## Ray of Hope? China and the Rise of Solar Energy

**EIEF 2023** 

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#### Outline

- Introduction
- Background
- 3 Data
- Model
- **6** Empirical Strategy
- **6** Results

#### Outline

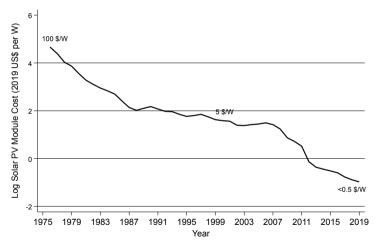
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# Clean energy essential to curbing emissions

- Around 73% of global greenhouse gas emissions are attributed to the energy sector
- Decarbonisation plans for many sectors reliant on electrification and therefore clean energy
- Emissions will grow if developing countries meet growing energy demand with fossil fuels

# Cost of solar has fallen dramatically

Figure: Global average price of solar PV modules (in 2019 US\$ per Watt)



Source: LaFond et al. (2017) & IRENA Database



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- Implement Synthetic DID approach (Arkhangelsky et al., 2021) exploiting introduction of city-level in solar policies over time
- Gather rich new micro-data on universe of solar panel manufacturers in China & including their production (in MWh) from ENF. Match to business register, patents (SIPO, PATSTAT, etc.), customs (exports), Orbis (revenue, labor, capital, productivity), ASIE, etc.

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- Preliminary analysis suggests benefits much larger than costs

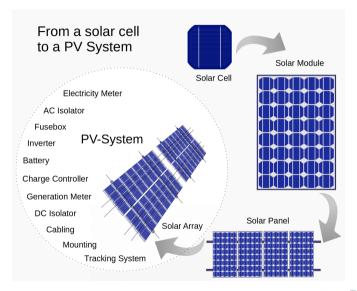
## **Some Existing Literature**

- Industrial Policy: Theory: 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, 2021); Criscuolo et al. (2019); Juhasz et al. (2022); Choi & Levchenko (2021); Choi & Shim (2022); Levitt et al. (2013); Liu & Ma (2022)
- (Green) Directed Technical Change: Aghion et al. (2016); Acemoglu et al. (2012, 2016, 2019); Arkolakis & Walsh (2023); Popp (2022, 2019); Newell et al. (1999)
- Chinese Growth & Policy: Kalouptsidi (2018); Barwick, Kalouptsidi and Zahur (2021); Aghion et al. (2015); Bai et al. (2019); Chen & Xie (2019); Wang & Yang (2021), Song et al. (2011); Konig et al. (2022); Wei et al. (2023)
- **Solar**: Bollinger & Gillingham (2021); Gerarden (2022); Gillingham & Tsvetanov (2019); de Groote & Verboven (2019); Nemet (2019); Ball et al. (2017)
- **Technology and Trade**: Melitz & Redding (2023); Bustos (2011); Coelli et al. (2020); Aghion et al. (2017)
- Place-Based Policies: Moretti (2011, 2012); Kline (2010); Gruber & Johnson (2019); Greenstone et al. (2010); Kline & Moretti (2014)

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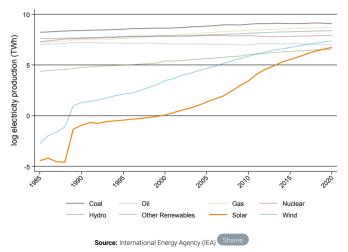
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### From cell to panels



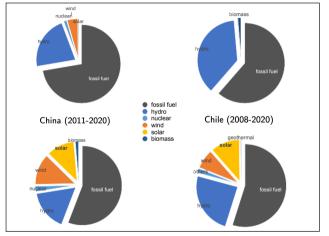
# Renewable electricity capacity, especially solar, has grown rapidly...

Figure: World electricity production by source



## .. Especially in some countries like China and Chile

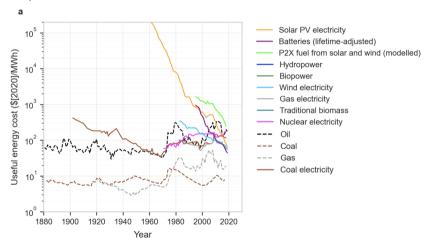
Figure: Installed Electricity generation capacity in China and Chile by source



Source: State Grid New Energy Cloud & CNE

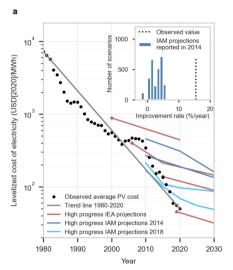
- World, 2011 to 2020: installed solar capacity went from 0.8% to 6.8%
- China, 2011 to 2020: installed solar capacity went from 0.19% to 11.35%
- Chile, 2008 to 2020: installed solar capacity went from 0% to 12%

# 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)

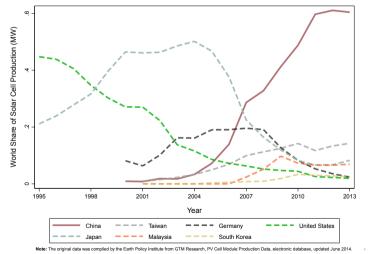


Source: Way, Ives, Mealy and Farmer (2021) "Empirically grounded technology forecasts and the energy transition"



# China's global share of solar production rose from near zero to 60% in the decade to 2013

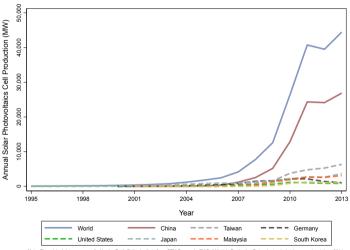
Figure: Share of Annual Solar Photovoltaics Cell Production in Leading Countries, 2000-2013



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### And this was in context of huge growth in solar production

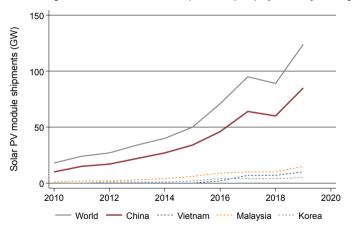
Figure: Solar PV cell production 2000-2013



Note: The original data was compiled by the Earth Policy Institute from GTM Research, PV Cell Module Production Data, electronic database, updated June 2014.

