DISRUPTION OR AUGMENTATION?
THE CHANGING DEMAND FOR AI SKILLS IN THE AGE OF GENERATIVE AI

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28 May 202

RESEARCH QUESTIONS

1. How has the demand for AI skills changed over time?
2. What is the impact of GenAI on labour demand?

- Online job ads (OJA) data allow answering both questions.
  1. Detailed classification framework to accurately measure the demand for AI skills.
  2. Robust identification strategy to estimate the impact of GenAI on labour demand.
     - DID estimation: the availability of ChatGPT-3 as a natural experiment that differently affected occupations that are exposed and not exposed to GPT-3.
  - To the best of our knowledge, first paper that proposes a classification framework and robust identification strategy to study the impact of GenAI on labour demand.

RELATED LITERATURE

The demand for AI skills using OJA data:

- Almaraz López (2025), Borgonovi *et al.* (2023) and many others.

➢ **Substantial cross-country and sector variation. The measurement of AI skills is either based on keywords' search or on classifications that identifies few categories of skills.**

The impact of GenAI on labour demand.

- Substitution effect (ex.: Demirci *et al.* 2025 and Teutloff *et al.* 2025 for online freelancers).
- Complementarity/augmentation effect (ex.: Peng *et al.* 2023; Noy and Zhang 2023).
- The impact depends on the occupation-specific tasks and skills (Ahmadi *et al.* 2024; Zarifhonarvar 2024).

➢ **Net impact depends on automatability of the tasks performed, and complementarity/substitutability of the skills employed.**

DATA

- Novel dataset jointly collected by Eurostat and Cedefop: the Web Intelligence Hub's Online Job Advertisement (WIH-OJA) database.
  - Information for over 200 million ads for jobs in all 27 EU countries and the UK since 2018 based on systematic data exchanges, scraping or crawling of several hundred data sources such as job search engines and websites with job advertisements managed by public employment services.
- OJAs refer to advertisements published on the web showing an employer's interest in recruiting workers with certain characteristics for performing certain work.
  - Employers can publish job ads for various reasons, for example to fill a current vacancy or to explore potential recruiting opportunities.
- We use:
  - Data from 2018 to 2024 for 22 countries (HR, CY, SV, MT and PL excluded)
  - Data on ESCO skills, occupation and location of the job ad

THREE-LEVELS AI SKILLS CLASSIFICATION

Level 1

AI-Specific & Highly Specialized

- Essential for AI-related tasks and with limited application outside the field of AI.
  - Examples: Deep Learning, Artificial Neural Networks.

Level 2

Directly Applicable AI Skills

- Not exclusive to AI but essential for AI-driven processes.
  - Examples: Unstructured Data, Computer Vision.

