Ray of Hope? China and the Rise of Solar Energy

Public Policies for Innovation, LBS

Ignacio Banares-Sanchez[1], Robin Burgess[1,2], David Laszlo[1],
Pol Simpson[1], **John Van Reenen**[1,2], Yifan Wang[1]

[1] London School of Economics [2] CEPR

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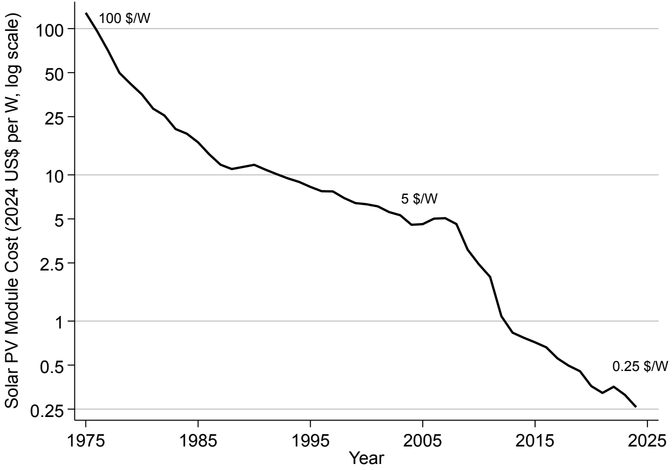
Outline

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 to obtain **local** effects
- Develop & structurally estimate equilibrium model to analyze **economy-wide** counterfactuals and welfare

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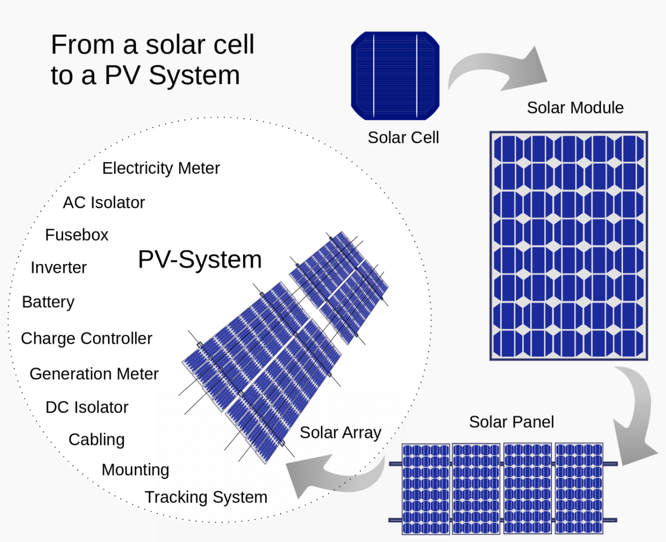
- Social Cost-Benefit
  - Policy generates net gains for Chinese citizens: **$1.65** for every **$1** of subsidy (& double this when adding in social costs of carbon).
  - But could be more cost-effective if policy mix had greater focus on innovation subsidies

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)

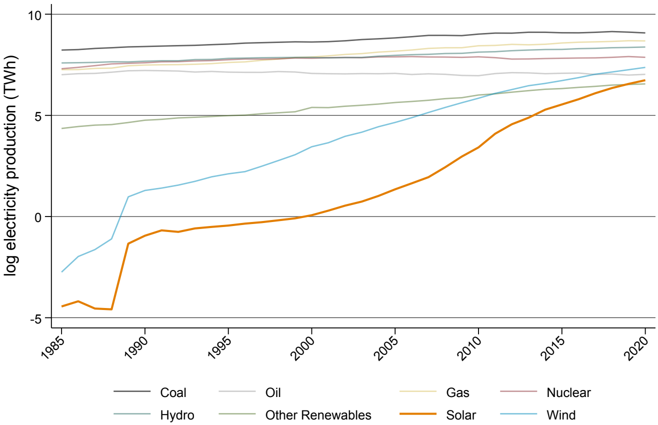
Outline

From cell to panels



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

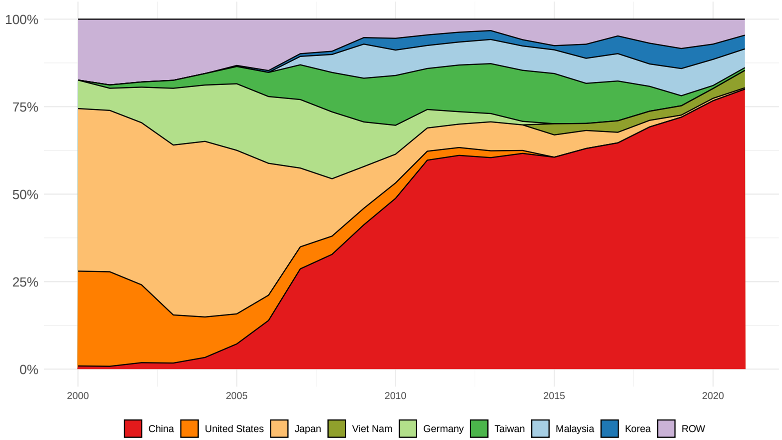
Figure: World electricity production by source



Source: International Energy Agency (IEA) Shares

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

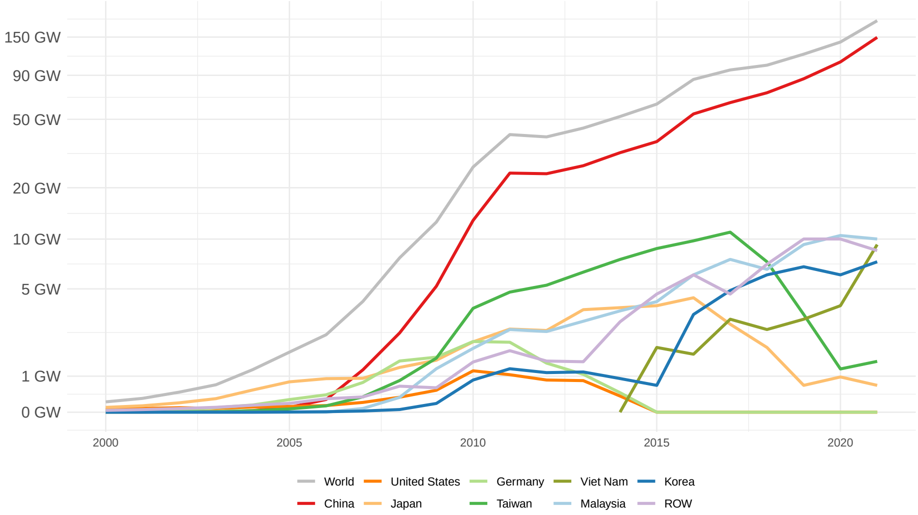
Figure: Share of Annual Solar Photovoltaics Cell Production in Leading Countries, 2000-2021



