The Impact of AI and Cross-Border Data Regulation on International Trade in Digital Services

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Facts About Mobile Apps

- **Mobile app revenue is growing rapidly**

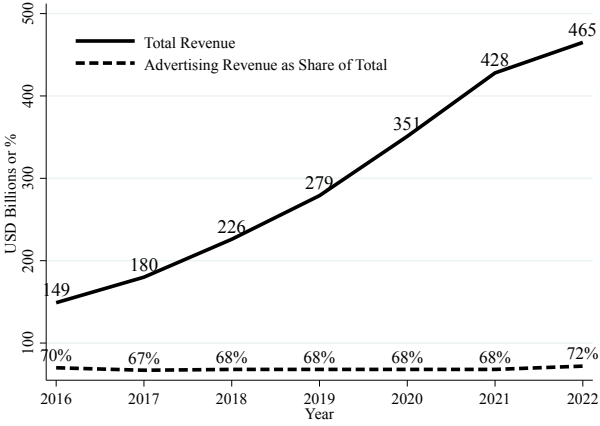

Figure: Mobile App Revenue, 2016 – 2020

Facts About Mobile Apps

- **Mobile app revenue is growing rapidly**
- **Mobile apps are globalized**

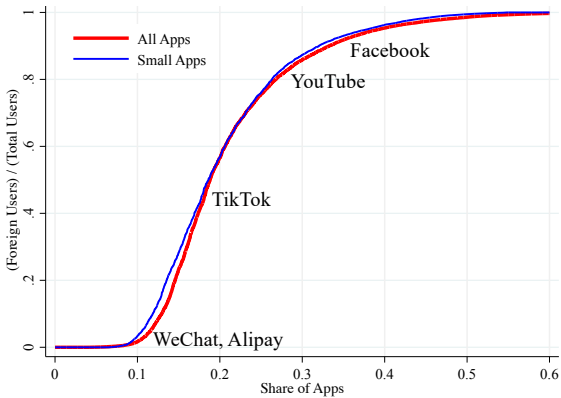

Figure: Foreign User Share by App, 2020

Facts About Mobile Apps

- **Mobile app revenue is growing rapidly**
- **Mobile apps are globalized**
- **Mobile apps often powered by data and AI algorithms**
  - Improving user experience so the users stay on the app

  $\Rightarrow$ Attention monetized via digital advertisements

  - E.g., recommenders (TikTok), DL translation (Google Translator), AI content generation (Fortnite Games)

Facts About Mobile Apps

- **Mobile app revenue is growing rapidly**
- **Mobile apps are globalized**
- **Mobile apps often powered by data and AI algorithms**
- **AI and cross-border data flows driving policy upheaval**

  Major disagreements internationally about how to proceed.

  - Anti-Regulation Initiatives: Strong backing from Big Tech, E-Commerce Chapters (e.g., NAFTA), 72 Bilateral Digital Trade Agreements, WTO Plurilateral
  - Pro-Regulation Initiatives: EU's GDPR, California's CCPA, China's Data Security Laws, many bans, AI Acts of China, EU and US ...

Facts About Mobile Apps

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A highly relevant setting backed by readily available data for studying AI, trade, and data policies.

Contribution

Contribution 1: Study of AI and International Trade

- **Does AI have causal impacts on international trade? (algorithms)**
- **Do restrictions on cross-border data flows limit the effectiveness of AI algorithms? (data policies)**

Contribution 2: Methodological – the use of LLMs

- **We link technology to individual products by applying an LLM to textual data**

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- **Does AI have causal impacts on international trade? (algorithms)**
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Contribution 2: Methodological – the use of LLMs

- **We link technology to individual products by applying an LLM to textual data**

Preview of Findings

Measure AI deployed in apps

- **Model**: AI primarily a quality shifter at product level

$\Rightarrow$ empirical specification & identification strategy

- **Measurement**: cosine similarity between the embeddings of app descriptions and patent abstracts.

Impact on Digital Services Trade of AI, both algorithms and data:

1. **Algorithms:** AI causally increases international trade in mobile app services by 3.5X.
2. **Data**: This increase is more than halved by cross-border data restrictions.