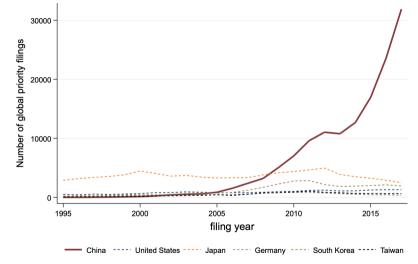
# China's rise in solar shipments has continued in later years

Figure: Solar PV module shipments (GW) by country of origin, 2010-2019



Source: International Energy Agency (IEA)

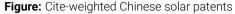
## China is not just imitating: Huge growth in Solar Patents

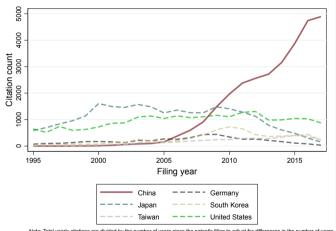


Source: PATSTAT - solar patents based on IPC/CPC



## **China is not just imitating: Citation-Weighted Solar Patents**

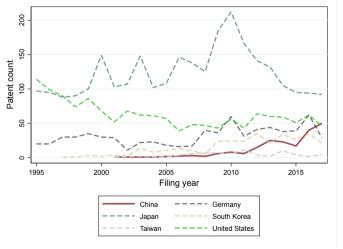




Note: Total yearly citations are divided by the number of years since the patent's filing to adjust for differences in the number of years when patents can be cited.

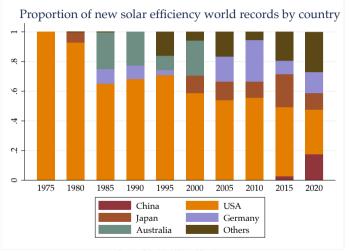
Source: PATSTAT database: Patents by priority date in all patent offices.

# **China is not just imitating: Triadic Solar Patents**



Source: PATSTAT database, Triadic patents = filed in USPTO, EPO and JPO

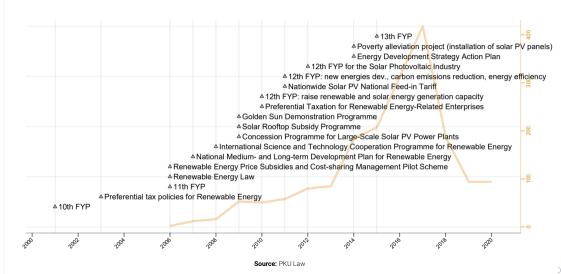
# China is innovating not just imitating: Technological Frontier



Source: Solar World Record Database

# Coincides with expansion of solar industrial policy in China

Figure: Number of new solar-related policies



# Much of 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)

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#### We need to measure

- Treatment: Solar industrial policies at the city 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

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- Distinguish subsidy policies into 3 types: (i) Demand (ii) Production & (iii) Innovation

Table: City-level solar policies

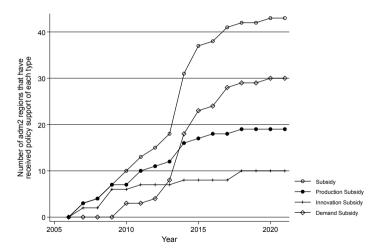
Type of policy	Number	Example
Subsidy	78	
1. Production subsidy	27	"The cost of a new solar production line built in Hefei will be subsidized by 12% (2018)"
2. Innovation subsidy	12	"Firms will be awarded 10,000 RMB if they earn provincial level R&D center certification (Guilin, 2011)"
3. Demand subsidy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

Source: Own analysis using PKULaw data

- 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



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- We define the solar industry as a set of firms who manufacture solar panels
- 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.)



#### **Coverage of Data across years**

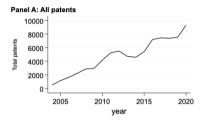


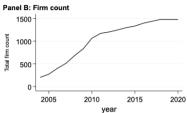
**Orbis:** Company accounts **ASIE:** Company accounts

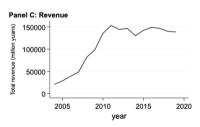
Customs: exports by HS8 code

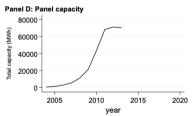


# **Chinese Solar industry evolution**

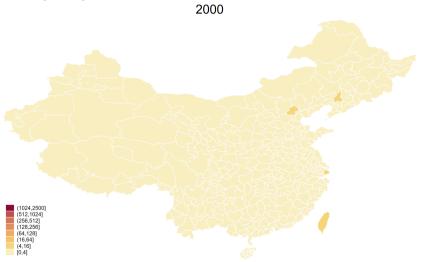








Here: patent counts and any subsidy



Here: patent counts (subsidy in black circles)



