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AI and Inequality in the US: Evidence from the American Community Survey Data

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Abstract. Artificial intelligence or AI is reshaping the U.S. economy; On one hand, it is improving potential for productivity and innovation, but on the other side it raises concerns about inequality. This paper investigates how AI-driven automation impacts income disparities across race, gender, and nativity. In the methodology of this paper, by using microdata from the ACS (American Community Survey), evaluating the regression analysis of log income, ceteris paribus, where demographic and contextual factors are controlled while AI exposure is interacted with key social categories. The analysis results in a tendency that higher AI exposure is associated with income, and that AI-intensive sectors yield an advantaged 0.0619 increase in log income. But the uneven distribution of benefits in gender, race, and nativity remains an issue, Specifically, there is a widening gender wage gap from the extra gain from men comparing to women, non-Blacks individuals earn 0.0286 log income more than Black workers, widening the racial wage gap by 9.4%, native individuals in the country has greater access to AI complementary employments, resulting a reduced log income gap by 35.8% comparing to non-natives. This is evidence that AI has the ability to reshape and reinforce inequality, and policies such as training or AI-targeting taxation should be counterpointed to ensure that AI automation promotes inclusion rather than deepening systematic disparities.

Keywords: Artificial intelligence, inequality, US economy

1. Introduction

Artificial intelligence (AI) has rapidly transformed modern society over the past decade, with breakthroughs in machine learning, natural language processing, and robotics reshaping industries, workplaces, and everyday interactions. Its potential and accelerating development have sparked a global debate, as AI is not only capable of automating routine tasks but also of performing complex decision-making processes once thought to be uniquely human. These advancements carry the power to significantly reshape our daily lives and influence the trajectory of our shared future.

This paper examines how AI-driven automation affects economic inequality in the United States, focusing in particular on its impact on income disparities across lines of race, gender, and nativity. Such an analysis is vital because while AI offers opportunities for efficiency, innovation, and economic growth, it also carries the risk of reinforcing or even deepening existing systemic inequalities. Without careful oversight, AI may exacerbate wage gaps, limit access to high-quality jobs for marginalized groups, and concentrate wealth and decision-making power in the hands of a few. These shifts could undermine social equity, disrupt economic balance, and strain the foundations

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of a democratic society. By investigating the distributional consequences of AI, this study aims to raise awareness of the multifaceted ways AI might shape the economy. Understanding these effects is crucial for ensuring that AI benefits are broadly shared, guiding the development of equitable policies, and implementing safeguards that mitigate disparities while fostering inclusive technological progress.

AI enhances productivity through automation, improving healthcare and advancing diagnostics, driving innovation across industries. However, it risks exacerbating existing inequalities in the US, especially racial and gender disparities that result in disproportionate incomes. While AI automation holds multiple possibilities, it may widen these gaps by disproportionately displacing jobs held by marginalized groups, benefiting only worker groups in high-skilled jobs, and limiting opportunities for those already disadvantaged. This paper builds on this background to analyze how AI widens or narrows income gaps across race, gender, and nativity.

The data used are from the American Community Survey (ACS), an ongoing survey conducted by the US government. The ACS collects miscellaneous categories of data content across a wide range, covering the entire United States, Puerto Rico, and other US territories. Data is collected from 4,276,327 individuals from 2018 to 2022.[1] A regression analysis is employed to examine the effects of AI exposure, along with race, gender, nativity, and age, on personal income. The methodology uses log income as the dependent variable while controlling for external factors of the year, birthplace, and workplace. Interaction terms between AI exposure and demographic variables help identify how AI influences income gaps across groups.

The analysis revealed that there will be larger income inequality in the us between genders and race (the African American community in particular). Jobs with higher AI exposure earn a 0.0619 increase in log-income, indicating that roles with high AI exposure pay better. However, benefits are uneven: in this case, males benefit more through AI automation than females by having a 0.0124 larger log income per unit of AI exposure in work, and Black workers gain 0.0286 less log income per unit of AI exposure compared to non-Black workers, widening the racial gap by about 9.40%. In contrast, there is a reduced income gap between Natives and non-Natives in the US, where natives earn a 0.109 larger log-income increase, reducing the nativity income gap by about 35.84%. This highlights how AI worsens racial and gender income disparities, while natives are likely to have greater access to jobs with higher AI exposure, narrowing the income gap between natives and non-natives.

