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How AI Will Affect Worker's Earnings, Working Hours, and Employment Status

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Abstract: This paper investigates the impact of AI on the labor market. Three outcomes in the labor market, including employment status, earnings, and working hours, are considered. By closely analyzing the data on the labor market before and after an AI shock happened, it is found that the impact of AI tends to increase earnings and working hours in the short term. Additionally, more obvious findings may occur in the long term rather than the short term. It points out that the anxiety caused by the boomed technology may be mainly caused by the reform process instead of the direct impact. It suggests that people should focus on how to make adjustments to the education and training system to solve the problem.

Keywords: Labor Market; Technology; Difference in Difference; Artificial Intelligence

1. Introduction

The global market of AI (Artificial Intelligence) is expected to grow twenty-fold by 2030. The high-speed development of AI technology encourages people to raise their academic awareness of the area (Thormundsson, 2023). In addition to changing people's way of life, the application of AI also causes debates on its controversial impact, as well as the ethical concern Felten et al. (2023). Whether people are better off or worse off under the impact of AI gradually become widely discussed. This paper focuses on the labor market specifically, studying how workers' well-being is affected by AI exposure.

Currently, the interest in the impact of AI on the labor market is mainly reflected in two aspects. The widely adopted automation will replace workers in some tasks, consequently causing unemployment. The increase in productivity boosted by AI that can make workers better off for real wages may increase, and the working hours may decrease (thus, people can enjoy more leisure). To investigate people's interests in the topic further, three outcomes, including employment, real wage, and working hours, will be studied in this paper. Additionally, workers in different industries are exposed to AI differently. Tech sectors not only play a critical role in pushing AI's advances but are also affected by AI itself at the task performance level. In this research, AI's impact on the outcomes will also be compared across tech and non-tech sectors.

Interest in the topic has been developed for decades. A study of the impact of AI on the labor market lies in the scope of how technology transforms economies. It is said that technology could potentially change the possibilities and processes of production, consumption patterns, and reward to skill given different kinds of workers Graetz et al. (2022).

Researchers have been analyzing the impact of AI on the labor market from different perspectives. Some concentrate on the tasks of a certain job that can be performed by AI while others investigate closely the change in companies' business. People study occupations' tasks and set up the concept of AI exposure that measures the degree an occupation is affected by AI. The task-based model introduced by Acemoglu and Autor (2011) is most generally used in the study of AI's impact on the labor market. The model theoretically compares the description of the tasks performed by this occupation with the description of the missions that can be executed by AI. By analyzing the common factors, researchers ranked the most and the least affected occupations. Furthermore, they also categorize the workers into different groups according to gender, age, or educational background and investigate how AI affects them differently. Those who study the impact on a business scope broadly collect the existing literature. When studying companies' business, researchers conducted interviews and summarized business reports; they investigated how AI is involved in companies' operations. Most of the existing research starts at a micro level and explores how AI can affect a specific aspect of the economy.

This research will be more result-oriented. Given that people who study the impact of AI are mainly concerned about the well-being of human lives. The author research directly on the representative outcomes that reflect the level of worker's well-being. While the other research uses theoretical models to predict them. The author will closely investigate the change in the labor market under AI shocks (e.g. a significant breakthrough in the AI area) from a macro perspective. The real-life data in this research could make the result more intuitive and explainable. In addition, the newly released ChatGPT, which changes people's lives significantly, will also be considered. More real-life-based research with the most updated data could consolidate the results of this empirical work.

The entire paper contains four parts. The first part is the introduction of the topic (section one) and the literature review (section two). In this section, the author will summarize the current situation regarding the study of AI and the labor market. And present a general idea of the broad interest in the impact of AI on the labor market. The author will also closely analyze the paper written by Webb (2019), which plays an important role in my research. Sections three to five form the second part of the paper; in this part, there will be an in-detailed explanation of my approach to studying the topic, including the explanation of why the author chose this approach, the interpretation of the econometrics model the author chose, and the main formulas the author used. The author will illustrate how my approach works when solving the AI's impact problem. The author uses Difference in Difference as the econometric model; thus, the author will describe how the author selected the event for the Difference in Difference study and how the treated group and untreated group are classified.

As the background information is stated and the research framework is built in the first half of the paper, the second half will start with an overview of the data, including data source, data structure, and how the author conducted the pre-data processing to prepare a panel data frame for the regression. In the following section, the main results found with the help of regressions and the graphs will be shown. The author will interpret the results of my findings in conjunction with the previous findings concluded by other research. For example, how productivity effect and replacement effects are reflected in this research. In the end, some of the specifications that could make the result robust will be explained with more evidence.

2. Literature Review

Historically, technological development drives social change. The advancement of artificial intelligence (AI) raised people's interest in its impact on society, especially in the labor market. Makridakis (2017) believed that the changes caused by AI technology development would be more significant than the industrial revolution. And the changes will be harder to predict due to the rapid advancement. Frank et al. (2019) emphasized the need for research on AI's impact on society, and they also pointed out that the challenges will be harder for high-speed AI innovation and the limited available models and data.

Though challenges exist in studying AI's impact, different methods that study how AI reforms the labor market still have been attempted. There are researchers who focus on the debate between optimism and pessimism. Pessimism mainly concerns the displacement effect caused by the application of AI, which will increase unemployment and inequality or decrease wages, while optimism claims that the new tasks created by technological innovation will offset the jobs lost due to AI's replacement. Moreover, people may also enjoy more leisure thanks to the productivity growth caused by AI (Makridakis, 2017). From the perspective of optimism, Bughin et al. (2017) conducted surveys on firms and found that most AI-aware firms expect an increased demand for new skills related to data work, which means that it hardly has a significant reduction in the workforce size. Stone et al. (2022) also mentioned that artificial intelligence is more likely to replace tasks rather than jobs.