Literature

- AI's impact on trade:
  - Empirical: Brynjolfsson et al. (2019), Beraja et al. (forthcoming), Beraja et al. (2023) and Sun and Trefler (2022).
  - Theory/qualitative: Goldfarb and Trefler (2019) and Ferencz et al. (2022).
- Digital Regulations:
  - Herman and Oliver (2022) and López González et al. (2023). See also Goldfarb and Tucker (2019), Johnson (2022), and Bian et al. (2023).
- Ads and market penetration costs:
  - Arkolakis (2010) and Eaton et al. (2011). See also Bar-Isaac et al. (2012), Sun et al. (2023), and Carballo et al. (2022).
- The Internet and Trade:
  - Freund and Weinhold (2002, 2004); Blum and Goldfarb (2006); Alaveras and Martens (2015), and Lendle et al. (2016).
  - On e-commerce specifically see Bai et al. (2022) and Carballo et al. (2022).

Roadmap

1. Data and Measurements
2. Model and Specification
3. Findings I: AI and Foreign Users
4. Findings II: Cross-Border Data Regulation on AI

Data: Apps and Patents

Years: App Store and Google Play, 2015–2020.

App Usage: monthly-active-users by app

- 59 producing/exporting countries
- 84 downloading/importing countries

Firms (Global Ultimate Owners): $1,276$

- linked with $27,727$ apps
- owning 10 million patents, including 64,000 AI patents (WIPO AI Report)

Patenting and Commercialization of AI

- Algorithms and software using AI techniques
- The rise of AI patents is associated with the commercialization in 2016

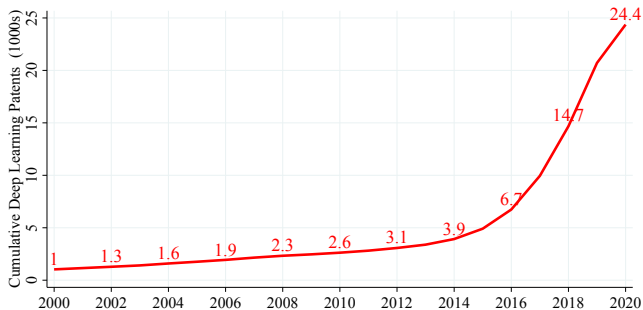

Figure: Rise of Deep Learning

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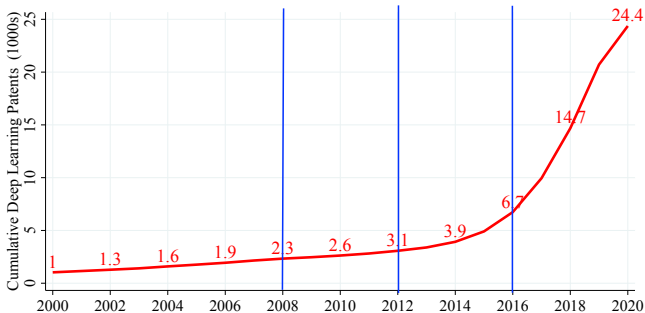

Figure: Rise of Deep Learning

Holy Grail: Link Specific Products to Specific Patents

- **Key**: Mobile apps have detailed product descriptions.

$\Rightarrow$ App descriptions (consumer-facing) and patent abstracts (legal-facing).

- **Problem**: Word frequency methods fail

$\Rightarrow$ e.g., I walk a river bank vs. I open a bank account;

- **Solution**: the use of Large Language Model (LLM) to link these texts.

LLM: Google's BERT

- **Transformer:** Extract features from text data;
- Decoded as *text embeddings*: 768-element unit vector.
- **Large language model**: Pre-trained on massive data ($\geq 10B$ params); creates 'subject areas'
- Two embeddings pointing to the same place in the model (measured by high cosine similarity) are about the same subject.
- Embeddings have no meaning outside the context of the model.

Measure of AI: AI_{at}

- Let ρ_{ap} be a cosine correlation.
- Let f be the firm that produced/owned app a
- Let $\mathcal{P}_{at}$ be set of patents owned by f, filed during 1992–t

$$AI_{at} = \sum_{p \in \mathcal{P}_{at}} \rho_{ap} = \underbrace{\overline{\rho}_{at}}_{\text{average 'directedness'}} \cdot \underbrace{|\mathcal{P}_{at}|}_{\text{\# of patents}}$$

Validation

1. Ground-truth for on-device AI (ρ_{ap}):
   - DL functions for real-time response to graph and video data are embedded on mobile device. (Xu et al., 2019; Almeida et al., 2021).

