Bringing Rigour to Energy Innovation Policy Evaluation

Jacquelyn Pless

MIT Sloan School of Management

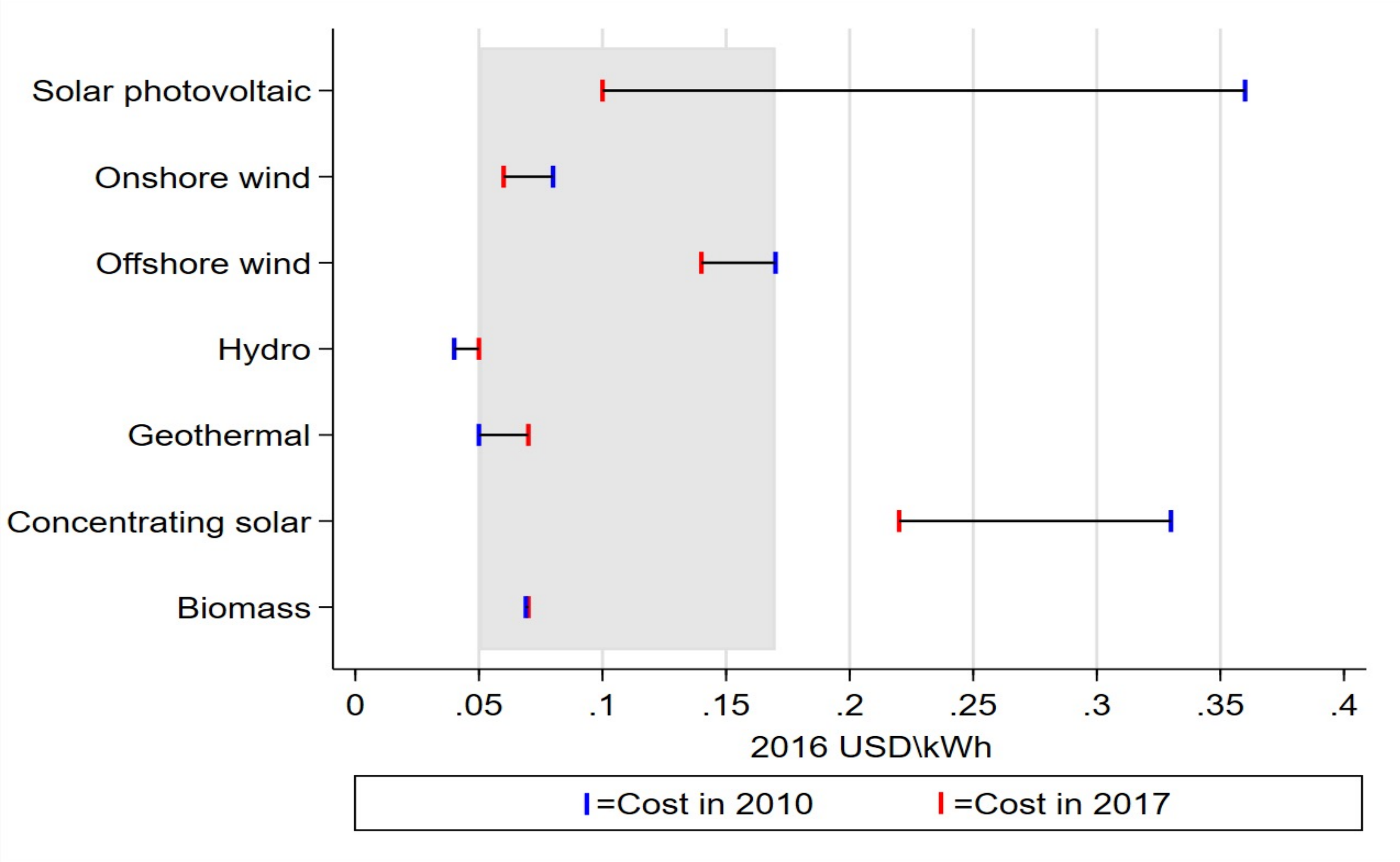
October 29, 2021

Greta Thunberg, 16-year-old climate activis
US on a zero-emissions sailboat

