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

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Motivations

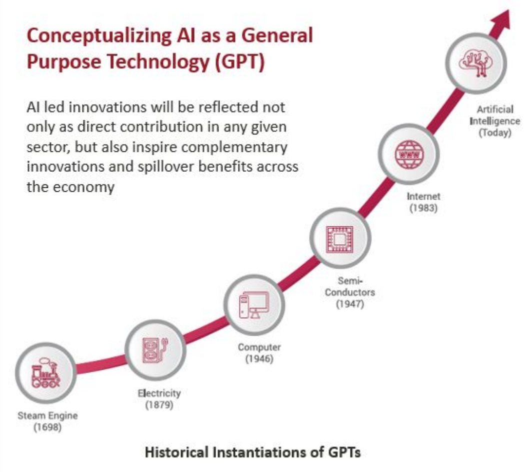
- Directing technological change is central to addressing climate change.
- Prior work has shown that a combination of taxes and research subsidies can effectively level the playing field between clean and dirty technologies

  $\Rightarrow$ incentivize the development of clean, which allows clean sectors' productivity to catch up to dirty in the longer term.
- However, the race between clean and dirty technologies is taking place against a backdrop of improvements in information and communication technologies (ICT) and artificial intelligence (AI).
- Does this matter for the clean transition?

ICT and AI as a General Purpose Technology

Characteristics of GPTs (Bresnahan 2010; Lipsey et al. 2005)

- Wide range of applications
- Eventually pervade many if not most sectors of the economy
- Transform modes of production
- May transform modes of inventing



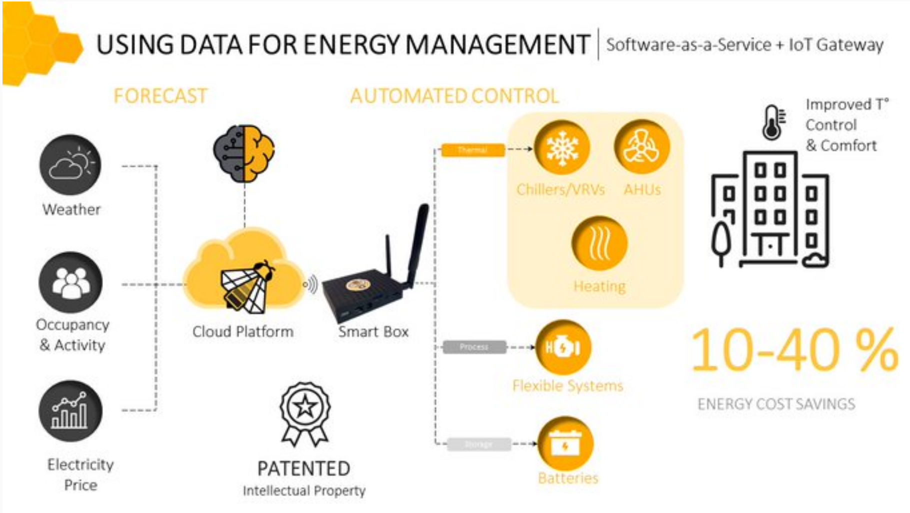
Source: www.businessprocessincubator.com

AI and Clean Energy: A New Hope

Applications in which AI Could Improve Green Tech:

- Wind and solar generation forecast
- Grid stability and reliability
- Demand forecast
- Demand-side management
- Energy storage
- Market design and operation

Example: Automation and Electricity Consumption



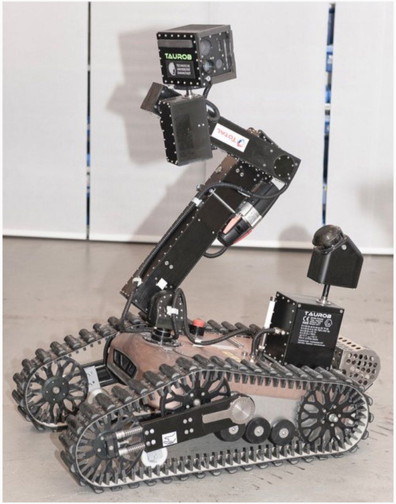
Source: www.beebryte.com

AI and Dirty Technologies: The Empire Strikes Back

AI also has the potential to enhance dirty technologies:

- Automatize tasks and redeploy workforce to more complex tasks
- IoT: huge inflow of data gathered via connected devices such as sensors placed along pipelines in oil and gas fields and power plants
- Improve utilization of physical capital, e.g. truck engine maintenance planning and execution
- Inventory management: material replenishment planning and optimization
- Exploration: subsurface, well data analysis...