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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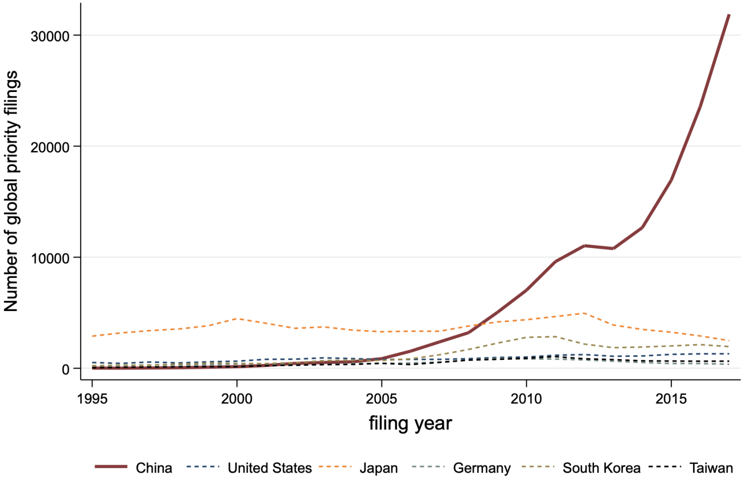
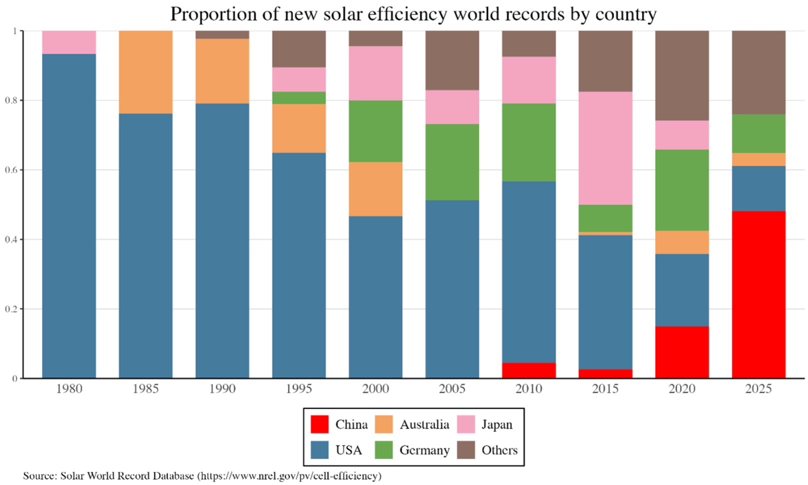
China is not just imitating: Massive growth in Solar Patents



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)

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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)"*

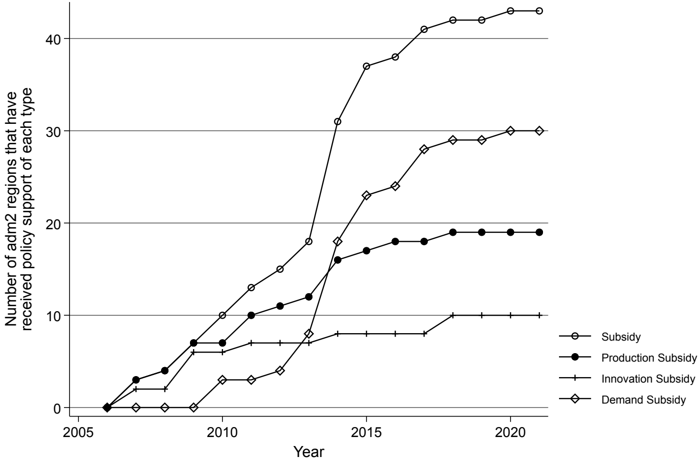
Source: Own analysis using PKULaw data

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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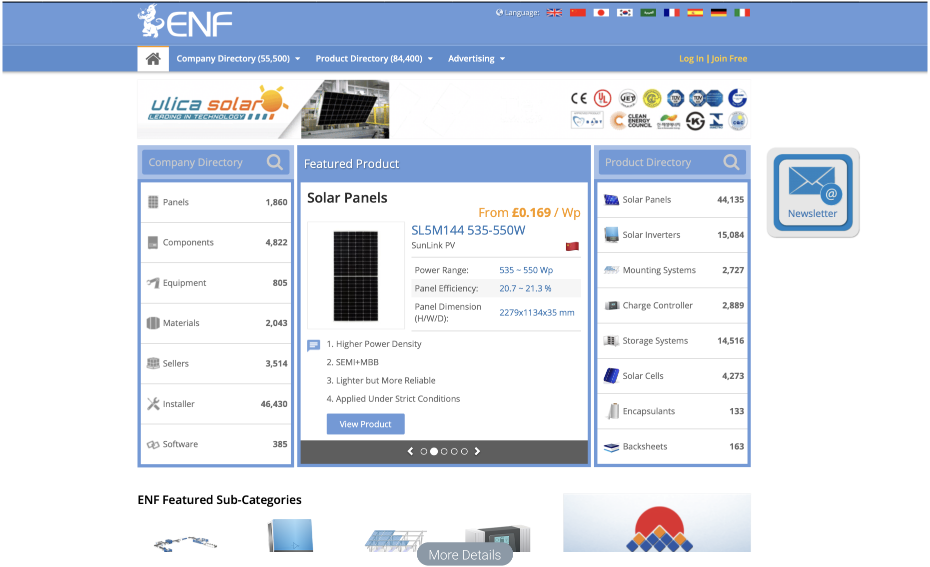
ENF
Language:
Company Directory (55,500)
Product Directory (84,400)
Advertising
Log In | Join Free
ulica solar
LEADING IN TECHNOLOGY
CLEAN ENERGY COUNCIL
Company Directory
Panels 1,860
Components 4,822
Equipment 805
Materials 2,043
Sellers 3,514
Installer 46,430
Software 385
Featured Product
Solar Panels
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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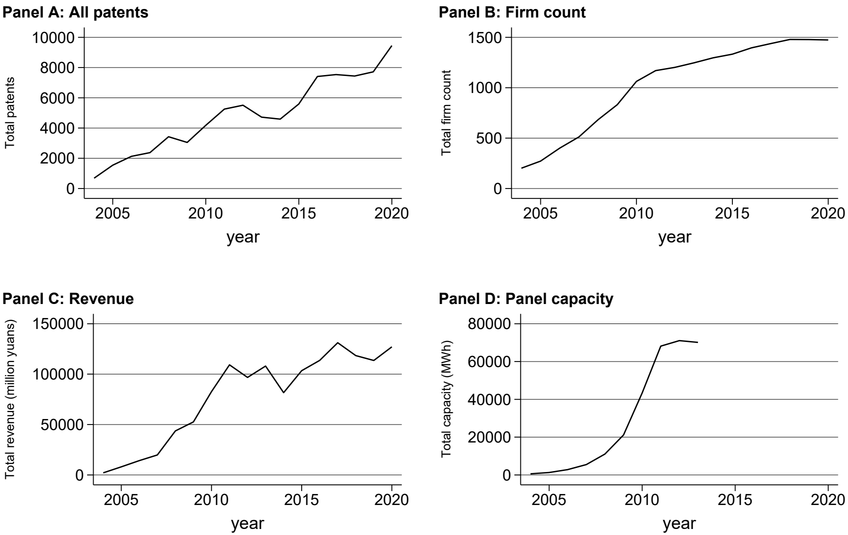
- Sample from **ENF Solar**, the largest online solar directory worldwide
- Identify 1,718 solar panel manufacturers in China (2004-2020)
- Cross-referencing aggregate statistics suggests we capture the whole industry

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.)

