

AI and Productivity: The Role of Innovation

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Does AI affect productivity?

- AI can **enhance** productivity:
 - task level: improve customer support (Brynjolfsson et al., 2025)
- **Cautious** views:
 - requires costly adjustment and complementary investments, generating **J-curve dynamics** in firm productivity (McElheran et al., 2025)
- **Aggregate productivity**:
 - task-based framework: translate task-level cost savings into aggregate total factor productivity (TFP)
 - 0.07 to 1.24 percentage points (pp) per year (Aghion and Bunel, 2024)
 - 0.064 pp per year (Acemoglu, 2025)
 - historical analogy to earlier general-purpose technology waves
 - 0.8 to 1.3 pp per year (Aghion and Bunel, 2024)

How does AI affect innovation?

The innovation channel:

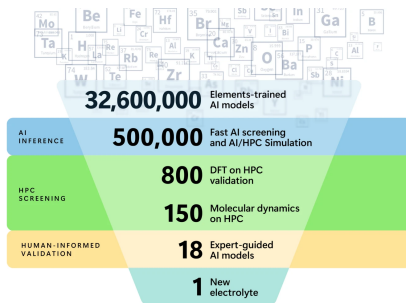
- AI affects productivity by increasing research productivity and reshaping the innovation process, functioning as [a method of invention](#) (Cockburn et al., 2018)

Mixed predictions on innovation impacts: [▶ detailed literature](#)

- AI can [strengthen](#) innovation
 - data processing, task automation, text analysis, strategic foresight, prediction and search
- AI can [weaken](#) innovation
 - requires complementary investments; concentrated gains; path dependence; generates low-quality patent drafts

How AI affects firm innovation: example

- Azure Quantum Elements, an **AI-powered** research platform
 - developed by Microsoft (Microsoft, 2024)
 - the resulting electrolyte compositions
 - **patent** publication number US2025/0105343 A1



* HPC: high-performance computing; DFT: density functional theory

Research questions

- Does AI adoption affect corporate **innovation**?
- Through which channels does AI adoption affect **innovation**?
- What are the firm-level impacts of AI adoption on **TFP** and other outcomes, and the implied aggregate **productivity** effects?

Key findings

Compared to non-adoptors, AI-adopting firms:

- Produce **more patents** after adoption
- Those patents receive **more citations**
- Adjust their innovation strategies to generate patents that
 - are more **original** and span more **distant technological areas**
 - are more **exploitative** (deepen utilization of their existing technological base)
 - are more **general** and contain more **claims** (the scope of a patentee's exclusive rights)
- Show stronger effects among firms with a **focused business scope**

Key findings

Potential channels:

- Efficiency
 - improving **inventor productivity** and **innovation efficiency**
- Inventor composition
 - employ more inventors
 - those with **no prior patenting experience**
 - those with **AI expertise**
 - deepen expertise in **specialized** technological areas
- Knowledge recombination
 - **larger** and **more** unique inventor teams
 - more distinctive **core skills**
 - greater use of **new knowledge**

Key findings

Productivity and economic outcomes of AI adoption:

- Increasing R&D but not capital expenditure
- No significant changes in operating costs
- Higher market value and firm-level productivity
- 8.87% AI-induced increase among firm-level TFP in AI adopters and 0.7% decrease in firm-level TFP among non-adopters, implying a 0.61% increase in aggregate value-added TFP

“As artificial intelligence evolves, we must remember that its power lies not in replacing human intelligence but in augmenting it. The true potential of AI lies in its ability to amplify human creativity and ingenuity.”

—Ginni Rometty, *Former CEO of IBM*

Data and sample

- 2,600 US public innovative firms with 791,040 patents
 - sample period: 2011-2021 (mitigate right truncation in granted patent data)
 - patent- and inventor-level data: USPTO
 - firm-level data: Compustat
 - linking patents to firms: combining Kogan et al. (2017), Wharton Research Data Services (WRDS), Stoffman et al. (2022), and manual data matching
 - exclude firms in financial industries (SIC code 6000 to 6999)
 - have filed at least one patent during the sample period
- Innovation output proxy:
 - innovation outcomes: patent-based innovation metrics
 - innovation timing: the filing date of a granted patent

Challenges in measuring firm-level AI adoption

- Previous studies use **proxies** for AI investment and AI exposure:
 - AI-related job postings (Babina et al., 2024)
 - task-level exposure to AI based on Occupational Information Network (O*NET) data (Eloundou et al., 2024; Acemoglu, 2025; Eisefeldt et al., 2025; Felten et al., 2021)
- We construct a direct **firm-level AI adoption** measure
 - based on historical IT installation data
 - captures adoption timing and locations

AI product data

- Data source: SWZD Historical Company Intelligence Database
 - tracks historical site-level **IT product installations** collected via engagements
 - captures approximately **90%** of global IT purchasing activity
- AI products:
 - ML frameworks and platforms: TensorFlow, Scikit-learn, H2O.ai
 - enterprise and cloud ML platforms: Microsoft Azure Machine Learning, Google Cloud Machine Learning Engine, Amazon Machine Learning
 - enterprise AI platform: Dataiku
 - AI applications and data infrastructure: Nara Logics, CrowdFlower

*These examples are illustrative rather than exhaustive

AI adoption measure

- AI adoption measure:
 - the earliest observed **installation date** of an AI product at any of the firm's **sites**
 - 518 firms adopt AI technology and 2,082 firms never do so
 - industry distribution **▶ industry distribution**
 - geographical distribution: San Francisco, New York, Washington D.C., Chicago, and Los Angeles **▶ geographical distribution**

