

Subsidy elasticity and peer effects in the diffusion of residential photovoltaic systems

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Motivations

Motivation: Economic (economic costs and benefits) and non-economic (peer pressure and social learning) determinants of low-carbon technology diffusion.

Why PVs? visible technology - geographical networks as proxy for the transmission of information and peer pressure rather than actual communication networks.

Previous literature:

- Graziano & Gillingham (2015): spatial and regression analysis of diffusion of residential PV in Connecticut.
- Richter (2013): diffusion of residential PV in UK but effects constrained within Post Code District boundaries.
- California: Bollinger & Gillingham (2012); Germany: Müller & Rode (2013), Rode & Weber (2016); Switzerland: Baranzini et al. (2017).
- Spatial analysis of residential PVs in the UK (mainly cross-section): Balta-Ozkan et al. (2015); Westacott & Candelise (2016).

Theoretical framework and research questions

Peer Effects and Tariff Elasticity: Theoretical Framework

Single agent problem

Agents as profit-maximising 'prosumers':

$$\max_{y_k} \Pi(y_k) = R(y_k) - C(y_k) = p * y_k - c * y_k \quad (1)$$

y_k : whether to adopt or not (i.e. whether to 'enter the market') / how much capacity to install

$\Pi(y_k)$: profits from installation

$R(y_k)$: revenues that can be obtained from the production of electricity

$C(y_k)$: cost of installation; agent is cost-taker

p subsidy (FIT tariff rate per kWh); agent is subsidy-taker

$$\text{subsidy elasticity} = \frac{\% \text{ change in installed capacity}}{\% \text{ change in subsidy}} = \frac{\Delta y^*}{\Delta p} \quad (2)$$

Peer Effects and Tariff Elasticity: Research Question

$$\text{subsidy elasticity} = \frac{\% \text{ change in installed capacity}}{\% \text{ change in subsidy}} = \frac{\Delta y(p, N)}{\Delta p} \quad (3)$$

- [H_{A1}] Subsidy elasticity is heterogeneous depending on the installations in the neighbourhood N (H_0 : no interaction between the two effects).
- [a] Peer effects in the form of **information sharing**: reduce uncertainties and imperfect information
⇒ **higher subsidy elasticity** in areas with more installations.
 - [b] Peer effects in the form of **herding and imitative behaviour**: individuals' utility by imitating neighbours (or equiv.: reduce cognitive efforts and information search cost by following others')
⇒ **lower subsidy elasticity** in areas with more installations.

Evolution of peer effects: Theoretical Framework

Demand aggregation problem - two models of adoption patterns in the presence of peer effects:

a. **Bass-style diffusion model with imitation at the local level**

Adopters are classified into innovators, who decide autonomously, and imitators, who also take into consideration the actions of their peers before making a decision. Innovators are the first to adopt, then the imitators begin to catch up, making the spillover effect stronger as time passes.

b. **Epidemic model of information diffusion through social learning**

The lower is the level of private information, the more the agents rely on the actions of peers, as a proxy. As information spreads through the network of peers and becomes less localized, the actions of others become less important, attenuating the spillover effect over time. The same would result as localized norms become more widely spread.

Evolution of peer effects: Research Questions

- [H_{A2}] PVs installations are clustered in space (H_0 : PVs occur at random).
- [H_{A3}] Peer effects are not stable over time (H_0 : constant peer effects over time).
 - [a] Peer effects increases over time (as predicted by the Bass-style diffusion model with localised imitation).
 - [b] Peer effects decreases over time (as predicted by the social learning model).

Policy Background

Feed-In Tariff for PV

UK **Feed-In Tariff** (FIT) scheme: started April 2010.