The implications of the findings of this paper inform the design of policies, such as an AI tax or modified income taxes, to promote greater income equality. The widening gender and racial income gaps suggest a need for targeted interventions. For example, an AI tax on high AI-exposure jobs could slow worker displacement and fund AI training programs for disadvantaged groups. Similarly, there could be more regulations set on AI industries, such as retraining or providing severance for displaced workers. There can also be investments in education for girls or students of color to gain skills and to prepare them for AI-driven roles at a lower risk of being displaced. For immigration policy, the reduced nativity gap suggests AI could level opportunities for non-native workers, supporting policies that encourage skill development for all. Modifying income tax structures to be more progressive could also be a way to reduce the disproportionate redistribution of gains.

This paper speaks to two strands of the literature. First, this paper contributes to the literature on the economic impacts of AI. Early work includes [1], starting a new model including automation factors, and [2] on labor displacement, which finds slower job growth because displacement occurs faster than new task creation [3]. introduce factors reducing labor share from AI automation, the work concludes a model of either full automation or co-existence of capital and labor [4]. and [5] are more

[1] In the sample, 2020 is excluded due to the COVID pandemic.

recent papers that provide up-to-date models [4]. tracks how AI changes job openings at companies rather than detectable aggregate effects. They present that AI adoption shifts firm-level hiring, but shows no aggregate employment or wage effects yet. And [5] develops a task exposure method to predict occupation-level impacts. The papers ([6] and [7]) highlight more on the economic Impacts of automation rather than AI. While papers on the economic impacts of AI and inequality focus primarily on manufacturing or task-level impacts, we cover all sectors in AI automation impacts.

Second, this paper is related to factors that influence inequality, especially in the US [8]. introduces the evolution of income inequality in the US, also providing trends of top income shares over the recent 100 years [9]. and [10] feature income inequality; the first discusses income inequality within developing countries rather than the USA, noting that inequality has been slowly rising over the last two decades. While [10] focuses on the US context, the paper finds that top income groups benefit more from economic growth from investments and bonuses, leading to inequality [11]. compares the consumption of groups and classes with the analysis of income [12], finds inequality from distributional issues caused by AI automation, where jobs are cut because of AI.

The remainder of this paper proceeds as follows. Section 2 introduces the background of this paper, including the advancements and economic impacts of AI and inequality in the US. Section 3 presents and discusses the data used in this paper. Section 4 establishes the empirical strategy and presents, analyzes the empirical results, and discusses potential policy responses. Finally, Section 5 concludes.

2. Background

2.1. AI and automation in human history

Artificial intelligence, or AI, refers to machines that perform tasks such as learning, reasoning, decision-making, or problem-solving. Artificial intelligence is sourced from the mid-20th century and is capable of mirroring and even extending human intelligence, such as through machine learning ([13]). Machines can enhance themselves by learning from data to handle tasks in numerous fields of work. Automation can be traced back to the Industrial Revolution nearly three centuries ago, when new technologies such as steam engines improved the productivity of manufacturing and transport in industries and rail transport during the Industrial Revolution. Automation increased efficiency and reduced physical labor, acting as a foundation for developing sophisticated mechanics for the future.

The automation of AI has a wide impact, as it affects many fields of work and everyday life, such as manufacturing, where AI can manage supply chains and pipelines ([14]). AI chatbots can now handle inquiries without the need to rest. The advantages of automation are 24/7 operations, increased efficiency, and improved safety. However, job displacements can occur as the automation of AI can replace low-skilled jobs, causing unemployment. High-skilled jobs might benefit from higher wages with the use of AI in their jobs, revealing inequality. Social inequality also persists with the presence of AI automation, widening the wealth gap in our society. Humans must find a point of balance in AI automation to maximize the benefits, ensuring the best way to coexist.

