Projection Bias in household investment? The case of solar photovoltaics in Germany.

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Research question

- Analyze household investment behavior: Are investment decisions fully rational or are they influenced by behavioral economic factors, i.e. Projection Bias?
- The role of "behavioral factors" in policy design for the diffusion of renewable energies?
  - Renewable energies, especially solar photovoltaics, receive high level of government support in form of subsidies and technology promotion

A simple model of Projection Bias

Loewenstein, O'Donoghue, and Rabin (2003):

- A person's instantaneous utility is period t is given by $u(c_t, s_t)$, where c_t is her period t consumption and her state s_t parameterizes her tastes
- The state might reflect past behavior or exogenous factors
- Assume a person, currently in state s, tries to predict her future instantaneous utility from consumption in state s'
- An accurate prediction would imply $\widetilde{u}(c, s'|s) = u(c, s')$
- Evidence suggests otherwise (food shopping)

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Predicted utility exhibits *Simple Projection Bias* if there exists $\alpha \ \epsilon \ [0,1]$ such that for all c, s, and future state s',

$$\widetilde{u}(c, s'|s) = (1-\alpha)u(c, s') + \alpha u(c, s)$$

Field evidence for Projection Bias:

- **Conlin, O'Donoghue, and Vogelsang (2007)** find evidence for *Projection Bias* in catalogue orders of cold-weather items
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Contribution:

- Provide evidence for Projection Bias in high stake environment (irreversible investment decision)
- Solar PV setup allows to test for direct channel of weather (sunshine) on technology adoption as input in household (electricity) production function and financial profits
- Contributes to the discussion on cost-efficient promotion policies for renewable energy

Projection Bias and durable good purchase (Loewenstein et al. (2003))

- Person's valuation of durable good in t given by random variable μ_t
- $\mu_t \sim iid$ across periods with finite sample mean $\overline{\mu}$
- Good purchased at price P and used for D days
- One-time buying opportunity, cannot be consumed on day of purchase
- Assume additive separable utility from other goods and $s_t = \mu_t$

True intertemporal utility when bought in period 1:

$$E_1[U_1] = E_1[\sum_{k=1}^{D} \mu_{1+k} - P] = D\overline{\mu} - P$$

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True intertemporal utility when bought in period 1:

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In the presence of *Projection Bias*:

$$E_1[\widetilde{U_1}] = E_1[\sum_{k=1}^{D} [(1-\alpha)\mu_{1+k} + \alpha\mu_1] - P] = D\overline{\mu} + \alpha D(\mu_1 - \overline{\mu}) - P$$

Then $\mu_1 > \overline{\mu}$ implies $E_1[\widetilde{U_1}] > E_1[U_1]$ and vice versa

Identification of Projection Bias

In order to test for $\alpha > 0$ in

$$E_1[\widetilde{U_1}] = D\overline{\mu} + \boxed{\alpha D(\mu_1 - \overline{\mu})} - P$$

I construct a series of extreme weather outliers at county-month level, looking at weather realizations outside the 1sd or 90 percentile

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Identification of PB:

- Utility of household directly linked to electricity produced, $f(sunshine)$
- Time lag between the installation decision and actual installation on site (5.3 weeks (2.2) in 2011)
- Long project horizon and irreversibility of investment
- Randomness of weather shocks (?)

Predictability of sunshine shocks (1sd)

Sunshine shock	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE
Total houses	0.00000***	0.00000***	-0.00003***	-0.00000
	(0.00000)	(0.00000)	(0.00001)	(0.00001)
Income HH pc	0.00000***	-0.00000**	0.00001*	0.00001
	(0.00000)	(0.00000)	(0.00001)	(0.00001)
Vote participation (%)	-0.00057	0.00003	-0.00124	-0.00179
	(0.00036)	(0.00053)	(0.00139)	(0.00261)
Unemployment rate (%)	0.00460***	0.00055	-0.01262***	-0.00295
	(0.00051)	(0.00046)	(0.00203)	(0.00184)
Vote green party (%)	0.17692***	0.09811	0.22079	-0.34689
	(0.06217)	(0.06754)	(0.27805)	(0.38021)
High school (%)	-3.09550**	-0.00573	-1.59402	-4.29472
	(1.26417)	(1.09971)	(3.00452)	(4.51395)
Agricult. surface (%)	-0.00663	0.01236**	0.27091	0.41845
	(0.00657)	(0.00575)	(0.52924)	(0.49663)
Residential buildings (%)	21.05895***	0.00826	-8.38986*	-3.81381
	(2.24938)	(1.66326)	(4.30429)	(3.32668)
Observations	32736	32736	32736	32736
R^2	0.004	0.240	0.279	0.292
time FEs	N	Y	Y	Y
county trends	N	N	Y	Y
State-yr FE	N	N	N	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors in parentheses.