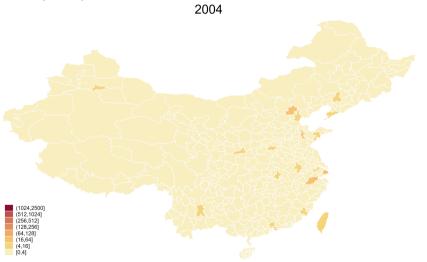
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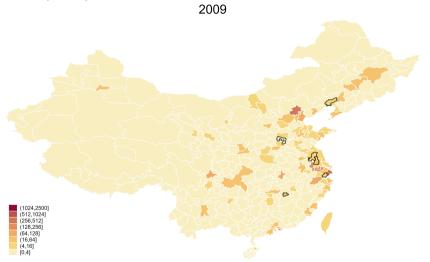
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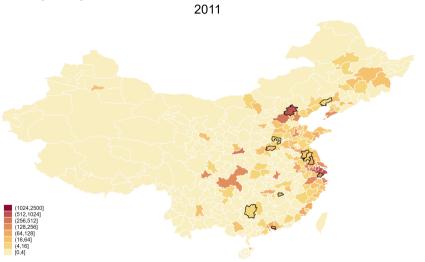
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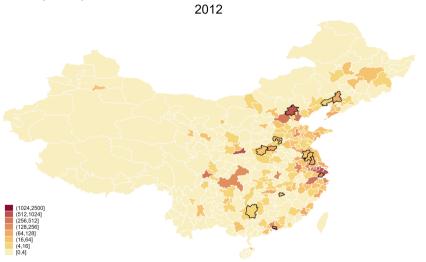
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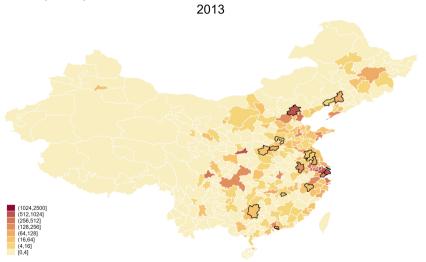
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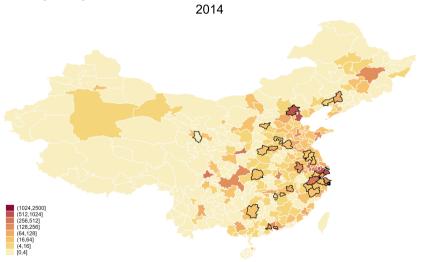
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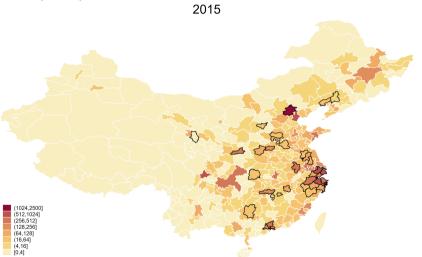
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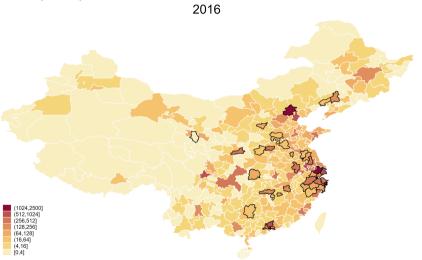
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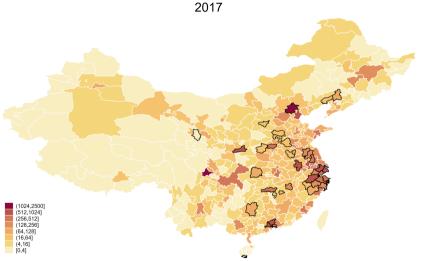
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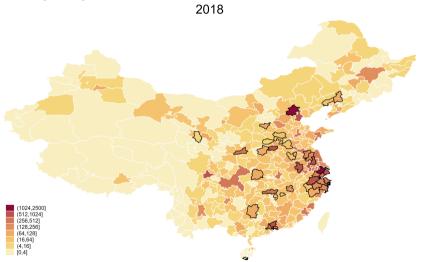
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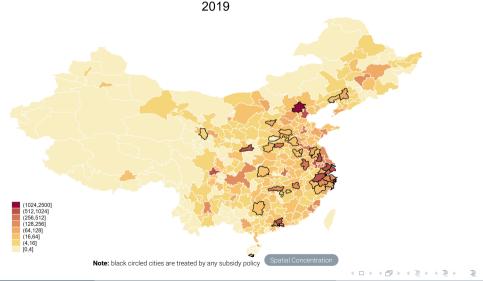
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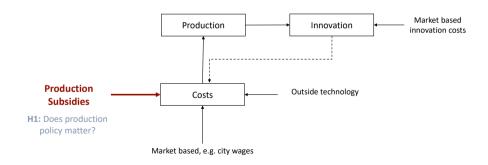
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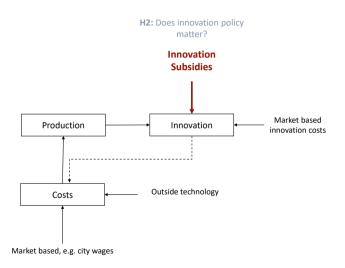
### **Research Questions**

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

# Causal Graph



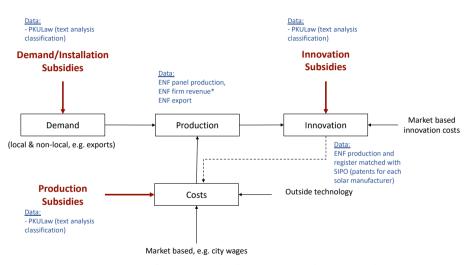
## Causal Graph



# Causal Graph

**H3:** Does demand policy matter? Demand/Installation Subsidies Market based Demand Production Innovation innovation costs (local & non-local, e.g. exports) Outside technology Costs Market based, e.g. city wages

### Data



Firm count: ENF register matched with Chinese firm registration platform (firm entry and exit dates for each solar manufacturer)

\*ENF firm revenue: ENF register matched with Orbis platform



### Model

#### Electricity generation using manufactured inputs

- Heterogenous firms model (power plant components manufacturers)
- Many (N) city-regions within China, plus 'Rest of World' (one foreign location)
- Representative consumer in each region demands electricity services
- Local "Grid Planner" builds solar and non-solar power plants using components (e.g. solar panels) sourced from manufacturers in all Chinese cities, subject to transport costs
- Manufacturers make endogenous entry, exit, production, exporting, and technology upgrading (innovation) decisions
- Model provides intuition for impacts of place-based subsidies

# **Timing of Decisions**

- **1** Entrepreneurs enter by paying a sunk cost, then draw productivity,  $\varphi$ . Decide whether to exit.
- 2 If continue, decide whether to pay fixed cost of innovation to further reduce marginal cost.
- 3 Then decide whether to export (another fixed cost) or just serve domestic Chinese market (Melitz, 2003)
- 4 These fixed costs help determine productivity cut-offs for: (i) exit, (ii) exporting & (iii) innovation.
- Producing firms in origin city o serve multiple destination cities d paying iceberg trade costs
- **6** Demand for intermediates across all Chinese cities from different grid planners (and overseas) influences solar manufacturer decisions.

