Directed Technological Change and General Purpose Technologies: Can AI Accelerate Clean Energy Innovation?

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Motivations

- **Innovation and technological change** are central to addressing climate change.
- Prior work has shown that a combination of taxes and research subsidies can effectively **level the playing field** between **clean** and **dirty** technologies

  $\Rightarrow$ incentivize the development of clean, which allows clean sectors' productivity to catch up to dirty in the longer term.

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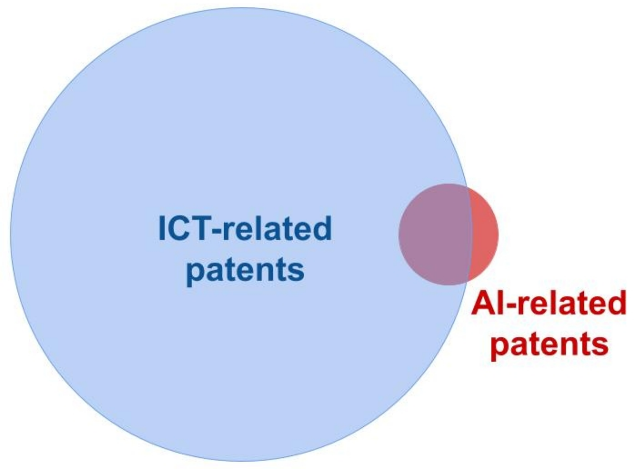
NB: AI refers to systems that change behaviour in response to data observed, collected and analysed.

ICT and AI as a General Purpose Technology



Characteristics of GPTs

Wide range of applications

Eventually pervade many if not most sectors of the economy

Transform modes of production

May transform modes of inventing

A New Hope for Clean Energy

AI/ICT could reduce costs of **clean** tech

Solar/wind forecast, grid stability and reliability, market design and operation, demand-side management ...

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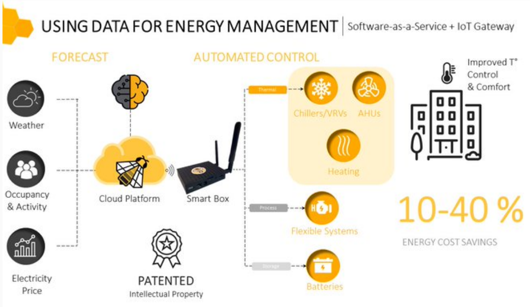
Example: Energy savings in buildings

www.beebryte.com



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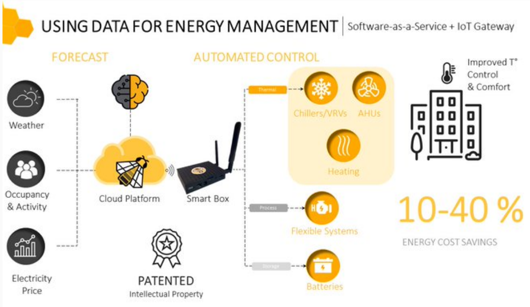

But Oil and Gas could Strike Back

AI/ICT could reduce costs of **dirty** tech

Via automation of complex/risky tasks; Internet of things, sensors along pipelines, exploration subsurface...

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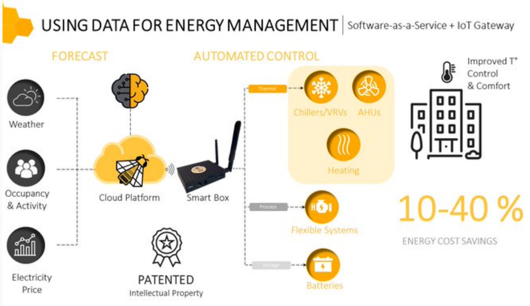

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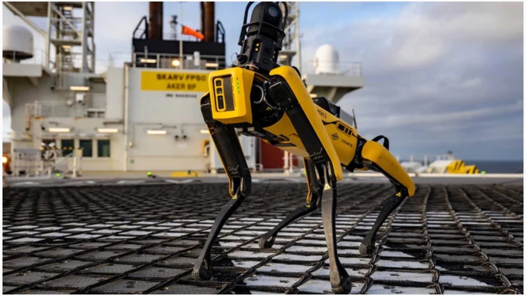
Example: Robotics for Offshore Oil and Gas

Aker BP and Cognite testing Spot, the quadruped robot developed by Boston Dynamics in the Norwegian Sea



https://akerbp.com/exploring-the-potential-of-robotics-in-the-oil-and-gas-industry

This Paper

- **Stylized Facts**

- **Dynamic General Equilibrium Model** [work in progress]

- **Firm-level Causal Evidence** [work in progress]

This Paper

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  - Patent data: backward and forward citations
  - AI/ICT Absorption leads to more forward citations
  - AI/ICT Absorption is higher for **clean** than **dirty** inventions
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  - Evaluate the policy implications of an AI/ICT spillover channel
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- **Firm-level Causal Evidence** [work in progress]
  - Can higher exposure to AI/ICT induce firms to absorb and innovate more in clean?
  - If so, this would open a new way of inducing green directed technological change.

Literature and Contribution

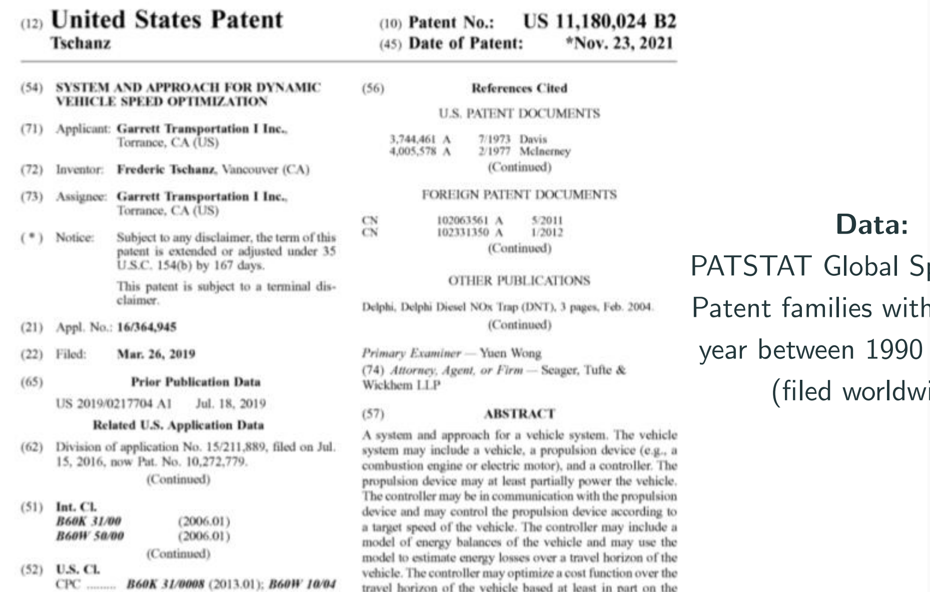
- **Economics of innovation**: Path dependence, R&D externalities (Griliches 1991; Jaffe and Trajtenberg 1999; Jaffe, Trajtenberg, and Fogarty 2000)
- **Economics of GPTs:** Bresnahan and Trajtenberg (1995), Cohen et al. (1990), and Helpman et al. (1996). Focus more so on the role of GPTs in economic growth, not necessarily in structural change.
- **AI and ICT as GPT:** Bresnahan (2010), Brynjolfsson et al. (2021), Cockburn et al. (2018), Lipsey et al. (2005), and Martinelli et al. (2021)
- **Clean (directed) technological change:** Acemoglu, Aghion, et al. (2012), Acemoglu, Akcigit, et al. (2016), Fried (2018), Jaffe, Newell, et al. (2005), and Popp, Newell, et al. (2010)
- Not much prior research at the intersection of those strands of literature (Verendel 2023)