Level 3

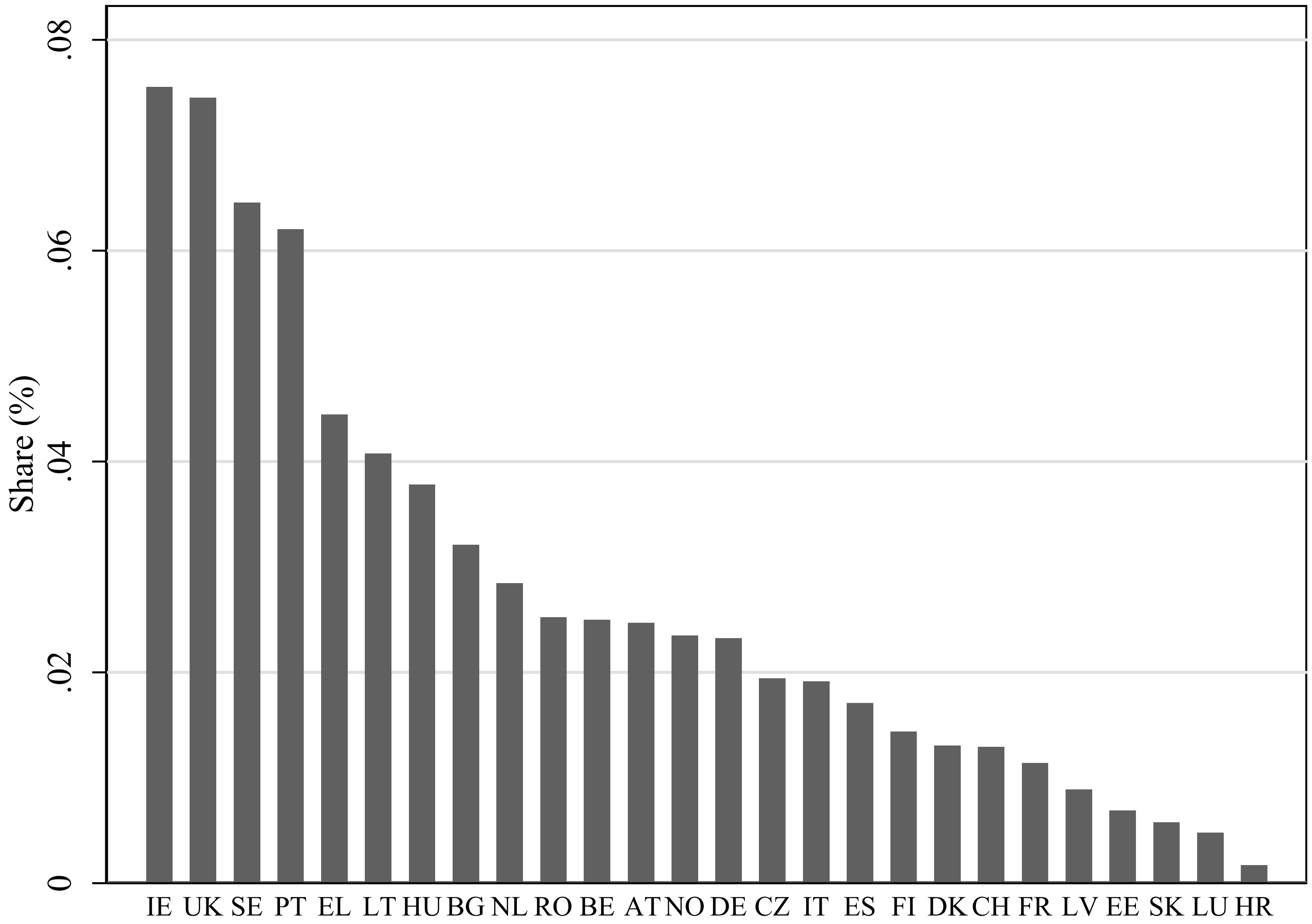
General & Complementary Skills

- Foundational skills supporting AI but widely used beyond AI.
  - Examples: Analyse Big Data, Computer Programming.

- Find all ESCO AI skills found in Borgonovi et al. (2023), Manca (2022) and the Lightcast taxonomy + AI skills required for ESCO AI occupations, like "AI engineer"
- We divide them in three levels
- We the share of online job ads that require at least one AI skill at Level 1 or 2 skills at Level 2 (level 3 is out of scope)

