Subsidies and Time Discounting in New Technology Adoption

Evidence from Solar Photovoltaic Systems

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Introduction

- Solar photovoltaic systems (PV) have been encouraged through
 - upfront investment subsidies
 - future subsidies for electricity production (e.g. FIT)
- Research questions
 - How do consumers respond to future production subsidies, i.e. what implicit interest rate do they use?
 - What do our findings imply for subsidy policy?
- Application: PV support policies in Flanders (Belgium)
 - Green Current Certificates (GCCs) increased benefits from electricity production (similar to FIT)

Outline of the presentation

• Industry, data and subsidy policies

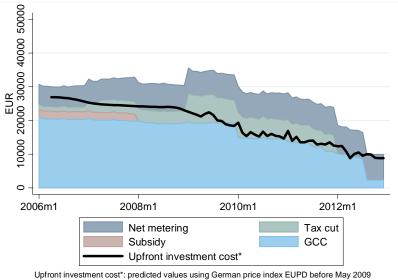
Dynamic discrete choice model of technology adoption

Empirical results and policy implications

Cost and benefits of a PV (2006-2012)

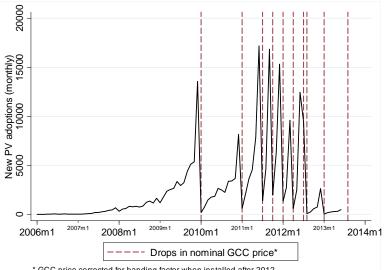
- Upfront investment subsidies and tax cuts
- Future benefits from net metering
 - Electricity bill = electricity price \times (consumption-production)
- Future production subsidies: Green Current Certificates (GCCs)
 - Households get a GCC per MWh for fixed number of years (mostly 20)
 - GCCs can be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

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



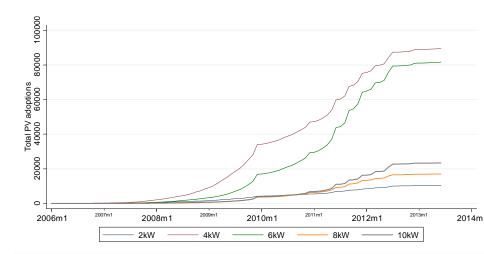
Real interest rate used to calculate present values = 3%

Evolution of new PV adoption and drops in GCC price

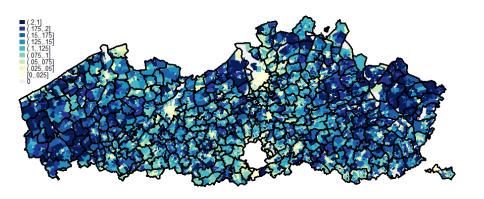


^{*} GCC price corrected for banding factor when installed after 2012

Evolution of total PV adoption by capacity



Distribution of PV adoption across Flanders



Model outline

- Structural dynamic discrete choice model
 - Investment trade-off: upfront costs and future benefits
 - Dynamic trade-off: adopt now, or postpone investment

- \bullet Apply the model to aggregate market data + include micro-moments for local adoption rates in Flanders
- ullet Infer the households' implicit annual interest rate $r \equiv eta^{-12} 1$

Contributions

- Other dynamic adoption models for solar PV: Burr (2016), Langer and Lemoine (2018), Feger, Pavanini and Radulescu (2017)
 - Don't estimate discount factor
 - Use nested fixed point algorithm of Rust (1987)
 - Requires specifying household's expectations of future investment opportunities
 - Difficult to account for household heterogeneity and endogeneity
- We derive a simple to estimate regression equation on market share data that looks similar to Berry (1994)
 - Uses CCP estimator (Hotz and Miller, 1993) and finite dependence (Arcidiacono and Miller, 2011)
 - Following Scott (2013), we can avoid strong assumptions on households' expectations of future prices and subsidies (see also Kalouptsidi et al. (2018))