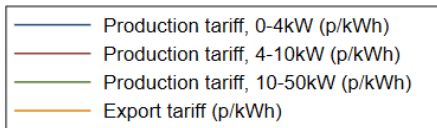
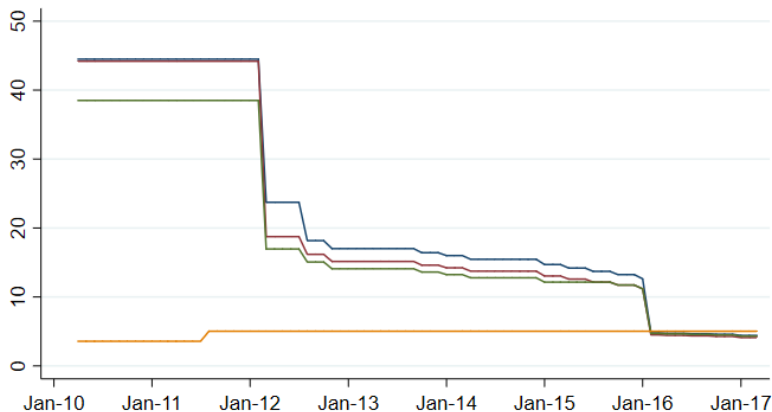
Production tariff on the total amount of generated electricity + export tariff on 50% (+ indirect benefits through savings in the electricity bills).

Tariff rates are assigned according to the date of the installation, depending on the technology and the installed capacity.

The rates are then paid for 20 years (25 for solar installations in the early years of the scheme), and are progressively adjusted for the inflation, according to the changes in the Retail Price Index over the previous year.

The budget for the scheme comes from the general electricity bills of all the energy suppliers' customers - as it is the case for other energy-related schemes in the country.

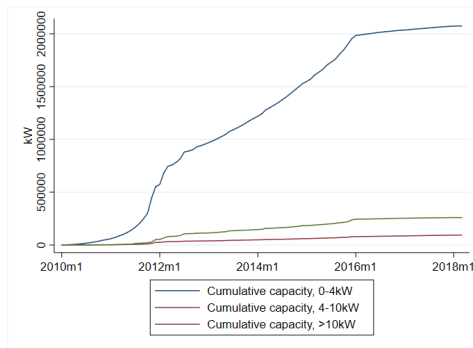
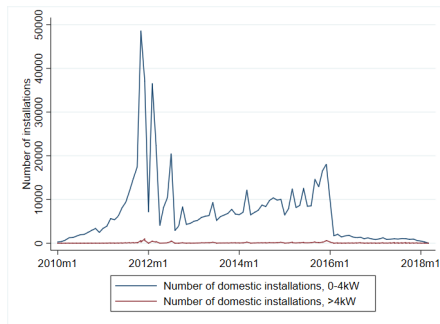
Feed-In Tariff for PV



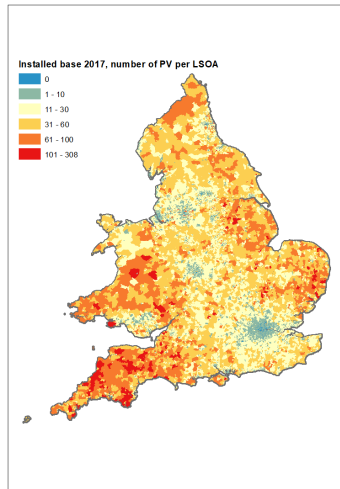
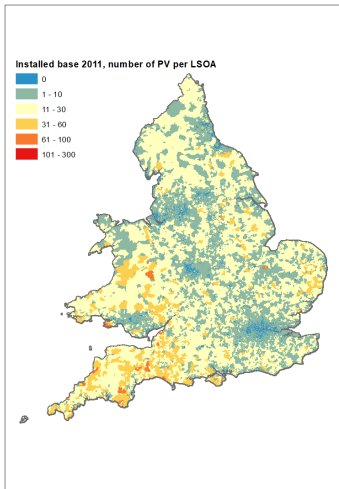
Installations' trends

Domestic installations < 4kW majority of small-scale installations, both in terms of number and cumulative capacity.

Major policy reforms in 2012 and 2016.



