

Automation without Borders: Generative AI and Cross-Border Service Outsourcing

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Motivation: A New Era of Automation

- **Generative AI represents a qualitatively new form** of automation
 - Unlike robots (physical, localized), GenAI performs *digital tasks globally*
 - 80% of U.S. workforce could see 10%+ of tasks affected (Eloundou et al., 2024)
 - Disproportionately targets high-skill, white-collar work (Felten et al., 2023)
- **Central question for global economy:** **How is this technology reshaping cross-border services trade?**



Source: Boston Globe, March 10, 2023

The Stakes: Digital Services as Development Strategy

- Digital services exports have been a **major engine of growth** for developing economies
 - India: IT-Business process outsourcing (BPO) ~36% of global market, employs 4M+
 - Philippines: BPO 7–11% of GDP & 1.3M workers; Poland: IT 8% of GDP
- Could services offshoring **enabled by ICT** potentially be **reversed by AI**?

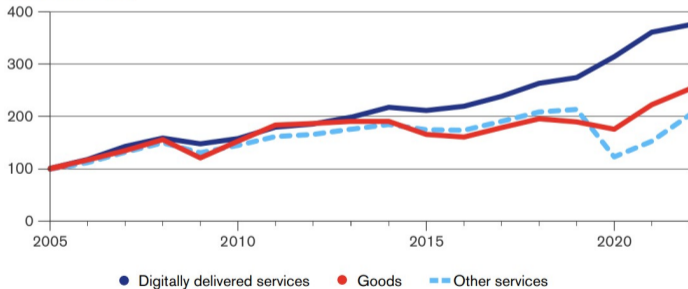
Digitally delivered services exports were worth
US\$ **3.82 trillion** in 2022

54% of total global services exports were delivered digitally in 2022

+375% The increase in digitally delivered services exports since 2005

Growth of digitally delivered services exports, 2005-2022

(Index 2005 = 100)



Source: WTO estimates (WTO, 2023).

Note: 'Digitally delivered services' comprise mode 1 exports of the following BOP categories: financial services, insurance and pension services, charges for the use of intellectual property not included elsewhere, telecommunication, computer and information services, and selected categories in business services and personal, cultural and recreational services.

How does generative AI reshape cross-border outsourcing in digital services?

Three waves of technology → three patterns:

- ① **ICT revolution (1990s–2000s):** Enabled *global dispersion* of work
 - Lower communication costs → routine cognitive tasks offshored (Blinder & Krueger, 2013)
- ② **Robotization (2010s):** Manufacturing *reshoring* to advanced economies
 - Automates physical tasks → erodes offshore labor cost advantage (Faber, 2020)
- ③ **Generative AI (2020s):** **Digital automation unbounded by geography**
 - Performs digital tasks *anywhere* with internet connection
 - Compresses wage arbitrage *while* potentially augmenting foreign workers
 - Net effect on international outsourcing: **theoretically ambiguous**

This Paper: Empirical Strategy

We provide new causal evidence on GenAI's impact on cross-border task flows

- 1 **Setting:** Cross-Border Online Labor Marketplaces (OLMs)
 - Global platform for digital services sourcing; 12.5% of global workforce (World Bank)
 - Observe task-level transactions, buyer behavior, worker skills
- 2 **Data:** Novel micro-data on 2,700+ skills (Jan 2022–Dec 2024)
 - Worker profiles, client characteristics, transaction-level outcomes
 - High-frequency variation at granular skills
- 3 **Identification:** Difference-in-differences exploiting:
 - *Time variation:* ChatGPT launch (and model releases) as shock
 - *Cross-section variation:* Skill-level GenAI automation exposure
- 4 **Exposure measure:** LLM-elicited self-assessment of skill substitutability
 - Capability-based mirroring how economic agents themselves assess & update beliefs