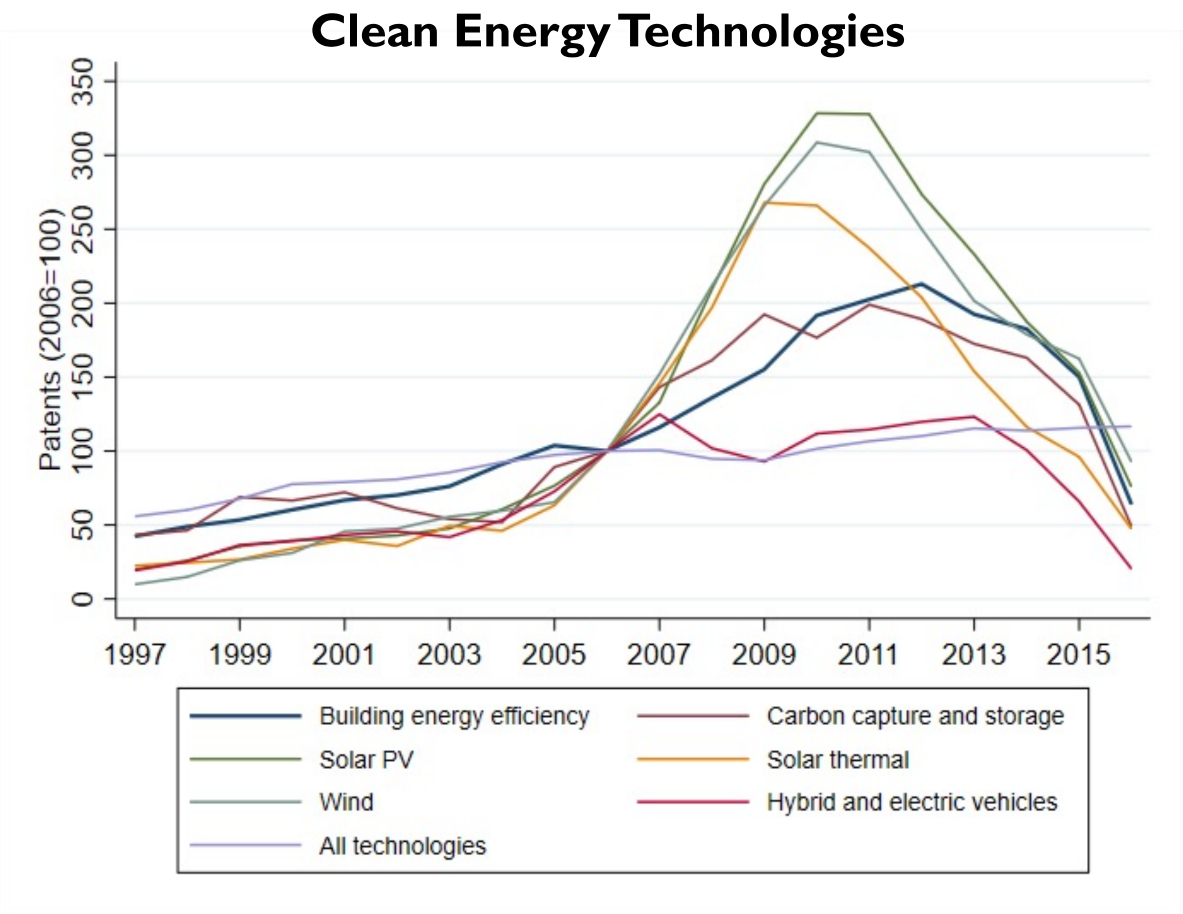
Source: https://www.commondreams.org/news/2019/08/14/well-wishes
climate-and-ecological

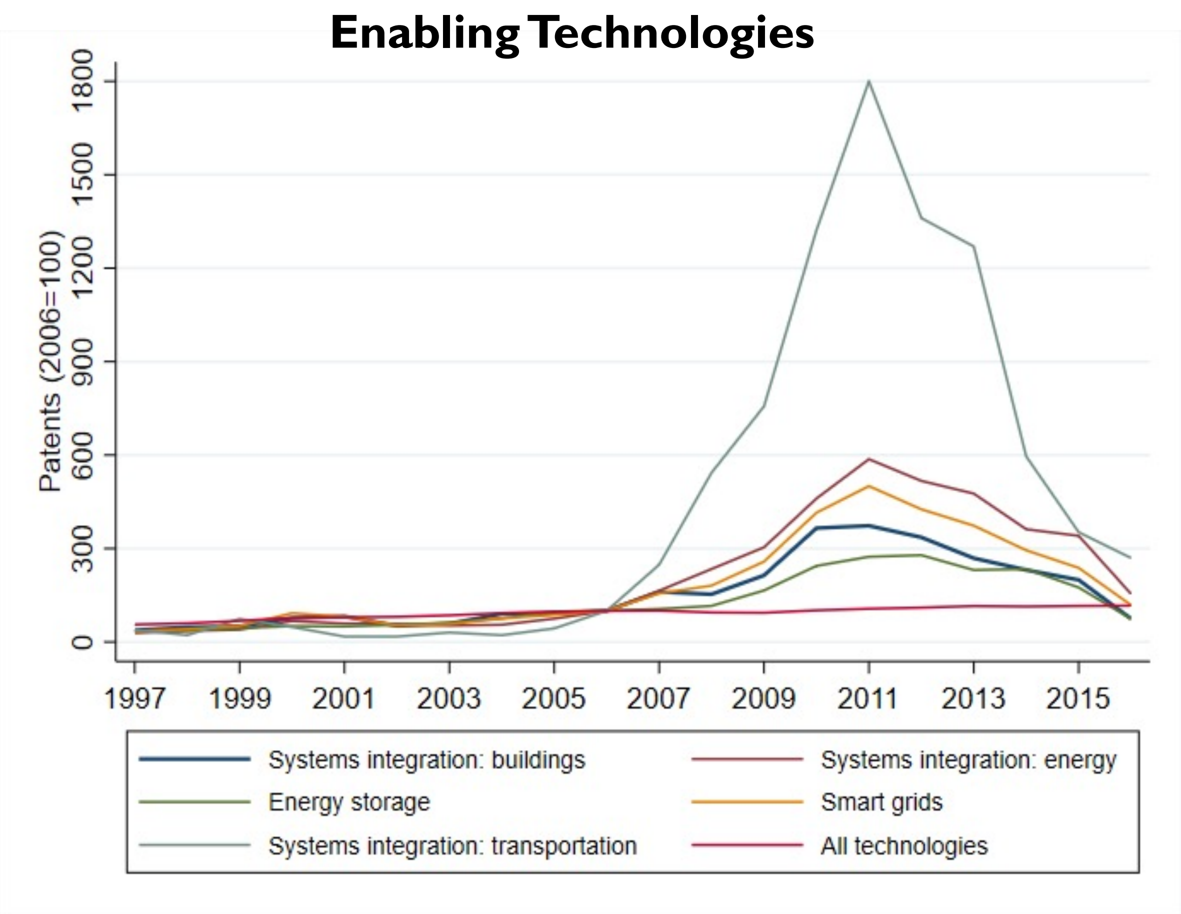
Protesting Climate Change, Young People Take to Streets in a Global Strike