Acemoglu and Restrepo (2018a) concluded that the effects of AI on the labor market can be classified as displacement effect, productivity effect, and reinstatement effect, where productivity effect and reinstatement effect positively affect the labor market and displacement effect act negatively. The productivity effect can be generated from capital accumulation and the deepening of automation. The reinstatement effect describes the phenomenon that new tasks will be created by new technologies, which will also contribute to a positive impact on the labor market. The displacement effect refers to the idea that jobs will be replaced by machines. The author revealed that whether the effect is positive or negative should depend on the dominant effect in a certain circumstance. Mutascu (2021) also considered inflation and found that unemployment can be reduced during a period of a low inflation rate while it remains neutral during a high-rate period. In addition, since the reallocation of tasks between employees and jobs takes time, the mismatch between skills and technologies will also affect the labor market. In response to this point, Bughin et al. (2017) emphasized the importance of worker reskilling.

Thinking of the methodology, several pieces of research were conducted according to Acemoglu and Pascual's task-based model. The model first introduced by Acemoglu and Autor (2011) set tasks and skills endogenous and investigated how technical change is involved in the substitution of tasks previously performed by labor. Acemoglu and Restrepo (2018b) further adopted the task-based model considering labor-capital allocation. They pointed out that both automation and the creation of new tasks will increase inequality in the labor market. Webb (2019) designed a string-matching model to measure the level of AI exposure. After plugging in the data of technology patents and task descriptions, the author found that different types of workers have different exposure to AI. Agrawal et al. (2019) contribute to the model by dividing the task into prediction tasks and decision tasks. The result shows that the two types of tasks complement each other, and it is difficult to tell which is likely to be a labor incentive or capital incentive task.

In my research, the author will further study the result of the paper written by Webb (2019). Based on the foundation of Acemoglu and Restrepo's (2018a) task-based model, Webb connects the tasks with occupations. By matching the tasks required by a certain occupation and the description of the technology, he ranked the occupations according to the level of it related to the technology, and the author listed the five most exposed to AI occupations and the five least exposed to AI occupations according to the result of the model. The author will use this result as one of the standards for the classification of the treated and untreated groups. Three kinds of technologies are analyzed in this paper. The writer tried to see how robots, software, and AI may affect the labor market with the help of a task-based model. The author further uses a regression analysis of the data from 1980 to 2010 to study the relationship between wages, change in employment, income distribution, and the level of AI exposure. How the impact of AI exposure varies with age, gender, and education are also compared. The author will combine the results of Webb's (2019) research and the most updated data. Discussing how the result concluded several years ago could be applied in the current situation when the ChatGPT (known as the significant breakthrough in AI's history) is widely used.

2.1 Discussion on the Topic

In summary, the current research on the impact of AI on the labor market mainly focuses on the improvement of the AI exposure measurement models and the discussion of the cause of the impact. AI exposure is studied theoretically for most of the time. The study of real-world cases in the labor market is demanded. The outcomes on the individual are sometimes ignored. Besides, most of the effects are studied aggregated, meaning that the industrial differences are not captured in the current study.

The improvements that can be potentially made in this work may reflected in three aspects. First, consider the methodology. The strength of Difference-in-Difference can be leveraged. It is an empirical method that can capture the effect of AI exposure over time. A more dynamic understanding of the relationship between AI exposure and the outcomes can be observed. Longitude insights will be discovered using this methodology. Second, while the majority of the research that studies AI exposure revolves around the tasks involved in different occupations, my work will be concentrated on the outcomes. This means that the author is studying the topic with a new perspective. Given that the purpose of investigating the labor market dynamics is to improve the well-being of humans. And the outcomes studied in this research are some critical indicators for the measurement of individual well-being. My result may help people get a more intuitive understanding of how AI may change their lives, which shows an ethical consideration of my work. The last aspect is about the connection between the available database and the approach to answer the question. The data availability is said to be the barrier to studying AI's impact in real cases. And there is no concrete indicator that represents the level of exposure. The relationship between labor market outcomes and AI exposure cannot be found directly. A study on the AI shock on tech (high-AI-related) industries and non-tech (low-AI-related) industries can be an attempt to connect AI exposure to measurable statistics. It will overcome the barrier to studying the impact of real-world AI. In the following section, the author will explain how this paper studies the topic with real-world statistics.

3. Basic Approach

In this section, there will be an explanation of the basic logic that supports the empirical study, including the objective to be realized by the approach and the interpretation of the model.

3.1 Objective

The objective of this research is to figure out whether workers are better or worse under the impact of AI. Specifically, how outcomes (the outcomes in this research are wages, working hours, and employment) in the labor market are affected by AI exposure. Where the level of AI exposure is assumed to present differently in different types of workers or in different industries, the critical elements to study the topic "How workers are affected by AI exposure" are outcomes and AI exposure. And the relationship between the two elements will show us the impact. The relationship will be studied with the help of the econometric model, which will be explained in the following section.

3.2 Interpretation of the Model

The topic will be studied with Difference-in-Difference, and the treatment will be the impact of an AI shock. The time of the treatment in this paper will be the time when an AI shock happened. In this case, we assume that a certain group of workers is more related to AI, meaning that they have a higher level of exposure to AI. The other group of workers has a lower level of exposure, which means that they are hardly affected by an AI shock. Thus, the workers in the group with higher AI exposure will be the treated group, and the workers in the group with lower AI exposure will be the untreated group.

To make a clear, reasonable, and unbiased classification of the tech and non-tech workers, the author will introduce two standards to decide which type of worker is in the higher exposure group and which type of worker is in the lower exposure group.

According to the basic framework of the Difference-in-Difference. The data on outcomes (employment, wages, working hours) in different periods is required. So, the author will collect the data before and after the event according to a time series designed to measure the outcomes from different industries. In the end, it is expected to get an average treatment effect from the Difference-in-Difference.

