# Economics of Renewables

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THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Programme on Innovation and Diffusion

- **Facts on renewables**
- Theory
- Empirics

# What are Renewables?

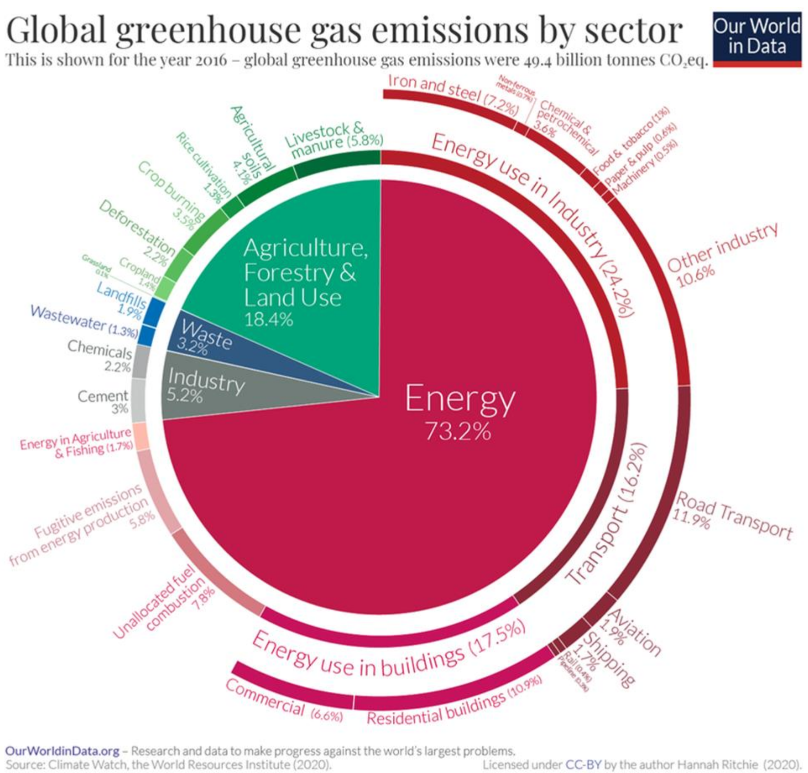
- Energy derived from natural sources that are replenished at a higher rate than they are consumed

- Examples:
  - Solar
  - Wind
  - Hydro
  - Geothermal
  - Ocean/tidal
  - Bioenergy

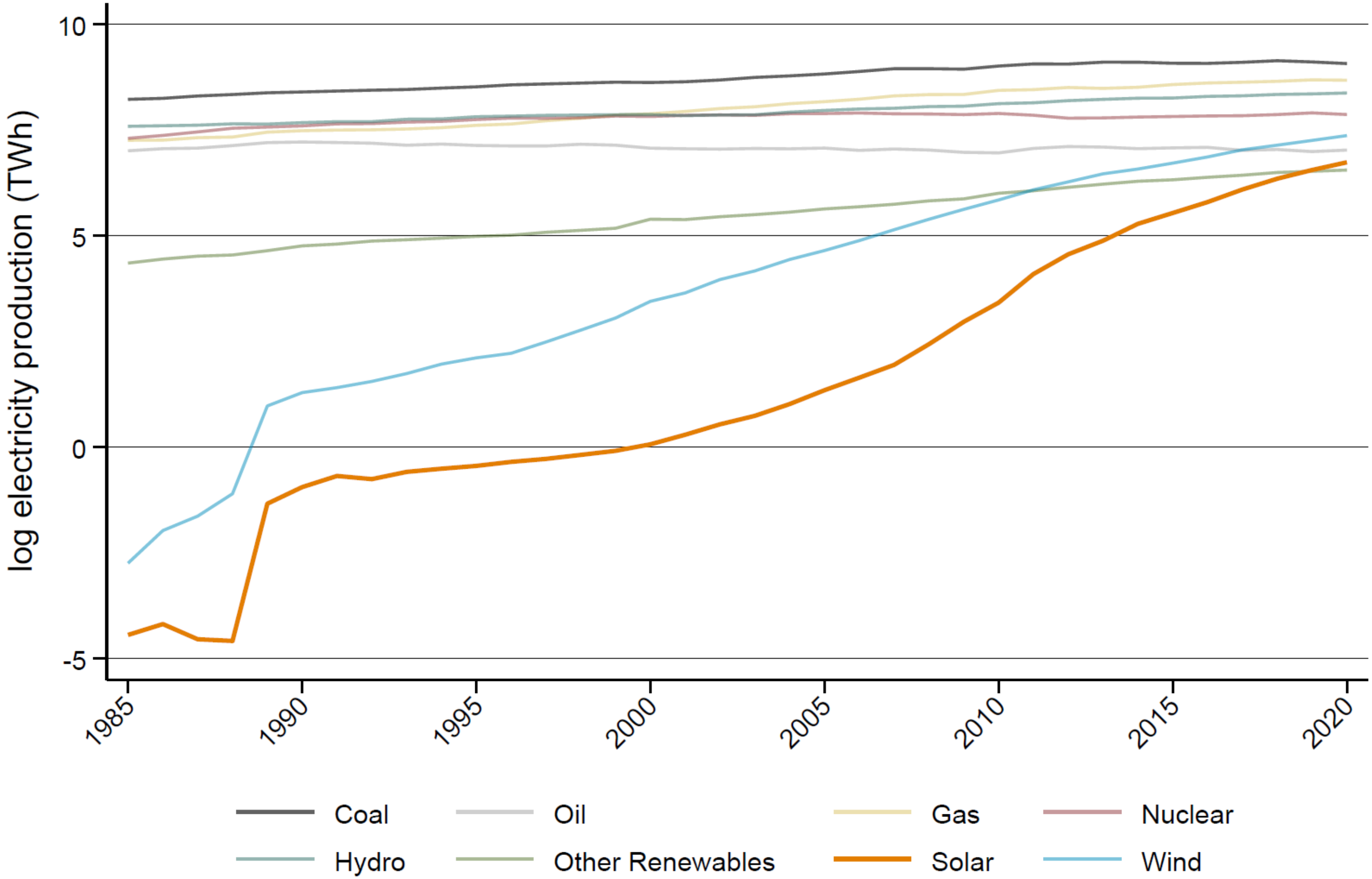

# The Challenge

- Around 73% of global greenhouse gas emissions are attributed to the energy sector

- De-carbonization plans for many sectors reliant on electrification and therefore clean energy

