Final Project Presentation

- Labor Economics I -

Kim Gyure
Sungkyunkwan University

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Outline

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Introduction : Motivation

- Artificial Intelligence (AI) is a majar technological change in recent days.
- According to many economic theories, technological change influence the changes in labor market.
- AI Impacts on Labor market
  - Acemoglu et al. (2022) : Exposure to AI $\longrightarrow$ Employment
  - Alekseeva et al.(2021) : Demand on the ability to work with AI
  - Brynjolfsson et al. (2023) : Impacts of generative AI on productivity
- November 30, 2022 : Introduction in ChatGPT

Introduction : Background

- November 30, 2022 : Introduction in ChatGPT
- ChatGPT : Generative AI and large language model
  - In first, the version of GPT is GPT-3
  - Gradually improve : GPT-4, GPT-4o, GPT-4o mini
  - Many people and firms have been using ChatGPT and making applications by ChatGPT in order to improve their productivity.
  - ChatGPT $\longrightarrow$ Labor market
- Impacts of ChatGPT
  - Eisfeldt (2023) : Firm value changes after ChatGPT by exposure to AI
  - Eisfeldt and Schubert (2024) : ChatGPT is a significant technological shock on finance sector

Data : AI Exposure

- AI Occupational Exposure (Felten et al., 2021)
  - AI Application Selection : image recognition, language modeling, and speech recognition, that have shown significant scientific progress and are likely to impact the workforce
  - Linking AI to Occupational Abilities (O*NET)
    1. categorize 52 workplace abilities relevant to different occupations
    2. A survey of gig workers on Amazon's Mechanical Turk (mTurk) : measure how related each AI application is to specific abilities, generating a matrix of relatedness scores from 0 to 1.
  - Calculating Ability-Level Exposure
  - Aggregating to the Occupation Level : Ability-level exposure was adjusted by weighting each ability's importance and prevalence in an occupation, yielding an occupation-level AI exposure score—AIOE

Data : US sensus

- Current Population Survey (CPS)
  - 2021.01 2024.08
  - Conducted by U.S. Census Bureau & Bureau of Labor Statistics.
  - Monthly, covering over 65,000 households.
  - Variables : Education, labor force status, demographics, etc.
- Crosswalk from U.S. Census Bureau
  - AIOE : Standard occupational classification (SOC)
  - US Census : Census occupational code
  - Crosswalk : SOC and census occupational code

Statistics

	Mean	SD	Min.	Max.
Hours worked per week at main job	129.68	281.19	.00	999.00
AIOE	.15	1.03	-2.11	1.53
Language Model Exposure	.20	.96	-1.85	1.93
Sex	.48			

Statistics

Table: Sample Size by Year and Month

	Jan	Fab	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2021	34,382	34,027	33,371	34,649	34,357	33,392	33,798	33,757	32,705	33,498	32,363	32,152
2022	32,176	32,466	31,563	32,549	33,512	32,784	32,582	32,920	32,317	32,037	31,502	31,143
2023	31,338	30,828	30,540	31,864	32,267	32,290	32,451	32,742	31,969	32,620	31,820	31,454
2024	31,565	31,746	30,712	31,635	31,862	31,746	32,093	32,058	-	-	-	-

Statistics


Work Hours Over Time
Average Work Hours
160
150
140
130
120
2021m1
2022m1
2023m1
2024m1
Time (Year-Month)

Empirical Strategy

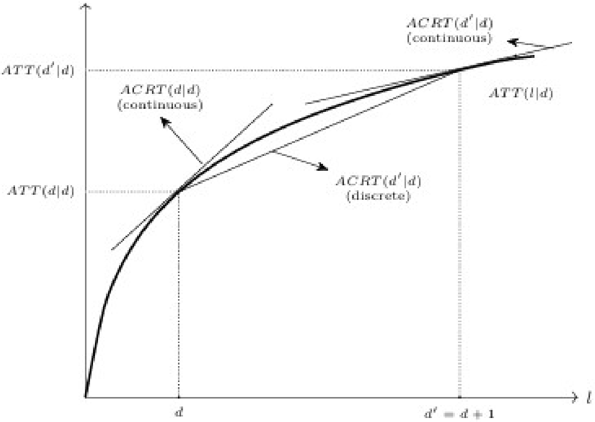
- Sample
  - Labor force $== 1$
  - Individuals who have missing values are filtered out
- Key variable
  - Outcome variable : Work hour in main job per week
  - Explanatory variable 1 : AIOE
  - Explanatory variable 2 : Indicator for ChatGPT launch
- Model

$$Y_{it} = \beta_1 After_t * AIOE_i + \beta_2 After_t + \beta_3 AIOE_i \beta_4 X_{it} + \delta_i + \gamma_t + \epsilon_{it}$$

Main coefficient : β_1

Empirical Strategy

Figure 2: Causal Parameters in a Continuous Difference-in-Differences Design



Empirical Strategy

- Continuous treatment effect (Callaway et al., 2024)

$$ACR_l = \frac{\partial E[Y|AIOE = l]}{\partial l}$$

$$Y_{it} = \beta_1 After_t * AIOE_i + \beta_2 After_t + \beta_3 AIOE_i + \beta_4 X_{it} + \delta_i + \gamma_t + \epsilon_{it}$$

$$\beta_1 = \int_l w(l) \frac{\partial E[Y|AIOE = l]}{\partial l} dl$$

Empirical Strategy

- Event-study with continuous treatment (Callaway et al., 2024)

$$Y_{it} = \beta_1 \sum_t Month_t * AIOE_i + \beta_2 AIOE_i + \beta_4 X_{it} + \delta_i + \gamma_t + \epsilon_{it}$$

- ChatGPT have been gradually improved
- Also, it is reasonable to assume that there are wide spillover effect after ChatGPT.

Result

Table: Estimation Result with any fixed effect and covariates

	Coefficient (s. e.)
AIOE $\times$ After	5.219 ***
	(0.455)
After	-13.676 ***
	0.474
AIOE	-24.527 ***
	0.318
Constant	139.6365
	(0.332)
Adj R-square : 0.0070	
Observation : 1,425,601	

Further research

- Filter 'outliers' for each variables (Lower and Upper 1%)
- Include fixed effects and covariates
- Suggest statistics using completely filtered samples
- Other outcome variables
  - Felten et al. (2021) estimated other exposure indexes.
  - Exposure to language model may be more proper than AIOE