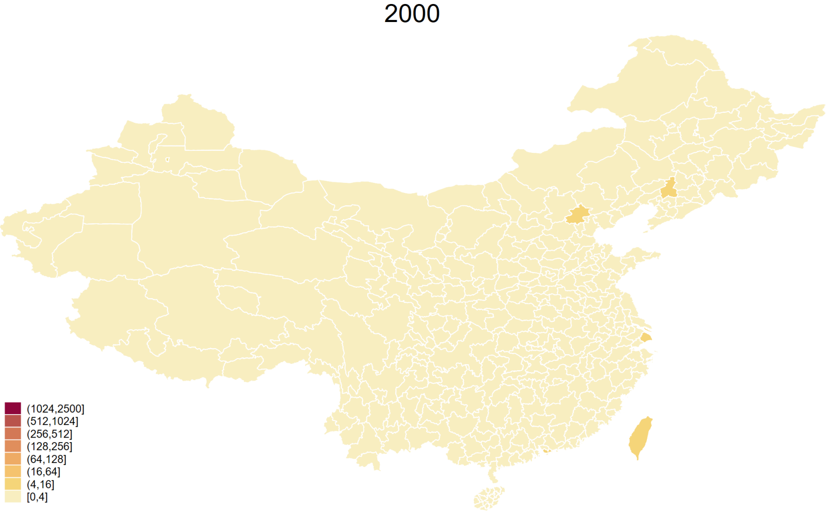
Descriptive Statistics Validation with ASIE

Chinese Solar industry evolution



Our analysis compares city-level policies & outcomes: Patents

Here: patent counts and any subsidy



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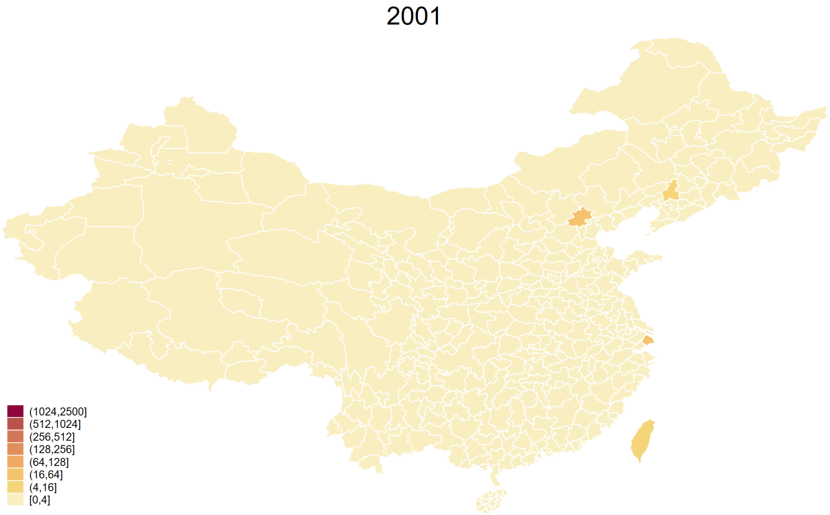
Our analysis compares policy and outcomes at the city level

Here: patent counts (subsidy in black circles)



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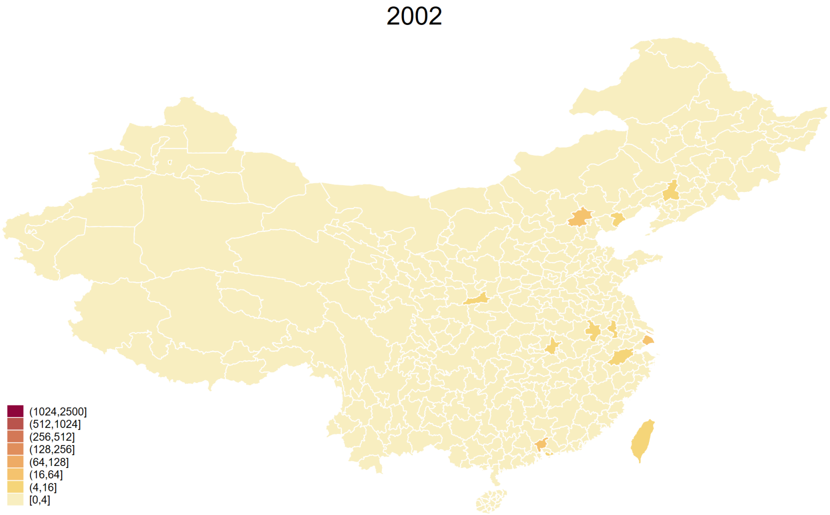

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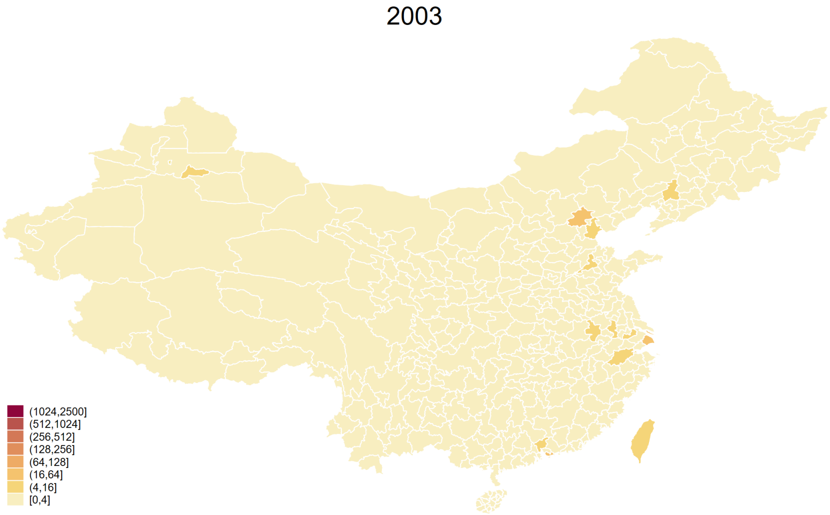