Contributions

- Add micro-moments to allow for local market heterogeneity
 - Petrin (2002), micro-BLP (2004), Nurski and Verboven (2016)
 - Local market fixed effects control for persistent unobserved heterogeneity
 - Observables affecting capacity choice and price sensitivity
- Identification strategy for discount factor in investment decisions
 - In general not identified from choice behavior (Magnac and Thesmar (2002), Abbring and Daljord (2017))
 - Additional source of variation that can be used: future benefits of an investment today

Dynamic discrete choice model of technology adoption

- Actions and payoffs
- Adopting (j = 1, ..., J) in month t is a terminal action

$$v_{i,j,t} + \varepsilon_{i,j,t}$$

- where $\varepsilon_{i,j,t}$ is i.i.d. type I extreme value
- Because of terminal nature, we can directly write v as a discounted sum of benefits, subtracted by the upfront investment cost
- ullet Not adopting (j=0) in month t leaves option of adopting later

$$v_{i,0,t} + \varepsilon_{i,0,t}$$

- This is where dynamics enter, households can still adopt in the future
- Accounting for household heterogeneity
 - First discuss without household heterogeneity

$$v_{i,j,t} = \delta_{j,t}$$

Next account for heterogeneity across local markets m

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

Conditional value of adoption

• Conditional value of adopting $(j \neq 0)$:

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

• Price consists of upfront cost and future benefits:

$$p_{j,t} = p_{j,t}\left(\beta\right) \equiv p_{j,t}^{INV}\left(\beta\right) - \underbrace{\frac{1 - \left(\beta^{G}\right)^{S_{t}^{G}}}{1 - \beta^{G}}}_{\rho_{t}^{G}} p_{j,t}^{GCC} - \underbrace{\frac{1 - \left(\beta^{E}\right)^{S^{E}}}{1 - \beta^{E}}}_{\rho^{E}} p_{j,t}^{EL}$$

where

$$\beta^{G} = (1 - \lambda)(1 - \pi)\beta$$

$$\beta^{E} = (1 - \lambda)(1 + \vartheta)\beta.$$



Conditional value of not adopting

• Conditional value of not adopting (j = 0):

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

• The ex ante value function \overline{V}_{t+1} is:

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

- Let $\eta_t \equiv \overline{V}_{t+1} E_t \overline{V}_{t+1}$ be a mean zero prediction error (Scott, 2013)
- Normalize $u_{0,t} + 0.577\beta = 0$
- Then

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



Conditional value of not adopting (cont.)

• To compute the logsum, take next period CCP of any terminal action, say j=1:

$$\mathcal{S}_{1,t+1} = \frac{\exp\left(\delta_{1,t+1}
ight)}{\sum_{j=0}^{J}\exp\left(\delta_{j,t+1}
ight)}$$

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

• This gives:

$$\begin{array}{lcl} \delta_{0,t} & = & \beta \left(\ln \sum_{j=0}^{J} \exp \left(\delta_{j,t+1} \right) - \eta_t \right) \\ \\ & = & \beta \left(\delta_{1,t+1} - \ln S_{1,t+1} - \eta_t \right) \end{array}$$

- Intuition:
 - replace expected utility from optimal choice next period, by utility of arbitrary terminal action
 - correct for probability that this will not be the optimal action

Market share and estimating equation

Market share of alternative j in month t

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

Invert to regression equation

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

Substitute expressions for mean utilities

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

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



Estimation and identification

Two sources of endogeneity: prices and future market share

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

Moment conditions

$$E(z_{j,t}e_{j,t})=0$$
 with $\theta=(\alpha,\beta,\gamma)$

- Instruments in z_{j,t}
 - product characteristics $x_{j,t}$
 - ullet price of Chinese PV modules to identify lpha
 - ullet GCC subsidies to identify eta