Full regression model:

$$\Delta inst_{c,t} = \alpha + \sum_{i=0}^{M} \beta_{1,i}(L_i) weather_{c,t} + \beta_2 X_{c,t} +$$

$$+\theta_t + \sum_{j=2}^{12} \delta_j m_j + \psi_c t + \nu_c t^2 + \gamma_{y,l} + \lambda_c + \epsilon_{c,t}$$

Where: County adoption

- θ_t and $\sum_{j=2}^{12} \delta_j m_j$ account for the nationwide trends (e.g. policy)
- $\psi_c t$ and $\nu_c t^2$ capture the county specific time trends
- $\gamma_{y,l}$ accounts for time varying regional differences across states
- λ_c is included to control for permanent differences across countries.

I construct a unique dataset combining all registered household solar PV plants in Germany with detailed weather data at county-month level (2000-2008).

German market for PV

Weather data: Two datasets

- Official weather data (1km x 1km grid) acquired from the German Weather Service: sunshine, temperature. 2000-2011 - monthly.
- Official weather data freely available for 70 counties: sunshine, temperature, rain, snow, etc. $\sim$ from 1950 - daily.

Installation data:

- Universe of registered solar PV installations from electricity network transmission operator. Until 2011 - address level - daily frequency.

1sd sunshine shock definition

Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
Sunshine shock:					
sun	-0.371***	-0.323**	-0.040	0.068	0.038
	(0.097)	(0.129)	(0.096)	(0.094)	(0.091)
L.sun	-0.760***	-0.199*	0.097	0.253***	0.225***
	(0.086)	(0.112)	(0.078)	(0.083)	(0.081)
L2.sun	-0.222***	0.102	0.314***	0.438***	0.413***
	(0.086)	(0.130)	(0.086)	(0.085)	(0.084)
L3.sun	-0.330***	-0.770***	-0.276***	-0.134	-0.152*
	(0.097)	(0.125)	(0.088)	(0.081)	(0.082)
L4.sun	-0.499***	-0.459***	-0.128*	-0.052	-0.065
	(0.085)	(0.112)	(0.072)	(0.075)	(0.073)
Observations	35568	35568	35568	35568	35568
R^2	0.002	0.216	0.600	0.623	0.487
time FE	N	Y	Y	Y	Y
County trends	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors in parentheses.

p(90) sunshine shock definition

Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
Sunshine shock:					
sun	-0.591***	-0.732***	-0.147	0.018	-0.060
	(0.119)	(0.148)	(0.126)	(0.121)	(0.119)
L.sun	-0.613***	-0.296**	0.248**	0.461***	0.382***
	(0.104)	(0.123)	(0.099)	(0.100)	(0.098)
L2.sun	0.009	-0.040	0.342***	0.542***	0.451***
	(0.098)	(0.124)	(0.098)	(0.099)	(0.098)
L3.sun	-0.378***	-1.020***	-0.248**	-0.081	-0.168*
	(0.093)	(0.131)	(0.098)	(0.096)	(0.096)
L4.sun	-0.337***	-0.622***	-0.095	-0.015	-0.088
	(0.088)	(0.118)	(0.084)	(0.080)	(0.081)
Observations	35568	35568	35568	35568	35568
R^2	0.001	0.216	0.600	0.623	0.487
time FE	N	Y	Y	Y	Y
County trends	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors in parentheses.