Presentation Structure

1. Data
2. Stylized Facts
3. Dynamic General Equilibrium Model
4. Firm-level Causal Evidence
5. Summary, Discussion, Next Steps

Data

We Measure Innovation and Knowledge Flows Using Patent Data



(12) **United States Patent**
Tschanz

(10) **Patent No.: US 11,180,024 B2**
(45) **Date of Patent: *Nov. 23, 2021**

(54) **SYSTEM AND APPROACH FOR DYNAMIC VEHICLE SPEED OPTIMIZATION**

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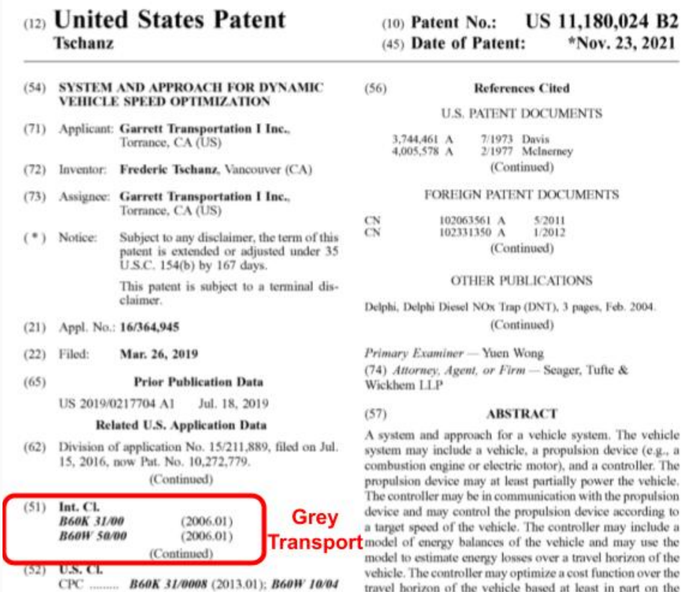
Data:

PATSTAT Global Spring 2021

Patent families with a priority year between 1990 and 2018 (filed worldwide)

CPC/IPC Codes to Identify Electricity and Transport



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Clean: Renewable energies, Nuclear, Batteries, Fuel cells, Elec. vehicles, Enabling

Grey: Energy Efficiency, Biomass and Waste

Dirty: Traditional Fossil Fuels, Internal combustion engine

Own harmonization of tech codes from prior literature (Aghion et al. 2016; Dechezleprêtre et al. 2017; Johnstone et al. 2010; Lanzi et al. 2011; OECD 2016; Popp, Pless, et al. 2020)

CPC/IPC Codes to Identify AI and ICT

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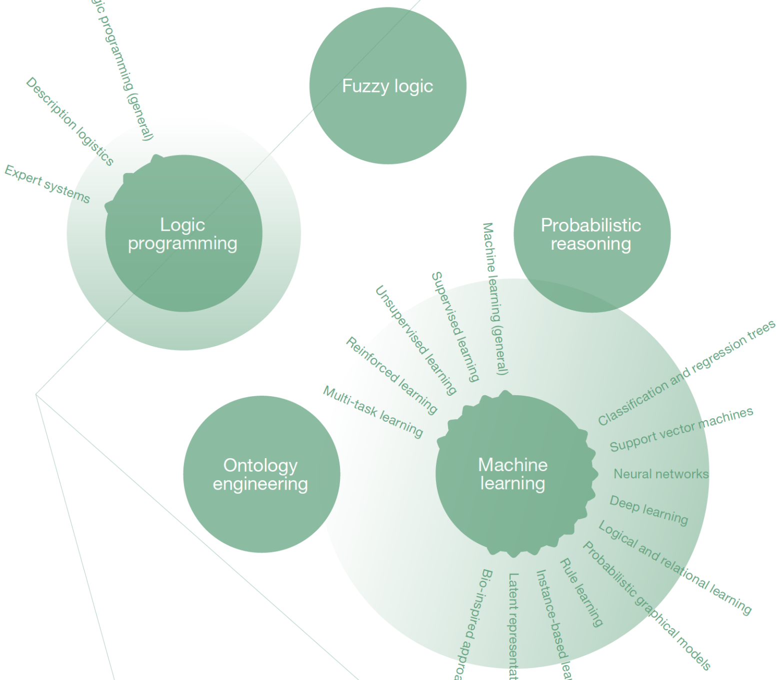
technology codes and keyword search of abstract and title, from WIPO (2019) ⇒ 548,641 AI families.

ICT:

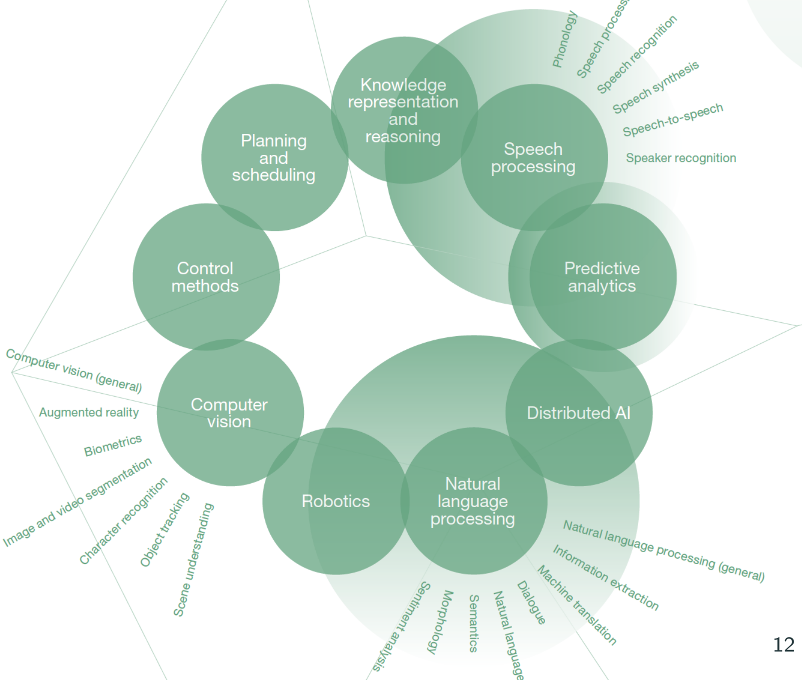
technology of codes from Inaba et al. (2017) ⇒ 10.9M ICT families

AI Techniques

(WIPO 2019)



Functional Applications of AI (WIPO 2019)



CPC/IPC Codes to Identify AI, ICT, Electricity and Transport

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Proxying Absorptive Capacity using Backward Citations

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Patent examiners identify "prior art" related to applications.