Preview of Findings

- 1 **Aggregate effect:** Sharp decline in international outsourcing to developing countries
 - Outsourced contracts ↓ 34%; outsourcing value ↓ 43% at mean exposure
 - Effects concentrated in **developing countries**
 - 2 **Task reorganization:** Fewer tasks, but higher value and complexity
 - Average contract value ↑; job posting budgets ↑
 - AI-related task demand rises but not in pay
 - 3 **Worker adjustment:** Displacement with selective adaptation
 - Number of active workers ↓ 35%; contracts per worker ↓ 37%
 - But: average contract value ↑ 41% among *continuing* workers
 - Workers transition to adjacent and interactive skills, but limited AI upskilling
 - 4 **Concentration:** Top 1% captures 17–20 pp larger share of jobs/earnings
- ⇒ **Reconfiguration of global task flows with asymmetric labor market effects**

1 GenAI and labor markets

- Exposure indices: Felten et al. (2021, 2023); Eloundou et al. (2024); Webb (2020)
- Productivity: Brynjolfsson et al. (2025); Noy & Zhang (2023); Dell'Acqua et al. (2023)

2 Online labor platforms

- Platform design: Agrawal et al. (2016); Pallais (2014); Stanton & Thomas (2016)
- GenAI effects: Hui et al. (2024); Teutloff et al. (2025); Demirci et al. (2025)

3 Automation, trade, and offshoring

- Theory: Acemoglu & Restrepo (2018, 2019); Grossman & Rossi-Hansberg (2008)
- Robots & trade: Faber (2020); Artuc et al. (2023); DeStefano & Timmis (2024)
- Digital trade: Brynjolfsson et al. (2019)

4 Technology adoption and reskilling

- Adoption: McElheran et al. (2024); Zolas et al. (2021); Bloom et al. (2012)
- Adjustment: Brynjolfsson et al. (2021); Tamayo, Sadun et al. (2023)

5 AI and development (World Bank 2025; ILO 2025)

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- **OLMs as “trade in tasks” infrastructure** (Horton 2010; Kässi & Lehdonvirta 2018)
 - Platform matches clients (demand) with freelancers (supply) globally
 - 12.5% of global workforce participates; 90%+ of transactions cross borders
 - Demand concentrated in U.S., Australia, UK; supply in developing countries (es. South Asia)
- **This study:** Leading global OLM with workers in 100+ countries
 - Clients: Large enterprises (Airbus, IBM, Deloitte) and SMEs
 - Over 2,700 skill areas spanning professional service categories
 - Cross-border: 91% of transactions
- **Why this OLM for studying AI and outsourcing?**
 - *Granular task data:* Contracts specify narrow skills (2,700+ categories)
 - *High-frequency adjustment:* Transaction data captures rapid response
 - *Both market sides observable:* buyer decisions, worker outcomes
 - *International by design:* Natural setting for cross-border task flows

Data: Three Linked Datasets

- **Worker Profiles**

- User ID, location, education, certifications, experience
- Complete job history with client reviews and ratings
- Skill portfolio (multiple skills per worker)

- **Client Records**

- Client ID, country, industry classification
- Hiring history, worker ratings given
- Enables tracking of *within-buyer* adjustments over time

- **Project/Transaction Data**

- Project title, description, skill categories (up to 5 per job)
- Budget range (min/max), final payment, hours worked
- Number of bids received, timing of award and completion
- Quality ratings: expertise, communication, timeliness, budget adherence

⇒ **Linked client-worker-skill transaction microdata for the global gig economy**

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Measuring Skill-Specific AI Automation Exposure

Challenge: Existing indices occupation level or outcome based, whereas contracts *skill specific*

Our approach: LLM-elicited self-assessment of skill substitutability

- For each of 2,700+ skills, prompt GPT with standardized task list
- Ask: “On a scale from 0 to 1, how well can generative AI perform the tasks requiring skill [] relative to a human, with minimal human input?”
- Repeat 100 times per skill → average score (reduce stochastic variation)

Why this approach?