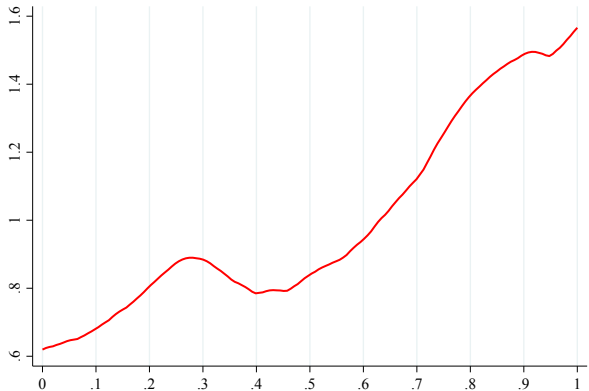

Figure: Density of Detected DL Frameworks

Validation

1. Ground-truth for on-device AI (ρ_{ap}):
2. Ground-truth for category prediction ($\rho_{a,a'}$):
   - Predict whether a and a' are in the same category

		Call-Video-Message											Email			
		WhatsApp	Messenger	Blackberry	QQ	WeChat	LINE	Skype	imo	Viber	Telegram	KakaoTalk	Zalo	Gmail	MS Outlook	Yahoo Mail	Mail.ru
Call-Video-Meesage	WhatsApp Messenger		10	10	10	10	10	10	10	10	10	10	9	·	·	·	·
	Messenger			10	10	10	10	10	10	10	10	10	10	·	·	·	·
	Blackberry Message				10	10	10	10	9	10	10	10	9	·	·	·	·
	QQ					10	10	10	10	10	10	10	10	·	·	·	·
	WeChat						10	10	10	10	10	10	10	·	·	·	·
	LINE							10	10	10	10	10	10	·	·	·	·
	Skype								10	10	9	10	9	·	·	·	·
	imo video calls									10	10	10	10	·	·	·	·
	Viber Messenger										10	10	9	·	·	·	·
	Telegram											10	9	·	·	·	·
	KakaoTalk												10	·	·	·	·
	Zalo													·	·	·	·
Email	Gmail														10	10	10
	Microsoft Outlook															10	9
	Yahoo Mail																10
	Mail.ru																

Roadmap

1 Data and Measurements

2 Model and Specification

3 Findings I: AI and Foreign Users

4 Findings II: Cross-Border Data Regulation on AI

Implications of Theory

- **Demand**: Physical goods (Arkolakis, 2010) + App

  consumer chooses one app or no apps from category c.

- **Supply**: firms with heterogenous quality ($\delta_a' = \alpha_a \delta_a$)

  δ_a: exo. idiosycratic draw

  α_a: endo. AI investment

- The optimal AI deployment is given by

$$\underbrace{\alpha_a}_{\text{AI deployment}} = \underbrace{\left(w_i^A\right)^{1-\eta_c}}_{\text{marginal cost}} \underbrace{\delta_a^{\eta_c-1}}_{\text{unobserved quality}} \underbrace{\left(P_c\right)^{\eta_c-1}}_{\text{price aggregator}}$$

1. Estimating Equation

$$\ln Users_{anc} = \ln \alpha_{ac} + \lambda_{nc} + \ln \delta_{ac}$$

- λ_{nc}: fixed effect capturing country n's market size
- $\ln \delta_{ac}$ is a structural error term
- Measurement of AI investments: $\ln \alpha_{ac} = \beta \ln(1 + AI_{ac})$

2. Endogeneity of AI_{ac}

$$\ln \alpha_{ac} = (1 - \eta_c) \ln w_i^A + \lambda_c + (\eta_c - 1) \ln \delta_{ac}$$

- Problem: idiosyncratic **demand** shocks δ_{ac} induce a correlation between AI investments and the second-stage residual.
- Solution: identification via **supply** shocks $(1 - \eta_c) \ln w_i^A$,

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Non-Parametric Construction of Instrument

Instrument AI_{at} with the AI of a similar firms.