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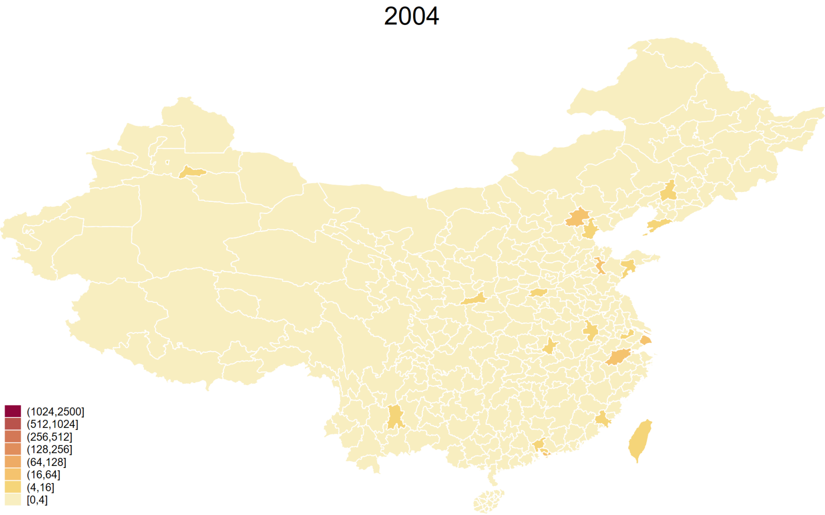

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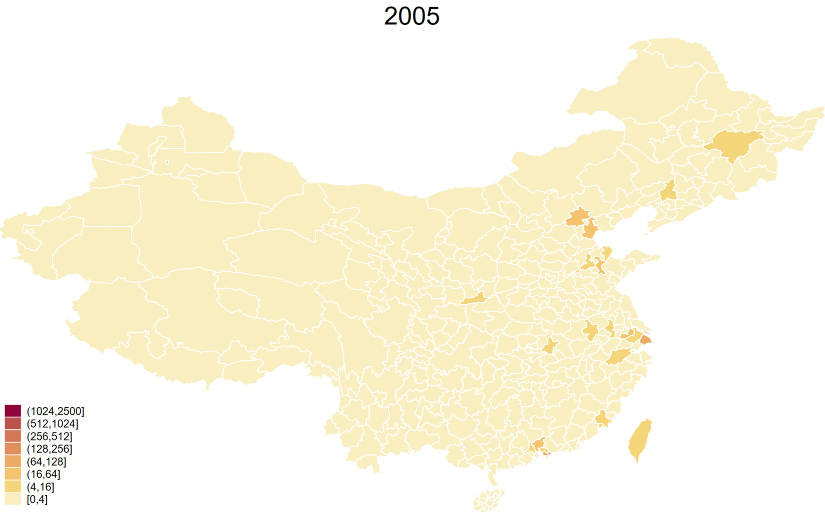

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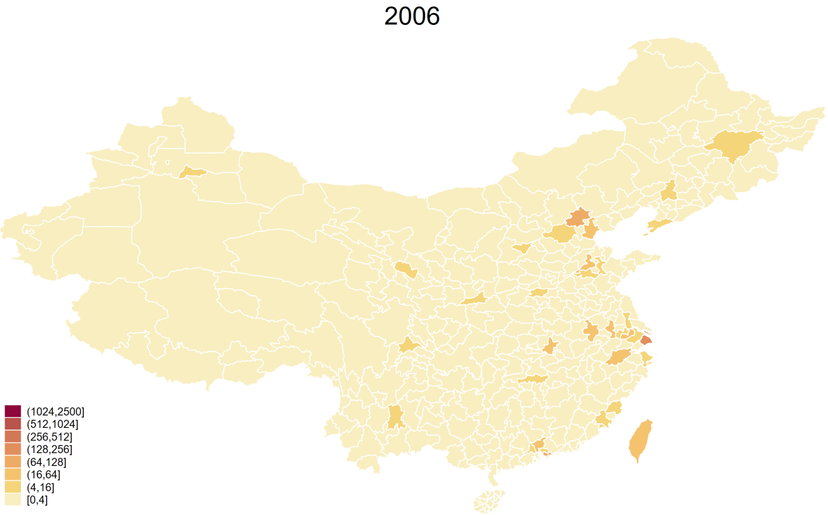

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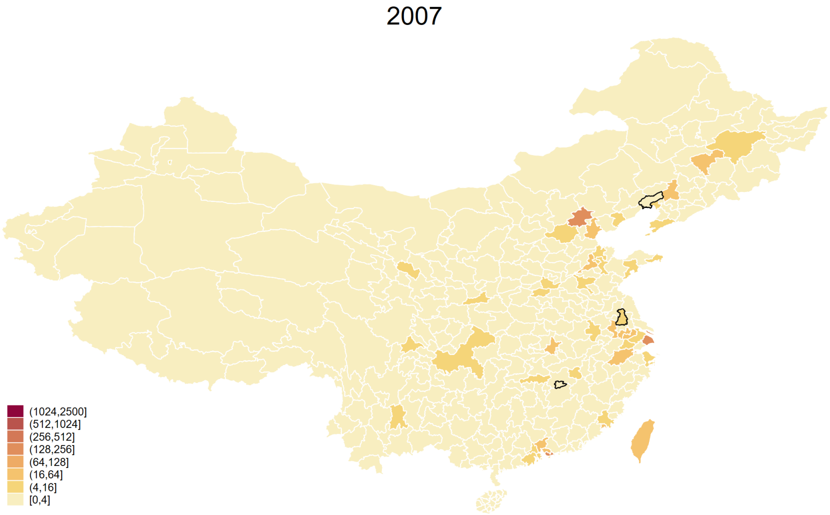

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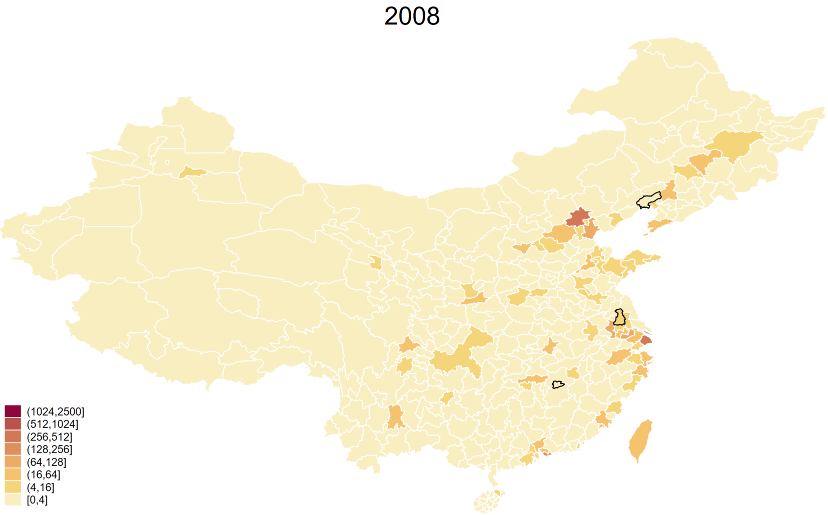