Backward citations between patent families to capture knowledge flows

We link PATSTAT to Orbis to obtain firm-level patent

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Disambiguate firms' name.
Provide other variables such as total assets, number of employees and years since incorporation.

Examples of Energy Patents and Reliance on AI

Application title	Sector	Type	Year	Citations to AI	
				#	%
Improved Flow Valve Port for a Gas Regulator	Electricity	Dirty	2007	49	67
Robotic cleaning device	Transport	Clean	2013	297	41
Virtual sensor system and method	Transport	Dirty	2007	37	26
Battery agnostic provisioning of power	Transport, Electricity	Clean	2016	119	13
System and approach for dynamic vehicle speed optimization	Transport	Grey	2015	51	10
Dual fuel heater with selector valve	Electricity	Grey	2011	38	9
Method and apparatus for configuring a communication interface	Electricity	Clean	2014	55	2

Stylized Facts

1) Energy Patents Citing AI/ICT Generate More Spillovers

	(1) AI	(2) AI	(3) AI	(4) AI	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Clean Family	0.508***	0.497***	0.413***	0.394***	0.508***	0.480***	0.413***	0.377***
	(0.024)	(0.022)	(0.042)	(0.041)	(0.024)	(0.040)	(0.042)	(0.042)
Grey Family	0.324***	0.322***	0.265***	0.262***	0.324***	0.342***	0.265***	0.262***
	(0.019)	(0.017)	(0.032)	(0.030)	(0.019)	(0.022)	(0.032)	(0.027)
AI Citing		0.240***		0.130***				
		(0.046)		(0.026)				
Clean X Citing AI		0.061***		0.119***				
		(0.014)		(0.022)				
Grey X Citing AI		0.008		0.042				
		(0.017)		(0.028)				
ICT Citing						0.335***		0.156***
						(0.047)		(0.039)
Clean X Citing ICT						-0.111***		0.007
						(0.005)		(0.020)
Grey X Citing ICT						-0.126***		-0.022
						(0.016)		(0.027)
Constant	-1.407***	-1.385***	-0.960***	-0.945***	-1.407***	-1.401***	-0.960***	-0.957***
	(0.088)	(0.093)	(0.090)	(0.095)	(0.088)	(0.090)	(0.090)	(0.091)
Sample								
Year FEs	X	X	X	X	X	X	X	X
Firm FEs			X	X			X	X
Quality Proxies	X	X	X	X	X	X	X	X
Pseudo R2	0.282	0.284	0.338	0.339	0.282	0.285	0.338	0.340
Observations	2.55e+06	2.55e+06	1.47e+06	1.47e+06	2.55e+06	2.55e+06	1.47e+06	1.47e+06

Poisson Pseudo-Likelihood Regression.
Standard Errors in Parentheses. Clustered at the type and firm level.
Dependent Variable: Citations Received Within 3 Years of Priority.

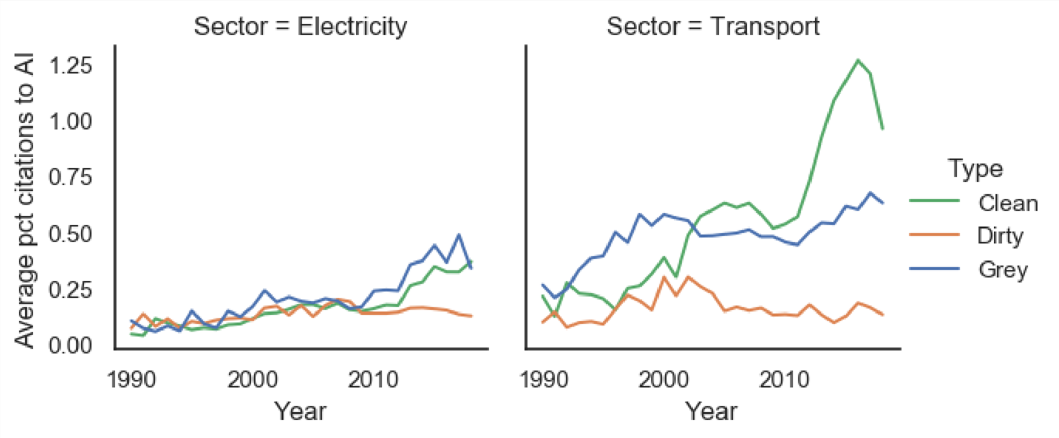
$\Rightarrow$ Consistent with the idea that absorbing the GPT is productivity-enhancing.

2) AI/ICT Absorption into Clean and Dirty

$$\text{AI/ICT Absorption} = \text{Aborptive Capacity} \times \text{Exposure to AI/ICT}$$

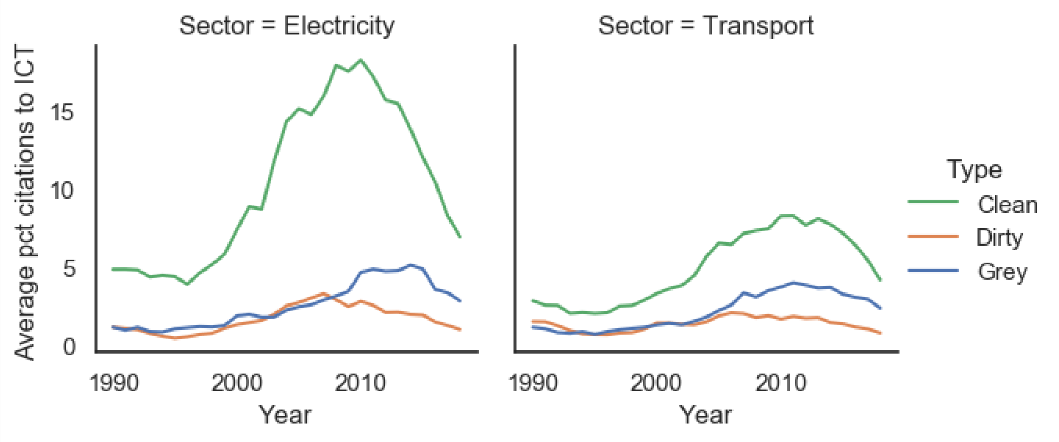
- Empirical proxies for Absorption: percentage of backward citations going to AI/ICT patents
- Aborptive Capacity: unobservable
- Accounting for differential exposure to AI/ICT: firm fixed effects, quality proxies

AI Absorption: Clean Patents Cite AI More Than Dirty Patents



The plots show the percentage of backwards citations made to AI by the average clean, grey or dirty electricity or transport patent family over time.

ICT Absorption: Clean Patents Cite ICT More Than Grey and Dirty Patents



The plots show the percentage of backwards citations made to ICT by the average clean, grey or dirty electricity or transport patent family over time.

