Social Effects in the Diffusion of Solar PV Technology in the UK

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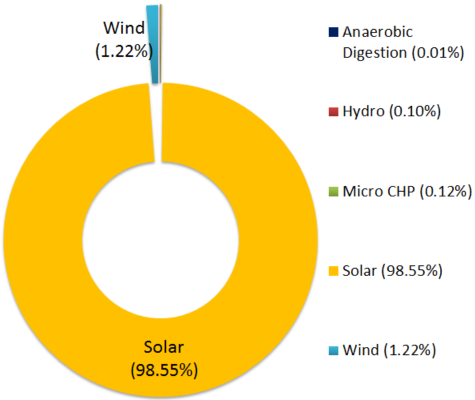
Overview

Financial and Non-financial Barriers and Drivers

- So far, feed-in-tariffs (FITs) are major instrument to promote micro-generation technology adoption
    - FITs deliver (threefold) financial benefits for adopters
    - re-distribution of income from non-adopters to adopters
      $\rightarrow$ reverse income tax if adopters mainly high-income
- But financial incentives are not enough for *sustained* growth of micro-generation technologies
- Non-financial factors should be considered as well:
    - non-financial barriers (2015 Microgeneration Strategy)
    - non-financial drivers (scarce literature)

Focus on Solar PV Technology

Solar PV technology dominates the market for micro-generation technologies in the UK:



98.55% of all micro-generation installations are solar PV.
Source: Ofgem, 2013.

Social Effects in Solar PV Adoption

- Limited data availability often often hampers the identification of the precise nature of social effects
  - social preferences, word-of-mouth, observational learning...
- However, for solar PV technology an argument for observational learning can be made:
  - visible for passers-by
  - social bonding not necessary
  - *spatial* definition of reference groups justified
- If observational learning leads to spatial clusters, targeted interventions, such as well-visible community installations, could promote diffusion

Research Question

Is the adoption rate of solar PV technology affected by social effects as measured by the installed base in the neighbourhood?

1. The Installed Base:
    - measure for social effects from spatially close households
    - cumulative number of solar PV installations within a neighbourhood z by the end of month t: $b_{zt} = \sum_{\tau=1}^{t} Y_{z\tau}$
        - Y_{zt}: number of new adoptions in neighbourhood z in month t
2. The Neighbourhood:
    - spatially defined reference group (e.g. postcode district in England & Wales)

Literature - Overview

1. **Social Effects in Technology Adoption:**
   Rogers' (1962); Rasul (2002); Narayanan and Nair (2011)
   - social effects such as observational learning in technology adoption are consistent with classical diffusion models
   - Rogers' theory of 'Diffusion of Innovations'(1962): observability as a major influential factor for adoption decision
2. **Solar PV Technology Adoption:**
   Beise (2004); Wüstenhagen (2006); Zhang et al. (2011)
   - examines effect of subsidy policies & cost reductions and consistently finds significant positive impact
3. **Social Effects in Solar PV Technology Adoption:**
   Bollinger and Gillingham (2012); Weber and Rode (2012)
   - both use the installed base as a measure for social spillovers and find positive significant effects

Model

Consider the concise & general linear dynamic panel model:

$$y_{zt} = \alpha_t + \beta \cdot b_{zt-3} + \underbrace{\alpha_{zq} + \epsilon_{zt}}_{u_{ztq}}$$

- 3 dimensions: neighbourhood (nhd) z, month t, quarter q
- $y_{zt} = \frac{Y_{zt}}{n_{zt}}$: adoption rate of solar PV panels in z in t
  Y_{zt}: number of *new* installations in z in t
  n_{zt}: number of owner-occupied households in z in t
- $b_{zt-3} = \sum_{\tau=1}^{t-3} Y_{z\tau} \forall z, t$: third lag of the installed base
  captures technology-specific time lag between *decision* to adopt a solar PV panel and *completion* of the installation
- 3 distinct unobservables: α_t, α_{zq}, ϵ_{zt}

3 Distinct Unobservables

3 distinct unobservables to focus on effect of interest:

$$\alpha_t, \alpha_{zq}, \epsilon_{zt}$$

- α_t: month effects
  - capture month specific effects such as policy announcements
  - explicitly included as months dummies
- α_{zq}: time-varying fixed-effects
  - control for all other factors affecting y_{zt}
    - i.e. for time-constant & time-varying factors that affect y_{zt}
    - especially for factors that are correlated with b_{zt-3} *and* y_{zt}
  - included in u_{ztq}
- ϵ_{zt}: an *i.i.d.* unobserved error term capturing random neighbourhood and month specific effects and $E(b_{zt-3}\epsilon_{zt}) = 0$

First Difference Estimator if $I = 3$

- Pooled OLS: biased & inconsistent estimates (e.g.OVB)
- Standard mean-differencing and first-differencing on month level does not fully eliminate the effects α_{qz}. *Why?*

- **Preferred strategy:** to fully eliminate the α_{qz} drop first month of each quarter and work with first difference equation:

$$\Delta y_{zt} = \Delta\alpha_t + \beta\Delta b_{zt-3} + \Delta\epsilon_{zt}$$

Proposition (see reasoning of proof in Appendix)

If $\nu < I - 1$, the proposed first differencing strategy yields consistent estimates of the installed base effect β.