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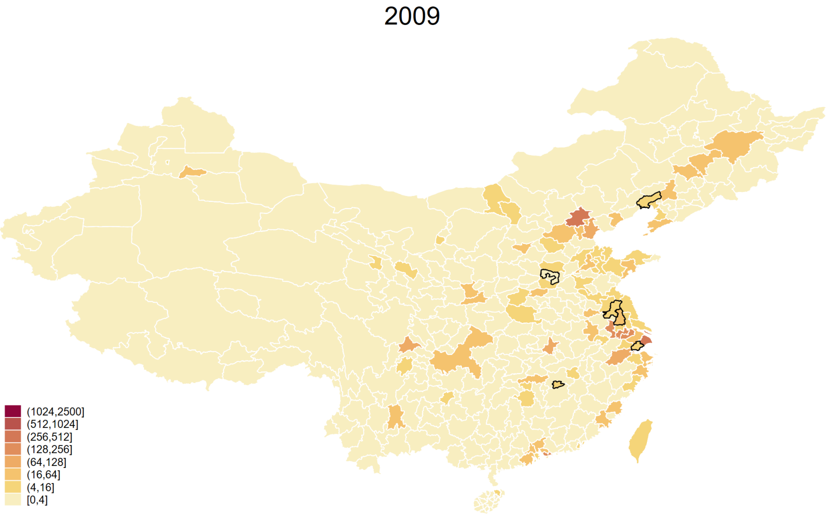

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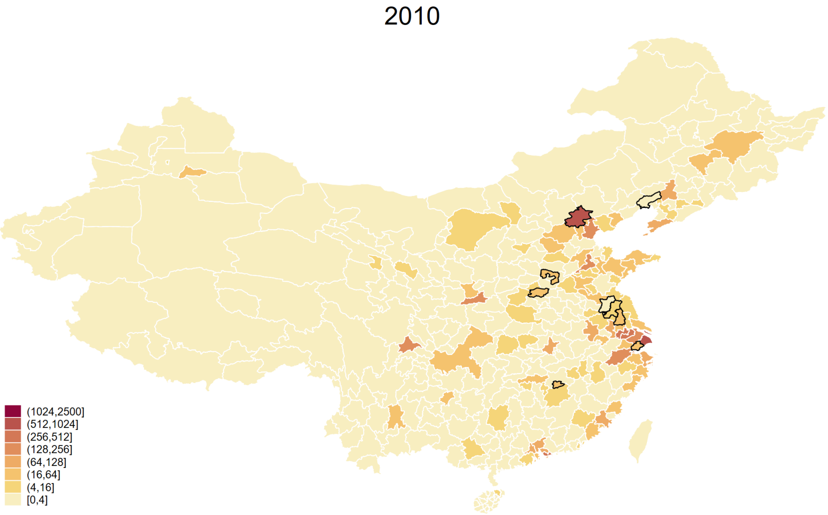

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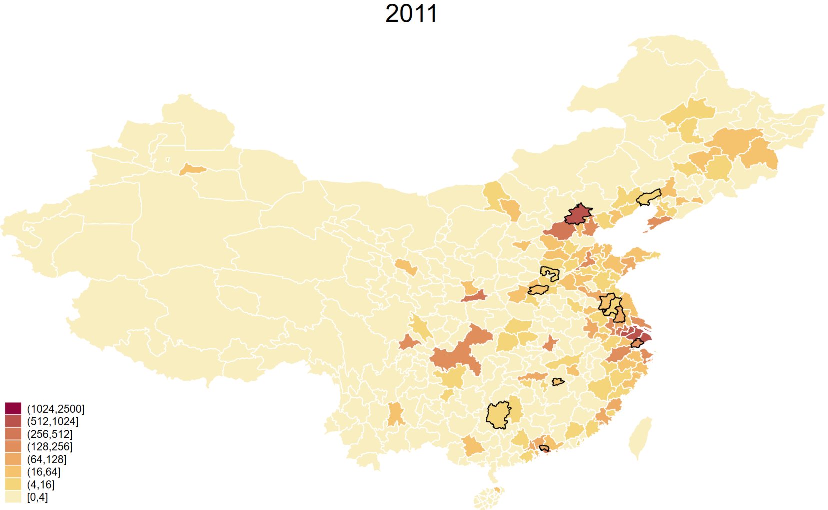

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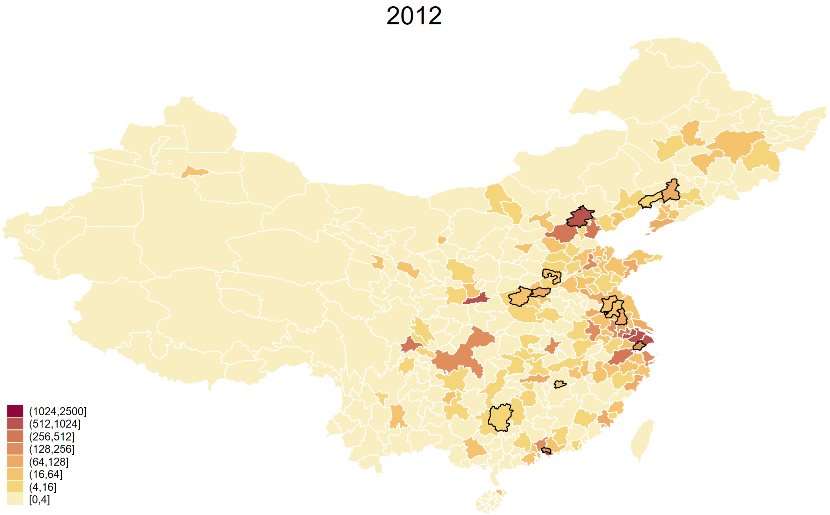

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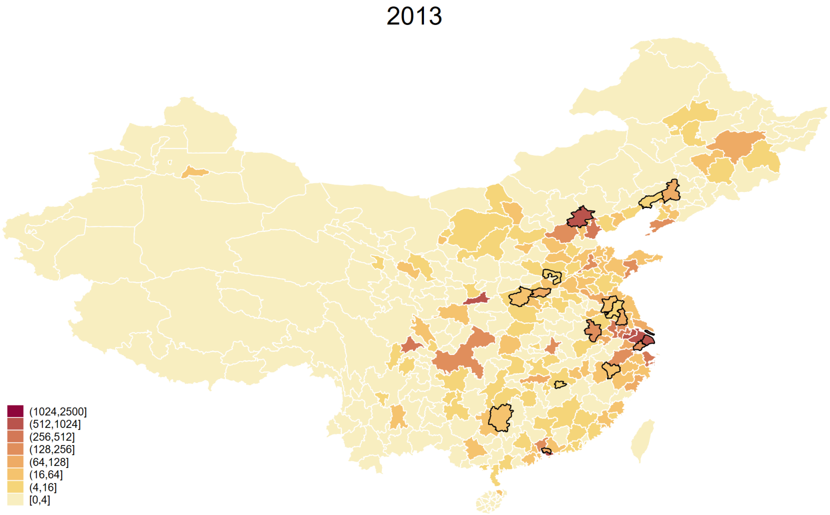

