The Implications of Artificial Intelligence on Wage Inequality

Final Year Project Proposal

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Even with the rapid development of AI, its impact on income inequality remains uncertain

Artificial Intelligence on Macroeconomics

1.5pp
increase in aggregate labor productivity growth in the US, through Generative AI

60%
of jobs may be impacted by AI, in advanced economies

Generative AI could increase global GDP by **7%** in the span of 10 years.

Growth of Artificial Intelligence

62.7%
increase in number of AI patents granted from 2021 to 2022

4-5x
increase in training compute of frontier AI models

The total number of AI publications nearly **tripled** from 2010-2022.

How is this translated into income inequality?

Widening Income Gap

- Use of AI is only relevant to directly improve high performers.
- AI affects the **value** workers produce through their labor.

Promoting Income Equality

- AI has benefitted lower-performing workers more than higher ones.
- AI reduces **productivity differentials** between workers.

Source: Georgieva (2024), Hatzius (2023), Goldman Sachs (2023), Maslej et al (2024), Rosalsky (2025), Georgieff (2024)

Current research explains some technology-caused wage disparities through various theories

Skill-Biased Technological Change (SBTC)

Historically, technological change **disproportionately benefits** high-skilled workers by making them more productive

Abstract reasoning and communication tasks - now computerised

Only high-skilled workers more productive

Demand for **high-skilled increases**, demand for low-skilled remains the **same or decreases**

Skill premium rises, increasing wage inequality

Task Polarisation Model

Task A

Task B

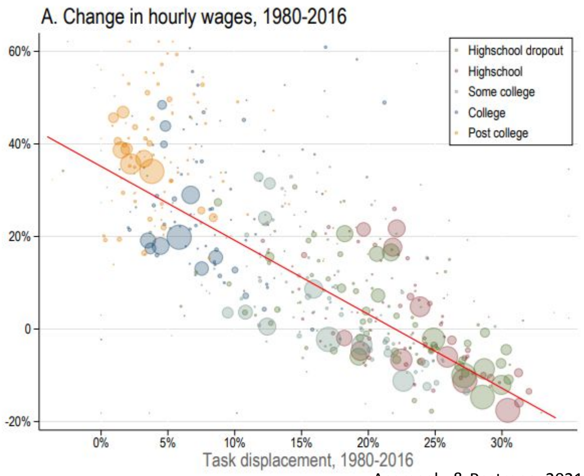
Task C

Routine tasks automated

50-70%

of wage changes are tied to automation displacing routine-task workers

Implies adverse impact of technological change on the earnings of less-skilled workers.



Acemoglu & Restrepo, 2021

Those **most exposed to task displacement** lost the most in **real earnings** terms.

Some tasks like waiting tables, cleaning rooms - **don't pay high wage** but **cannot be automated** - cannot be replaced

Source: Card & DiNardo (2002), Acemoglu & Restrepo (2021), Autor (2022))

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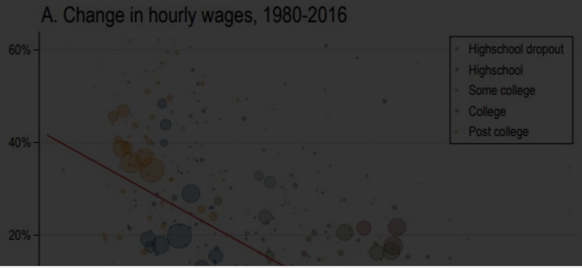

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These theories focus on *technology* on wage disparity, but does this apply to *AI* on wage disparity?

Source: Card & DiNardo (2002), Acemoglu & Restrepo (2021), Autor (2022))

Case studies focused on AI and value-addition have mixed results, primarily micro-level focused

Existing research has explored impact of AI on specific organisations and individuals AI models…

On Entrepreneurial Performance

Flawed recommendations
Gen AI may yield overconfident or flawed recommendations for real-world business problems
→ Low-skilled workers perform worse with AI

In the Workplace

Low-Skilled Workers
AI tool helps newer or less-skilled agents move more quickly through the learning curve
→ 34% increase in productivity, making low-skilled workers behave more like high-skilled workers

High-Skilled Workers
Gen AI disseminates best practices
→ However, impact is minimal on high-skilled workers who already know this information

… but link between AI parameters and inequality is missing

Most research focused on individual studies

… leading to lack of clarity on AI implications on specific skill groups

AI Uncertainty

Initially, technology was only capable of taking only routine tasks, but now, AI is able to take over non-routine tasks as well

Source: Otis et al. (2024), Brynjolfsson & Raymond (2025), Autor(2022)

Our Model Equation will be plugged into a Fixed Effects Panel Regression

Hypothesis

AI adoption will predict an increase in wage inequality between skill groups, with high-skilled workers benefiting the most.