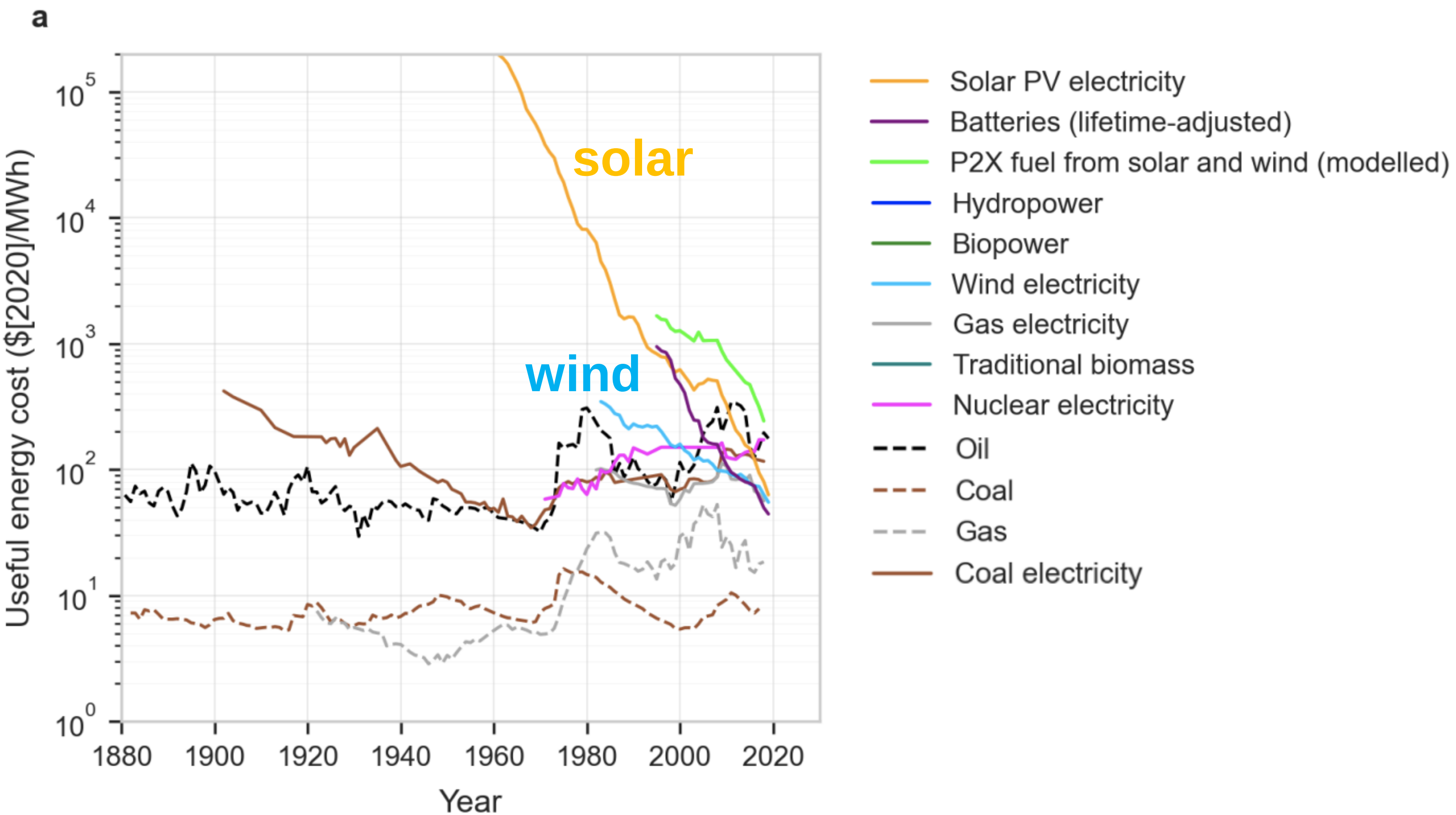


# Huge Growth in Renewables as share of electricity production, but fossil fuels still dominant



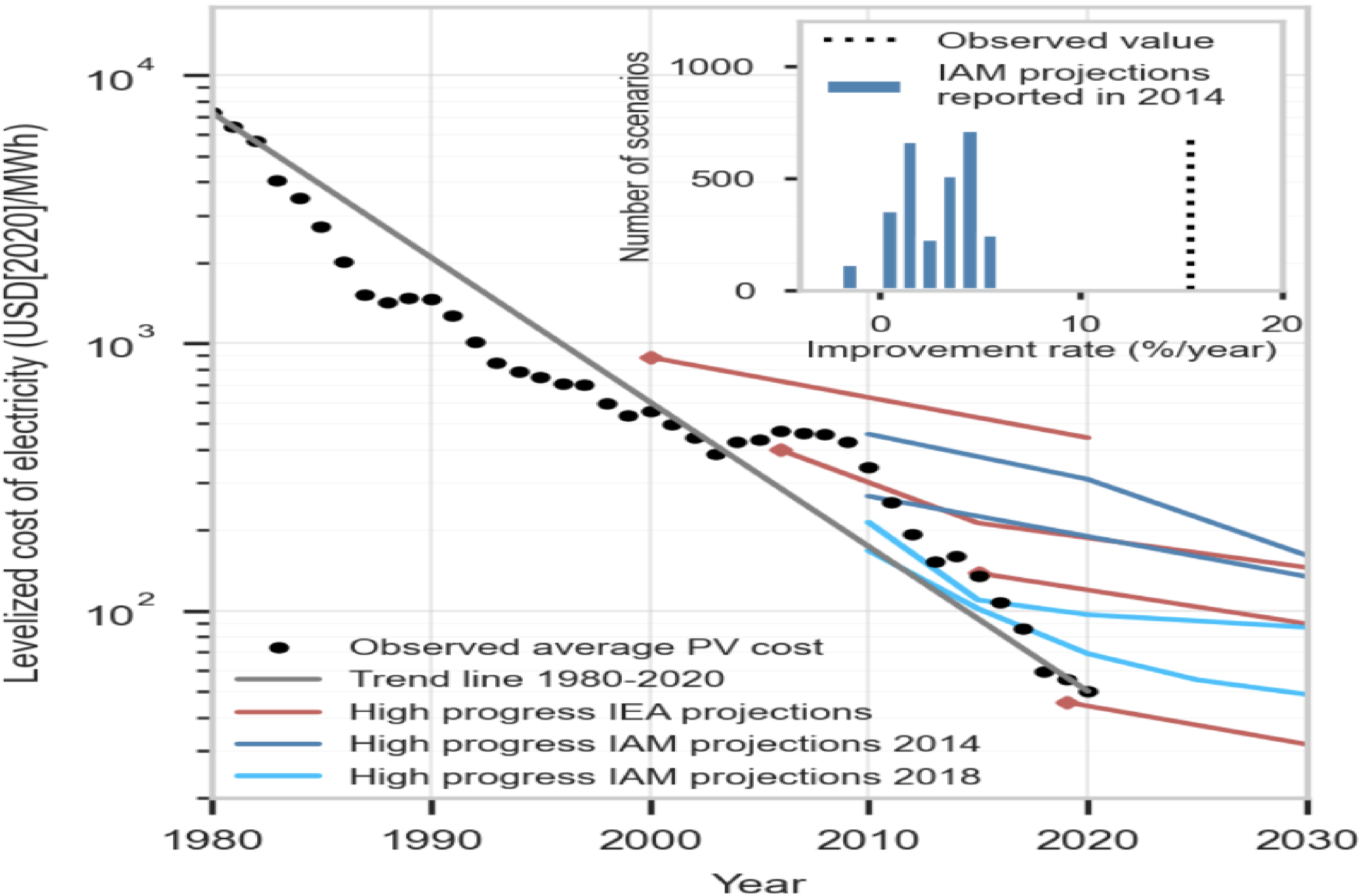

**Source:** International Energy Agency (IEA)

# Price of renewables has fallen much faster than other source of energy




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

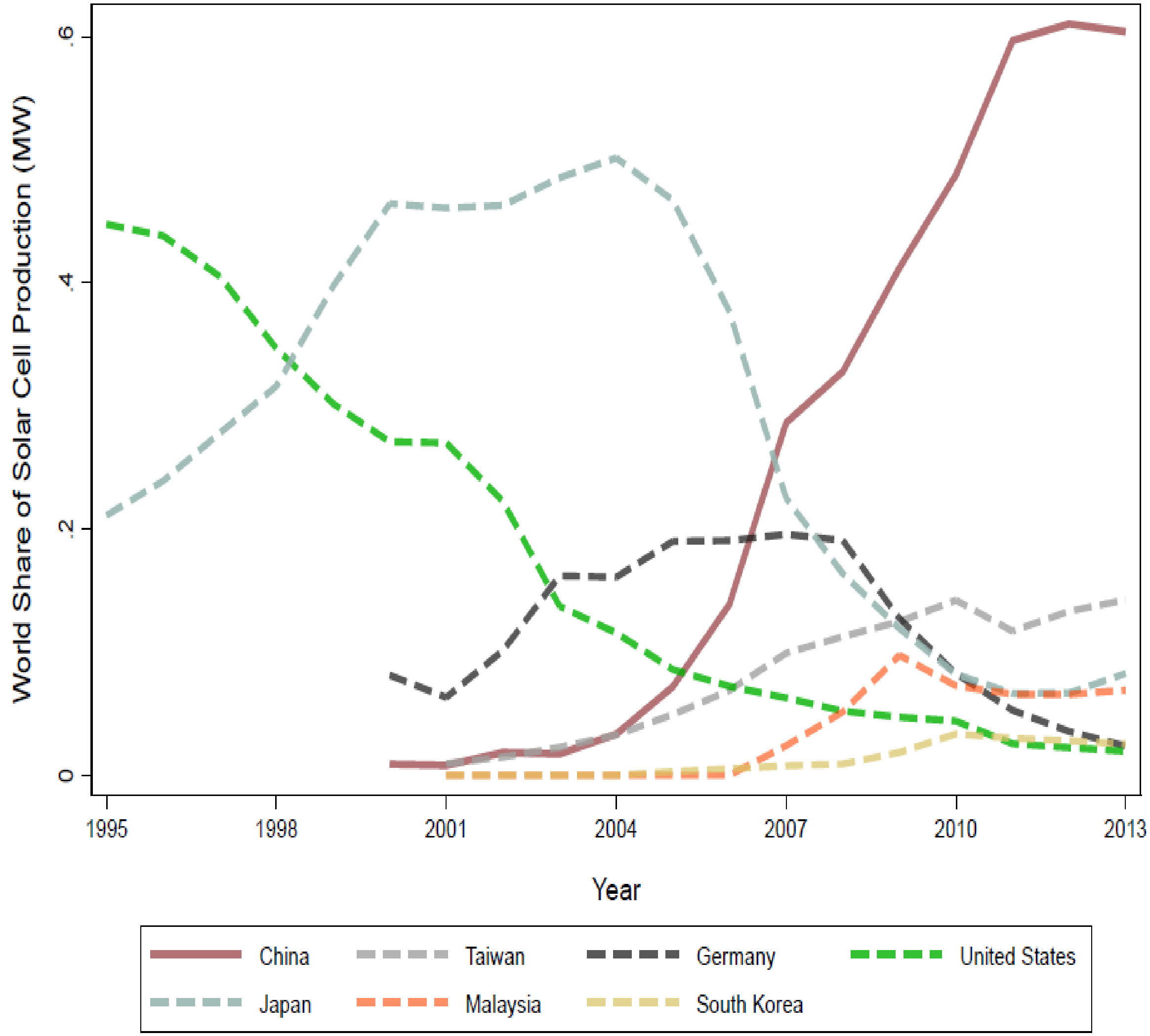
# Solar Price Falls much faster than predicted