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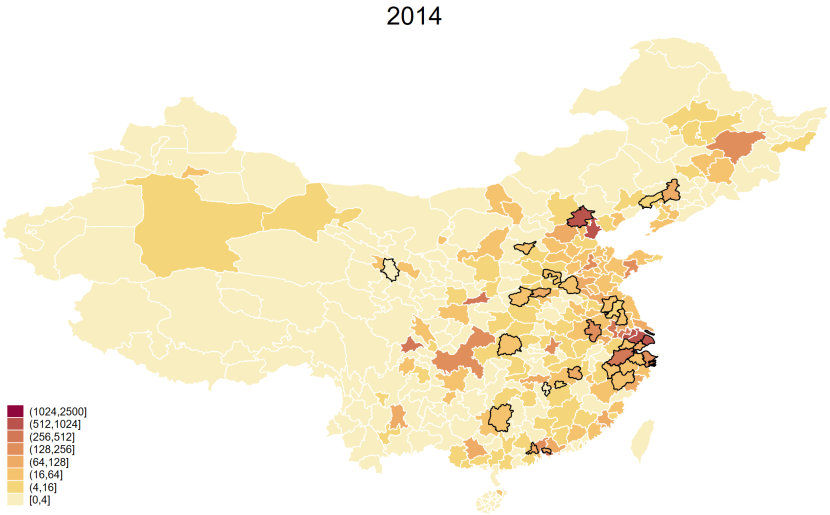

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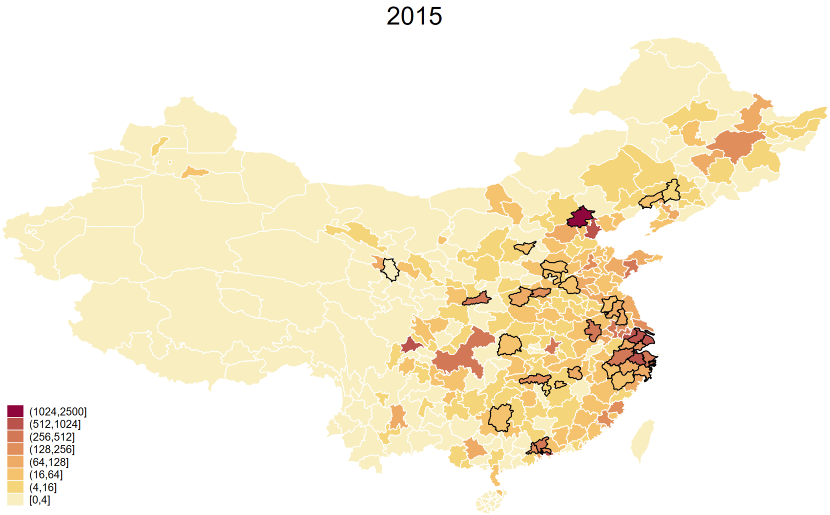

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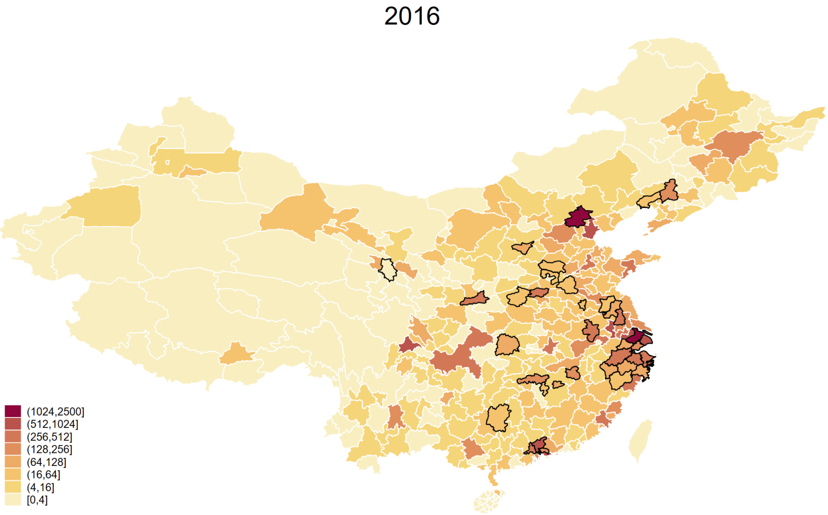

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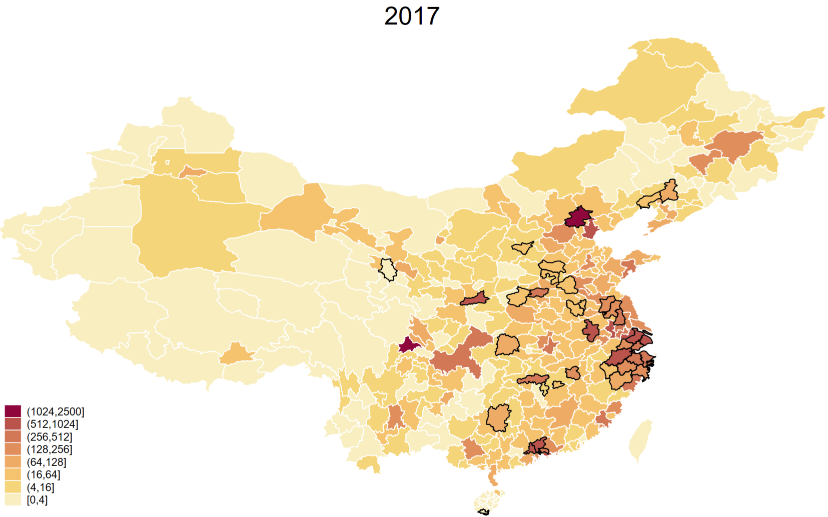