- ① **Fine-grained:** Matches contract-level skill specification in OLMs
- ② **Capability-based:** Captures *potential* exposure, not realized adoption
- ③ **Perceived feasibility:** Reflects how agents evaluate and act on AI capabilities
- ④ **Scalable & consistent:** Uniform assessment across 2,700+ skills

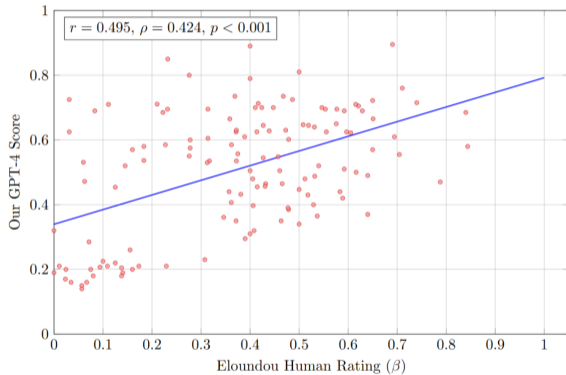
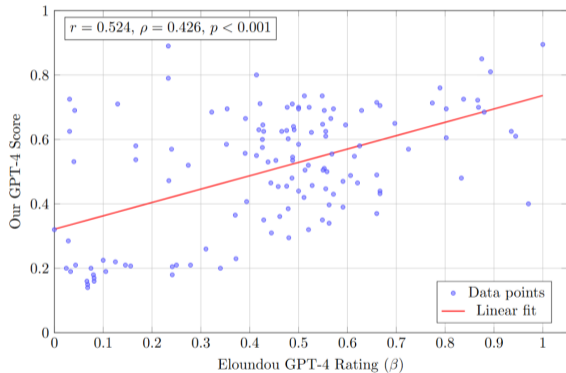
Validations: internal (across model releases; prompts) and external validations

Most and Least Exposed Skills

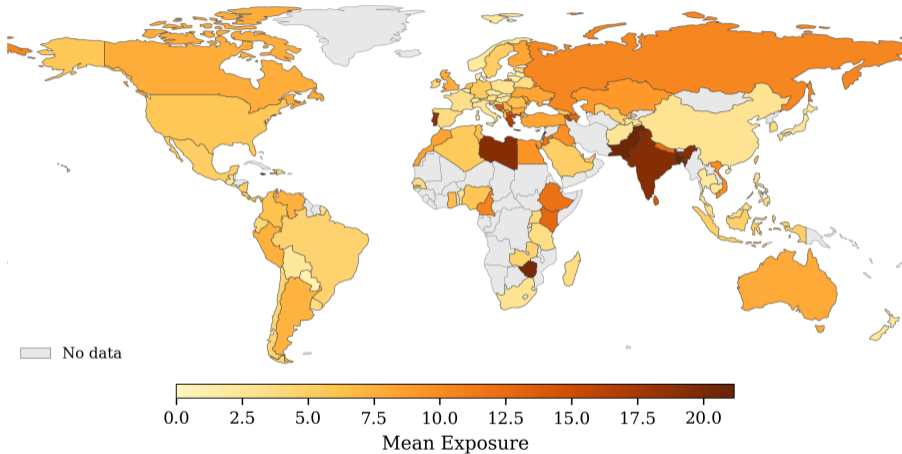
Most Automatable Skills			Least Automatable Skills		
Rank	Skill	Score	Rank	Skill	Score
1	Google Search	9.479	2718	Anthropology	3.144
2	Software Engineering	9.434	2719	Attic Access Ladders Making	3.140
3	English Spelling	9.295	2720	Christmas	3.117
4	Programming	9.290	2721	Genealogy	3.080
5	English Grammar	9.284	2722	Abnormal Psychology	3.061
6	Coding	9.250	2723	Forth (Programming Language)	3.061
7	Word Processing	9.240	2724	Feng Shui	3.020
8	English (UK) Translation	9.206	2725	Alto Flute	2.949
9	HTML	9.162	2726	Palm	2.948
10	Adobe Photoshop	9.141	2727	Soldering	2.868
11	Android Development	9.125	2728	COBOL	2.820
12	Proofreading	9.052	2729	ASHSP	2.785
13	CMS	9.051	2730	MMORPG	2.737
14	Mathematics	9.050	2731	Building Certification	2.582
15	Writing	9.050	2732	Symbian	2.536
16	English (US) Translation	9.042	2733	Asbestos Removal	2.500
17	Typing	9.041	2734	Papiamento	2.438
18	Google Chrome	9.032	2735	Sculpturing	2.326
19	ChatGPT Usage	9.024	2736	Google Buzz	2.250
20	Web Development	9.021	2737	Firefighting	2.240
21	Copy Typing	9.020	2738	ECPay	2.000
22	Firefox	9.010	2739	Fashion Modeling	1.920
23	Photoshop	8.989	2740	Google Wave	1.913
24	Web Applications	8.956	2741	MySpace	1.444
25	Drawing / Artist	8.949	2742	Flash Mob	1.323