**Source:** Way et al. (2021)

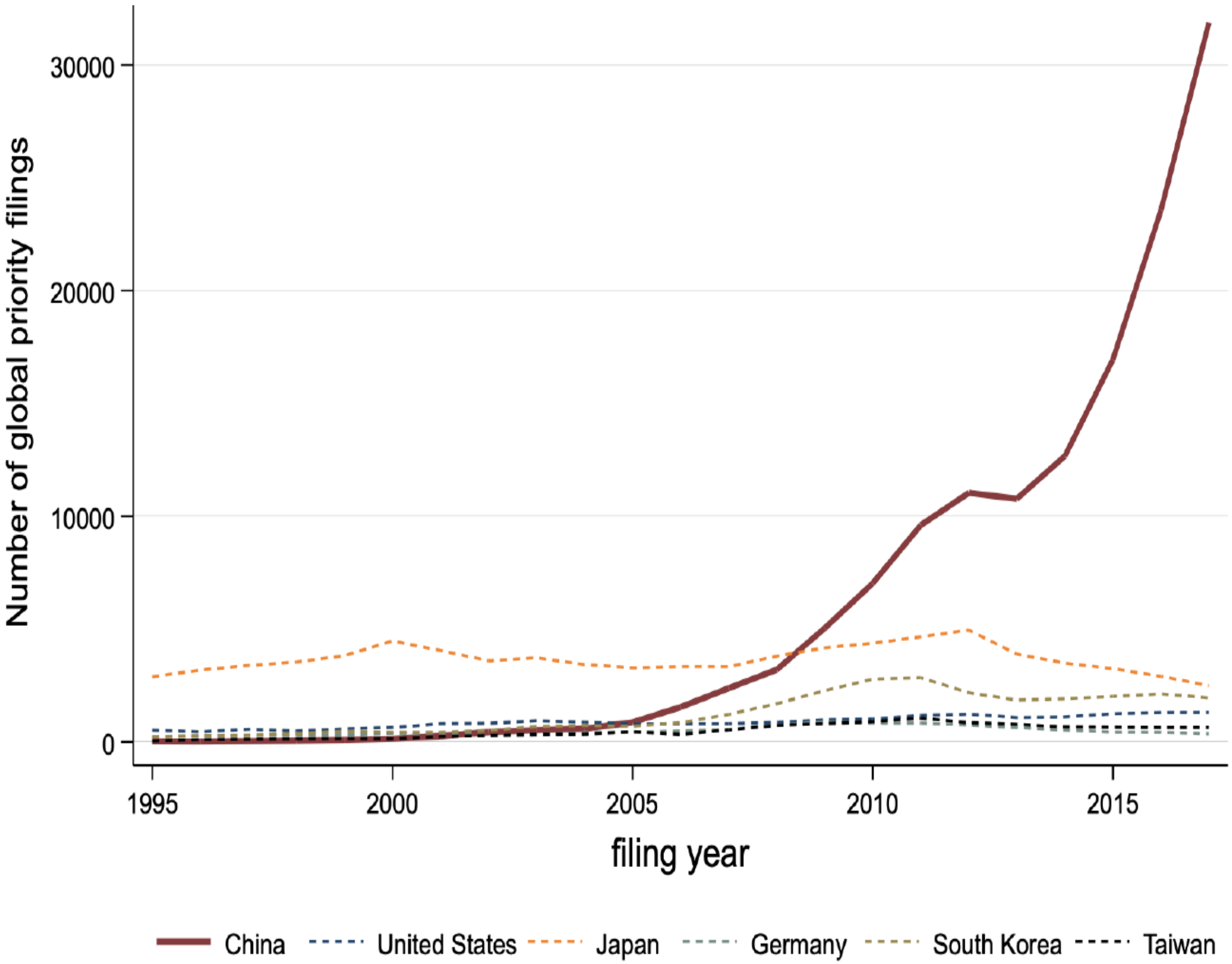
# China's global share of solar production rose from near zero to 60% i the decade to 2013

**Figure:** Share of Annual Solar Photovoltaics Cell Production in Leading Countries, 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 also innovating: Solar patenting by country




codes

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

- Facts on renewables
- **Theory**
- Empirics

# Renewable Adoption

- Key decision makers are electricity generators. For example, when building a new power plant, choose coal-fired (“dirty”) or solar (“clean”)?
- Also, household decision over whether to adopt clean technologies (e.g. install solar panels; use heat pump, etc.)

# Renewable Adoption

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- Many factors determine this, but a key one will be **cost of producing energy and price paid for energy produced**
  – Current *and* expected costs & prices as decision is a (partially irreversible) investment.
  – Uncertainty over future (especially over govt. policies) will therefore matter
    - Higher uncertainty means people "wait and see". This will tend to reduce investment, especially with risk-aversion (real options effect in S-s rules)

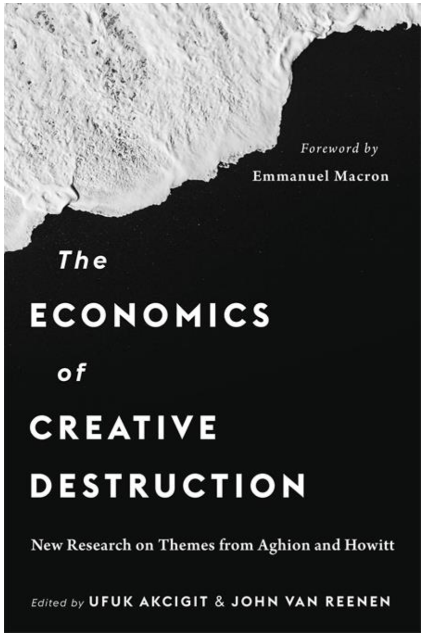
# Factors in adoption problem

- Cost of energy sources (including security of supply)
- Prices received
- Demand
- Policies
- Existing stock of power plants. Major issue is when to retire older plants (e.g. coal fired) as marginal cost is low as much of fixed cost is sunk.

# Innovation theory

- Old view saw technical change as exogenous. “Manna from Heaven” – Brilliant inventors and/or government labs

- Modern (endogenous) growth theory: innovation depends on firm decisions over how much to invest in R&D
  - This responds to incentives. How much profit does a firm expect to make from investing in R&D?



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- Productivity increases (& so cost decreases) through these innovations, but also depends on how these innovations diffuse
  – Often slow due to (e.g.) information, low skills, bad incentives, etc.
  – Focus on innovation for now

- Example model (see Dechezlepretre & Hemous, 2023)

# Directed Technical Change

- Aghion, Acemoglu, Bursztyn & Hemous, 2012; AABH), Focus on substitute case (elasticity of substitution: ε > 1)

- Final good (numeraire), ***Y***

$$Y_t = \left(Y_{ct}^{\frac{\varepsilon-1}{\varepsilon}} + Y_{dt}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$$

Clean input
(e.g. solar)

Dirty input
(e.g. coal)

# Directed Technical Change

- Greenhouse gas emissions a function of dirty, $P_t = \xi Y_{dt}$
  - Innovations reduce costs of producing either clean or dirty
  - Abstract from "grey" innovations that reduce emission intensity of dirty (see "extensions")
- Production of energy in each sector (clean & dirty), $j \epsilon \{c, d\}$

$$Y_j = \frac{1}{1-\beta} L_j{}^{\beta} \int_0^1 A_{ji}{}^{\beta} \, x_{ji}{}^{1-\beta} di$$

labor

Level of **productivity** for machine $i \epsilon [0,1]$ employed in sector *j*

**Machine** $i$ employed in sector *j* (production costs 1-β of final good)

# Innovation

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- Innovation prob. in sector *j* is $\eta_j$ increases machine quality by $1+\gamma$ ("step size")
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- Technology leader charges monopoly price & patents last one period. Aggregate technology in sector *j* is $A_j = \int_j A_{ji} \quad di$
- Law of motion for input $j \epsilon \{c, d\}$ is $A_{jt} = (1+\gamma\eta_j S_{jt}) \quad A_{jt-1}$, $S_{jt}$ = mass of scientists in sector *j* & $\eta_j$ their productivity

- **Key externality.** Innovators build on shoulders of giants, but do not internalize this spillover (so too little R&D investment)

# Producers (skip details)

**Profits** $\pi_{ji} = p_{ji}x_{ji} - (1-\beta)x_{ji}$

**Markup** $1/(1-\beta)$

**Output** $x_{ji} = p_j^{1/\beta} L_j A_{ji}$

**Equilibrium intermediate input** $Y_j = \frac{1}{1-\beta} p_j^{(1-\beta)/\beta} L_j A_j$

**Expected technology obtained by innovator in sector *j*** $(1+\gamma)A_{jt-1}$

**Expected profits of scientists working for sector j**

$$\Pi_{jt} = \eta_j(1+\gamma)\beta\left(p_{jt}\right)^{\frac{1}{\beta}} L_{jt}A_{jt-1} = \frac{\eta_j\gamma\beta p_{jt}Y_{jt}}{1+\gamma\eta_j s_{jt}}$$

# Ratio of expected profits of R&D in clean vs. dirty

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \underbrace{\frac{\eta_{ct}}{\eta_{dt}}}\ \underbrace{\left(\frac{p_{ct}}{p_{dt}}\right)^{\frac{1}{\beta}}}_{\text{Price effect}}\ \underbrace{\frac{L_{ct}}{L_{dt}}}_{\text{Market size effect}}\ \underbrace{\frac{A_{ct-1}}{A_{dt-1}}}_{\text{Direct productivity effect}}$$

Innovation is targeted on sector where revenue is greatest (Kennedy, 1964)

# Implications

- Assume that dirty technologies are initially the most advanced sector, i.e. $\frac{A_{ct-1}}{A_{dt-1}} < 1$

- **Key Lessons**
  1. ***Path dependence***: Innovation is directed at most advanced sector in *laissez-faire*: societies with lots of part dirty innovation will have more of it in future