Example: Robotics for Offshore Oil and Gas



The £36m Offshore Robotics for Certification of Assets (Orca) Programme is developing autonomous and semi-autonomous AI-enabled robots, capable of inspecting, repairing, maintaining and certifying offshore energy installations.

Source: BBC shorturl.at/hjES9

This Paper

- Theory: How should we expect a GPT like AI to change the dynamics of the "race" between clean and dirty technologies?
    - A GPT can lessen the path-dependence arising from the history of innovation, especially if the newer clean technologies have *higher absorptive capacity*

This Paper

- Theory: How should we expect a GPT like AI to change the dynamics of the "race" between clean and dirty technologies?
  - A GPT can lessen the path-dependence arising from the history of innovation, especially if the newer clean technologies have *higher absorptive capacity*
- Empirics: Backwards citations between patents to capture knowledge flows and measure absorptive capacity
  - Clean inventions "absorb" AI/ICT more than dirty ones.
  - Both within and across firms
  - Firm-level AI stock correlates with AI absorption in energy patents, esp. for clean
  - High 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

Literature Review 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; Helpman et al. 1996)
- AI as GPT (Brynjolfsson et al. 2021; Cockburn et al. 2018; Martinelli et al. 2021)
- "Clean" (*directed*) technological change (Acemoglu, Aghion, et al. 2012; Acemoglu, Akcigit, et al. 2016; Jaffe, Newell, et al. 2005; Popp, Newell, et al. 2010)
- Not much prior research at the intersection of those strands of literature (Verendel 2023)

Presentation Structure

1. Theory
2. Data
3. To What Extent are AI and ICT Absorbed Into Clean and Dirty Inventions?
4. Firm-Level Mechanisms
5. Summary & Discussion

Theory

Basic Ingredients of Directed Technological Change Model

Acemoglu et al. *AER* 2012

Final good

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

Clean and dirty inputs,
produced with a continuum of machines

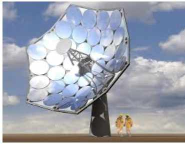
$$Y_{jt} = L_{jt}^{1-\alpha} \int_0^1 A_{ijt}^{\alpha} x_{ijt}^{\alpha} di$$

Scientists work on improving clean or dirty machines. They obtain temporary patent right to monopolistically produce machine i if they have a successful invention increasing its productivity.

$$\boxed{I_{ij} \sim Poisson(\eta_j) \Rightarrow A_{ijt} = (1+\gamma)A_{ijt-1}}$$

Rate of arrival of innovations

Incremental improvement



Evolution of the technological possibility frontier

$$A_{jt} \stackrel{\text{def}}{=} \int_0^1 A_{ijt} di = (1 + \gamma\eta s_{jt})A_{jt-1}$$

Mass of scientists in sector j

Technological Change is Geared towards the Most Productive Sector

Equilibrium ratio of expected profit of innovating in the clean vs dirty sector:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c}{\eta_d}\left(\frac{1+\gamma\eta_c s_{ct}}{1+\gamma\eta_d s_{dt}}\right)^{-(1-\epsilon)(1-\alpha)-1}\left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{-(1-\epsilon)(1-\alpha)}$$

A_{jt}: average productivity of machines sector j

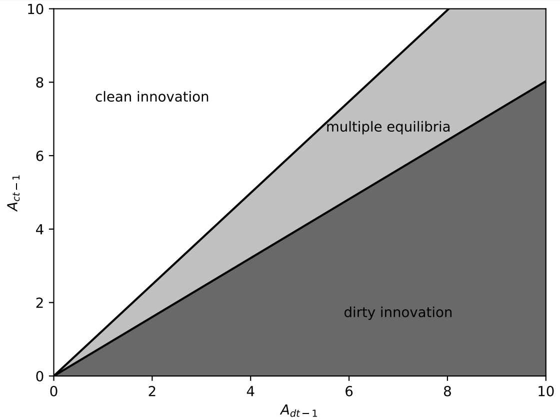
η_j: prob of successful innov in sector j