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

$$e_d = \left(\kappa_{d,s} e_{d,s}^{\rho} + \kappa_{d,s'} e_{d,s'}^{\rho}\right)^{1/\rho} \tag{2}$$

### **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  $\omega$  manufactured in city o supplied to d using CES:

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

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

$$\max_{e_{d,s},e_{d,s'}} \left( \kappa_{d,s'} e_{d,s'}^{\rho} + \kappa_{d,s} e_{d,s}^{\rho} \right)^{1/\rho}$$
s.t.  $P_{d,s} e_{d,s} + P_{d,s'} e_{d,s'} = I_{d}$ 

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$$P_{d,s}e_{d,s} + P_{d,s'}e_{d,s'} = I_d$$

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

$$e_{d,s}^{*}(P_{d,s}, P_{d,s'}, I_{d}) = \left(\frac{\kappa_{d,s}}{P_{d,s}}\right)^{\sigma} \frac{I_{d}}{\kappa_{d,s'}^{\sigma} P_{d,s'}^{1-\sigma} + \kappa_{d,s}^{\sigma} P_{d,s}^{1-\sigma}}; \tag{4}$$

where  $\sigma = 1/(1 - \rho)$ 



# Demand for Energy manufactured inputs (e.g. solar PV modules)

- To meet the optimal energy demand, grid planner chooses solar modules 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:

$$q_{od,s}(\omega) = \left(\frac{p_{od,s}(\omega)}{P_{d,s}}\right)^{-\sigma_s} \left(\frac{\kappa_{d,s}}{P_{d,s}}\right)^{\sigma} \frac{I_d}{\kappa_{d,s'}^{\sigma} P_{d,s'}^{1-\sigma} + \kappa_{d,s}^{\sigma} P_{d,s}^{1-\sigma}}$$
(5)

# Manufacturing technology

#### **Production decision:**

- Firms use a composite factor of production  $L_{o,s}$  with unit cost  $w_{o,s}$
- ullet They need to pay a sunk cost  $w_{o,s}f_{o,s}^e$  to enter
- After paying this cost, they draw productivity  $\varphi$ , from Pareto distribution
- To produce  $q_{o,s}(\varphi)$  units of a variety, costs firm  $f_{o,s}+\frac{q_{o,s}}{\varphi}$ , where  $f_{o,s}$  is fixed cost and  $\frac{1}{\varphi}$  is marginal cost of production

#### Innovation decision:

- Upon observing its initial productivity  $\varphi$ , 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  $\xi_{o,s}>1$

# Exporting and Prices

- 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  $\tau = 1$ ).
- There is a market access fixed cost for selling overseas (but not within China)
  - In order to serve overseas firm in o pays fixed cost  $w_{o,s}f_{od,s}^x$
- Implies manufacturers' optimal prices are a constant markup over marginal costs

$$p_{od,s}(\varphi) = \frac{\sigma_s}{\sigma_s - 1} \frac{w_{o,s} \tau_{od,s}}{\xi_{o,s} \varphi} \tag{6}$$

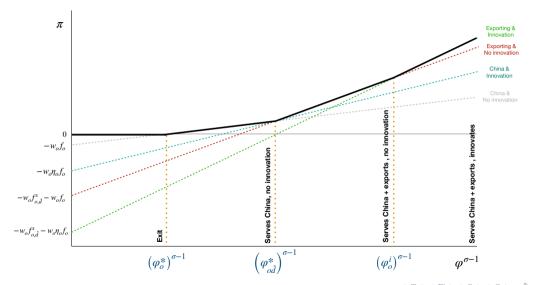
# Optimal Profits (3 regimes)

$$\Pi_{o,s}(\varphi) = \max \left\{ \sum_{d \neq \tilde{d}} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1 - \sigma_s}} \left( \frac{w_{o,s} \tau_{od,s}}{\varphi} \right)^{1 - \sigma_s} \right\} - w_{o,s} f_{o,s}, 
\sum_{d} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1 - \sigma_s}} \left( \frac{w_{o,s} \tau_{od,s}}{\varphi} \right)^{1 - \sigma_s} \right\} - w_{o,s} f_{o,\tilde{d},s}^x - w_{o,s} f_{o,s}, 
\sum_{d} \left\{ \frac{(\sigma_s - 1)^{\sigma_s - 1}}{\sigma_s^{\sigma_s}} \frac{E_{d,s}}{(P_{d,s})^{1 - \sigma_s}} \left( \frac{w_{o,s} \tau_{od,s}}{\xi_{o,s} \varphi} \right)^{1 - \sigma_s} \right\} - w_{o,s} f_{o,\tilde{d},s}^x - w_{o,s} \eta_{o,s} f_{o,s} \right\}$$

## Optimization

- Solution involves solving for vector of price indices for energy in each city
- We can characterize solution in terms of three productivity cut-offs
  - Least productive firms exit
  - Next most productive firms sell only in China and do not innovate  $(\varphi_o^*)$
  - Next most productive firms also export  $(\varphi_{o\tilde{d}}^*)$
  - Highest productivity firms export and innovate  $(\varphi_{od}^i)$

# Productivity thresholds determine regimes (optimal profits, $\pi$



# Solar industrial policy

#### Production subsidies

• We model production subsidies  $s_{o,s}$  as a reduction in input costs in city o, manufacturers, marginal cost becomes  $\frac{1-s_{o,s}}{\varphi}$ .

