Ray of Hope? China and the Rise of Solar Energy

Bank of Portugal

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Outline

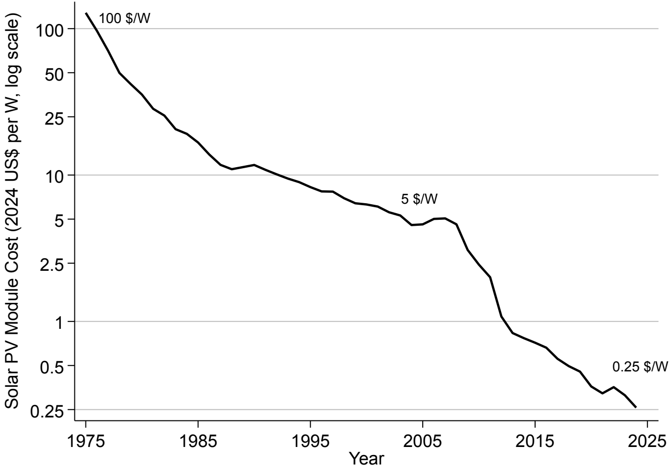
1. **Background**
2. **Data**
3. **Modelling Framework**
4. **Empirical Strategy**
5. **Main Econometric Results**
6. **Aggregate Model: Theory**
7. **Aggregate Model: Quantification**

Chinese Solar: A Successful Local Green Industrial Policy?

- Around 73% of global greenhouse gas emissions are attributed to the energy sector
- Decarbonisation plans for many sectors reliant on clean renewable energy
- China embarked on being world leader in solar. But how causally important was it & did it help their citizens over and above environmental benefits?

Cost of solar has fallen dramatically

Figure: Global average price of solar PV modules (in 2024 US$ per Watt)



Source: Our World in Data, LaFond et al. (2017) & IRENA Database

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- Implement Synthetic DID approach (Arkhangelsky et al., 2021) exploiting staggered introduction of city-level solar policies over time
- Develop & structurally estimate equilibrium model to analyze counterfactuals and welfare

Preview of City-Region Empirical Results

- **Innovation & Production subsidy** policies both generate more city-wide solar **innovation** (e.g. citation weighted patents)

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- **Extensions:** Cross-city "business stealing" dominated by positive spillovers; placebos on non-solar patents & GDP; some effects via learning by-doing; etc.

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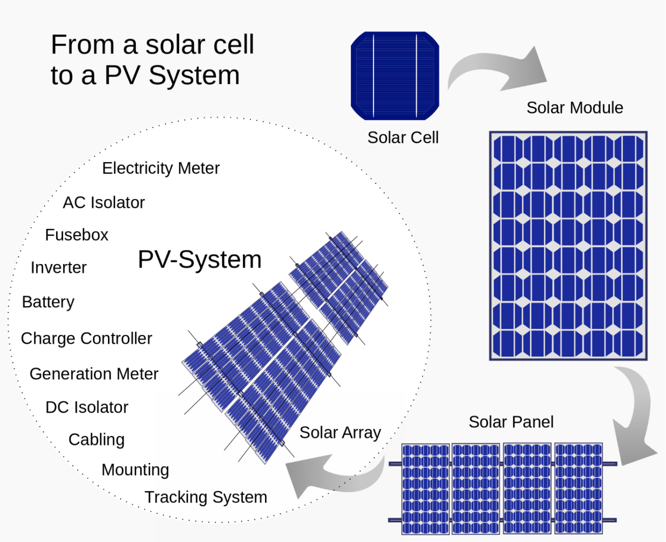
- Social Cost-Benefit
  - Policy generates net gains for Chinese citizens: **$1.65** for every **$1** of subsidy (& double this when adding in social costs of carbon).
  - But could be more cost-effective if policy mix had greater focus on innovation subsidies

Some Existing Literature

- **Industrial Policy: Theory**: Garg (2024); Rodrik (2004); Harrison & Rodriguez-Clare (2010) survey; Liu (2019); Bartelme et al. (2021), Buera et al. (2013); Itskhoki & Moll (2019); Murphy et al. (1989)
- **Industrial Policy: Empirics (inc. LBD)**: Lane (2020, 2025); Criscuolo et al. (2019); Juhasz et al. (2022); Goldberg et al. (2025); Choi & Levchenko (2021); Choi & Shim (2022); Liu & Ma (2022)
- **(Green) Directed Technical Change**: Acemoglu et al. (2012, 2016, 2019); *Aghion et al. (2016)*; Arkolakis & Walsh (2023); Newell et al. (1999); Popp (2022, 2019); Shapiro & Walker (2018)
- **Chinese Growth & Policy**: Branstetter & Li (2024), Kalouptsidi (2018); Barwick et al. (2019, 2021); Aghion et al. (2015); Bai et al. (2019); Chen & Xie (2019); Wang & Yang (2025), Song et al. (2011); Konig et al. (2022); Wei et al. (2023); Branstetter et al. (2022); Wu et al. (2019)
- **Solar**: Ball et al. (2017); Bollinger & Gillingham (2021); Gerarden (2022); Gerarden et al., (2025); Gillingham & Tsvetanov (2019); Gonzales et al. (2023); de Groote & Verboven (2019); Nemet (2019); Way et al. (2021); Gentile et al., (2025); Garg & Saxena (2025)
- **Place-Based Policies**: Moretti (2011, 2012); Kline (2010); Gruber & Johnson (2019); Greenstone et al. (2010); Kline & Moretti (2014)

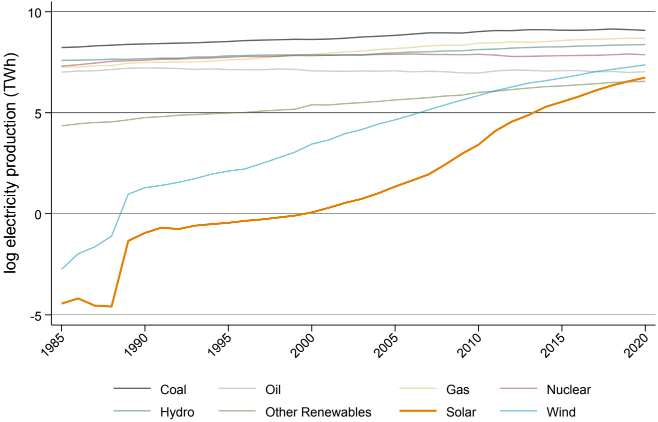
Outline

From cell to panels



Renewable electricity capacity, especially solar, has grown rapidly...

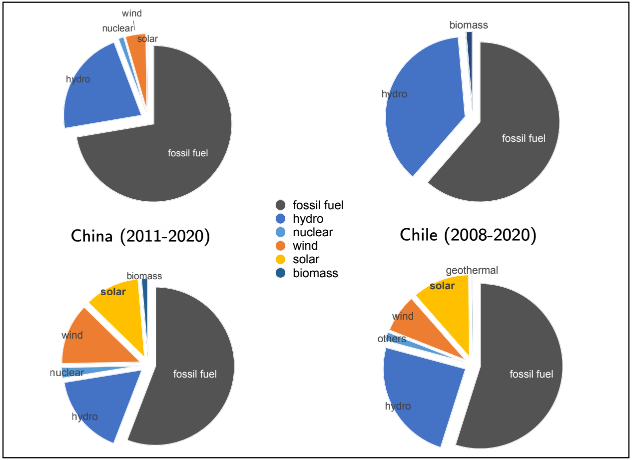
Figure: World electricity production by source



Source: International Energy Agency (IEA) Shares

..Especially in some countries like China and Chile

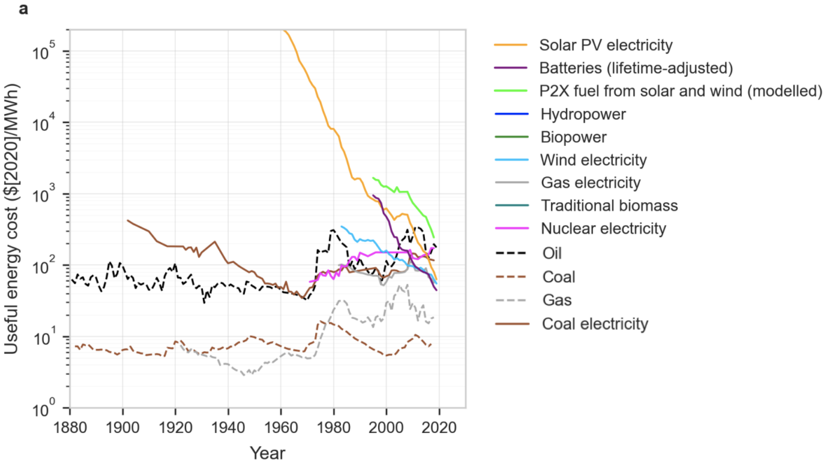
Figure: Installed Electricity generation capacity in China and Chile by source



Source: State Grid New Energy Cloud & CNE

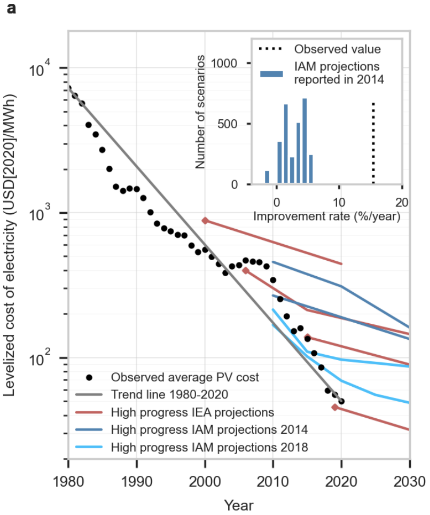
- **World, 2011 to 2020**: installed solar capacity went from 0.8% to 6.8%
- **China, 2011 to 2020**: installed solar capacity went from 0.19% to 11.35%
- **Chile, 2008 to 2020**: installed solar capacity went from 0% to 12%

Huge fall in cost of solar relative to other energy sources (1880-2020)



Source: Way, Ives, Mealy and Farmer (2021) "Empirically grounded technology forecasts and the energy transition"

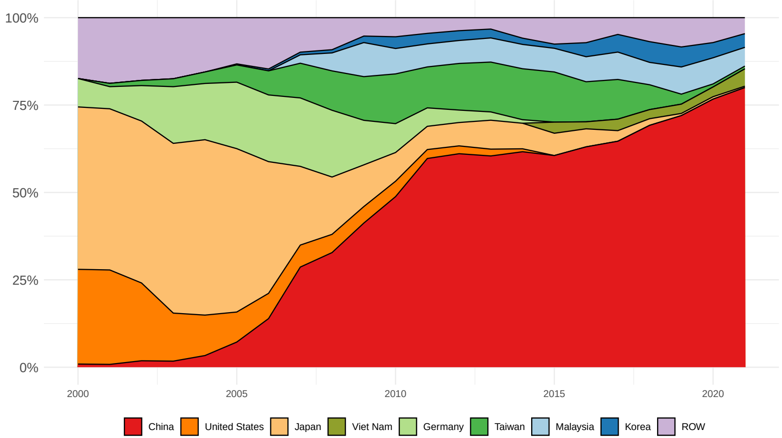
Solar price falls were much faster than forecast (1980-2030)



Source: Way, Ives, Mealy and Farmer (2021) “Empirically grounded technology forecasts and the energy transition”

China's global share of solar production rose from near zero to more than 80 % in 2021

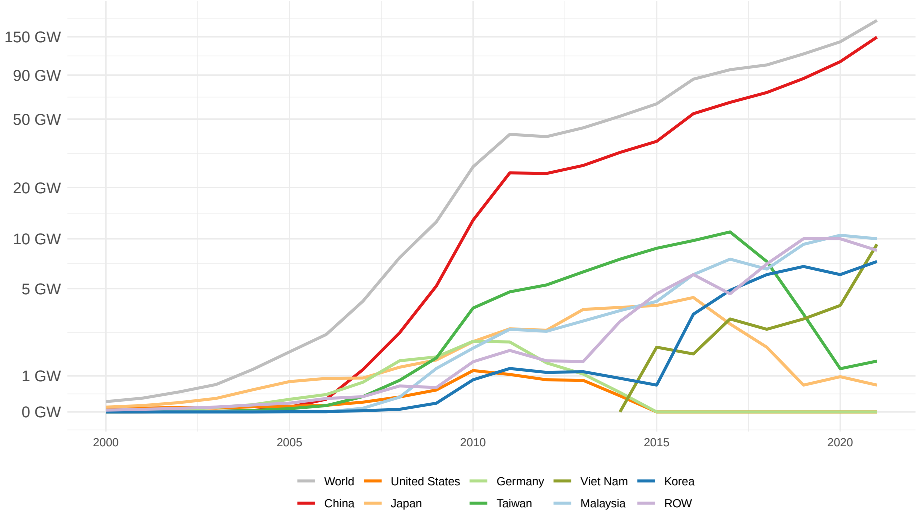
Figure: Share of Annual Solar Photovoltaics Cell Production in Leading Countries, 2000-2021



Source: International Energy Agency (IEA) & Earth Policy Institute

And this was in context of huge growth in solar production

Figure: Solar PV cell production 2000-2021



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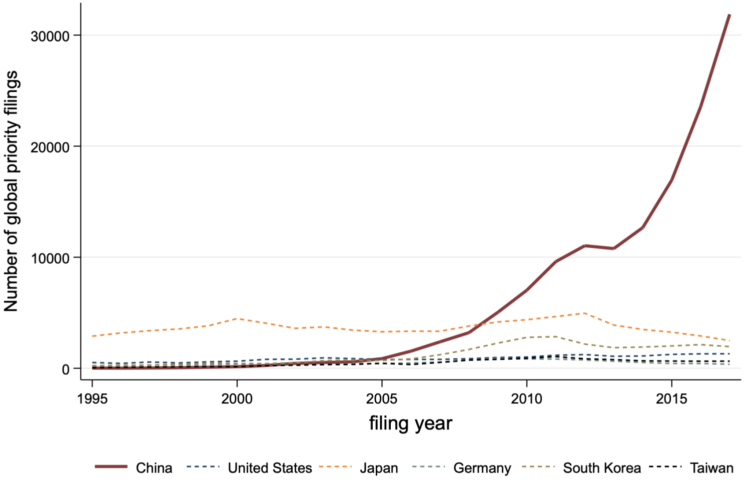
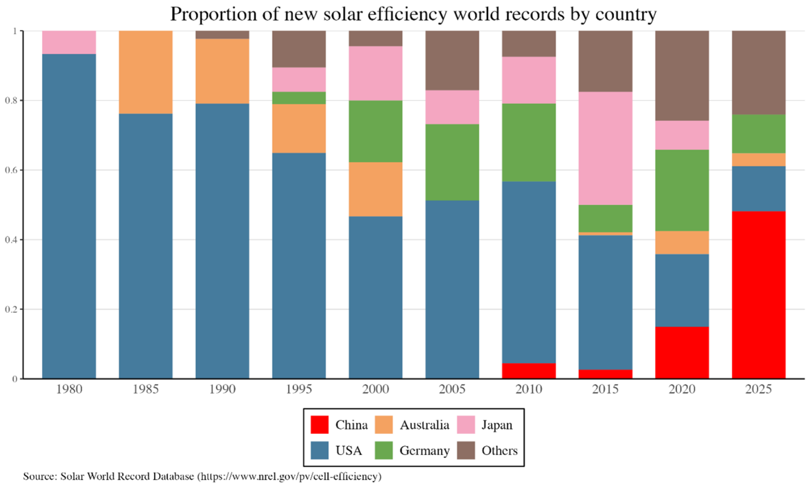
China is not just imitating: Massive growth in Solar Patents



Source: PATSTAT - solar patents based on IPC/CPC codes

Citations Triadic Patents

China is innovating not just imitating: Technological Frontier



Source: Solar World Record Database

This industrial policy was led by local government

- Industry histories suggest important role of local government (Ball et al. 2017; Chen, 2016)
- City governments have significant policy autonomy (Text of policy documents makes this clear)
- City governments have budget to implement meaningful industrial policies (Bai, Hsieh, and Song, 2019)
- Local bureaucrats have strong incentives to promote economic growth e.g. career concerns (Jia et al. 2015; Li and Zhou, 2005)

Outline

We need to measure

- **Treatment:** Solar industrial policies at the city-region level
- **Outcomes:** Combined activity of new / existing solar firms in a given city-year
    - Innovation
    - Outputs and Inputs
    - Exports

Measure solar industrial policy using PKULaw Database

- Use key words to extract solar policies from database of all laws, regulations and policies in China

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- Identify financial subsidies based on text (with quantitative info)
- Distinguish subsidy policies into 3 types: (i) Demand (ii) Production & (iii) Innovation

Measure solar industrial policy using PKULaw Database

Table: City-level solar policies

Type of policy	Number	Example
Subsidy	78	
1. Production subsidy	27	*"The cost of a new solar production line built in Hefei will be subsidized by 12% (2018)"*
2. Innovation subsidy	12	*"Firms will be awarded 10,000 RMB if they earn provincial level R&D center certification (Guilin, 2011)"*
3. Demand subsidy	61	*"1 RMB per watt for the electricity generated by solar projects installed in Beijing (2010)"*

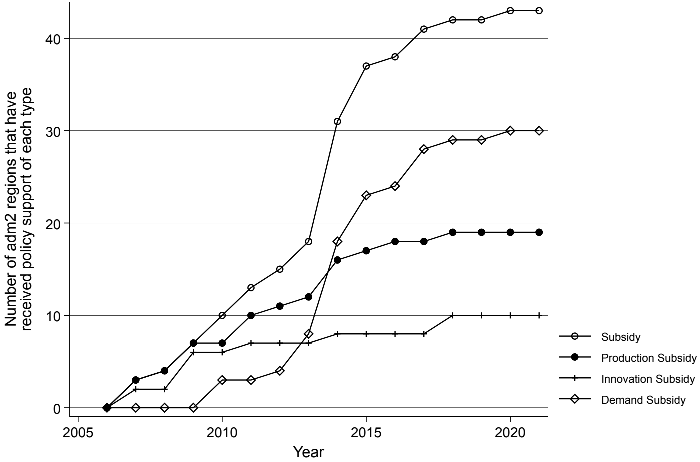
Source: Own analysis using PKULaw data

Measure solar industrial policy using PKULaw Database

- For each policy we observe implementing authority (city vs. province vs. national) and date
- Focus on treatment at the city level: first year the city implements a solar subsidy

Time series of policy support

Figure: Number of cities treated with supply & demand subsidies



We study the outcomes of solar panel manufacturers

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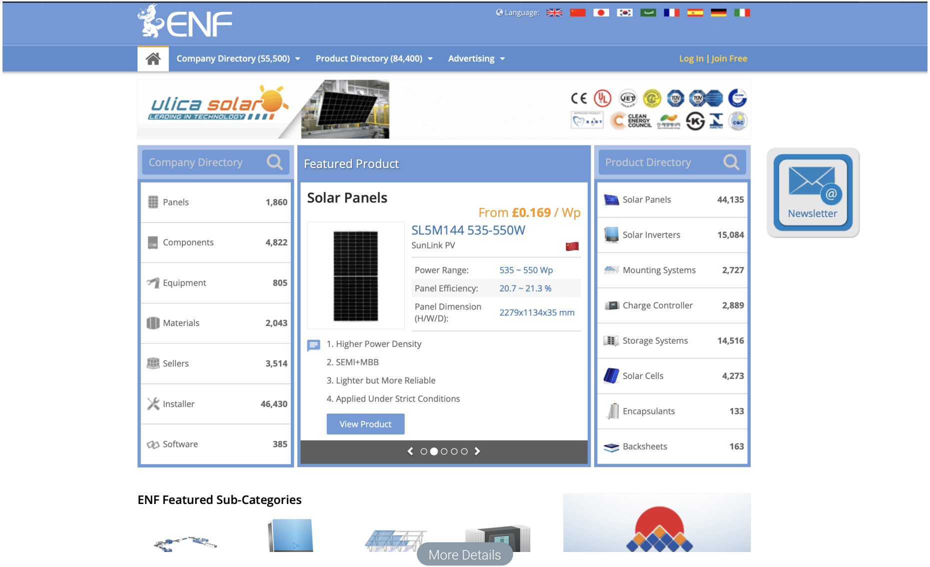
ENF
Language:
Company Directory (55,500)
Product Directory (84,400)
Advertising
Log In | Join Free
ulica solar
LEADING IN TECHNOLOGY
Company Directory
Panels 1,860
Components 4,822
Equipment 805
Materials 2,043
Sellers 3,514
Installer 46,430
Software 385
Featured Product
Solar Panels
From £0.169 / Wp
SL5M144 535-550W
SunLink PV
Power Range: 535 ~ 550 Wp
Panel Efficiency: 20.7 ~ 21.3 %
Panel Dimension (H/W/D): 2279x1134x35 mm
1. Higher Power Density
2. SEMI+MBB
3. Lighter but More Reliable
4. Applied Under Strict Conditions
View Product
Product Directory
Solar Panels 44,135
Solar Inverters 15,084
Mounting Systems 2,727
Charge Controller 2,889
Storage Systems 14,516
Solar Cells 4,273
Encapsulants 133
Backsheets 163
Newsletter
ENF Featured Sub-Categories
More Details

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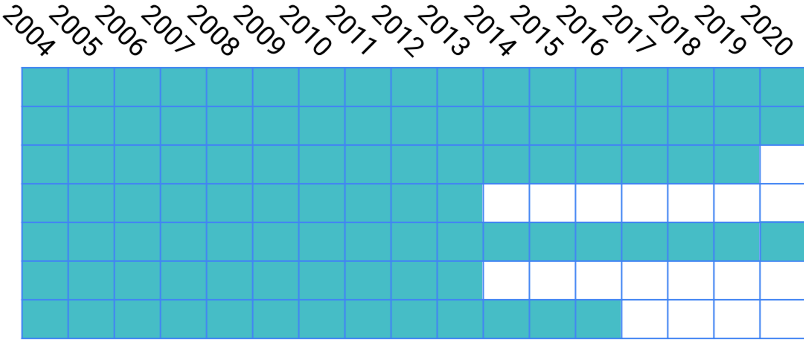
- Sample from **ENF Solar**, the largest online solar directory worldwide
- Identify 1,718 solar panel manufacturers in China (2004-2020)
- Cross-referencing aggregate statistics suggests we capture the whole industry

Aggregating the firm data gives us outcomes at the city-year level

- **Innovation**: All patents filed by solar firms in city-year (text, citations, etc.) Example patents
- **Revenues**: Total revenues (and employment, capital, etc.)
- **Production capacity**: Total MWh capacity of all solar panels manufactured
- **Firm count**: Number of solar firms
- **Exports**: Total Exports (values, volume, etc.)