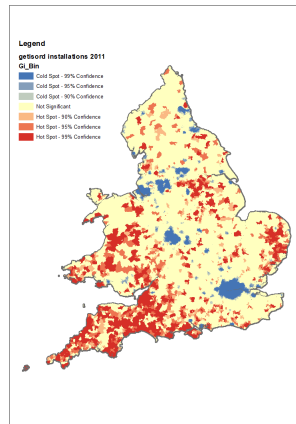
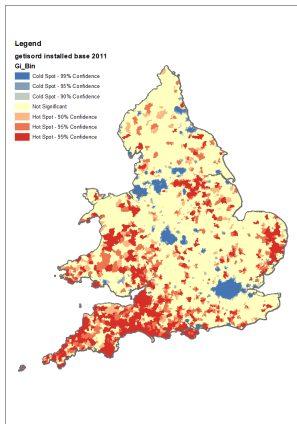
Installations' distribution



Cluster analysis

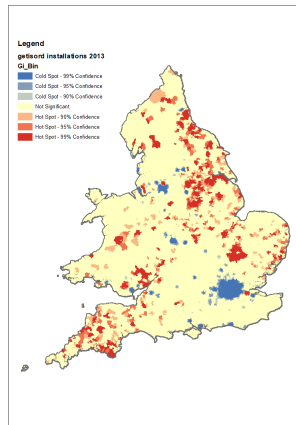
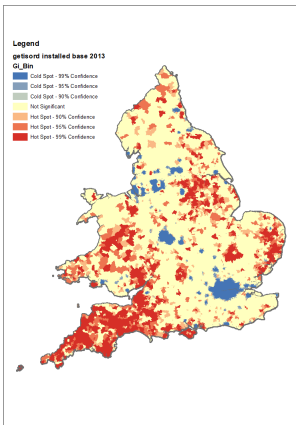
Optimised Getis-Ord G_i^*

Hot-spots (Cold-spots): areas with high (low) number of installations, surrounded by areas with high (low) number of installations, where the hypothesis of random distribution of installations is rejected with statistical significance.



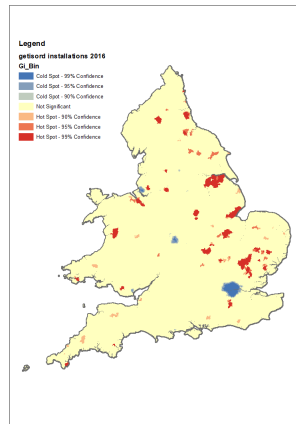
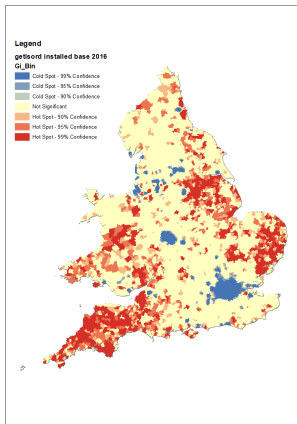
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Regression analysis

Data

PV data and Census covariates

Panel Data: **monthly** data (2010-2015) for **LSOA** areas.

Minimum 1,000 residents, average 1,500 (~650 households).

Size of resident population, geographical proximity and information on the prevalent type of dwelling, tenure, etc. are used to ensure a compact shape and socio-demographic homogeneity.

Installations data: type of technology, installed capacity, the LSOA and the application/commissioned date from Ofgem database of Feed-In Tariff recipients.

Covariates: from the 2011 Census database

- saturation share (cumulative number of installed PV in the LSOA / number of owned-houses);
- density (population / surface area);
- number of residents age 40-64;
- number of residents above 65.