#### Innovation subsidies

• We model innovation subsidies ( $\phi_{o,s} < 1$ ) in city o as a reduction in fixed costs of technological upgrading, which becomes  $\phi_{o,s}(\eta_{o,s}f_{o,s})$ 

#### ② Demand/Installation subsidies

• We model solar demand subsidies in d as  $\theta_d$ , shifting  $e_d = \left(\kappa_{d,s'}e^{\rho}_{d,s'} + \theta_d\kappa_{d,s}e^{\rho}_{d,s}\right)^{1/\rho}$ 

Figure: Place-based demand subsidies

Demand Subsidy $ heta_o$			
Innovation $_o$	≈ +		
Firm count <sub>o</sub>	≈ +		
Panel production <sub>o</sub>	≈ +		
$Revenue_o$	≈ <b>+</b>		
$Exports_o$	≈ +		

**Notes:** All outcome variables and subsidy policies are referred to the same region o. The table shows no prediction on how policies in region o 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: + + + > + + > + + > +.

Figure: Place-based production subsidies

	Production Subsidy s <sub>o</sub>	
$Innovation_o$	+	
Firm $count_o$	++	
Panel production <sub>o</sub>	++	
Revenue <sub>o</sub>	++	
$Exports_o$	++	

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: +++>++>++>++

Figure: Place-based innovation subsidies

	Innovation $Subsidy  \phi_o$	
Innovation <sub>o</sub>	++	
Firm count <sub>o</sub>	+	
Panel production <sub>o</sub>	+	
Revenue <sub>o</sub>	+	
$Exports_o$	+	

**Notes:** All outcome variables and subsidy policies are referred to the same region o. The table shows no prediction on how policies in region o 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: +++>++>++>++

Figure: Predictions to the data

	Demand Subsidy $\theta_o$	Production Subsidy s <sub>o</sub>	Innovation Subsidy φ <sub>o</sub>	Production & Innovation Subsidy $s_o + \phi_o$
Innovation <sub>o</sub>	≈ +	+	++	+++
Firm count <sub>o</sub>	≈ +	++	+	+++
Panel production <sub>o</sub>	≈ +	++	+	+++
Revenue <sub>o</sub>	≈ +	++	+	+++
$Exports_o$	≈ +	++	+	+++

**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: +++>++>+.

### Outline

- Introduction
- Background
- Operation
- Model
- **6** Empirical Strategy
- Results

# **Empirical Strategy**

- Effectiveness of solar industrial policy
  - Look at dynamics: persistent benefit in the long-term is key justification for industrial policy
- Challenges in evaluating industrial policy:
  - Allocation of solar industrial subsidies by firm 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)
  - Although no systematic differences in observables in cities, some mild pre-trends.
- We follow the synthetic-difference-in-differences (SDID) methodology (Arkhangelsky et al 2021)

# Synthetic-difference-in-differences (SDID)

- Outcomes: Patents, number of firms, panel production, revenue, exports
- Treatments: Subsidy policies (demand, production, innovation)
- <u>Variation</u>: 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  $\omega_i$ : chosen so that average pre-treatment outcome for control units is  $\approx$  parallel to pre-treament outcome for treated units
- Time weights  $\lambda_t$ : more weight on time periods which better predict post-treatment outcomes for control

### SDID Intuition

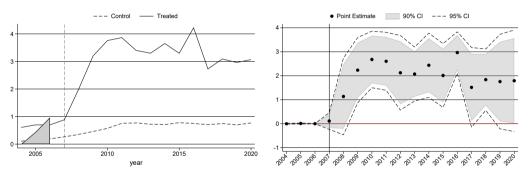
- Construct synthetic control group such that pre-trends are approximately parallel
- 2 Compute treatment effect using diff-in-diff between treatment and synthetic control
  - Allows us to relax the parallel trends assumption
- Comparison with TWFE
  - SDID as a generalization of TWFE that allows for 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

- Introduction
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- **6** Results

### **Results: Patents**

Figure: Patent Counts (Example of 2007 Cohort)



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.





### **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.



## **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 LBD/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
- 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**

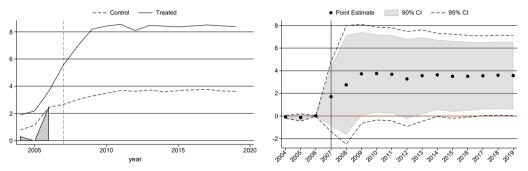
**Table:** Learning-by-doing Patents (Aggregate ATT)

	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: Revenue (quicker & larger effect than patents)**

#### Figure: Revenue (2007 Cohort)



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.

### **Results: Revenue**

**Table:** Revenue (Aggregate ATT)

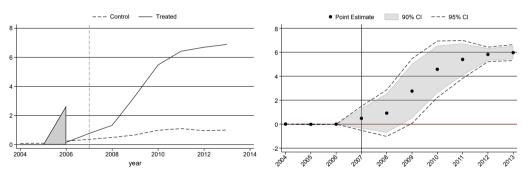
	Any subsidy	Demand subsidy	Production subsidy	Innovation subsidy
Revenue	1.100**	0.192	1.887**	2.670 **
	(0.456)	(0.199)	(0.767)	(1.193)
Observations	5,728	5,728	5,728	5,728

Notes: \* 0.1 \*\* 0.05 \*\*\* 0.01. SDID estimates on 358 cities 2004-2019. Outcome is IHS of revenue of solar firms in a city-year pair.



# **Results: Production Capacity**

Figure: Panel Production Capacity (2007 Cohort)



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.