- Highest exposure: Writing, coding, translation, basic design
- Least exposure: Physical skills, obsolete technologies, highly specialized domains

Benchmarking with Occupation Exposure Measures: Eloundon et al.



Geographic Distribution of Exposure



- Exposure of online workers varies significantly across countries
- Countries that specialized in IT-BPO services face disproportionate exposure

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Main Results: Aggregate Effects on Developing Countries

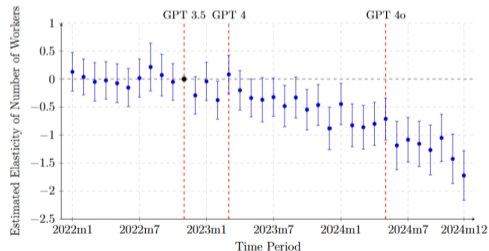
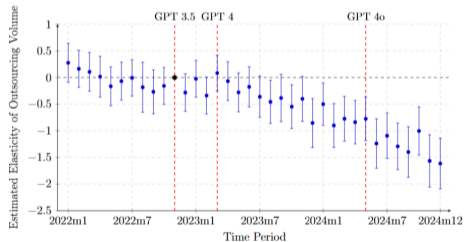
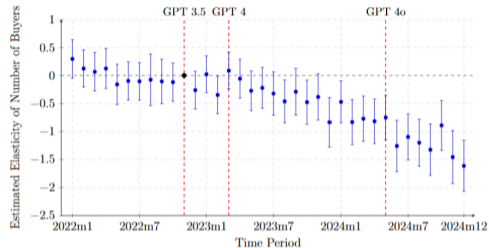
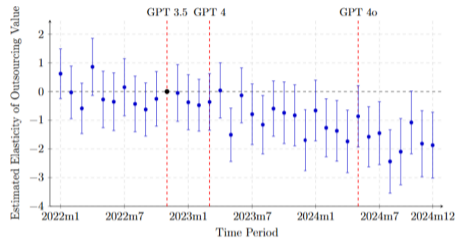
	(1) Log(Value)	(2) Log(Contracts)	(3) Log(Buyers)	(4) Log(Workers)
Post-GPT \times Exposure	-0.820*** (0.147)	-0.608*** (0.089)	-0.601*** (0.085)	-0.612*** (0.079)
Skill FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
R^2	0.637	0.887	0.892	0.884
Observations	88,800	90,045	90,045	90,045

Interpretation at mean exposure (6.5):

- Outsourcing value: -53%; Contracts: -34%
- Buyers: -34%; Workers: -35%

Both demand (buyers) and supply (workers) margins adjust substantially

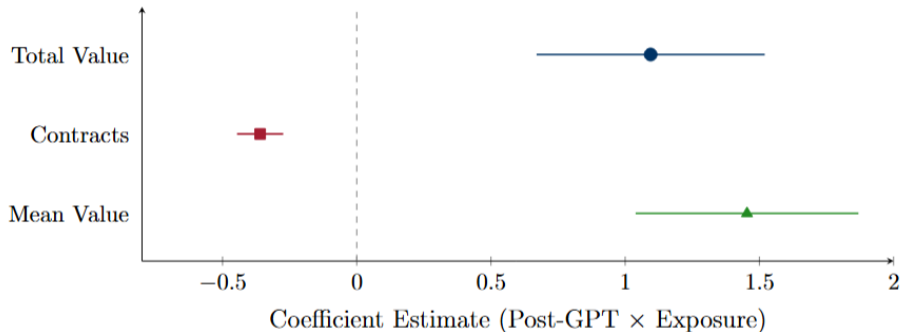
Event Study: Pre-Trends and Dynamic Effects