Theil Index between skill level

$$\sum_{g=1}^{G}\left(\frac{n_g}{N}\cdot\frac{\overline{y_g}}{y}\cdot\ln\left(\frac{\overline{y_g}}{\overline{y}}\right)\right) = \alpha_i + \gamma_t + \beta_1 \%\Delta\, AI\, Parameters + \beta_2 \%\Delta\, AI\, Patents + \beta_3 \%\Delta\, (AI\, Parameters \times Skill\, Level) + \beta_4 \%\Delta Employment + \beta_5 \%\Delta\, GDP\, Growth + \beta_6 \%\Delta\, PCE\, Growth + \epsilon$$

- G = Number of skill groups (e.g., low/middle/high-skilled)
- n_g = Number of workers in group *g*
- $\overline{y_g}$ = Mean wage of group *g*

Our analysis is based on a diverse source of reputable data sources

Wage Data
Employment Number
Skill Level Classification

AI Parameters
AI Patents

US GDP Growth

Minimum Wage Policy

Dependent variable: Combining US BLS wage data and ILO occupation categories

Our Approach to Categorise Skill-Based Income

Data form	BLS wage and occupations data, ILO categories
Objective	Merge BLS income data with the ILO classifications
NLP Methodology	RoBERTa Word Embeddings
Feature Engineering	Vector Standard Scaling and ADASYN Oversampling
ML Methodology	Support Vector Machine (SVM) Classifier, PCA

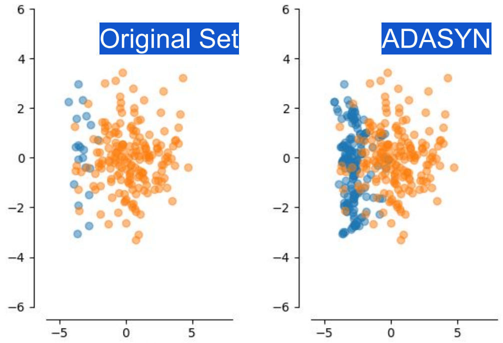
We also considered XGBoost, a robust ML classifier

On Our Data: Why Oversampling is Needed

	Low Skill	**Medium Skill**	**High Skill**
Pre Oversampling	47	260	273
Post Oversampling	270	260	273

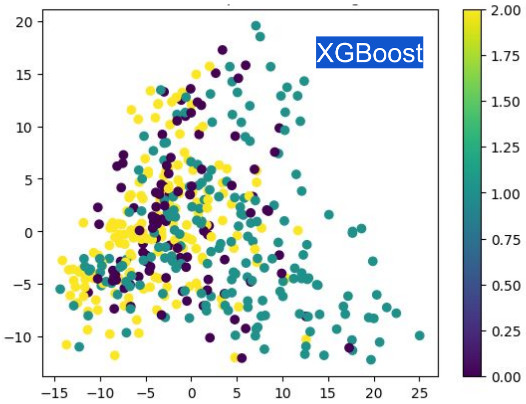
Avoid classifier training that emphasize too much on majority classes

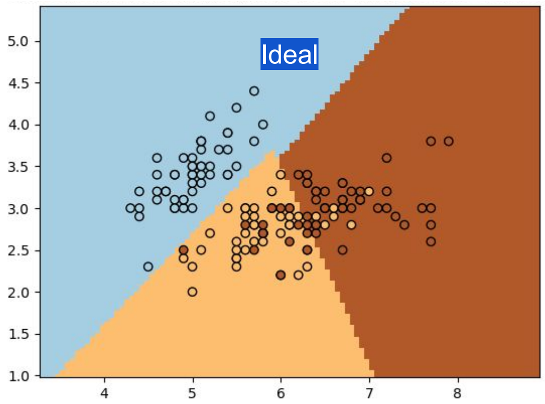
A Simple Example: The Intuitive Effects of ADASYN