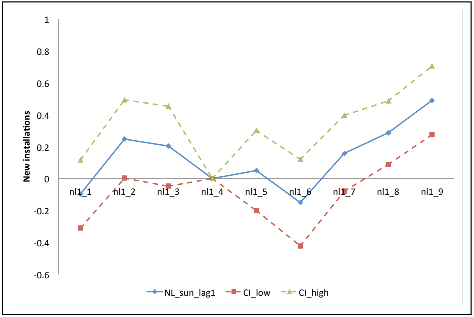
p(90) sunshine and temperature shock

Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
Sunshine shock:					
L.sun	-0.238**	-0.218*	0.221**	0.479***	0.400***
	(0.112)	(0.126)	(0.101)	(0.105)	(0.102)
L2.sun	0.057	-0.190	0.270***	0.489***	0.395***
	(0.102)	(0.129)	(0.104)	(0.103)	(0.103)
Temperature shock:					
L.temp	-1.096***	-0.157	0.198	-0.018	-0.015
	(0.100)	(0.141)	(0.123)	(0.133)	(0.131)
L2.temp	0.024	0.544***	0.465***	0.110	0.130
	(0.088)	(0.120)	(0.113)	(0.113)	(0.113)
Observations	35568	35568	35568	35568	35568
R^2	0.003	0.216	0.600	0.623	0.487
time FE	N	Y	Y	Y	Y
State trend	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

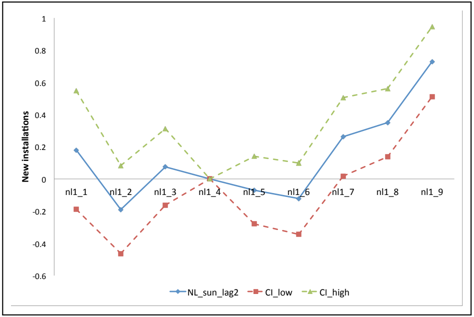
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors in parentheses.

Non-linear effects: Sunshine deviations from l.-t. mean

Lag1 of specification (4)



Lag2 of specification (4)



Robustness

- Model specification: include forward lag
- Include set of control variables in main regression (2002-08)
- Harvesting and intertemporal substitution (Busse, Pope, Pope, and Silva-Risso (2012))

Use a series of 62 freely available weather stations that allow for additional controls and data at higher frequency

p(90) sun, temp, snow and rain - reduced sample

Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
L.sun	-0.160	0.073	-0.037	0.143	0.219
	(0.265)	(0.278)	(0.245)	(0.210)	(0.193)
L2.sun	0.367	0.450*	0.250	0.411*	0.480**
	(0.266)	(0.249)	(0.229)	(0.225)	(0.210)
L.temp	-0.774***	0.013	0.301	0.128	0.070
	(0.194)	(0.253)	(0.205)	(0.229)	(0.223)
L2.temp	-0.162	0.387*	0.368	0.049	-0.001
	(0.174)	(0.226)	(0.233)	(0.220)	(0.208)
L.snow	2.191**	0.795	0.589	0.498	0.513
	(0.898)	(0.786)	(0.510)	(0.429)	(0.421)
L2.snow	0.320	0.149	0.092	0.088	0.130
	(0.747)	(0.747)	(0.392)	(0.352)	(0.374)
L.rain	-0.664**	0.121	-0.006	-0.288	-0.177
	(0.273)	(0.189)	(0.172)	(0.175)	(0.180)
L2.rain	-0.275	-0.074	-0.200	-0.371*	-0.250
	(0.271)	(0.214)	(0.180)	(0.186)	(0.185)
Observations	6510	6510	6510	6510	6510
R^2	0.005	0.173	0.541	0.576	0.412

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors in parentheses.