γ: incremental improvement in A_j from innovation

s_{jt}: share of scientists innovating in sector j

ϵ: Elas.subst. between clean and dirty inputs

α: Elas.subst. labor and machines



Adding GPT Spillovers and Absorptive Capacity

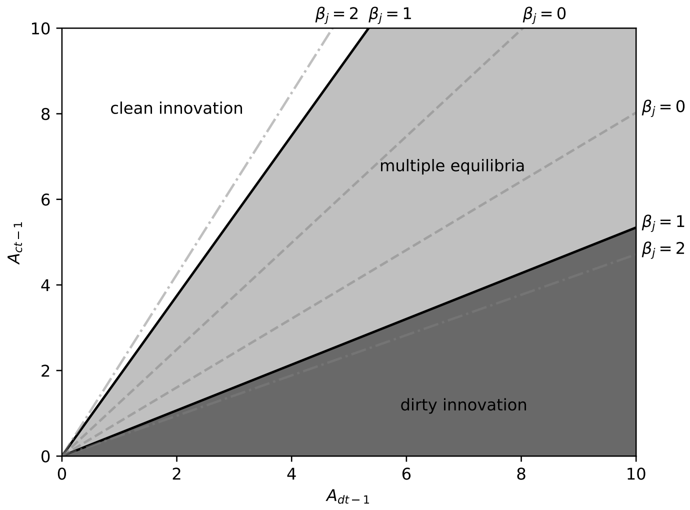
- Modify the innovation function to include GPT spillovers:

$$A_{jit} = (1 + \gamma + \beta_j GPT_t) A_{jit-1}$$

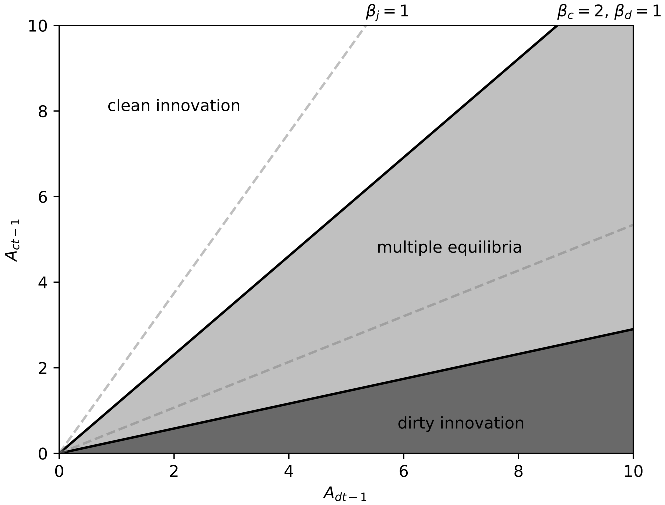
- β_j is the *absorptive capacity* of sector j (Cohen and Levinthal, 1990)
- GPT_t is exogenous
- The ratio of expected profits becomes:

$$\frac{\Pi_{ct}}{\Pi_{dt}} \equiv f(s_c, s_d) = \frac{\eta_c}{\eta_d} \frac{1+\gamma+\beta_c GPT_t}{1+\gamma+\beta_d GPT_t} \left(\frac{1+(\gamma+\beta_c GPT_t)\eta_c s_c}{1+(\gamma+\beta_d GPT_t)\eta_d s_d} \right)^{-\phi-1} \left(\frac{A_{ct-1}}{A_{dt-1}} \right)^{-\phi}$$

When $\beta_C = \beta_D > 0$: The Window of Multiple Equilibria Expands



When $\beta_C > \beta_D > 0$: The Area of Clean Equilibria Expands



From Theory to Empirics

- The area of clean equilibria expands if $\beta_C > \beta_D > 0$
- We need an empirical proxy for the relative absorptive capacity of clean vs dirty

    $\Rightarrow$ Patents' backward citations to AI/ICT
- To what extent clean patents cite more AI/ICT inventions then dirty patents?