Neighbouring PVs

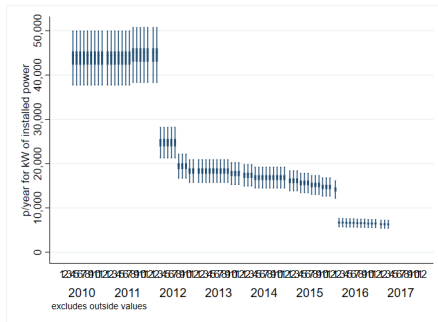
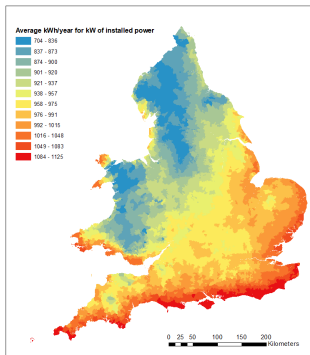
Preferred definition of 'neighbourhood':

- variable-radius buffer: consider all pw-centroids that lie within a circular buffer of the same surface area as the reference LSOA.
 - Pros: larger buffers for areas that are sparse and less densely populated, where residents are more likely to travel further away in their daily routines, and smaller buffers for urban and dense areas.

Other definitions of 'neighbourhood':

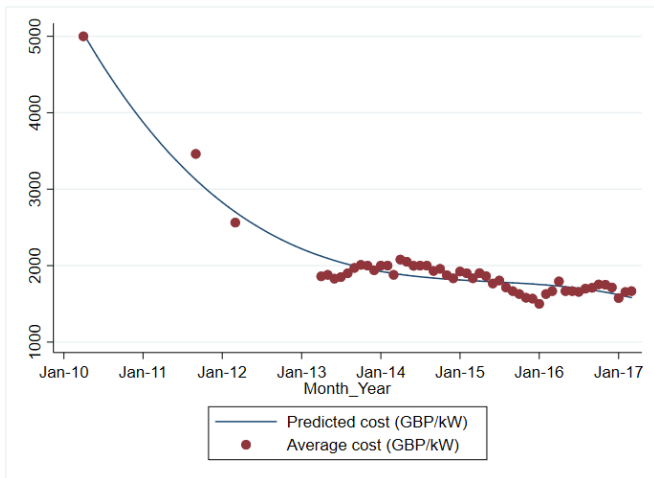
- fixed-radius multi-ring buffers: 0-2km; 2-4km; 4-8km.
- 'expected number' of PVs in the buffer assuming PV uniformly distributed in the LSOA.
- installed base (i.e. within LSOA boundaries).

'Expected' revenues distribution



Photovoltaic Geographic Information System (PV-GIS) data

Cost of PV installations over time



Source: DECC, 2017 "Annual Cost of Small-Scale Solar Technology Summary" and Green Business Watch report, "UK residential solar panel costs and returns: 2010-2017".

Identification and Regression model

Identification challenges:

self-selection, correlated unobservables (Manski, 1993):

simultaneity (Manski, 1993):

LSOA fixed effects in non-linear models -> incidental parameters issue:

Nickell's bias in within-group estimator with lags (Nickell, 1981):

Identification strategy:

quarterly-varying LSOA-specific fixed effects (Richter, 2013).

households can only be affected by peer installations up to the moment they make their choice, but they only start affecting others once their panels are installed, i.e. once they are visible and the household has some experience and information to share - assume lag of three months $s = 3$ (Bollinger & Gillingham, 2012).

use linear models only.

use first-difference estimator dropping the first month, and within-group estimator de-meanded using quarter-LSOA mean (Richter, 2013).

Regression model

$$y_{i,t} = \alpha + \beta N_{i,t-s} + \gamma' X_{i,t} + u_{i,t} \text{ where } u_{i,t} = \eta_{i,q} + \epsilon_{i,t} \quad (4)$$

$y_{i,t}$: new installations in LSOA i at time t

$X_{i,t}$: covariates, including potential revenues from the adoption and costs of the installation

$N_{i,t-s}$: neighbouring installations already completed at the time in which the decision to adopt the new installations was made

$\eta_{i,q}$ LSOA-quarter fixed effect, due to unobservable characteristics of each LSOA, that may change over time (although we assume that changes are slow, i.e. are negligible within each quarter)

$\epsilon_{i,t}$: zero-mean i.i.d component $\epsilon_{i,t}$, such that $E[N_{i,t-3}\epsilon_{i,t}] = 0$.