Outline

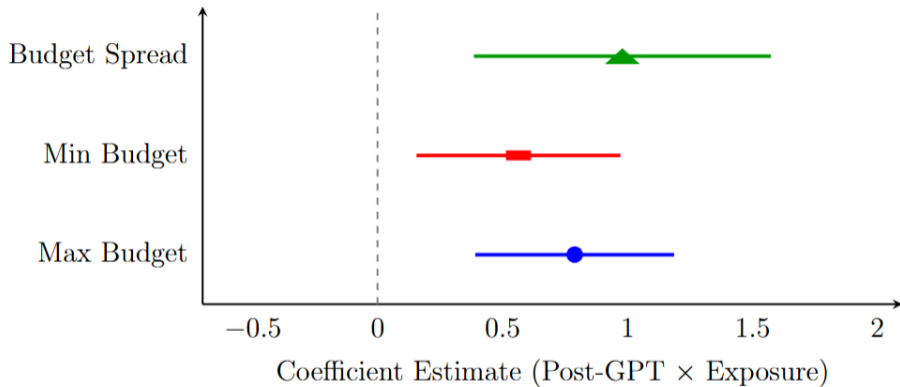
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Buyer Adjustments: Fewer Contracts, Higher Value



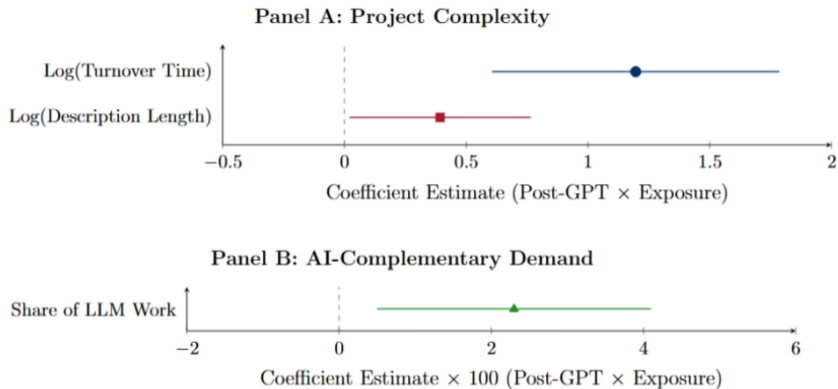
- **Continuing buyers** reduce number of contracts but increase average value
- Consistent with: (1) automating routine tasks; (2) outsourcing only complex work

Willingness to Pay: Budget Increases



- Job posting budgets **increase** in high-exposure skill areas
- Buyers willing to pay more for tasks that require human judgment/oversight
- “Hollowing out” of routine tasks; premium for complex/creative work

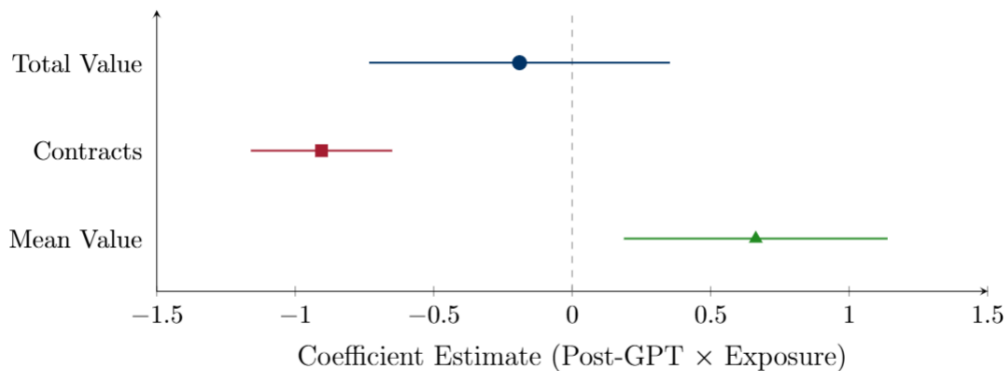
Task Reorganization: Complexity and AI Demand