Estimating the Absorptive Capacity of Clean Relative to Dirty Technologies

$$Absorption_{ijt} = \beta_0 + \beta_c \mathbf{Clean}_i + \beta_g \mathbf{Grey}_i + \mathbf{bX}_i + \delta_t + \delta_j + \epsilon_{ijt}$$

- $Absorption_{ijt}$: percent of backward citations going to AI or ICT for patent family i filed by firm j in year t.
- $\mathbf{Clean}_i$ and $\mathbf{Grey}_i$: binary variables that equal 1 if family i is classified as clean or grey, respectively (either in transport or in electricity).
- β_0: the intercept which, in this context, corresponds to the reference category: **Dirty**.
- $\mathbf{X}_i$ a series of variables proxying the quality of family i: the number of forward citations received by family i in three first years of its filing, the size of family i and the number of countries where family i was filed.
- δ_t and δ_j are year and firm fixed effects.

Clean Families Absorb AI More (Even with Quality Controls and Firm FEs)

	(1)
Clean Family	0.437***
	(0.024)
Grey Family	0.264***
	(0.001)
Nbr Citations Made (1000s)	8.134***
	(0.497)
Constant	0.121***
	(0.010)
Year FEs	X
Adjusted R2	0.006
Observations	2,550,428

Linear Regression.
Standard Errors in Parentheses. Clustered at the type and firm level.
Dependent Variable: Percentage of backward citations going to AI

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Linear Regression.
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Dependent Variable: Percentage of backward citations going to AI

- Ratio **Clean**/**Dirty** $= \frac{100 \times \beta_c}{mean_d}$, where $mean_d$ is the % of backward citations going to AI/ICT in the average **dirty** family

Clean Families Absorb AI More (Even with Quality Controls and Firm FEs)

	(1)	(2)
Clean Family	0.437***	0.530**
	(0.024)	(0.069)
Grey Family	0.264***	0.040
	(0.001)	(0.105)
Nbr Citations Made (1000s)	8.134***	3.081**
	(0.497)	(0.610)
Constant	0.121***	0.245**
	(0.010)	(0.042)
Ratio Clean/Dirty	304.35***	212.71**
	(16.63)	(27.86)
Year FEs	X	X
Firm FEs		X
Adjusted R2	0.006	0.043
Observations	2,550,428	1,495,048

Linear Regression.
Standard Errors in Parentheses. Clustered at the type and firm level.
Dependent Variable: Percentage of backward citations going to AI

- Ratio **Clean**/**Dirty** $= \frac{100 \times \beta_c}{mean_d}$, where $mean_d$ is the % of backward citations going to AI/ICT in the average **dirty** family
- Firm FEs absorb part of the Ratio Consistent with clean inventions being done by firms "better able to apply AI/ICT"

Clean Families Absorb AI More (Even with Quality Controls and Firm FEs)

	(1)	(2)	(3)
Clean Family	0.437***	0.530**	0.463**
	(0.024)	(0.069)	(0.077)
Grey Family	0.264***	0.040	-0.124
	(0.001)	(0.105)	(0.098)
Nbr Citations Made (1000s)	8.134***	3.081**	0.177
	(0.497)	(0.610)	(0.302)
Constant	0.121***	0.245**	0.575***
	(0.010)	(0.042)	(0.033)
Ratio Clean/Dirty	304.35***	212.71**	94.15**
	(16.63)	(27.86)	(15.77)
Sample			Gr. Triadic
Year FEs	X	X	X
Firm FEs		X	X
Adjusted R2	0.006	0.043	0.058
Observations	2,550,428	1,495,048	131,564

Linear Regression.
Standard Errors in Parentheses. Clustered at the type and firm level.
Dependent Variable: Percentage of backward citations going to AI

- Ratio **Clean**/**Dirty** $= \frac{100 \times \beta_c}{mean_d}$, where $mean_d$ is the % of backward citations going to AI/ICT in the average **dirty** family
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- Quality Proxies further narrow gap

Clean Families Absorb AI More (Even with Quality Controls and Firm FEs)

	(1)	(2)	(3)	(4)
Clean Family	0.437***	0.530**	0.463**	0.420**
	(0.024)	(0.069)	(0.077)	(0.070)
Grey Family	0.264***	0.040	-0.124	-0.151
	(0.001)	(0.105)	(0.098)	(0.103)
Nbr Citations Made (1000s)	8.134***	3.081**	0.177	-0.434
	(0.497)	(0.610)	(0.302)	(0.235)
Constant	0.121***	0.245**	0.575***	0.624***
	(0.010)	(0.042)	(0.033)	(0.030)
Ratio Clean/Dirty	304.35***	212.71**	94.15**	85.39**
	(16.63)	(27.86)	(15.77)	(14.24)
Sample			Gr. Triadic	Gr. Triadic
Year FEs	X	X	X	X
Firm FEs		X	X	X
Quality Proxies				X
Adjusted R2	0.006	0.043	0.058	0.060
Observations	2,550,428	1,495,048	131,564	131,564

Linear Regression.
Standard Errors in Parentheses. Clustered at the type and firm level.
Dependent Variable: Percentage of backward citations going to AI

- Ratio **Clean**/**Dirty** $= \frac{100 \times \beta_c}{mean_d}$, where $mean_d$ is the % of backward citations going to AI/ICT in the average **dirty** family
- Firm FEs absorb part of the Ratio Consistent with clean inventions being done by firms "better able to apply AI/ICT"
- Quality Proxies further narrow gap
- Controlling for # citations received within three years, family size and # countries where the family was filed

Clean Families Absorb AI More (Even with Quality Controls and Firm FEs)

	(1)	(2)	(3)	(4)
Clean Family	0.437***	0.530**	0.463**	0.420**
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Grey Family	0.264***	0.040	-0.124	-0.151
	(0.001)	(0.105)	(0.098)	(0.103)
Nbr Citations Made (1000s)	8.134***	3.081**	0.177	-0.434
	(0.497)	(0.610)	(0.302)	(0.235)
Constant	0.121***	0.245**	0.575***	0.624***
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	(16.63)	(27.86)	(15.77)	(14.24)
Sample			Gr. Triadic	Gr. Triadic
Year FEs	X	X	X	X
Firm FEs		X	X	X
Quality Proxies				X
Adjusted R2	0.006	0.043	0.058	0.060
Observations	2,550,428	1,495,048	131,564	131,564

Linear Regression.
Standard Errors in Parentheses. Clustered at the type and firm level.
Dependent Variable: Percentage of backward citations going to AI

Significant gap remains

If controls appropriately capture different exposures to AI/ICT, this can be interpreted as:

Clean having a higher **absorptive capacity** for AI/ICT than **Dirty**

i.e., some **intrinsic technological differences** that bias AI/ICT towards **Clean**

Dynamic General Equilibrium Model

Assessing Policy Implications: a DGE Model with Endogenous Innovation

- Build from Fried (2018) *Climate Policy and Innovation: A Quantitative Macroeconomic Analysis*, AEJ Macro.
- Model solves for the carbon tax which reduces emissions by 30% over 20 years.
- Calibrated/estimated on US data
- We maintain the model structure, which includes 3 sectors: green, fossil and non-energy
- We model non-energy as a sector where a GPT develops and generates spillovers to green and fossil