2.2. Inequality in the US

The United States faces persistent and miscellaneous inequalities, including wealth, racial, and educational disparities ([15]). Economically, where there is a wide wealth gap between the rich and poor, a small percentage of the population holds a large share of the country's wealth. Even though the middle class has been stagnant in its income growth, the top wealthy group in the country ceaselessly accumulates significant assets, accelerating social division ([16]). The difference in

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wealth influences living conditions, health, and opportunities, producing a vicious cycle. According to the World Bank group, the country has reached a Gini coefficient of 0.418 in 2023[2].

Socially, racism remains a major issue in America in multiple dimensions, including education, employment, and criminal justice. Historically, groups such as African Americans, Hispanics, and Native Americans have generally endured lower income than the national average level, compounded with a high unemployment rate and low access to quality education and healthcare. African Americans, in particular, bear the highest wealth gap in America and the most entrenched redlined districts. Poverty and disadvantages are passed down through generations because discrimination in society's systems and hidden barriers lock racism in place ([17]).

Educationally, inequality plays a major role, primarily affecting inequality in the US ([18]). Funding for public schools relies on local contributions of property taxes, and schools serving mainly low-income minority students are unable to provide education like high-income neighborhoods. An achievement gap would be made as students in underfunded schools are more likely to score lower, which leads to college barriers for these students who are disadvantaged in underfunded schools ([19]). These disadvantaged students will have limited choices in the labor market and will have lower income, and lower-income neighborhoods result in underfunded schools, putting the next generation in the same situation, and ending up in a vicious cycle of poverty just from education. Generally, education inequality needs to be fixed to achieve a more equitable society, as it is the doorway to social mobility and economic opportunity.

Gender Inequality: Gender inequality in the US occurs politically and economically. Women earn approximately 82 cents [3] for every dollar earned by men, and especially women of color have a wider income gap compared to men. Females face more disadvantages in the workplace as they have insecure career progression because of childcare or eldercare ([20]). Employers hold a bias when hiring women due to concerns about maternity leave, while outright discrimination is illegal, personal bias and structural disadvantages still affect women's employment opportunities. Females are underrepresented in leadership roles in Congress and senior executive positions, despite making up half of the population.

Gender inequality in the US is associated with the gender wage gap ([21]). The gender wage gap in the United States refers to the persistent difference in average earnings between men and women, with women generally earning less than men for full-time, year-round work. This disparity is influenced by a combination of factors, including occupational segregation, differences in work experience and hours worked, discrimination, and the disproportionate burden of unpaid caregiving placed on women. The gap is even wider for women of color—Black, Latina, and Native American women earn substantially less compared to white, non-Hispanic men—highlighting the intersection of gender and racial inequalities. While education and experience can explain part of the difference, research shows that a substantial portion of the wage gap persists even after accounting for these variables, pointing to structural and systemic barriers in the labor market.

Racial Inequality: In the US, Black and Hispanic groups are overrepresented in low-wage routine jobs. Colored groups also face higher displacement in jobs stemming from historical discrimination and unequal access to education. Disadvantages in education also cause people of color to face larger barriers to learn skills and transitioning into new jobs ([22]). Geographically, many highly paid jobs are concentrated in expensive cities, and redlining or housing discrimination excludes Black or Hispanic groups from these areas, reducing opportunities for the disadvantaged by raising geographical immobility for employment.

Racial inequality is also associated with the racial wage gap ([23]). The racial wage gap in the United States refers to the enduring disparity in earnings between racial and ethnic groups, with

[2] The data sources is data.worldbank.org/indicator/SI.POV.GINI?end=2023&locations=us.
[3] The data source is www.statista.com/statistics/244202/us-gender-wage-gap-by-industry.