Descriptive Statistics Validation with ASIE

Coverage of Data across years



Chinese Business/ENF Register

SIPO: Patents in China

PATSTAT: Patents globally

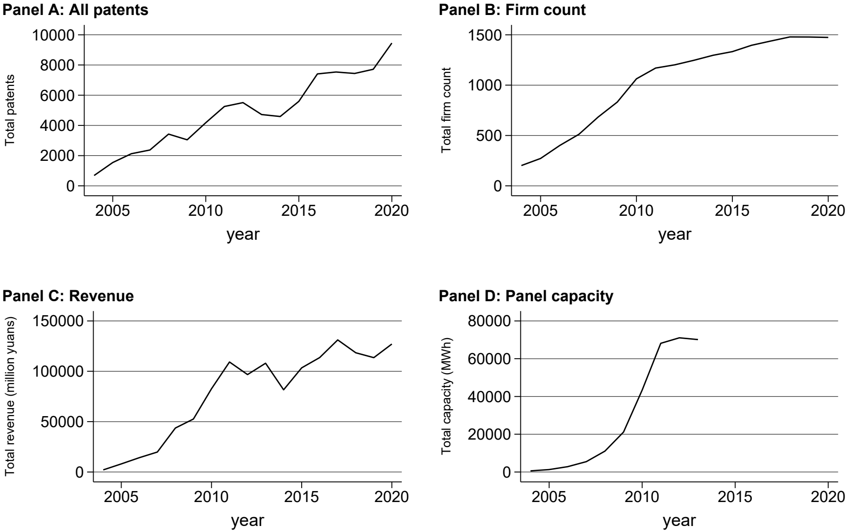
ENF: Market research reports

Orbis: Company accounts

ASIE: Company accounts

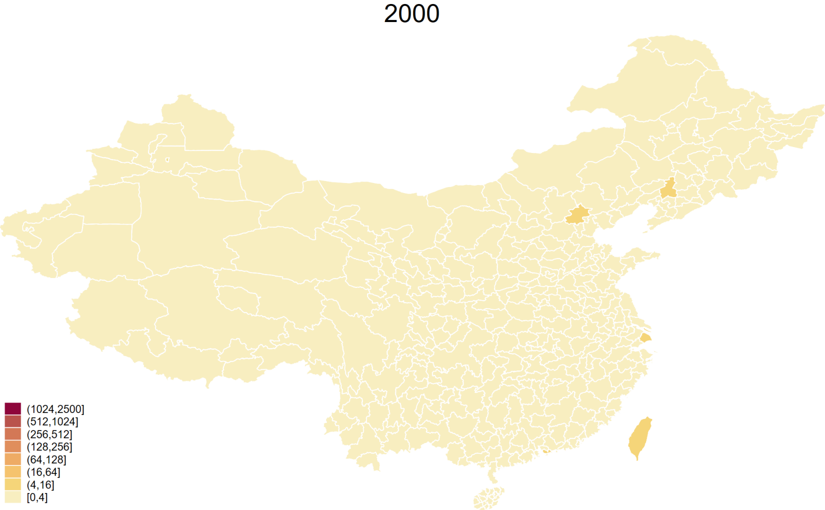
Customs: exports by HS8 code

Chinese Solar industry evolution



Our analysis compares city-level policies & outcomes: Patents

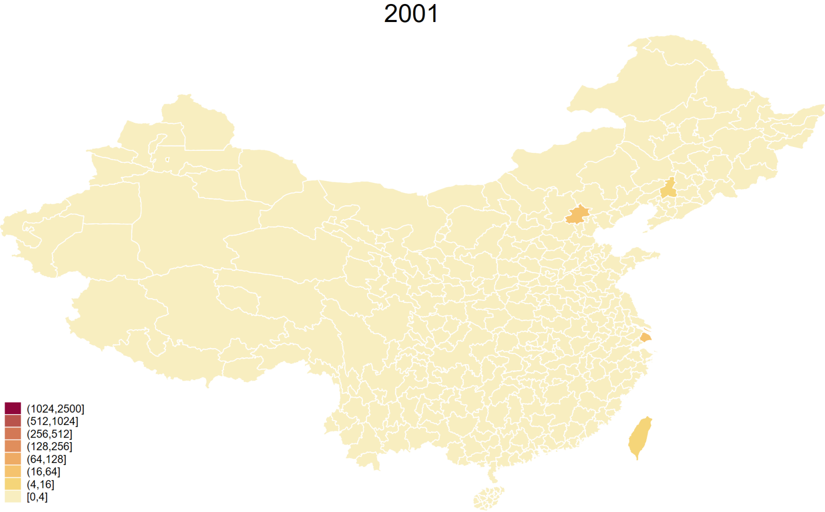
Here: patent counts and any subsidy



Note: black circled cities are treated by any subsidy policy

Our analysis compares policy and outcomes at the city level

Here: patent counts (subsidy in black circles)



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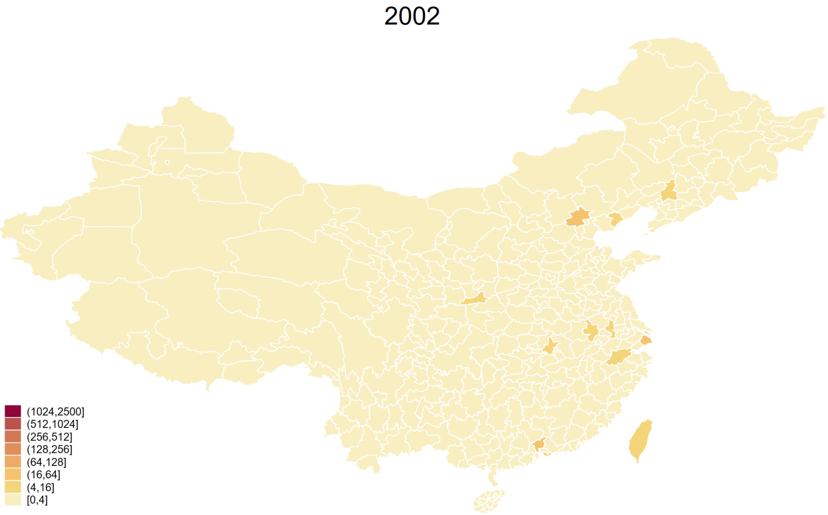

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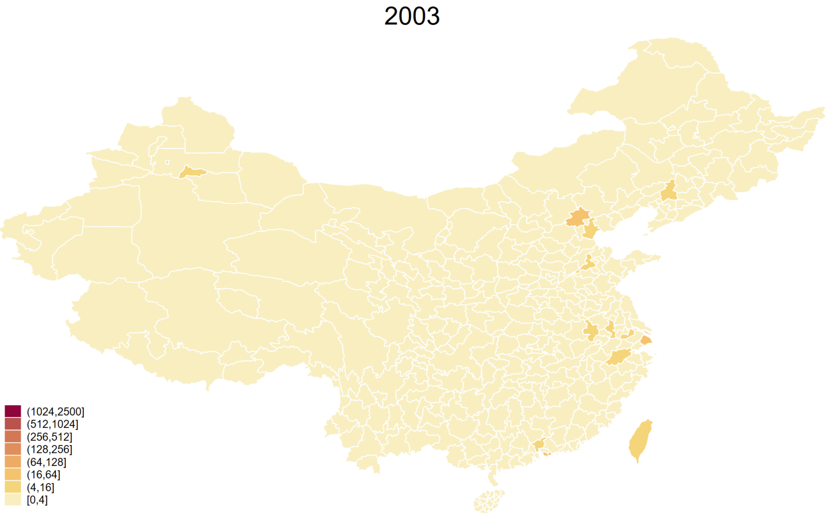

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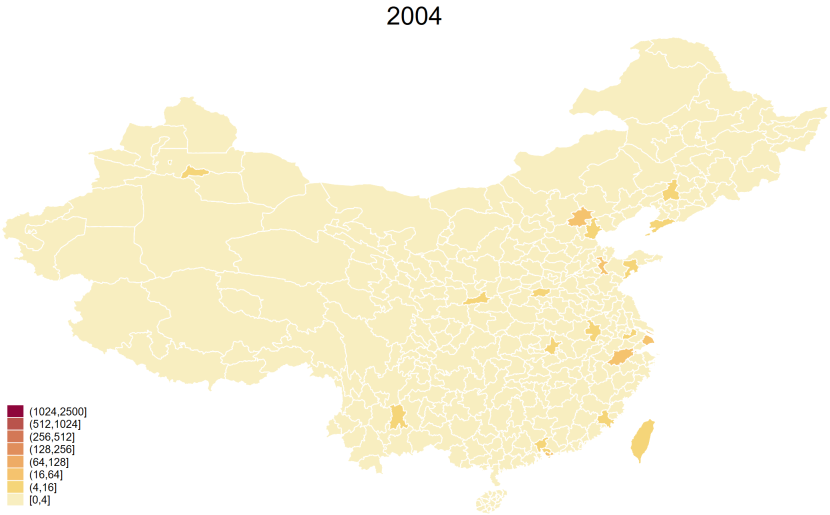

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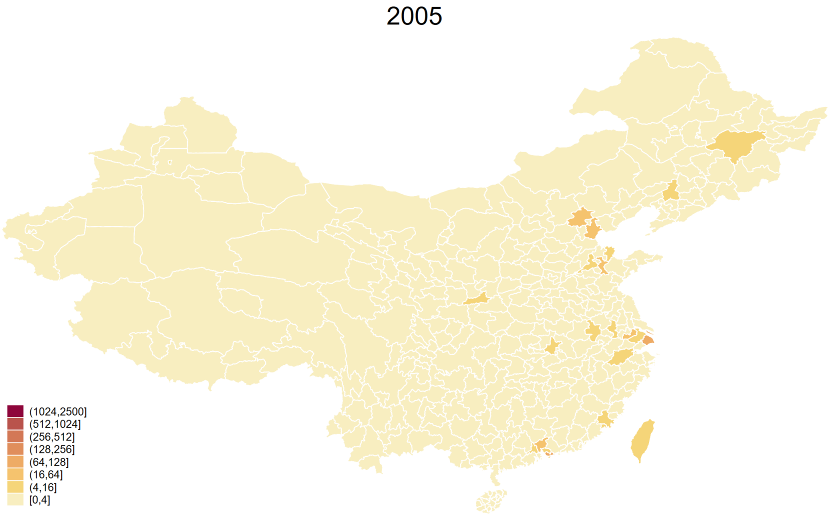

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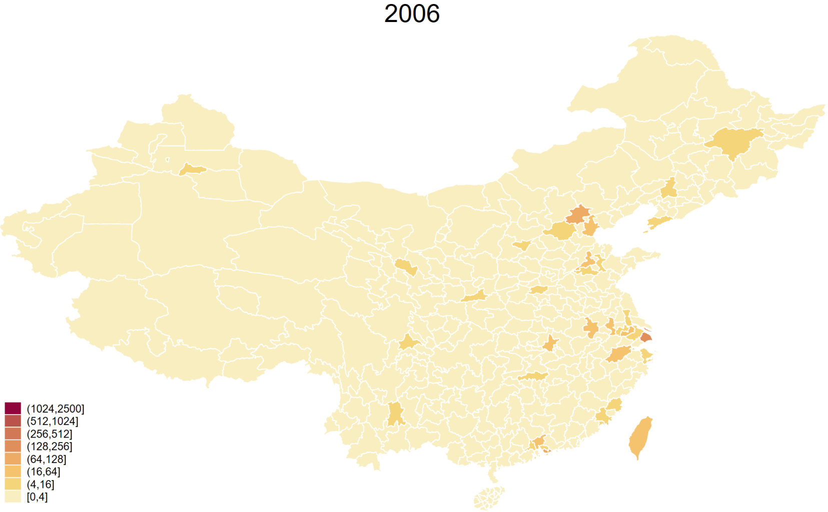

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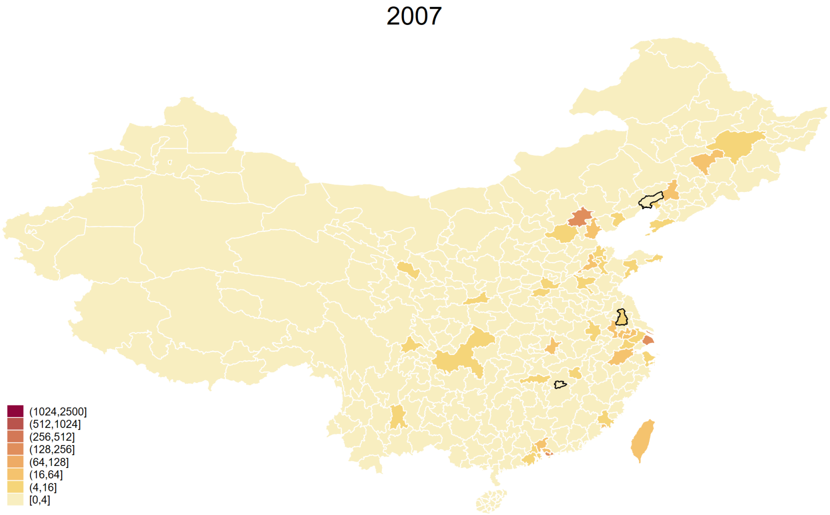

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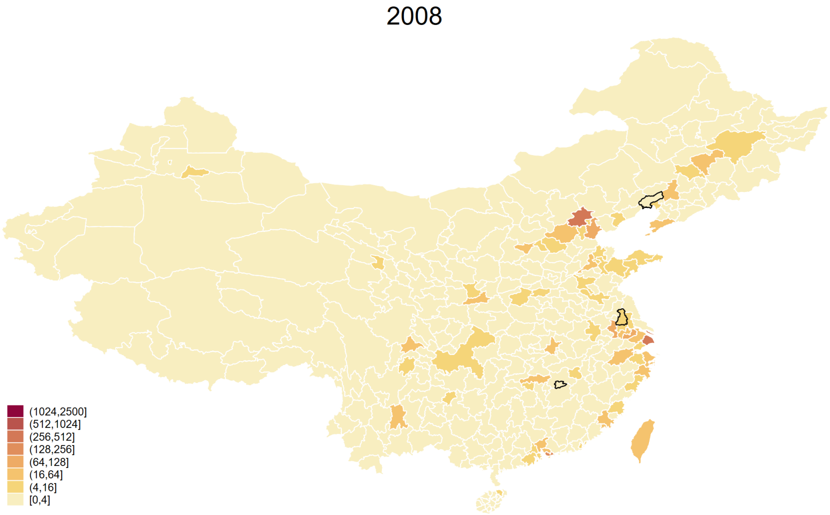

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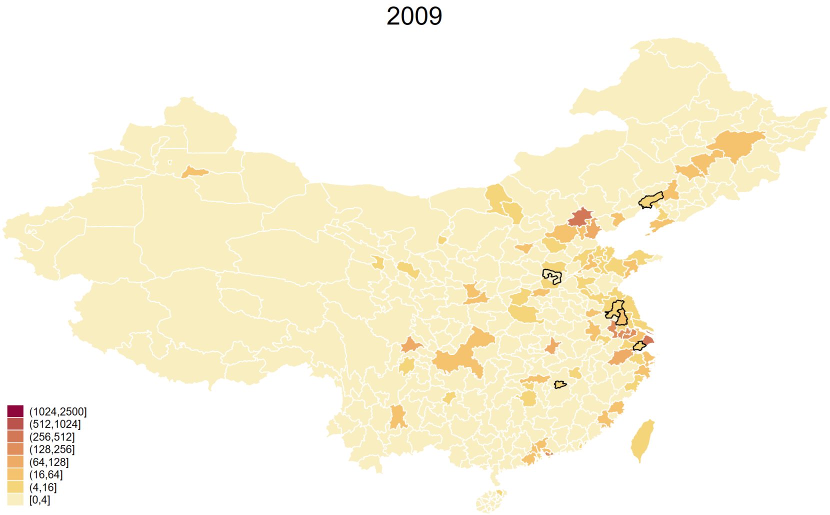

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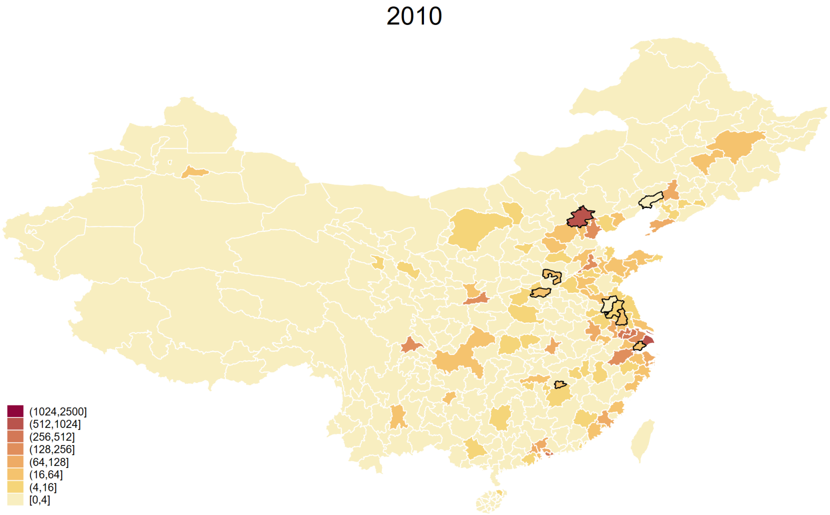

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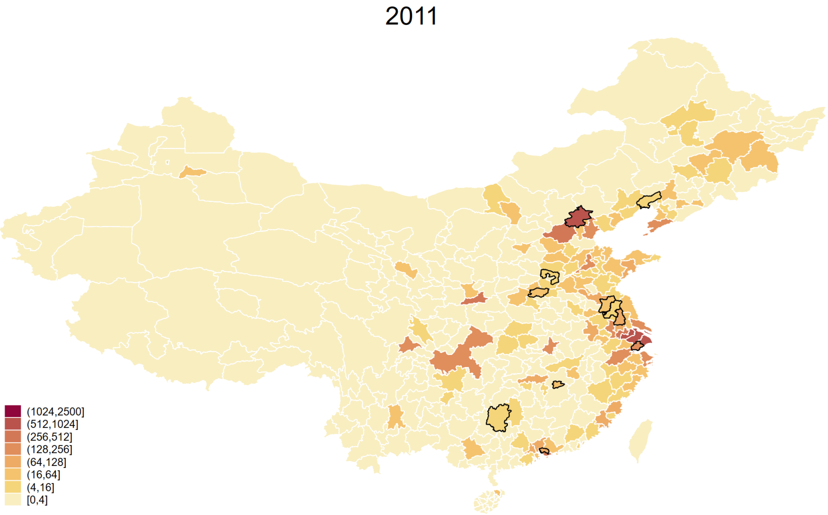

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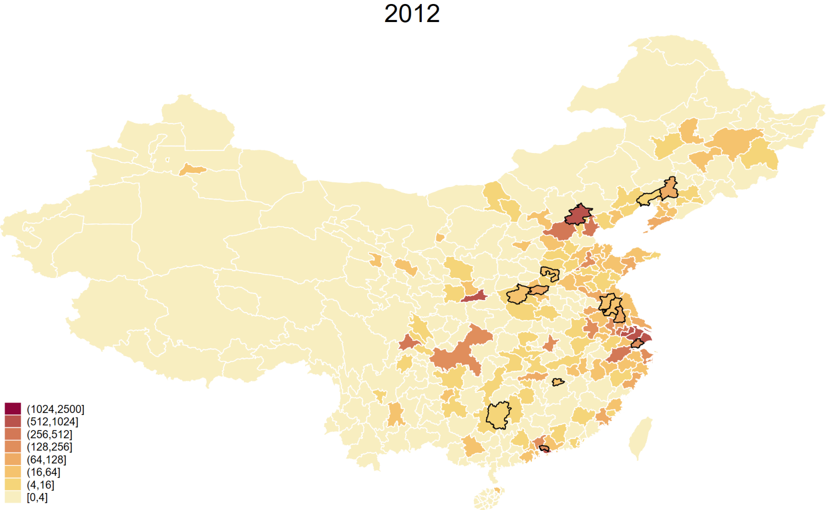

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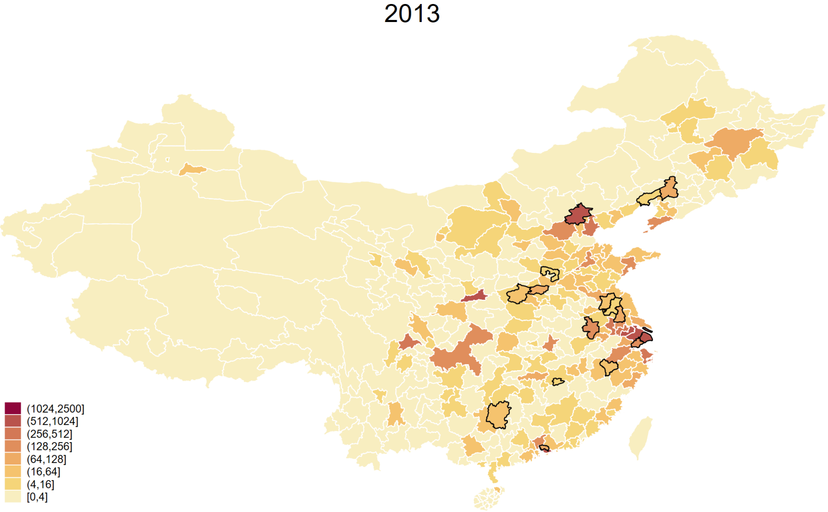

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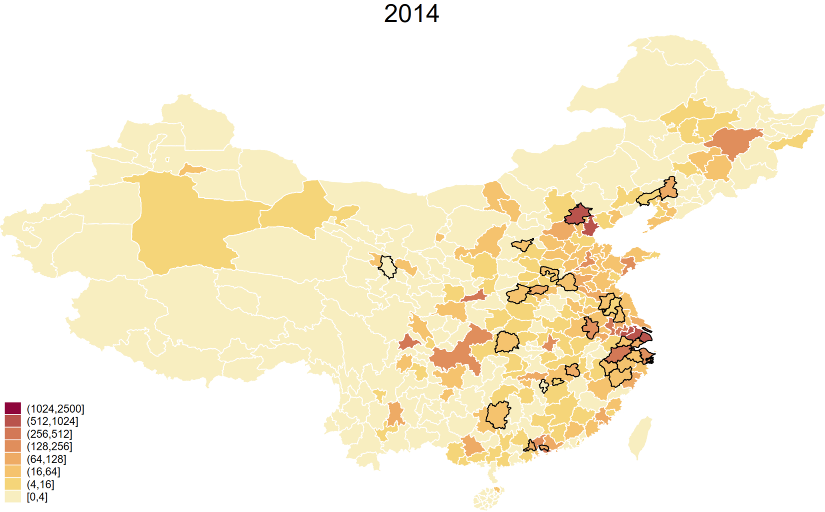