- Task **complexity** increases post-ChatGPT
- **AI-related task demand** rises as routine task value falls
- Consistent with Dell'Acqua et al. (2023): “jagged frontier” between AI and human tasks

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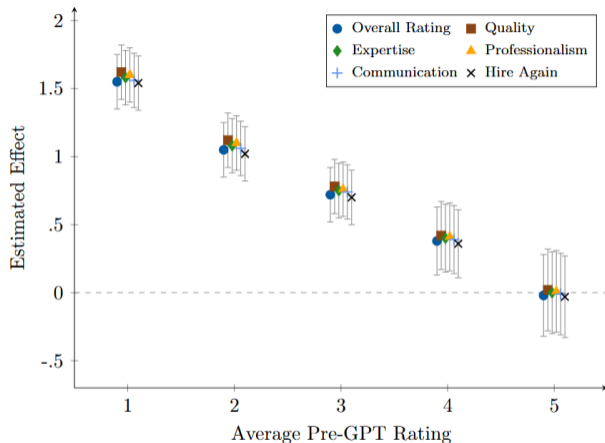
Worker Outcomes: Fewer Jobs, Higher Value per Job



- At mean exposure: **37% fewer jobs** per worker
- But: **41% higher value** per remaining contract
- Net effect on *continuing* workers: insignificant

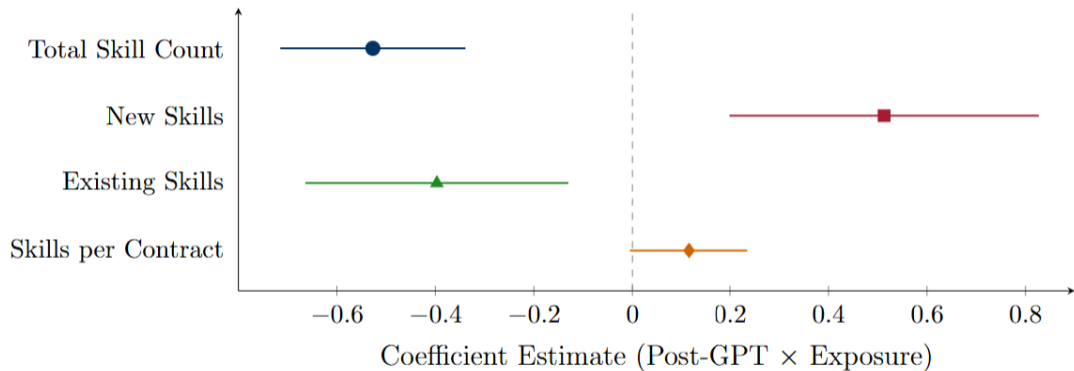
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Quality Effects: GenAI Benefits Lower-Performing Workers



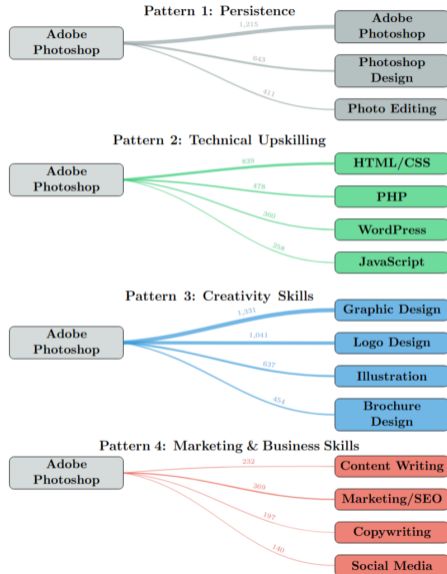
- **Average quality:** No significant overall change
- **Heterogeneity:** Quality gains among workers with *lower* pre-GPT ratings
- Consistent with Brynjolfsson et al. (2025): AI compresses quality distribution

Skill Dynamics: Increased Skill Adjustments and Task Complexity



- Workers **drop old skills** while simultaneously **acquiring new skills**
- Task complexity (skills per project) **increases**

Reskilling Patterns: Where Do Workers Go?