# **Results: Production Capacity**

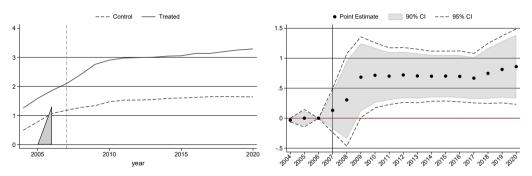
**Table:** Solar Panel Production Capacity (Aggregate ATT)

	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 2004-2019. Outcome is IHS of production capacity of solar firms in a city-year pair.

### **Results: Firm Count**

**Figure:** Firm Count - Number of Solar Firms (2007 Cohort)



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.

### **Results: Firm Count**

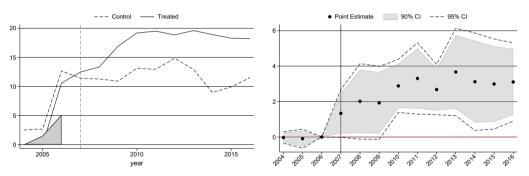
### **Table:** Firm Count - Number of Solar Firms (Aggregate ATT)

	Any subsidy	Demand subsidy	Production subsidy	Innovation subsidy
Firm count	0.186***	0.060	0.288***	0.381***
	(0.064)	(0.043)	(0.090)	(0.135)
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: Exports**

**Figure:** Export Value (2007 Cohort)



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.

# **Results: Exports**

**Table:** Exports (Aggregate ATT)

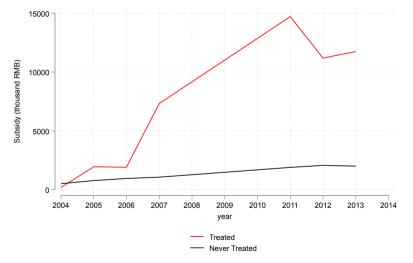
	(1)	(2)	(3)	(4)
	Any subsidy	Demand subsidy	Production subsidy	Innovation subsidy
Export value	2.451**	0.658	3.217**	4.160**
	(1.178)	(1.130)	(1.443)	(2.143)
Solar export value	4.688***	1.443	6.464***	9.360***
	(1.302)	(0.918)	(1.734)	(2.230)
Observations	4,654	4,654	4,654	4,654

Notes: \* 0.1 \*\* 0.05 \*\*\* 0.01. Solar exports classified via HS8. SDID on 358 cities 2004-2016. Outcome is IHS.

### **Extensions & Robustness**

- Business stealing vs. agglomeration (business stealing results)
- Productivity productivity results
- Total solar patents (including universities, non-solar firms, etc.) City-level patents
- Adding controls to SDID (GDP, population, income, tax revenue, ...)
- Placebos on GDP, non-solar patents, etc.
- Results in levels, etc. (e.g. Chen and Roth, 2022) results in levels
- Magnitudes and Cost-Benefit

# Mean subsidy for solar firms in treated vs. control cities ( RMB13m per city after 2009



# SDID analysis of impact on ASIE subsidies of introduction of policy

**Table:** Subsidy value (level)

	(1)	(2)	(3)	(4)
	Any subsidy	Demand subsidy	Production subsidy	Innovation subsidy
Subsidy value (million RMB)	13.601*	-0.527	15.993*	24.177
	(7.693)	(1.293)	(9.276)	(17.621)
Observations	2,457	2,457	2,457	2,457
Mean of Dep. var.	1.492	1.492	1.492	1.492

 $<sup>\</sup>rightarrow$  These are: US\$1.9 million for any subsidy, US\$2.2 m for production subsidy, US\$3.4 m for innovation subsidy.

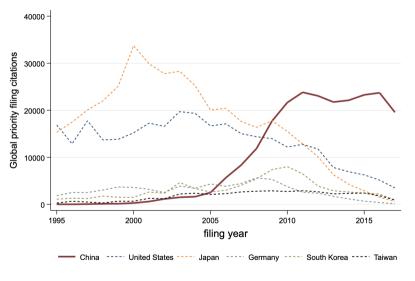
# **Back of Envelope Cost-Benefit**

- Consider steady state and abstract from GE effects. (split sample IV effect of subsidy)
- Using mean observed cost or estimated ATT marginal cost of subsidy + admin costs + 40% deadweight cost of taxation = US \$3m p.a. per policy
- Revenue benefits five to ten times higher.
- Removing all subsidy policies would reduce aggregate Chinese solar patent flow by about a 25% a year
- Caveat: Might be missing hidden costs such as other subsidies and distortions (e.g. Kalouptsidi (2018); Barwick, Kalouptsidi and Zahur (2021))

# **Conclusions and next steps**

- 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)
- Initial assessment of the cost of the policies points towards positive returns
- Theoretical model's initial predictions consistent with empirical analysis
- Next steps: model quantification and counterfactual analysis. Consider international version to look at global effects