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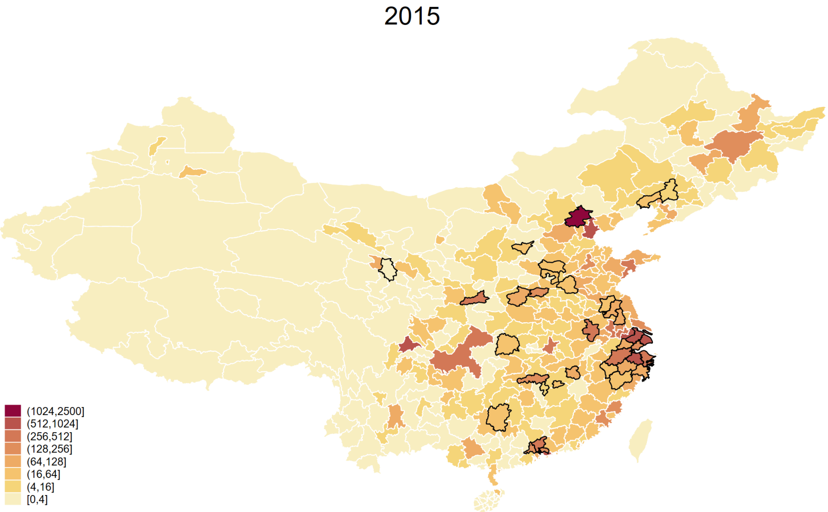

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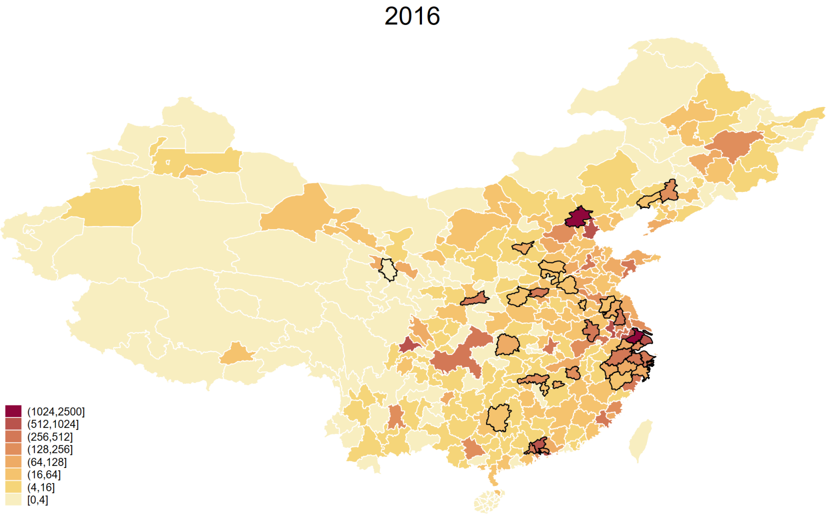
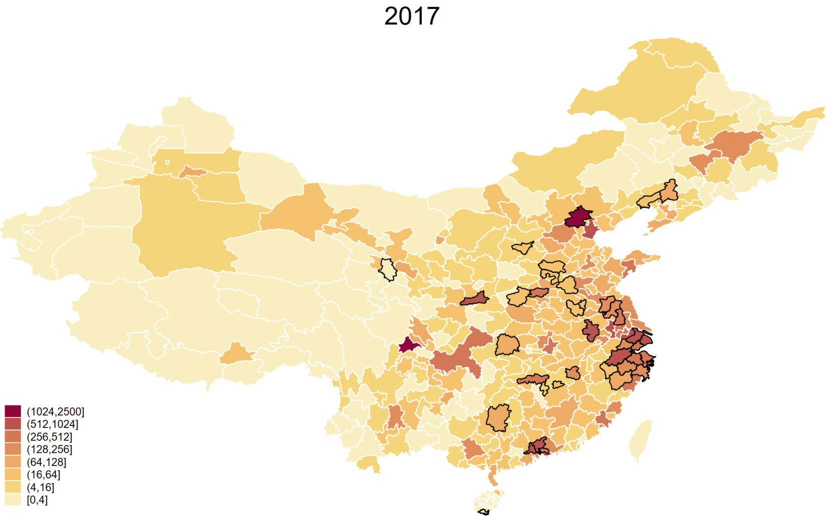


Note: black circled cities are treated by any subsidy policy

Our analysis compares policy and outcomes at the city level

Here: patent counts and any subsidy



Note: black circled cities are treated by any subsidy policy

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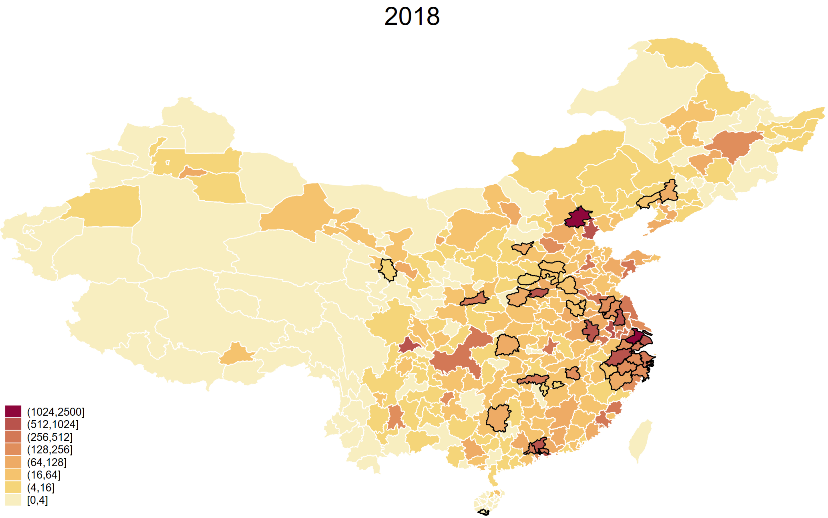
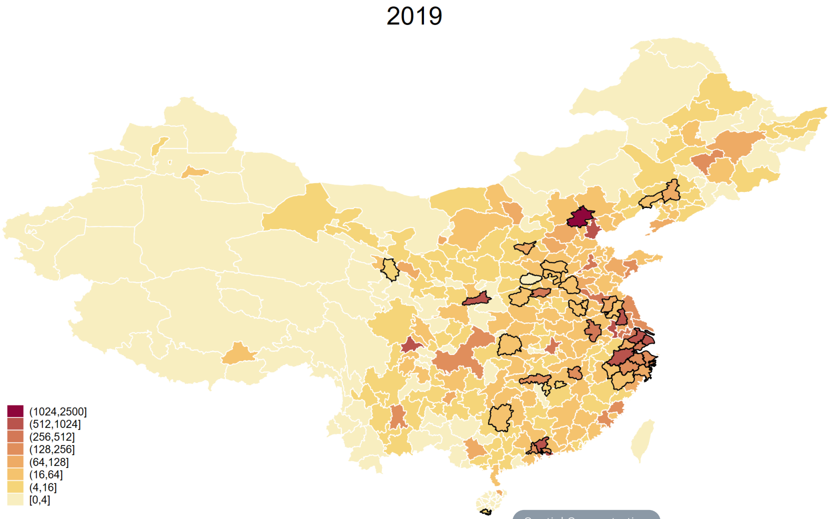


Note: black circled cities are treated by any subsidy policy

Our analysis compares policy and outcomes at the city level

Here: patent counts and any subsidy



Note: black circled cities are treated by any subsidy policy

Spatial Concentration

Outline

Research Questions

- Does the introduction of subsidies increase **innovation**?

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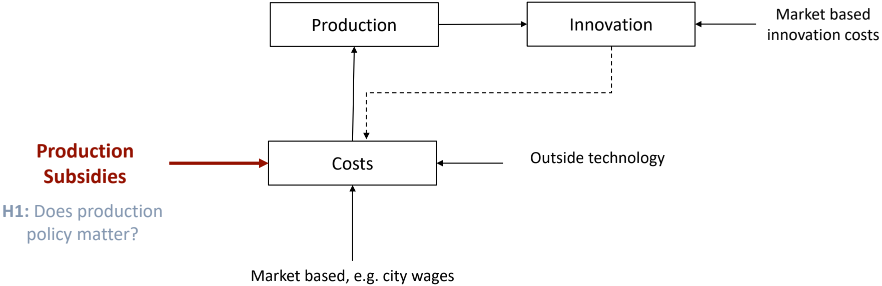
- Does the introduction of subsidies increase **output (production, revenue, number of firms, exports)**?

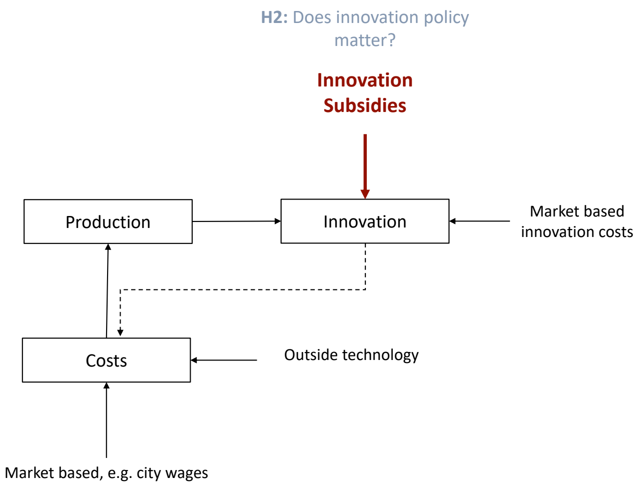
Research Questions

- Does the introduction of subsidies increase **innovation**?
- Does the introduction of subsidies increase **output (production, revenue, number of firms, exports)**?
- How do the effects differ by subsidy type: demand, production, innovation?

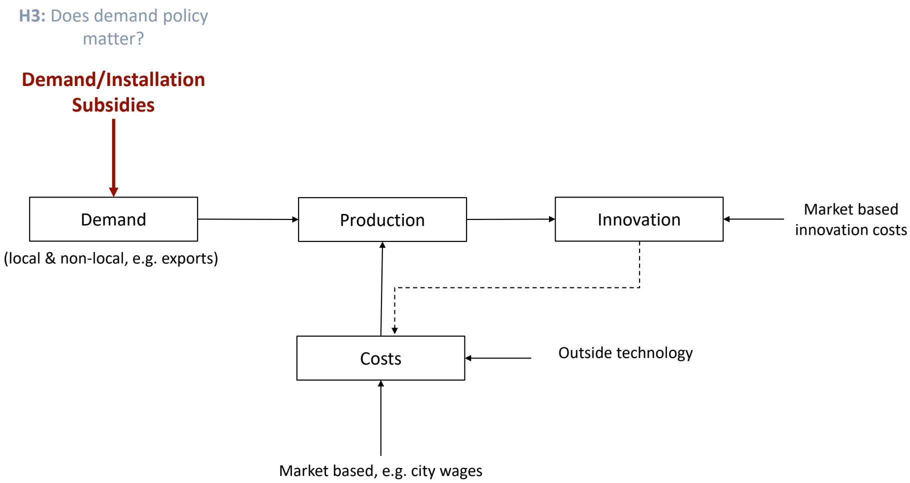
Causal Graph



Causal Graph



Causal Graph



Model

Electricity generation using manufactured inputs

More Model Details

- Heterogeneous firm model (power plant input manufacturers like solar PV) under monopolistic competition
- Many (N) Chinese City-regions (plus 'Rest of World') with different productivities
- Representative consumer in each region demands electricity services
- Local "Grid Planner" builds clean (solar) and dirty (coal) power plants using inputs sourced from manufacturers in all Chinese cities, subject to transport costs
- Manufacturers make endogenous **entry, exit, production, exporting, and technology upgrading (i.e., innovation)** decisions
- Model provides (i) comparative statics for local and national impact of place-based subsidies; (ii) quantifiable framework for analyzing aggregate effects (counterfactuals & welfare)

Theoretical predictions

- Can prove many analytic results in simplified model
    - Initially two symmetric Chinese city-regions
    - Consider single energy sector (just solar)
    - Comparative statics with respect to three subsidy types (demand, production and innovation)
    - Propositions 1-4 have comparative statics on local effects of local subsidies (demand, production and innovation)
    - Confirm in numerical simulations of full model

Theoretical predictions: Local

Figure: Place-based demand subsidies

	Demand Subsidy χ_o	
Innovation$_o$	$\approx +$	
Firm count$_o$	$\approx +$	
Panel production$_o$	$\approx +$	
Revenue$_o$	$\approx +$	
Exports$_o$	$\approx +$	

Notes: All outcome variables and subsidy policies are referred to the same region o. The table shows no prediction on how policies in region d affect outcomes in region o. A 'prediction' in this table represents the sign and magnitude of a potential treatment effect for each type of policy and outcome variable. That is, we are predicting the relative difference between treated and untreated regions. The last column corresponds to the type of innovation subsidies that we observe in the data, which are always implemented together with some policy support towards production. $\approx +$ indicates that we expect effects to be plausibly positive but there is some ambiguity in their sign. We rank unambiguously positive effects to provide qualitative intuition on the effectiveness of different policies on improving each outcome. The ranking, from higher to lower effects, is: $+++ > ++ > +$.

Theoretical predictions: Local

Figure: Place-based production subsidies

	Production Subsidy a_o	
Innovation_o	++	
Firm count_o	++	
$\text{Panel production}_o$	++	
Revenue_o	++	
Exports_o	++	

Notes: All outcome variables and subsidy policies are referred to the same region o. The table shows no prediction on how policies in region d affect outcomes in region o. A 'prediction' in this table represents the sign and magnitude of a potential treatment effect for each type of policy and outcome variable. That is, we are predicting the relative difference between treated and untreated regions. The last column corresponds to the type of innovation subsidies that we observe in the data, which are always implemented together with some policy support towards production. $\approx +$ indicates that we expect effects to be plausibly positive but there is some ambiguity in their sign. We rank unambiguously positive effects to provide qualitative intuition on the effectiveness of different policies on improving each outcome. The ranking, from higher to lower effects, is: $+++ > ++ > +$.

Theoretical predictions: Local

Figure: Place-based innovation subsidies

	Innovation Subsidy ϕ_o	
Innovation$_o$	+	
Firm count$_o$	+	
Panel production$_o$	+	
Revenue$_o$	+	
Exports$_o$	+	

Notes: All outcome variables and subsidy policies are referred to the same region o. The table shows no prediction on how policies in region d affect outcomes in region o. A 'prediction' in this table represents the sign and magnitude of a potential treatment effect for each type of policy and outcome variable. That is, we are predicting the relative difference between treated and untreated regions. The last column corresponds to the type of innovation subsidies that we observe in the data, which are always implemented together with some policy support towards production. $\approx +$ indicates that we expect effects to be plausibly positive but there is some ambiguity in their sign. We rank unambiguously positive effects to provide qualitative intuition on the effectiveness of different policies on improving each outcome. The ranking, from higher to lower effects, is: $+++ > ++ > +$.

Theoretical predictions: Local

Figure: Predictions to the data

	Demand Subsidy χ_o	*Production Subsidy* a_o	*Innovation Subsidy* ϕ_o	*Production & Innovation Subsidy* $a_o + \phi_o$
Innovation$_o$	$\approx +$	++	+	+++
Firm count$_o$	$\approx +$	++	+	+++
Panel production$_o$	$\approx +$	++	+	+++
Revenue$_o$	$\approx +$	++	+	+++
Exports$_o$	$\approx +$	++	+	+++

Notes: All outcome variables and subsidy policies are referred to the same region o. The table shows no prediction on how policies in region d affect outcomes in region o. A 'prediction' in this table represents the sign and magnitude of a potential treatment effect for each type of policy and outcome variable. That is, we are predicting the relative difference between treated and untreated regions. The last column corresponds to the type of innovation subsidies that we observe in the data, which are always implemented together with some policy support towards production. $\approx +$ indicates that we expect effects to be plausibly positive but there is some ambiguity in their sign. We rank unambiguously positive effects to provide qualitative intuition on the effectiveness of different policies on improving each outcome. The ranking, from higher to lower effects, is: $+++ > ++ > +$.

Theoretical Predictions: Aggregate

- Multiple spillovers such as business stealing, learning spillovers & demand mean aggregate effects different from local effect

- Structurally Estimate Full Model in 3 steps:
  1. "External calibration" from literature (e.g., inter-city transport costs) & our firm level panel data (e.g., impact of innovation on own productivity & spillovers; shape of productivity distribution)
  2. Use model inversion on pre-policy data (2004-06) to obtain fixed costs & city productivities
  3. Post policy data after 2007 to match ATT using minimum distance to get subsidy magnitudes

Outline

Empirical Strategy

- Effectiveness of solar industrial policy
  - Look at dynamics: does effect persist?
- Challenges in evaluating industrial policy:
  - Allocation of solar industrial subsidies to a firm is highly non-random
  - So focus on introduction of city level subsidy **policies**
  - These are staggered over time - first ones in 2007 (encouraged by Eleventh Five Year Plan)
  - Some mild pre-trends for some outcomes.
- We follow the **synthetic-difference-in-differences (SDID)** methodology (Arkhangelsky et al 2021)

Synthetic-difference-In-Differences (SDID)

- Outcomes (Y_{it}): Patents, number of firms, panel production, revenue, exports
- Treatments (W_{it}): Subsidy policies (demand, production, innovation)
- Variation: Exploit city-level variation in solar policies and their timing

- SDID: Two-way FE regression with time and unit weights

$$\left(\hat{\tau}^{\text{sdid}}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{arg\,min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau^{\text{sdid}} \right)^2 \hat{\omega}_i^{\text{sdid}} \hat{\lambda}_t^{\text{sdid}} \right\}$$

- Unit weights ω_i: chosen so that average pre-treatment outcome for control units is $\approx$ parallel to pre-treament outcome for treated units
- Time weights λ_t: more weight on time periods which better predict post-treatment outcomes for control

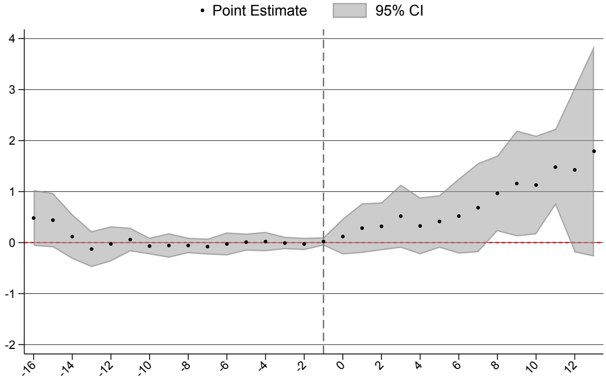
SDID Intuition

1. Construct synthetic control group such that pre-trends are approximately parallel
2. Compute treatment effect using diff-in-diff between treatment and synthetic control

- Allows us to relax the parallel trends assumption
- Comparison with TWFE
  - SDID as a generalization of Two Way Fixed Effects (TWFE) that allows for weighting the control group to construct a better counterfactual
  - We use cohort-by-cohort estimation approach, with never treated as control group
  - We aggregate these policy cohort estimates to obtain one aggregate ATT for each type of policy

Outline

Results: Patents, Any subsidy



Notes: SDID on 358 cities with 43 treated. Cohort-year specific ATTs aggregated into event studies. Outcome: IHS of patents by solar firms in a city-year.

Treatment is any subsidy. 95% SE cluster bootstrapped by city.

2007 - IHS 2007 - raw 2013

Results: Patents

Table: Patent Counts (Aggregate ATT)

	Any subsidy	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
All patents	0.496**	0.236	0.871***	1.060***
	(0.200)	(0.275)	(0.227)	(0.367)
Observations	6,086	6,086	6,086	6,086

Notes: * 0.1 ** 0.05 *** 0.01. SDID on 358 cities 2004-2020. Outcome is IHS of patent count by solar firms in city-year pair (level av. = 13.1). SE cluster bootstrapped by city.

Levels

Results: Quality-adjusted Patents I (Citation-weighted)

Table: Patent Citations (Aggregate ATT)

	Any subsidy	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
Patent citations	0.676***	0.388	0.854***	1.076**
	(0.218)	(0.328)	(0.300)	(0.482)
Observations	6,086	6,086	6,086	6,086

Notes: *0.1 ** 0.05 *** 0.01. SDID on 358 cities 2004-2020. Outcome is IHS of patent count (weighted by future citations) by solar firms in a city-year pair. SE cluster bootstrapped by city.

Results: Quality-adjusted Patents II (patent type)

Table: Invention (high value) vs. Design Patents (low value)

	Any subsidy	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
All patents	0.496**	0.236	0.871***	1.060***
	(0.200)	(0.275)	(0.227)	(0.367)
☐ Design patents	0.186	0.277	0.237	0.151
	(0.138)	(0.216)	(0.173)	(0.253)
☐ Invention/utility model patents	0.529***	0.201	0.937***	1.097**
	(0.201)	(0.274)	(0.232)	(0.373)

Notes: * 0.1 ** 0.05 *** 0.01. SDID on 358 cities 2004-2020. Outcome is IHS of patent count.

Classifying Patents as Learning By Doing/process innovation

- Liu (2023) classifies random sample of 3,299 Chinese solar patents into whether they are productivity improving (vs. product innovation) based on text Example patents
- Use this as a training dataset to classify all our patents into these process innovations (so closer to LBD) using random forest algorithm
- Cross validate using 15% hold-out sample and find high (90% +) accuracy
- Using counts of this sub-sample as an outcome

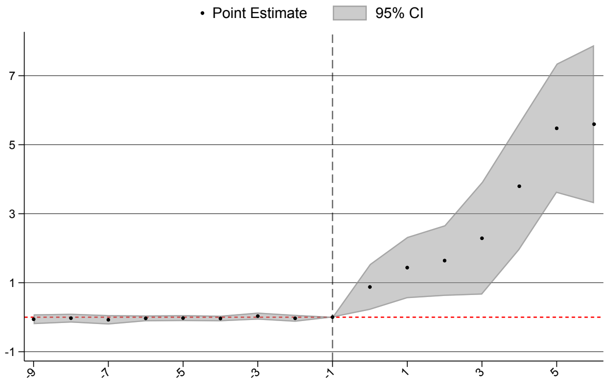
Results: LBD Patents

Table: Learning-by-doing Patents (Aggregate ATT)

	Any subsidy	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
Patent	0.365**	0.187	0.604***	0.914***
	(0.149)	(0.186)	(0.235)	(0.377)
Observations	5,728	5,728	5,728	5,728

Notes: * 0.1 ** 0.05 *** 0.01. 358 cities with 43 treated. 2004-20. Outcome is IHS of “LBD” patents count

Results: Production Capacity, Any subsidy



Notes: SDID on 358 cities with 43 treated (2004-2013). Cohort-year specific ATTs aggregated into event studies. Outcome: IHS of total panel production capacity MWh by solar firms in a city-year. Treatment is any subsidy. 95% SE cluster bootstrapped by city.