Endogenizing Absorptive Capacity

- Invest in absorptive capacity: $\beta_j = b_j B_j$ at a cost $-\psi B_j^2$
- We show that:

Result

In equilibrium, investments in absorbing the GPT in a given sector increase with the existing accessible stock of the GPT_t and with the intrinsic absorptive capacity of the application sector:

(a) $\frac{dB_j^*}{dGPT_t} > 0$

(b) $\frac{dB_j^*}{db_j} > 0$

(c) *At the equilibrium for type j:* $\frac{d^2 B_j^*}{dGPT_t db_j} > 0$

From Theory to Empirics

- Intrinsic vs Endogeneous part: $\beta_j = b_j B_j$:
  - Firm fixed effects and controls to get as close as possible to intrinsic
- Theoretical predictions: $\frac{dB_j^*}{dGPT_t} > 0$, $\frac{d^2 B_j^*}{dGPT_t db_j} > 0$
  - Firms develop energy inventions that rely *more* on the GPT if they have a greater GPT knowledge stocks.
  - More so for clean than dirty inventions, if clean has higher intrinsic absortive capacity.

Accounting for Technological Maturity: Aging and Technological "Lock-In"

- Mature technologies are less able to undergo radical changes: aging causes lock-in.
- We allow absorptive capacity to decay with the stock of knowledge A_j:

$$\beta_j = b_j A_{jt-1}^{-\delta} B_j,$$

where $\delta \geq 0$ represents an ageing factor.

Result

The maturity of the technology in the application sector can impact absorptive capacity:

- *If the ageing factor is large ($\delta > 1$), then $\frac{dB_j^*}{dA_{jt-1}} < 0$ (tech lock-in)*
- *If not ($\delta < 1$), then $\frac{dB_j^*}{dA_{jt-1}} > 0$*

From Theory to Empirics

- Theoretical predictions: $\frac{dB_j^*}{dA_{jt-1}} > 0$ or > 0?

  $\Rightarrow$ Tech lock-in if firms with higher energy stocks ("incumbents") develop energy inventions that rely *less* on the GPT.

Recap - From Theory to Empirics

- Empirical proxy for the relative absorptive capacity of clean vs dirty ($\frac{\beta_C}{\beta_D}$)
  - Patents' backward citations to AI/ICT
- Intrinsic vs Endogeneous part: $\beta_j = b_j B_j$:
  - Fixed effects and controls to get as close as possible to intrinsic
- Theoretical predictions: $\frac{dB_j^*}{dGPT_t} > 0$, $\frac{d^2 B_j^*}{dGPT_t db_j} > 0$ and $\frac{dB_j^*}{dA_{jt-1}} > 0$
  - Firms with greater GPT knowledge stocks develop energy inventions that rely *more* on the GPT. More so for clean if clean has higher intrinsic absortive capacity.
  - Tech lock-in if firms with higher energy stocks develop energy inventions that rely *less* on the GPT.

Data

We Measure Innovation and Knowledge Flows Using Patent Data

- PATSTAT Global Spring 2021: energy families with a priority year between 1990 and 2018 (filed worldwide)
- We aggregate patent applications at the level of DOCDB families
- We use citations between patent families as a proxy for knowledge flows
- We link PATSTAT to Orbis to obtain firm-level patent counts and covariates
- We use patent technology codes (CPC and IPC) and keywords to identify inventions relevant to electricity, transport, AI and ICT.

Identifying Inventions in Energy, AI and ICT

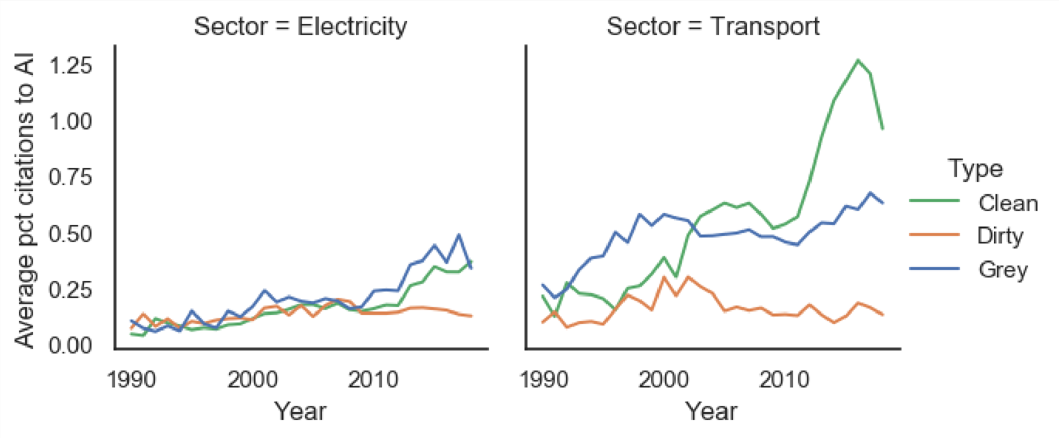
- Transport and Electricity: Clean/Grey/Dirty
  - CPC and IPC code's own harmonization of prior literature (Aghion et al. 2016; Dechezleprêtre et al. 2017; Johnstone et al. 2010; Lanzi et al. 2011; OECD 2016; Popp, Pless, et al. 2020)
  - We find 1.7M electricity families (48% clean) and 1.3M transport families (61% clean)
- AI
  - We follow the methodology presented in World Intellectual Property Organization (2019) (combination of technology codes and keyword search of abstract and title)
  - We find 548,641 AI families.
- ICT
  - Taxonomy of codes provided by Inaba et al. (2017)
  - We find 10.9M ICT families