Estimators

First-Difference:

$$y_{i,t} - y_{i,t-1} = \beta(N_{i,t-3} - N_{i,t-4}) + \gamma'(X_{i,t} - X_{i,t-1}) + (\epsilon_{i,t} - \epsilon_{i,t-1}) \quad (5)$$

where

$$t, t-1 \in q \text{ and } t-3, t-4 \in q-1$$

after taking the first difference the first month of each quarter is dropped, so that $\eta_{i,q}$ cancels out.

Within-Group Estimator (de-meanned using the LSOA-quarter mean):

$$y_{i,t} - \bar{y}_{i,q} = \beta(N_{i,t-3} - \bar{N}_{i,q-1}) + \gamma'(X_{i,t} - \bar{X}_{i,q}) + (\epsilon_{i,t} - \bar{\epsilon}_{i,q}) \quad (6)$$

where

$$t \in q \text{ and } t-3 \in q-1$$

each term is de-meanned using the LSOA-quarter mean, so that $\eta_{i,q}$ cancels out and the peer group only includes installations up to $q-1$, and are not correlated with the error term $\epsilon_{i,t}$.

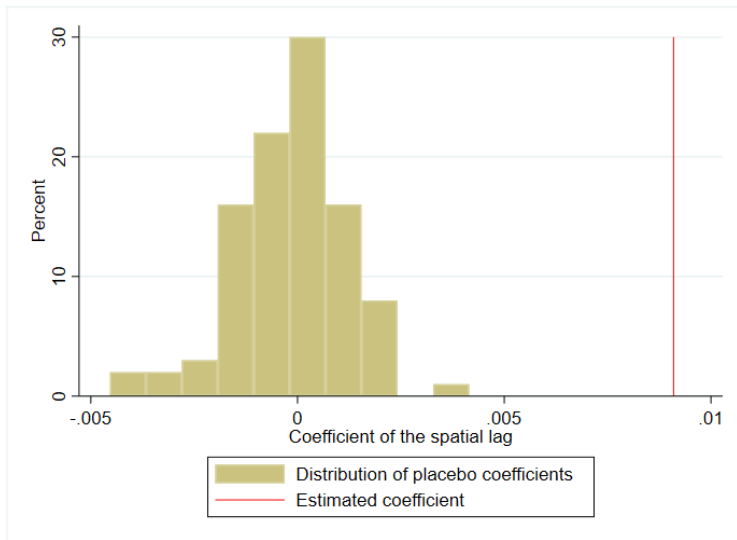
Results

	FD(1)	WG(1)	FD(2)	WG(2)	FD(3)	WG(3)
neighbourpv	-1.225*** (0.021)	-1.103*** (0.015)	0.022*** (0.002)	0.001* (0.001)	0.009*** (0.001)	0.001* (0.001)
sqneighbourpv			-0.000*** (0.000)	-0.000 (0.000)		
neighbXlogrev	0.127*** (0.002)	0.114*** (0.002)				
logpotentialrev	0.719*** (0.021)	0.171*** (0.015)	1.481*** (0.016)	0.780*** (0.012)	1.475*** (0.016)	0.780*** (0.012)
logcost	-2.107*** (0.149)	-3.451*** (0.087)	-3.531*** (0.150)	-4.687*** (0.086)	-3.745*** (0.147)	-4.691*** (0.085)
saturationshare	1.734*** (0.229)	-0.407** (0.160)	2.096*** (0.229)	0.003 (0.160)	2.139*** (0.229)	0.004 (0.160)
density	-0.001** (0.000)	-0.000 (0.000)	-0.001** (0.000)	-0.000 (0.000)	-0.001** (0.000)	-0.000 (0.000)
population4064	0.331** (0.143)	0.477*** (0.084)	0.429*** (0.144)	0.546*** (0.085)	0.421*** (0.144)	0.545*** (0.085)
population65plus	1.587*** (0.189)	0.650*** (0.111)	1.064*** (0.189)	0.288*** (0.111)	1.055*** (0.189)	0.287*** (0.111)
<i>N</i>	722599	1151844	722599	1151844	722599	1151844
<i>r</i> ² _a	0.016	0.010	0.011	0.006	0.011	0.006
<i>F</i>	1500.732	1448.458	1049.223	798.623	1189.789	912.682