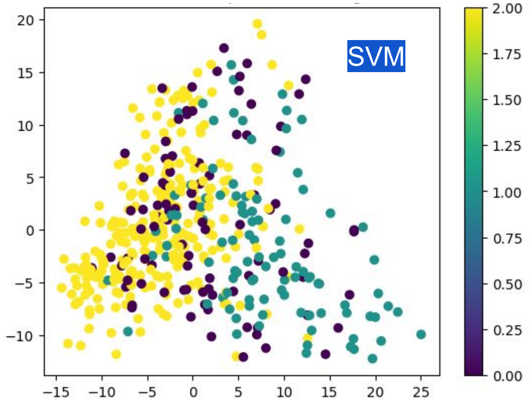


Source: Official Imbalanced-learn Library Documentation

Dependent variable: Classifier model selection for generating skill categories



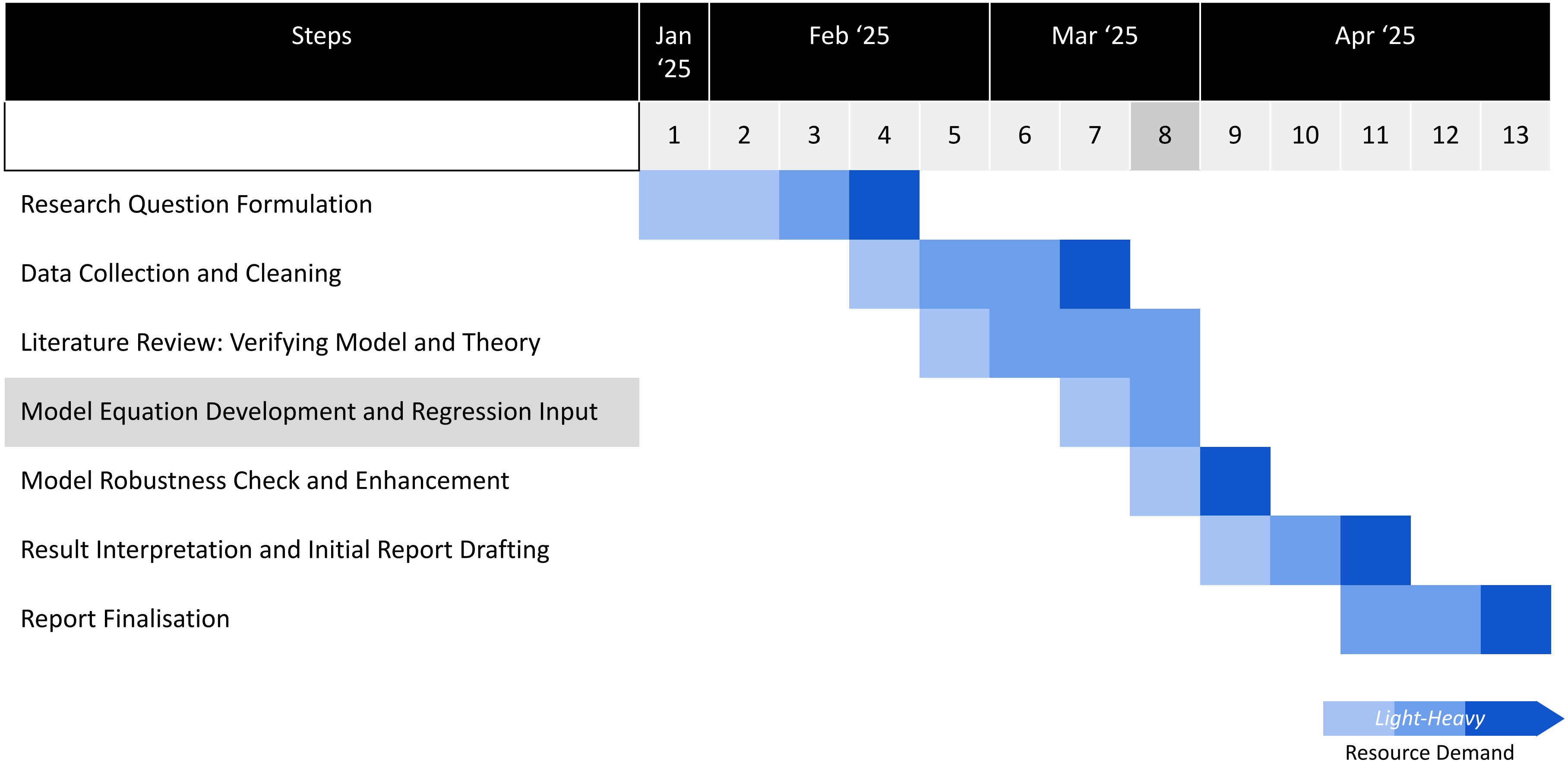




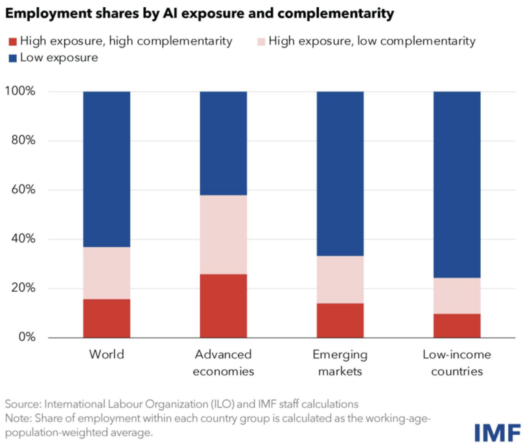
	Definition	Low Skill	Medium Skill	High Skill	Weighted Average
Precision	How many of the positively classified are correct?	95%	90%	87%	91%
Recall	How good is it at detecting the positive classes?	100%	82%	90%	91%
F1-Score	Combined measure to gauge both precision and recall	97%	86%	88%	91%
Error Rate	From all classes, positive and negative, how many were predicted incorrectly?	9.32%	**Accuracy**	From all classes, positive and negative, how many were predicted correctly?	**90.68%**