1. Countries: divide into 6 bins based on L_i^A/L_i. abundance by country
2. Firms: divide into 2 bins based on $D_{f,2008}$.
3. Country×Firm bins: fix a country×firm bin and consider apps within it:
4. App a in the bin: calculate the cosine similarity between any two apps $\rho(a, a')$. Pick k apps with the highest $\rho(a, a')$ and define this set $\mathcal{A}_{at}^k$ intensity by category
5. Instrumental Variable Z_{at}: instrument AI_{at} by $\frac{1}{k}\Sigma_{a' \in \mathcal{A}_{at}^k} AI_{a't}$, precisely

$$Z_{at} = \ln(1 + \frac{1}{k}\Sigma_{a' \in \mathcal{A}_{at}^k} AI_{a't}).$$

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Empirical Specification

$$\ln(Users_{at}) = \beta \ln(1 + AI_{at}) + \sum \gamma_{xt} X_a \times D_t + \lambda_f + \lambda_t + \varepsilon_{at} \ .$$

c	:	category (15)	t	:	year $(2015, \ldots, 2020)$
a	:	unified app (31,855)	f	:	firm (1,185)

- X_a includes app age, downloading price, an in-app purchases dummy, a dummy for buying ads, and a dummy for selling ads.
- Baseline: $k = 3$ (same for $k = 1 \ldots, 5$)

Impact of AI – OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS: $\ln(Users_{at})$							
$\ln(1+AI_{at})$	1.23*	1.23*	1.42*	1.36*	1.57*	1.17*	1.33*	1.55*
	(0.11)	(0.11)	(0.14)	(0.13)	(0.14)	(0.12)	(0.13)	(0.17)
$\ln(1+non\ AI_{ft})$					-2.13*		-1.61*	-2.40*
					(0.37)		(0.36)	(0.45)
$\ln(1+undirected\ AI_{at})$						-0.45*	-0.44*	
						(0.05)	(0.05)	
$\ln(Assets_{ft})$								2.29*
								(0.59)
$\ln(Turnover_{ft})$								0.87
								(0.44)
$(App\ controls_a) \times Year_t$	N	N	N	Y	Y	Y	Y	Y
FEs	*f, c, t*	*f, c, i, t*	*f, cit*	*f, cit*	*f, cit*	*f, cit*	*f, cit*	*f, cit*
Observations	115,459	115,459	115,027	115,027	115,027	115,027	115,027	55,824
R^2	0.23	0.23	0.25	0.30	0.30	0.31	0.31	0.30

Impact of AI – Instrumental Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IV: $\ln(Users_{at})$							
$\ln(1+AI_{at})$	1.13*	1.13*	1.19*	1.26*	1.42*	1.53*	1.69*	1.45*
	(0.31)	(0.31)	(0.44)	(0.41)	(0.45)	(0.41)	(0.44)	(0.56)
$\ln(1+non\ AI_{ft})$					-2.00*		-1.94*	-2.33*
					(0.54)		(0.54)	(0.60)
$\ln(1+undirected\ AI_{at})$						-0.44*	-0.43*	
						(0.05)	(0.05)	
$\ln(Assets_{ft})$								2.32*
								(0.61)
$\ln(\text{Sales}_{ft})$								0.86
								(0.44)
$(App\ controls_{a}) \times Year_{t}$	N	N	N	Y	Y	Y	Y	Y
FEs	*f, c, t*	*f, c, i, t*	*f, cit*	*f, cit*	*f, cit*	*f, cit*	*f, cit*	*f, cit*
Observations	115,459	115,459	115,027	115,027	115,027	115,027	115,027	55,824
Weak Inst. F (KP)	1,381	1,381	1,063	1,063	1,068	1,059	1,067	766

One IQR increase in $\ln(1 + AI_{at})$ raises users by 1.26 log points or 3.5-fold first stage