AI Applications Can Enhance Many Energy Technologies

Application title	Sector	Type	Year	Citations to AI #	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

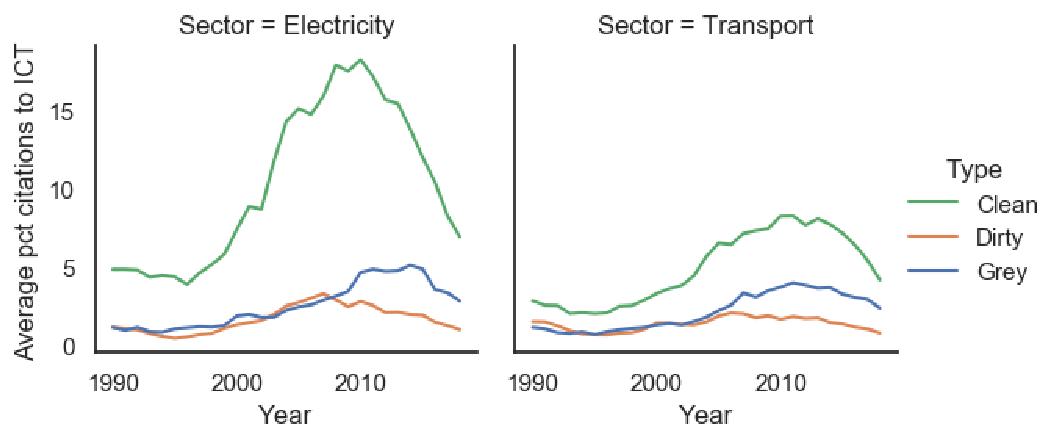
To What Extent are AI and ICT Absorbed Into Clean and Dirty Inventions?

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.

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

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

- $Absorption_{ijt}$: the percentage of backward citations going to AI or ICT for patent family i filed by firm j in year t.
- $Clean_i$ and $Grey_i$: 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.

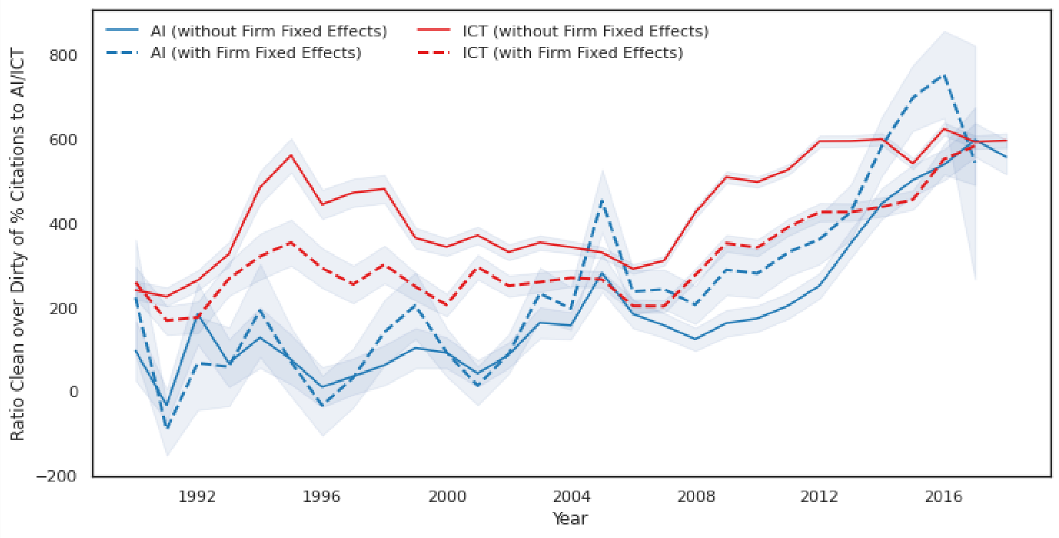
Clean Families Absorb AI More (Even with Quality Controls and Firm FEs)