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workers of color—particularly Black, Latino, and Native American individuals—consistently earning less than white, non-Hispanic workers. This gap is shaped by a complex mix of factors, including occupational segregation that channels minority workers into lower-paying jobs, unequal access to quality education and professional networks, historical and ongoing discrimination, and differences in wealth that affect career mobility. Even when controlling for education, work experience, and location, significant wage disparities remain, suggesting that systemic and structural barriers—such as biased hiring, promotion practices, and pay-setting—play a substantial role. These inequities compound over time, contributing to broader racial wealth gaps and limiting economic mobility across generations.

2.3. AI and the labor market

AI affects human labor through two key mechanisms: it can either complement or substitute jobs, depending largely on how well AI systems perform relative to humans in a given task ([24]). In occupations where work is highly repetitive, routine, and predictable, AI is more likely to replace human labor entirely, as it can execute these tasks faster, more accurately, and at a lower cost than people. Examples include data entry, basic accounting, and certain administrative functions, where AI algorithms and robotic process automation can handle large volumes of work without fatigue or error ([25]). In contrast, jobs that are complex, creative, or require high levels of problem-solving tend to benefit from AI as a complement rather than a replacement. In these roles—such as those of doctors, engineers, researchers, and designers—AI can take over repetitive, labor-intensive, or time-consuming components of the work, such as processing large datasets, generating design prototypes, or identifying patterns in medical scans, freeing up human workers to focus on strategic decision-making, creative innovation, or patient interaction ([26]). Over time, these two trends reshape the labor market: workers whose tasks can be fully automated may experience job loss and see their wages decline to a minimum or even disappear entirely, while those whose productivity is enhanced by AI may see higher earnings and improved career prospects. This divergence in outcomes between displaced workers and AI-augmented workers widens wage gaps, reinforces occupational polarization, and contributes to growing inequality in the labor market, potentially amplifying preexisting disparities by education, skill level, and socioeconomic background ([1]).

2.4. AI and inequality

AI increases inequality by raising the income of certain jobs while simultaneously reducing the earnings of others, thereby deepening economic divides ([27,28]). Occupations that benefit from AI's complementarity tend to be those that require advanced graduate degrees, specialized expertise, and the ability to perform complex, creative, or highly analytical tasks that AI cannot easily replace. In these roles—such as medical specialists, data scientists, engineers, or strategic managers—AI tools enhance productivity by automating tedious elements of work, enabling professionals to focus on higher-level decision-making, innovation, and problem-solving ([29]). As productivity rises, so do wages, bonuses, and opportunities for advancement, disproportionately benefiting individuals who already possess significant educational and skill advantages. By contrast, jobs involving simple, routine, and repetitive tasks—such as assembly line work, basic clerical duties, or customer service—are more susceptible to full or partial automation, since AI can perform these tasks faster, cheaper, and with greater consistency ([30]). As these positions are replaced or reduced, the workers who relied on them face declining wages, fewer job opportunities, and, in many cases, outright unemployment. This dynamic creates a feedback loop: individuals from wealthier backgrounds, who can afford higher education and have access to networks and resources, are more likely to move into AI-complemented roles and reap higher incomes. Meanwhile, those from less advantaged

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backgrounds, with fewer educational opportunities and lower skill levels, are concentrated in vulnerable occupations that are easily automated. The resulting job losses or wage cuts push many into economic precarity, making it harder to invest in training or education to transition into more resilient careers. Over time, this pattern not only widens the income gap but also entrenches long-term social and economic inequality, with wealth and opportunity becoming increasingly concentrated among those best positioned to work alongside AI rather than be replaced by it ([31]).

3. Data and measurements

3.1. AI exposure

My AI exposure score at the occupation level follows [4] and [5]. In this framework, firms hire tasks to be done, performed either by humans $\ell_e(x)$, or by AI algorithms $\alpha(x)$. It is assumed that AI and human labor are perfect substitutes performing given tasks. It is also denoted that each firm uses varying tasks $\mathcal{T}_e$, so exposure to AI varies based on the type of task the firm does, and $\mathcal{T}^A$ shows whether AI can perform the task. AI exposure is measured using occupation-level suitability scores derived from O*NET-based indices (such as [26] and [5]), and aggregated using job posting data from Burning Glass Technologies (data 2010-2012).