2007 - IHS

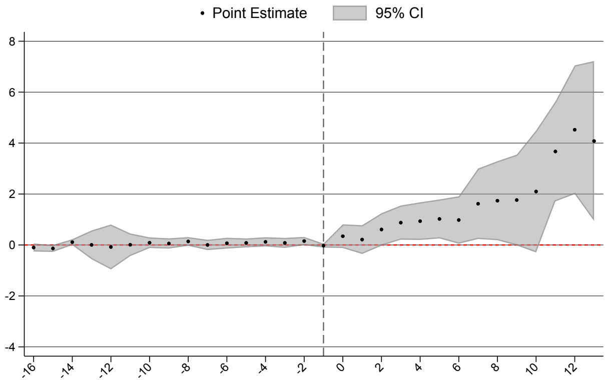
Results: Production Capacity

Table: Solar Panel Production Capacity (Aggregate ATT)

	Any subsidy	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
Panel production	2.098***	0.587	2.496***	2.930***
	(0.532)	(0.467)	(0.575)	(0.773)
Observations	3,580	3,580	3,580	3,580

Notes: * 0.1 ** 0.05 *** 0.01. SDID estimates on 358 cities 2004-2013. Outcome is IHS of production capacity of solar firms in a city-year pair.

Results: Revenue



Notes: SDID on 358 cities with 43 treated. Cohort-year specific ATTs aggregated into event studies. Outcome: IHS of total revenue by solar firms in a city-year.

Treatment is any subsidy. 95% SE cluster bootstrapped by city. 2004-2020.

2007 - IHS | 2007 - raw | 2013

Results: Revenue

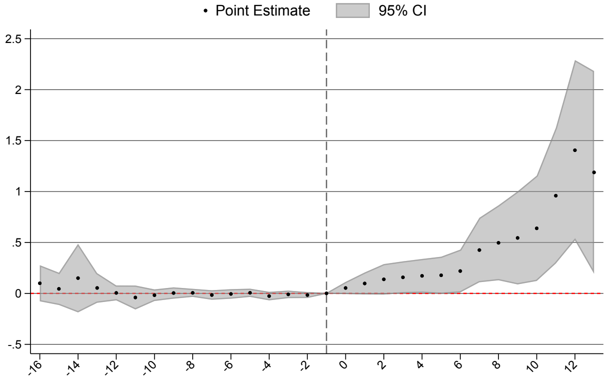
Table: Revenue (Aggregate ATT)

	Any subsidy	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
Revenue	0.994**	0.060	1.772***	2.502***
	(0.448)	(0.278)	(0.615)	(0.819)
Observations	6,086	6,086	6,086	6,086

Notes: * 0.1 ** 0.05 *** 0.01. SDID estimates on 358 cities 2004–2020. Outcome is IHS of production capacity of solar firms in a city-year pair.

Levels

Results: Firm Count, Any subsidy



Notes: SDID on 358 cities with 43 treated. Cohort-year specific ATTs aggregated into event studies. Outcome: IHS of total number of solar firms in a city-year.

Treatment is any subsidy. 95% SE cluster bootstrapped by city. 2004-2020.

2007 - IHS

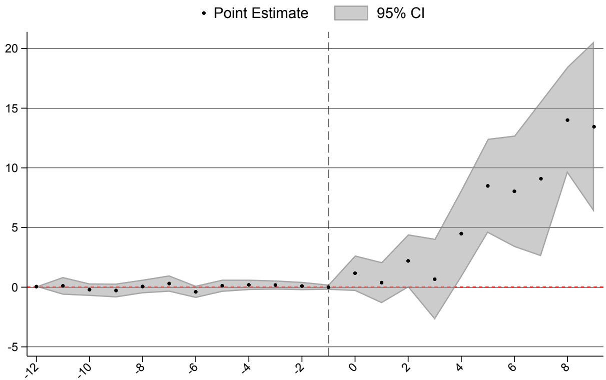
Results: Firm Count

Table: Firm Count - Number of Solar Firms (Aggregate ATT)

	Any subsidy	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
Firm count	0.212**	0.031	0.377**	0.412***
	(0.096)	(0.038)	(0.155)	(0.148)
Observations	6,086	6,086	6,086	6,086

Notes: * 0.1 ** 0.05 *** 0.01. SDID estimates on 358 cities 2004-2020. Outcome is IHS of count of solar firms in a city-year pair.

Results: Solar exports, Any subsidy



Notes: SDID on 358 cities with 43 treated. Cohort-year specific ATTs aggregated into event studies. Outcome: IHS of total solar export value of solar firms in a city-year.

Treatment is any subsidy. 95% SE cluster bootstrapped by city. 2004-2016.

2007 - IHS

Results: Solar exports

Table: Solar exports (Aggregate ATT)

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Solar export value	3.192***	1.153	4.298***	6.092**
	(1.231)	(1.145)	(1.498)	(2.366)
Observations	4,654	4,654	4,654	4,654

Notes: * 0.1 ** 0.05 *** 0.01. Solar exports classified via HS6. SDID on 358 cities 2004-2016. Outcome is IHS.

Total exports

Extensions & Robustness

- **Business stealing vs. technology spillovers** business stealing results
- Productivity productivity results
- Pollution $PM_{2.5}$ results CO_2 results
- Placebos on GDP, non-solar patents, etc. placebo
- Adding controls to SDID (GDP, population, income, tax revenue, ...) results with controls
- Total solar patents (including universities, non-solar firms, etc.) city-level patents
- Adjustment based on factory locations plants
- Compositional change and dynamic effects results for cohorts between 2007 and 2013
- Results in levels, etc. (e.g. Chen and Roth, 2022) results in levels
- Magnitudes and Cost-Benefit

Results

Table: Positive Spillovers outweighs Business Stealing (cf. Bloom, Schankerman & Van Reenen, 2013)

	(1) All patents	(2) Firm count	(3) Revenue	(4) Panel capacity	(5) Solar export value
Any subsidy in an adjacent city	0.373***	0.099	0.617***	0.385	1.099**
	(0.096)	(0.055)	(0.199)	(0.263)	(0.491)
Observations	5,049	5,049	5,049	3,210	3,861

Notes: * 0.1 ** 0.05 *** 0.01.

Back

Extensions & Robustness

- Business stealing vs. technology spillovers business stealing results
- Productivity productivity results
- **Pollution** $PM_{2.5}$ results
- Placebos on GDP, non-solar patents, etc. placebo
- Adding controls to SDID (GDP, population, income, tax revenue, ...) results with controls
- Total solar patents (including universities, non-solar firms, etc.) city-level patents
- Adjustment based on factory locations plants
- Compositional change and dynamic effects results for cohorts between 2007 and 2013
- Results in levels, etc. (e.g. Chen and Roth, 2022) results in levels
- Magnitudes and Cost-Benefit

Results

Table: $PM_{2.5}$ concentration (Levels, Aggregate ATT)

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
PM 2.5 concentration	-0.611	-1.192***	-0.167	-0.161
	(0.441)	(0.581)	(0.394)	(0.584)
Observations	6,086	6,086	6,086	6,086
Mean of Dep. var.	38.58	38.58	38.58	38.58

Notes: * 0.1 ** 0.05 *** 0.01. The LHS variable is annual average $\mu g/m^3$ concentration of $PM_{2.5}$ at 0.1 x 0.1 degree resolution. From this, we calculate area-weighted averages. The source is the V5. GL.02 data set.

Outline

Timing of Decisions

More Model Details

1. Entrepreneurs enter by paying a sunk cost, then draw productivity, φ. Productivity also depends learning spillovers from other firms, κ
2. Decide whether to further reduce marginal cost by ξ by paying fixed cost of innovation (Bustos, 2011).
3. Decide whether to pay fixed cost of production & compete a la monopolistic competition (Melitz, 2003)
4. Producing firms in origin city o serve multiple destination cities d (inc. overseas markets) paying iceberg trade costs
5. Fixed costs determine productivity cut-offs for: (i) exit, (ii) production & (iii) innovation.
6. Demand for intermediates across all Chinese cities from different grid planners (and overseas) influences solar manufacturer decisions.

Solar industrial policy

1. **Production subsidies**
   - Production subsidies $a_{o,s} < 1$ are a reduction in input costs in city o, manufacturers, marginal cost becomes $\frac{a_{o,s}}{\xi_{o,s}\varphi\kappa_s}$.
2. **Innovation subsidies**
   - Innovation subsidies ($\phi_{o,s} < 1$) in city o as a reduction in fixed costs of technological upgrading, which becomes $\phi_{o,s} w_o f_s^i$
3. **Demand subsidies**
   - Demand subsidies in d are $\chi_d < 1$ that pre-multiplies $P_{d,s} e_{d,s}$ in the Grid-Planner problem

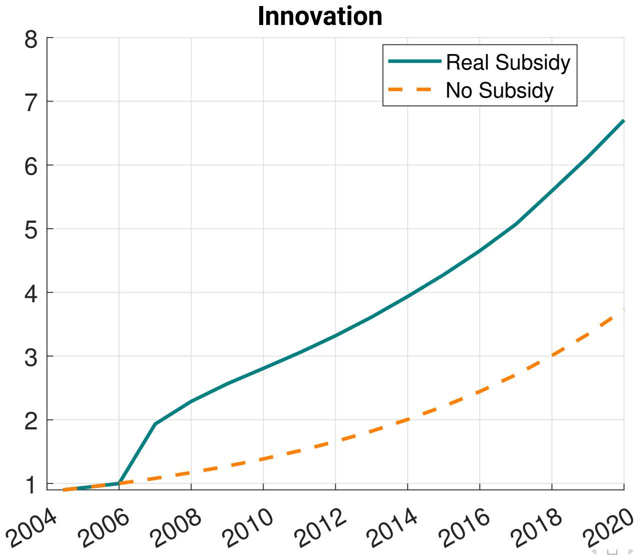
Outline

Model Quantification Strategy

Parameter		Value	Identification/Moments	
Preference Parameters				
σ	Elasticity of substitution across energy sectors (solar vs non-solar)	3	Jo (2023), Papageorgiou et al. (2017)	External
$\sigma_s, \sigma_{s'}$	Elasticity of substitution across power plant input varieties (e.g., solar panel models)	5, 8.18	Shapiro and Walker (2018)	External
Production Technology Parameters				
$\theta_s, \theta_{s'}$	Shape parameter (of Pareto distribution)	5.3, 11.7	Sales revenue (ASIE, ENF)	External
$b_s, b_{s'}$	Industry average scale parameter (of Pareto distribution)	0.267, 0.256	Sales revenue (ASIE, ENF)	External
$b_{o,s}, b_{o,s'}$	Location-specific scale parameter (of Pareto distribution)	2 values for each region	Local solar and coal revenue 2004–2006	Model inversion
$f_s^e, f_{s'}^e$	Sunk entry cost	24.05, 0.0016	Average productivity of solar and coal	Model inversion
$f_s, f_{s'}$	Production fixed cost	0.05607, 0.0462	Solar and coal average revenue	Model inversion
$f_s^i, f_{s'}^i$	Innovation fixed cost	0.05610, 0.2784	Share of solar and coal innovators	Model inversion
$\xi_s, \xi_{s'}$	Productivity gain from innovating	1.058	Estimated (Appendix Table E19, col. 3)	External
δ	Knowledge spillover parameter	1.084	Estimated (Appendix Table E20, col. 2)	External
Trade Parameters				
τ_{od}	Iceberg trade costs (intra-China)	$e^{0.032\, tt_{od}}$	Egger et al. (2023)	External
Policy Parameters				
a_s	Production subsidy	16%	Revenue and innovation empirical ATTs	Minimum distance
χ_s	Demand subsidy	8%	Revenue and innovation empirical ATTs	Minimum distance
ϕ_s	Innovation subsidy	12%	Revenue and innovation empirical ATTs	Minimum distance

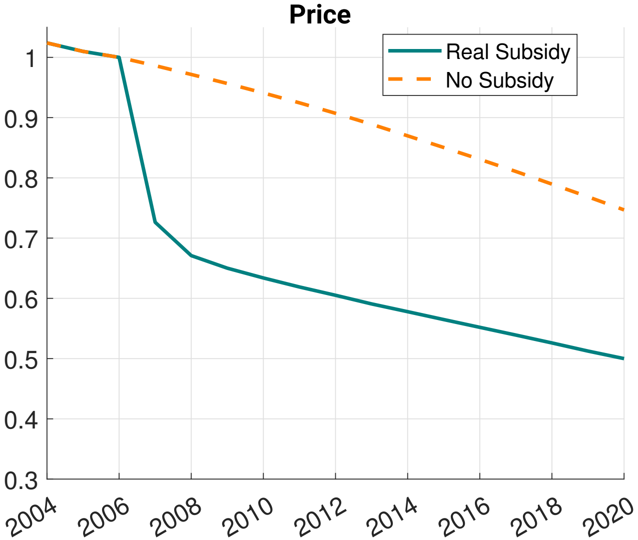
Counterfactuals without subsidies

Industrial policies explain about half of increase in Chinese Innovation



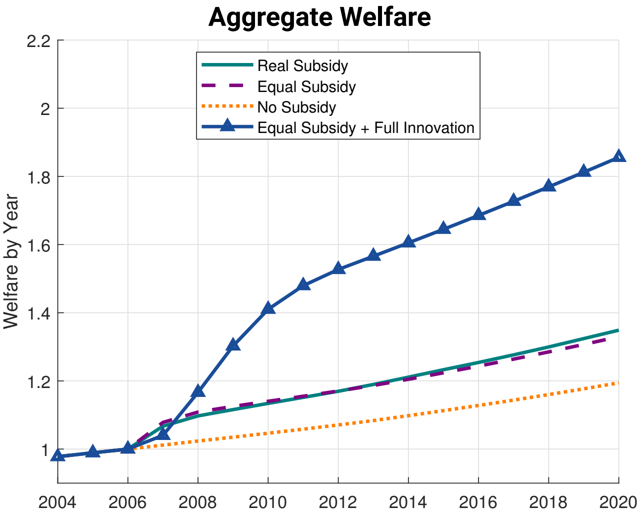
Counterfactuals without subsidies

Industrial policies explain about half of fall in Solar Prices



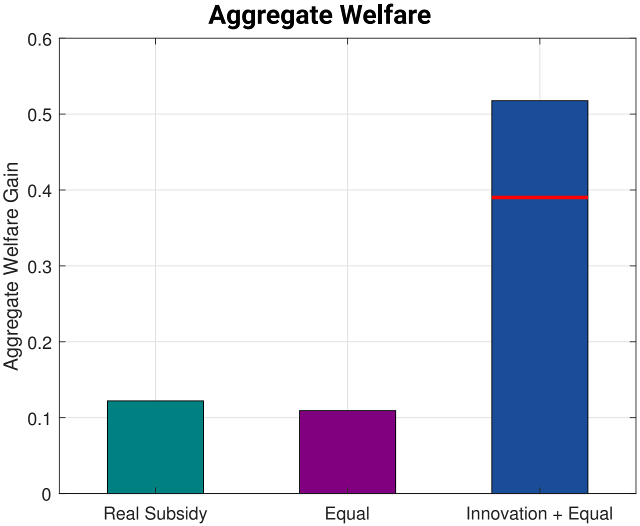
Welfare Counterfactuals: Flows

Policy increases consumer welfare from energy; but an innovation-focused strategy has much larger welfare effects



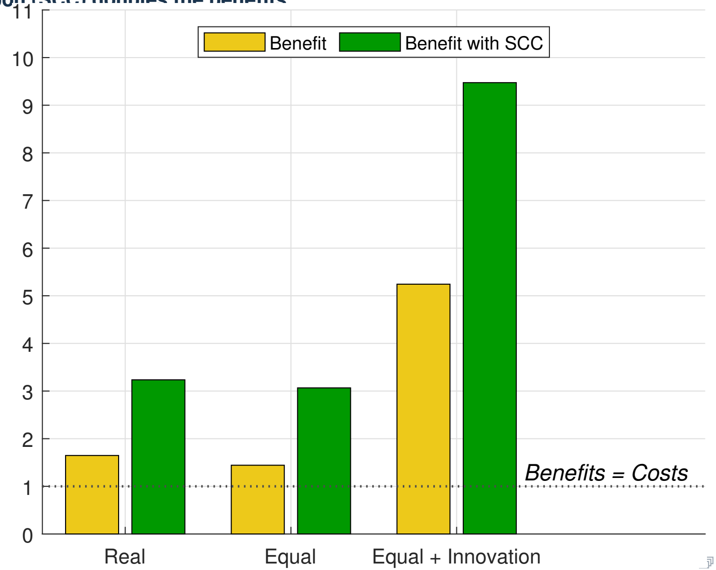
Welfare Counterfactuals: Present Value

- Consumer welfare from energy by 12%, could quadruple if innovation focused
- Giving equal subsidy in every city no better than locally driven approach



Modelling Counterfactuals: Social Benefit-Cost Ratios

Inc. Social Cost of Carbon (SCC) doubles the benefits



Conclusions

- New and comprehensive database on the Chinese solar industry and local solar industrial policy
- China's local solar production and innovation subsidies are effective at stimulating local solar industry (innovation, firm numbers, revenue, production, exports)
- Theoretical model's predictions consistent with empirical analysis
- Positive effects persist at aggregate level: policy explains about half of change in innovation, revenue and prices
- Social Benefits to Chinese citizens 65% larger than subsidy costs. But innovation subsidy focused policy would be even more effective

Manufacturing technology

Production decision:

- Firms use a composite factor of production $L_{o,s}$ with unit cost w_o
- They need to pay a sunk cost $w_o f_s^e$ to enter
- Then draw productivity φ, from Pareto distribution (city-specific scale parameter, $b_{o,s}$, & common shape parameter θ_s)
- To produce $q_{o,s}(\varphi)$ units of a variety, costs firm $w_0 f_s + \frac{q_{o,s}}{\varphi \kappa_s}$, where κ_s governs spillovers as function of mass of innovators in last period.

Innovation decision:

- Upon observing its initial productivity φ, a firm can upgrade its technology (innovate)
- By incurring a fixed cost $w_o f_s^i$, it reduces marginal cost to: $\frac{1}{\xi_{o,s} \varphi \kappa_s}$, with $\xi_{o,s} > 1$

Demand for energy sources

- In each destination city d, representative consumer utility from electricity services e_d (e.g. from solar farms):

$$U_d = u\left(e_d\right) \tag{1}$$

- Electricity services installed in city by Grid Planner, builds power plants combining output from (k=2) energy sectors: clean (s) & dirty (s'), i.e., solar vs. coal:

$$e_d = \left(e_{d,s'}^{\rho} + e_{d,s}^{\rho}\right)^{1/\rho}$$

Demand for manufactured inputs

(e.g. solar panels, $k = s$)

- Grid planner supplies as much energy as possible in the minimal cost way given expenditure of representative consumer, E_d and prices, $P_{d,s}$, $P_{d,s'}$

$$\max_{e_{d,s},e_{d,s'}} \left(e_{d,s'}^{\rho} + e_{d,s}^{\rho}\right)^{1/\rho}$$

$$\text{s.t. } \chi_{d,s} P_{d,s} e_{d,s} + P_{d,s'} e_{d,s'} = E_d$$

Demand for manufactured inputs

(e.g. solar panels, $k = s$)

- Grid planner supplies as much energy as possible in the minimal cost way given expenditure of representative consumer, E_d and prices, $P_{d,s}$, $P_{d,s'}$

$$\max_{e_{d,s}, e_{d,s'}} \left(e_{d,s'}^{\rho} + e_{d,s}^{\rho} \right)^{1/\rho}$$

$$\text{s.t. } \chi_{d,s} P_{d,s} e_{d,s} + P_{d,s'} e_{d,s'} = E_d$$

- Which yields our solar installation demand function, $e_{d,s}$:

$$e_{d,s} = \left(\frac{1}{P_{d,s}} \right)^{\sigma} \frac{E_d}{P_{d,s'}^{1-\sigma} + (\chi_{d,s} P_{d,s})^{1-\sigma}}; \tag{2}$$

Demand for manufactured inputs

(e.g. solar panels, $k = s$)

- Grid planner supplies as much energy as possible in the minimal cost way given expenditure of representative consumer, E_d and prices, $P_{d,s}$, $P_{d,s'}$

$$\max_{e_{d,s},e_{d,s'}} \left(e_{d,s'}^{\rho} + e_{d,s}^{\rho}\right)^{1/\rho}$$

$$\text{s.t. } \chi_{d,s}P_{d,s}e_{d,s} + P_{d,s'}e_{d,s'} = E_d$$

- Which yields our solar installation demand function, $e_{d,s}$:

$$e_{d,s} = \left(\frac{1}{P_{d,s}}\right)^{\sigma} \frac{E_d}{P_{d,s'}^{1-\sigma} + (\chi_{d,s}P_{d,s})^{1-\sigma}}; \tag{2}$$

- To generate output for each energy sector, combine intermediate inputs, $q_{od,s}(\omega)$ = quantity of variety ω manufactured in city o supplied to d using CES:

$$e_{d,s} = \left(\sum_{o} \int_{\omega\in\Omega_{o,s}} q_{od,s}(\omega)^{\frac{\sigma_s-1}{\sigma_s}} d\omega\right)^{\frac{\sigma_s}{\sigma_s-1}} \tag{3}$$

note: $\sigma = 1/(1-\rho)$

Demand for manufactured inputs

- To meet the optimal energy demand, grid planner chooses solar modules from all cities given their prices, $p_{od,s}$ to minimize costs.
- Solving this constrained optimization problem gives a demand for each variety:

$$q_{od,s}(\omega) = \left(\frac{(p_{od,s}(\omega))^{-\sigma_s}}{P_{d,s}^{1-\sigma_s}} \right) E_{d,s} \tag{4}$$

- This will determine price indices $P_{d,s}$ and $P_{d,s'}$.

Prices and trade costs

- Firms can sell to grid planners in China and overseas: both are subject to iceberg trade costs:
    - To serve market d, firm in o needs to produce $\tau_{od,s} q_{od,s}(\varphi)$ of variety, $\tau_{od,s} \geq 1$ (if o = d then τ = 1).