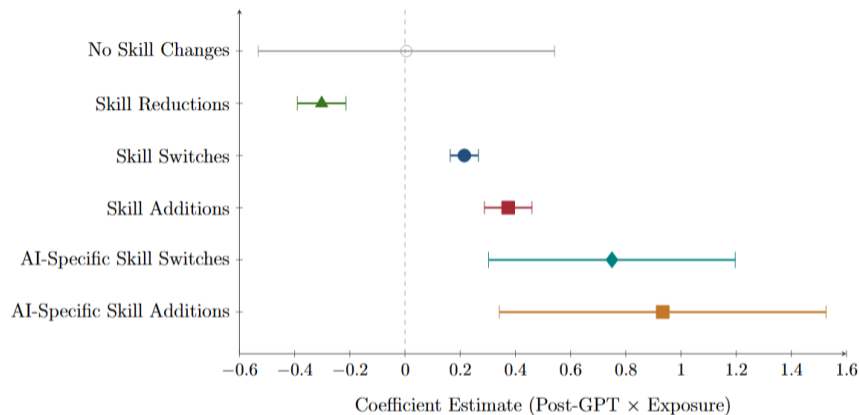


Reskilling: Transition Determinants

	(1)	(2)	(3)	(4)	(5)
	Log(Flow)	Log(Flow)	Log(Flow)	Log(Flow)	Log(Flow)
Relatedness	0.828*** (0.008)	0.816*** (0.007)	0.828*** (0.008)	0.829*** (0.007)	0.817*** (0.007)
Automation Exposure		0.590*** (0.089)			0.592*** (0.089)
AI Skill			-0.010 (0.039)		-0.016 (0.036)
Interactive Skill				0.157*** (0.058)	0.160*** (0.059)
Constant	0.132*** (0.007)	-0.307*** (0.068)	0.133*** (0.008)	0.086*** (0.018)	-0.356*** (0.069)
Source Skill FE	Yes	Yes	Yes	Yes	Yes
Observations	357,852	357,726	357,852	357,852	357,726
R^2	0.739	0.743	0.739	0.740	0.743

- Workers transition to related skills and **automation exposure persists**
- No systematic evidence of AI upskilling, but increasing application of **interactive/soft skills**

Earning Responses to Reskilling

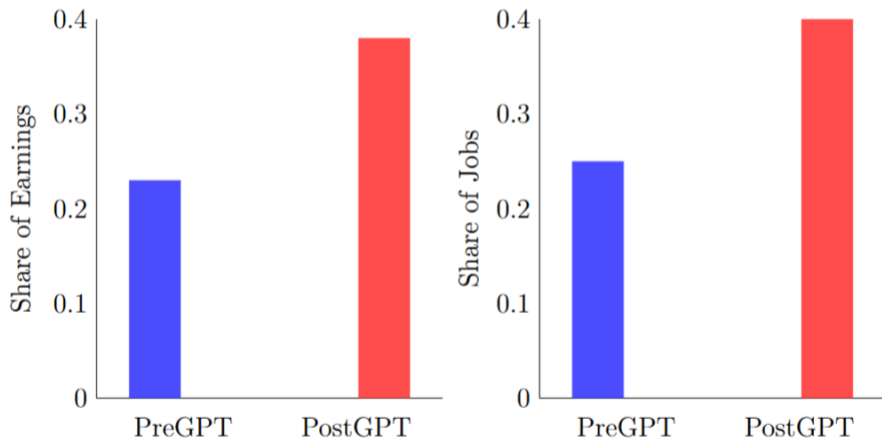


- **Skill additions** pay off; skill reductions hurt
- **AI-specific reskilling**, when adopted, yields the highest returns
- Active adaptation is essential for exposed workers