Final Good Producer

- Nested CES composite of non-energy, green energy, domestic fossil and oil imports
- Final good producer chooses intermediate quantities of intermediates to max profits, taking prices as given.
- Exogenous oil price, shocks to which help calibrate the model

$$Y_t = \left(\delta_y E^{\frac{\epsilon_y - 1}{\epsilon_y}} + (1 - \delta_y) N_t^{\frac{\epsilon_y - 1}{\epsilon_y}} \right)^{\frac{\epsilon_y}{\epsilon_y - 1}}$$

$$E_t = \left(\tilde{F}^{\frac{\epsilon_e - 1}{\epsilon_e}} + G_t^{\frac{\epsilon_e - 1}{\epsilon_e}} \right)^{\frac{\epsilon_e}{\epsilon_e - 1}}$$

$$\tilde{F}_t = \left(\delta_{\tilde{F}} E^{\frac{\epsilon_f - 1}{\epsilon_f}} + (1 - \delta_{\tilde{F}}) (O_t^*)^{\frac{\epsilon_f - 1}{\epsilon_f}} \right)^{\frac{\epsilon_f}{\epsilon_f - 1}}$$

Intermediate Good Producers

- Constant returns to scale production function with machines and labour for the green, fossil and non-energy sectors
- Intermediate goods producer chooses machines and labor to maximize profits, taking prices as given.
- A_{ji}: technology embodied in machine X_{ji}

$$F_t = L_{ft}^{1-\alpha_f} \int_0^1 X_{fit}^{\alpha_f} A_{fit}^{1-\alpha_f} di$$

$$G_t = L_{gt}^{1-\alpha_g} \int_0^1 X_{git}^{\alpha_g} A_{git}^{1-\alpha_g} di$$

$$N_t = L_{nt}^{1-\alpha_n} \int_0^1 X_{nit}^{\alpha_n} A_{nit}^{1-\alpha_n} di$$

Machine Producers

- Unit mass of machine producers (in each of the three sectors) choose the quantity of machines, the machine price, and the number of scientists, to maximize profits.
- Hire scientists to innovate on the embodied technology.
- Technology evolution of non-energy. Same as in Fried (2018):

$$A_{nit} = A_{nt-1}\left(1 + \overset{\text{Scientist efficiency}}{\boxed{\gamma\left(\frac{S_{nit}}{\rho_n}\right)^{\eta}}} \quad \overset{\text{TFP catchup ratio}}{\boxed{\left(\frac{A_{t-1}}{A_{nt-1}}\right)^{\phi}}}\right)$$

- We modify the equations governing the evolution of technology for green and fossil

- For Green and Fossil, we add asymmetric spillovers from the non-energy sector:

$$A_{fit} = A_{ft-1}\left(1+\gamma\left(\frac{S_{fit}}{\rho_f}\right)^{\eta}\left(\frac{A_{t-1}}{A_{ft-1}}\right)^{\phi}\overset{\text{GPT spillover}}{\boxed{A_{nt-1}^{\phi_f}}}\right)$$

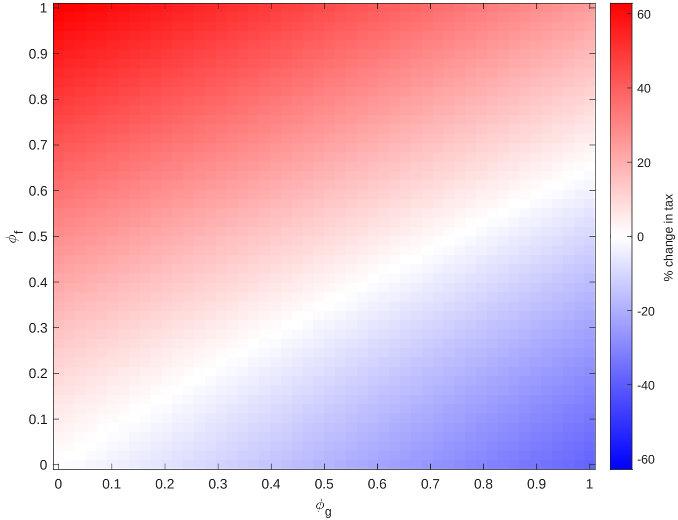
$$A_{git} = A_{gt-1}\left(1+\gamma\left(\frac{S_{git}}{\rho_g}\right)^{\eta}\left(\frac{A_{t-1}}{A_{gt-1}}\right)^{\phi}\boxed{A_{nt-1}^{\phi_g}}\right)$$

- ϕ_g and ϕ_f can be interpreted as absorptive capacities

Parameters

Parameter	Model value	Source
Final good production		
Output elasticity of substitution: ε_y	0.05	—
Energy elasticity of substitution: ε_e	1.50	—
Fossil elasticity of substitution: ε_f	6.24	Method of moments
Distribution parameter:[†] δ_y	1.44e-38	Method of moments
Distribution parameter: $\delta_{\tilde{F}}$	0.47	Method of moments
Intermediates production		
Labor share in fossil energy: $1-\alpha_f$	0.28	Data
Labor share in green energy: $1-\alpha_g$	0.09	Method of moments
Labor share in nonenergy: $1-\alpha_n$	0.64	Data
Number of workers: L	1	Normalization
1971–1975 productivity shock: ν	0.64	Method of moments
Research		
Cross-sector spillovers: ϕ	0.50	—
Diminishing returns: η	0.79	Method of moments
Scientist efficiency: γ	3.96	Method of moments
Sector size: ρ_f	0.01	Data
Sector size: ρ_g	0.01	Data
Sector size: ρ_n	1	Normalization
Number of scientists: S	0.01	Data
Climate		
Emissions conversion: ω	1.03	Data

The GPT Spillovers Can Increase or Decrease the Carbon Tax



- We solve for the carbon tax that would achieve a 30% emission reduction within 20 years.
- NB: the baseline required tax is 24.5\$/tCO2 (2013 \$)
- If ϕ_g is large enough relative to ϕ_f, the GPT spillovers reduce the required carbon tax
- If ϕ_g not large enough, path dependency dynamics still favor the fossil sector

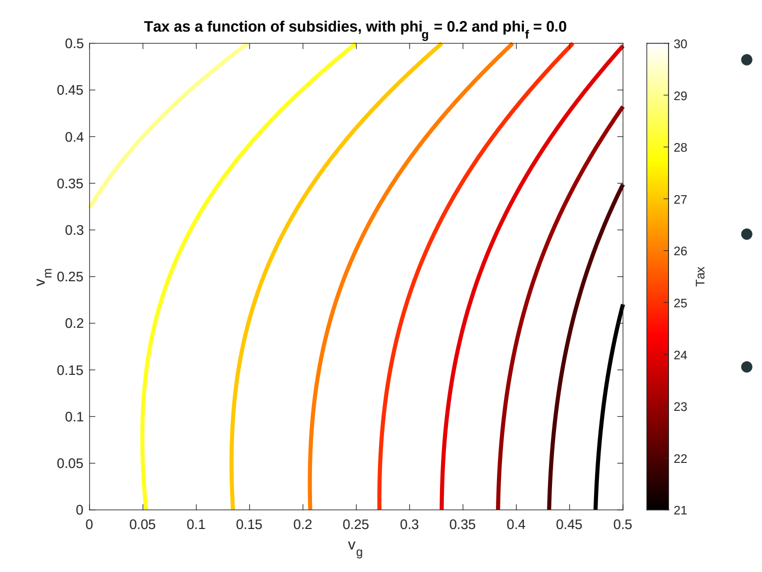
Modelling Research Subsidies

- Can a subsidy for non-energy / GPT be a useful complement to a carbon tax and green subsidy?
- Research subsidies help pay the wages of scientists:

$$w_{sgt} = \frac{\eta\gamma A_{gt-1} A_{nt-1}^{\phi_g} \left(\frac{A_{t-1}}{A_{gt-1}}\right)^{\phi} P^{x}_{git} X_{gt} A_t}{\rho_g^{\eta} \left(\frac{1}{1-\alpha_g}\right) S_{gt}^{1-\eta} A_{gt}} \frac{1}{1-v_g}$$

where v_g is the green subsidy.