- Implies manufacturers' optimal prices are a constant markup over marginal costs

$$p_{od,s}(\varphi) = \frac{\sigma_s}{\sigma_s - 1} \frac{w_o \tau_{od,s}}{\xi_{o,s} \varphi \kappa_s} \tag{5}$$

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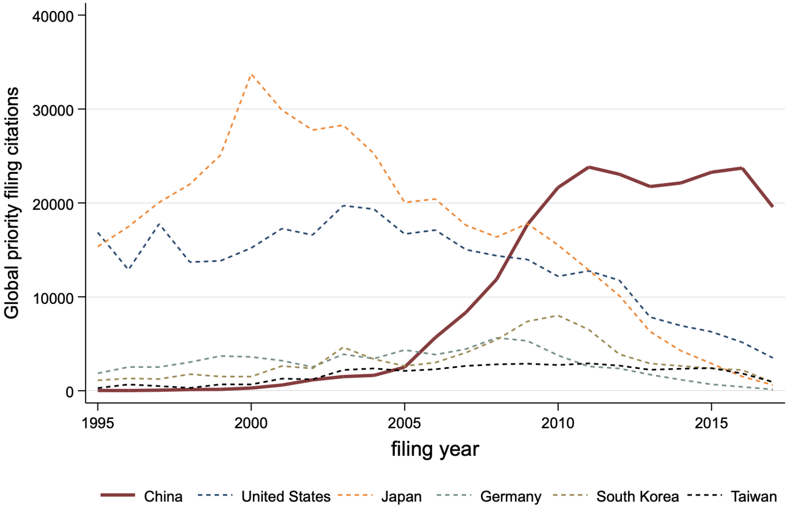
Citations



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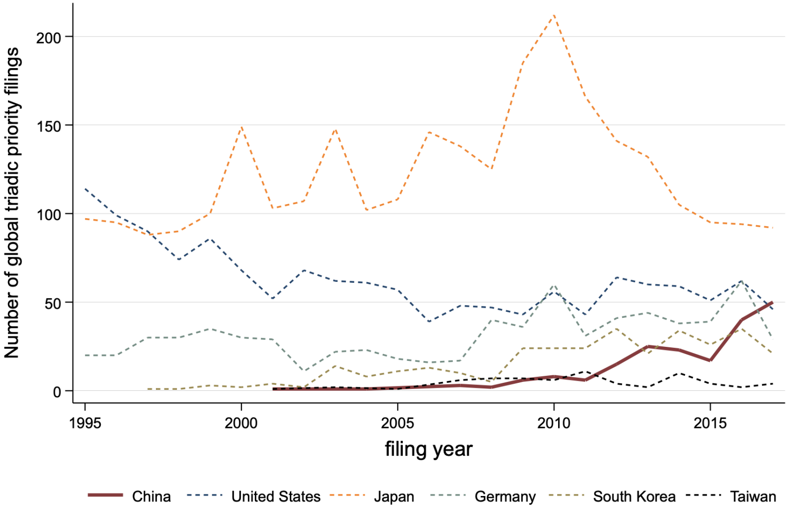
Triadic patents



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Company Name		Region	No. Staff	No. of Known Sellers	Power Range(Wp)
1st Sunergy		United States			175-290
2ES		France	15		135-150
2Power		Germany	50	1	215-325
3D Energy	€	Italy	20		200-450
3G-Solar		Germany			155-300
3Hz Solar		China			140-540
3KM Power		China			410
3S	€	China	300	1	40-600
3S Swiss Solar Solutions		Switzerland		1	115-200
5Star Solar		China		1	240-370
8.33 Solar		Spain		5	270-345
A. D. Global Synergies		India			3-300
A.R.E.		Egypt			325-340
Abba		Italy			230-300
Abcw Power		China			5-350
ABi-Solar		United States		18	275-470
Abotree Solar		China			0.3-360
Abshine		China	100		255-270
Access Solar		India		1	3-330

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Featured Product (Solar Panels)

XL120H-360~380W

XLA Solar

From £0.104 / Wp

Cell Type:	Monocrystalline
Dimensions:	1755x1038x35 mm
Weight:	19.5 kg
Cell Size:	166×166 mm
Glass Thickness:	--

More

Featured Product (Solar Panels)

GSM-MP3/132-BM...

Grand Sunergy

Cell Type:	Bifacial, PERC
Dimensions:	2384x1303x35 mm
Weight:	38.5 kg
Cell Size:	--
Glass Thickness:	--

More

ENF

Language:

Company Directory (55,500) | Product Directory (84,400) | Advertising | Log In | Join Free

AmSolar 富乐新能源

Monocrystalline -- Solar Panel Manufacturers

Companies involved in monocrystalline panel production. 1,446 monocrystalline panel manufacturers are listed below.

Solar Panels / Crystalline / Monocrystalline

Ad

Company Name	Region	No. Staff	No. of Known Sellers	Power Range(Wp)
Horay Solar	China	400	2	50-660
Grand Sunergy	China			
Mysolar USA	United States			

Company Name	Region	No. Staff	No. of Known Sellers	Power Range(Wp)
1st Sunergy	United St…			175-290

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Featured Product (Solar Panels)

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Featured Product (Solar Panels)

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Weight:	38.5 kg
Cell Size:	--
Glass Thickness:	--

Solar Panels / Monocrystalline / 3Hz Solar

Guangzhou 3HZ Solar Technology Co., Ltd.

Building C5, Huachuang Industrial Park, Shiji Town, Panyu District, Guangzhou, Guangdong, 511430
+86 20 34784859
fang@3hz-solar.com
www.3hz-solar.com
China

Staff Information

Useful Contacts	Fang 总经理	Jack Sales	陈芳 采购

Company Description Ad

Guangzhou 3Hz Solar Technology Co., Ltd. is a private and new high tech enterprise which specializes at solar photovoltaic and wind-solar hybrid products' R&D, manufacturing and sales. We mainly engage in the researching, manufacturing ,sales and after-sales service of the products such as home solar battery, photovoltaic system engineering, solar energy application, wind-solar hybrid application. Since it's foundation, our company has devoted the mind to business development and continuous product innovation, drawn large-scale automated production line and set up a professional R&D technology center. We have powerful technical resources, sophisticated equipment and advanced production technology, would like to propose all-around solution of solar and wind-solar hybrid systems integration for customers, promote the popularization and application of solar energy. Our products has passed certificates such as CE and ROHS, and a number of them have obtained national patents.

Panels | Components

Business Details

Monocrystalline, Polycrystalline

Featured Product (Solar Panels)

Aurora TOPCon 182 RS41...
Runda Solar
From £0.147 / Wp

Cell Type:	TOPCon
Dimensions:	1722x1134x30 mm
Weight:	21 kg
Cell Size:	--
Glass Thickness:	--

More

Featured Product (Solar Panels)

N-Type SF-M18/144 topcon
Shinefar Solar
From £0.169 / Wp

Cell Type:	Monocrystalline
Dimensions:	2278x1134x35 mm
Weight:	28 kg
Cell Size:	182x182 mm
Glass Thickness:	3.2 mm

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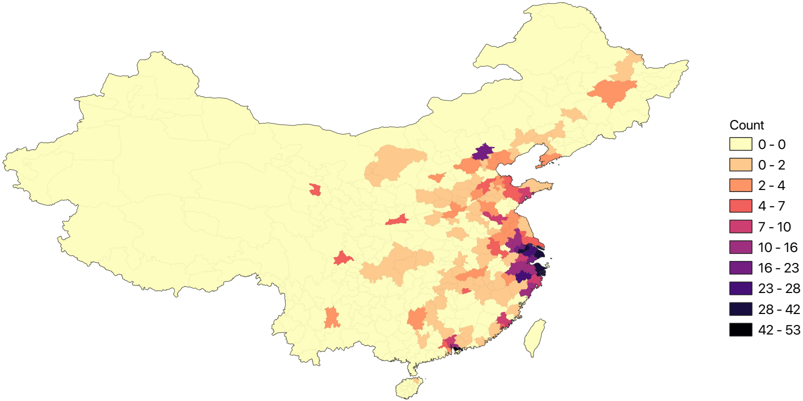
Spatial concentration of the Chinese solar industry



Note: Number of solar firms in different Chinese cities, 2019

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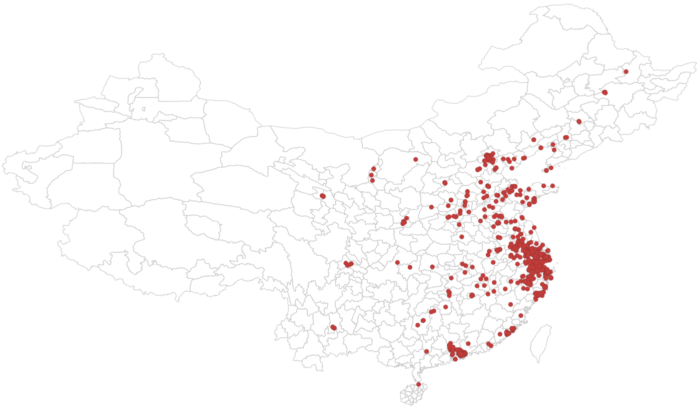
Spatial concentration of the Chinese solar industry



Solar PV in the Chinese government's Five-Year Plans

- **2001-2005 Tenth Five-Year Plan:**
  - Solar a targeted sector for first time, together with other renewable energies.
  - In 2001 no solar industry.
  - In 2005 considerable growth.
- **2006-2010 Eleventh Five-Year Plan:**
  - Solar industry as an opportunity to attain technological leadership.
  - Included funding for R&D and manufacturing development for the first time.
  - Solar industry witnessed exceptional growth
- **2011-2015 Twelfth Five-Year Plan:**
  - Government kept pushing for solar adoption, supply-chain expansion and indigenous R&D.
  - R&D goals gained in detail and scope
- **2016-2020 Thirteenth Five-Year Plan:**
  - Targeting capacity and R&D expansion, as well as industry-wide cost-reduction.
  - Includes Thirteenth Five Year Plan for Solar Energy Development.

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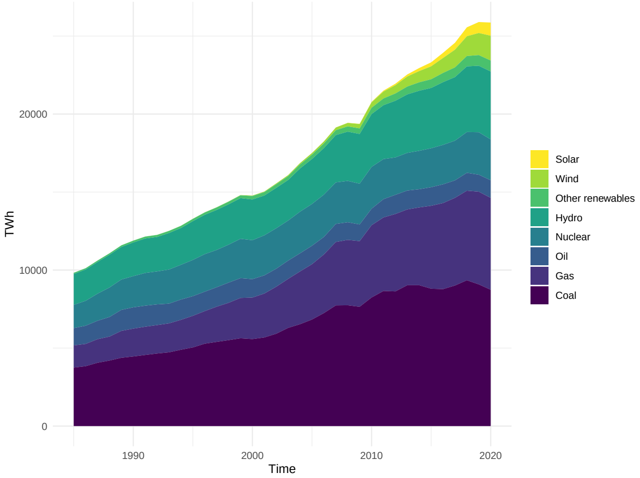
Renewable electricity capacity, especially solar, has grown rapidly

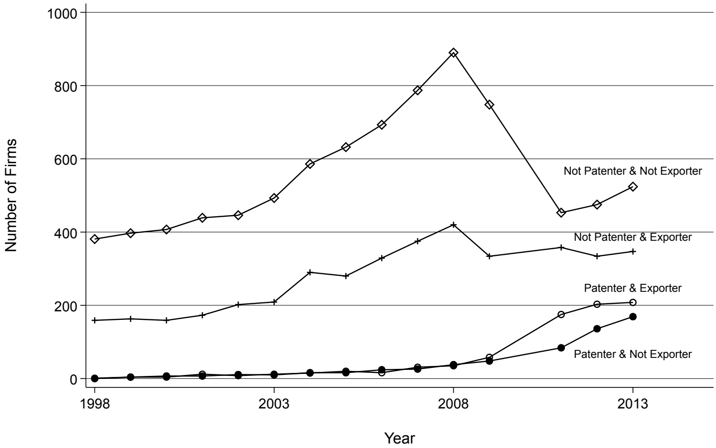
Figure: World electricity generation by source



Source: International Energy Agency (IEA) Back

The productivity thresholds in the data

Figure: Number of firms (ASIE) in each group



Note: Firm-level data from ASIE, merged with SIPO.

Optimal Profits (3 regimes)

$$\pi_{o,s}(\varphi) = \max\left\{ \sum_{d \neq \tilde{d}} \left\{ p_{od,s}(\varphi) q_{od,s}(\varphi) - w_o \frac{\tau_{od,s} a_{o,s} q_{od,s}(\varphi)}{\varphi} \right\} - w_o f_{o,s}, \right.$$

$$\sum_{d} \left\{ p_{od,s}(\varphi) q_{od,s}(\varphi) - w_o \frac{\tau_{od,s} a_{o,s} q_{od,s}(\varphi)}{\varphi} - w_o f^x_{o,\tilde{d},s} \right\} - w_o f_{o,s},$$

$$\left. \sum_{d} \left\{ p_{od,s}(\varphi) q_{od,s}(\varphi) - w_o \frac{\tau_{od,s} a_{o,s} q_{od,s}(\varphi)}{\xi_{o,s} \varphi} - w_o f^x_{o,\tilde{d},s} \right\} - w_o f_{o,s} - w_o \phi_{o,s} f^i_{o,s} \right\}$$

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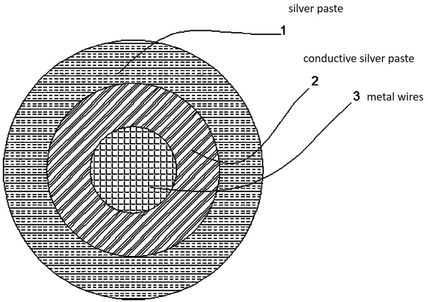
LBD-Patent: Patent as process innovation

Grid Line Structure for Solar Cell manufacturing (CN104752533A)

This invention comprises metal wires and conductive silver paste. The grid line is woven from metal wires, with a layer of silver paste applied to the metal wires which ensures excellent adhesion between the silver paste and the metal wires as well as strong ohmic contact between the sub-grid line and the silicon wafer. The silver paste used for the main grid line does not contain glass material, which ensures good adhesion between the main grid line and the silicon wafer and reduces the recombination of minority carriers under the main grid line. **Compared with the prior art, the present invention greatly reduces the amount of (expensive) silver paste used generating big cuts in production costs. It ensures excellent aspect ratios of the grid lines, eliminating the possibility of broken lines and false prints, thereby improving the photovoltaic conversion efficiency of the solar cell, and being suitable for large-scale industrial production.**



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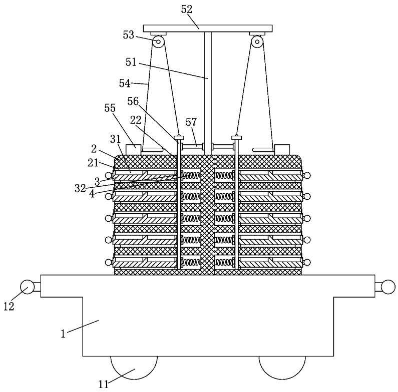
LBD-Patent: Patent as process innovation

Transfer Assembly of a Solar Cell (CN208706675U)

The utility model discloses a transfer assembly of a solar cell piece with a metal-stacked electrode. The assembly comprises a trolley body, a storage member arranged on the top of the trolley body, and a positioning component arranged on the storage member. A plurality of slots are opened on the storage member, and a storage plate is slidably connected in each slot. The top of the storage plate is provided with a groove, a spring is provided on the inner wall of each slot, the spring is connected to the storage plate, a first connecting hole is opened on the storage plate, and a second connecting hole penetrating all the slots is opened on the storage member. The positioning component includes a support column, a crossbar, a pulley, a rope, a motor, a limit rod, and a sliding block. **The utility model delivers the solar cell piece through the newly designed transfer assembly. The structure is simple, easy to install and transport, and will not damage the solar cell piece during transportation, reducing the defect rate and ensuring product quality.**



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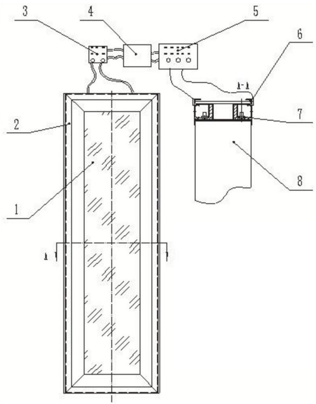
Non-LBD Patent

Road Cliff Lighting Device (CN212273899U)

This utility model patent relates to a road cliff photovoltaic lighting device, which includes a road cliff stone or road guardrail connected to the outer surface of a photovoltaic component. The photovoltaic component is connected to the inverter and battery through a controller in sequence, and the controller is connected to the light strip. The light strip is located on one side of the road cliff stone or road guardrail facing the center of the road. By combining the photovoltaic power generation system with the road cliff or guardrail lighting, photovoltaic power generation, which serves as green energy, is closely integrated with transportation, solving the power supply and subsequent maintenance problems of traditional road lighting and reducing construction and maintenance costs. It also produces an uninterrupted power supply to indicate the road dividing lines and boundary lines, guiding the passage of vehicles and pedestrians, relieving driving fatigue and beautifying the road.



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Non-LBD Patent

New Phosphide Material

The present invention provides a carbon-doped P-type gallium phosphide material, in which carbon is used as the doping element of the P-type gallium phosphide semiconductor material. The preparation method of the material is to use metal organic chemical vapor deposition technology, introduce organic gallium source and phosphorus source into the reaction chamber, let them decompose at high temperature, and react on the surface of the substrate to produce gallium phosphide material. During the generation of gallium phosphide material, carbon impurities are introduced by inputting substances containing carbon elements, or by utilising carbon atoms generated by the organic gallium source during thermal decomposition. In the present invention, carbon replaces Mg or Zn. Since carbon doping has a small diffusion coefficient and stable properties, highly doped GaP materials can be produced, which are characterised by high efficiency, low diffusion, and high stability. Back to Data Section

Descriptive Statistics

	Mean	Std. Dev.	Sample Size
SIPO, 2004-2020, 358 cities:			
Total patents by solar firms	13.1	111.3	6,086
Design patents	1.2	10.4	6,086
Utility model and invention patents	11.9	102.8	6,086
Orbis and Qichacha, 358 cities:			
Total number of solar firms, 2004-2020	2.9	10.2	6,086
Total revenue of solar firms, RMB, billions, 2004-2020	0.218	1.38	6,086
Customs, 358 cities:			
Total export value of solar firms, millions USD, 2004-2016	24.8	186	4,654
Total export volume of solar firms, millions, 2004-2015	3.18	43.7	4,296
Average export price of solar firms, USD, 2004-2015	9,716	480,762	4,296

Notes: Each observation is city-year pair. There are up to 358 cities between 2004 and 2020 (6,086 observations), but different datasets may have lower numbers of observations as noted in the table. The revenue numbers are adjusted to account for multi-product firms.

Back to Data Section

Descriptive Statistics

	Mean	Std. Dev.	Sample Size
ENF, 2004-2013, 358 cities:			
Total Solar Panel capacity, MWh	82.4	483.3	3,580
Total Solar Panel production, MWh	40.7	265.5	3,580
Total Solar Cell capacity, MWh	50.8	353.4	3,580
Total Solar Cell production, MWh	31.3	233.0	3,580
Total Number of Solar Panel firms	0.9	3.5	3,580
Total Number of Solar Cell firms	0.2	1.0	3,580
Statistics Yearbook, 2004-2020, 284 cities:			
GDP, billion RMB	196.0	307.2	4,828
Population, thousand	4,453	3,176	4,828
GDP per capita, RMB	43,497	46,936	4,828

Notes: Each observation is city-year pair. There are up to 358 cities between 2004 and 2020 (6,086 observations), but different datasets may have lower numbers of observations as noted in the table.

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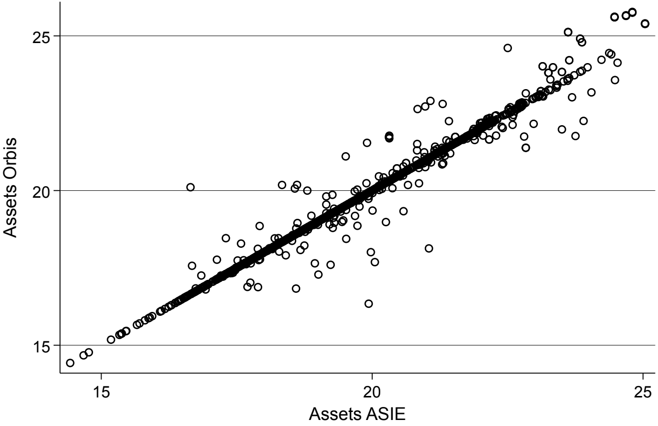
Validation with ASIE



Notes: The axis is the log(assets) in the ASIE data set, and the y-axis is the log(assets) in the Orbis data set. Each point is one firm in one year. If we fit a linear line, the coefficient is 1.01, p¡0.01, and R^2 = 0.9679

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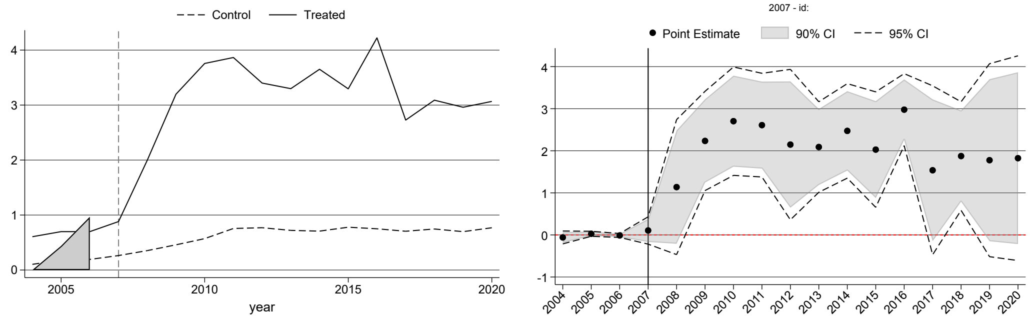
Results: 2007 cohort, Patents

Figure: Number of patents by solar firms - Any subsidy (2007 example)



Notes: SDID on 358 cities, 3 (Jonzhou, Xinju & Yangzhou) introduced policy in 2007. Outcome: IHS of patents by solar firms in a city-year. SE cluster bootstrapped by city.