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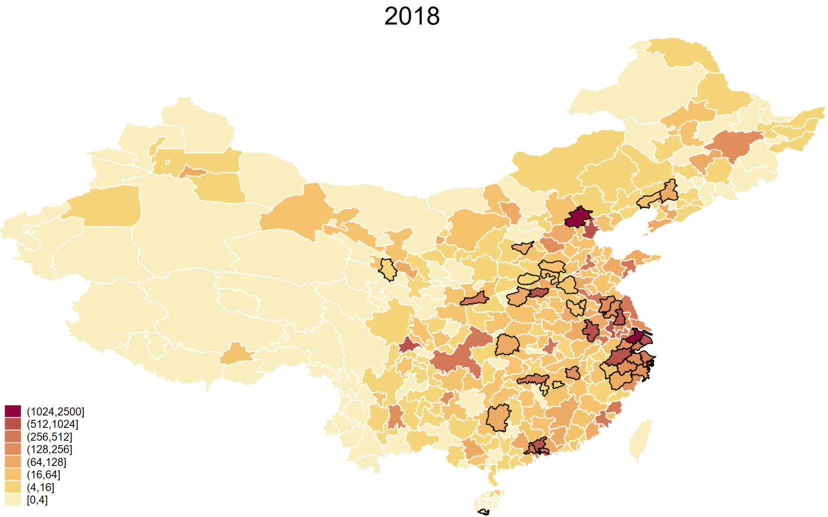

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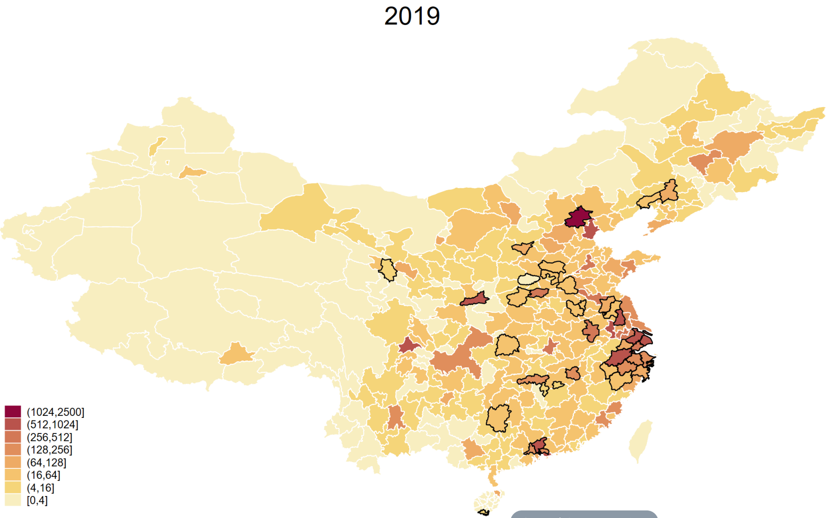

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Spatial Concentration

Outline

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: 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$_o$	++	
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

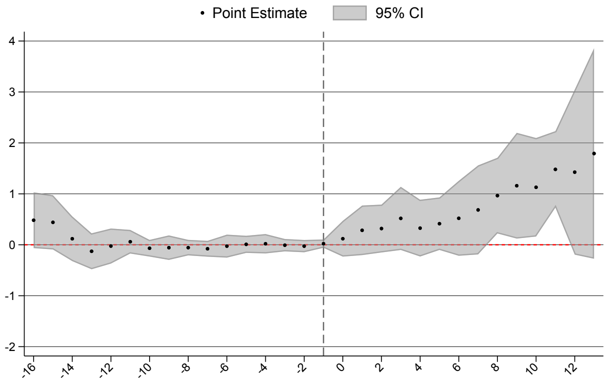
Outline

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)

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

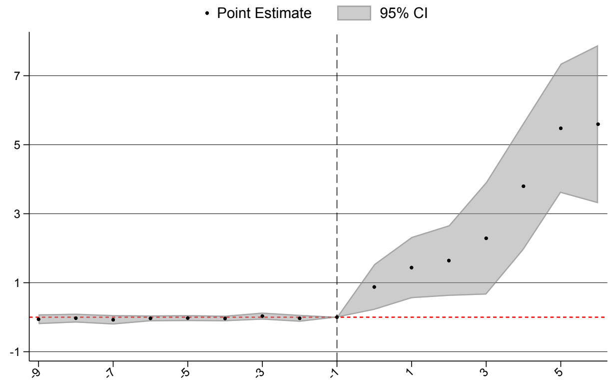
Results: LBD Patents

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

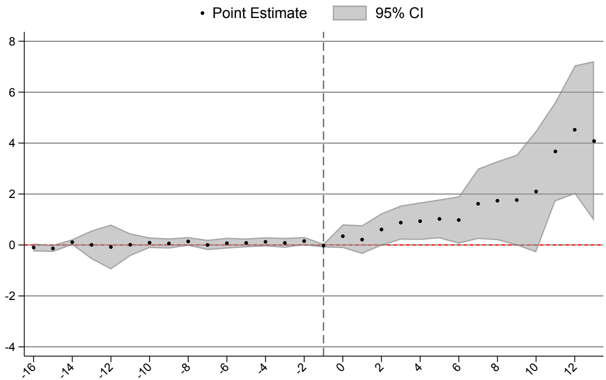
Results: Production Capacity

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

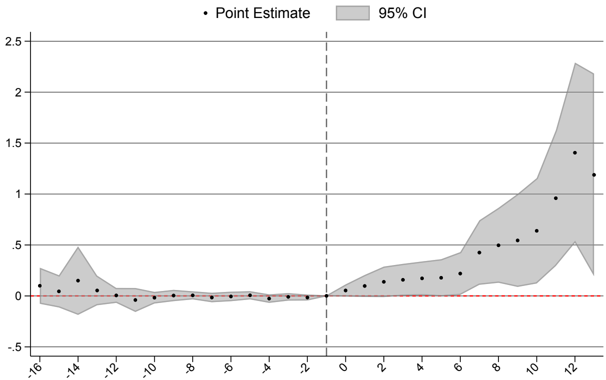
Table: Revenue (Aggregate ATT)