The GPT subsidy and the green subsidy have opposite effects on the tax



- The green subsidy v_g decreases the tax required to reach the emissions reduction goal
- An increase in v_m requires an increase in v_g to avoid having to increase the carbon tax
- Likely due more scientists allocated to non-energy and fewer to green making it harder to counteract path dependency.

To Sum Up

- Absorption of AI/ICT is key to redirect technological change towards clean
  - Dynamics of green directed technical change are heavily constrained by path dependency
  - Higher absorption in clean can act as a countervailing force
- Can absorption be induced?
  - If so, this would open a new way of inducing green directed technological change.
  - Recall stylized facts: Firm f.e. absorbed part of the differential between clean and dirty
  - What makes a firm better able to absorb AI into clean/dirty? Can we induce it?

Firm-level Causal Evidence

Empirical Proxies at the Firm Level

$$\textbf{FirmInnovation}_{jt} = \beta_1 \textbf{ExposureToGPT}_{jt} + \mathbf{bX}_{jt} + \epsilon_{jt}$$
$$\textbf{FirmAbsorption}_{jt} = \beta_1 \textbf{ExposureToGPT}_{jt} + \mathbf{bX}_{jt} + \epsilon_{jt}$$

- **FirmInnovation**$_{jt}$: Number of patents filed by firm j in year t
- **FirmAbsorption**$_{jt}$: Percentage of firm j's families citing at least one AI/ICT family
  $\Rightarrow$ Captures the extent to which the firm absorbs AI/ICT
- **ExposureToGPT**$_{jt}$: proxies firm j's cumulative exposure to AI/ICT up to year t
  $\Rightarrow$ Within-firm spillovers: **Firm's own AI/ICT Patent Stock**
  $\Rightarrow$ Geographical spillovers: **Local AI/ICT Patent Stock**

Interpretation of $\beta_1 > 0$?

$$\textbf{FirmInnovation}_{jt} = \beta_1 \textbf{ExposureToGPT}_{jt} + \mathbf{bX}_{jt} + \epsilon_{jt}$$
$$\textbf{FirmAbsorption}_{jt} = \beta_1 \textbf{ExposureToGPT}_{jt} + \mathbf{bX}_{jt} + \epsilon_{jt}$$

- **Causal story:** higher exposure to AI/ICT lead to higher absorption and more innovation (esp in clean)
  - Absorptive capacity (ϕ_j) could be constant and the effect is driven mainly by the fact that there is simply more to absorb
  - But exposure could also lead to investments to make techs better able to absorb the GPT, i.e., absorptive capacity may increase
  - Firms may choose to work on techs with higher absorptive capacities

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    - Firms may choose to work on techs with higher absorptive capacities
- **Specialization story:** firms with higher exposure to AI/ICT also happen to specialize in technologies with higher intrinsic capacity
  $\rightarrow$ We can test this by adding increasingly fine-grained technology controls
  If β_1 goes down, then the specialization story is at play.

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  $\rightarrow$ We can test this by adding increasingly fine-grained technology controls
  If β_1 goes down, then the specialization story is at play.
- Other channels?

Quasi-Random Variation with a Shift-Share Instrument

$$\textbf{FirmInnovation}_{jt} = \beta_1 \textbf{ExposureToGPT}_{jt} + \mathbf{bX}_{jt} + \epsilon_{jt}$$
$$\textbf{FirmAbsorption}_{jt} = \beta_1 \textbf{ExposureToGPT}_{jt} + \mathbf{bX}_{jt} + \epsilon_{jt}$$

where:

$$\textbf{ExposureToGPT}_{jt} = \sum_{l=1}^{L} w_{jl} StockAI_{lt}$$

- w_{jl}: share of firm j's patents in a preperiod (e.g., 2000-2005) that have an address in location l
- Intuition: preperiod location of energy firms is unrelated to determinants of the development of AI/ICT
- Some energy firms over time receive more exposure than others due to their location rather than their specilization.
- Use this as an intrument for firms' internal AI/ICT stock and/or geographical stock.

What We Have Done So Far

$\Rightarrow$ Prior AI/ICT within-firm experience correlates with greater absorption

$$\begin{aligned}\textbf{FirmAbsorption}_{jtk} &= \beta_0 + \beta_1 \textbf{StockGPT}_{jt-1} + \beta_2 \textbf{StockEnergy}_{jt-1} \\ &+ \beta_c \textbf{Clean}_k + \beta_g \textbf{Grey}_k + \beta_t \textit{Transport}_k + \mathbf{bX}_{jt} + \delta_t + \delta_j + \epsilon_{jtk}\end{aligned}$$

- **FirmAbsorption**$_{jtk}$: % of families filed by firm j in year t in portfolio k citing some AI/ICT patents
  6 types of *portfolio*: clean/grey/dirty and electricity/transport
- **Clean**$_k$/**Grey**$_k$/*Transport*$_k$: binary variables equal to 1 for clean/grey/transport portfolios.
- **StockGPT**$_{jt-1}$: count of AI/ICT families firm j had filed at time $t-1$ (discounted)
- **StockEnergy**$_{jt-1}$: count of energy families (of any type) firm j had filed at time $t-1$ (discounted)
- $\mathbf{X}_i$ is a series of firm-level controls that include total assets, number of employees and years since incorporation.
- δ_t and δ_j are year and firm fixed effects.
- Additional specifications with interactions between $StockGPT_{jt-1}$ and the different types of portfolios: $Clean_k$, $Grey_k$, $Transport_k$

Across Firm Variation in AI Absorption

- Firms patenting mainly in electricity
- Firms patenting mainly in transport
- Firms patenting in both electricity and transport

Across Firm Variation in AI Absorption

- Firms patenting mainly in electricity
  - **GE** – Patent portfolio: **8%**/**45%**. Citations to AI: **14%**/**5%**.
  - **Sharp Corporation** – Patent portfolio: **87%**/**8%**. Citations to AI: **1%**/**0%**.
- Firms patenting mainly in transport
  - **Toyota** – Patent portfolio: **54%**/**11%**. Citations to AI: **5%**/**1%**.
  - **Bosch** – Patent portfolio: **33%**/**9%**. Citations to AI: **11%**/**3%**.
- Firms patenting in both electricity and transport
  - **Panasonic** – Patent portfolio: **85%**/**10%**. Citations to AI: **2%**/**0%**.
  - **Sanyo Electric Co.,Ltd.** – Patent portfolio: **97%**/**2%**. Citations to AI: **0%**/**0%**.