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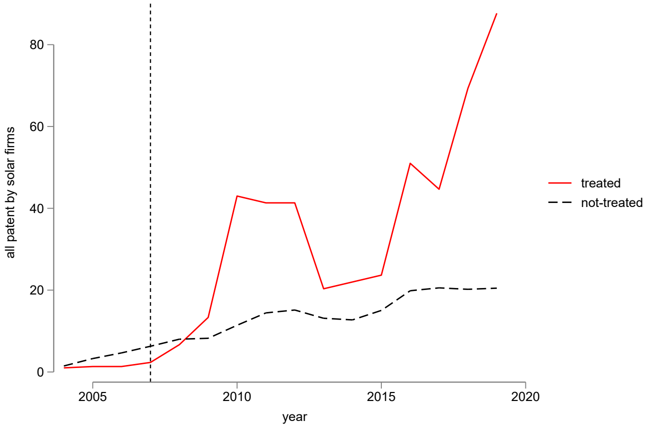
Results: 2007 cohort raw trends, Patents

Figure: Number of patents by solar firms for the treated and control group in 2007



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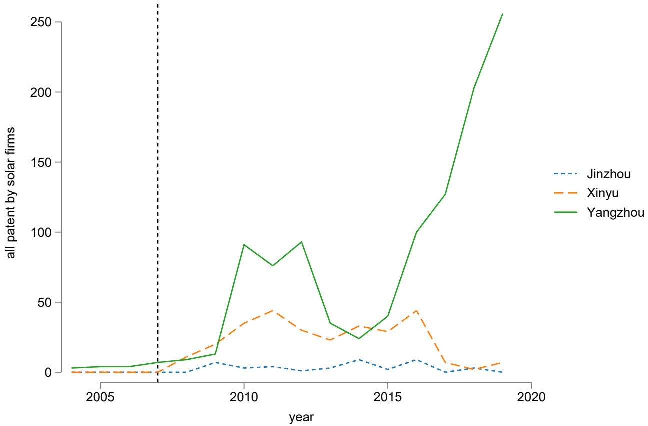
Results: 2007 cohort raw trends, Patents

Figure: Number of patents by solar firms for the three cities treated in 2007



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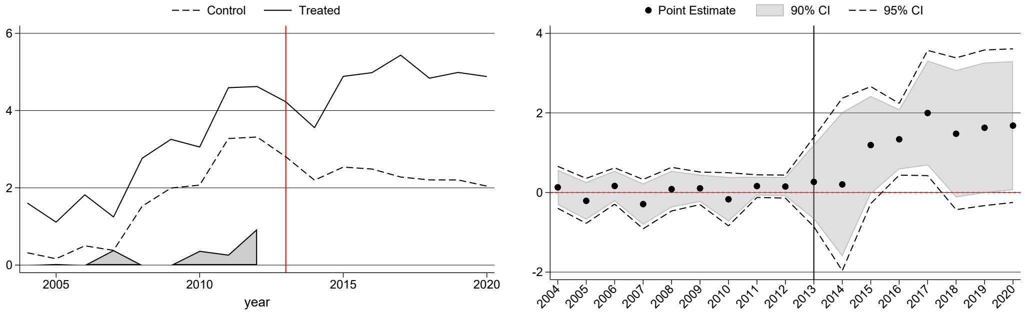
Results: 2013 cohort, Patents

Figure: Patent - Any subsidy (2013 example)



Notes: SDID estimates on 358 cities, focusing on the 3 that introduced a policy in 2013. Outcome IHS of patents by solar firms in a city-year. SE cluster bootstrapped by city.

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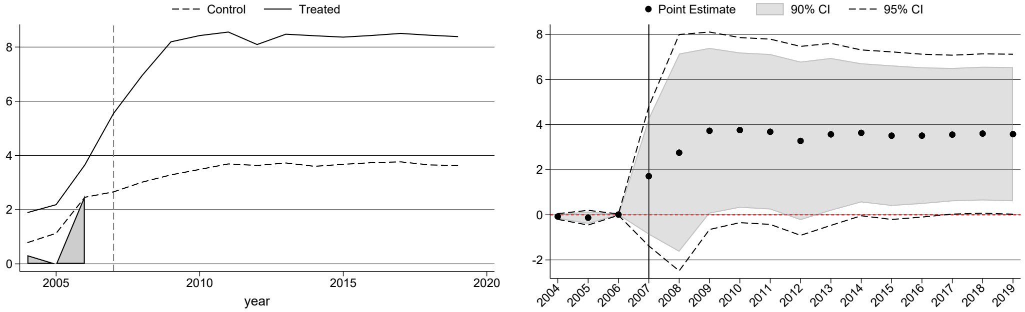
Results: 2007 cohort, Revenue

Figure: Revenue - Any subsidy (2007 example)



Notes: SDID estimates on 358 cities, focusing on the 3 that introduced a policy in 2007. Outcome is IHS of revenue of solar firms in a city-year pair.

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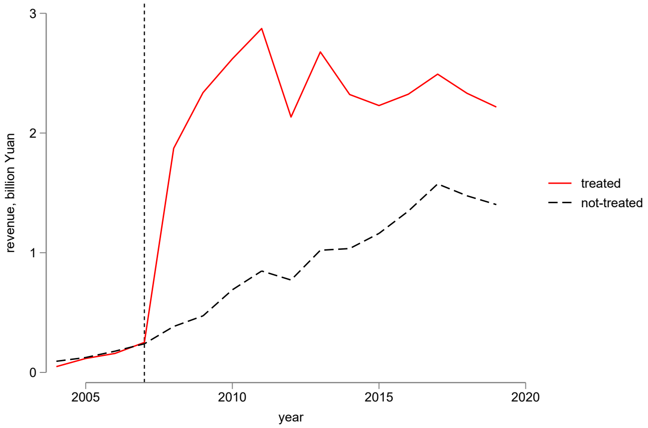
Results: 2007 cohort raw trends, Revenue

Figure: Total revenue by solar firms for the treated and control group in 2007



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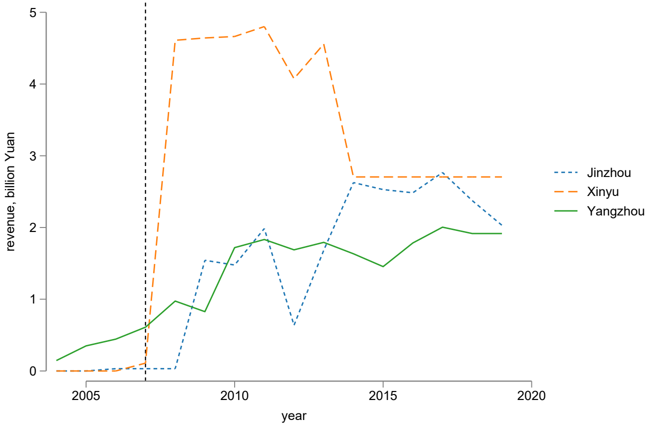
Results: 2007 cohort raw trends, Revenue

Figure: Total revenue by solar firms for the three cities treated in 2007



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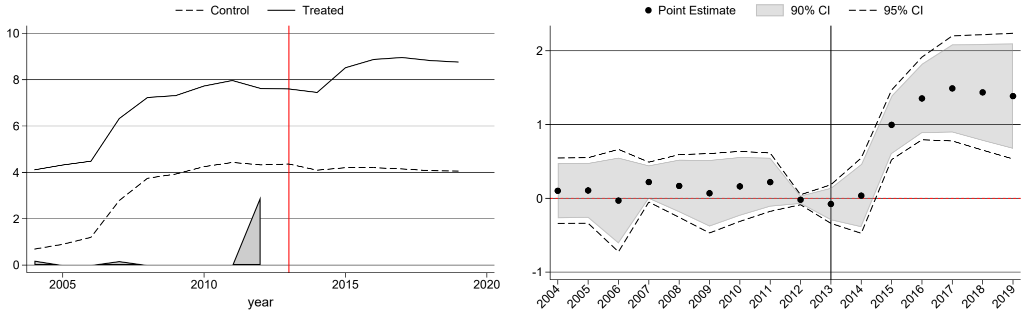
Results: 2013 cohort, Revenue

Figure: Revenue - Any subsidy (2013 example)



Notes: SDID estimates on 358 cities, focusing on the 3 that introduced a policy in 2013. Outcome is IHS of revenue of solar firms in a city-year pair. SE cluster bootstrapped by city.

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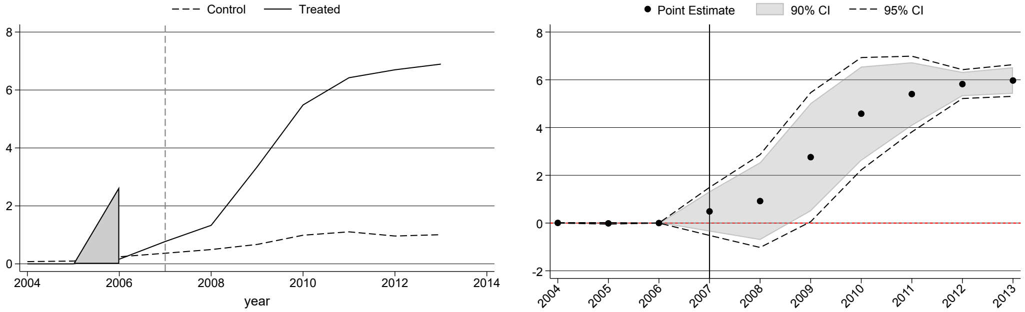
Results: 2007 cohort, Production Capacity

Figure: Panel Production Capacity - Any subsidy (2007 example)

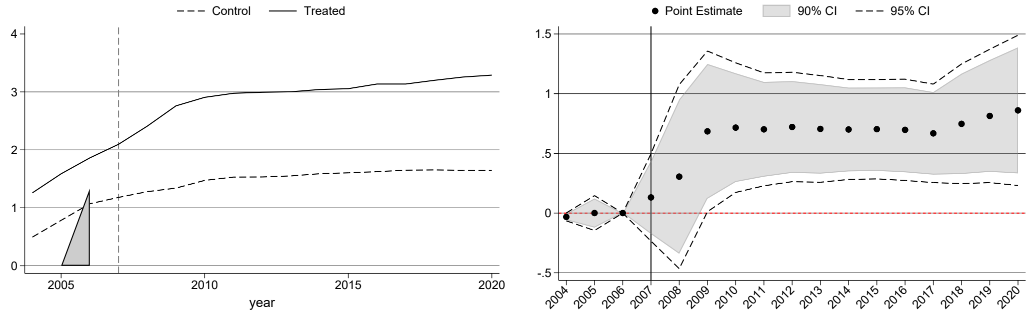


Notes: SDID estimates on 358 cities, focusing on the 3 that introduced a policy in 2007. Outcome is IHS of Solar Panel production capacity in a city-year pair.

2007 - IHS

Results: 2007 cohort, Firm count

Figure: Firm Count - Number of Solar Firms - Any subsidy (2007 example)



Notes: SDID estimates on 358 cities, focusing on the 3 that introduced a policy in 2007. Outcome is IHS of number of solar firms in a city-year pair.

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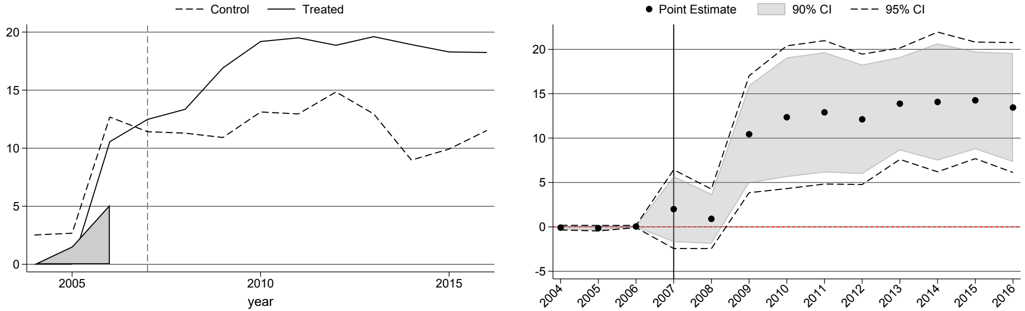
Results: 2007 cohort, Solar export value

Figure: Solar export value - Any subsidy (2007 example)



Notes: SDID estimates on 358 cities, focusing on the 3 that introduced a policy in 2007. Outcome is IHS of export value of Solar firms in a city-year pair.

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Results: Total exports

Table: Total exports (Aggregate ATT)

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Export value	2.451**	0.658	3.217**	4.160**
	(1.178)	(1.130)	(1.443)	(2.143)
Observations	4,654	4,654	4,654	4,654

Notes: * 0.1 ** 0.05 *** 0.01. SDID on 358 cities 2004-2016. Outcome is IHS.

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Results

Table: Productivity (Aggregate ATT)

Panel A	(1)	(2)	(3)	(4)
Period: 2004-2020	*Any subsidy*	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
Revenue	1.015**	0.069	1.802***	2.563***
	(0.455)	(0.277)	(0.629)	(0.844)
Labor	0.788**	0.042	1.498***	1.815**
	(0.350)	(0.203)	(0.575)	(0.825)
Capital	0.526	-0.186	1.260**	1.712**
	(0.354)	(0.175)	(0.518)	(0.799)
Observations	6,086	6,086	6,086	6,086

Notes: * 0.1 ** 0.05 *** 0.01. The revenue, labor and capital numbers are adjusted to account for multi-product firms leveraging firm-level export data

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Results

Table: Productivity (Aggregate ATT) cont.

Panel B	(1)	(2)	(3)	(4)
Period: 2004-2013	*Any subsidy*	*Demand subsidy*	*Production subsidy*	*Innovation subsidy*
Revenue	1.776***	0.294	2.221***	2.653***
	(0.570)	(0.209)	(0.654)	(1.017)
Panel production capacity	2.098***	0.587	2.496***	2.930***
	(0.532)	(0.467)	(0.575)	(0.773)
Labor	1.444**	0.139	1.809**	2.049**
	(0.606)	(0.242)	(0.721)	(1.032)
Capital	1.177**	0.103	1.494**	1.792*
	(0.524)	(0.246)	(0.611)	(0.923)
Observations	3,580	3,580	3,580	3,580

Notes: * 0.1 ** 0.05 *** 0.01. The revenue, labor and capital numbers are adjusted to account for multi-product firms leveraging firm-level export data

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Results

Table: $PM_{2.5}$ concentration (Levels, Aggregate ATT)

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
PM 2.5 concentration	-0.611	-1.192***	-0.167	-0.161
	(0.441)	(0.581)	(0.394)	(0.584)
Observations	6,086	6,086	6,086	6,086
Mean of Dep. var.	38.58	38.58	38.58	38.58

Notes: * 0.1 ** 0.05 *** 0.01. The LHS variable is annual average $\mu g / m^3$ concentration of $PM_{2.5}$ at 0.1 x 0.1 degree resolution. From this, we calculate area-weighted averages. The source is the V5. GL.02 data set.

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Results

Table: CO_2 EMISSIONS

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Annual CO_2 emissions	-0.038^{**}	-0.042^{*}	-0.028	-0.020
	(0.015)	(0.023)	(0.017)	(0.028)
Observations	4,872	4,872	4,872	4,872

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 348 admin2 regions in China with available data. Time: 2004-2017. Each column is one SDID regression. The coefficient is the ATT which averages the staggered treatment effect. The outcome variable is annual CO_2 emissions and it is transformed using IHS. Its source is the county-level annual data set of J. Chen et al (2020), which we remap to our admin2 regions. All regressions without controls.

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Results

Table: Positive Spillovers outweighs Business Stealing (cf. Bloom, Schankerman & Van Reenen, 2013)

	(1) All patents	(2) Firm count	(3) Revenue	(4) Panel capacity	(5) Solar export value
Any subsidy in an adjacent city	0.373***	0.099	0.617***	0.385	1.099**
	(0.096)	(0.055)	(0.199)	(0.263)	(0.491)
Observations	5,049	5,049	5,049	3,210	3,861

Notes: * 0.1 ** 0.05 *** 0.01. The revenue numbers are adjusted to account for multi-product firms leveraging firm-level export data

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Spillover discussion

- Cross-city spillovers positive, but smaller coefficients than own-effects. Also true for other policies.

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- Might expect this from demand policies, but supply policies expected to have negative effects through business stealing
- Suggestive of positive cross-city technological spillovers that outweigh business stealing (see Bloom, Schankerman and Van Reenen, 2013).
- Investigating using patent citation patterns and alternative distance metrics.

Back

Other policies: Innocom

- Wei et al. (2023) and Chen et al. (2021) examine Innocom, a major policy which after 2008 increased incentives for patenting and R&D through lower tax
- Had many features which led to low quality patents and relabeling of expenses
- But unlikely that this correlated with solar policies (a time effect). Placebo on non-solar patents show zero effects
- Wei et al. (2023) show many purchases of patents to hit six patents used by bureaucrats as indicator
- We only use first filing. Also examine through dropping firms with a spike at 6 patents.

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Results

Table: Controlling for GDP per capita

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
All patent	0.483**	0.226	0.867***	1.001***
	(0.205)	(0.242)	(0.220)	(0.341)
☐ Design patents	0.187	0.275	0.240	0.141
	(0.132)	(0.190)	(0.167)	(0.254)
☐ Invention/utility model patents	0.527**	0.191	0.960***	1.051***
	(0.213)	(0.241)	(0.232)	(0.361)
• Solar patents	0.523***	0.247	0.802***	0.875***
	(0.191)	(0.230)	(0.204)	(0.339)
• Non-solar patents	0.254	-0.061	0.739***	0.801**
	(0.182)	(0.215)	(0.217)	(0.349)
Firm count	0.210***	0.030	0.380***	0.396***
	(0.081)	(0.031)	(0.125)	(0.138)
Revenue	1.007***	0.083	1.767***	2.496***
	(0.458)	(0.197)	(0.505)	(0.686)

Notes: * 0.1 ** 0.05 *** 0.01. The revenue numbers are adjusted for to account for multi-product firms.

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Results

Table: Controlling for GDP per capita (cont.)

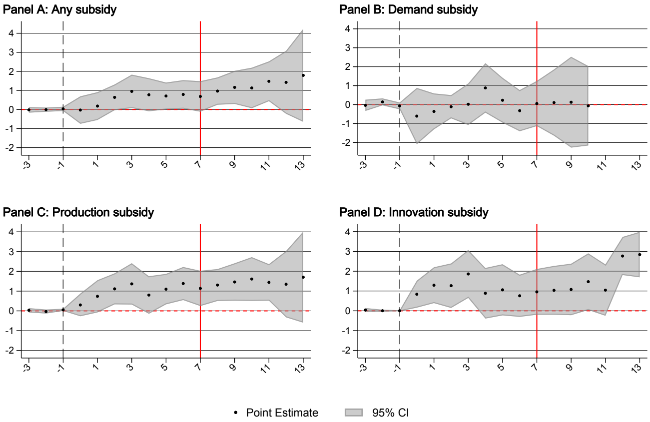
	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Panel capacity	2.025***	0.531	2.415***	2.848***
	(0.466)	(0.428)	(0.470)	(0.705)
Solar export value	4.515***	1.367*	6.250***	8.967***
	(0.970)	(0.741)	(1.428)	(2.136)
Export value	2.409***	0.577	3.210**	4.041**
	(0.886)	(1.009)	(1.292)	(1.992)

Notes: * 0.1 ** 0.05 *** 0.01.

Back

Results: Patents, Cohorts between 2007 and 2013

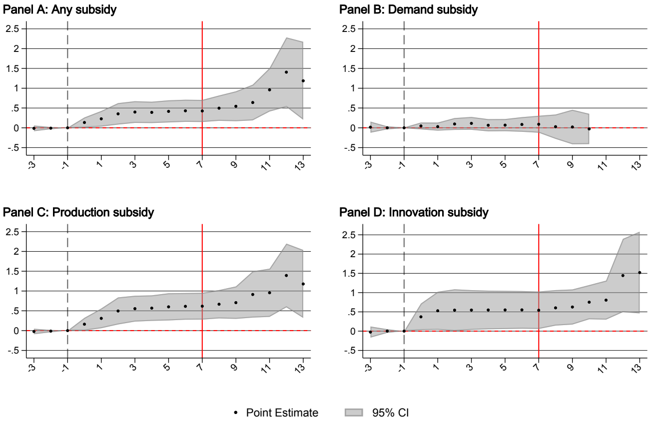
Figure: Total patents, cohorts between 2007 and 2013



Notes: Back

Results: Firm count, Cohorts between 2007 and 2013

Figure: Firm count, cohorts between 2007 and 2013



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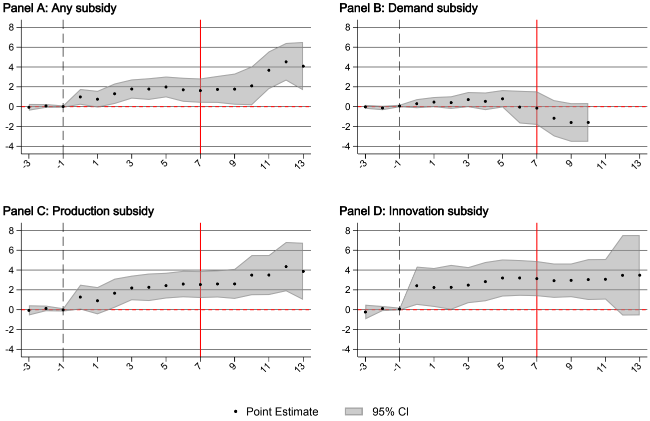
Results: Revenue, Cohorts between 2007 and 2013

Figure: Revenue, cohorts between 2007 and 2013



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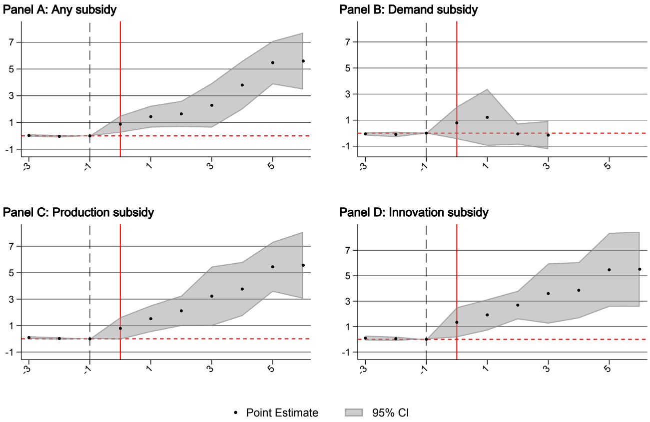
Results: Panel capacity, Cohorts between 2007 and 2013

Figure: Panel capacity, cohorts between 2007 and 2013



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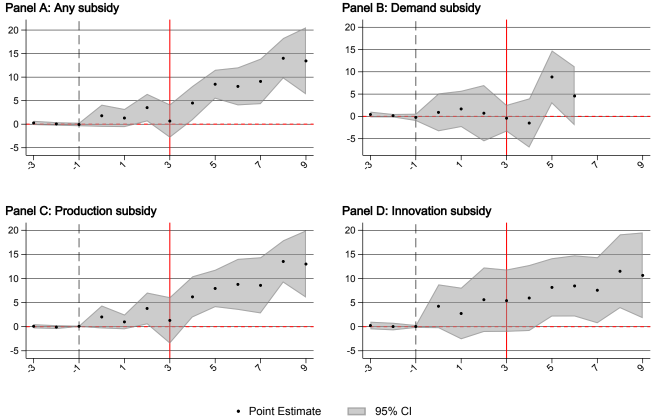
Results: Solar export value, Cohorts between 2007 and 2013

Figure: Solar export value, cohorts between 2007 and 2013



Notes:

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Results

Table: Levels results (Patents)

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
All patents	6.310	-7.076	20.046**	25.613*
	(9.949)	(14.578)	(9.569)	(14.873)
Observations	6,086	6,086	6,086	6,086
Mean of Dep. var.	13.128	13.128	13.128	13.128

Notes: * 0.1 ** 0.05 *** 0.01.