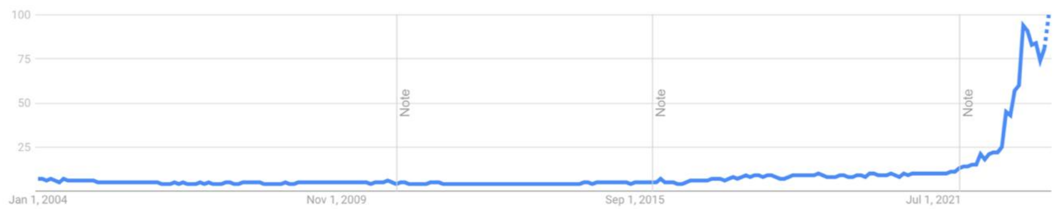
4. Preparation

Given that the purpose of this research is to figure out what is the impact of AI exposure on working hours, wages, and employment. The economic model applied will be Difference-in-Difference. In the following content, the author will explain the preparation required before collecting the data. The preparation process includes the selection of the events and treatment design.

4.1 Selection of the Events

To make the selection of shock reasonable, considering both the significance of the shock and the data availability, the author select two shocks in this paper: the advent of ChatGPT and the race between AlphaGo and Lee Sedol. Google Trends is used as a reference to prove that the event has a significant impact on society. Therefore, this section will start with the selection of AI shocks where shocks are the containers of the treatment that present a comprehensive impact on society. It could be a significant increase in the number of users for an AI technology or a big change in people's expectations of AI.

Figure 1: The Interest on Artificial Intelligence Overtime



The first shock selected is the advent of ChatGPT. ChatGPT was initially released on 30 November 2022. **Figure 1** shows that the interest in AI increased sharply in 2022, which coincides with the time when ChatGPT came into the world. ChatGPT also shows an outstanding performance in terms of user growth. While it takes ten months for Facebook to gain one million users, ChatGPT only takes 5 days Duarte (2023). Both the interest in the topic and the degree of application in the public show that the advent of ChatGPT could be a crucial representative of the "AI shock".

The second shock is the game between AlphaGo and Lee Sedol. AphaGo is said to have a considerable influence on AI field Wang et al. (2016). Additionally, it will also have a non-negligible impact on the business world. It was expected that the speed of information management would largely increase Agrawal et al. (2022). The impact of the race between AlphaGo and Lee Sedol on society is both significant technically and economically. It could also be a representative of the AI shock.

Both of the events are said to be representative of machines' ability to achieve human-like performance. The race between AlphaGo and Lee Sedol results in a higher expectation towards AI and leads to more investment in the AI industry while the impact of ChatGPT is revolutionized. By studying both of the events, we could comprehensively investigate the impact of AI on the entire society. Additionally, considering the dynamic labor market caused by the pandemic lockdown as well as the layoff at technology firms, studying both of the events could bring a more critical result to the research.

4.2 Treatment Design

To complete the treatment design for the Difference in Difference in this research, the author also needs to classify the treated and untreated workers according to some standards. The author investigates two ways of dividing the treated group and the untreated group. Both of the approaches will be based on the occupation code in the 2018 Census Classification Scheme, which is also referred to in the original data set.

The first approach is to classify the tech workers as the treated group and classify the non-tech workers as the untreated group. The tech group is assumed to be the workers who work in Computer, Engineering, and Science Occupations, while the non-tech group is set to be the workers not in the Computer, Engineering, and Science Occupations. According to the occupation codes book, the occupation codes within the range of 1005 to 1240 (both included) are Computer, Engineering, and Science Occupations. In the following content, the author will call this approach the first standard.

The second way to classify the treated and untreated groups is based on the result from Michael Webb's research Webb (2019). He listed five occupations that were exposed to AI most and five occupations that were least exposed to AI. All occupations are listed in the census occupations book with codes, with small changes in the classification. The author set occupations that were exposed to AI most as the treated group and the occupations that were least exposed to AI as the untreated group. This approach will be referred to as the second standard in the following content.

In both approaches, the treated group is those workers with higher exposure to AI, while the untreated group is less likely to be exposed to AI.

In the study of Difference in Difference, the author investigates the impact of the shock on each individual. This means that the control variable in this model is personal identity. This indicates that gender, comparative age, and any other variables that hardly change for a person in the short term are controlled.

5. Main Formulas

The model chosen in this research is Difference in Difference. Two main regression formulas were used in this research.

The first formula breaks the treatment and time effect into two parts and adds an interaction term. This is the standard version that follows the formula,

$$Y_{it} = \beta_0 + \beta_1 T_i + \beta_2 P_t + \beta_3 I_t + \epsilon_{it}$$

Where Y_{it} is the outcome of individual i at time t. T_i is the treatment of individual i, P stands for time, $P = 0$ if the time is before the shock, and $P = 1$ if it is after the shock. I is the interaction term $T_i \times P_t$. There is one dependent variable with three independent variables Under this formula. The Treatment, Time effect, and the Treatment*Time effect are studied separately. Under this formula, the change in the treatment is not considered.

The simplified version follows 'the model of observed outcomes', which is the formula below. In this formula, Y_{it} is the outcome of individual i in time t, α_i is the individual fixed effect, δ_t is the time fixed effect in time t, θ_t is the treatment effect in time t, and ε_{it} is random disturbance of i in time t.

$$Y_{it} = \alpha_i + \delta_t + \theta_t D_{it} + \epsilon_{it}$$

Based on the panel data frame, the author calculate the difference in the outcomes between 2022 and 2023 and build a new data frame to run the regression for Difference-in-Difference. The new data frame shows the change in treatment, X_i, and the difference in outcomes between 2022 and 2023, Y_i. In those samples, the employment status remains the same for all individuals in two years. It makes no sense to run the regression on the change in the employment status. So, the author will run the regression of change in earnings and working hours on the change in treatment separately according to the formula.

$$Y_i = \beta_0 + \beta_i D_i + \mu_i$$

The value of β_i, which is the coefficient of the regression, will show the treatment effect on outcomes of AI exposure. This will tell the degree of the impact of AI shock on the outcome.