Empirical design

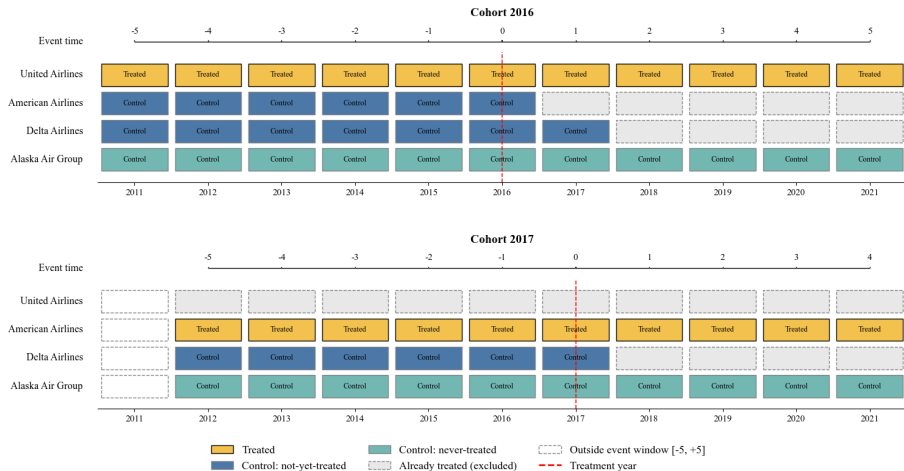
- **Staggered adoption** \Rightarrow stacked difference-in-differences (DiD) approach
- **Pre-adoption parallel trends** \Rightarrow cohort-specific event-time lead-lag regressions
- **Endogeneity** \Rightarrow control function with an instrumental variable (IV)

Robustness tests:

- **Selection on observables** \Rightarrow entropy balancing (balanced covariate distribution across adopters and non-adopters)
- **Confounding** \Rightarrow placebo test (randomly assign fictitious AI adoption among never-adopters)

Stacked DiD: an illustration

- Define cohorts by adoption year
- Re-index calendar year relative to event year $[-5, +5]$
- Stack all cohort comparisons
- Estimate average treatment effects using within-cohort variation



- Stacked Difference-in-Differences for staggered AI adoption

- **treated**: firms adopting AI at different times (AI-adopting firms)
- **control**: firms that have not yet adopted AI (non-adopting firms)
- **cohort**: based on AI adoption year, event window $[-5, +5]$

$$\mathbb{E}[Y_{i,j,c,t+h} | \cdot] = \exp\left(\beta_h AI_{i,j,c,t} + \alpha_{i,c} + \psi_{t+h,c}\right)$$

- $AI_{i,j,c,t} = 1$ if a firm i of industry j in cohort c adopts AI in year t and 0 otherwise
- $Y_{i,j,c,t+h}$: innovation measures for firm i in year $t+h$, $h \in \{1, 2, 3\}$
- $\alpha_{i,c}$: firm-by-cohort FEs \rightarrow absorb time-invariant firm heterogeneity within cohorts
- $\psi_{t+h,c}$: year-by-cohort FEs \rightarrow absorb cohort-specific shocks
- standard errors: clustered at the firm level
- identification: compare treated and control firms within the same cohort-year, net of persistent firm differences
- Pseudo-Poisson Maximum Likelihood (PPML) models: **count and count-like variables with many zeros** (Cohn et al., 2022)

AI and innovation: quantity and quality

How does AI adoption affect innovation **quantity and quality**?

- Patent count: sum of granted patents
- Adjusted citation: average of time and technology class adjusted forward citations
- Relative to non-adopters, AI-adopters:
 - increase post-adoption patenting
 - receive more adjusted citations

Variable	Patent count			Adjusted citation		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.131*** (3.02)	0.149*** (3.60)	0.175*** (4.56)	0.265*** (6.05)	0.277*** (5.71)	0.331*** (5.96)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.928	0.933	0.938	0.261	0.255	0.248
Observations	60,738	48,606	38,245	53,623	42,190	32,551

AI and innovation: strategy

How does AI adoption affect innovation novelty?

- Originality: 1 - average Herfindahl–Hirschman Index (HHI) of cited patents
- Distance: average technology propinquity between patents and the overall technology expertise of its owning firm (Akcigit et al., 2016)
- AI adopters' post-adoption patents:
 - built on broader technology domains
 - more technologically distant from prior portfolios

Variable	Originality			Distance		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.169*** (5.55)	0.214*** (6.52)	0.195*** (5.20)	0.137*** (4.54)	0.162*** (4.98)	0.125*** (3.51)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0885	0.0846	0.0805	0.116	0.117	0.118
Observations	56,947	45,518	35,653	51,366	42,174	33,865

AI and innovation: strategy

How does AI adoption shift innovation **direction**?

- Exploitative (explorative):
 - $\geq 80\%$ of backward citations are (not) based on **existing expertise**
 - Existing expertise: patents filed in the prior five years and their backward citations
- Relative to non-adopters, AI-adopters:
 - deepen the utilization of their existing technological base
 - explore new technological knowledge

Variable	Exploitative			Explorative		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.147*** (6.50)	0.162*** (6.59)	0.154*** (5.69)	0.185** (2.12)	0.204** (1.97)	0.191* (1.69)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.109	0.104	0.0988	0.139	0.144	0.152
Observations	48,478	38,951	30,639	51,702	39,704	30,331

AI and innovation: strategy

How does AI adoption shift innovation **reach**?