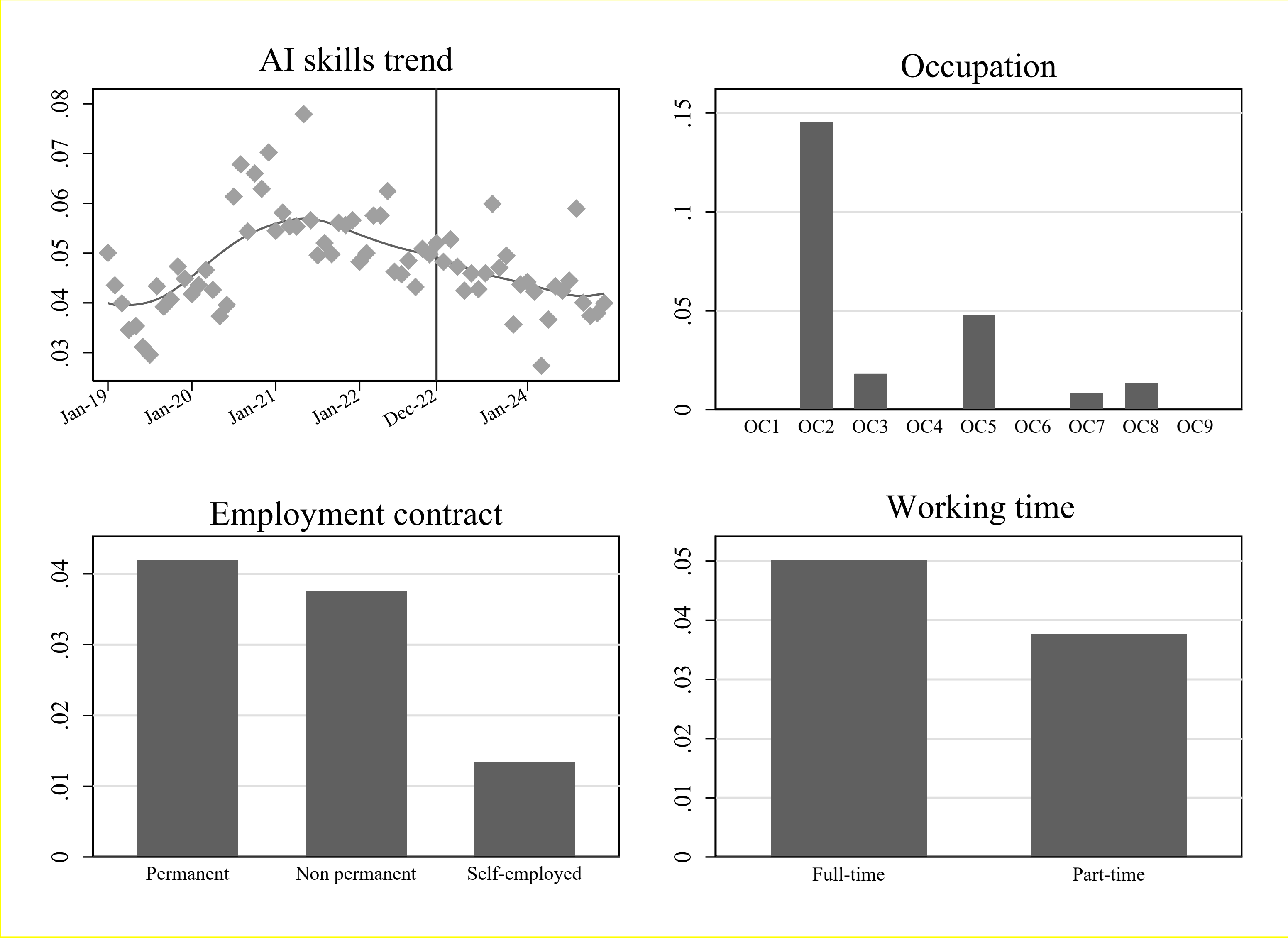
THE DEMAND FOR AI SKILLS BY COUNTRY

Share of AI online job ads (level 2 ESCO) by country, Jan. 2019 – Dec. 2024.



THE DEMAND FOR AI SKILLS OVER TIME, BY SECTOR OF OCCUPATION, EMPLOYMENT CONTRACT, AND WORKING TIME

AI online job ads (level 2 ESCO) Jan. 2019 – Dec. 2024.



THE IMPACT OF GENAI ON LABOUR DEMAND

- We model GenAI with the release of ChatGPT-3 on November 30 2022 as an exogenous labour market shock that affected the demand for occupations that are exposed to ChatGPT.

- **How to define exposure to ChatGPT?**

  - For occupation *i* in country j in month *t*, the degree of exposure to ChatGPT depends on the extent to which the core (most frequent) task required to perform occupation *i* can be outsourced to ChatGPT.

MEASURING EXPOSURE TO CHATGPT

- Two main classification frameworks:
  - ➢ Anelli *et al.* (2024): AI-exposed according to at least two of three main classifications (Felten *et al.* 2021, Tolan *et al.* 2021, Webb 2019), and, within these occupations, using O*NET data to define the "most frequent core task" for each occupation, then query ChatGPT itself on the level of exposure, using the exposure classification system developed by Eloundou *et al*. (2023):
    - ❖ ChatGPT-exposed: occupations that are unanimously "directly exposed to LLMs" across all iterations.
    - ❖ Not ChatGPT-exposed: occupations that are AI-exposed but not ChatGPT-exposed.
  - ➢ Gmyrek *et al*. (2023): automation score-based methodology directing GPT-4 to generate ten uniform tasks per occupation and to assign automation scores for each task. Overall occupational exposure score by averaging the task-level scores: very low (0–0.25), low (0.25–0.5), medium (0.5–0.75), and high (>0.75).
    - ❖ ChatGPT-exposed/not exposed: occupations with scores>/<0.5

TREATED AND CONTROL OCCUPATIONS

- Treated/Control occupations: occupations that are exposed/not exposed to ChatGPT **both according to Anelli *et al.* (2024) and to Gmyrek *et al*. (2023)**.