The first formula contains more information on the impact of each variable on the outcomes and what will happen when we combine those variables, while the second formula pays more attention to the change in the variable over time. In the circumstance of the first formula, time is treated as a variable, while in the second formula, time is set to be a condition. Since the first formula is the standard version and contains more variables that may bring more information related to the graphs, the result of this research will mainly come from the first formula.

6. Overview of the Data

Data plays an important role in an econometric model. The Difference in Difference model in this research requires micro data on individuals' outcomes over time. This section explains where the author obtained my raw data and how the author transferred the raw data into the panel data to run the regression. The explanation includes a description of the data sources and the features of the database, followed by a description of how the panel data was constructed.

6.1 Data Source

This research will be studied within the scope of the US. Thus, the author obtained the data on the outcomes (wages, working hours, employment) from the IPUMS CPS Flood et al., 2023. To make an accurate classification of the treated and untreated group, the author categorized the data of outcomes into two groups according to each observation's occupation code. The data on occupations is collected from the U.S. Bureau of Labor Statistics U.S. Bureau of Labor Statistics (2023), which is the bureau data that is widely used in analyzing workers' occupations. All the data in this research are government official data that are authoritative, providing more solid support to the result of the research.

6.2 Database

This research focuses on the change in outcomes of individuals in the labor market, so the author collected the data from the IPUMS CPS (Current Population Survey). This database provides monthly updated micro-data that includes the variables that observe the performance of an individual in the labor market. The latest data was released in August 2023. This database contains both cross-sectional and one year apart longitudinal samples. The data for cross-sectional samples is included every month in a year, with data in March being three times more than the other months. The cross-year longitudinal data provided are the samples from March.

The data in IPUMS CPS is collected through the population survey, meaning that the figures were reported by households and individuals themselves. So, the pre-processing process to eliminate the abnormal terms is required. Additionally, the data are not adjusted according to CPI (Consumer Price Index), so the figures that use currency as the unit are in nominal terms. I did not adjust the nominal earnings into the real earnings in my research because weekly data is used in this research, and the weekly change in price level is negligible.

The classification of the occupations used the 2018 Standard Occupational Classification System as a reference. The 2018 Standard Occupational Classification System published a code book that matched the name of the occupation with the codes. The figure for each individual's occupation variable represents the occupation code.

6.3 Pre-Data Processing

The variables in the original data set can be divided into three types, the identity variables, including serial number, person record, household record, etc., the time variables, including month and year of the observations. And the labor market outcomes variables, including whether the worker is in the labor force, his/her employment status, weekly earnings, and weekly working hours. This research concentrates on the impact of AI on individuals, so the personal record number is used to identify them.

The original data contains individuals who are not in the labor force. So, the author derives the individuals in the labor force from the original data. After dropping the person who is not in the labor force, there are still observations that indicate working hours, earnings, or occupations data not available. To organize the data, the author dropped the data that indicates working hours higher than 168 (people should have at most 168 hours per week) and earnings data that is not available (equals 9999.99). the author processed the data for employment outcomes differently. Because labor that is currently not at work may contribute abnormal figures to the results of earnings and hours, the author only consider the labor who is currently at work at that time when studying the earnings and working hours. If the author still use this dataset to study unemployment, it makes no sense to study only the people who are at work all the time, as the unemployment rate will always be zero. So, when getting prepared for the data to study unemployment, the author only drop the people who are not in the labor force. The number higher than 20 indicates unemployed for labor in the labor force, and the number under 20 indicates currently employed.

6.4 Panel Data

To improve the quality of the data and make the result more trustworthy, I built panel data for the Difference-in-Difference. The original data set comes from the longitude data set in IPUMS CPS, which tracks the outcomes of individuals each year in March.

In this process, the author tried to construct the panel data using both standards to classify the treated and untreated groups. However, the second standard to classify the treated and untreated group only considers about 10 occupations; the number of samples is not sufficient to support running a regression. Thus, only the first standard is considered, with two types of formulas. The author initially decided to run 12 regressions in this research.

Table 1: Data Structure for Individual i

Time	Outcome Y earnings	Outcome Y hours	Treatment D
Before t=1	E_{i1}	H_{i1}	1 if tech, 0 otherwise
After t=2	E_{i2}	H_{i2}	1 if tech, 0 otherwise

6.4.1 ChatGPT

For the event of ChatGPT, the author obtained the longitudinal data from 2022 to 2023. The original data captured the 36919 observations in March 2022 and March 2023. After dropping all the abnormal figures, 28418 observations remained in the entire data set, with 14209 observations each year. Based on this data set, the author constructed a new data frame that sets the treatment equal to zero if the worker is in a non-tech (low AI exposure) occupation and sets the treatment equal to one if the worker is in a tech (high AI exposure) occupation.

6.4.2 AlphaGo

The race between AlphaGo and Lee Sedol happened in the week of March 9, 2016. The author obtained the longitudinal data from 2016 to 2017. The longitudinal data was collected each year on March 1. This means that the longitudinal data from 2016 was collected before the race happened. The data from 2017 was collected after the event. The original data captured the 41995 observations in the March of each year. After dropping all the abnormal figures, there are 33672 observations in the entire dataset, with 16836 observations each year. The remaining processes are the same as ChatGPT.

7. Summary of Main Results

According to the methodology and preparation work described in the previous section, there are several results that can potentially answer the question about the relationship between technology and the labor market.

7.1 Trend Analysis

The application of Difference in Difference requires paralleled trends for the data. So the author drew line graphs to test the pre-trend and to grasp some intuition of the potential results. Six graphs are presented under each shock. The graphs are line graphs that show the change in outcomes. The graphs in the first row of each figure show the different trends of the treated group and untreated group classified according to the first standard, and the graphs in the second row show the different trends under the second standard. Apart from the lines that show monthly changes, the author also adds lines that indicate the annual trend as a more intuitive reference of the trend analysis for Differences in Difference.