In the application the required autocorrelation tests yield sufficient results for consistency. I.e. AR(2) in ϵ can be rejected.

Data

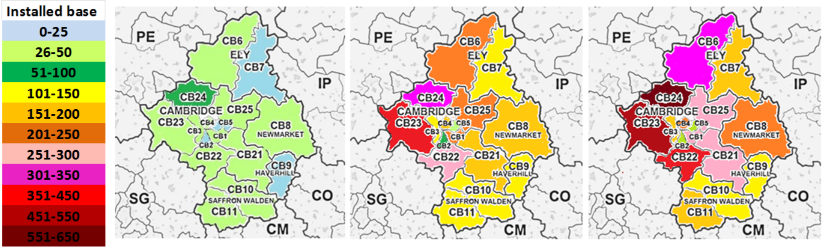
Central FIT Register, April 2010 - March 2013 (DECC, 2013):

- Individual identifier, location (to LSOA), completion date, installed capacity
- For the analysis only districts with at least 1 domestic solar PV system considered (i.e. 98.7% of all postcode districts)
  - 30 postcode districts without domestic solar PV: city centres (e.g. in London, Manchester)
- Cleaned data set: 332,216 domestic solar PV installations in 2,239 postcode districts in England & Wales

Census 2011 Neighbourhood Statistics (ONS, 2013):

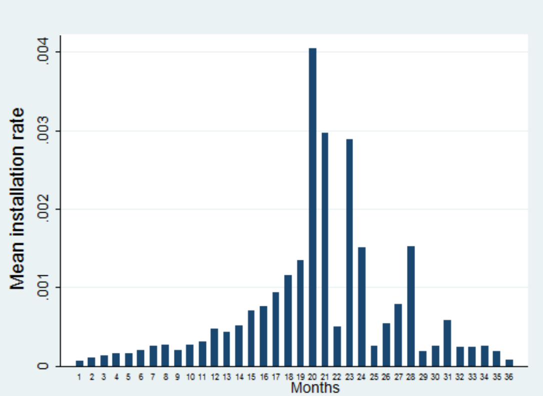
- One cross-section only (March 2011)
- Data for 2,269 postcode districts in England & Wales
- Characteristics such as tenure, deprivation level, education, social class are used to evaluate differences of social effects

Installed Base in Postcode District CB



Installed base in the CB postcode districts (March 2011, 2012, 2013).
Clustering within neighbourhoods is visible.
Source: Ofgem, ONS, own calculations.

Data - Time Effects in Adoption



The average adoption rate (installations per owner-occupied household in a postcode district) increased from 0.00007 to 0.0002 and peaked in November 2011 with 0.004. *Source: Ofgem, ONS, own calculations.*

Main Results

Table : Estimates of the installed base effect on the adoption rate within a postcode district. The first difference estimate FD_{cl} is the preferred estimate. The results are consistent with social effects within neighbourhoods.

Variable	$POLS_{cl}$	WG_{cl}	FD_{cl}
Installed Base (L.3)	1.93e-06***	6.59e-06***	$\boxed{7.48\text{e-}06^{***}}$
	(1.20e-07)	(2.44e-06)	(2.66e-06)
Observations	73,887	73,887	49,258
R-squared	0.145	0.080	0.075

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Main Results

The results are consistent with theory and suggest small, but positive and significant social effects:

1. One more solar PV panel in a postcode district increases the adoption rate y_{zt} three months later by $7.48e^{-06}$
2. At the average installation rate of 0.0007, this is equivalent to a 1% increase in the adoption rate
3. At the average installed base (68.2) and the average installation rate (0.0007), the installed base elasticity is 0.71
4. At the average number of 6,629 owner-occupied households it would require 20 panels for social effects *alone* to cause a new installation in the neighbourhood three months later

The adoption rate of solar PV technology is affected by social effects as measured by the installed base!