  2. ***Front-loading.*** Social planner can avoid this with clean subsidies and/or carbon tax. Heavier action earlier until clean more advanced, then policy can be relaxed

  3. Carbon tax generally insufficient for first best: need to combine with ***research subsidy***

# Extensions/Applications

- **Acemoglu, Akcigit, Hanley & Kerr (2016)**
  - More realistic firm level dynamics with multi-product firms (a la Klette Kortum, 2004)
  - Calibration to US economy suggests switch to clean innovation occurs too late, so need clean research subsidy

# Acemoglu, Aghion, Barrage & Hemous (2021) on Shale gas revolution

- Electricity produced as a CES of clean, gas & coal (with $\varepsilon > 1$);
- Gas cleaner than coal, but dirtier than clean
- In short-run fall in price of shale reduced emissions as coal less used.
- But in long-run market for fossil fuel (gas+coal) expands at expense of clean. So, clean innovation falls
- Find evidence in support than ratio of green to fossil fuel patents declined substantially after 2011 (2 year after beginning of Shale boom in 2009)
- <u>Policy implication: </u>need for clean R&D subsidies

# Alternatives

- **Complementarity case:** energy saving innovation
  - Hassler, Krussell and Olovsson (2021)
  - Elasticity of substitution of energy & capital-labor aggregate closer to zero ($\varepsilon<1$)
  - BGP with complementarity between energy and other inputs. This means price effect dominates
  - Hence, economy favors clean innovation and no need for clean research subsidies (carbon tax does all the "heavy lifting" for transition)

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# Some conclusions from theory

1. Directed Technical Change provides policy answers that differs from models with exogenous technology

2. Environmental policy should be frontloaded to kickstart the green innovation machine

3. Carbon taxes important tool, but not the only one: need to be combined with R&D subsidies

4. Bridge technologies (e.g. shale gas) may actually backfire if not accompanied by efforts to have carbon free technologies

- Facts on renewables
- Theory
- $\boxed{\textbf{Empirics}}$

# Literature reviews

- Grubb et al (2021)
- Popp (2019)
- Popp et al. (2010)
- A key focus has been on impact of energy price changes (proxy for a carbon tax) on innovation

# Energy prices and directed technical change

- **Newell et al (1999)**
  - Energy efficiency of home appliances 1958-93. Technical change in air conditioners biased against energy efficiency in ‘60s (energy prices low, reversed in ‘70s after oil price ↑
- **Popp (2002)**
  - Time series on patent applications in US 1970-1994 across 11 energy technologies (e.g. solar panels, fuel cells, heat pumps or waste heat recovery)
  - Regresses these on energy prices. Long-run elasticity of 0.35 (1/2 of effect in first 5 years). SR impact 0.03-0.06

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- **Crabb & Johnson** (2010) US cars 1980-99 using Popp method (find LR elasticity of 0.3); **Verdolini & Galetotti** (2011) 17 countries 1979-98; **Kruse & Wetzel** (2016) 26 countries 1978-09; **Constantini et al.** (2017) 23 countries 1990-10: residential energy tax induces patents in energy efficient tech in buildings

# Energy prices and directed technical change

- **Issue:** All of above use macro data on prices and tax, so cannot include time dummies

# Energy prices and directed technical change

- **Issue:** All of above use macro data on prices and tax, so cannot include time dummies
- **Aghion, Dechezlepretre, Hemous, Martin & Van Reenen (2016, JPE):**
  - Car industry across world using **firm level data**
  - Tax-adjusted fuel prices across countries weighted by firm's exposure to country (depends on expected market share in that country).
  - Elasticity of fuel price
    - wrt clean innovation = 1
    - wrt grey innovation = 0.3
    - wrt dirty innovation = -0.5
  - Find evidence for path dependence
  - Simulations show that path dependence exacerbates gap between clean and dirty knowledge

# Energy prices and directed technical change

- Similar to Aghion et al (2016):
  - **Noailly & Smeets** (2015) show dirty innovation in electricity production sector responds to fuel price as well as market size

# Do renewable <u>policies</u> encourage renewable innovation?

- **Calel & Dechezlepretre (2016)** (**ETS** cap and trade)
  - European Emissions Trading System after 2005 created carbon price for electricity generation & heavy industry
  - Use plant-level regulatory thresholds (ETS only applies to large facilities over a production threshold)
  - ETS increased low carbon patenting by 30%
- **Pollution Abatement Control Expenditures (PACE)** positively correlated with innovation (R&D or green patents)
  - Lanjouw & Mody (1996), Jaffe & Palmer (1997), Brunnermeier & Cohen (2003)
- **Renewable energy policies**
  - Johnstone et al (2010) patents & renewable energy policy; Nicolli & Vona (2016): Feed-in tariffs increased solar PV patents); Dechezlepretre & Glachant (2014) wind power innovation responds to home policies

# Do policies to encourage renewable innovation work?

- Much less <u>direct</u> evidence on renewable innovation policy than indirect evidence on energy prices (and regulation)

- Larger literature on the impact of innovation policies more generally (Bloom, Van Reenen and Williams, 2019, survey)
  - Lots of evidence that R&D tax incentives in general work
  - Smaller, but growing literature on whether direct grants effective (example of Howell, 2017, AER)

# Howell (2017, AER)

- US Department of Energy green Small Business Innovation Research (SBIR) awards
- Admin data on applications, scores and future outcomes
- Implement a sharp Regression Discontinuity Design (RDD)
- Results: “Phase I” award doubles chances of future cite-weighted patents (as well as VC and revenue)
  - Stronger effects for financially constrained firms

# Positive effect on innovation (future citation-weighted patents)

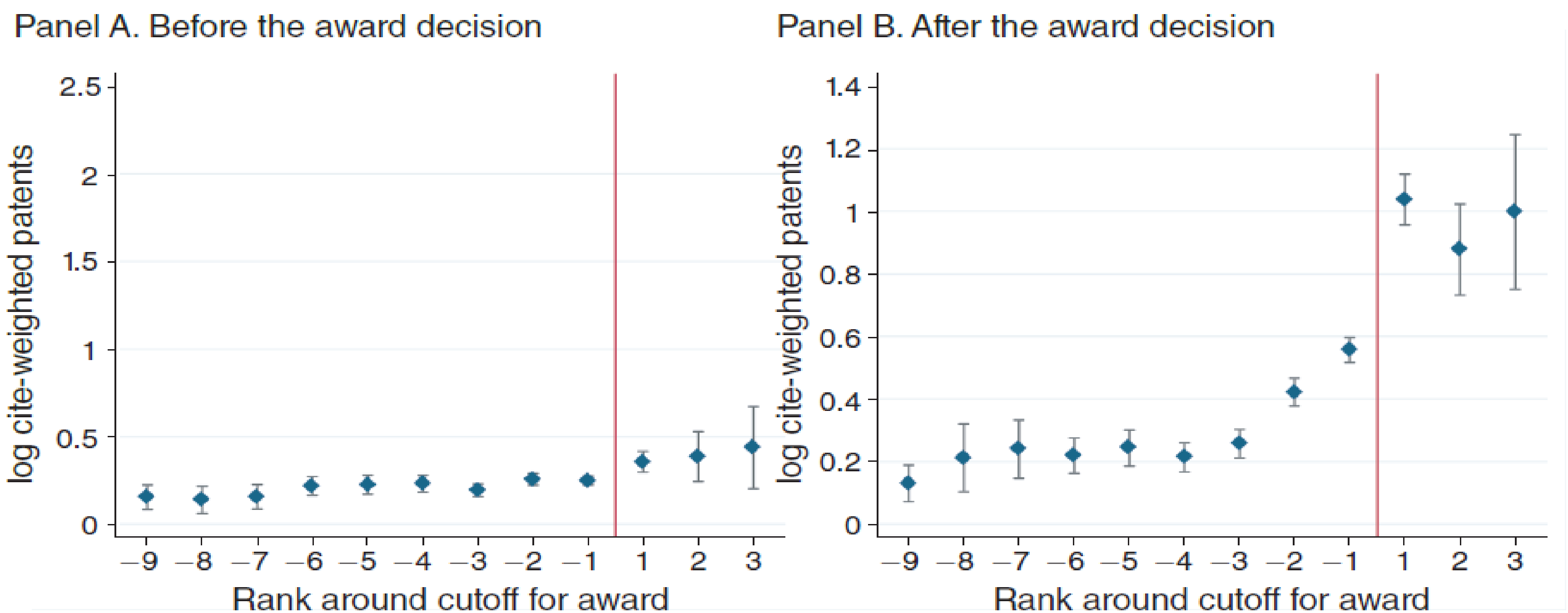



FIGURE 2. CITE-WEIGHTED PATENTS BEFORE AND AFTER PHASE 1 GRANT BY RANK

*Notes:* This figure shows $\ln(1 + Cites_i^{post})$ before and after the Phase 1 grant award decision, using the patent application date. DOE's rank is centered so $rank_{ic} > 0$ indicates a firm won an award. Ninety-five percent confidence intervals shown.