- Generality: 1 - average HHI of citing patents
- Claim: scope of a patentee's **exclusive rights**
- AI adopters' post-adoption patents:
 - shape future innovation across various technological fields
 - have broader legal scope

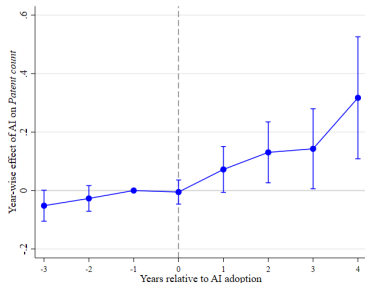
Variable	Generality			Claim		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.298*** (5.33)	0.317*** (4.93)	0.449*** (5.34)	0.142*** (6.01)	0.155*** (6.13)	0.161*** (5.69))
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.115	0.112	0.109	0.308	0.304	0.299
Observations	40,887	31,240	23,334	60,678	48,574	38,215

Dynamic effects

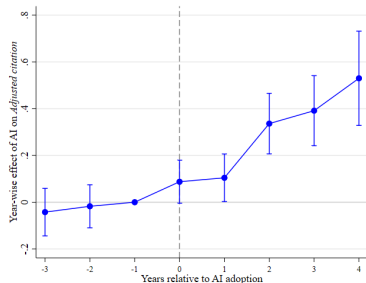
- Pre-adoption parallel trends

- $Y_{i,j,c,t+1}$: innovation outcome for firm i in year $t+1$
- reference period: one year before adoption

Panel A: Innovation Quantity and Quality



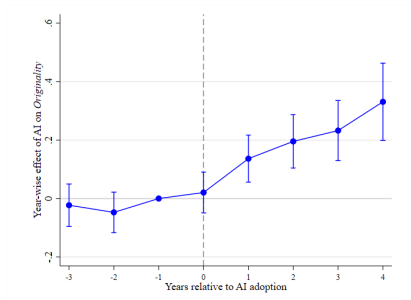
(a) Patent count



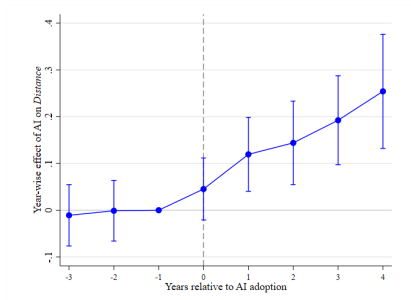
(b) Adjusted citation

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Panel B: Innovation Strategy (Novelty)



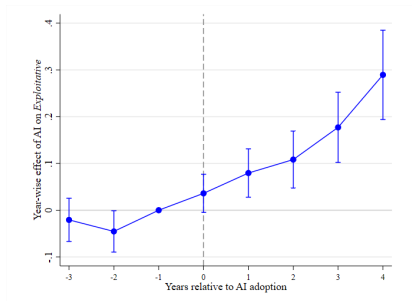
(c) Originality



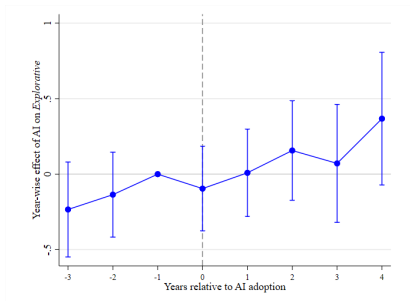
(d) Distance

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Panel B: Innovation Strategy (Direction)



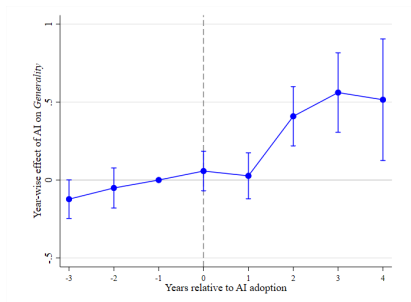
(e) Exploitative



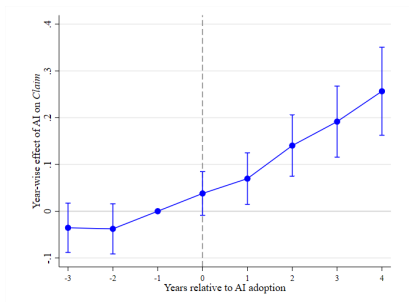
(f) Explorative

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Panel B: Innovation Strategy (Reach)



(g) Generality



(h) Claim

Endogeneity

- AI adoption is **endogenous**:
 - omitted variables: unobservables drive both adoption and innovation
 - reverse causality: innovation affects AI adoption decisions
 - forward-looking selection: expected future innovation drives adoption
 - To mitigate endogeneity:
 - compare average R&D investment: adopting firms spend **significantly less** on R&D than non-adopting firms
 - fixed effects, event-time lead-lag regression, entropy balancing, placebo test
- ⇒ **control function** approach with an **instrumental variable (IV)**

Endogeneity: control function approach

- Alleviates **endogeneity bias** in **non-linear models** (Wooldridge, 2015)
 - 2SLS: suitable for linear models
- First stage:
 - uses IV to isolate **exogenous variation** in the endogenous variable
 - provides separate variation in the **generalized residuals**
- Second stage:
 - includes generalized residuals as **a control function**
 - the endogenous variable becomes **conditionally exogenous**

Control function approach

- IV: *AI exposure*
 - focal firm's exposure to AI-strong universities via the firm-university STEM worker hiring networks as of 2010 (Babina et al., 2024)
- **Relevance** condition:
 - firms with higher exposure have a better access to AI-trained talent and are more likely to adopt AI
- **Exclusion** restriction:
 - measured *ex-ante* before AI boom
 - AI talent and high-quality human capital **do not necessarily overlap**

Control function approach

First stage:

- **Probit** model on the stacked panel

$$AI_{i,j,c,t}^* = \beta AI \text{ exposure}_{i,j,c} + \theta \text{ Top 10 exposure}_{i,j,c} + \gamma_{j,c} + \tau_{t,c} + u_{i,j,c,t},$$
$$AI_{i,j,c,t} = \mathbf{1}\{AI_{i,j,c,t}^* > 0\}, \quad \Pr(AI_{i,j,c,t} = 1 \mid \cdot) = \Phi(\mathbf{z}'_{i,j,c,t}\boldsymbol{\delta})$$

- $AI \text{ exposure}_{i,j,c}$: exposure to AI-strong universities via firm–university STEM hiring networks as of 2010 (Babina et al., 2024)
- $\text{Top 10 exposure}_{i,j,c}$: exposure to the top-10 universities (2010 U.S. News & World Report) via the same networks
- $\gamma_{j,c}$ and $\tau_{t,c}$: industry-by-cohort and year-by-cohort fixed effects
- $\mathbf{z}_{i,j,c,t}$: the regressors and fixed effects
- $\boldsymbol{\delta}$: the corresponding coefficient vector
- $\Phi(\cdot)$: the standard normal CDF
- standard errors: clustered at the firm level

Control function approach

- Generalized residuals from the first-stage probit model:

$$\widehat{Residual}_{i,j,c,t} = AI_{i,j,c,t} \frac{\phi(\mathbf{z}'_{i,j,c,t} \hat{\boldsymbol{\delta}})}{\Phi(\mathbf{z}'_{i,j,c,t} \hat{\boldsymbol{\delta}})} - (1 - AI_{i,j,c,t}) \frac{\phi(\mathbf{z}'_{i,j,c,t} \hat{\boldsymbol{\delta}})}{1 - \Phi(\mathbf{z}'_{i,j,c,t} \hat{\boldsymbol{\delta}})},$$

- $\mathbf{z}_{i,j,c,t}$: the regressors and fixed effects
- $\hat{\boldsymbol{\delta}}$: the first-stage estimate
- $\phi(\cdot)$ and $\Phi(\cdot)$: the standard normal PDF and CDF

Control function approach

Second stage:

- Pseudo-Poisson Maximum Likelihood model
 - include [the generalized residuals](#) from the first stage

$$\mathbb{E}[Y_{i,j,c,t+h} | \cdot] = \exp\left(\beta AI_{i,j,c,t} + \theta \text{Top 10 exposure}_{i,j,c} + \kappa \widehat{\text{Residual}}_{i,j,c,t} + \gamma_{j,c} + \psi_{t+h,c}\right)$$

- $Y_{i,j,c,t+h}$: innovation outcome for firm i in year $t + h$, $h \in \{1, 2, 3\}$
- $\gamma_{j,c}$ and $\psi_{t+h,c}$: industry-by-cohort and year-by-cohort fixed effects
- standard errors: computed using a firm-level cluster bootstrap with 1,000 replications

Control function approach

- After accounting for the **endogeneity** of AI adoption:

Variable	1st Stage	2nd Stage: Quantity and Quality	
	AI	Patent count	Adjusted citation
	(1)	(2)	(3)
AI exposure	0.572*** (4.68)		
AI		6.118*** (4.36)	1.485*** (2.17)
Top 10 exposure	-0.685 (-1.54)	0.477 (0.74)	1.061** (2.41)
Residual		-2.240*** (-2.95)	-0.473 (-1.26)
Year-Cohort FE	Yes	Yes	Yes
Industry-Cohort FE	Yes	Yes	Yes
Wald χ^2	541.82		
Pseudo R^2	0.1149	0.427	0.0753
Observations	19,918	6,271	6,199

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Control function approach

Variable	2nd Stage: Innovation Strategy					
	Originality	Distance	Exploitative	Explorative	Generality	Claim
	(4)	(5)	(6)	(7)	(8)	(9)
AI	1.071*** (2.89)	0.832** (1.96)	1.664*** (4.42)	-0.811 (-0.93)	1.822** (2.03)	1.348*** (3.68)
Top 10 exposure	0.274 (0.93)	0.367 (1.00)	0.388 (1.60)	0.730 (0.52)	1.266** (2.11)	0.469** (2.03)
Residual	-0.394** (-1.99)	-0.194 (-0.86)	-0.608*** (-3.00)	0.311 (0.65)	-0.646 (-1.30)	-0.479*** (-2.61)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0464	0.0560	0.0565	0.0310	0.0466	0.0969
Observations	6,271	6,271	6,213	6,243	5,939	6,271

⇒ AI's effect on corporate innovation remain **robust**

Underlying channels

- **Efficiency** ▶ results for the efficiency channel
 - inventor productivity
 - innovation efficiency
- **Inventor composition** ▶ results for inventor composition
 - inventor pool
 - first-time inventor
 - AI-experienced inventor
 - specialization
- **Knowledge recombination** ▶ results for knowledge recombination
 - team size
 - unique inventor team
 - core skill breadth
 - new cite ratio

Efficiency channel

AI adopters exhibit higher **inventor productivity** and greater **innovation efficiency**:

- Inventor productivity: average number of patents filed by firm i 's inventors
 - patents with multiple inventors: assign equally-weighted fractions of the patent to each of its inventors (Moretti, 2021)
- Innovation efficiency: number of patents/R&D

Variable	Inventor productivity			Innovation efficiency		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.144*** (4.73)	0.166*** (5.24)	0.162*** (4.32)	0.161*** (5.02)	0.149*** (4.22)	0.166*** (4.27)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.142	0.139	0.136	0.122	0.121	0.120
Observations	60,738	48,606	38,245	58,601	46,813	36,746

[▶ Back to channels](#)

Inventor composition channel

AI adopters expand their **inventor pool** and employ more **specialized inventors**