Robustness and Discussion

- Does AI Help Create New Products? Yes

  Apps with positive AI deployment are less similar with competitors

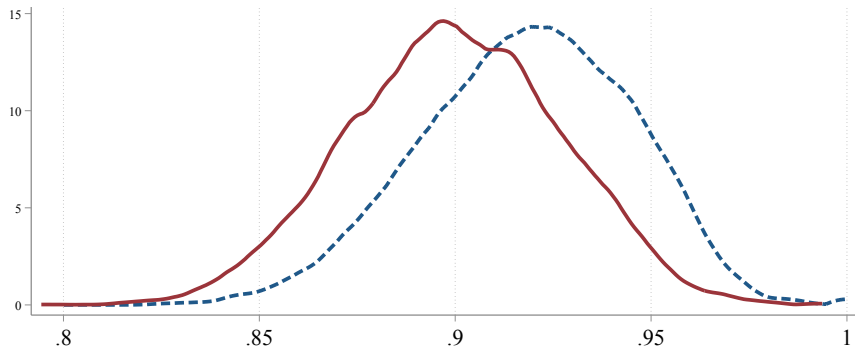

Figure: Distribution of $\rho_{aa'}$ for AI and non-AI apps

Robustness and Discussion

- Does AI Help Create New Products? Yes
- Placebo Test by Randomizing ρ_{ap}: 1.26 $\rightarrow$ 0.2

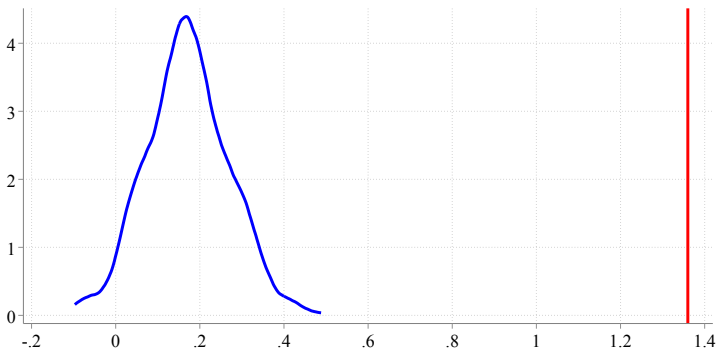

Figure: IV estimates with randomized ρ_{ap}

Robustness and Discussion

- Does AI Help Create New Products? Yes
- Placebo Test by Randomizing ρ_{ap}: $1.26 \rightarrow 0.2$
- Falsification Test for the Instrumental Variables: Checked
  - Identification requires $\mathcal{E}(Z_a \cdot \delta_{ac}) = 0$.
  - Falsify: replace unobserved δ_{ac} with observed correlates X_{ac} e.g., ratings.

	$ln(Users_{at})$	$ln(1+AI_{at})$	Instrument Z_{at}
	(1)	(2)	(3)
$Ratings_a$	0.716*	0.0042*	-0.0109
	(0.027)	(0.0015)	(0.0054)
Observations	110,237	110,237	110,237
R^2	0.33	0.28	0.28

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Motivation Page

Global Debate on Data Regulation

- GDPR is next on the list of the EU's crusade against overregulation
- "Senate Bill 1047" under California Consumer Privacy Act
- China's Data law in response to the cases of DiDi and TikTok

$\Rightarrow$ Increasing tension between data regulation and innovation competition

Restrictions on Cross-Border Data Flows

- OECD Digital Services Trade Restrictiveness Index (DSTRI): 2014–2022
- *Data Flow* restrictions:
  - the limitations on cross-border data flows
- *Data Generation* restrictions:
  - performance requirements affecting cross-border digital trade, i.e., downloading, streaming, and online advertising.
- How do country n's cross-border data restrictions limit the effectiveness of AI for apps used in market n?

$$\ln(Users_{ant}) = \beta \ln(1 + AI_{at}) - \theta Data_{nt} \cdot \ln(1 + AI_{at}) + \lambda_f + \lambda_{cnt} + \varepsilon_{ant}$$

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- How do country n's cross-border data restrictions limit the effectiveness of AI for apps used in market n?

$$\ln(Users_{ant}) = \beta \ln(1 + AI_{at}) - \theta Data_{nt} \cdot \ln(1 + AI_{at}) + \lambda_f + \lambda_{cnt} + \varepsilon_{ant}$$

Result 2. Restrictions on Cross-Border Data Flows

	(1)	(2)	(3)
	IV: $\ln(Users_{ant})$		
$Data_{nit} \cdot \ln(1+AI_{at})$	-3.14*	-3.17*	
	(0.13)	(0.13)	
$Flows_{nit} \cdot \ln(1+AI_{at})$			-3.85*
			(0.22)
$Generate_{nit} \cdot \ln(1+AI_{at})$			-2.27*
			(0.24)
$\ln(1+AI_{at})$	1.24*	1.14*	1.14*
	(0.10)	(0.13)	(0.13)
$(App\ controls_a) \times Year_t$	Y	Y	Y
FEs	*f, cnt*	*f, cnt, cxt*	*f, cnt, cxt*
Observations	1,559,932	1,559,865	1,559,865
Weak Inst. F (KP)	7,236	6,195	4,122