**Source:** Howell (2017)

## Banares-Sanchez, Burgess et al. (2023) “Ray of Hope”

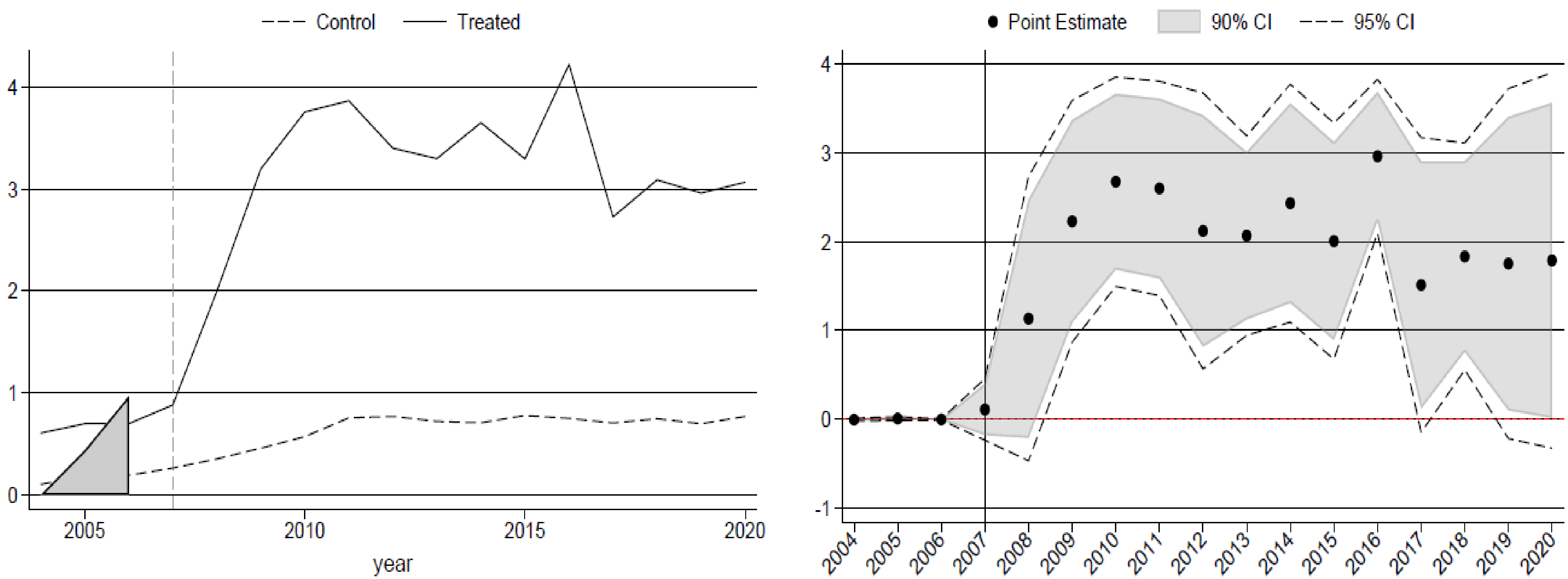
- Look at impact of Chinese industrial policy towards solar industry

- City-regions implement different subsidy policies at different times 2004-19. Examine impact on solar production and **innovation** using Synthetic-Diff-In-Diffs approach

- Supply side policies (production and R&D subsidies) have large effects on output, productivity and **cite-weighted patents**

- Mechanism could be through learning by doing and cross-firm spillovers

# 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.

2013 raw

# Some conclusions from empirical literature

- Evidence that renewable innovation can be induced (directed technical change) from:
  - Tax adjusted energy prices
  - Indirectly via renewable policies
  - Directly via renewable R&D subsidies
- Progress on identification
- Patenting data has strengths but also weaknesses (many innovations are not patented; very heterogeneous valuations, etc.)
  - Would be good to see more direct measures of energy cost reduction (e.g. Gerarden, 2022 on solar)
  - Spillovers (some evidence that these might be larger for clean – see Dechezlepretre, Martin & Mohnen, 2017)
  - Radical vs. incremental (e.g. LBD) innovation

# Adoption of Renewables

- Residential Solar
  - Bollinger & Gillingham (2021)
  - Gerarden (2022)
  - Gillingham & Tsvetanov (2019)
  - de Groote & Verboven (2019)
  - Nemet (2019)

# General Conclusions

- Rapid technological change in renewables which are now competitive on price with many fossil fuels
- Important role of China (e.g. solar)
- Understanding renewable innovation an important application of Directed Technical Change
  - Theoretical models suggest that key factors are price effects & market size effects
  - If clean & dirty substitutable need intensive early intervention due to path-dependency.
  - Carbon taxes unlikely to be enough by themselves
- Empirical work gives optimism, but not enough on direct policy evidence

- **<u>Lots of room for contributions!</u>**

# SOME KEY READINGS

Acemoglu, Daron (2023) "Distorted Innovation" AER Distinguished Lecture https://economics.mit.edu/sites/default/files/2023-01/Distorted%20Innovation%20-%20Does%20the%20Market%20Get%20the%20Direction%20of%20Technology%20Right.pdf

(*) Acemoglu, D., Aghion, P., Bursztyn, L., and Hemous, D. (2012) "The Environment and Directed Technical Change" *American Economic Review*, 102 (1):131–166.

Acemoglu, Daron, Ufuk Akcigit, Douglas Hanley and William Kerr (2016) "Transition to Clean Technology," *Journal of Political Economy*, 124(1): 52-104.

Aghion, Philippe, Antoine Dechezleprêtre, David Hemous, Ralf Martin and John Van Reenen (2016) "Carbon Taxes, Path Dependency and Directed Technical Change: Evidence from the Auto Industry" *Journal of Political Economy*, 124(1) 1-51

Bloom, Nicholas, John Van Reenen and Heidi Williams (2019), "A Toolkit of Policies to promote Innovation" *Journal of Economic Perspectives* 33(3) 163–184

Banares-Sanchez, Burgess Robin et al, (2023) "Ray of Hope" LSE mimeo

**(*) Dechezlepretre, Antoine and David Hemous (2023) "Directed Technical Change and Environmental Economics" in Akcigit, Ufuk and John Van Reenen (2023) *The Economics of Creative Destruction*,**

De Groote, Olivier and Frank Verboven (2019) "Subsidies and Time Discounting in New Technology Adoption" *American Economic Review*, 109, 6, 2137-2172

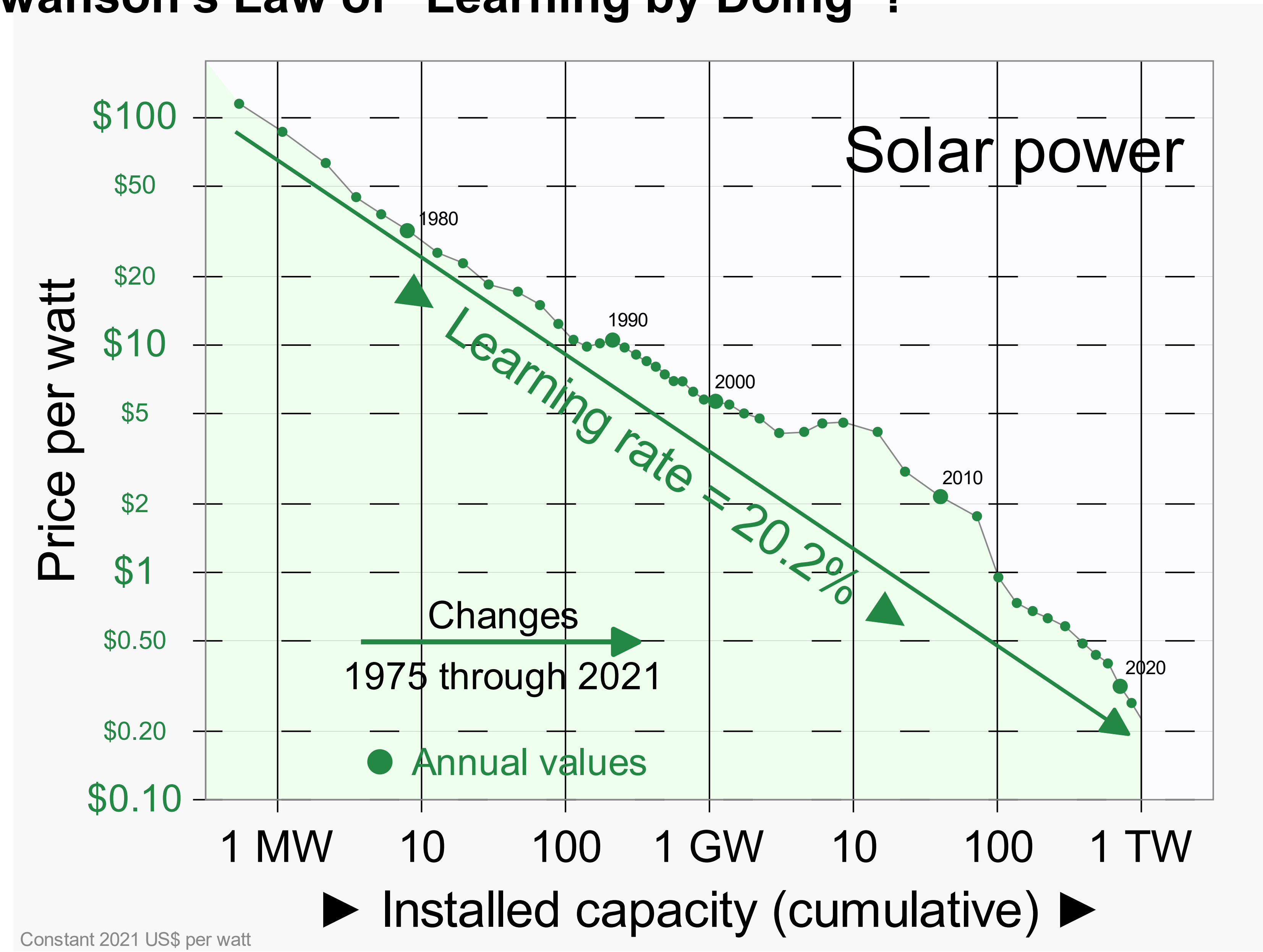
Jones, Ben and Austan Goolsbee (2022) *Innovation and Public Policy* Chicago: University of Chicago Press https://press.uchicago.edu/ucp/books/book/chicago/I/bo138500594.html

Popp D. (2002). "Induced Innovation and Energy Prices" *The American Economic Review*, 92(1):160–180.