- Inventor pool: number of unique inventors
- Specialization: average specialization score of inventors in each inventor team
 - inventor specialization score: HHI of her 3-digit CPC classes, computed using patents applied for up to year $t - 1$ (Li and Wang, 2023)

Variable	Inventor pool			Specialization		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.077* (1.65)	0.094** (2.16)	0.127*** (3.43)	0.148*** (6.37)	0.144*** (5.32)	0.148*** (5.02)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.948	0.952	0.956	0.0927	0.0886	0.0844
Observations	60,738	48,606	38,245	59,355	47,522	37,417

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Inventor composition channel

AI adopters increase **first-time inventors** and **AI-experienced inventors**:

- First-time inventor: average share of inventors on a patent team with no prior USPTO patent applications before year t
- AI-experienced inventor: average share of inventors on a patent's team who have previously filed AI patent applications before year t , as identified by Giczy et al. (2022)

Variable	First-time inventor			AI-experienced inventor		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.164*** (2.93)	0.214*** (3.52)	0.199*** (2.80)	0.064* (1.69)	0.070* (1.75)	0.037 (0.87)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0930	0.0932	0.0955	0.177	0.172	0.167
Observations	51,044	40,567	31,523	46,628	37,336	29,300

[▶ Back to channels](#)

Knowledge recombination channel

AI adopters increase **inventor team size** and **unique team compositions**

- Team size: average number of inventors per patent
- Unique inventor team: number of distinct inventor teams (unique combinations of inventors)

Variable	Team size			Unique inventor team		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.142*** (5.69)	0.150*** (5.43)	0.154*** (5.08)	0.080* (1.67)	0.106** (2.35)	0.159*** (4.17)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.237	0.231	0.227	0.939	0.944	0.948
Observations	60,738	48,606	38,245	60,738	48,606	38,245

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Heterogeneous effects

- Stronger effects among firms:
 - with a **focused business scope** ▶ results for focused firms
- Not primarily driven by
 - large firms ▶ results for large firms
 - financial constraints ▶ results for unconstrained firms
 - technological capabilities ▶ results for technological capabilities

Heterogeneous effects: business focus

Firms with a **focused business scope**:

- Focused firm: firms with only one business segment in 2015
 - higher quality and more coherent internal data
 - deeper domain expertise and tacit knowledge

Variable	Patent count	Adjusted citation
	(1)	(2)
AI	0.175*** (4.41)	0.315*** (5.52)
AI x Focused firm	0.445 (1.63)	0.368 (1.16)
Year-Cohort FE	Yes	Yes
Firm-Cohort FE	Yes	Yes
Year-Cohort-Focused firm FE	Yes	Yes
Firm-Cohort-Focused firm FE	Yes	Yes
Pseudo R^2	0.938	0.251
Observations	36,792	39,862

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Heterogeneous effects: business focus

Variable	Originality	Distance	Exploitative	Explorative	Generality	Claim
	(3)	(4)	(5)	(6)	(7)	(8)
AI	0.178*** (4.50)	0.119*** (3.20)	0.148*** (5.08)	0.144 (1.21)	0.420*** (4.70)	0.134*** (4.52)
AI x Focused firm	0.411*** (2.98)	0.370** (2.12)	0.251** (2.37)	0.374 (0.88)	0.592 (1.37)	0.348*** (2.84)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort-Focused firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort-Focused firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0812	0.118	0.100	0.142	0.108	0.301
Observations	34,292	32,743	29,514	37,663	22,786	36,762

▶ Back to heterogeneous effects

Productivity and economic outcomes

- Intangible versus tangible investment ▶ results for investment
 - R&D investment
 - capital expenditure
- Operating costs ▶ results for operating costs
 - production cost
 - non-production cost
 - total operating cost
- Market value ▶ results for market value
 - Tobin's q
 - Total q
- Firm-level productivity ▶ results for productivity
 - value-added TFP
 - labor
 - capital

Economic outcomes

Does AI adoption affect R&D or physical capital investment?

- R&D: R&D/total assets
- Capital expenditure: capital expenditures/total assets

Variable	R&D			Capital expenditure		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.006*** (3.19)	0.006*** (3.09)	0.006*** (2.92)	-0.000 (-0.12)	-0.001 (-0.71)	-0.001 (-0.58)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.847	0.857	0.863	0.650	0.663	0.676
Observations	65,054	54,278	44,353	65,018	54,250	44,332

▶ Back to economic consequences

Does AI reduce **operating costs**?

- Production cost: cost of goods sold/total sales
- Non-production cost: (selling, general and administrative expenses - R&D expenses - advertising expenses)/total sales
- Total operating cost: total operating expenses/total sales

Variable	Production cost			Non-production cost			Total operating cost		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AI	0.145 (1.04)	0.154 (1.14)	0.121 (1.01)	-0.001 (-0.07)	-0.013 (-0.91)	-0.017 (-1.30)	0.132 (0.61)	0.063 (0.30)	0.000 (0.00)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.617	0.619	0.639	0.761	0.787	0.816	0.623	0.632	0.661
Observations	65,054	54,278	44,353	56,546	47,539	39,179	65,054	54,278	44,353

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Do AI-adopting firms receive higher **market valuations**?

- Tobin's q : (total assets + market value of equity - book value of equity)/total assets
- Total q : incorporates an estimate of intangible capital (Peters and Taylor, 2017)

Variable	Tobin's q			Total q		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.273*** (4.27)	0.246*** (3.59)	0.163** (2.40)	0.329*** (3.72)	0.337*** (3.59)	0.242*** (2.63)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.713	0.728	0.752	0.715	0.714	0.710
Observations	64,938	54,174	44,260	64,620	53,917	44,081

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Firm-Level Productivity

Does AI adoption affect **firm-level productivity**?