Tremendous progress but…



Decline in patenting since ~2010

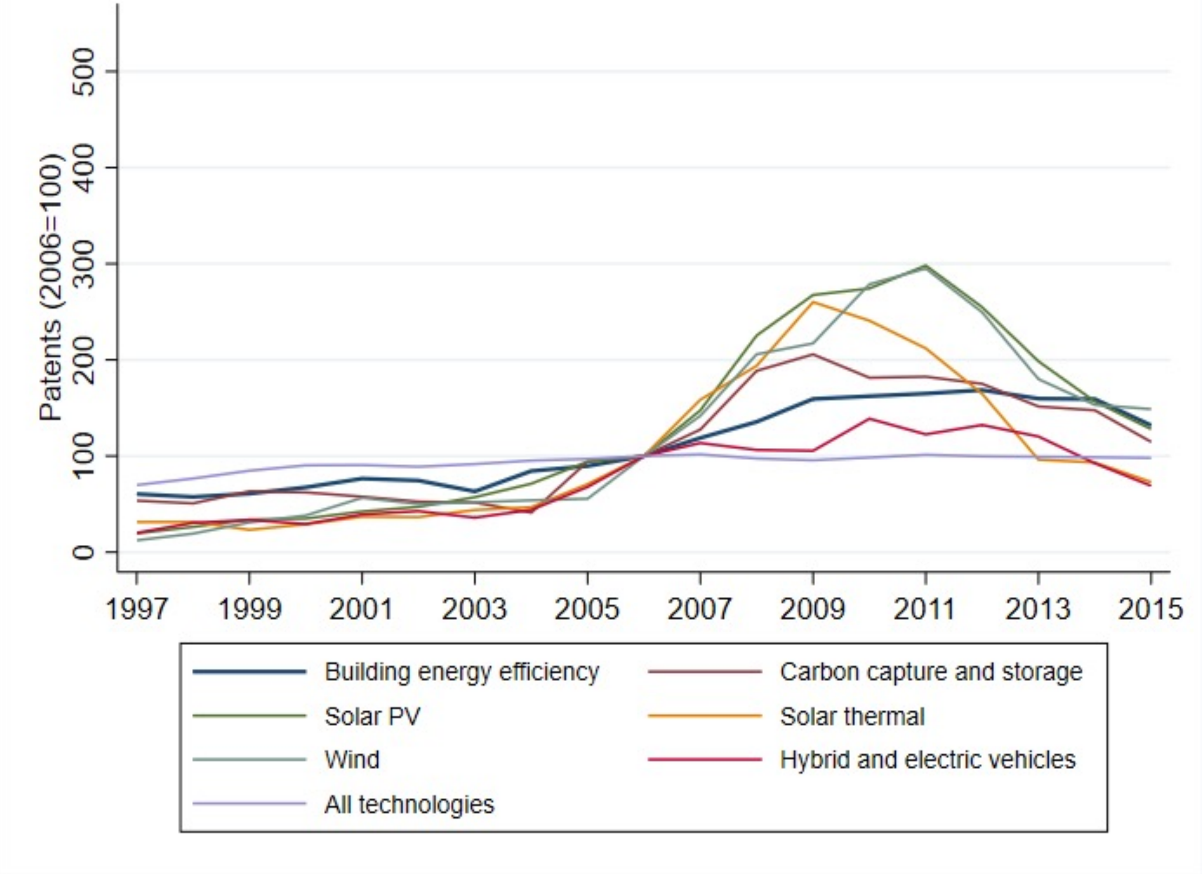




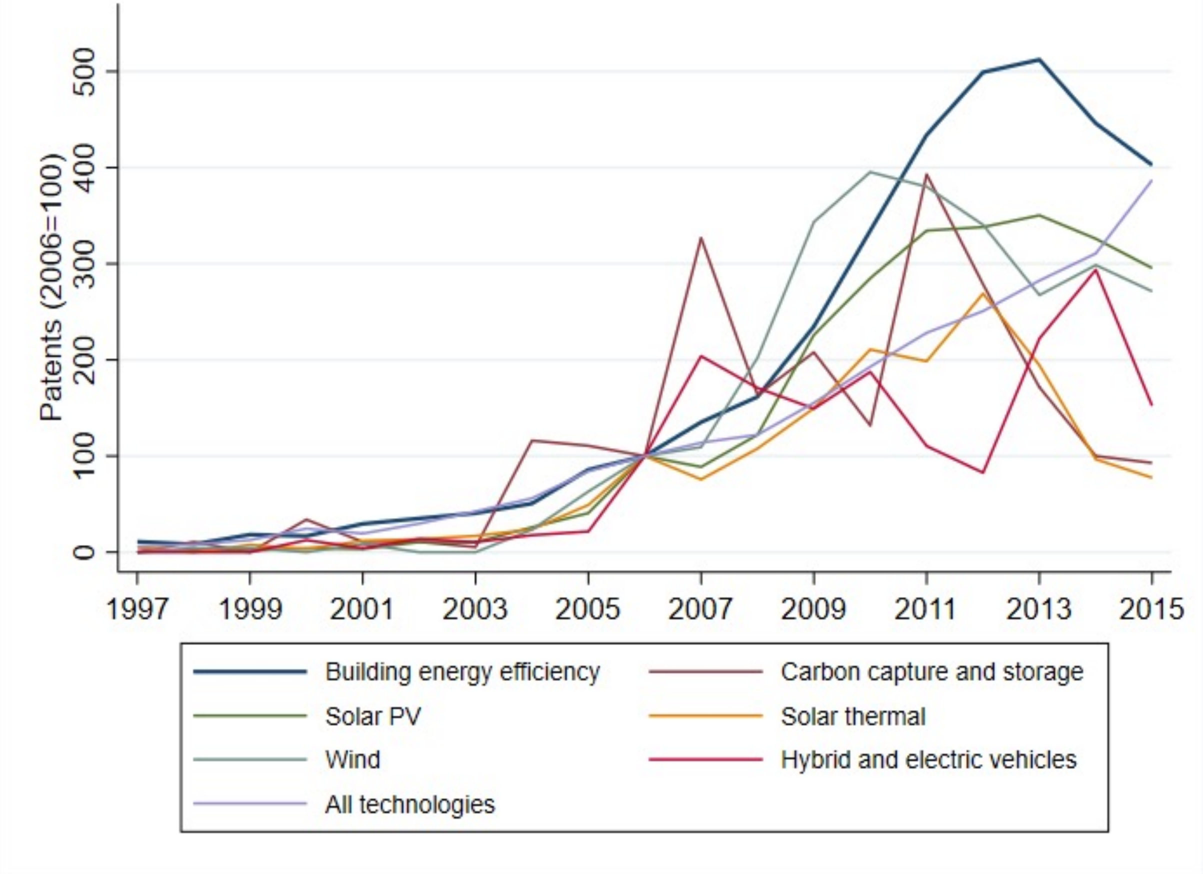
Figures show global counts of energy patents filed in two or more countries sorted by year. All counts normalized so that 2006 = 100. Patents from PATSTAT.