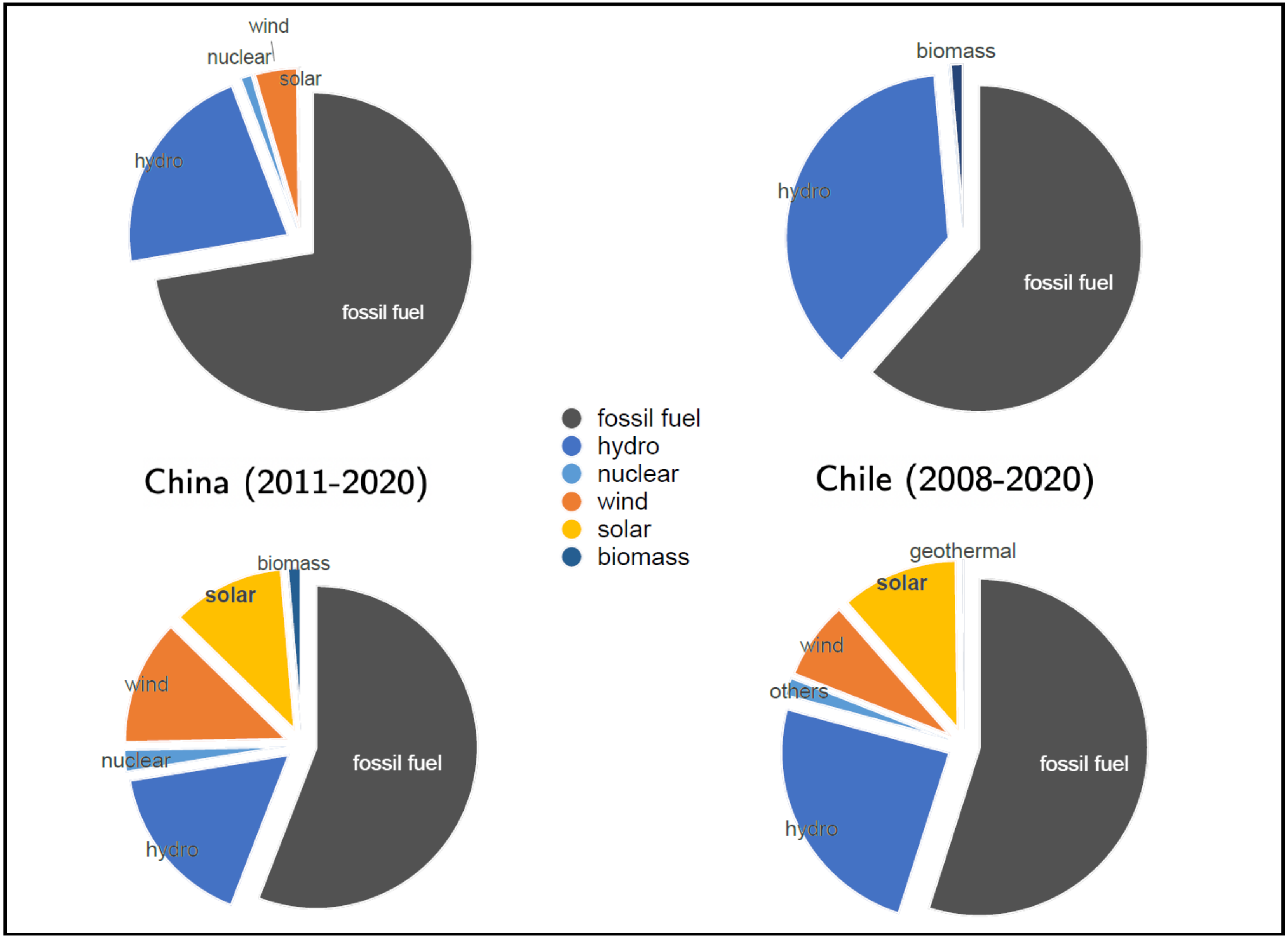
Popp, D. (2019) "Environmental policy and innovation: a decade of research" CESifo *Working Paper No. 7544* *https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3352908*

Way, Rupert, Matthew Ives, Penny Mealy and J. Doyne Farmer (2021) "Empirically grounded technology forecasts and the energy transition" INET Oxford Working Paper No. 2021-01