- Value-added TFP: residual from a Cobb–Douglas value-added production function estimated with the generalized method of moments (GMM) approach of Wooldridge (2009)
- Labor: natural logarithm of labor (L)
- Capital: natural logarithm of capital (K)

Variable	Value-added TFP			Labor			Capital		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AI	0.082*** (4.73)	0.080*** (4.44)	0.093*** (4.67)	0.019 (0.86)	0.024 (1.11)	0.029 (1.39)	-0.009 (-0.37)	0.001 (0.02)	0.007 (0.27)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R ²	0.878	0.887	0.893	0.977	0.981	0.983	0.979	0.982	0.984
Observations	59,981	49,987	40,841	59,981	49,987	40,841	59,981	49,987	40,841

Firm-Level Productivity

Do **non-adopters** experience significant improvement in value-add TFP, labor, and capital?

Variable	Value-added TFP			Labor			Capital		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Post</i>	-0.009*** (-5.59)	-0.007*** (-4.26)	-0.005*** (-3.48)	0.002 (0.96)	0.002 (1.17)	0.002 (1.14)	0.003 (1.52)	0.002 (0.87)	0.001 (0.64)
<i>Adopter × Post</i>	0.084*** (4.84)	0.083*** (4.53)	0.094*** (4.72)	0.020 (0.89)	0.025 (1.15)	0.030 (1.42)	-0.009 (-0.36)	0.001 (0.05)	0.007 (0.28)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R ²	0.878	0.887	0.893	0.977	0.981	0.983	0.979	0.982	0.984
Observations	59,981	49,987	40,841	59,981	49,987	40,841	59,981	49,987	40,841

▶ Back to economic consequences

What are the implied **aggregate productivity** effects?

- Use a first-order Hulten-style aggregation (Hulten, 1978) to translate AI-induced firm-level TFP gains into aggregate productivity growth

$$d \ln A_h^{\text{agg}} = \sum_{i \in S} w_i d \ln A_{ih} + \sum_{j \in N} w_j d \ln A_{jh} \quad (1)$$

- S : AI adopters, N : non-adopters
- $d \ln A_{ih}$ ($d \ln A_{jh}$): the horizon- h change in firm-level value-added TFP for adopter i (non-adopter j)
- w_i (w_j): firm's Domar-style weight, defined as its value-added share of GDP

Aggregate Productivity

- Let $w^S \equiv \sum_{i \in S} w_i$ and $w^N \equiv \sum_{j \in N} w_j$
- Weighted-average value-added TFP changes for adopters and non-adopters

$$g_h^S \equiv \frac{\sum_{i \in S} w_i d \ln A_{ih}}{w^S}, \quad g_h^N \equiv \frac{\sum_{j \in N} w_j d \ln A_{jh}}{w^N}$$

⇒ Rewrite Equation (1) as

$$d \ln A_h^{\text{agg}} = w^S g_h^S + w^N g_h^N \quad (2)$$

Aggregate Productivity

- $\hat{\beta}_h$: approximation of the difference in weighted-average value-added TFP changes between adopters and non-adopters

$$\hat{\beta}_h \approx g_h^S - g_h^N \quad (3)$$

- $\hat{\beta}_h^N$: approximation of the average change in value-added TFP among non-adopters

$$\hat{\beta}_h^N \approx g_h^N \quad (4)$$

- Substituting Equation (3) and Equation (4) into Equation (2) yields:

$$d \ln A_h^{\text{agg}} \approx w^S \hat{\beta}_h + (w^S + w^N) \hat{\beta}_h^N \quad (5)$$

Aggregate Productivity

- AI adopters' contribution to aggregate value-added TFP:
 - 0.085 log points increase in value-added TFP relative to non-adopters
 - Domar-style weight: 8.72%
 - ⇒ 0.74% ($e^{0.0872 \times 0.085} - 1$) increase in aggregate value-added TFP
- Non-adopters' contribution to aggregate value-added TFP:
 - -0.007 log points change in value-added TFP
 - Domar-style weight: 9.89%
 - ⇒ -0.07% ($e^{-0.007 \times 0.0989} - 1$) change in aggregate value-added TFP
- Implied aggregate contribution using Hulten-style aggregation:
 - 0.0061 log points in a typical post-adoption year
 - ⇒ 0.61% ($e^{0.0061} - 1$) increase in aggregate value-added TFP

- Entropy balancing ▶ results for entropy balancing
 - achieve **covariate balance** between AI-using and control firms
- Placebo test ▶ results for placebo test
 - **randomly assign** fictitious AI adoption among never-adopters
- Alternative control group ▶ results for alternative control group
 - firms that **never adopt AI technology (never-treated)**
- Excluding AI patents ▶ results for excluding AI patents
 - extend beyond **AI-specific technological domains**

AI adoption is followed by higher productivity

⇒ Evidence consistent with the **innovation** channel:

- innovation increases, innovation efficiency improves, inventor composition shifts, and knowledge recombination strengthens
- R&D increases; while tangible investment and operating costs show no significant change

Caveats and future work

- This paper does not examine technology diffusion or spillovers
- We are assembling site-level data to extend firm-level evidence

Contributions

- The economic implications of AI:
 - firm value and growth, patent examination, disclosure strategies, industry dynamics, labor markets (Babina et al., 2024; Zheng, 2025; Cao et al., 2023; Einfeldt et al., 2025; Lu et al., 2024; Brynjolfsson et al., 2025; Chen and Wang, 2024)
 - AI adoption enhances corporation innovation and firm-level productivity
- AI, innovation, productivity:
 - ongoing debate about whether and how AI affects corporate innovation and productivity (Cockburn et al., 2018; Mühlroth and Grottko, 2020; Bresnahan and Trajtenberg, 2017; Ouellette et al., 2025; McElheran et al., 2025)
 - AI adoption reshapes the innovation production function and contributes to aggregate productivity growth
- Organizational determinants of AI-driven innovation:
 - data availability, computing capacity, domain-specific expertise, operation integration (Brynjolfsson and McAfee, 2017; Cockburn et al., 2018; Agrawal et al., 2018; Zha et al., 2025; Whang et al., 2023)
 - firms with a focused business scope realize larger innovation gains

Thank you!