An occupation is considered to have high AI exposure if its core tasks closely align with capabilities that AI can currently perform, such as language or data processing. In contrast, jobs that heavily rely on social intelligence or physical interactions are expected to be less exposed.

The exposure to AI for the task e is given by equation (1):

$$\text{Exposure to AI}_e = \frac{\int_{x \in \mathcal{T}_e \cap \mathcal{T}^A} \ell_e(x)dx}{\int_{x \in \mathcal{T}_e} \ell_e(x)dx}, \tag{1}$$

where $\mathcal{T}_e$ denotes tasks performed by firm e, $\mathcal{T}^A$ denotes tasks that can now be done by AI, and $\ell_e(x)$ denotes human labor used for task x.

To quantify exposure to AI, occupation codes (SOC codes) are mapped to O*Net databases to obtain the required skills ($\mathcal{T}_e$). These tasks are then evaluated against AI capability benchmarks to identify $\mathcal{T}^A$, reflecting the exposure metric.

The ten most exposed occupations are: Aero flight crew (6.54), physicists (5.91), surgeons (5.78), commercial pilots (5.68), air traffic controllers (5.68), dentists (5.41), biology studies (5.27), maxillofacial surgeons (5.21), wildland fire supervisors (5.21), and municipal fire supervisors (5.21). Their weighted impact of AI exposure ranges from 5.21- 6.54. The ten least exposed occupations are: Models (1.42), telemarketers (1.51), room attendants (1.52), graders and sorters (1.57), shampooers (1.84), housekeeping cleaners (1.85), vehicle cleaners (1.86), slaughterers (1.90), cafeteria attendants (1.90), and food servers (1.94). Their weighted impact of AI exposure ranges from 1.42-1.94.

Figure 1 presents the kernel density of the AI exposure score at the occupation level. The distribution resembles a normal distribution whose mean is around 3.5 and whose standard deviation is around 0.7. In the empirical analysis, I link the occupation-level AI exposure to each individual in the ACS data.

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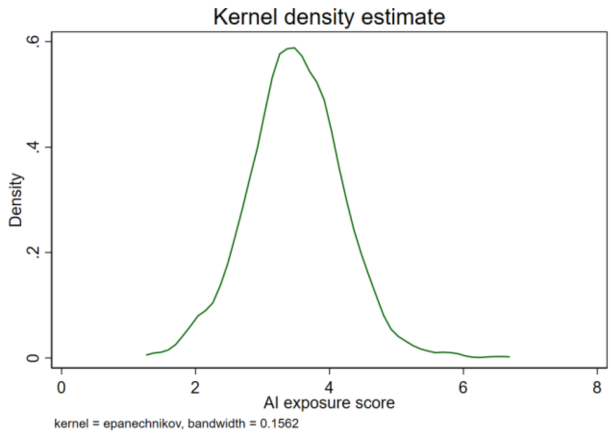

Figure 1. Kernel density of AI exposure score

3.2. American Community Survey

The American Community Survey (ACS) is used throughout our research.[4] It is an ongoing survey conducted by the U.S. Census Bureau, providing data from households across the United States, ranging from social, economic, housing, and demographic dimensions. ACS data were used by policymakers, researchers, and other key professionals to visualize trends and analyze community characteristics.

The key features of ACS data are evaluated through criteria of coverage, frequency, data content, sample size, and cases of use. The ACS collects data from 3 million households each year, covering the entire United States and parts of the U.S. commonwealths, highlighting the wide range ACS is covering. For frequency, the data is perpetually collected annually at different geographic levels from block groups up to nations. Its data content is diverse, covering sections of age, sex, race, income, employment, education, housing tenure, and utilities. These data are also precise for use with a robust sample size, allowing data breakdowns at various geographic levels. However, it is expected that there might be higher degrees of error in terms of smaller localities. The ACS gathers data for Public Use Micro Areas (PUMAs), which represent populations of 100,000+ from areas used for detailed Census microdata. The use cases for ACS data cover planning, policy development, resource allocation, research, and demographic analysis. Overall, the ACS provides wide, current demographic and socioeconomic data at disaggregated geographic units that support decision-making across numerous sectors.