Robustness Checks

1. **Allowing for Heterogeneous Social Effects** (Appendix):
   - social effects decrease with size of installed base & over time
   - but they are stronger in months of announcements of FIT cuts
   - social effects vary across neighbourhood characteristics
2. **Testing Different Lags:**
   - lag 2 is positive & significant, lag 4 is negative & insignificant
   - social effects spread in a rather narrow time window
3. **Redefining the Neighbourhood** (Appendix):
   - social effects on local authority level are less pronounced:
4. **The Model in Terms of Installed Capacity:**
   - results are consistent with main specification results

Limitations & Suggestions for Further Research

1. Social effects are assumed to spread within defined neighbourhoods, only
   - Spatial econometric methods could allow for more diverse spillovers, e.g. across postcode district borders
2. Findings are consistent with social effects and observational learning, but the analysis is done on the neighbourhood level
   - Use of household level data could improve the analysis
3. Inertia in the decision process might lead to a partial adjustment process that could confound the estimation
   - Compare to technology for which observability is not crucial

Conclusion

1. First econometric analysis of solar PV diffusion in the UK
2. Empirical evidence for social effects in micro-generation technology adoption
3. Results are consistent with significant positive social effects
4. Social effects vary over time & are more pronounced on the more localized level
5. More affluent neighbourhoods & economically active neighbourhoods show weaker social effects

Implication of Results

Targeted interventions, such as well-visible community installations, could promote diffusion & mitigate re-distributional effects of FITs.

Thank you.

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APPENDIX

APPENDIX - Endogeneity Issues

1. Self-Selection into Neighbourhoods
   - Energy conscious households might select into 'green' neighbourhoods
   - This unobserved preference might also make them behave similarly regarding the adoption of solar PV technology
   - Implies non-randomness on neighbourhood level
2. Correlated Unobservable Neighbourhood Characteristics
   - Solar PV supplier activities or local advertising campaigns can result in spatial clustering of adoption behaviour

$\Rightarrow$ Spurious correlation of installed base with installation rate

3. Manski's (1993) 'reflection problem' is *not* a problem .
   - The reflection problem (Manski, 1993) refers to the *simultaneous* determination of individual and group behaviour.
   - In case of solar PV technology, this simultaneity is *not* a problem: Technology-specific time lag between *decision* to adopt and installation.

APPENDIX - Time-Varying Fixed Effects α_{qz}

- Why specify the fixed effects on the neighbourhood-*quarter*?
  - b_{zt-3} is defined on neighbourhood-*month* level
  - α_{zt}, time-varying fixed-effects on the neighbourhood-*month* level would be perfectly collinear with b_{zt-3}
  - α_{qz} can be included
  - Changes of nhd statistics within a quarter: assumed negligible

APPENDIX - Time Constant Fixed Effects

Table : Results withtime-constant unobservables. As before, POLS and the within-group/fixed-effects estimator seem downwards biased. Bias of WG estimator is more pronounced due to correlation of mean differenced error with mean differenced installed base exhibited in this model.

Variable	POLS	WG	FD
Installed Base (L.3)	1.93e-06***	-1.43e-06***	3.96e-06*
	(1.20e-07)	(1.24e-07)	(2.35e-06)
Observations	73,887	73,887	71,648
R-squared	0.145	0.154	0.087
Number of zips		2,239	

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

APPENDIX - Within-Group Estimator if $l = 3$

- Standard mean-differencing on the month level does not fully eliminate neighbourhood-quarter effects. *Why?*
- For full elimination first differencing must be performed on neighbourhood-quarter level. This yields:

$$(y_{zt} - \overline{y}_{zq}) = (\alpha_t - \overline{\alpha}_q) + \beta \cdot (b_{zt-3} - \overline{b}_{z3q}) + (\epsilon_{zt} - \overline{\epsilon}_{zq})$$

- Deriving the within-group estimator, substituting in the equation for y_{zt} and rearranging yields by ST, CMT, WLLN:

$$\lim_{N \to \infty} (\hat{\beta}_{WG} - \beta) = \frac{E[\widetilde{(b_{zt-3} - \overline{b}_{z3q})}(\epsilon_{zt} - \overline{\epsilon}_{zq})]}{E[\widetilde{(b_{zt-3} - \overline{b}_{z3q})}^2]} = \frac{A}{B} = 0$$

- $\widetilde{(b_{zt-3} - \overline{b}_{z3q})}$: residual from a regression of the mean-differenced installed base on the mean-differenced time-dummies.
- Consistency heavily depends on lag length (see Appendix)!