Questions and suggestions are welcome

How AI affects innovation

- AI can **strengthen** innovation
 - processing unstructured data; automating knowledge retrieval and recombination across technological domains; analyzing patent texts and claims; improving strategic foresight and search; using prediction to accelerate knowledge discovery and target high-value opportunities
 - Cockburn et al. (2018); Mühlroth and Grottke (2020); Ludwig and Mullainathan (2024); Agrawal et al. (2019); Alderucci and Sicker (2019); Setchi et al. (2021)
- AI can **weaken** innovation
 - requires complementary investments for effective deployment; concentrates gains among early leaders due to scale and data advantages; exhibits path dependence rooted in historical data and reinforces existing technological trajectories; generates low-quality patent drafts that render otherwise patentable inventions unpatentable
 - Bresnahan and Trajtenberg (2017); Cockburn et al. (2018); Agrawal et al. (2024); Ouellette et al. (2025); Yordy (2021)

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Heterogeneous effects: firm size

Big firms:

- Big firm: firms with total assets equal to or larger than the Fama & French 49 industry average value in 2015
- Greater financial resources and extensive data assets
→ more likely to adopt AI
- Economies of scale, greater market influence, and broader patent portfolios
→ better innovation regardless of AI adoption

Variable	Patent count	Adjusted citation
	(1)	(2)
AI	0.524** (2.08)	-0.017 (-0.12)
AI x Big firm	-0.360 (-1.41)	0.295* (1.83)
Year-Cohort FE	Yes	Yes
Firm-Cohort FE	Yes	Yes
Year-Cohort-Big firm FE	Yes	Yes
Firm-Cohort-Big firm FE	Yes	Yes
Pseudo R^2	0.937	0.247
Observations	36,215	30,979

(continued on next page)

Heterogeneous effects: firm size

Variable	Originality	Distance	Exploitative	Explorative	Generality	Claim
	(3)	(4)	(5)	(6)	(7)	(8)
AI	0.281** (2.34)	-0.026 (-0.21)	0.036 (0.37)	-0.057 (-0.29)	0.071 (0.25)	0.057 (0.74)
AI x Big firm	-0.131 (-1.02)	0.166 (1.28)	0.134 (1.30)	0.302 (1.22)	0.361 (1.20)	0.087 (1.04)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort-Big firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort-Big firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0811	0.117	0.101	0.150	0.109	0.302
Observations	33,729	32,171	29,009	28,977	22,333	36,185

▶ Back to heterogeneous effects

Heterogeneous effects: financial constraints

Firms without financial constraints:

- Unconstrained firm: firms that have the risk to delay investments due to issues with liquidity equal to or smaller than the 2015 Fama & French 49 industry average (Hoberg and Maksimovic, 2015)
- Face fewer financial constraints to pursue AI investment
→ more likely to adopt AI
- Expand R&D investment and enhance talent acquisition
→ more innovation regardless of AI adoption

Variable	Patent count	Adjusted citation
	(1)	(2)
AI	0.177*** (3.73)	0.374*** (5.93)
AI x Unconstrained firm	-0.018 (-0.24)	-0.187 (-1.37)
Year-Cohort FE	Yes	Yes
Firm-Cohort FE	Yes	Yes
Year-Cohort-Unconstrained firm FE	Yes	Yes
Firm-Cohort-Unconstrained firm FE	Yes	Yes
Pseudo R^2	0.938	0.245
Observations	36,792	31,509

(continued on next page)

Heterogeneous effects: financial constraints

Variable	Originality	Distance	Exploitative	Explorative	Generality	Claim
	(3)	(4)	(5)	(6)	(7)	(8)
AI	0.205*** (4.94)	0.151*** (3.70)	0.164*** (5.26)	0.208 (1.54)	0.510*** (5.00)	0.169*** (5.18)
AI x Unconstrained firm	-0.026 (-0.28)	-0.076 (-0.89)	-0.024 (-0.36)	-0.094 (-0.37)	-0.256 (-1.38)	-0.045 (-0.67)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort-Unconstrained firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort-Unconstrained firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0811	0.118	0.100	0.150	0.108	0.301
Observations	34,292	32,726	29,514	29,465	22,786	36,762

► Back to heterogeneous effects

Heterogeneous effects: technological capabilities

Firms with high technological capabilities:

- High-tech firm: firms that operate in 2-digit NAICS sectors 51 (“Information”) and 54 (“Professional, Scientific, and Technical Services”) in 2015 (Babina et al., 2024)
- Pre-existing advantages in R&D infrastructure and inventor expertise
 - more likely to adopt AI
 - better innovation regardless of AI adoption

Variable	Patent count	Adjusted citation
	(1)	(2)
AI	0.138*** (3.46)	0.341*** (5.62)
AI x High-tech firm	0.149 (1.11)	-0.029 (-0.19)
Year-Cohort FE	Yes	Yes
Firm-Cohort FE	Yes	Yes
Year-Cohort-High-tech firm FE	Yes	Yes
Firm-Cohort-High-tech firm FE	Yes	Yes
Pseudo R^2	0.938	0.245
Observations	36,792	31,509

(continued on next page)