Interpretation

For a country with high levels of restrictiveness in data (0.22), **its cross-border data-flow restrictions lowers AI's impact by more than half compared with a country without restrictions (US):**

- from a 3.13 log point impact to a 1.56 log point impact.
- **from a 3.5-fold impact to a 1.6-fold impact.**

Sensitivity

	OLS: $ln(Users_{ant})$				
	(1)	(2)	(3)	(4)	(5)
$ln(1+AI_{at}) \cdot Data_{nit}$	-3.09*	-3.49*	-3.63*	-2.87*	-3.39*
	(0.13)	(0.17)	(0.14)	(0.13)	(0.17)
$ln(1+AI_{at})$	1.38*	1.76*	1.60*	1.35*	1.59*
	(0.04)	(0.10)	(0.05)	(0.04)	(0.10)
Additional Interactions:					
1. $ln(1+AI_{at}) \cdot (GDP\ per\ capita)_{nt}$		-0.03*			-0.00
		(0.01)			(0.01)
2. $ln(1+AI_{at}) \cdot (Democracy\ Score)_{nt}$			-0.02*		-0.02*
			(0.00)		(0.00)
3. $Data_{at} \cdot (AI\ Abundance)_{nt}$				-2.80*	-2.75*
				(0.08)	(0.08)
R^2	0.28	0.28	0.28	0.28	0.28

Conclusions

Impact on Digital Services Trade of AI, both algorithms and data:

1. **Algorithms:** AI causally increases international trade in mobile app services by 1.26 log points or by more than 3.5-fold.

2. **Data**: This increase is more than halved by restrictions on cross-border data flows.

Caveats and Future Research: welfare, externality, privacy and etc.

References I

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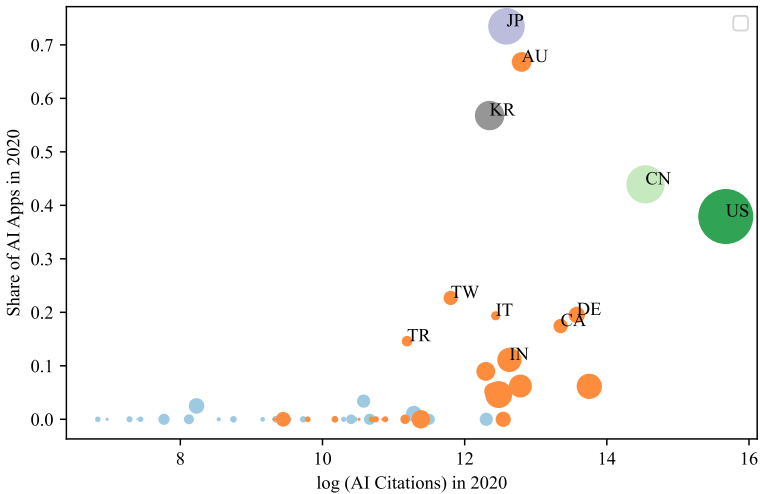
AI-Abundant Countries Produce AI-Intensive Apps



instrument

Category Intensity

Category Name	Average AI Intensity (normalize)
Developer Tools	1.00
Business	0.87
Social Networking	0.85
Education	0.81
Sports	0.79
Books	0.72
Entertainment	0.72
Finance	0.69
Music	0.66
Weather	0.64
Shopping	0.59
Navigation	0.51
Lifestyle	0.31
Food & Drink	0.11
Games	0.00

instrument

Impact of AI – First Stage and Reduced Form

	First Stage: $\ln(1+AI_{at})$							
Instrument Z_{at}	0.26*	0.26*	0.20*	0.20*	0.19*	0.21*	0.19*	0.18*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	-0.01
	Reduced Form: $\ln(Users_{at})$							
Instrument Z_{at}	0.29*	0.29*	0.24*	0.26*	0.27*	0.32*	0.33*	0.26*
	(0.08)	(0.08)	(0.09)	(0.08)	(0.09)	(0.09)	(0.09)	(0.10)

back

Thanks