APPENDIX - Within-Group Estimator

1. $\lim_{N \to \infty} E[b_{zt-3}\epsilon_{zt}] = 0$:
   b_{zt-3} is by construction correlated with all previous ϵ, but uncorrelated with all future errors, as ϵ_{zt} is $i.i.d$ by assumption.
2. $\lim_{N \to \infty} E[\overline{b}_{z3q}\epsilon_{zt}] = 0$:
   Since lag length is $l = 3$, in all 3 month of q the observations entering $\overline{b}_{z3q}$ lie in quarter $q - 1$, while ϵ_{zt} lies in q.
3. $\lim_{N \to \infty} E[b_{zt-3}\overline{\epsilon}_{zq}] = 0$:
   In all 3 months of any q, b_{zt-3} lies in $q - 1$ while $\overline{\epsilon}_{zq}$ is calculated based on errors in q.
4. $\lim_{N \to \infty} E[\overline{b}_{z3q}\overline{\epsilon}_{zq}] = 0$:
   In all 3 month of any q, $\overline{b}_{z3q}$ is calculated based on observations in $q - 1$, while $\overline{\epsilon}_{zq}$ is based on ϵ_{zt} within q.

Overall, if there is no autocorrelation across quarters, the mean differenced lagged installed base, $(b_{zt-3} - \overline{b}_{z3q})$ is uncorrelated with the mean differenced error $(\epsilon_{zt} - \overline{\epsilon}_{zq})$ and A converges to zero.

APPENDIX - Within-Group Estimator - Consistency

- It turns out to be crucial, that all installed base observations entering the mean lagged installed base $\overline{b}_{z3q}$ lie in $q-1$. These are by assumption uncorrelated with all ϵ_{zt} in q.
- Consistency breaks down when including the first or second lag of the installed base. This is due to a correlation of the mean differenced installed base with the mean differenced error.

Proposition

For lags of the installed base that exceed the length of a quarter, i.e. lags larger than 2, mean-differencing on the neighbourhood-quarter level eliminates the neighbourhood-quarter effects and allows to consistently estimate the installed base effect by POLS on the mean-differenced equation.

APPENDIX - First Difference Estimator - Consistency

With

$$\Delta b_{t-3} = \Delta \sum_{t=1}^{t-3} Y_{zt} = (\sum_{t=1}^{t-3} Y_{zt} - \sum_{t=1}^{t-4} Y_{zt}) = Y_{zt-3}$$

The exogeneity condition can be written as:

$$E(Y_{zt-3}\Delta\epsilon_{zt}) = E(Y_{zt-3}\epsilon_{zt}) - E(Y_{zt-3}\epsilon_{zt-1}) = 0$$

By construction of the main equation, Y_{zt-3}, hence ϵ_{zt-3}, is correlated with ϵ_{zt-3} and all previous errors:

$$E(\epsilon_{zt-3}\epsilon_{zt-\tau}) \neq 0 \; \forall \tau \geq 3$$

However, if ϵ_{zt-3} is uncorrelated with ϵ_{zt-1} and all following errors, i.e. if the order of autocorrelation $\nu < 2$, POLS on the differenced equation yields a consistent estimate of the installed base effect.

Proposition (see reasoning of proof below)

If $\nu < l - 1$, the proposed first differencing strategy yields consistent estimates of the installed base effect β.

APPENDIX - First Difference Estimator - Consistency

Reasoning of Proof

Consider lag l of the installed base. The following exogeneity assumption is necessary for consistent estimation:

$$E(\Delta b_{t-l} \Delta \epsilon_{zt}) = 0$$

Plugging in the installed base, this yields:

$$E(Y_{zt-l} \Delta \epsilon_{zt}) = E(Y_{zt-l} \epsilon_{zt}) - E(Y_{zt-l} \epsilon_{zt-1}) = 0$$

This effectively requires: $E(\epsilon_{zt-l} \epsilon_{zt-1}) = 0$ i.e. the order of autocorrelation ν of ϵ must be smaller than $l-1$: $\nu < l-1$.