Second stage: use approximation of optimal instruments



Accounting for local market heterogeneity

- 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

ullet Estimation of Λ by adding micro-moments to GMM estimator



Summary statistics: adoption and country level variables

Variable	Notation	Mean	Std. Dev.	Obs.
Adoptions				
Country level	$q_{j,t}$	901.1	1309.58	220
Local level	$q_{m,j,t}$	0.10	0.41	2,020,040
Price variable (in 10 ³ EUR)				
Investment cost	$p_{j,t}^{GROSS}$	20.70	10.85	220
Monthly GCC subsidies	$p_{i,t}^{GCC}$	0.14	0.08	220
Monthly electricity bill savings	$p_{i,t}^{EL}$	0.09	0.04	220
Tax cut year 1	$taxcut_{i,t+12}$	2.63	1.62	220
Tax cut year 2	$taxcut_{i,t+24}$	1.83	1.57	220
Tax cut year 3	$taxcut_{j,t+36}$	1.20	1.50	220
Tax cut year 4	$taxcut_{j,t+48}$	0.55	1.11	220
Excluded instruments				
Module price (10 ³ EUR)	$p_{i t}^{MOD}$	7.81	5.01	220
Oil price (EUR / barrel)	p_t^{OIL}	68.37	12.10	44

Summary statistics: local market variables

Variable	Notation	Mean	Std. Dev.	Obs.
Local market variables $(N_m \text{ and } D_m)$				
Households	N_m	295.26	320.88	9,182
Pop. density $(10^4 \text{ inhab } / \text{ m}^2)$		0.16	0.24	9,182
Average house size		5.93	0.64	9,182
Average household size		2.47	0.34	9,182
Average house age (decades)		5.19	1.49	9,182
Median income (10 ⁴ EUR)		2.40	0.36	9,182
% home owners		0.77	0.17	9,182
% higher education		0.26	0.11	9,182
% foreign		0.06	0.09	9,182

Parameter estimates: country level

	(1)	(2)	(3)
	Static	Dynamic	+ 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

Note: standard errors clustered within 44 time periods. For the micro moments we additionally cluster across time periods within each of the local markets. Instruments are approximations of optimal instruments (Chamberlain, 1987). Standard errors of r obtained via delta method. **** p<0.01, *** p<0.05, * p<0.1

Parameter estimates: local market variables

	(3)	
	+ micro-moments	
	x capacity	x price
Pop. density $(10^4 \text{ inhab } / \text{ m}^2)$	-0.689***	
	(0.029)	
Average house size	0.057***	
	(0.009)	
Average household size	0.124***	
	(0.016)	
Average house age (decades)	0.011***	
	(0.002)	
Median income (10 ⁴ EUR)	-0.066***	0.049***
,	(0.030)	(0.007)
% home owners	-0.075* [*] *	,
	(0.038)	
% higher education	-0.128* [*] *	
_	(0.041)	
% foreign	0.383***	
-	(0.040)	

Parameter estimates: summary

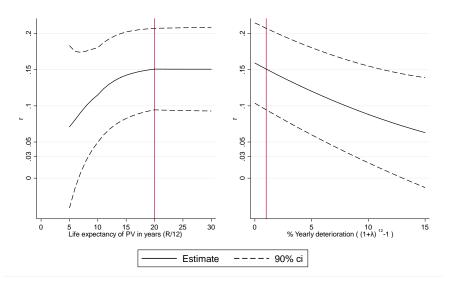
• Implicit annual interest rate of about 15% (with standard error of 3%)

 Model with local market variables: robust conclusions + additional findings, e.g.

• High incomes: smaller capacities, less price sensitive

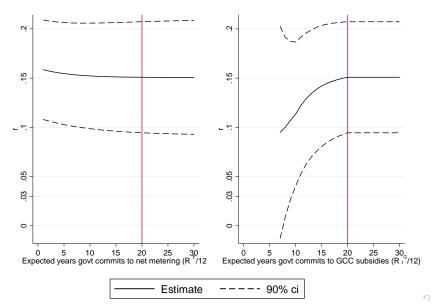
Larger households and house size: larger capacities