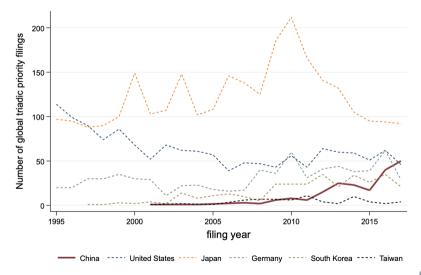
### **Citations**







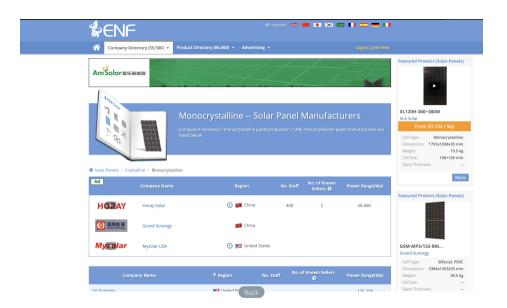
## **Triadic patents**

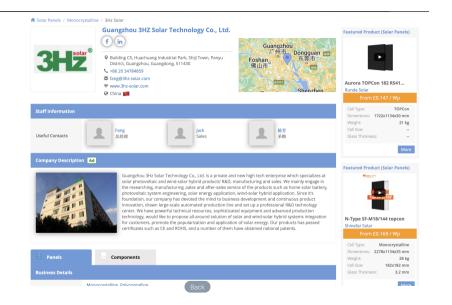


		₹ Region		No. of Known Sellers	Power Range(Wp)
1st Sunergy		United States			175-290
2ES		France	15		135-150
2Power		Germany	50	1	215-325
3D Energy	€	<b>■</b> Italy	20		200-450
3G-Solar		Germany			155-300
3Hz Solar		China			140-540
3KM Power		China			410
3S	€	[ China	300	1	40-600
35 Swiss Solar Solutions		Mark Switzerland		1	115-200
5Star Solar		[ China		1	240-370
8.33 Solar		<b>Spain</b>		5	270-345
A. D. Global Synergies		🍱 India			3-300
A.R.E.		Egypt			325-340
Abba		<b>■</b> Italy			230-300
Abow Power		China			5-350
ABi-Solar		Inited States		18	275-470
Abotree Solar		China			0.3-360
Abshine		China	100		255-270
Access Solar		India India	Back	1	2.220

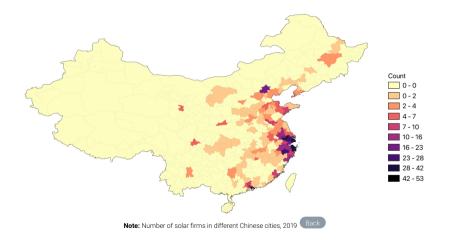








# **Spatial concentration of the Chinese solar industry**



# **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

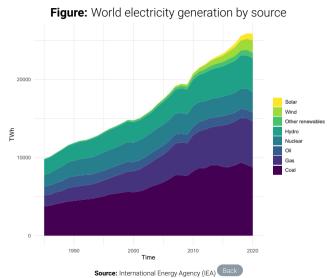
#### 2016-2020 Thirteenth Five-Year Plan:

- Targeting capacity and R&D expansion, as well as industry-wide cost-reduction.
- Includes Thirteenth Five Year Plan for Solar Energy Development.



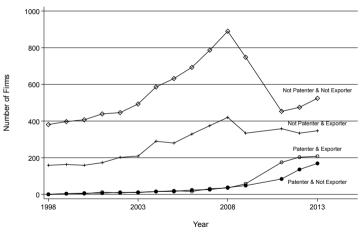


## Renewable electricity capacity, especially solar, has grown rapidly



# The productivity thresholds in the data

Figure: Number of firms (ASIE) in each group



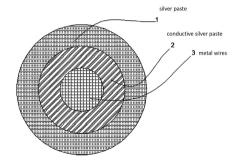
Note: Firm-level data from ASIE, merged with SIPO.

### **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.

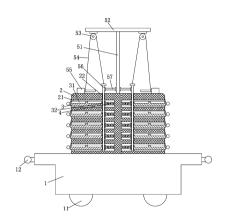


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### **LBD-Patent: Patent as process innovation**

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.

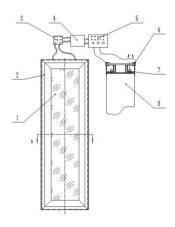




### **Non-LBD Patent**

#### 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 quardrail 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.



Back to Data Section

### 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.

# **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, 2004-2019	0.304	1.15	5,728
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.

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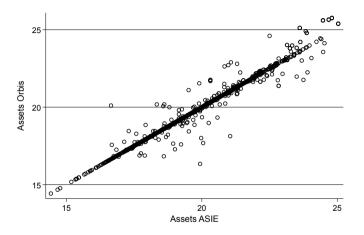
## **Descriptive Statistics**

	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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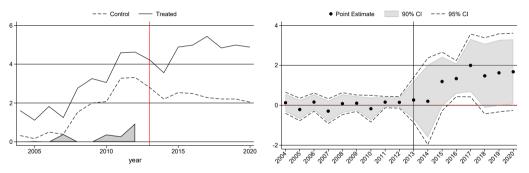
### **Validation with ASIE**



**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,  $p_i$ 0.01, and  $R^2$  = 0.9679

### **Results 2013 Cohort**

Figure: Patent (2013 Cohort)

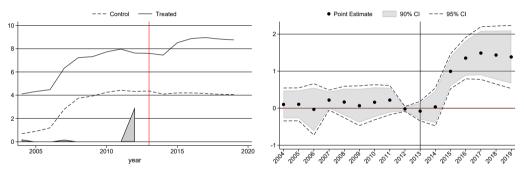


Notes: SDID estimates on 358 cities, focusing on the 3 that introduced a policy in 2013. Outcome IHS of patents by solar firms in a city-year. SE cluster bootstrapped by city.



### **Results 2013 Cohort**

Figure: Revenue (2013 Cohort)



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.



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

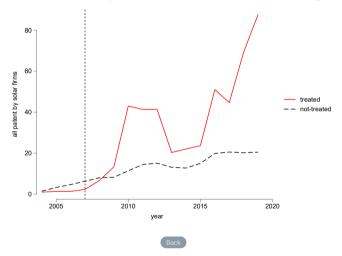


Figure: Number of patents by solar firms for the three cities treated in 2007

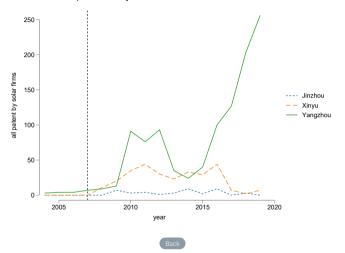


Figure: Total revenue by solar firms for the treated and control group in 2007

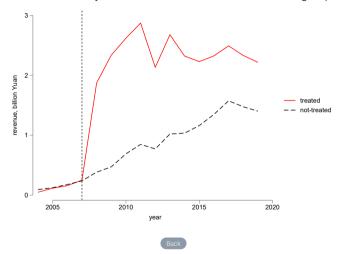
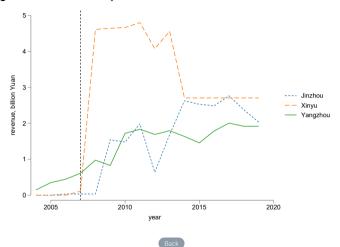