p(90) weather shocks - reduced sample - weekly

New PV installations	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
L6.sun	-0.190***	-0.082**	-0.107***	-0.097***	-0.099***
	(0.038)	(0.033)	(0.034)	(0.029)	(0.029)
L7.sun	-0.087*	0.016	-0.030	-0.021	-0.024
	(0.048)	(0.042)	(0.039)	(0.038)	(0.039)
L8.sun	-0.065**	-0.000	-0.028	-0.022	-0.025
	(0.030)	(0.032)	(0.028)	(0.028)	(0.028)
L6.temp	0.024	0.008	0.087**	0.072**	0.073**
	(0.044)	(0.039)	(0.038)	(0.034)	(0.034)
L7.temp	0.022	-0.046	0.009	-0.004	-0.004
	(0.025)	(0.029)	(0.028)	(0.028)	(0.028)
L8.temp	-0.067	-0.014	0.022	0.010	0.010
	(0.042)	(0.030)	(0.026)	(0.026)	(0.027)
L6.rain	0.079	0.149	0.126	0.118	0.120
	(0.120)	(0.130)	(0.130)	(0.130)	(0.130)
L7.rain	-0.054	0.027	0.008	-0.002	-0.001
	(0.039)	(0.042)	(0.038)	(0.036)	(0.036)
L8.rain	-0.044	-0.014	-0.017	-0.032	-0.030
	(0.035)	(0.037)	(0.031)	(0.030)	(0.030)
Observations	28458	28458	28458	28458	28458
R^2	0.001	0.103	0.278	0.295	0.186

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors in parentheses.

p(90) rain and snow - model selection

New PV installations	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
rain	0.004	0.096*	0.066	0.063	0.068
	(0.061)	(0.052)	(0.053)	(0.054)	(0.053)
L.rain	-0.217***	-0.125***	-0.148***	-0.149***	-0.145***
	(0.044)	(0.037)	(0.034)	(0.034)	(0.034)
L2.rain	-0.129***	-0.008	-0.029	-0.035	-0.031
	(0.040)	(0.036)	(0.027)	(0.028)	(0.028)
L3.rain	0.016	0.076*	0.052	0.043	0.046
	(0.036)	(0.039)	(0.037)	(0.036)	(0.036)
snow	-0.123	-0.157	-0.212**	-0.224**	-0.208**
	(0.132)	(0.129)	(0.102)	(0.092)	(0.093)
L.snow	0.030	0.026	-0.010	-0.006	0.006
	(0.104)	(0.100)	(0.081)	(0.071)	(0.074)
L2.snow	0.134	0.090	0.053	0.059	0.072
	(0.101)	(0.097)	(0.072)	(0.066)	(0.067)
L3.snow	0.449***	0.228*	0.203***	0.215***	0.234***
	(0.133)	(0.119)	(0.073)	(0.067)	(0.068)
Observations	28830	28830	28830	28830	28830
R^2	0.002	0.104	0.278	0.296	0.188
time FE	N	Y	Y	Y	Y
County trends	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors in parentheses.

Heterogeneous effects: all counties

Dependent variable: New PV installations (county-month)	VotePart_{p50} β / SE	VoteGreen_{p50} β / SE	VoteGreen_{p75} β / SE	HhInc_{p75} β / SE	Unemp_{p75} β / SE	East β / SE
L.sun	0.510***	0.361**	0.382***	0.460***	0.512***	0.566***
	(0.099)	(0.141)	(0.114)	(0.109)	(0.121)	(0.103)
L2.sun	0.392***	0.414***	0.470***	0.504***	0.619***	0.591***
	(0.101)	(0.124)	(0.098)	(0.094)	(0.105)	(0.092)
L.sun x treat	0.066	0.346*	0.596***	0.328	0.087	-0.217
	(0.200)	(0.198)	(0.195)	(0.206)	(0.158)	(0.155)
L2.sun x treat	0.358**	0.296*	0.358**	0.258	-0.168	-0.206
	(0.179)	(0.169)	(0.168)	(0.191)	(0.147)	(0.152)
Observations	27962	27962	27962	27962	27962	27962
R^2	0.704	0.704	0.704	0.704	0.704	0.704
Inclusion Treatment	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
FE & time trends	Y	Y	Y	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors in parentheses.

Summary

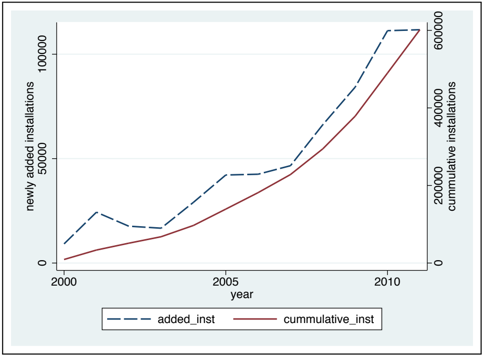
- Evidence for *Projection Bias* for irreversible household investment decision robust to shock definition and model specification
- Behavioral factors seem to play an important role in solar PV investment decisions and should be taken into account when objective is to formulate cost-efficient promotion strategies (political orientation)
- Relevance for wider set of household investment decisions.