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Simulation with randomly re-assigned (first-difference) neighbours:



Other measures of y and N :

- average installed capacity,
- capacity.

	av.kw-FD	av.kw-WG	kw-FD	kw-WG
neighbourpv	0.004*** (0.001)	0.001*** (0.000)	-0.008 (0.007)	-0.000 (0.001)
sqneighbourpv	-0.000*** (0.000)	-0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)
logpotentialrev	5.026*** (0.046)	2.793*** (0.034)	0.250*** (0.028)	0.139*** (0.010)
logcost	-13.803*** (0.411)	-14.917*** (0.234)	-1.378*** (0.329)	-0.758*** (0.077)
N	722599	1151844	64380	280294
r^2_a	0.017	0.009	0.002	0.001
F	1544.185	1237.172	16.033	44.869

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Other definitions of 'neighbourhood':

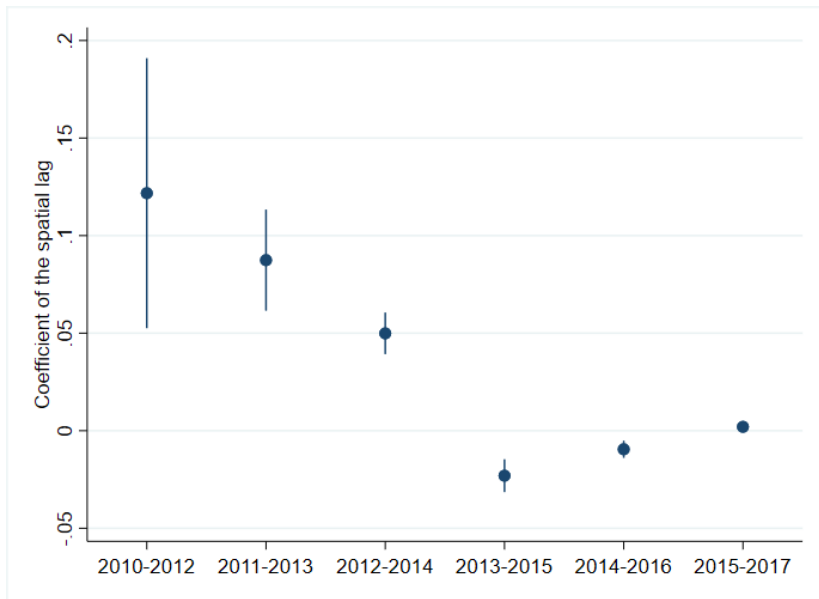
- fixed-radius multi-ring buffers: 0-2km; 2-4km; 4-8km.
- 'expected number' of PVs in the buffer assuming PV uniformly distributed in the LSOA.
- installed base (i.e. within LSOA boundaries).