Source: Official Scikit-learn Library Documentation

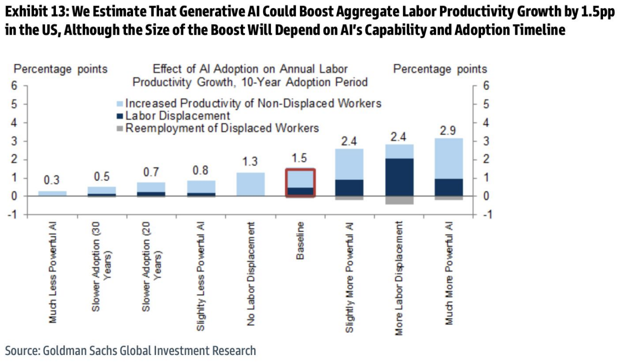
Our team is currently running model equation and testing the regression model



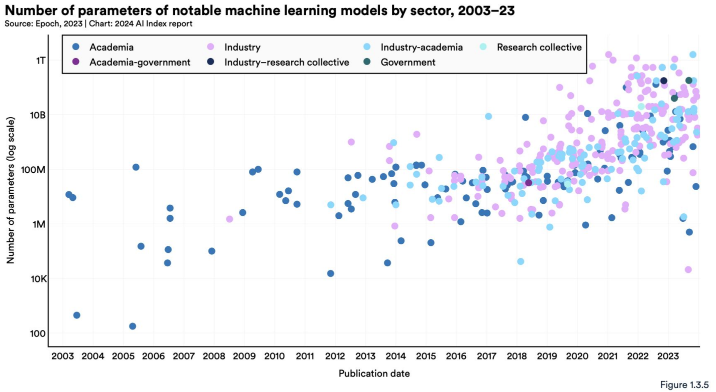
Appendix



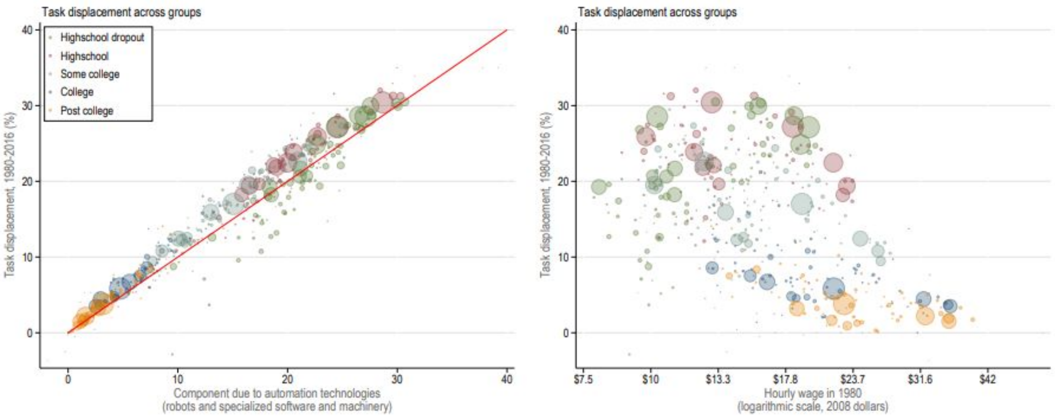
Georgieva (2024)



Hatzius (2023)



Maslej et al. (2024)



Within-Group Inequality: Measures Wage Inequality within each skill group

$$T_{Within} = \sum_{g=1}^{G} \left(\frac{n_g}{N} \cdot \frac{\overline{y_g}}{\overline{y}} \cdot T_g \right)$$

AI on Income Inequality

Acemoglu, Restrepo (2021)

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Thank You!