	(1)	(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

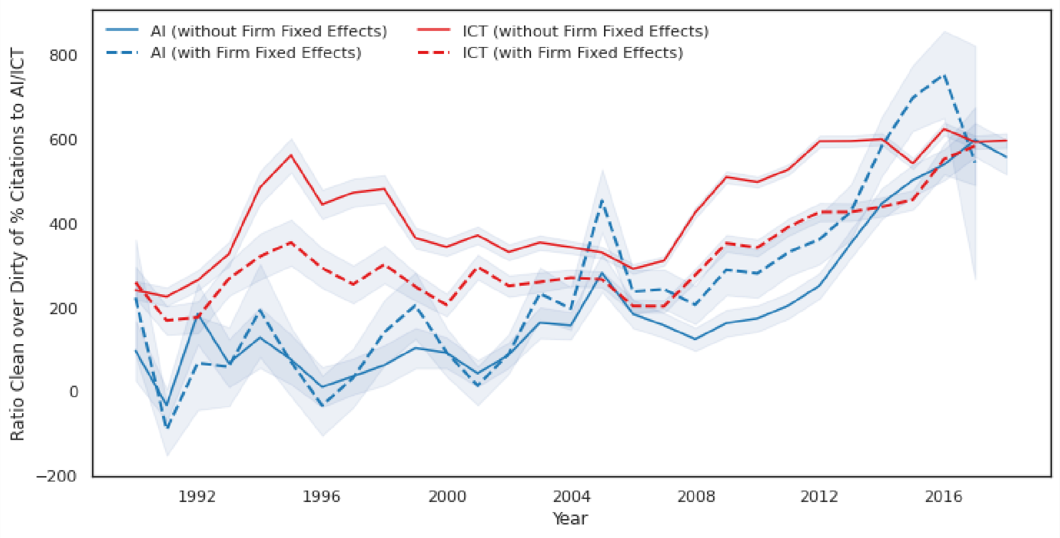
- Ratio Clean/Dirty $= \frac{100 \times \beta_c}{mean_d}$, where $mean_d$ is the % of backward citations going to AI (or ICT) in the average dirty family
- Quality Proxies: # citations received within three years, family size and # countries where the family was filed.
- Controls and Firm f.e. significantly reduce Ratio Clean/Dirty
- Similar results for ICT (not reported here).

Mind the Gap: Clean AI Absorption Relative to Dirty Increases Over Time



Within- and between-firm estimates start to diverge around 2005 for ICT and around 2014 for AI.

Within vs Between Firm Estimates: Firm-Level Characteristics Seem to Matter



Within- and between-firm estimates start to diverge around 2005 for ICT and around 2014 for AI.

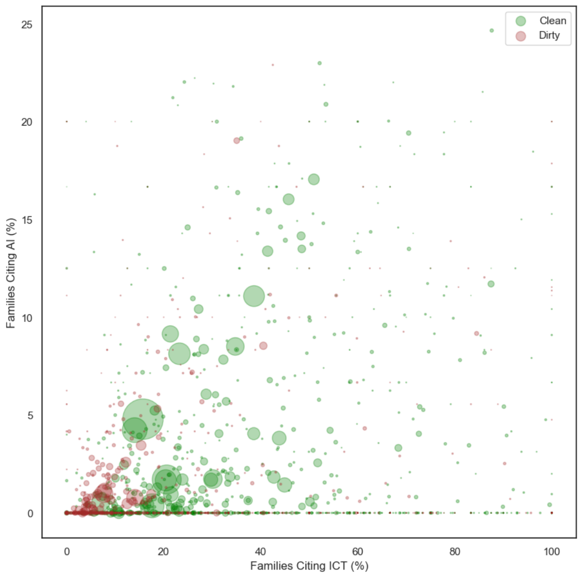
Firm-Level Mechanisms

Investigating the Role of Firms' Knowledge Stocks in Driving AI Absorption

- Firm-level measure of absorption: percent of a firm's families citing AI
- We construct a dataset at the firm-year-*portfolio* level

  6 types of *portfolio*: clean electricity, clean transport, grey electricity, grey transport, dirty electricity or dirty transport.
- For each firm-year-portfolio observation, we calculate the percentage of families that cites at least one AI or ICT.