This phenomenon is global

European Union



China



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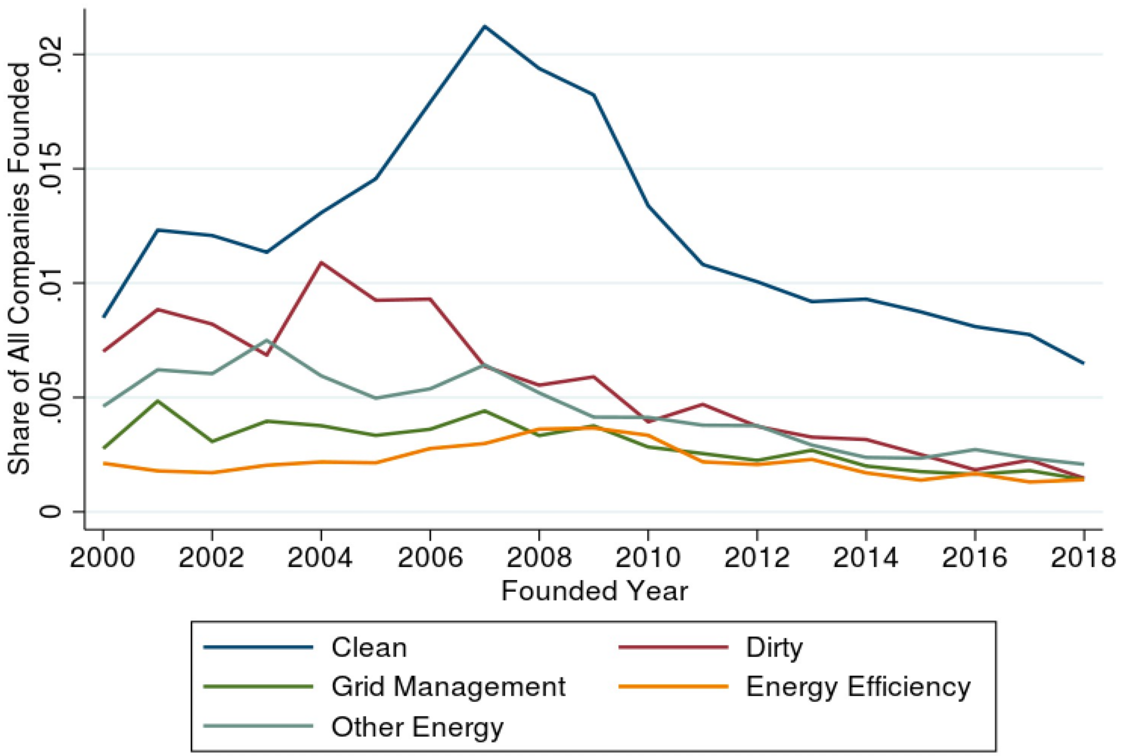
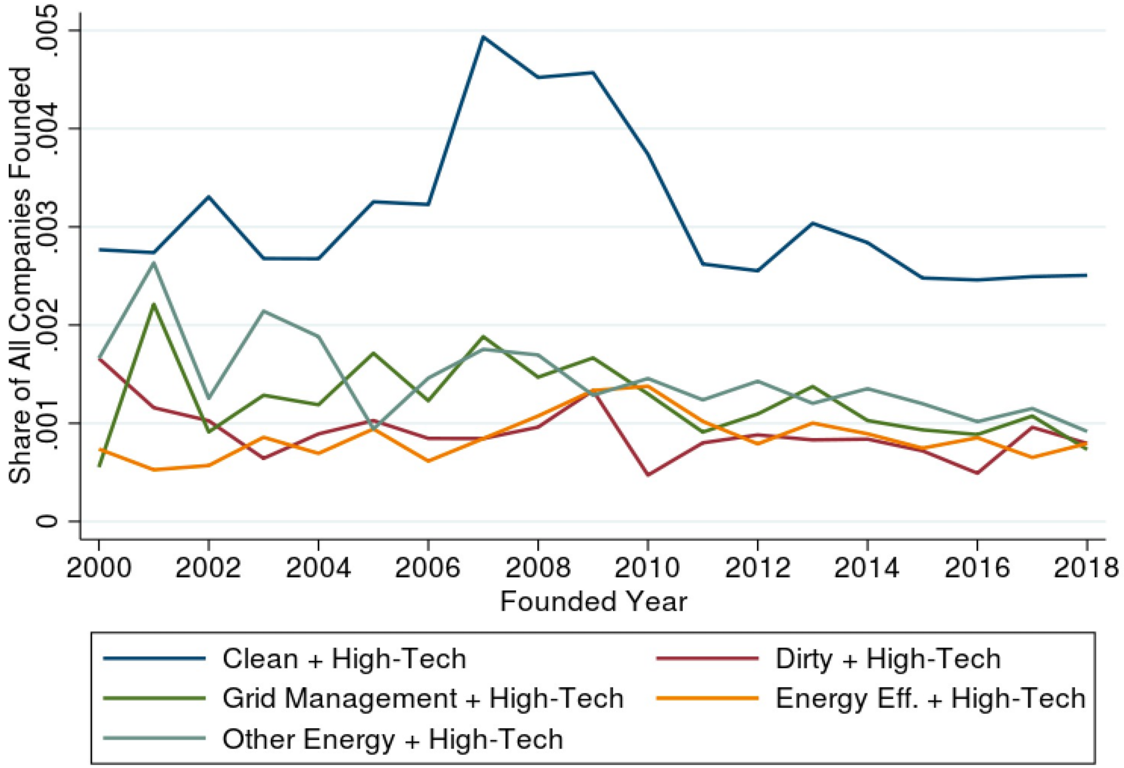
"Bubble" of clean energy start-ups and then decline





DIVE BRIEF

Biden proposes more than $2B for clean energy infrastructure, $14B+ increase in climate spending

Published June 1, 2021

By Emma Penrod

MISSION INNOVATION

NEWS

UK Government announces country's electricity to be green by 2035

By Sam Tabahriti | 04 Oct 2021 (Last Updated October 4th, 2021 16:01)

Prime Minister Boris Johnson is set to pledge huge investment in clean energy as the UK seeks to reduce its dependence on fossil fuels.

VOL. XXIX, NO. 2, WINTER 2013

The Hidden Risks of Energy Innovation

BY MICHAEL LEVI

Skepticism abound…

"…ill-conceived government efforts to cut the cost of clean energy would simply **spend taxpayer funds without producing any real world payoff**."

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Skepticism abound…

"…ill-conceived government efforts to cut the cost of clean energy would simply **spend taxpayer funds without producing any real world payoff.**"

For good reason?

"Policymakers will need, however, to confront the **challenges of crafting effective technology policy** head on. They will also need to take special care to **maximize the odds that their policies are well designed.**"

Bringing rigour to energy innovation policy evaluation

nature energy

Jacquelyn Pless[1,2*], Cameron Hepburn[2,3,4] and Niall Farrell[5,6]

Getting policy design "right" requires getting the <u>evaluation</u> methods "right"

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nature energy

Getting policy design "right" requires getting the <u>evaluation</u> methods "right"

And enabling robust evaluation requires careful consideration of program design <u>upfront</u>.