In order to draw the graph and analyze the trend, apart from dealing with the abnormal figures, the author also needs to organize the data according to time and the treatment design. In the following section, the author will state how this research processes the data and draw the graphs for each event with the cross-sectional data.

7.1.1 ChatGPT

ChatGPT was released on November 30, 2022. So, the author collected both the cross-sectional data from 2021 to 2023 for the trend analysis. The original dataset contains 32 months, with 12 months in 2021, 12 months in 2022, and 8 months in 2023. There are 3,760,628 observations in total.

The number of observations in the labor force is 1,839,654. After the pre-data processing mentioned in the previous content was done, the author plotted line graphs that show the change in outcomes over time. After dropping the abnormal figures, the data set for workers is ready. This contains 365,641 observations.

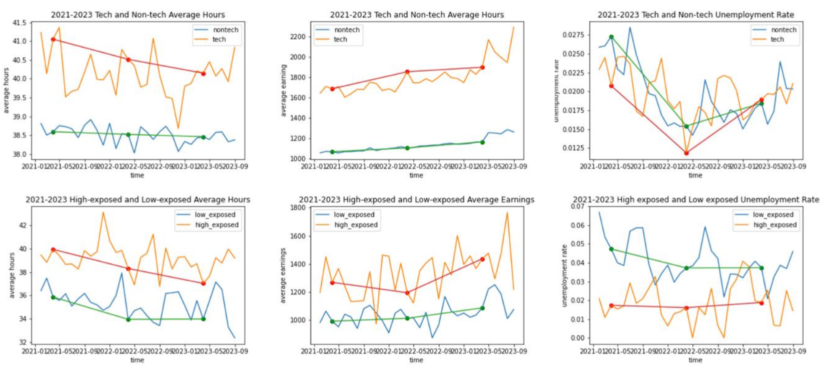
According to the standard of classifying the treated and untreated group and the occupation variables in the data frame, a treated group of tech workers with 14483 observations (5344 in 2021, 5419 in 2022, 3720 in 2023) and an untreated group of non-tech workers with 351158 observations (134994 in 2021, 130114 in 2022, 86050 in 2023) is ready.

To test the trend of earnings, the author count the average weekly earnings of each group in every month and then draw the line graph. The graphs in **Figure 2** in the first row show the change in working hours, earnings, and unemployment rate according to the first standard (tech-nontech) to classify the treated and untreated groups. The graphs in the second row show the change in hours, average earnings, and unemployment rate according to the second standard (high exposure-low exposure), as well as the change in average working hours according to the second standard. The author also added lines that marked the value of the average outcomes in March each year, given that the panel data will use the data collected on March 1 each year. Thus, the first half of the red and the green line shows the trend before the shock happened, and the second half of the line shows the trend after the shock happened. According to **Figure 2**, we can see that the graph of employment status under the first standard and the graph of earnings under the second standard fit most to the assumptions of Difference in Difference.

The graph on the first row in **Figure 2** shows the trend of changes in outcomes according to the first standard. It can be seen that the outcomes for both earnings and working hours present a paralleled trend in general, with more fluctuations for the workers in the treated group. Though the change in the unemployment rate presents a dynamic in this graph, the change in value is quite small. Additionally, the annual trend from 2021 to 2022 is paralleled.

For the second standard (classify the groups according to Webb's article) in the second row of **Figure 2**, I use the data for 2022-2023 to test the trend. The graph shows the trend for the average weekly earnings before 2023 is quite the same. In 2023, the two groups changed oppositely in general, with more fluctuations in the tech group. When it comes to working hours, the two groups change in the same trend until February 2023. The graph for the unemployment rate shows that the monthly change in outcomes is opposite for the treated and untreated groups, while the annual group does not show a great difference and presents an almost paralleled trend.

Figure 2: Test of Trend for ChatGPT



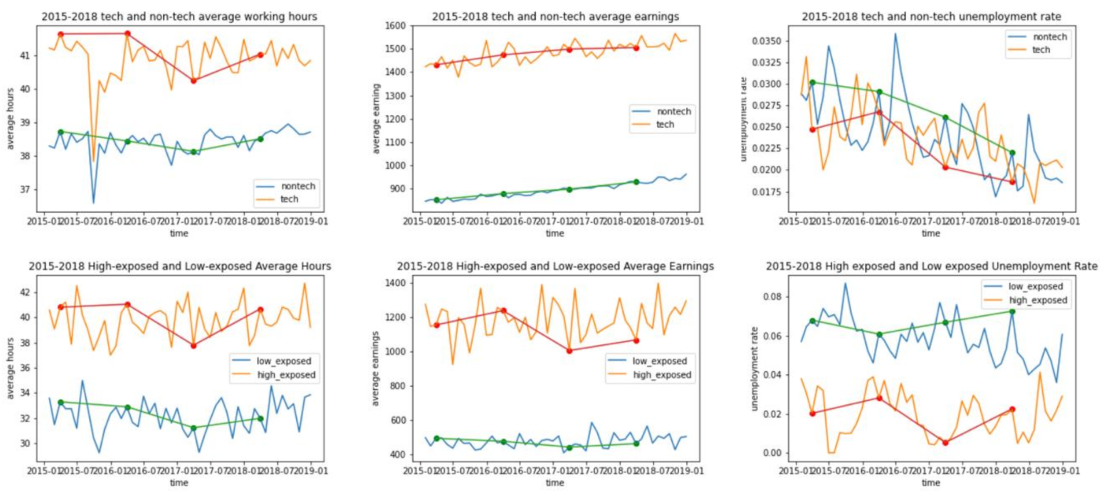
7.1.2 AlhpaGo

The second event selected in this research is the race between AlphaGo and Lee Sedol. The race happened in March 2016. To analyze this event, the author collected the data from 2015 to 2018 and tested the change in outcomes. The four-year data covers 48 months of changes (12 months for each year). Thus, the annual trend lines contain three periods. The number of observations is of the same magnitude as the ChatGPT, which can provide a fair and unbiased result. As with ChatGPT shock, the author used average earnings, average working hours, and unemployment rate to draw the graphs.