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

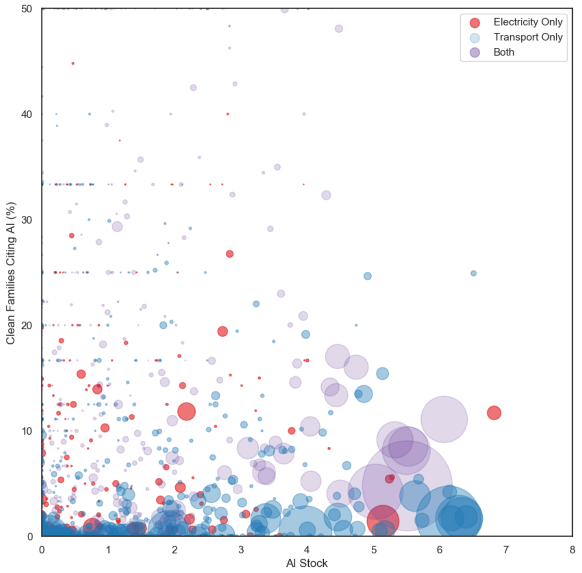
Over Time: Firm-Level Absorption is Increasing for Clean Technologies

- 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

Examples of Top Energy Patenting Firms

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

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



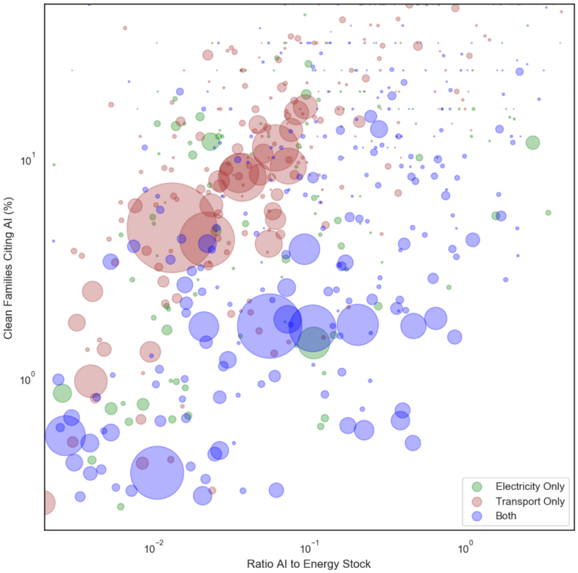
- Y-axis: % of clean families citing AI
- X-axis: AI stock (log)
- Bubble size proportional to # clean families
- Significant variation across firms
- Firms doing both have higher AI stock: e.g. Panasonic, Mitsubishi

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

Firm-Level Specifications

$$\begin{aligned} FirmAbsorption_{jtk} = {} & \beta_0 + \beta_1 StockGPT_{jt-1} + \beta_2 StockEnergy_{jt-1} \\ & + \beta_c Clean_k + \beta_g Grey_k + \beta_t Transport_k + \mathbf{bX}_{jt} + \delta_t + \delta_j + \epsilon_{jtk} \end{aligned}$$

- $FirmAbsorption_{jtk}$: % of families in portfolio k citing some AI/ICT patents
- $StockGPT_{jt-1}$: 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)
- $Clean_k / Grey_k / Transport_k$: binary variables equal to 1 for clean/grey/transport portfolios.
- $\mathbf{X}_i$ 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: $Clean_k$, $Grey_k$, $Transport_k$

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
- Clean and transport portfolios cite more AI, even within firms
- AI stock more strongly correlates with AI absorption in clean portfolios
  $\Rightarrow$ an intrinsic component to the absorptive capacity of clean tech and of transport vs electricity?
- Within firms: changes in AI stock over time does not correlate strongly with AI absorption
- Similar results for ICT

Summary & Discussion

Summary

- A GPT can lessen the path-dependence arising from the history of innovation, especially if the newer clean technologies have higher absorptive capacity.