Understanding what works and why is hard

- Case studies and qualitative deep dives
  - Useful but hard to extrapolate
- Policy simulations
  - Tons of assumptions
- Data collection and correlation analysis
  - Getting there but with a lot of room for improvement

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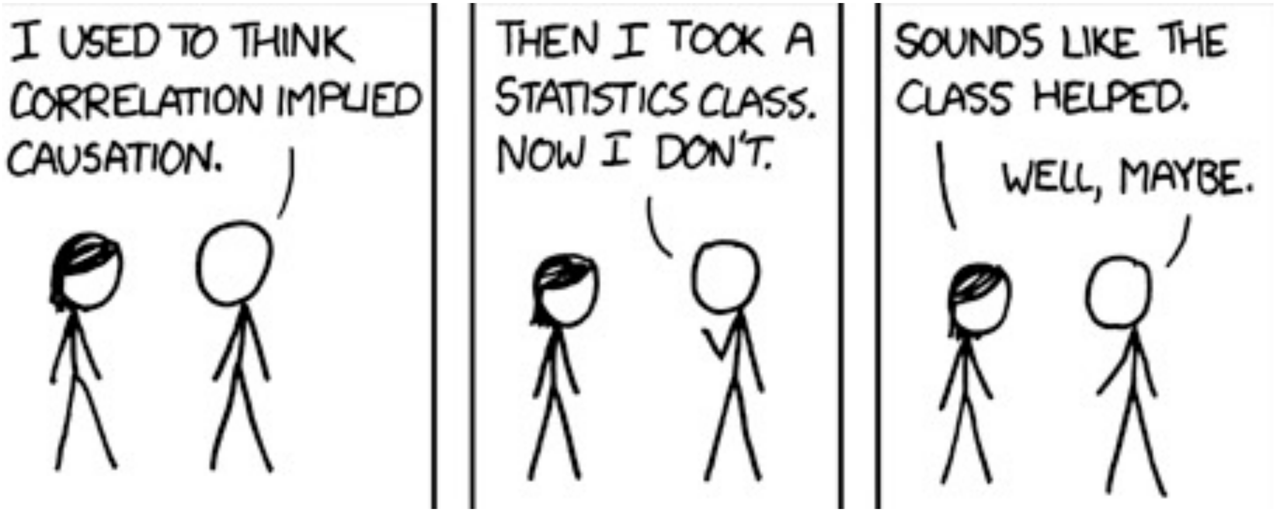
But the evidence on what works best, and why, is still (perhaps surprisingly) limited.

Challenge #1: Quantifying "causal effects"



Correlation is not causation ☺

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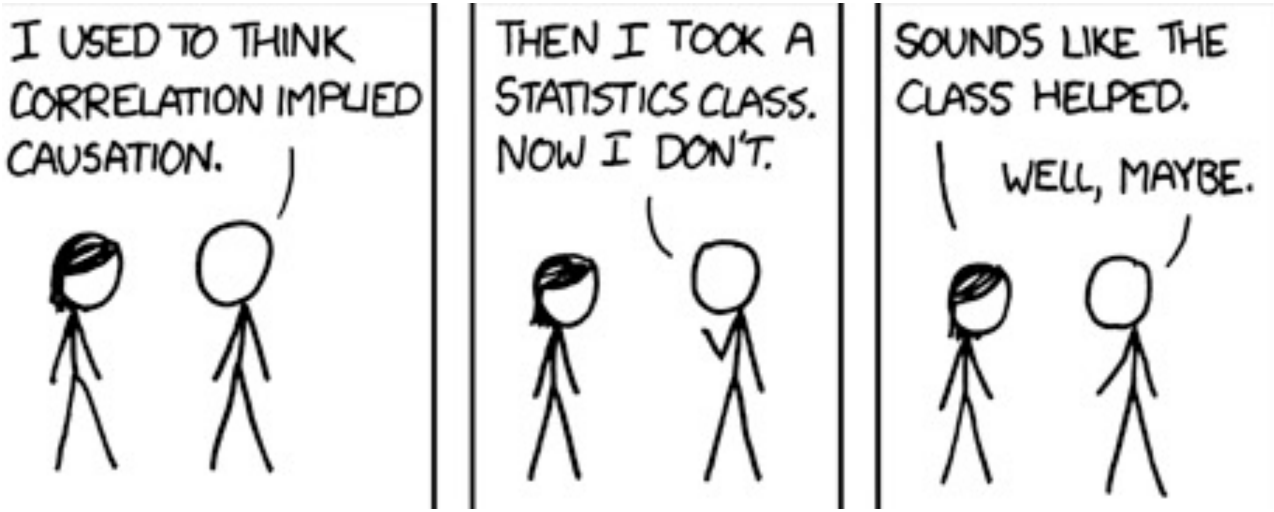

Correlation is not causation ☺

Causal effect: change in some outcome (e.g., patents, technology cost reduction, deployment) that can be directly attributed to the funding or policy.