According to **Figure 3**, the average weekly earnings and hours present a paralleled trend in general for both the treated group and the untreated group under the first standard. And there were more fluctuations for tech workers. In terms of the unemployment rate, both groups are going down in the general trend although the fluctuations are changing differently. The author added lines of three periods (pre-trend, trend, post-trend) in this shock. The lines show that the trends for each outcome under the first classification standard are quite the same, while the trend under the second standard presents differently.

The line graphs in the second row of **Figure 3** show the trend under the second classification standard. The trend for both groups is generally parallel for the outcomes of earnings and working hours. The trend for unemployment is quite different until 2017.

Figure 3: Test of Trend for AlphaGo



7.1.3 Who is More Exposed to AI

The graphs that support trend analysis could also give some intuition and expectation of the result. Given that the requirement to explain a causal relationship is strict and often needs the support of a rigorous econometrics model, the intuition delivered by the graphs may only explain some simple relationship, and it is not sufficient to explain the causal relationship.

The first insights provided by the graphs should be the standard to classify the treated group and untreated group, namely, which types of workers are more easily affected by AI.

The first standard (tech and non-tech) to classify the treated and untreated group as assumes that the worker whose work may be more related to AI. Because the Computer Science and Engineering industry plays a crucial role in pushing the development of technology. They may not only be boosted when technology becomes popular but also may be affected negatively when the new technology comes out and replaces the original technology. The second standard refers to Webb's paper, the extensions of the results of the string matching process. This means that it assumes that the workers whose tasks are more likely to be performed by AI are more exposed to AI. For example, the art performers are seen as least exposed to AI, while the deliver are said to be highly exposed to AI. Thinking of the difference between different standards with the help of Acemoglu and Restrepo (2018a), the first standard could better explain the productivity effect, while the second standard is focused on the replacement effect.

When it comes to the result of different classification standards, the graphs show that the difference in both the comparative value of the outcomes and their trends is not so big. For both events and both standards, the workers with higher AI exposure have higher weekly earnings, longer working hours, and lower unemployment rates. Since this result is only presented by the graphs, it is not sufficient to say that people with higher exposure tend to earn more. However, this may serve as extra evidence for the findings in the previous research that workers with a higher income level are more exposed to AI.

The differences for each outcome in the absolute value are larger under the second standard. This may suggest that the replacement effect could be significant in affecting workers' well-being.

In both periods, the tech occupations and the higher exposed occupations tend to have higher weekly earnings and longer working hours. The unemployment rates under the first standard did not show a significant difference. However, under the second standard, the unemployment rate for high-exposed workers was lower, and the trend for both groups of workers was almost in the opposite direction.

7.2 Results of the First Formula

Based on the regression formulas, the author made some adjustments to the data frame and found that under the simplified formula, the author need to calculate the change in outcomes before and after the shock. However, the employment status of the samples did not change at all. So, the author did not run the regression for the employment outcome under the simplified formula. In sum, 10 regressions were remained.

After running all the regressions according to the formula table, the author summarized the results as follows. **Table 3** exhibits the result of regressions under the standard formula. The first line in each row indicates the coefficient between the dependent and the independent variables, and the numbers in brackets are standard errors.

In those results, the earnings and hours have real meaning, while the numbers for employment do not. In the dataset, if the labor is currently employed, the employment status for this person will be marked 10 (at work last week) or 12 (not at work last week), and if the person is currently unemployed, the employment status will be marked greater than 20 and the number varies depends on their working experience. This means that in the model, the higher the number for the employment variable, the worse the employment status.

Table 2: Standard Regression Results: ChatGPT and AlphaGo

	ChatGPT			AlphaGo		
	Earnings	Hours	Employment	Earnings	Hours	Employment
Treatment	186.5374*** (28.320)	1.4537*** (0.543)	0.0159** (0.007)	138.2383*** (23.806)	1.3495*** (0.565)	0.0169** (0.008)
Time	15.5573** (7.833)	-0.397*** (0.150)	0.0021 (0.002)	4.9506 (5.933)	-0.5256*** (0.141)	0.0070*** (0.002)
Interation term	-1.0546 (39.675)	0.2133 (0.760)	-0.0018 (0.009)	50.8081 (33.809)	0.1303 (0.803)	0.0034 (0.011)
constant	276.5510*** (5.536)	39.6513*** (0.106)	-0.506 (0.172)	219.9816*** (4.196)	39.8474*** (0.100)	0.9634*** (0.001)
R-Squared	0.003	0.001	0.000	0.003	0.001	0.001
AIC	4.485e+05	2.238e+05	-2.826e+04	5.187e+05	2.668e+05	-2.347e+04
N	28418	28418	31500	33672	33672	37816

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 2 illustrates the regression results based on the first formula (standard version), the coefficient between treatment and the outcomes, time and the outcomes, and the interaction term (time*treatment) and the outcomes are presented in the table.

According to **Table 3**, the significance level of the model is quite low. Several reasons may explain the phenomenon. First, the time series only contains two years in the model. This means that this research is studying the short-term impact of AI exposure rather than the long-term effect. The impact of shocks may be small in the short term; thus, the significant level of the model is low. Second, the classification of the treated group and untreated group may have a great impact on the result, and no defined standard tells which occupations are exposed to AI more. Third, other factors may affect the data. Given that the data was collected in March every year, the monthly data may not be sufficient to explain the long-term effect of an event.

Nevertheless, it is still worth looking at the results of the regressions. When looking at the effect of time and treatment (AI exposure) separately, the results show that, in general, tech workers or higher AI-exposed workers tend to have higher earnings and work longer under the circumstances of both shocks, which is also obvious according to the graphs. The earnings of the workers increased, and the working hours decreased after the shocks happened. When combining the impact of the shocks and the treatment, the significant level of the model decreased. However, if we assume the result can still tell something. It indicates that under the shock of ChatGPT, workers' earnings will decrease by a negligible amount, and working hours will increase. Under the shock of AlphaGo, the combined term of time and the treatment made both workers' working hours and their earnings increase.