Heterogeneous effects: technological capabilities

Variable	Originality	Distance	Exploitative	Explorative	Generality	Claim
	(3)	(4)	(5)	(6)	(7)	(8)
AI	0.219*** (5.28)	0.135*** (3.44)	0.190*** (6.46)	0.067 (0.51)	0.482*** (5.01)	0.170*** (5.33)
AI x High-tech firm	-0.094 (-0.85)	-0.010 (-0.09)	-0.165* (-1.87)	0.418 (1.48)	-0.296 (-1.28)	-0.045 (-0.57)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort-High-tech firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort-High-tech firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0812	0.118	0.100	0.150	0.108	0.301
Observations	34,292	32,743	29,514	29,465	22,786	36,762

Heterogeneous effects: excluding high-tech firms

Excluding firms operating in **high-tech sectors**:

- Exclude firms that operate in 2-digit NAICS sectors 51 (“Information”) and 54 (“Professional, Scientific, and Technical Services”) in 2015 (Babina et al., 2024)

Variable	Patent count	Adjusted citation
	(1)	(2)
AI	0.138*** (3.46)	0.341*** (5.62)
Year-Cohort FE	Yes	Yes
Firm-Cohort FE	Yes	Yes
Pseudo R^2	0.938	0.249
Observations	31,679	27,109

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Heterogeneous effects: excluding high-tech firms

Variable	Originality (3)	Distance (4)	Exploitative (5)	Explorative (6)	Generality (7)	Claim (8)
AI	0.219*** (5.28)	0.135*** (3.44)	0.190*** (6.46)	0.067 (0.51)	0.482*** (5.01)	0.170*** (5.32)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0808	0.115	0.103	0.147	0.111	0.299
Observations	29,771	28,344	25,535	25,215	19,381	31,666

⇒ AI adoption benefits a wide range of economic sectors

▶ Back to heterogeneous effects

Robustness: entropy balancing

- Entropy balancing:
 - covariate balance on the means, variances, and skewnesses of $\ln(\text{total assets})$, cash, and Tobin's q in fiscal years before 2015

Variable	Patent count	Adjusted citation
	(1)	(2)
AI	0.129* (1.87)	0.153** (2.18)
Year-Cohort FE	Yes	Yes
Firm-Cohort FE	Yes	Yes
Pseudo R^2	0.944	0.209
Observations	36,096	30,860

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Robustness: entropy balancing

Variable	Originality (3)	Distance (4)	Exploitative (5)	Explorative (6)	Generality (7)	Claim (8)
AI	0.111*** (2.70)	0.043 (0.96)	0.083*** (2.75)	0.183 (1.35)	0.240** (2.23)	0.100*** (3.17)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0710	0.100	0.0781	0.181	0.0874	0.291
Observations	33,685	32,273	28,987	29,025	22,386	36,066

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Robustness: placebo test

- Placebo test:

- **randomly assign** fictitious AI adoption among never-adopters, given the actual number of adopters observed in the original data

Variable	Patent count	Adjusted citation
	(1)	(2)
AI	-0.211*** (-2.83)	-0.274*** (-3.12)
Year-Cohort FE	Yes	Yes
Firm-Cohort FE	Yes	Yes
Pseudo R^2	0.945	0.229
Observations	34,993	30,227

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Robustness: placebo test

Variable	Originality (3)	Distance (4)	Exploitative (5)	Explorative (6)	Generality (7)	Claim (8)
AI	-0.086 (-1.57)	-0.069 (-1.26)	-0.123*** (-2.61)	0.084 (0.63)	-0.348** (-2.50)	-0.084* (-1.85)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.077	0.114	0.091	0.165	0.100	0.305
Observations	32,672	31,273	28,429	28,937	22,629	34,976

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Robustness: alternative control group

Never-treated firms as the control group:

- Not-yet-treated firms may change their innovation behavior in anticipation of AI adoption

Variable	Patent count	Adjusted citation
	(1)	(2)
AI	0.253*** (4.56)	0.376*** (6.17)
Year-Cohort FE	Yes	Yes
Firm-Cohort FE	Yes	Yes
Pseudo R^2	0.918	0.257
Observations	31,495	26,424

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Robustness: alternative control group

Variable	Originality (3)	Distance (4)	Exploitative (5)	Explorative (6)	Generality (7)	Claim (8)
AI	0.225*** (5.66)	0.163*** (4.29)	0.189*** (6.28)	0.201* (1.74)	0.500*** (5.42)	0.187*** (6.16)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0852	0.121	0.104	0.138	0.119	0.300
Observations	29,313	27,505	24,854	24,607	18,202	31,465

⇒ Results are not driven by **anticipatory behavior** among future adopters

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Robustness: excluding AI patents

Excluding AI patents:

- Machine learning, natural language processing, computer vision, speech, knowledge processing, AI hardware, evolutionary computation, and planning and control (Giczy et al., 2022)

Variable	Patent count	Adjusted citation
	(1)	(2)
AI	0.212*** (4.86)	0.340*** (6.25)
Year-Cohort FE	Yes	Yes
Firm-Cohort FE	Yes	Yes
Pseudo R^2	0.930	0.245
Observations	37,694	31,747

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Robustness: excluding AI patents

Variable	Originality (3)	Distance (4)	Exploitative (5)	Explorative (6)	Generality (7)	Claim (8)
AI	0.186*** (4.95)	0.119*** (3.37)	0.150*** (5.62)	0.295** (2.44)	0.448*** (5.30)	0.169*** (6.05)
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0804	0.116	0.0995	0.151	0.116	0.298
Observations	34,882	33,117	30,268	29,036	22,354	37,672

⇒ AI adoption strengthens innovation **beyond AI-specific domains**

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