Figure: Total revenue by solar firms for the three cities treated in 2007



### **Results**

**Table:** Productivity (Aggregate ATT)

Panel A	(1)	(2)	(3)	(4)
Period: 2004-2019	Any subsidy	Demand subsidy	Production subsidy	Innovation subsidy
Revenue	1.100**	0.190	1.887**	2.670**
	(0.456)	(0.198)	(0.767)	(1.193)
Labor	0.859**	0.249	1.443**	1.832*
	(0.435)	(0.291)	(0.664)	(1.034)
Capital	0.609	-0.130	1.302*	1.858
	(0.408)	(0.198)	(0.767)	(1.193)
Observations	5,728	5,728	5,728	5,728

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



### **Results**

**Table:** Productivity (Aggregate ATT) cont.

Panel B	(1)	(2)	(3)	(4)
Period: 2004-2013	Any subsidy	Demand subsidy	Production subsidy	Innovation subsidy
Revenue	1.926**	0.285	2.392**	3.058**
	(0.767)	(0.193)	(0.944)	(1.517)
Panel production capacity	2.098***	0.587	2.496***	2.930***
	(0.532)	(0.467)	(0.575)	(0.773)
Labor	1.382**	0.523	1.581*	1.773
	(0.677)	(0.442)	(0.848)	(1.188)
Capital	1.470**	0.310	1.784**	2.307
	(0.711)	(0.282)	(0.905)	(1.426)
Observations	3,580	3,580	3,580	3,580

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



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

	(1)	(2)	(3)	(4)	(5)
	All patents	Firm count	Revenue	Panel capacity	Export value
Any subsidy in an adjacent city	0.373***	0.099	0.485***	0.385	0.659
	(0.096)	(0.055)	(0.177)	(0.263)	(0.432)
Observations	5,049	5,049	4,768	3,210	3,861



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- 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.



## 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.



Table: Controlling for GDP per capita

	(1)	(2)	(3)	(4)
	Any subsidy	Demand subsidy	Production subsidy	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)
<ul> <li>Solar patents</li> </ul>	0.523***	0.247	0.802***	0.875***
	(0.191)	(0.230)	(0.204)	(0.339)
<ul> <li>Non-solar patents</li> </ul>	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	1.076**	0.170	1.882***	2.557***
	(0.458)	(0.205)	(0.727)	(1.102)





**Table:** Controlling for GDP per capita (cont.)

	(1)	(2)	(3)	(4)
	Any subsidy	Demand subsidy	Production subsidy	Innovation subsidy
Panel capacity	2.025***	0.531	2.415***	2.848***
	(0.466)	(0.428)	(0.470)	(0.705)
Export value	2.409***	0.577	3.210**	4.041**
	(0.886)	(1.009)	(1.292)	(1.992)
Export volume	2.066**	0.038	2.841**	3.726**
	(0.812)	(0.699)	(1.208)	(1.851)
Export price	0.925**	0.176	1.078**	1.354
	(0.407)	(0.483)	(0.534)	(0.896)
Solar export value	4.515***	1.367*	6.250***	8.967***
	(0.970)	(0.741)	(1.428)	(2.136)
Solar export volume	3.848***	0.905	5.120***	7.231***
	(0.864)	(0.688)	(1.251)	(1.803)
Solar export price	1.485***	0.134	2.001***	3.186***
	(0.422)	(0.379)	(0.665)	(0.833)

**Table:** Levels results (Patents)

	(1)	(2)	(3)	(4)
	Any subsidy	Demand subsidy	Production subsidy	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



Table: Levels results (Revenue)

	(1)	(2)	(3)	(4)
	Any subsidy	Demand subsidy	Production subsidy	Innovation subsidy
Revenue (million RMB)	273**	76.5	427**	576*
	(111)	(96.4)	(179)	(344)
Observations	5,728	5,728	5,728	5,728
Mean of Dep. var.	304	304	304	304

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

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Table: Levels results (Panel capacity)

	(1)	(2)	(3)	(4)
	Any subsidy	Demand subsidy	Production subsidy	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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**Table:** Levels results (Firm count)

	(1)	(2)	(3)	(4)
	Any subsidy	Demand subsidy	Production subsidy	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

**Table:** Levels results (Exports)

	(1)	(2)	(3)	(4)
	Any subsidy	Demand subsidy	Production subsidy	Innovation subsidy
Export value (million RMB)	51.4**	22.8	56.3*	85.9**
	(23.9)	(31.0)	(28.8)	(42.9)
Observations	4,654	4,654	4,654	4,654
Mean of Dep. var.	24.791	24.791	24.791	24.791

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

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#### Table: City-level total solar patents

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

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



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Table: LEARNING-BY-DOING PATENTS

	(1)	(2)	(3)	(4)
	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. 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.





#### **Placebo Non-solar Patents**

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

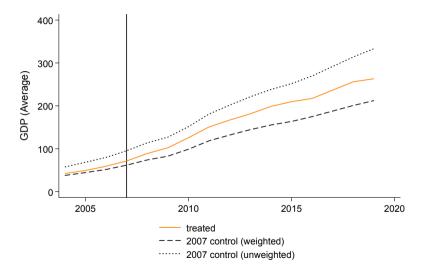
	(1)	(2)	(3)	(4)
	Any subsidy	Demand subsidy	Production subsidy	Innovation subsidy
Patent	-0.064	0.004	-0.118	-0.034
	(0.438)	(0.965)	(0.309)	(0.811)
Observations	6,086	6,086	6,086	6,086

**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





## **Characterising the control group**



# **Potential pretrend**