Possible concerns:

- Climate change (Li, Johnson, and Zaval (2011))
- Supply side effects

Thank you!

Household investment in solar PV in Germany



- Newly added household installations ($\leqslant$ 10kwp) 2000-11
- Germany is the world-market leader for installed capacity in solar PV

Table : Sample means by technology adoption: 342 counties

	all	> median inst.	<= median inst.
PV installations and weather: 2000-08			
new installations county month	5.48	9.03	1.93
sun_1sd	0.15	0.15	0.15
sun_p90	0.08	0.08	0.08
temp_1sd	0.16	0.16	0.16
temp_p90	0.09	0.09	0.10
Observations	36936	18468	18468
Covariates: 2002-08			
houses	40195	50368	30082
HHinc_pc	17400	18109	16696
population	176687	206450	147098
unemploy_percent	10.77	8.18	13.34
highschool_rat	0.30	0.24	0.37
surf_agricul_rat	31.97	32.22	31.72
vote_particip	78.13	80.06	76.21
p_vote_cdu	39.29	44.71	33.91
p_vote_green	6.98	6.97	6.99
p_vote_fdp	8.23	8.46	8.00
p_vote_linke	6.40	3.36	9.43
p_vote_other	3.48	3.39	3.56
Observations	28644	14280	14364

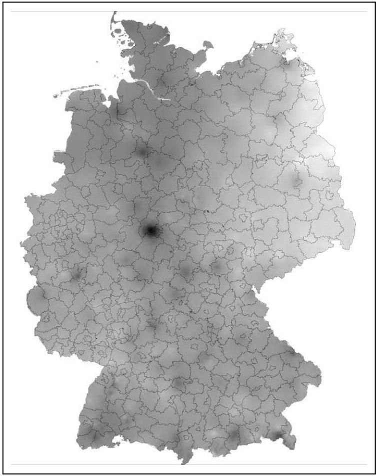
p(90) sunshine shock - reduced sample of 62 stations

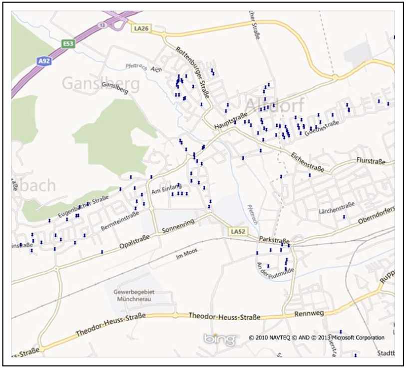
Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
Sunshine shock:					
sun	-0.534***	-0.572**	-0.606***	-0.363*	-0.284
	(0.183)	(0.228)	(0.182)	(0.204)	(0.187)
L.sun	-0.344	-0.071	-0.125	0.108	0.188
	(0.249)	(0.284)	(0.244)	(0.215)	(0.190)
L2.sun	0.414*	0.449*	0.192	0.349	0.436**
	(0.245)	(0.264)	(0.223)	(0.229)	(0.209)
L3.sun	-0.119	-0.439	-0.363	-0.231	-0.149
	(0.213)	(0.263)	(0.224)	(0.229)	(0.196)
L4.sun	-0.136	-0.232	-0.237	-0.206	-0.131
	(0.263)	(0.295)	(0.194)	(0.170)	(0.164)
Observations	6448	6448	6448	6448	6448
R^2	0.001	0.171	0.542	0.575	0.411
time FE	N	Y	Y	Y	Y
County trends	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

