SLS with instruments
  - product characteristics to identify γ
  - price of Chinese PV modules to identify α
  - present value of benefits to identify θ

Budgetary implications I

- Main parameter of interest here: θ
- Households perceived the benefits from GCCs as follows

$$\frac{1-(\beta)^R}{1-\beta}\theta GCC_{j,t}$$

- But the government is paying

$$\frac{1-(\beta)^R}{1-\beta}GCC_{j,t}$$

- So providing the first number by reducing the upfront investment cost has same effect and is cheaper if $\theta < 1$
- Note: this is a "counterfactual" that does not require any solving!

Back to the actual paper

- In contrast to Grigolon et al. (2018), we have dynamics which means we now have 2 parameters measuring myopia: θ and β
- Instead of assuming a value for β, we set $\theta = 1$ and estimate β (which also enters through $b_{j,t}$!)
- Intuition is the same as above, but model becomes nonlinear
- Furthermore, we allow for heterogeneity at the local market level

Identification I

- Note that a discount factor is usually difficult to identify (Magnac and Thesmar (2002), Abbring and Daljord (2018))
- Until now, we always made several parametric and distributional assumptions
- Magnac and Thesmar (2002) show that in dynamic models, many of them are crucial to be able to identify primitives, we need
  - Distribution of taste shocks
  - Normalization of utility one option for each value of the state
  - Discount factor
- However, in this application identification of β is not arising from arbitrary functional form assumptions

Identification II

- We see how people respond differently to a change in investment benefits (in particular GCC subsidies) and a change in prices
- This shift in future utility is therefore the main source of identification behind β (in a model with $\theta = 1$)

Estimates I

	(1) Static	(2) Dynamic	(3) + micro-moments
Price sensitivity in 10^3 EUR	-0.318	-0.470	-0.604
$(-\alpha)$	(0.074)	(0.098)	(0.100)
Monthly discount factor	0.9886	0.9884	0.9884
(β)	(0.0016)	(0.0025)	(0.0024)
Annual real interest rate	14.82%	15.09%	15.00%
$(r \equiv \beta^{-12} - 1)$	(2.28%)	(3.43%)	(3.42%)
Choice-specific constants	YES	YES	YES
Local market fixed effects	NO	NO	YES
Demographics x (capacity, price)	NO	NO	YES
Obs. macro moments (JxT)	220	220	220
Obs. micro moments (NxJxT)	0	0	935,440

Budgettary implication

- Our counterfactual with an estimated β is now a bit different too:
  - Households perceived the benefits from GCCs as follows

$$\frac{1-(0.9884)^R}{1-0.9884}GCC_{j,t}$$

  - But the government is paying

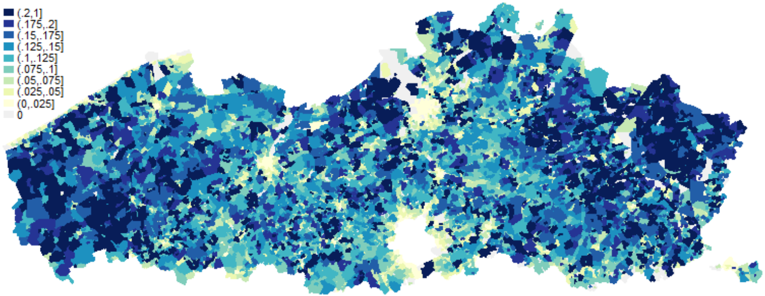
$$\frac{1-(0.9975)^R}{1-0.9975}GCC_{j,t}$$

- Adding some further technical corrections, we find that an upfront subsidy would have implied a saving of 51% or €1.9 billion (€700/hh)

Other examples of ECCP estimators

- Because the regression to estimate can be interpreted as a discretized version of an Euler equation, the method introduced by Scott (2013) is now often called ECCP estimators, see Kalouptsidi et al. (2021) for general framework
- Also works with individual data: calculate choice probabilities for types of individuals instead of market shares
- See Traiberman (2019) for application in labor/trade
- See Almagro & Domınguez-Iino (2021) for application in housing

Extra: PV adoption across Flanders



Extra: Local market heterogeneity I

- Heterogeneity only entered through iid ε_{ijt}
- In static model we know this is problematic because of correlation between similar goods
- Similar solutions exist in a dynamic model, CCP still holds for extension like nested logit
- But in dynamic models, also nested logit doesn't solve another issue: correlation over time!
- Possible solutions in the literature: random coefficients as in BLP (see e.g. Gowrisankaran and Rysman, 2012) or types (see e.g. Scott, 2013)
- Alternative in this paper: test robustness by incorporating local market heterogeneity using micro-moments

Extra: Local market heterogeneity II

- Add covariates of 9,182 local markets m with an average of 295 households
- Add local market-specific term to conditional value of adoption

$$v_{i,j,t} = \delta_{j,t} + \mu_{m,j,t}$$

$$= \delta_{j,t} + w_{j,t}\lambda_m$$

where $w_{j,t}\lambda_m = w_{j,t}\Lambda D_m$ and Λ contains interactions between product characteristics $w_{j,t}$ and local market variables D_m

- We allow for a large set of local market fixed effects to control for unobserved heterogeneity
- And interactions of demographics with capacity and price

Extra: Local market heterogeneity III

- Estimation of Λ by adding micro-moments to GMM estimator
  - Micro-moments match the observed covariances between the demographic variables and product characteristics to the models predictions, as well as the total number of adopters in each market at the end of the sample
  - They can be derived from a likelihood model that maximizes the likelihood to observe the local market shares

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