APPENDIX - The Installed Base over time

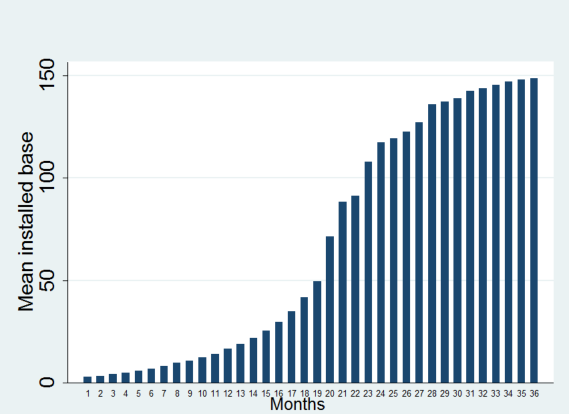
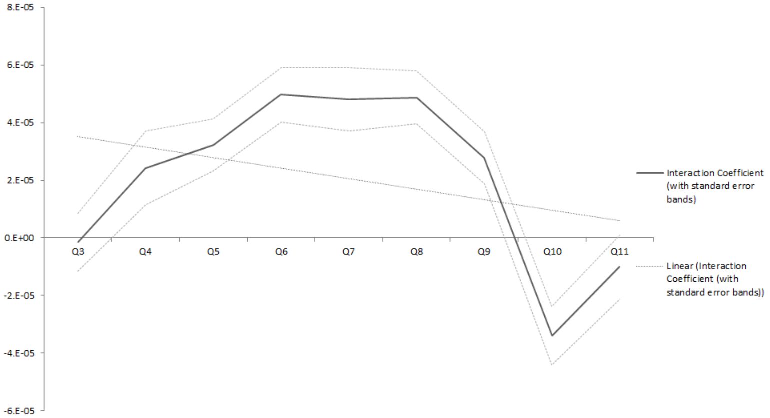


Figure : The average installed base within a postcode districts increased from 2.3 solar PV systems to 148.4 by the end of March 2013. $\frac{1}{2,239}\sum_{z}^{2,239} b_{zt} \forall t = 1 \cdots 36$. *Source: Ofgem, own calculations.*

APPENDIX - Time-Varying Installed Base Effect

While information spillovers initially increase, they decrease and turn negative towards the end of the considered twelve quarters. This suggests that during times of negative policy announcements, spillovers turned negative as well.



APPENDIX - Quadratic Installed Base Effect

Variable	$POLS_{cl}$	FD_{cl}
Installed Base (L.3)	6.78e-06***	1.45e-05***
	(3.34e-07)	(3.88e-06)
Installed Base Squared (L.3)	-5.56e-09***	-1.17e-08***
	(6.73e-10)	(3.10e-09)
Observations	73,887	49,258
R-squared	0.148	0.075

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

APPENDIX - Different Lags of the Installed Base

Social effects are effective within 2 to 3 months

Table : First Difference Estimates for Different Lags of the Installed Base. Lag 2 and 3 have a significant positive impact on the adoption rate. The coefficient of lag 4 is negative, but not significant. This might suggest that social effects are effective in a narrow time window.

Variable	$FD_{cl}L.2$	$FD_{cl}L.3$	$FD_{cl}L.4$
Installed Base	3.81e-06**	7.48e-06***	-2.15e-06
	(1.78e-06)	(2.66e-06)	(1.69e-06)
Observations	49,258	49,258	47,019
R-squared	0.074	0.075	0.074

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

APPENDIX - Social Effects in Local Authorities

Table : Installed base effect in local authorities. The results suggest that social effects, as measured by the installed base, are stronger on a more local level than in broader defined neighbourhoods like local authorities.

	$POLS_{cl}$	WG_{cl}	FD_{cl}
Installed Base (L.3)	3.14e-07***	1.60e-06*	$\boxed{\text{1.77e-06*}}$
	(5.71e-08)	(8.24e-07)	(9.21e-07)
Observations	11,451	11,451	7,634
R-squared	0.396	0.341	0.346

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX - Do Social Effects Vary Across Neighbourhoods?

(How) do social effects vary across neighbourhoods?

- Dummy variables, D_z, indicate whether the postcode district characteristic lies above the 60th percentile.

$$y_{zt} = \alpha_t + \beta_1 \cdot b_{zt-3} + \beta_2 \cdot D_z + \beta_3 \cdot (D_z \cdot b_{zt-3}) + \alpha_{zq} + \epsilon_{zt}$$

- First differencing this equation as above, results in:

$$\Delta Y_{zt} = \Delta\alpha_t + \beta_1 \cdot \Delta b_{zt-3} + \beta_3 \cdot \Delta(D_z \cdot b_{zt-3}) + \Delta\epsilon_{zt}$$

- POLS on this differenced equation.

APPENDIX - Heterogenous Social Effects Across Neighbourhood Characteristics

Social effects vary across neighbourhood characteristics

- A high share of unshared houses decreases social effects
  - Might suggest higher likelihood to interact with neighbours in immediate living environment (e.g. in attached houses)
- Relatively affluent neighbourhoods show less pronounced social effects
  - Might suggest that those households are early adopters and hence learning from others is less important
- In neighbourhoods with a high ratio of economically active people, social effects are relatively low
  - Can from the fact that those people spend less time in their neighbourhood
- See Appendix for model and estimation strategy.