p(90) sunshine - reduced sample - weekly

Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
L5.sun	-0.157***	-0.046	-0.034	-0.024	-0.028
	(0.041)	(0.037)	(0.038)	(0.034)	(0.035)
L6.sun	-0.186***	-0.098***	-0.105***	-0.097***	-0.101***
	(0.040)	(0.035)	(0.033)	(0.029)	(0.030)
L7.sun	-0.071	0.006	-0.022	-0.016	-0.020
	(0.049)	(0.044)	(0.040)	(0.038)	(0.039)
L8.sun	-0.059**	-0.004	-0.020	-0.018	-0.021
	(0.027)	(0.032)	(0.028)	(0.027)	(0.026)
L9.sun	-0.033	0.033	0.012	0.017	0.014
	(0.059)	(0.062)	(0.062)	(0.061)	(0.060)
L10.sun	-0.054	0.018	-0.002	0.001	-0.002
	(0.042)	(0.035)	(0.033)	(0.032)	(0.033)
Observations	28272	28272	28272	28272	28272
R^2	0.001	0.102	0.277	0.294	0.184
time FE	N	Y	Y	Y	Y
County trends	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

GIS data





LA26
E53
A92
Gansberg
Altdorf
bach
Rottenburger Straße
Hauptstraße
Goethestraße
Eichenstraße
Flurstraße
Am Einfang
Eugenbacher Straße
Bernsteinstraße
Sonnenring
Opalstraße
Im Moos
LA52
Parkstraße
Lärchenstraße
Oberndorfers
An der Flutmulde
Gewerbegebiet Münchnerau
Theodor-Heuss-Straße
Rennweg
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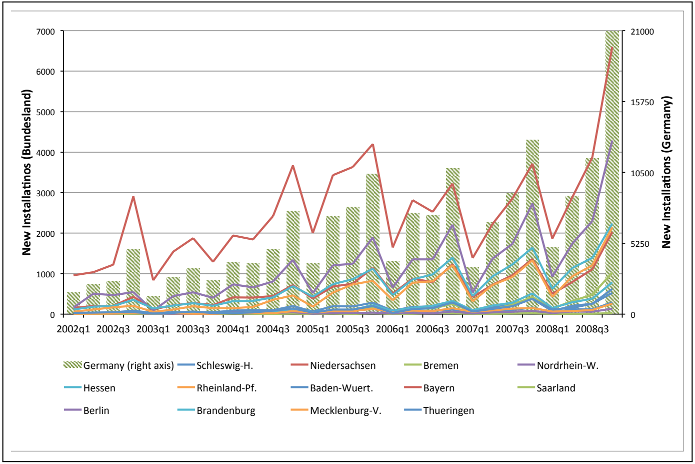
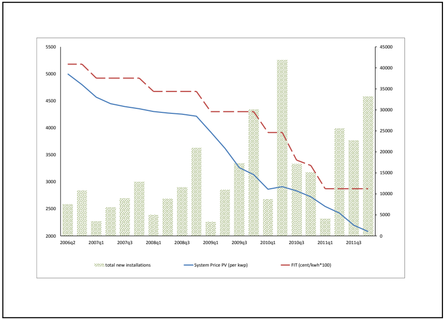
Weather stations - reduced sample

Heterogeneous technology adoption at state level



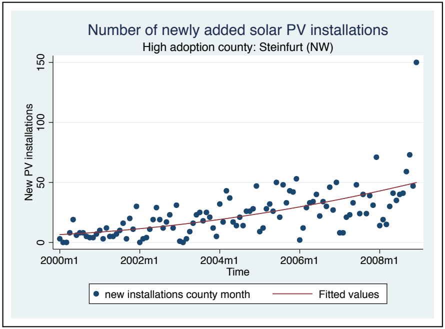
The German market for solar PV

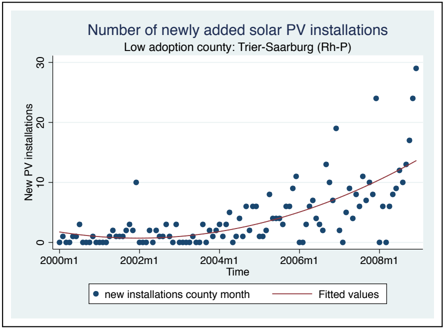


- Major revision of FIT support schemes in 2004, 2009 and 2012.
- Strong price decrease in solar technology

Data

The German market for solar PV





Estimation