- Focus on representative and known professions across multiple sectors. Occupations that have been studied in the literature (e.g. "Web Developers" Borgonovi *et al.* 2023) or are experiencing technological advancement (e.g. in healthcare Faiyazuddin *et al.* 2025).
  - Example: "5111 Travel attendants and travel stewards" satisfies both Anelli et al. (2024) and Gmyrek et al. (2023) as a control occupation; however, according to ESCO statistics, it was the least common and representative, thus it was excluded.

TREATED AND CONTROL OCCUPATIONS

TREATED GROUP: GPT-exposed occupations.

SOC / ISCO Title	SOC Code	ISCO Code
Mathematicians / Mathematicians, actuaries and statisticians	15-2021	2120
Dietitians and Nutritionists / Dieticians and nutritionists	29-1031	2265
Computer Programmers / Application programmers	15-1251	2514
Economists / Economists	19-3011	2631
Sociologists / Sociologists, anthropologists and related professionals	19-3041	2632
Loan Officers / Credit and loans officers	13-2072	3312
Meeting, Convention, and Event Planners / Conference and event planners	13-1121	3332
Human Resource Specialists / Employment agents and contractors	13-1071	3333
Computer Network Support Specialists / Computer network and systems technicians	15-1231	3513
Web and Digital Interface Designers / Web technicians	15-1255	3514

CONTROL GROUP: Not GPT-exposed occupations.

SOC / ISCO Title	SOC Code	ISCO Code
Education Administrators, Preschool and Childcare Center/Program / Child care services managers	11-9031	1341
Veterinarians / Veterinarians	29-1131	2250
Dentists / Dentists	29-1020	2261
Kindergarten Teachers, Except Special Education / Early childhood educators	25-2012	2342
Radiation Therapists / Medical imaging and therapeutic equipment technicians	29-1124	3211
Paramedics / Ambulance workers	29-2043	3258
Photographers / Photographers	27-4021	3431
Electricians / Building and related electricians	47-2111	7411
Construction Laborers / Building construction labourer	47-2061	9313

DID ESTIMATION

DID design where the treated group includes occupations that are exposed to ChatGPT and the control group includes occupations that are not exposed to GPT. We estimate the following model:

$$share\ job\ posting_{ijt} = \beta_0 + \beta_1(Treated) + \beta_2(After) + \beta_3(Treated \times After) + \gamma_j + \varepsilon_{ijt}$$

Share job posting: share of AI job adds for occupation *i* in country *j* in month *t*.