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Results

Table: Levels results (Revenue)

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Revenue (million RMB)	135	-0.95	329^{**}	397^{**}
	(123)	(109)	(148)	(179)
Observations	6,086	6,086	6,086	6,086
Mean of Dep. var.	157	157	157	157

Notes: * 0.1 ** 0.05 *** 0.01. The revenue numbers are adjusted to account for multi-product firms leveraging firm-level export data

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Results

Table: Levels results (Panel capacity)

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Panel capacity (MWh)	319.567**	138.574	366.728**	480.764***
	(128.377)	(127.902)	(147.783)	(175.088)
Observations	3,580	3,580	3,580	3,580
Mean of Dep. var.	82.449	82.449	82.449	82.449

Notes: * 0.1 ** 0.05 *** 0.01.

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Results

Table: Levels results (Firm count)

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Firm count	1.199	-0.257	2.505*	2.900
	(0.898)	(0.617)	(1.462)	(2.122)
Observations	6,086	6,086	6,086	6,086
Mean of Dep. var.	2.872	2.872	2.872	2.872

Notes: * 0.1 ** 0.05 *** 0.01.

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Results

Table: Levels results (Solar exports)

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Solar export value (mill dollar)	22.1^{*}	4.6	26.9^{**}	31.9^{*}
	(12.4)	(13.7)	(12.7)	(17.3)
Observations	4,654	4,654	4,654	4,654
Mean of Dep. var.	19.27	19.27	19.27	19.27

Notes: * 0.1 ** 0.05 *** 0.01.

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Results

Table: City-level total solar patents

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Patent	0.444***	0.114	0.662***	1.029***
	(0.150)	(0.138)	(0.213)	(0.219)
Observations	6,086	6,086	6,086	6,086

Notes: * 0.1 ** 0.05 *** 0.01.

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Results

Table: Outcome variable divided equally among plant locations

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Panel capacity	1.415^{***}	-0.052	1.816^{***}	1.730^{**}
	(0.505)	(0.282)	(0.547)	(0.745)
Observations	3,580	3,580	3,580	3,580

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 358 admin2 regions in China. Time: 2004-2013. The sample is restricted to ENF production firms. The outcome variable is divided equally among the three plant locations listed in this database instead of being allocated to firms' headquarters.

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Results

Table: LEARNING-BY-DOING PATENTS

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Patent	0.365^{**}	0.187	0.604^{***}	0.914^{***}
	(0.149)	(0.186)	(0.235)	(0.377)
Observations	5,728	5,728	5,728	5,728

Notes: * 0.1 ** 0.05 *** 0.01. Each observation is an admin2 level region and there are 358 admin2 regions in China. 43 regions are treated by any subsidy. Time: 2004-2020. Each column is one sdid regression. Without controls. The coefficient is the ATT which averages the staggered treatment effect. All regressions without controls. 25.6% of the utility + invention patents are classified as LBD patents.

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Placebo Non-solar Patents

Table: PLACEBO: CITY-LEVEL TOTAL NON-SOLAR PATENTS

	(1) *Any subsidy*	(2) *Demand subsidy*	(3) *Production subsidy*	(4) *Innovation subsidy*
Patent	-0.064	0.004	-0.118	-0.034
	(0.438)	(0.965)	(0.309)	(0.811)
Observations	6,086	6,086	6,086	6,086

Notes: * 0.1 ** 0.05 *** 0.01. Outcome is total patents (mainly non-solar) Each observation is an admin2 level region and there are 358 admin2 regions in China. 43 regions are treated by any subsidy. Time: 2004-2020. Each column is one sdid regression. The coefficient is the ATT which averages the staggered treatment effect. All regressions without controls

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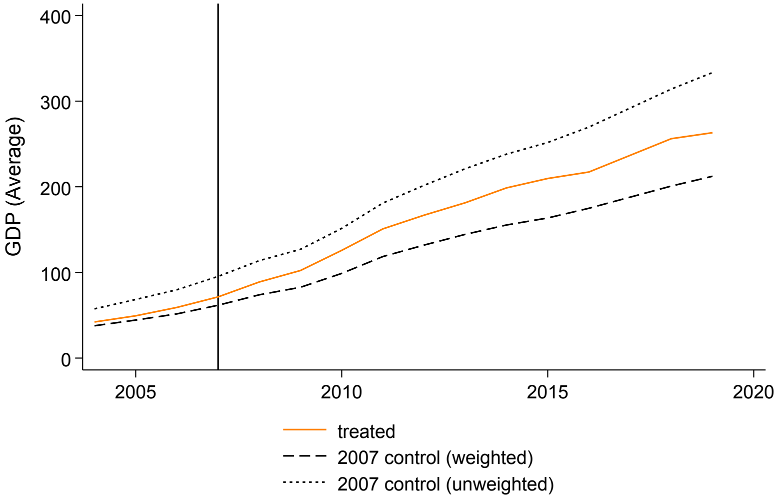
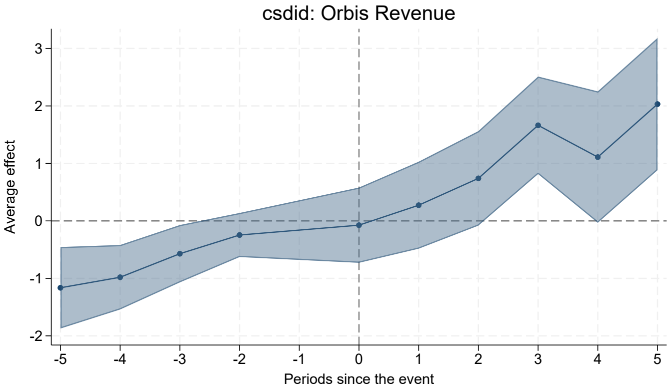
Characterising the control group



Potential pretrend



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Calibration

Parameter		Value	Identification/Moments	Source
Preference Parameters				
σ	Elasticity of substitution across energy sectors (solar vs non-solar)	3	(Jo, 2023), (Papageorgiou et al., 2017)	External
$\sigma_s, \sigma_{s'}$	Elasticity of substitution across power plant input varieties (e.g., solar panel models)	5, 8.18	(Shapiro and Walker, 2018)	External
Production Technology Parameters				
$\theta_s, \theta_{s'}$	Shape parameter of Pareto distribution (dispersion of productivity draws within energy)	3.5, 11.6	Sales revenue (ASIE, ENF)	External
$b_{o,s}, b_{o,s'}$	Location parameter of Pareto distribution	$e^{12.5}, e^{12.5}$	Sales revenue (ASIE, ENF)	External
$f_s^e, f_{s'}^e$	Sunk entry cost	1	Total output, solar & non-solar	Internal
$f_s, f_{s'}$	Production fixed cost	1	Mass of firms, solar & non-solar	Internal
$f_s^i, f_{s'}^i$	Innovation fixed cost	1	Innovator share, solar & non-solar	Internal
$\xi_{o,s}, \xi_{o,s'}$	Productivity gain from innovating	1.06	Regression results	External
δ	Knowledge spillover parameter	1.4	Innovator ratio between solar and non-solar	Internal
Trade Parameters				
τ_{ij}	Iceberg trade costs	1.4	Regression results	External
τ_i^x	Iceberg trade costs (foreign)	1.4	Distance model results	External
μ_s	Distance trade cost elasticity	0.32, 0.18	Monte et al. (2018)	External
$f_s^x, f_{s'}^x$	Exporting fixed cost	1	Exporters share, solar & non-solar (ASIE, ENF-customs)	Internal

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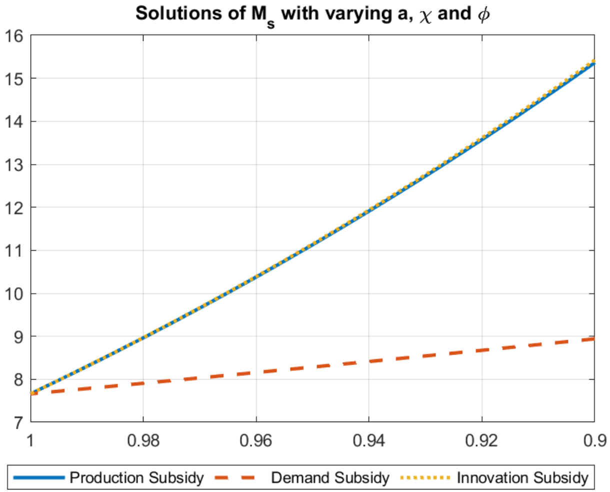
Simulation Results: Number of Firms



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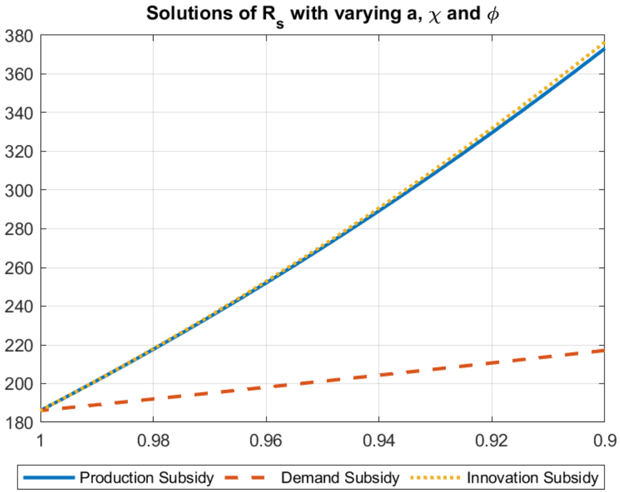
Simulation Results: Revenue



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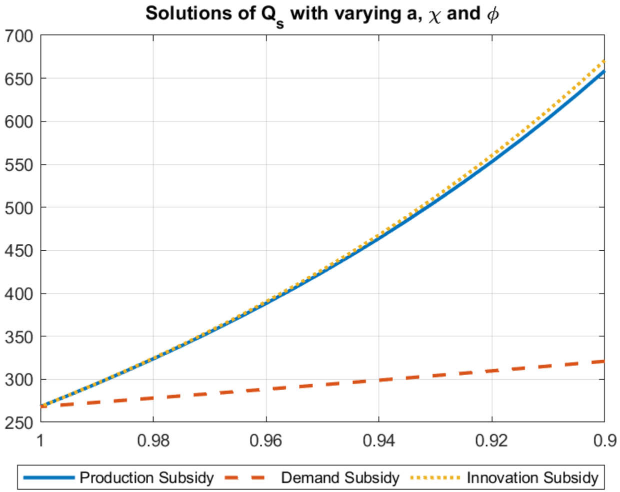
Simulation Results: Quantity



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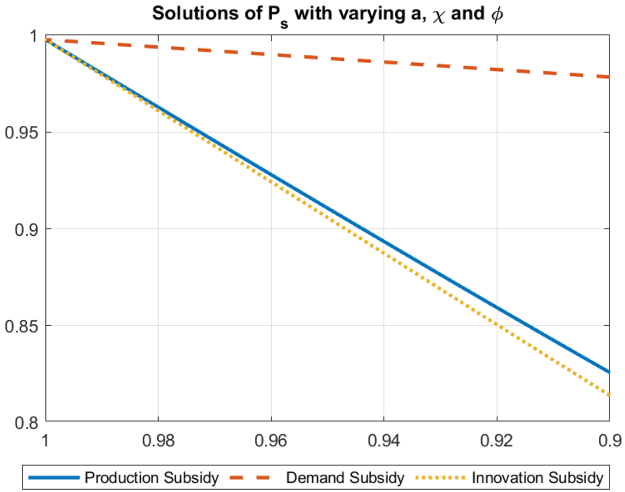
Simulation Results: Price



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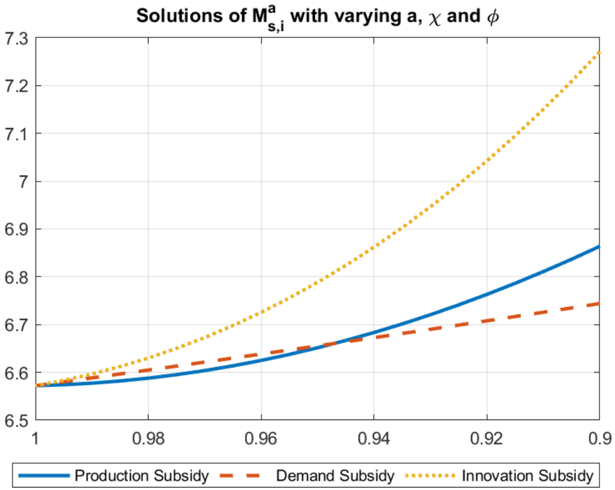
Simulation Results: Aggregate



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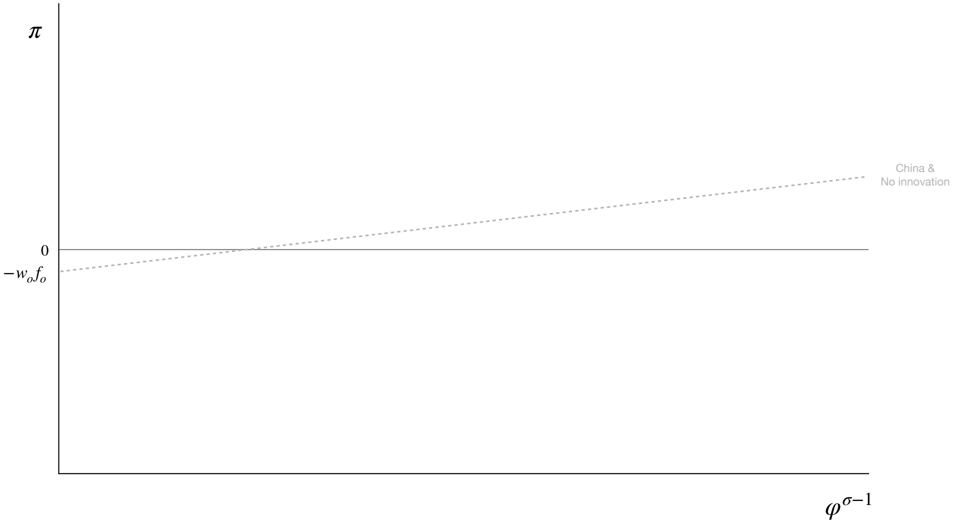
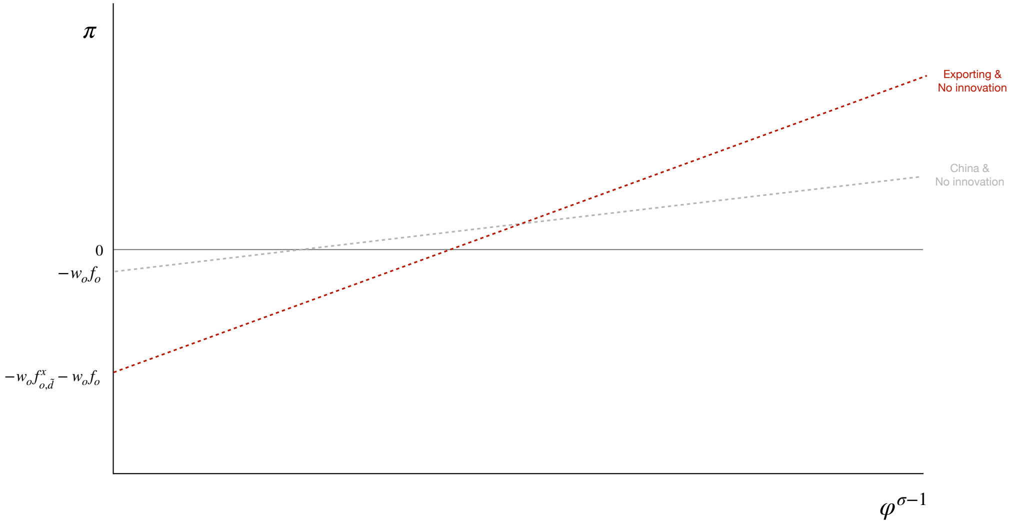
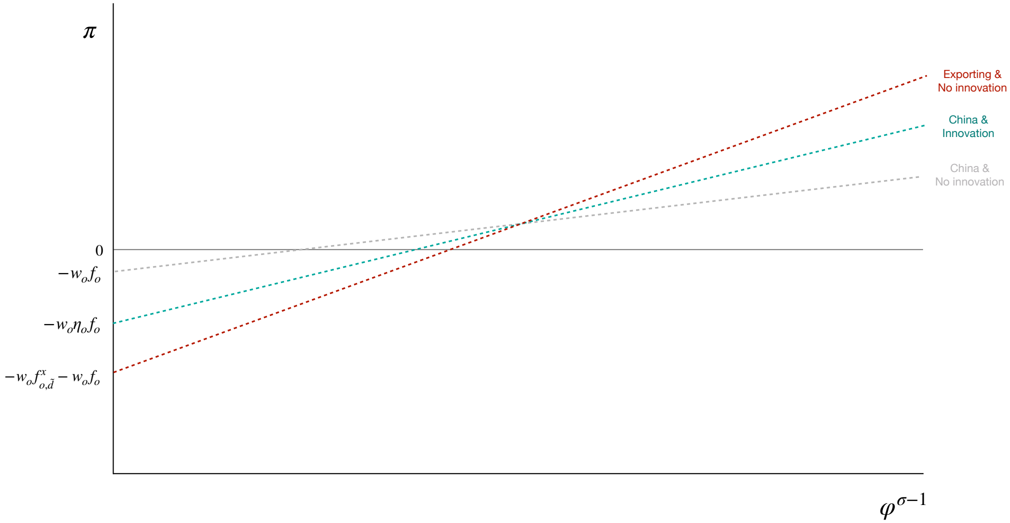
Impact of place-based subsidies