Examples

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Causal Inference Methods

- **Randomized control trials** (“RCTs”) are gold standard
  - But they’re **typically difficult to implement** in the innovation context

- **Quasi-experimental approaches** are powerful (and less risky) alternatives

Example of quasi-experimental approach

- Set **cut-offs** in the ratings of applications that determine funding status or funding rates

- Likely to be very similar on each side of the threshold

- **Compare outcomes just under and over threshold**

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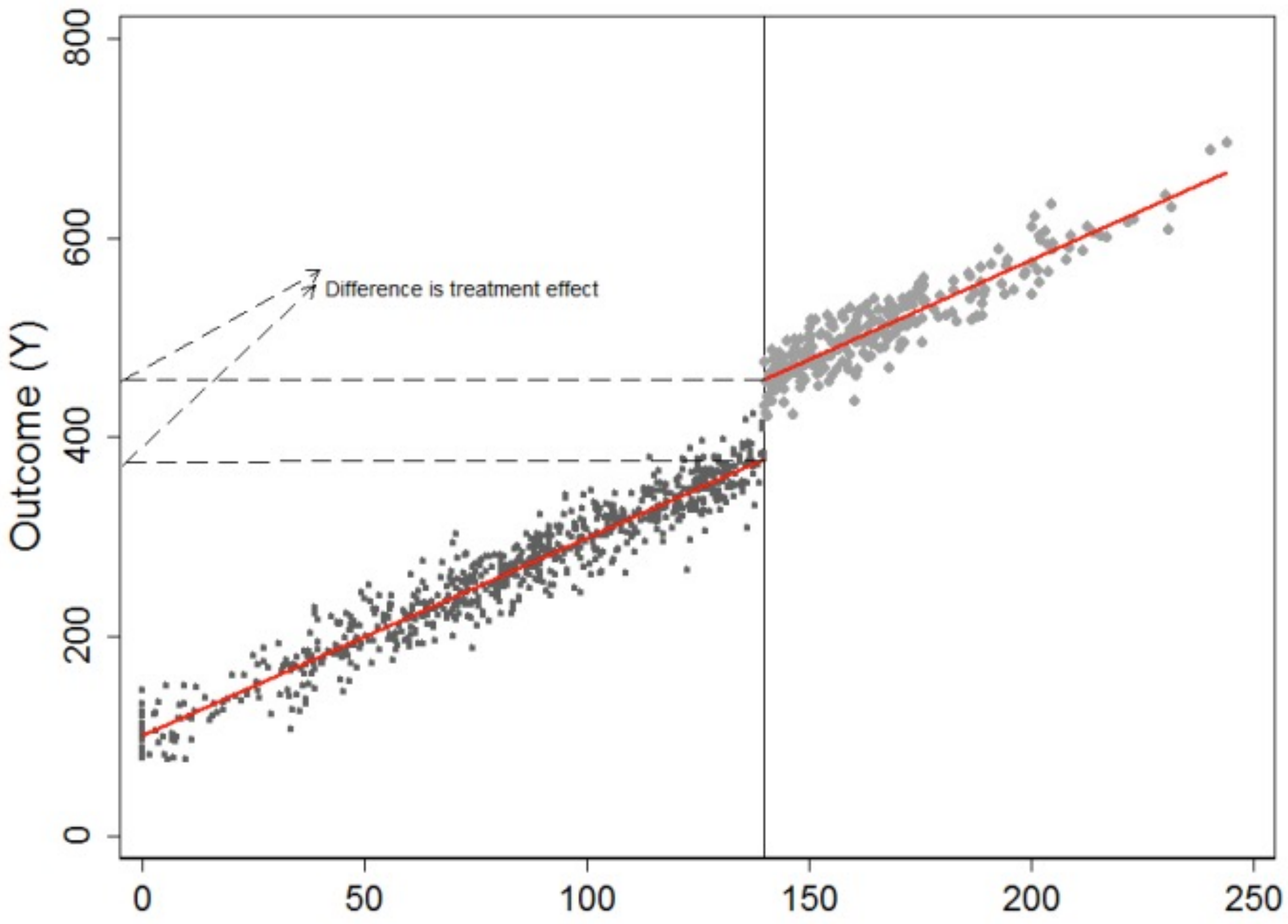

Causal Inference Methods

- **Randomized control trials** ("RCTs") are gold standard
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- **Quasi-experimental approaches** are powerful (and less risky) alternatives

- Requires **upfront planning and building certain features** into policy design to do so
  - **Building in "randomness"**
  - **These features already exist in many cases** but require additional effort on documenting them and studying all applicants

Challenge #2: Data!

- Measuring **level and quality** of innovation (outcomes)
  - Patents, publications, etc. tend to be the norm
  - But for energy… **Costs? Tech efficiency? Deployment?**
  - **Product launches?**

- Gathering data on **not just winners but all applicants**, or at the least, keep record of the entities that apply and their rankings/ratings

- Frequently a **disconnect** between what funding agencies consider to be good data and what a researcher considers good data

Outputs

The data is available in two formats.

Interactive dashboard – researchfish outputs

Interactive dashboards show different types of outputs including knowledge generation, collaborations, intellectual property, engagement activities and further funding.

[View the interactive dashboards: researchfish outputs 2013 to 2020 (Tableau)].