# Price has fallen as cumulative solar capacity has risen: Swanson's Law of "Learning by Doing"?

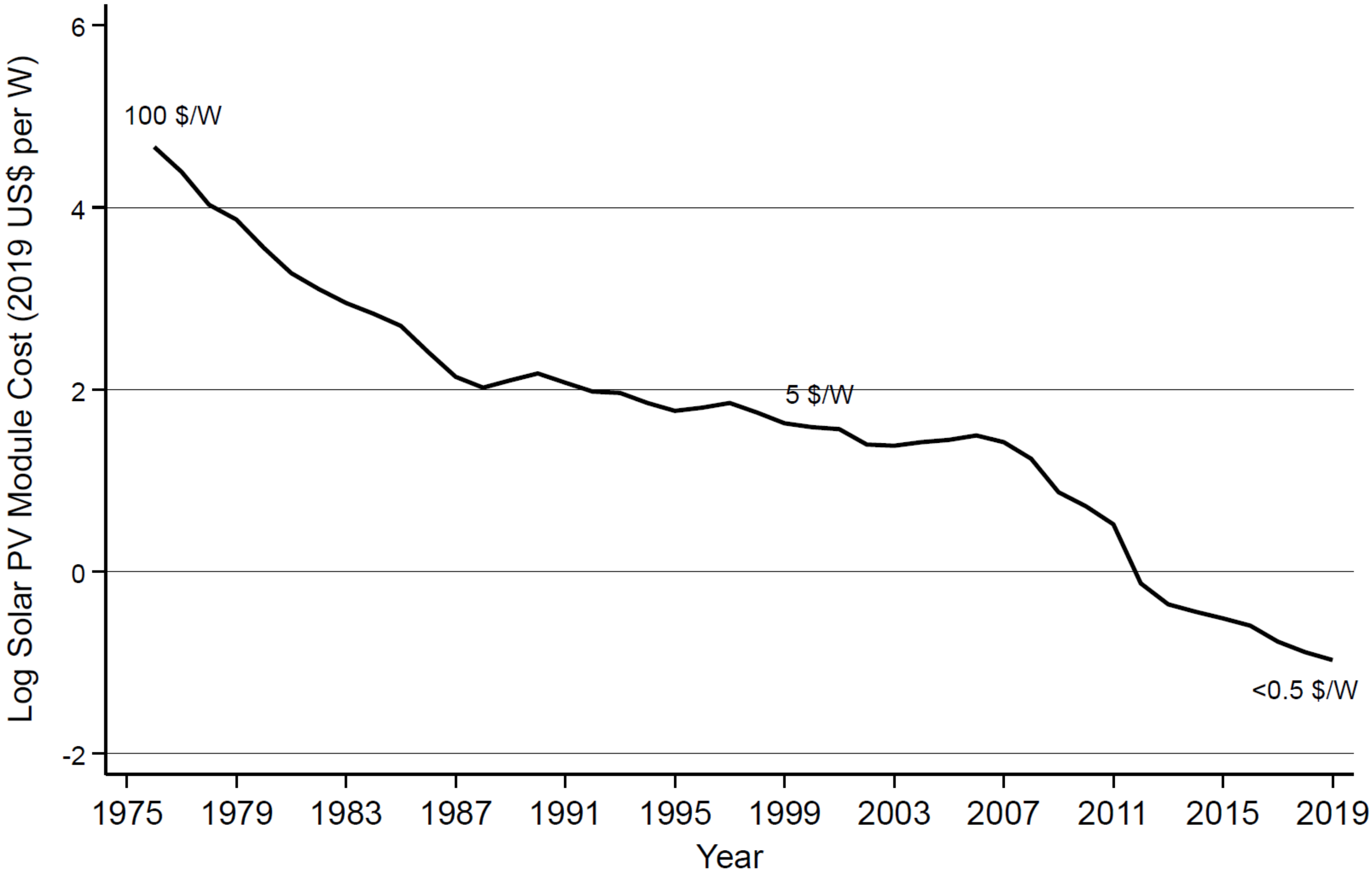


# ….stronger growth in some countries like China and Chile




**Source: State Grid New Energy Cloud & CNE**

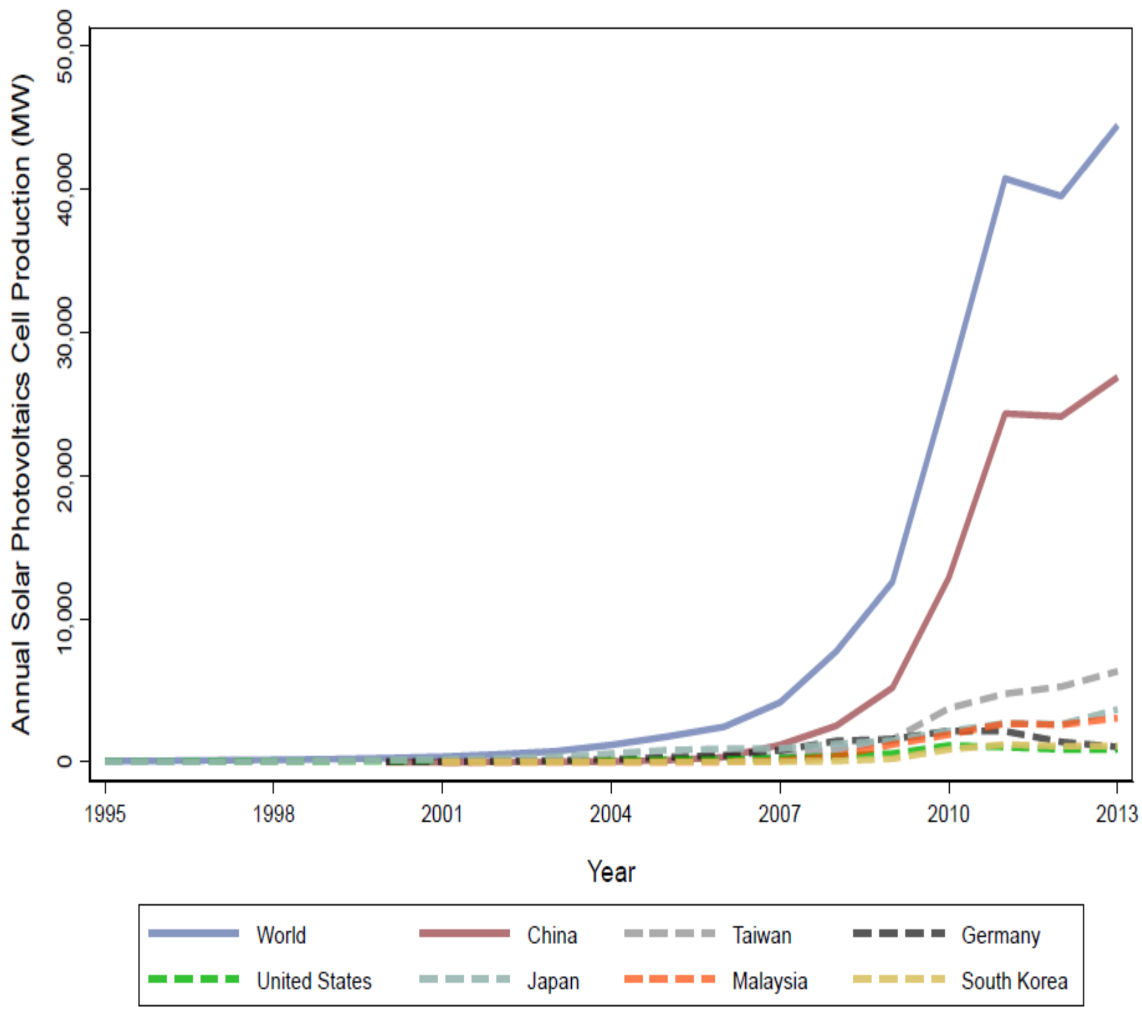
# Cost of solar has fallen dramatically




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

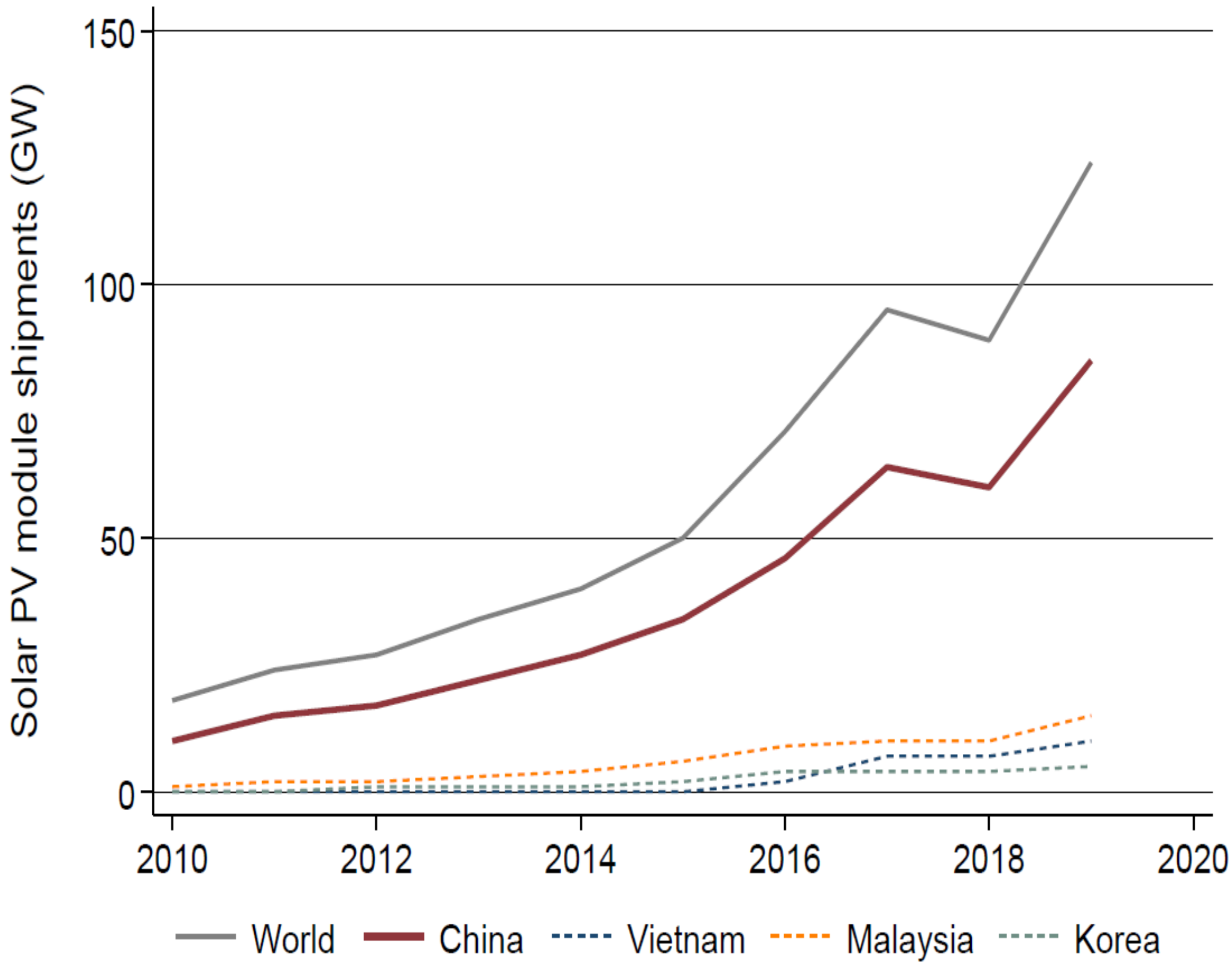
# And this was in context of huge growth in solar production

**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.

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




**Source:** International Energy Agency (IEA)

# Ratio of expected profits of R&D in clean vs. dirty innovation

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c}{\eta_d} \left(\frac{1+\gamma\eta_c S_{ct}}{1+\gamma\eta_d S_{dt}}\right)^{\sigma-2} \underbrace{\left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{\sigma-1}}_{\text{Creates path-dependency as } \sigma>1 \text{ (sub.)}}$$

$\sigma=1+\beta(\varepsilon-1)>1$ as $\varepsilon>1$

# Hassler, Krussell and Olovsson (2021, HKO)

- AABH focus on decarbonization of energy production.
- Alternative way to reduce emissions via energy-saving innovations (elasticity of substitution: ε > 1)
- $Y_{Pt}$ is a production input, $Y_{Et}$ energy-services input

$$Y_t = \left(Y_{Pt}^{\frac{\varepsilon-1}{\varepsilon}} + Y_{Et}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$$

production input

Dirty input (e.g. coal)

- $Y_{Pt}$ produced with sector specific machines & a capital-labor aggregate, *L*
- $Y_{Et}$ energy-services input produced with energy

# Other approaches/applications

- **Stern, Pezzey and Lu (2020)**
  - Transition from wood to coal in Industrial Revolution
  - Falls in coal price encourage growth of market and innovation in coal
- **Gars and Olovsson (2019)**
  - Great Divergence in C19
  - As more countries use coal, price rises and this discourages fossil fuel innovation
- **Fried (2018)**
  - 1970s oil shocks
  - Calibrates DTC model with energy CES of local fossil fuel, oil imports & green with $\sigma>1$
  - Carbon tax necessary to cut emissions is 19% smaller in DTC world.