If we say that working less and earning more indicates a higher level of well-being for the workers, the result of the ChatGPT shock shows that workers are worse off under the shock of AI. Given that the working hours have a positive relationship with the combined term of time and treatment under the shock of AlphaGo, the earnings are also positively correlated with the combined term. Additionally, the coefficient between hours and the combined term is even higher under ChatGPT. However, the impact of the AI shock is not severe, and there may be other reasons for the increase in working hours and the decline of weekly earnings.

7.2.1 Earnings

Earning has a positive relationship with both treatment and time under both shocks. However, the earnings present a negative relationship with the interaction term under the shock of ChatGPT, which suggests that the impact of AI, when taking both the type of occupation and the time effect of the shock into consideration, earnings of the worker will be lower. This seems disappointing. However, if we look closely at the figure, the absolute value of the coefficient is quite small, meaning that the impact is not that big. And there may also be some external factors that may affect the result. Under the shock of AlphaGo, the result of the integration term is different from that of ChatGPT, and the earning is positively related to the term time*treatment.

7.2.2 Working Hours

Working hours are positively related to the treatment and negatively related to the time effect, meaning that people whose occupation is more exposed to AI tend to work more, and people work fewer hours after the "shock". Those results are consistent with the information presented in the graphs.

When it comes to the interaction term, the coefficients are positive under both shocks. Since working hours are increased with the increase in interaction terms in both circumstances, it may suggest that people's expectation to work shorter and enjoy more leisure may not be realized in the short term. This may be because the application of AI needs workers to be able to perform new tasks, and the reskilling process, such as training and finding suitable workers, increases current working hours. This does not mean that people will need to work longer as a consequence of the development of technology. People in many places were able to take two-day rest rather than one-day thanks to productivity growth. However, the transition from one-day rest to two-day rest is a long-term process. The result of the regressions shows that in the short term (not long after the boost of technology happened), the longer working hours for reskilling are dominant.

7.2.3 Unemployment

The results suggest that the impact of AI on unemployment may be negligible. As stated in the previous content, the higher the number, the worse. However, since 10 represents work and over 20 represents unemployment, a shift from employment to unemployment needs the number of this variable to increase by about ten units. The absolute value of the result of coefficients is all under 0.02, meaning that employment is neither worse nor better under the impact of AI in the short term.

7.2.4 Combination of the Results Based on the First Formula

After closely analyzing the results of the three outcomes separately, the author will interpret the results of the outcomes together in this part.

In the previous content, it can be seen that the consistency of the result for working hours is the best. The features of the coefficient are the same under both shocks. This suggests that when studying the impact of AI on the labor market, working hours may serve as a high-quality parameter.

7.3 Results of the Second Formula

The second formula is the simplified version; it focuses on the change of the treatment over time. The result of this formula may suggest how the outcomes will change when people shift from the lower exposure occupations to the higher exposure occupations, namely, how their earnings and working hours will change when they are more exposed to AI.

Table 3: Simplified Regression Results: ChatGPT and AlphaGo

	ChatGPT		AlphaGo	
	Earnings	Hours	Earnings	Hours
Change in Treatment:D	65.8367*** (17.958)	0.7927 (0.608)	-2.8876 (15.697)	-0.0701 (0.091)
constant	17.7023*** (2.874)	-0.3884*** (0.097)	6.4263*** (2.361)	-0.5224*** (0.604)
R-squared	0.001	0.000	0.000	0.000
AIC	2.062e+05	1.100e+05	2.405e+05	1.309e+05
N	14209	14209	16836	16836

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 2 shows the result of the regressions under the Simplified formula. The significance level is even lower. However, the results are different in the two shocks. While both workers' earnings and hours have positive relationships with the level of AI exposure under the shock of ChatGPT, the outcomes have a negative relationship with the level of AI exposure under the shock of AlphaGo. Still, if we look at the figure closely, the absolute value of the coefficients is small under the circumstances of AlphaGo, and this may be because the relationship between the outcomes and AI exposure is not obvious under the AlphaGo shock. In this table, the coefficient between the earnings and the change in the treatment under ChatGPT shock is more trustworthy. It suggests that people can earn more when their AI exposure is higher. This violates the result found based on the first formula. However, as mentioned in the previous content, the absolute value of the coefficient under the first formula is small. Thus, in general, we may think that the second formula indicates people with higher AI exposure will earn more and work longer, which is consistent with the result obtained from the graphs.

7.4 Summary of the Regression Results

In summary, a higher level of AI exposure tends to make people work longer and earn more in general. This is the short-term impact of AI on the labor market. Working hours could be a good parameter for studying AI's impact on the labor market, given its consistency in different forms of regressions. Employment status is less likely to be affected by AI in the short term. According to the regressions, employment is either changed in a negligible amount with the change in the level of AI exposure or hardly affected at all. So, the employment investigation may be more suitable for long-term study.

8. Conclusion

After all the works stated in this paper, here comes to several conclusion of the research.

8.1 Review of the Objective and the Model

Given that people's interest in the relationship between technology and society. As AI technology becomes increasingly integrated into people's lives, this research concentrated on the labor market specifically. The objective of this research is to see whether the worker is better off or worse off under the impact of AI. The indicators are selected as earnings, working hours, and unemployment rate, considering both data availability and their real meaning. Worker's level of well-being is improved as their real wages increase, or they can enjoy more leisure. Additionally, a lower unemployment rate indicates better circumstances in the labor market.

The topic is studied with the help of Difference in Difference. The classification of the treatment is designed according to two standards. The first standard is to classify the workers who work in the computer science and engineering industry as treated group (higher exposed) workers, while the rest of the workers are classified as the untreated group (lower exposed to AI) workers. The second standard is to classify the five occupations that are most exposed to AI listed in Webb's (2019) research as a treated group and the five least exposed to AI occupations as an untreated group. I also studied two events in this research: the advent of ChatGPT and the race between AlphaGo and Lee Sedol.