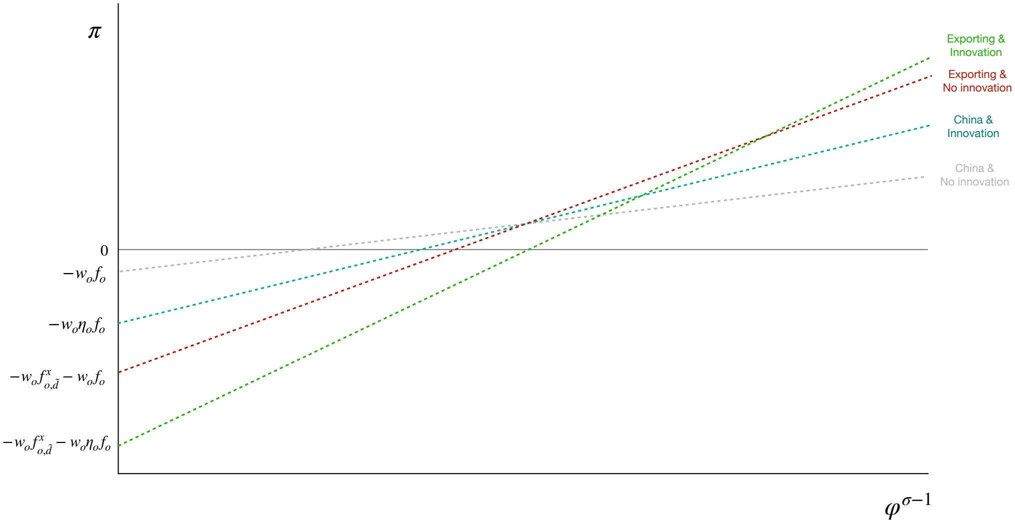
Impacts of place-based subsidies



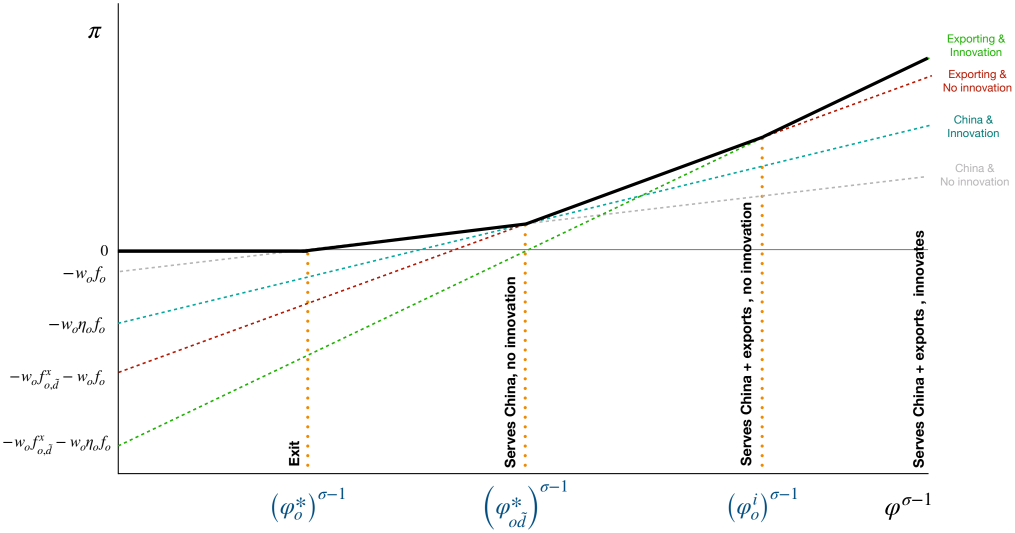
Impacts of place-based subsidies



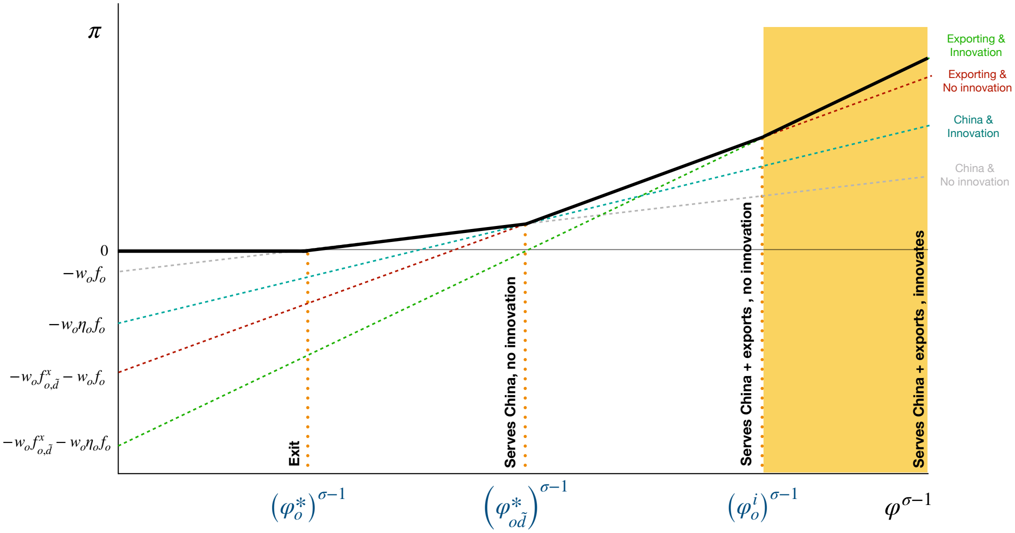
Impacts of place-based subsidies



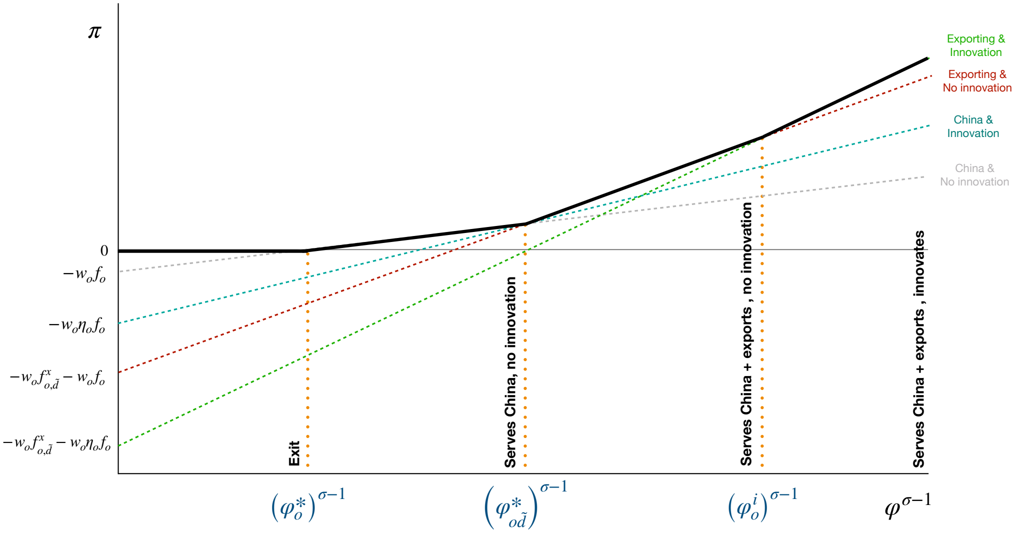
Impacts of place-based subsidies



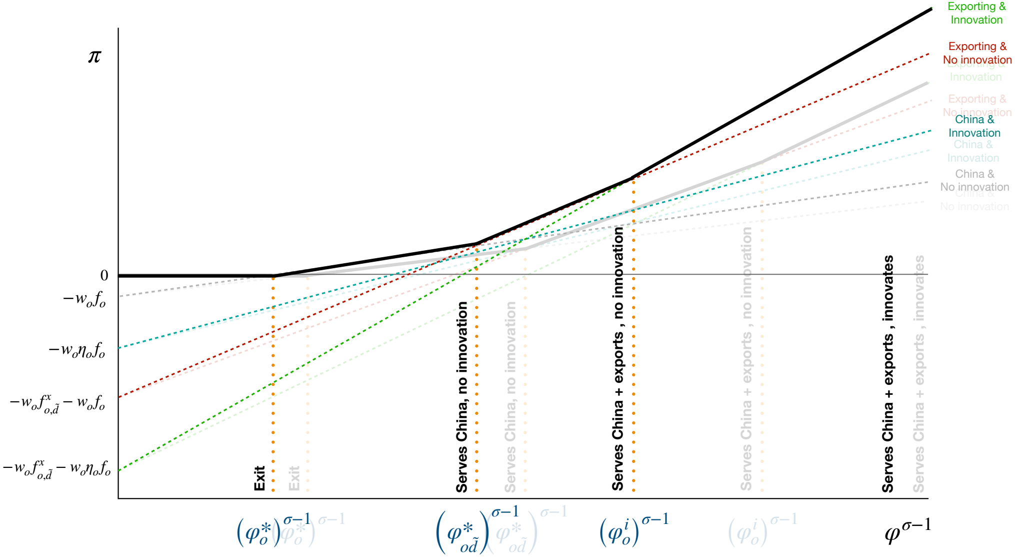
Impacts of place-based subsidies



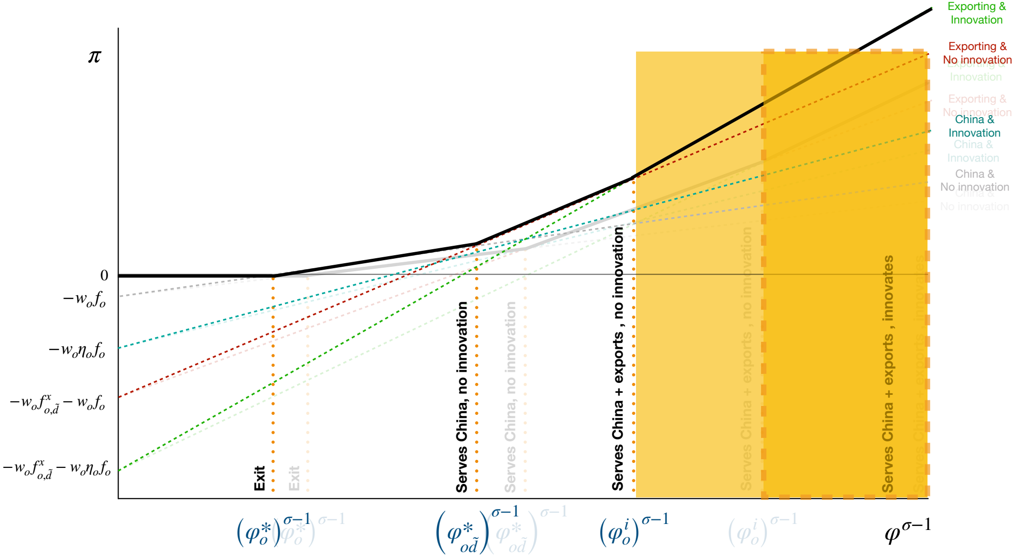
Impacts of place-based PRODUCTION subsidies



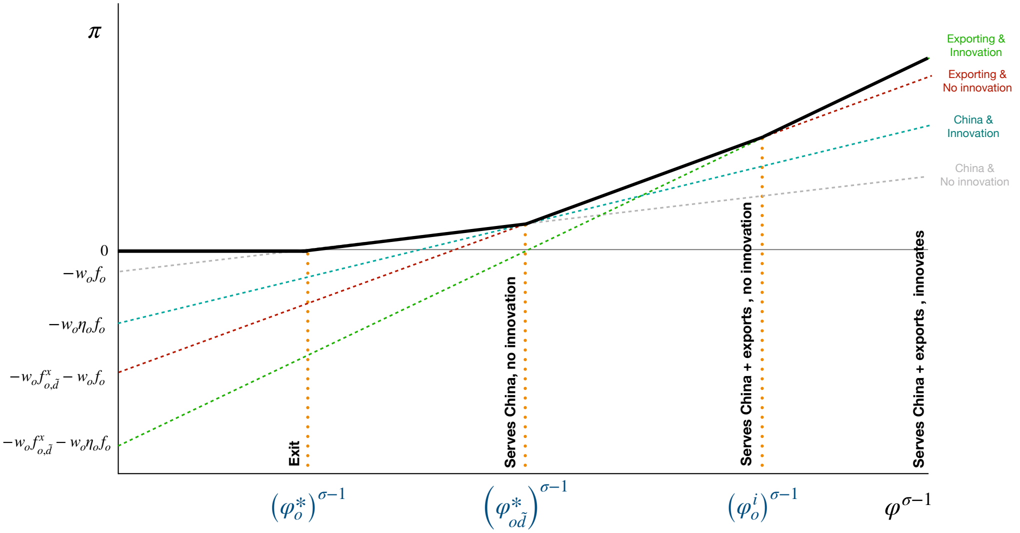
Impacts of place-based PRODUCTION subsidies



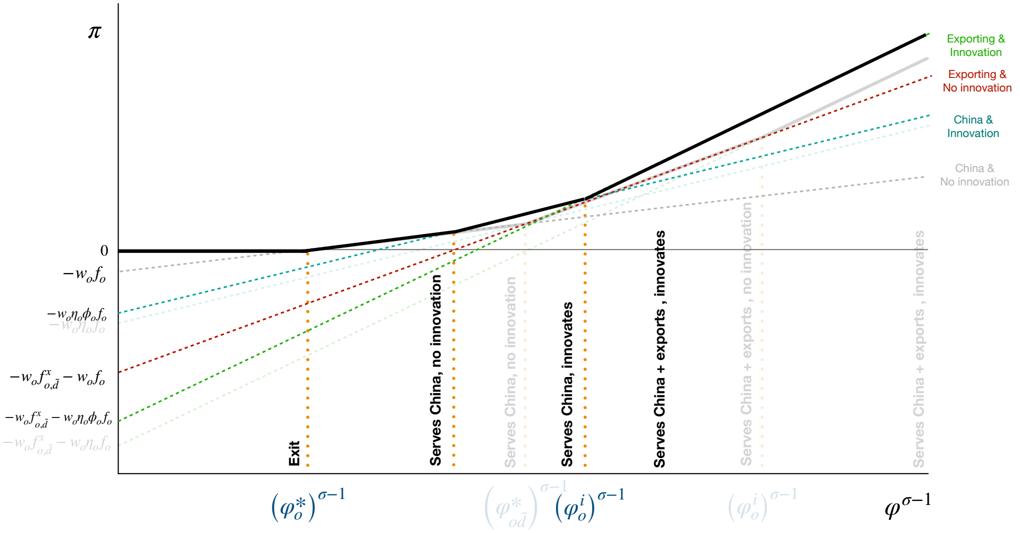
Impacts of place-based PRODUCTION subsidies



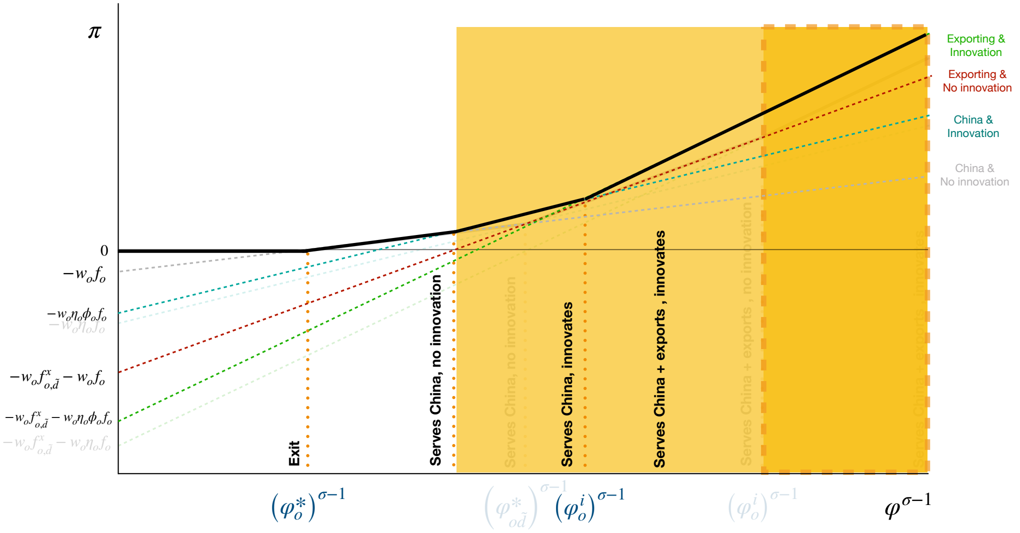
Impacts of place-based INNOVATION subsidies



Impacts of place-based INNOVATION subsidies



Impacts of place-based INNOVATION subsidies



Impacts of place-based DEMAND subsidies

$$\Pi_{o,s}(\varphi) = \max \left\{ \begin{array}{l} \underbrace{\sum_{d \neq \tilde{d}} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s} (1 - s_{o,s})}{\varphi} \right)^{1-\sigma_s} \right\} - w_o f_{o,s},}_{\text{Serves China, no innovation}} \\ \underbrace{\sum_{d} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s} (1 - s_{o,s})}{\varphi} \right)^{1-\sigma_s} \right\} - w_o f^x_{o,\tilde{d},s} - w_o f_{o,s},}_{\text{Serves China \& exports, no innovation}} \\ \underbrace{\sum_{d} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1-\sigma_s}} \left(\frac{w_o \tau_{od,s} (1 - s_{o,s})}{\xi_{o,s}\varphi} \right)^{1-\sigma_s} \right\} - w_o f^x_{o,\tilde{d},s} - w_o \phi_{o,s} \eta_{o,s} f_{o,s}}_{\text{Serves China \& exports, innovates}} \end{array} \right\}$$

Model

Summary

- Demand for electricity decided locally (Nested CES)
- A local "Grid Planner" builds **clean and dirty power plants** (e.g. solar vs. coal) using **components** (e.g. solar panels) sourced across **multiple Chinese cities** (subject to transport costs)
- Local **solar manufacturers** have **heterogeneous productivity**.
- They make endogenous **entry, exit, production, exporting, and technology upgrading** (innovation) decisions
- Model provides intuition for differential impact of **differentially targeted place-based subsidies** (installation/demand, production, and innovation) on these multiple outcomes

Timing of Decisions

1. Entrepreneurs pay a sunk entry cost (enter), draw productivity, and decide whether to:
    1. produce (stay in the market)
    2. produce and export overseas
    3. produce, export and innovate
2. Three fixed costs (& associated productivity cutoffs):
    1. production
    2. exporting
    3. innovation
3. Innovation reduces marginal cost of production
4. Producing firms in origin city o serve multiple destination cities d paying iceberg trade costs
5. Demand for intermediates across all Chinese cities (and overseas) from different grid planners influences solar manufacturer decisions

Demand for energy sources

- In each destination city d, representative consumer utility from electricity services e_d:

$$U_d = u\left(e_d\right) \tag{6}$$

- Electricity services installed in each city by Grid Planner, who builds power plants combining output from a clean and dirty energy sector, s and s' (e.g. solar vs. coal):

$$e_d = \left(\kappa_{d,s} e_{d,s}^{\rho} + \kappa_{d,s'} e_{d,s'}^{\rho}\right)^{1/\rho} \tag{7}$$

Demand for energy sources

- Grid planner supplies as much energy as possible in the minimal cost way given income of representative consumer, I_d

$$\max_{e_{d,s},e_{d,s'}} \left(\kappa_{d,s'} e_{d,s'}^{\rho} + \kappa_{d,s} e_{d,s}^{\rho}\right)^{1/\rho}$$

$$\text{s.t. } P_{d,s} e_{d,s} + P_{d,s'} e_{d,s'} = I_d$$

- Which yields our solar installation demand function, e_s^*:

$$e_{d,s}^* \left(P_{d,s}, P_{d,s'}, I_d\right) = \left(\frac{\kappa_{d,s}}{P_{d,s}}\right)^{\sigma} \frac{I_d}{\kappa_{d,s'}^{\sigma} P_{d,s'}^{1-\sigma} + \kappa_{d,s}^{\sigma} P_{d,s}^{1-\sigma}} \tag{8}$$

Demand for energy sector manufactured inputs (e.g. solar panels)

- To generate output for each energy sector, Grid Planner in city d combines intermediate inputs, $q_{od,s}(\omega)$ = quantity of variety ω manufactured in city o supplied to d using CES:

$$e_{d,s} = \left(\sum_o \int_{\omega \in \Omega_{o,s}} q_{od,s}(\omega)^{\frac{\sigma_s - 1}{\sigma_s}} d\omega \right)^{\frac{\sigma_s}{\sigma_s - 1}} \tag{9}$$

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- To meet the optimal energy demand, grid planner chooses solar panels from all cities given their prices, $p_{od,s}$. This will determine price indices $P_{d,s}$ and $P_{d,s'}$.
- Solving this constrained optimization problem gives a demand for each variety:

$$q_{od,s}(\omega) = \left(\frac{p_{od,s}(\omega)}{P_{d,s}} \right)^{-\sigma_s} \left(\frac{\kappa_{d,s}}{P_{d,s}} \right)^{\sigma} \frac{I_d}{\kappa^{\sigma}_{d,s'} P^{1-\sigma}_{d,s'} + \kappa^{\sigma}_{d,s} P^{1-\sigma}_{d,s}} \tag{10}$$

Solar Panel manufacturing technology

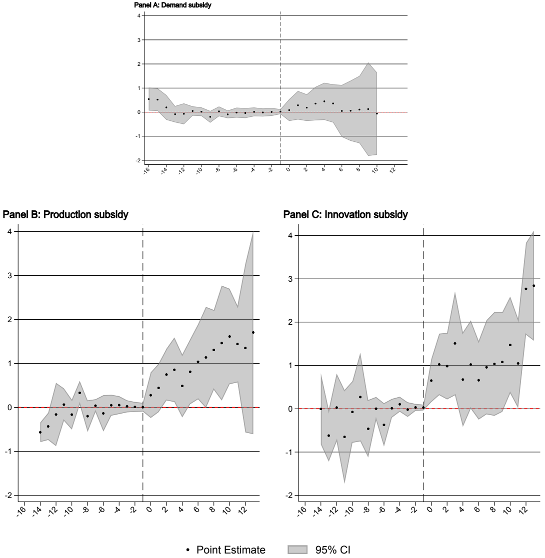
Production process:

- Firms first need to pay a sunk cost $w_o f^e_{o,s}$ to operate
- After paying this cost, they draw their production productivity φ, from a Pareto distribution
- To produce, firms use a composite factor of production $L_{o,s}$ with unit cost w_o
- Producing $q_{o,s}(\varphi)$ units of a variety, involves a cost $w_o f_{o,s} + \frac{w_o q_{o,s}}{\varphi}$, where:
    - $f_{o,s}$: fixed cost
    - $\frac{1}{\varphi}$: marginal cost

Innovation/technology upgrading:

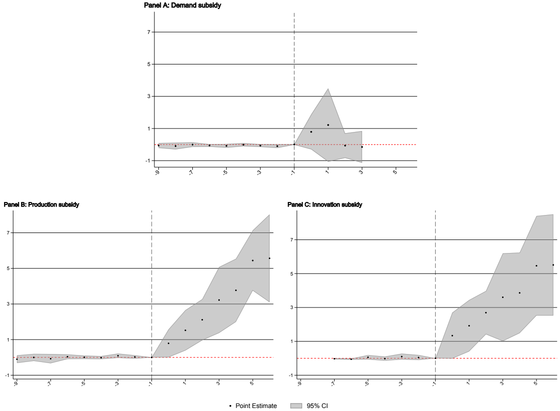
- Upon observing its initial productivity φ, a firm can upgrade its technology (innovate)
- By incurring a fixed cost: $\eta_{o,s} f_{o,s}$, with $\eta_{o,s} > 1$, it reduces marginal cost to: $\frac{1}{\xi_{o,s}\varphi}$, with $\xi_{o,s} > 1$

Results: Patents, Subsidy Types



Notes: SDID on 358 cities with 43 treated. Cohort-year specific ATTs aggregated into event studies. Outcome: IHS of patents by solar firms in a city-year.

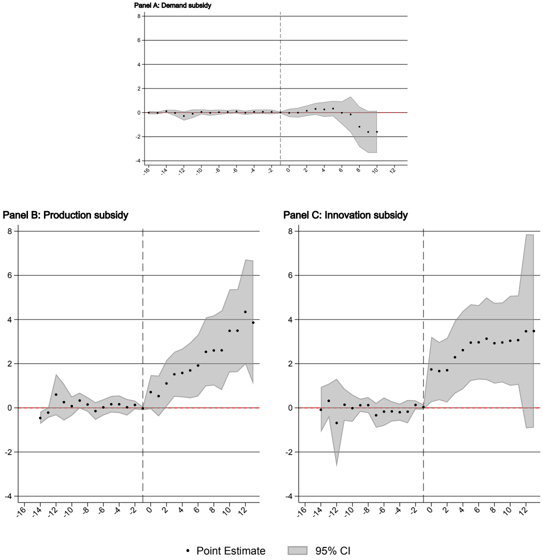
Results: Production Capacity, Subsidy types



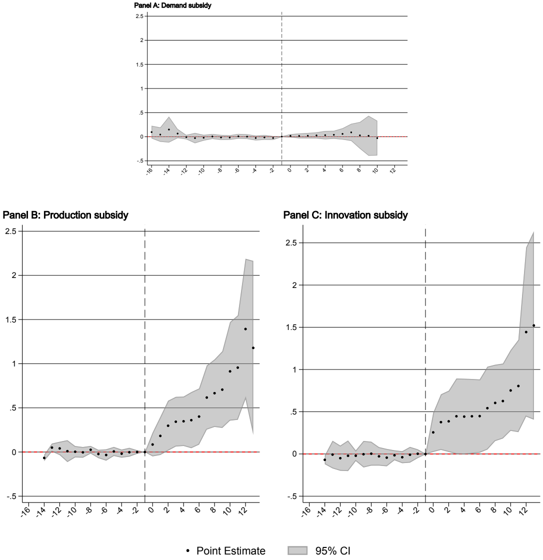
Notes: SDID on 358 cities with 43 treated. Cohort-year specific ATTs aggregated into event studies. Outcome: IHS of total panel production capacity MWh by solar firms in a city-year.

Treatment varies by panel. 95% SE cluster bootstrapped by city.

Results: Revenue, Subsidy types

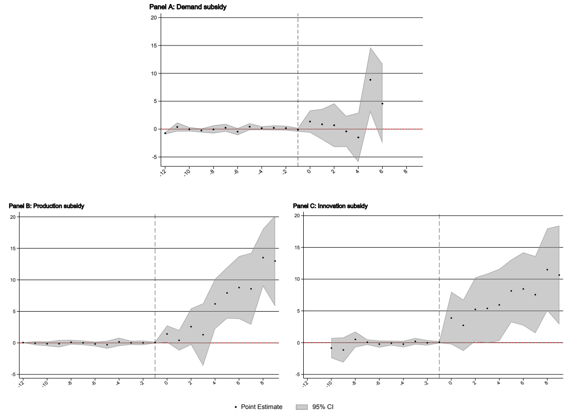


Results: Firm Count, Subsidy types



Results: Solar exports, Subsidy types

Figure: Solar export value - Subsidy types



Notes: SDID on 358 cities with 43 treated. Cohort-year specific ATTs aggregated into event studies. Outcome: IHS of total solar export value of solar firms in a city-year. Treatment varies by panel. 95% SE cluster bootstrapped by city.