# Alternatives

- **Complementarity case:** energy saving innovation
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  - Elasticity of substitution of energy & capital-labor aggregate closer to zero ($\varepsilon<1$)
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- Incorporating 'grey innovation'
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# Regulation and Renewable Innovation

- Porter hypothesis: regulation stimulates innovation

- **Pollution Abatement Control Expenditures (PACE)** positively correlated with innovation (R&D or green patents)
  - Lanjouw & Mody (1996), Jaffe & Palmer (1997), Brunnermeier & Cohen (2003)

- **Renewable energy policies**
  - Johnstone et al (2010) on EPO patents & public policy on renewable energy
  - Nicolli and Vona (2016): 19 EU countries 1980-2007. Feed-in tariffs increased solar PV patenting
  - Dechezlepretre and Glachant (2014) wind power innovation responds more to home policies than foreign policies

# Innovation Policies: R&D Grants

- In contrast to horizontal policies such as tax, R&D grants can be more targeted (e.g. specific technologies)
- **Upsides:**
  - Target to where social benefits are highest – e.g., big spillovers; climate change to tackle “double externality”, etc.
  - With R&D tax credits firms focus on **private** value projects
- **Downsides:**
  - Informational asymmetry over what projects are valuable
  - Administrative costs of deciding what & who to fund
  - Political economy risks: capture (Akcigit et al. 2022); difficulty to stop failing projects; big firms game system (Criscuolo et al., 2019)

# Identification Challenges with R&D grants

- Unlike tax rules, grants are only awarded to specific “winners”, so more variation in who receives
- **But** highly selected - grants are consciously awarded to where agency thinks/claims they will do the most use. Estimating effects on later innov:
  - Bias **upwards** if successful firms more likely to get funds
  - Bias **downwards** if money goes to compensate “losers”
- Comparing all winners vs. all losers unlikely to get around endogeneity biases. **Solution?:**
- Looking at “just winners” vs. “just losers” in a Regression Discontinuity Design type approach (e.g. Bronzini and Iachini, 2014, 2016 on Italian R&D program; Changes in funding rules generates nonlinearities, Einiö, 2014)
  - Howell (2017) on green energy …..

# Econometric model

- Regression Discontinuity Design (RDD) based on normalized rank of proposal *i* for competition topic *T* ($Rank_{iT} = 0$ for threshold)

Competition fixed effects

Treatment effect

Running variable

$$
\begin{aligned}
Y_{iT} = \alpha_T + \beta\,[1|Rank_{iT} > 0] + \gamma_1[Rank_{iT}|Rank_{iT} > 0] \\
+ \gamma_2[Rank_{iT}|Rank_{iT} < 0] + \varepsilon_{iT}
\end{aligned}
$$

# Positive effect on VC funding

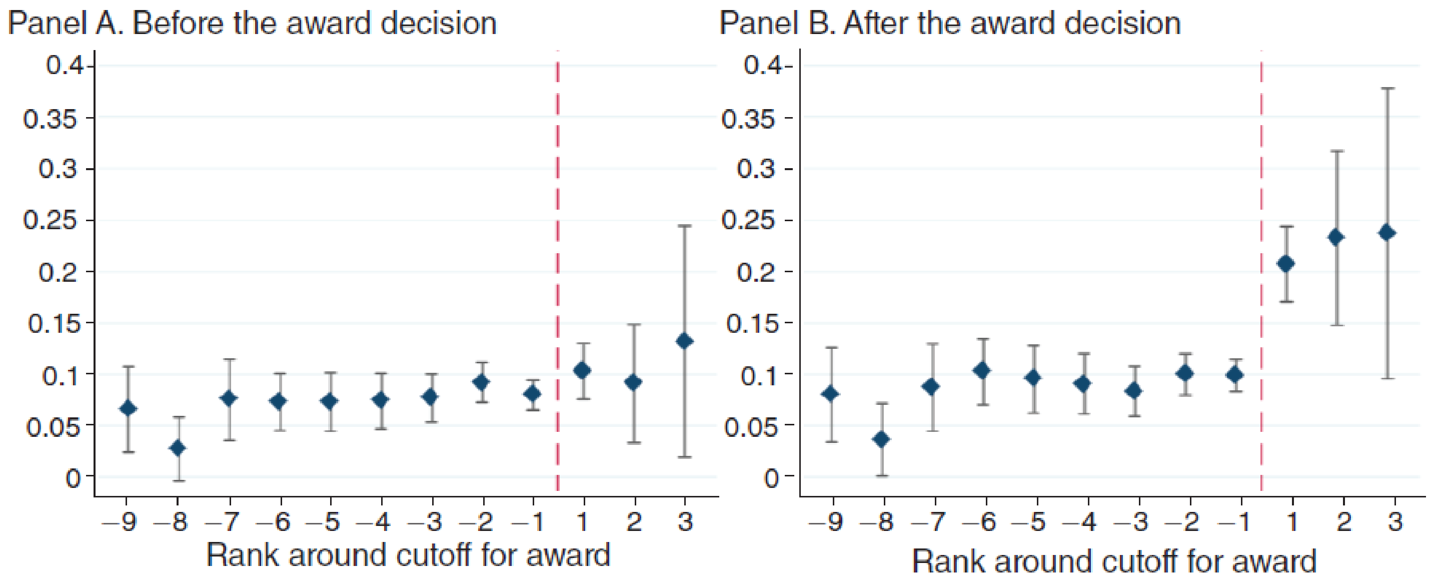



FIGURE 3. PROBABILITY OF VENTURE CAPITAL BEFORE AND AFTER GRANT BY RANK

*Notes:* This figure shows the fraction of applicants who received VC before and after the Phase 1 grant. Ninety-five percent confidence intervals shown.

**Source:** Howell (2017)

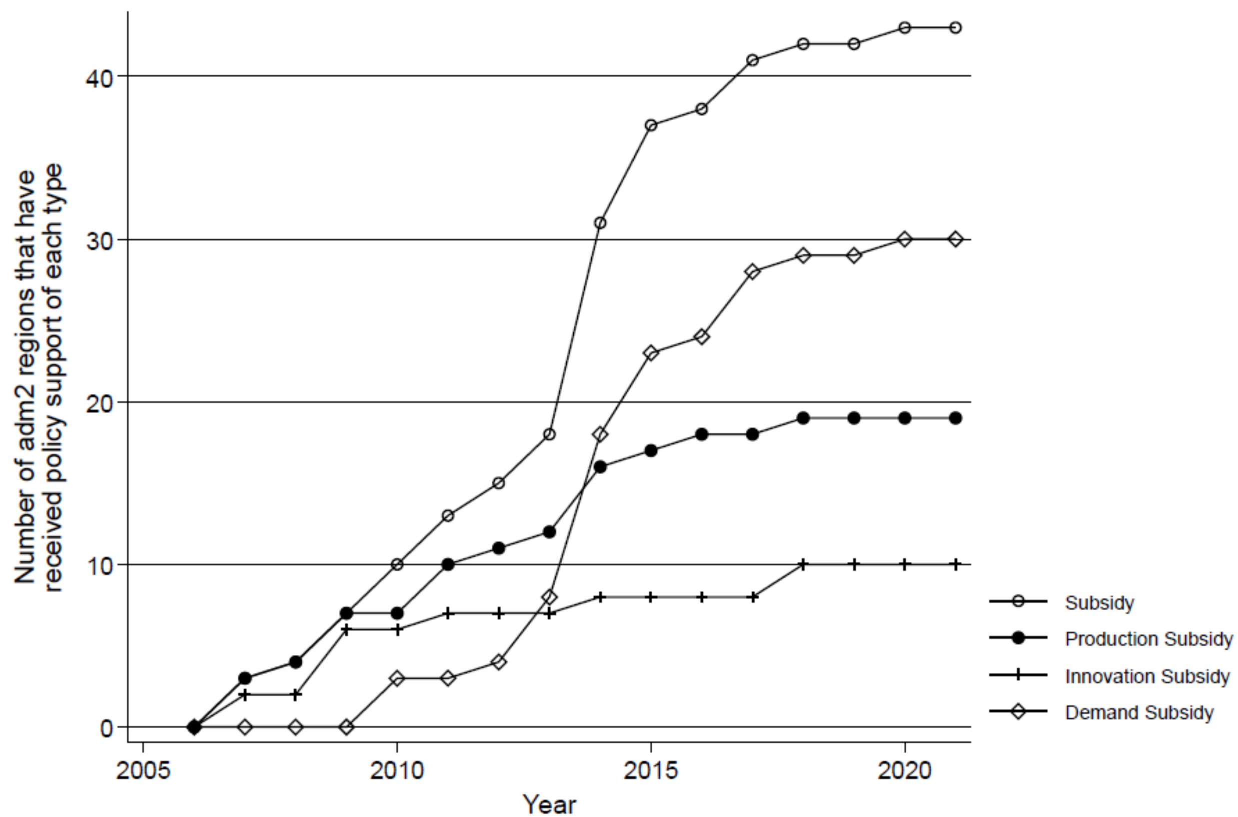
**Figure:** Predictions to the data

| | *Demand Subsidy* $\theta_o$ | *Production Subsidy* $s_o$ | *Innovation Subsidy* $\phi_o$ | *Production & Innovation Subsidy* $s_o + \phi_o$ |
|---|---|---|---|---|
| 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: $+++ > ++ > +$.

# Time series of policy support

**Figure:** Number of cities treated with supply & demand subsidies



## 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 a city-year pair (av. = 13.1). SE cluster bootstrapped by city.

Levels