Firms With Higher AI Stock And Smaller Energy Stock Absorb More AI

	(1)	(2)	(3)	(4)
Family Count (log)	0.982***	0.922***	1.064***	1.017***
	(0.044)	(0.045)	(0.126)	(0.042)
Clean Portfolio	0.750***	1.014***	0.350***	0.006
	(0.147)	(0.273)	(0.112)	(0.184)
Stock AI (log, t-1)	0.273***	0.020	0.333***	-0.067
	(0.066)	(0.096)	(0.082)	(0.087)
Clean X Stock AI (log, t-1)	0.138*	0.137*	-0.030	-0.014
	(0.073)	(0.074)	(0.101)	(0.047)
Stock Energy (log, t-1)	-0.199***	-0.186**	-0.136***	-0.048
	(0.045)	(0.083)	(0.051)	(0.063)
Clean X Energy Stock (log, t-1)	-0.029	-0.007	-0.112*	0.033
	(0.046)	(0.065)	(0.068)	(0.042)
Portfolio Type	Transport	Transport	Electricity	Electricity
Portfolio FEs	X	X	X	X
Year FEs	X	X	X	X
Firm FEs		X		X
Firm level controls		X		X
Observations	26,810	9,610	41,591	9,097
R2	0.660	0.742	0.335	0.449

Poisson pseudo-maximum likelihood regression.
Standard errors in parentheses, Clustered at firm level.

Dependent variable: % of families citing AI
Firm level controls include total assets, number of employees and years since incorporation

- Firms with higher **AI stock** and smaller **energy stock** absorb more **AI**, esp into their **clean** inventions
- Also true of their **dirty** inventions but effects sligtly weaker
- Prior experience in energy seems to be a barrier to the use of AI. New entrants may be critical to accelerating the diffusion of AI into clean
- Within firms: changes in AI stock over time does not correlate strongly with AI absorption
- Similar results for ICT

Summary, Discussion, Next Steps

Conclusions

- **AI seems set to accelerate clean innovation**
  - Clean technologies absorbs more on AI, especially in transport. Clean families also absorbed more of the earlier ICT "GPT wave" (especially electricity).
  - Absorbing AI/ICT is associated with greater innovative value (proxied by citations received)

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  - Absorbing AI/ICT is associated with greater innovative value (proxied by citations received)
- **A GPT can lessen the path-dependence** arising from the history of innovation if the newer **clean technologies** have sufficiently **higher absorptive capacity**.
  - GPTs can not only drive growth, but also direct technological change towards clean
  - Green innovation policies may want to consider supporting spillover mechanisms between AI/ICT and clean technologies as a complementary way of redirectig technical change

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  - Green innovation policies may want to consider supporting spillover mechanisms between AI/ICT and clean technologies as a complementary way of redirectig technical change
- So far, we find that higher in AI absorption correlates with **within-firm** exposure to AI. Need to understand better the mechanisms

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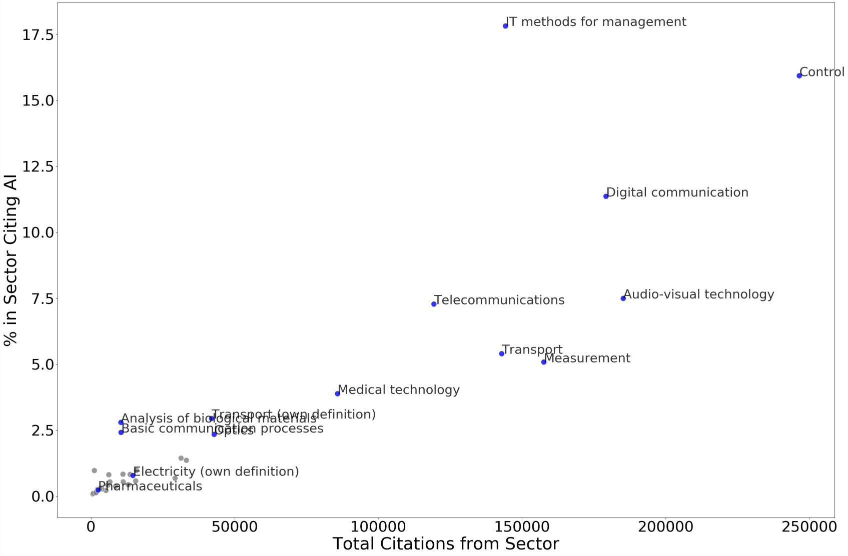
- **A GPT can lessen the path-dependence** arising from the history of innovation if the newer **clean technologies** have sufficiently **higher absorptive capacity**.
  - GPTs can not only drive growth, but also direct technological change towards clean
  - Green innovation policies may want to consider supporting spillover mechanisms between AI/ICT and clean technologies as a complementary way of redirectig technical change
- So far, we find that higher in AI absorption correlates with **within-firm** exposure to AI. Need to understand better the mechanisms
- Bigger picture: absorption still low compared with other application sectors.

Absorption in Other Application Sectors Much Higher



Any question/comment, email me: e.dugoua@lse.ac.uk

Thank you!

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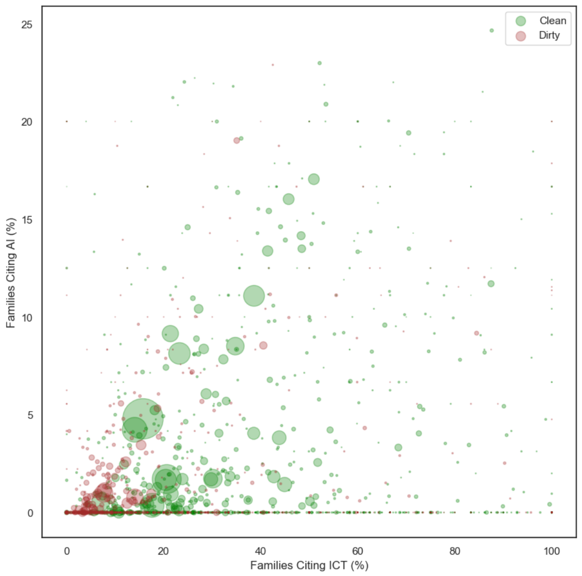
“Tesla big battery paves way for AI to dominate energy trades”

“Relative to a human trader, algorithmic bidding software can increase the revenues of a battery by about five-times.”