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Market Concentration: Winners Take More



- Top 1% of workers capture **17–20 percentage point** larger share of jobs/earnings
- AI may increase the concentration of work → winners-take-more

Summary of Findings

- 1 **Aggregate displacement:** GenAI significantly reduces international service outsourcing to developing countries
 - 34–43% decline in contracts and value at mean exposure
 - Effects concentrated in developing countries; null in developed countries
- 2 **Task reorganization:** Firms shift toward higher-value, more complex tasks
- 3 **Worker adjustment:** Displacement with selective adaptation
 - Fewer workers, fewer jobs per worker, but higher value per job
 - Workers reskill in both AI-exposed and AI-complementary domains
 - Lower-performing workers see quality gains (skill compression)
- 4 **Concentration:** Top performers capture increasing share
 - Winner-take-more dynamics in AI-exposed skill areas

Implications and Policy

For theory:

- GenAI as “geography-unbounded” automation: qualitatively different from robots
- Task-based trade models need updating for cognitive automation

For policy:

- **Monitor skill demand shifts:** Real-time tracking of OLM data
- **Targeted reskilling:** Focus on AI-complementary skills, not AI avoidance
- **Limited AI Upskilling:** Technology barriers limit AI adoption
- **Development strategy:** Rethink reliance on services exports as growth engine

Open questions:

- Long-run equilibrium: Will new tasks emerge where developing countries have advantage?
- Firm-level adoption: How do MNCs reallocate tasks across global value chains?
- Welfare: What happens to displaced workers outside the platform?

Thank you!

Contact:

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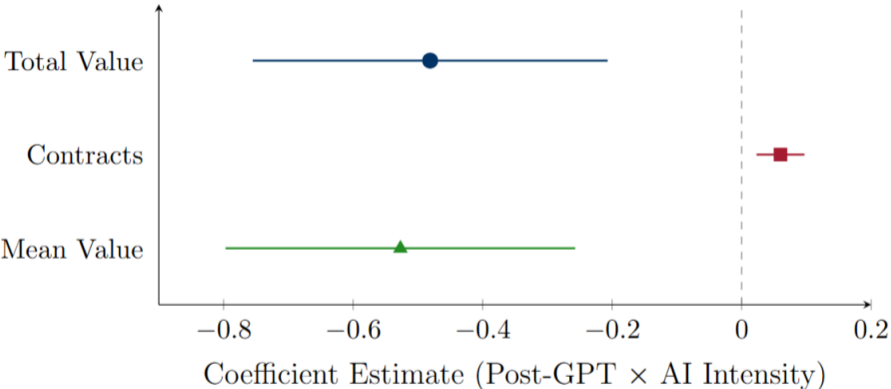
Appendix: Within-Field Variation in Exposure



- Substantial within-category variation in exposure
- Not all “IT” or “Writing” skills equally affected
- Supports skill-level (not category-level) analysis

[▶ Back to rankings](#)

Appendix: AI Intensity and Outsourcing Margins



▶ [Back to buyer results](#)

Appendix: Worker Profile Variables

Variable	Description
Identifiers	User ID
Registration Date	Time on platform
Location	145 countries represented
Primary Currency	9 currencies (USD: 73%)
Primary Language	25 languages (English: 93.6%)
Job History	Accepted, completed, incomplete jobs; reviews
Average Ratings	Quality, professionalism, communication, timeliness, budget adherence

Appendix: Project Variables

Variable	Description
Identifiers	Project ID, Client ID, Worker ID
Project Type	Fixed price or hourly
Title/Description	Job content and requirements
Skill Categories	Up to 5 per project
Budget	Min/max budget (local currency → USD)
Payment	Final amount paid
Bids	Number received, accepted amount, average
Timing	Award date, completion date
Ratings	Quality, expertise, communication (0–5)