Sensitivity analysis: durability of the PV technology

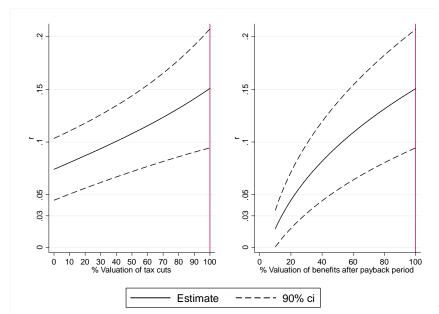


Note: vertical line indicates assumption used in the baseline model

Sensitivity analysis: consumer expectations



Sensitivity analysis: perceived tax cuts and payback period



Sensitivity analysis: summary

- Durability of PV technology Implicit interest rate only equal to market interest rate under implausible assumptions
 - Lifetime of PV less than 5 years
 - Annual deterioration at least 15%
- Consumer expectations
 - Beliefs in government's commitment to net metering unimportant for estimate of interest rate
 - Distrust in government's commitment to GCCs can partly explain high interest rate
- Perceived tax cuts and payback period
 - May only partly be driven by undervaluation of tax cuts
 - Miscalculations after payback period might explain high interest rate

Budgetary and distributional implications

- Investment subsidy instead of GCC subsidy
- $oldsymbol{eta}$ tells us exactly what investment subsidy makes households indifferent
- If government can borrow at real interest rate of 3%, it could have saved 51% or \leqslant 1.92 billion
- This is more than 700€ per household (while "only" 8.3% actually adopted)
- Results hold regardless of explanation behind undervaluation future benefits

Conclusion

- We proposed
 - Simple estimating equation with aggregate data for dynamic discrete choice models with a terminal choice
 - A strategy to identify the discount factor in investment decisions
 - Computionally tractable approach to account for local market heterogeneity
- We obtain the following findings regarding subsidies and PV adoption
 - Households undervalue future benefits from production subsidies
 - Same adoption rates could have been achieved in by providing larger upfront investment subsidies, this would have been 50% cheaper

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Estimation with micro data I

• Conditional value function for $j \neq 0$:

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

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

• Conditional value function for j = 0:

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

$$= \beta (v_{i,1,t+1} - \ln s_{m,1,t+1} - \eta_t)$$

Estimation with micro data II

Choice probabilities in market m

$$\begin{split} s_{m,j,t} &= \frac{\exp(v_{i,j,t} - v_{i,0,t})}{1 + \sum_{j'=1}^{J} \exp(v_{i,j',t} - v_{i,0,t})} \\ &= \frac{\exp(\widetilde{\delta}_{j,t} + \widetilde{w}_{j,t} \lambda_m + \beta \ln \hat{s}_{m,1,t+1})}{1 + \sum_{j'=1}^{J} \exp(\widetilde{\delta}_{j',t} + \widetilde{w}_{j',t} \lambda_m + \beta \ln \hat{s}_{m,1,t+1})} \end{split}$$

where $\widetilde{\delta}_{j,t} \equiv \delta_{j,t} - \beta(\delta_{1,t+1} - \eta_t)$ and $\widetilde{w}_{j,t} \equiv w_{j,t} - \beta w_{1,t+1}$

- 2-stage procedure
 - ullet ML to obtain individual parameters and fixed effects $\begin{cases} \widetilde{\delta}_{j,t} \colon$

$$\max_{\widetilde{\delta},\Lambda} \ln L(\widetilde{\delta},\Lambda) = \sum_{m,j,t} q_{m,j,t} \ln s_{m,j,t}(\widetilde{\delta},\Lambda),$$

• IV regression to obtain α and γ :

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

using moment conditions $E(z_{i,t}e_{i,t}) = 0$

Estimation with micro data III

Simultaneous GMM with moments

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

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

$$\begin{array}{lcl} \frac{\partial \ln L(\widetilde{\delta},\Lambda)}{\partial \widetilde{\delta}_{j,t}} & = & \sum_{m} N_{m,t} \left(\frac{q_{m,j,t}}{N_{m,t}} - s_{m,j,t}(\widetilde{\delta},\Lambda) \right) \\ \\ \frac{\partial \ln L(\widetilde{\delta},\Lambda)}{\partial \lambda^h} & = & \sum_{t} \sum_{m} N_{m,t} \sum_{j} \left(\frac{q_{m,j,t}}{N_{m,t}} - s_{m,j,t}(\widetilde{\delta},\Lambda) \right) w_{m,j,t} D_m^h \end{array}$$

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Sensitivity analysis: allowing for heterogeneity