Quote from an AMS executive (US-based software-as-a-service platform provider)

Source: https://reneweconomy.com.au/tesla-big-battery-at-hornsdale-delivers-world-record-output-of-150mw-26392/

Cross-Section: Firm-Level Absorption is Higher for Clean Technologies



- Each bubble represents a firm
- Values are firm-level annual averages for period 2005-2015
- Y-axis: % of clean/dirty families citing AI
- X-axis: % of clean/dirty families citing ICT
- Bubble size proportional to # families in portfolio (either clean or dirty)

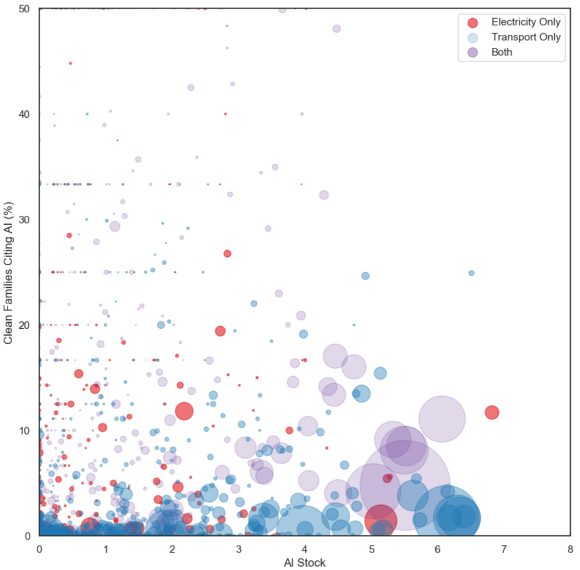
Bottom Line:

- Clean portfolios use AI and ICT a lot more
- Portfolios using more AI also use more ICT, but the opposite not necessarily true

Over Time: Firm-Level Absorption is Increasing for Clean Technologies

- We plot the average % of families in a firm's portfolio which cites AI/ICT over time
- Clean dominates dirty in both
- In AI, the gap widens after 2010

Higher AI Stocks and AI Absorption for Firms Innovating in Both Sectors



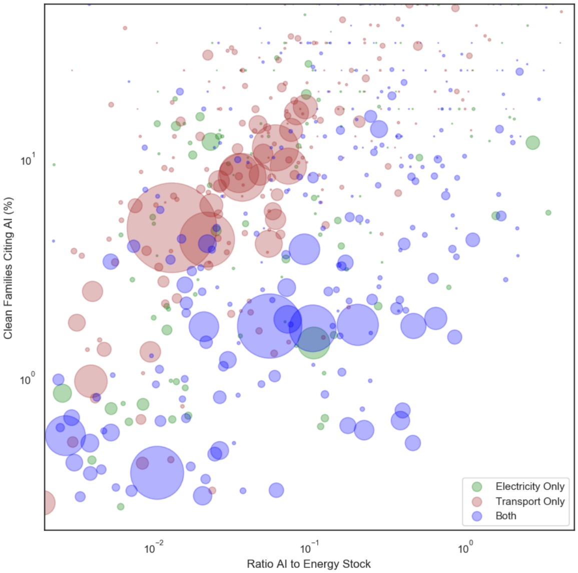
- Y-axis: % of clean families citing AI
- X-axis: AI stock (log)
- Bubble size proportional to # clean families
- Significant variation across firms
- Firms doing both have higher AI stock: e.g. Panasonic, Mitsubishi

Reminder:

Each bubble represents a firm

Values are firm-level annual averages for period 2005-2015

Absorption Increases with the Ratio of AI to Energy Stock



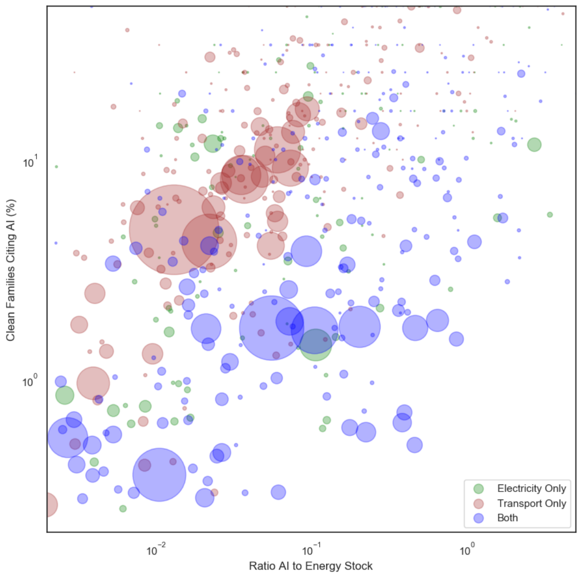
- Y-axis: % of clean families citing AI
- X-axis: ratio of AI to Energy Knowledge Stock
- Bubble size proportional to # families in portfolio (either clean or dirty)
- Higher AI absorption in firms with relatively more AI compared to energy knowledge
- Similar trends for ICT

Reminder:

Each bubble represents a firm

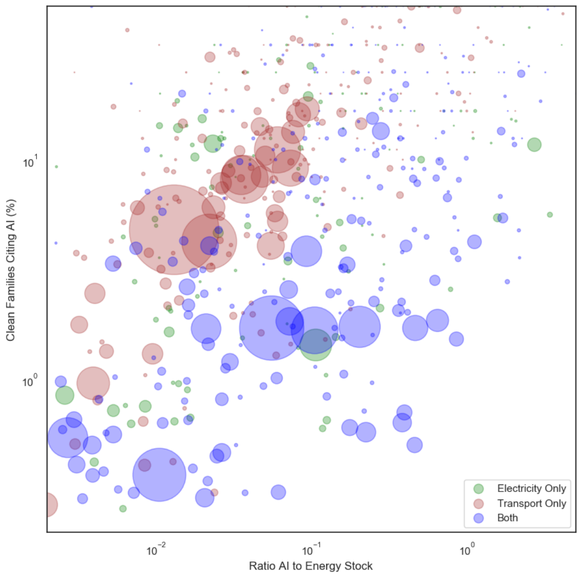
Values are firm-level annual averages for period 2005-2015

Correlation between Firm-Level Absorption and AI and Energy Patent Stock



- Each bubble represents a firm
- Bubble size proportional to # **clean** families
- **Y-axis:** AI Absorption into **clean**, i.e., % of **clean** families citing AI
- **X-axis:** ratio of AI to Energy Patent Stock
- Values are firm-level annual averages for period 2005-2015

Absorption Increases with the Ratio of AI to Energy Stock



- Higher AI absorption in firms with relatively more AI compared to energy knowledge
  $\Rightarrow$ Firms with higher AI stock and smaller energy stock absorb more AI into their **clean** inventions
- Also true of their **dirty** inventions but effects sligtly weaker
- Similar trends for ICT

Similar Results for ICT, with Stronger Magnitude

	(1) ICT	(2) ICT	(3) ICT	(4) ICT
Stock ICT (log, t-1)	5.229***	5.715***	-0.877**	-0.733*
	(0.128)	(0.152)	(0.434)	(0.441)
Stock Energy (log, t-1)	-4.218***	-4.221***	-1.978***	-1.972***
	(0.146)	(0.145)	(0.425)	(0.425)
Clean Portfolio	21.427***	20.078***	19.539***	16.514***
	(0.309)	(0.415)	(0.386)	(0.641)
Grey Portfolio	4.867***	4.794***	3.819***	3.052***
	(0.289)	(0.400)	(0.356)	(0.580)
Transport Portfolio	-1.775***	2.430***	-3.418***	0.920*
	(0.263)	(0.353)	(0.317)	(0.507)
Clean X Stock ICT (log, t-1)		0.470***		0.822***
		(0.115)		(0.144)
Transport X Stock ICT (log, t-1)		-1.589***		-1.192***
		(0.095)		(0.115)
Portfolio FEs	X	X	X	X
Year FEs	X	X	X	X
Firm FEs			X	X
Firm level controls			X	X
Observations	134,891	134,891	91,329	91,329
R2	0.111	0.113	0.336	0.337