	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

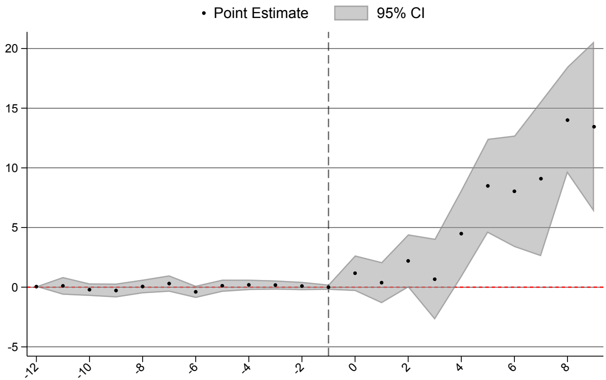
Results: Firm Count

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

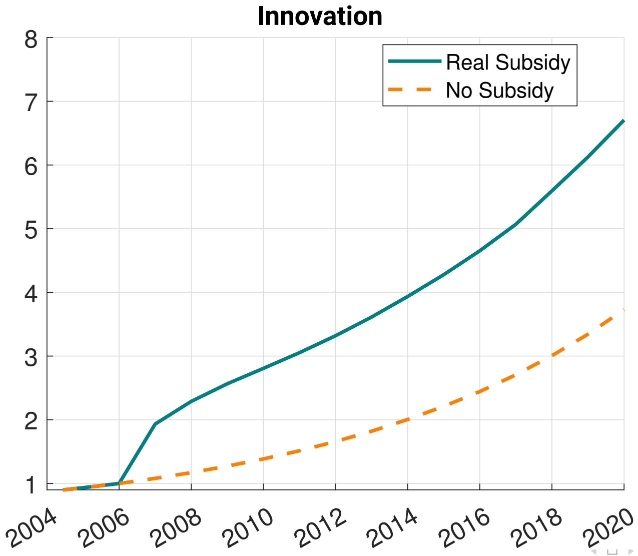
Outline

Model Quantification Strategy

Parameters		Values	Identification/Moments	
Preference Parameters				
σ	Elasticity of substitution across energy sectors (solar vs non-solar)	3	Jo (2025), 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 & Walker (2018)	External
Trade Parameters				
τ_{od}	Iceberg trade costs (intra-China)	$e^{0.032\, tt_{od}}$	Egger et al. (2023)	External
Production Technology Parameters				
$\xi_s, \xi_{s'}$	Productivity gain from innovating	1.058	Estimated (Appendix Table E.17 column 3)	External
δ	Knowledge spillover parameter	1.084	Estimated (Appendix Table E.18 column 2)	External
$\theta_s, \theta_{s'}$	Shape parameter (of Pareto distribution)	5.3, 11.7	Sales revenue (ENF, ASIE)	External
$b_s, b_{s'}$	Industry average scale parameter (of Pareto distribution)	0.267, 0.256	Sales revenue (ENF, ASIE)	External
$b_{o,s}, b_{o,s'}$	Location specific scale parameter (of Pareto distribution)	2 values for each of 358 cities	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
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

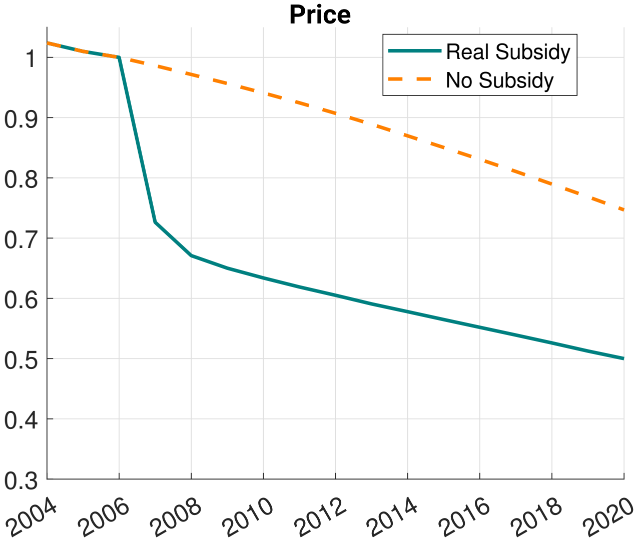
Counterfactuals without subsidies

Industrial policies explain about half of increase in Chinese Innovation



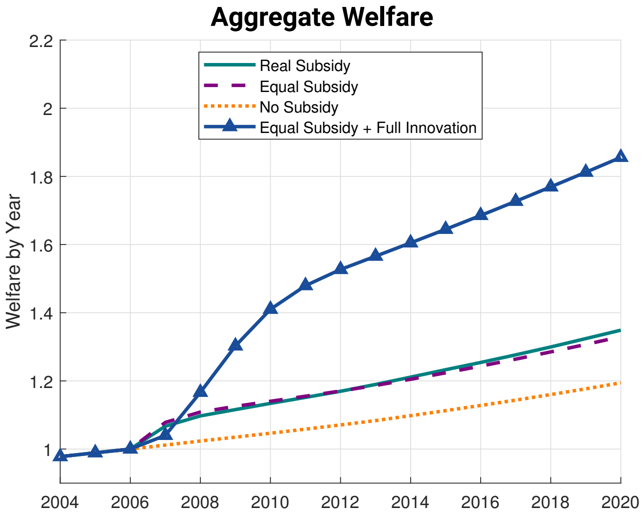
Counterfactuals without subsidies

Industrial policies explain about half of fall in Solar Prices



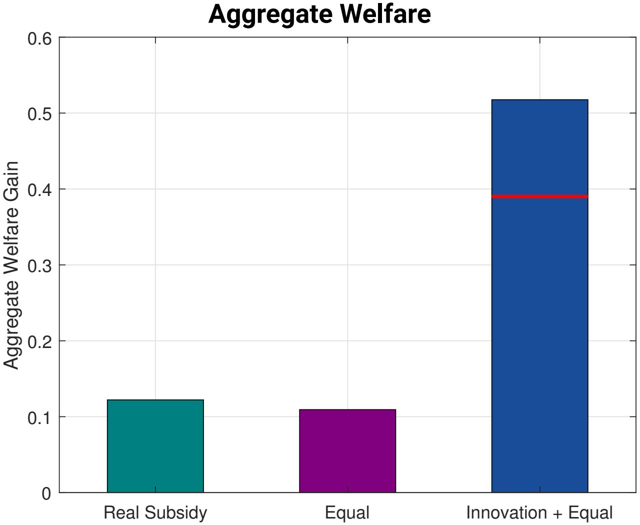
Welfare Counterfactuals: Flows

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



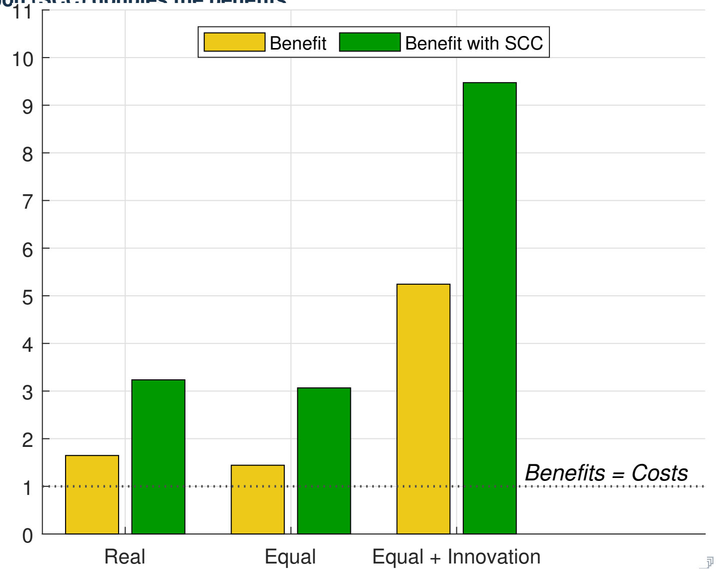
Welfare Counterfactuals: Present Value

- 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
- Next steps: Global version of model; Other industrial policies (e.g., wind, batteries, EVs); more on demand policies