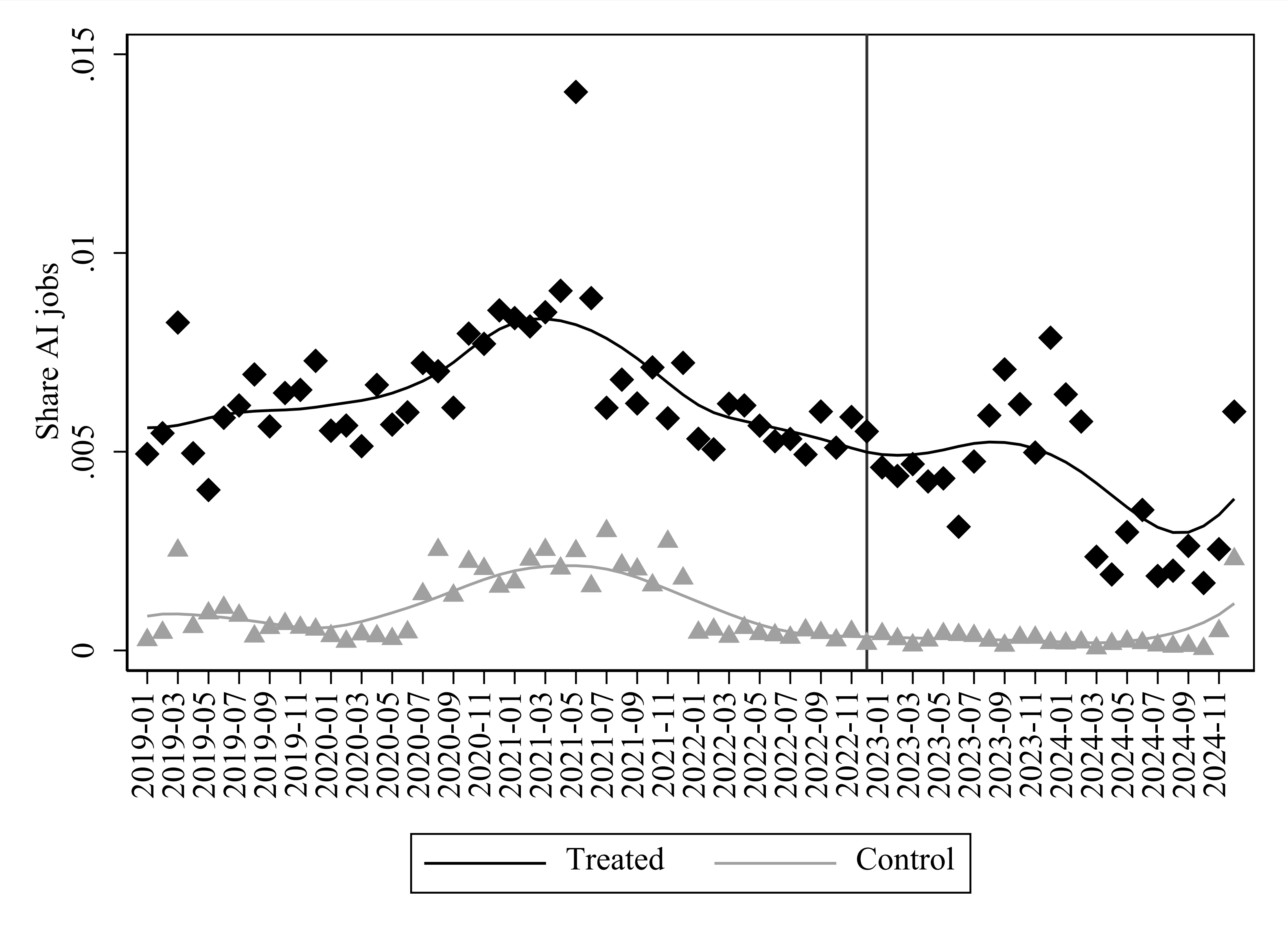
After: dummy variable that is 1 after the public launch of ChatGPT 3 on November 30, 2022.

Treated: dummy variable that is 1 if the job add is for an occupation in the treated group.

γ: country fixed effects to control for country-specific variation in labor demand.

<u>Robustness</u>: time trend (linear and quadratic) to account for seasonal variation in labor demand.

COMMON TREND ASSUMPTION



DID RESULTS

Difference-in-Differences estimates of Share Jobs Before and After GPT-3.

Notes: robust standard errors in parenthesis.

	Model 1	Model 2	Model 3
Treated	0.452***	0.452***	0.452***
	(0.032)	(0.032)	(0.032)
After	-0.026*	-0.002	0.067*
	(0.013)	(0.031)	(0.040)
Treated*After	**-0.223***	**-0.223***	**-0.223***
	(0.046)	(0.046)	(0.046)
Time trend	NO	YES	YES
Quadratic Time trend	NO	NO	YES
Constant	0.045***	0.061***	-0.009
	(0.008)	(0.021)	(0.026)
Observations	3,312	3,312	3,312
R^2	0.151	0.151	0.152

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

- **GenAI decreases the demand for occupations whose most frequent core task is automatable through ChatGPT.**

ROBUSTNESS CHECKS

- DID where the treated group includes occupations that are Not ChatGPT-exposed but AI-exposed and the control group includes occupations that are Not AI-exposed.
- The differential impact of ChatGPT between the two groups should close to 0
  - Results: Still significant “TreatedXAfter” coefficient, but about 1000 times smaller that in the baseline framework
- One-by-one exclusion of occupational groups from treatment and control
  - ➢ The coefficient of interest is always positive and significant

ONGOING AND FUTURE RESEARCH

- Improve the AI variable by better exploiting the three-levels of the AI skill classification
- Assess the accuracy of the AI variable
- Develop a classifier based on job ads’ full text (NLP data flow)

QUESTIONS?