  i.e., GPTs can not only drive growth, but also direct technological change

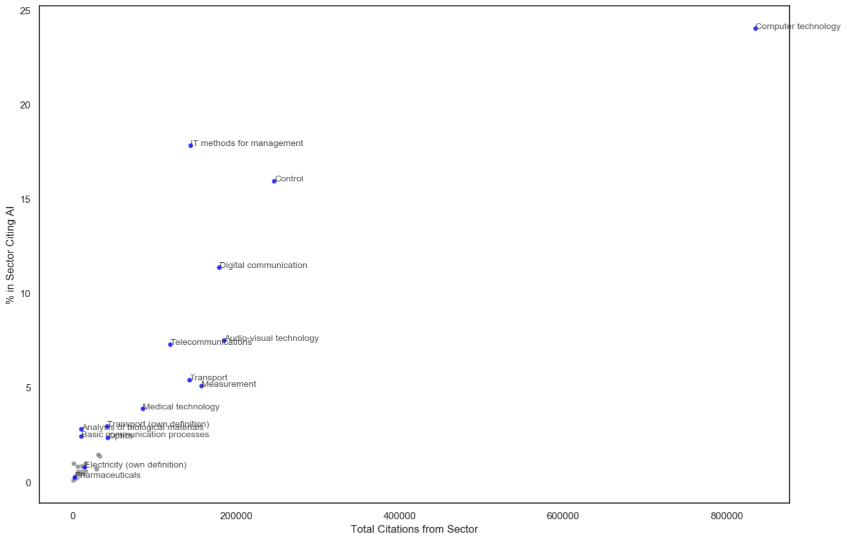
- AI seems set to accelerate clean innovation
  - Clean technologies rely more on AI, especially in transport. Widening gap.
  - Using AI is associated with greater innovative value (proxied by citations received)
  - Variation in AI absorption can be explained partially by firm spillovers
  - Tentative evidence that there is variation in the intrinsic absorptive capacity of different technologies.

$\Rightarrow$ Firms as essential locus for knowledge spillovers btw GPT and energy tech

$\Rightarrow$ Joint support for firm-level capabilities in digital and low-carbon technologies

Encouraging Conclusion but..

Absorption in Other Application Sectors Much Higher



Limitations... Future Work Needed!

- Better understanding of mechanisms needed to draw conclusions for policy practice
  - Spillovers captured by new entrants versus established firms
  - Role of co-location
- Analysis does not distinguish between specific applications or types of AI, some of which may have more of a GPT character than others
- Much of AI is not patented

Thank you!

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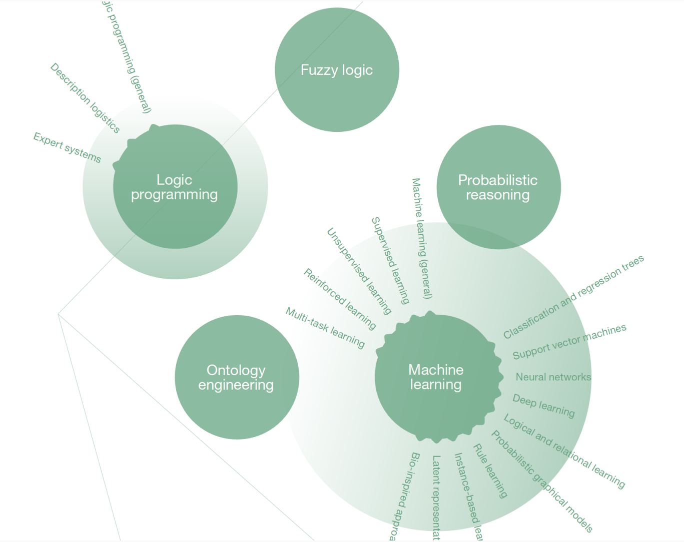
Who's Who: AI, Big Data, Internet of Things...

- The IoT typically consists of a network of smart devices that have sensors
    - Generate (big) data
- Big Data is then used to develop algorithm
- AI refers to systems that, in response to data observed, collected and analysed, change behaviour
    - The sensors can implement these algorithms, "make decisions" and act

5 Clusters of AI Techniques



Source: World Intellectual Property Organization (2019)

Who's Who: AI, Big Data, Internet of Things...

Functional applications of AI include natural language and speech processing, prediction, robotics, and others

Source: World Intellectual Property Organization (2019)

Energy Patents Citing AI 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.