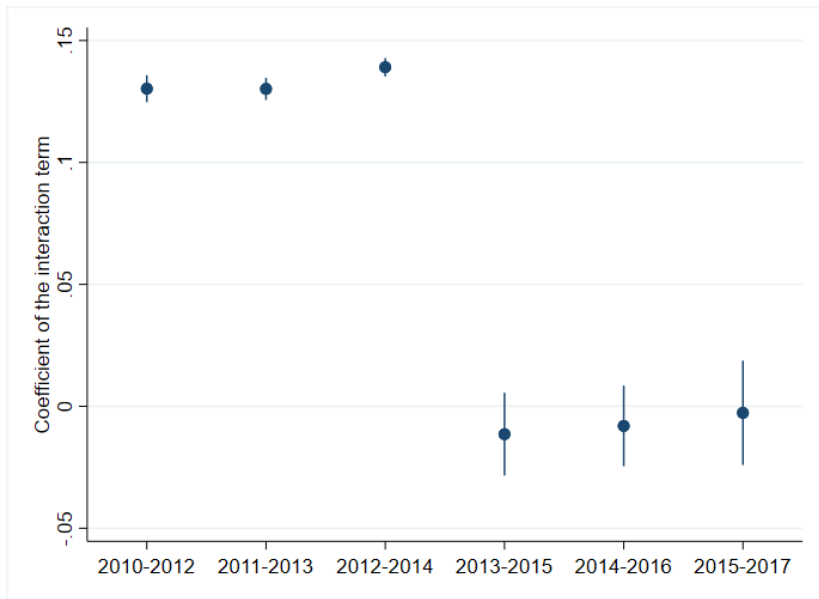
	multirings-FD	multirings-WG	weighted-FD	weighted-WG	installedbase-FD	installedbase-WG
neighbourpv	0.019*** (0.002)	0.000 (0.001)	0.016*** (0.002)	0.001 (0.001)	0.064*** (0.002)	0.049*** (0.001)
neighbpv2ring	0.004*** (0.001)	0.003*** (0.001)				
neighbpv3ring	0.004*** (0.000)	0.001*** (0.000)				
sqneighbourpv	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
sqneighbpv2	-0.000*** (0.000)	-0.000*** (0.000)				
sqneighbpv3	-0.000*** (0.000)	-0.000*** (0.000)				
N	695916	1110243	542935	865089	1299448	2017679
r2_a	0.013	0.006	0.013	0.006	0.009	0.005
F	754.478	552.327	889.366	688.940	1459.482	1187.727

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Evolution of the effects over time





Conclusions and Next steps

Conclusions

Agents have a **positive subsidy elasticity**, as the number of installations decreases in response to cut to the subsidies.

The coefficient of the **interaction term** $\text{subsidy} \# \text{peer installations}$ is **positive**, i.e. peer effects increase the sensitivity to changes in the tariff, consistent with the **information-sharing** framework set up in the paper.

Peer effects are present but **fade out the further away the installations are in both time and space**, and are **decreasing the more nearby installations** there are (although very slowly).

Larger installations have a **stronger effect** and are associated with **larger new installations**.

The effect is not constant over time, but **decreases over the years**, consistent with the **information-sharing** framework set up in the paper.

Next steps

- Use **internal rate of return** instead of revenues and cost separately.
- Include **connectivity, accessibility and other geographic features** in definition of “neighbourhood”.
- **IV model**, e.g. Narayanan & Nair (2013) on electric vehicles.
- Use an **RDD model** exploiting local policies.
- ...

- Theoretical **model** of technology diffusion with localized information sharing and peer pressure.
- **Simulations** under different policies.

→ Policy implications and distributional issues: how to set more efficient and equitable policies.

Thank you!
Questions, feedback, comments?

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Descriptive statistics

	p50	mean	sd	min	max
pvcount	0.00	0.24	1.02	0.00	120.00
capacity	0.00	0.75	2.79	0.00	311.41
avcapacity	3.30	3.16	0.97	0.08	10.00
neighbourpv_variablerad	7	11.13	14.42	0	451
neighbourkw_variablerad	26.52	56.86	86.10	0.00	2765.14
neighbourpv_2km	55	67.42	56.28	0	493
neighbourpv_4km	150	189.22	160.91	0	1299
neighbourpv_8km	434	556.17	470.83	0	3467
potentialrev	19843.95	28271.41	12722.19	11548.71	52554.80
pcost	2338.07	2709.64	937.41	1797.65	5035.27
saturation	0.01	0.02	0.04	0.00	1.00
density	3358.93	4184.94	4227.39	2.46	67585.05
pred_4064popul	521.00	537.12	127.32	52.00	5199.67
pred_65uppopul	269.25	284.81	120.80	4.00	1258.00
LSOAreakm2	0.48	4.40	14.82	0.02	683.75
ownedhouses	414.00	401.41	164.90	1.00	3864.00
pred_population	1578.00	1658.02	422.56	675.33	17708.33