Excel data – research and innovation outputs

These are summaries of the data, by output type.

[View the data: research and innovation output data 2013 to 2020 (Excel, 69KB)].

Challenge #3: Distinguishing the *direction* of innovation

- Not all innovations are created equally!
  - Dirty versus clean energy innovation

- Measuring output alone does not capture whether the innovation is "good" for clean energy and environmental progress

- How to do this?
  - Patents can be classified – most commonly used in the literature so far
  - Moving forward? Machine learning and natural language process
  - Still needed?

Challenge #4: Accounting for time lags and uncertainty

- Energy innovation is characterized by particularly **long time horizons** from idea generation to commercialization

- Need to analyze outcomes for **at least 10 years post-funding**
  - Studies limited to a few years underestimate the effects

- But the clock is ticking – what can we do in the meantime?
  - Consider **intermediary outputs** that are correlated with final outcomes of interest
  - Develop better data on **products and commercialization outcomes**

Challenge #5: Examining policy *interactions*

Policies and funding programs are typically designed and evaluated independently…

but they're not independent.

Triple the challenge!

But not impossible.

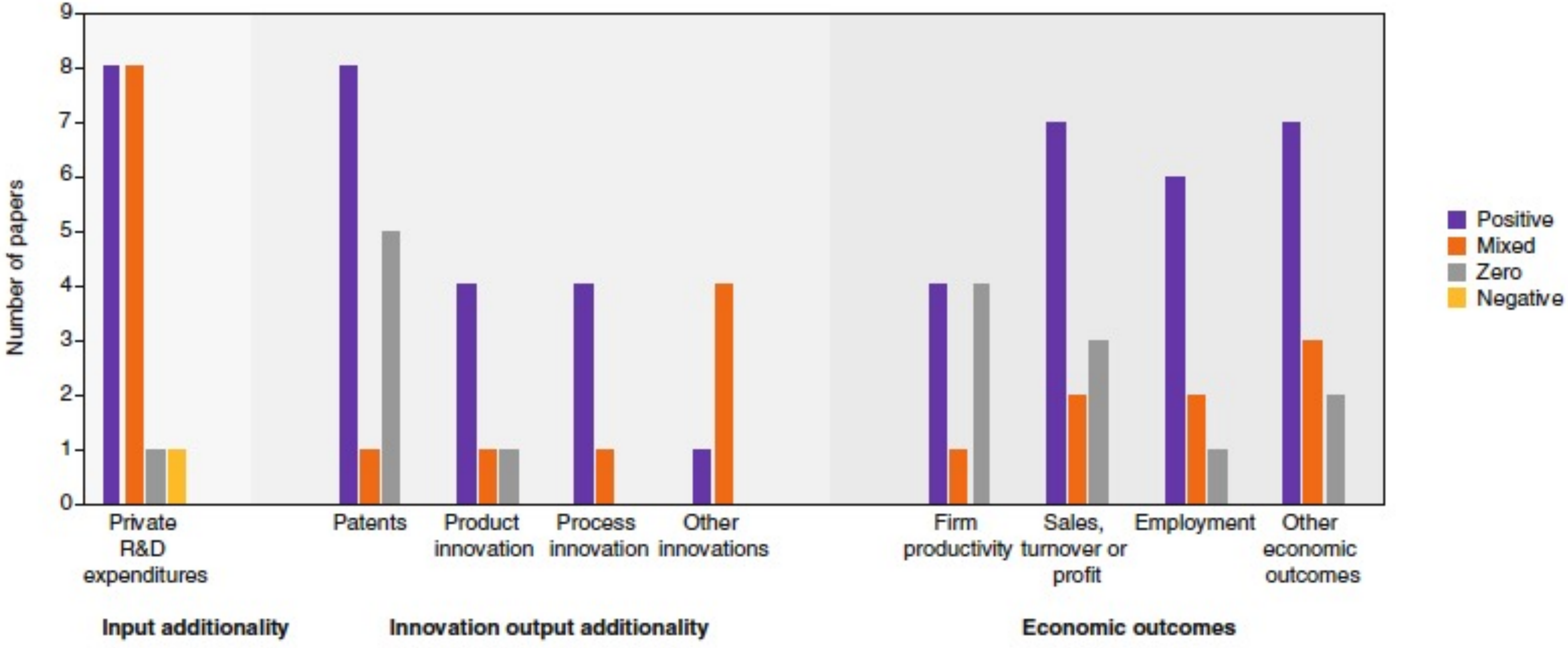
Are "Complementary Policies" Substitutes? Evidence from R&D Subsidies in the UK

Jacquelyn Pless*

February 13, 2021

Where do we stand today?

Too few studies specifically on energy, but for innovation overall…



Policy considerations moving forward

- **Data, data, data** – be proactive **upfront**
  - Innovation outcomes as well as inputs
  - Document all applicant information even if ”losers” are not tracked over time
  - Facilitate convenient merging of multiple datasets

- Build in features **upfront** that enable evaluation of **“causal effects”**

- **Work with researchers** at universities, think tanks, labs, etc. **upfront**

- Develop **questions** of interest **upfront**

Thank you!

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