Two formulas are considered to run the regression, with one focusing on the effect of time and the treatment separately while the other study how the outcome is affected as the treatment changes over time. The majority of the data comes from IPUMS CPS. I used cross-sectional data to draw the graph of the trends, transformed the longitude data into panel data, and plugged the panel data into the regression formula.

8.2 Summary of the Results

The results of this paper can be mainly reflected in the graphs and the regression results. They contain information about how the outcomes change with the change in different ways of classifying the high AI exposure workers and low AI exposure workers, as well as how outcomes will change after a significant AI shock happens.

The trend graphs plotted with cross-sectional data suggest that for those who have a higher level of AI exposure, their working hours and earnings tend to be larger. Additionally, the different standards to classify the treated and untreated groups do not show a great difference in terms of a general trend. However, the difference in the values of the outcome between the treated and untreated groups is larger under the second standard. The trend analysis also proves that the paralleled trend holds for most of the time, meaning that difference in difference is suitable for this topic.

According to the results presented by regressions, the impact of AI exposure is ambiguous when considering both the type of occupations and the impact of AI shocks. And the influence of AI on employment status is small in the short term. This may be because of the classification of the occupations or the insufficient of the time series. However, in general, it can still be seen that people tend to earn more and work longer with a higher level of AI exposure, which is consistent with the findings shown by the graphs.

Google Trends shows that the interest in AI after the advent of ChatGPT is significantly higher than that of AlphaGo. So, if the research focuses on ChatGPT, the result of longer working hours is more obvious. However, the first regression formula suggests that a higher exposure to AI will hardly change workers' earnings. The second formula still shows that higher AI exposure leads to higher earnings. Thus, in conclusion, we could say that the impact of AI results in higher earnings and longer working hours.

8.3 How the Findings Related to the Existing Evidence

The existing research studies to what extent the replacement effect and the productivity effect are dominant in the impact of AI on the labor market. The replacement effect of introducing AI to the industry may cause people to work less and earn less, given that it suggests people's tasks are performed by AI instead. And it should also lead to a higher unemployment rate. The productivity effect will cause a higher level of earnings and longer leisure time. It should lower the unemployment rate. The results of my research show an increase in working hours as well as earnings, indicating a mix of the two effects in the short term.

Considering the previous research, an increase in earnings and working hours, together with a stable employment status, shows that both the replacement effect and the productivity effect of AI are small in short-term periods. Given that the process of worker-reskilling needs time, the adjustment of features of the occupations also needs time. During the technological development period, people tend to work more and earn more to adapt to new technology.

As suggested by the findings, the adjustment process is important. People should figure out ways to improve the efficiency of the reskilling process and ensure that the application technology will not cause severe unemployment.

8.4 Limitations

Given the findings stated in this paper, the results are limited due to the quality and the scope of the data. Meanwhile, this research only focuses on three outcomes under two shocks. Further research is also suggested to deepen the understanding of the relationship between society and technology.

The data is collected within the scope of the US, meaning that the result may not be sufficient to explain the phenomenon globally, given that the mechanism of the labor market in other countries may be different. To make the result apply in more places, the variety of data could be improved. For example, the nature of the labor market in Asia is different from that of the US, it is improper to use US data to explain the Asian market.

Apart from the limitation of the data, as mentioned in the previous content, the economic condition is sophisticated at the end of 2022 and the beginning of 2023, given the pandemic lockdown and wide layoff in the tech sector. Those external factors may affect the data as the outcomes of this research are the indicators that may be affected by the macroeconomic condition. Though the author have introduced an extra event of AlphaGo and different standards to classify the treatment to improve the robustness of the findings, the result may still be affected by those external factors.

8.5 Why the Topic is Important and Suggestions for Future Research

The interest in AI's impact is huge not only because it changes the way people produce and live, but also because the ethical concern of AI is also important. The concern is not limited to the problems such as data privacy and explainability. Its impact on labor should also be considered as an ethical concern. Given that AI may cause job displacement and reskilling. The concern that the wide application of AI will cause unemployment is worrying. This suggests that when applying AI and forming AI regulation policies, the relationship between AI and the labor market should be taken into account as an ethical consideration.

For future studies, a high-quality and recognized matrix to measure the level of AI exposure for all occupations is required. The previous methods to measure AI exposure are diversified, making it hard to comprehensively study the impact of AI on all industries. It is also hard to extract the impact of AI on outcomes from other factors that may also affect those outcomes. Moreover, researchers could construct a database that collects all the research that ranks the level of AI exposure. By comparing those results, the understanding of AI and the labor market could be deeper. The impact of AI on different groups of workers is also worth studying. AI may affect workers in different age groups or in different genders differently. Comparing the impact of AI among different groups can help governments form more targeted policies to deal with the challenges brought by AI. Finally, there are more outcomes such as income distribution, work-life balance, and work security. For example, while people are worrying that technology may replace humans and cause unemployment, technology can also perform work that may have a negative impact on human health.

Conducting research on the impact of AI not only allows people to adopt this technology more cautiously, considering the potential consequences, but it can also help leverage the full ability of AI to boost productivity and improve the quality of human life.

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Author Contributions

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

Availability of Data and Materials

This research will be studied within the scope of the US. Thus, the author obtained the data on the outcomes (wages, working hours, employment) from public available databases IPUMS CPS Flood et al., 2023. To make an accurate classification of the treated and untreated group, the author categorized the data of outcomes into two groups according to each observation's occupation code. The data on occupations is collected from the U.S. Bureau of Labor Statistics U.S. Bureau of Labor Statistics (2023), which is the bureau data that is widely used in analyzing workers' occupations. All the data in this research are government official data that are authoritative, providing more solid support to the result of the research.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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