In our research, we include ACS data sets ranging from 2018-2023[5] of the place of birth, whether the individual is native-born, the racial identification of the individual in single and multiple categories, employment characteristics (the status and workplace location), and the age and gender. The variables used are given in recodes or estimates. Variables such as nativity are dummy variables, while other variables, such as place of work, need an interpretation from a code book. The ACS data serves as a pooled cross-sectional dataset for its data collected from multiple subjects throughout different points in time.

Table 1 provides summary statistics, demonstrating data from 4,276,327 observations. The calculation considers the race, the nativity, the gender, the age, the personal income, and the AI exposure of each individual of all observations. The race, gender, and nativity are recorded with dummy variables. The Personal Income averages $52,233.35 annually but is accompanied by a large

[4] The database can be retrieved using https://www.census.gov/programs-surveys/acs/data.html
[5] Data of 2020 is missing in the database.

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standard deviation ($67,062.96), reflecting a wide income distribution and the presence of top income earners (up to $1,641,800). On the other hand, AI exposure has a small standard deviation relative to the range (1.510 to 5.206), hinting that most individuals have exposure levels clustered around the mean (3.288).

Table 1. Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Nativity	4,276,327	1.139	0.346	1	2
American Indian and Alaska Native	4,276,327	0.023	0.151	0	1
Asian	4,276,327	0.068	0.251	0	1
Black	4,276,327	0.092	0.289	0	1
Gender	4,276,327	1.513	0.500	1	2
Age	4,276,327	44.673	16.276	16	97
Personal income	4,276,327	52233.350	67602.960	0	1641800
AI exposure	4,276,327	3.288	0.680	1.510	5.206

Notes: The sample originates from ACS data covering 2018, 2019, 2021, and 2022 from 4,276,327 observations.

Table 2 presents the mean level of total annual personal income by social group. A disproportionate income is revealed between gender and race, where Male individuals annually earn $20,000 more on average than Females, Non-Black individuals annually average $15,000 more than Black residents, and Asian individuals annually out-earn $8,000 more on average than Non-Asian residents. In contrast, the nativity of the individual holds a negligible difference in the mean annual income ($31). These results suggest that nativity has a minimal association with income levels, while race and gender tightly correlate with income gaps. These differences prove the inequalities in the US previously introduced, and the data will be further analyzed.

Table 2. Mean personal income by group

Total annual personal income			
Obs	Mean	Obs	Mean
Native residents		Non-native residents	
3,682,308	52237.74	594,019	52206.14
Male residents		Female residents	
2,081,538	62514.48	2,194,789	42482.73
Non-black residents		Black residents	
3,881,585	53580.58	394,742	38985.78
Non-Asian residents		Asian residents	
3,987,450	51714.45	288,877	59395.87

Notes: The sample originates from ACS data covering 2018, 2019, 2021, and 2022 from 4,276,327 observations.

Figure 2 presents the yearly trends[6] of AI exposure of different social groups, by linking the measure of AI exposure at the occupation level to ACS data. Figure 2(a) illustrates the annual trends of AI exposure for Black and non-Black individuals, ranging from 2018-2022. Both trends of the population are positive in a steady upward trajectory, reflecting the increasing integration of AI in occupations. Non-black individuals represented by pink starting at 3.28 in 2018 and climbing to 3.32 by 2022. These groups often have occupations involving data processing or technical tasks aligned with AI automation. Black individuals began with a mean AI exposure of 3.13 in 2018, which steadily increased to 3.15 in 2021 and then rose sharply to 3.17 in 2022, maintaining a lower mean AI exposure of approximately 0.15 compared to non-black individuals. In general, blacks have limited access to high AI exposure jobs due to occupational segregation. The pattern supports the paper's findings that AI exposure widens the income gap between racial groups.

[6] 2020 is excluded because of the pandemic.

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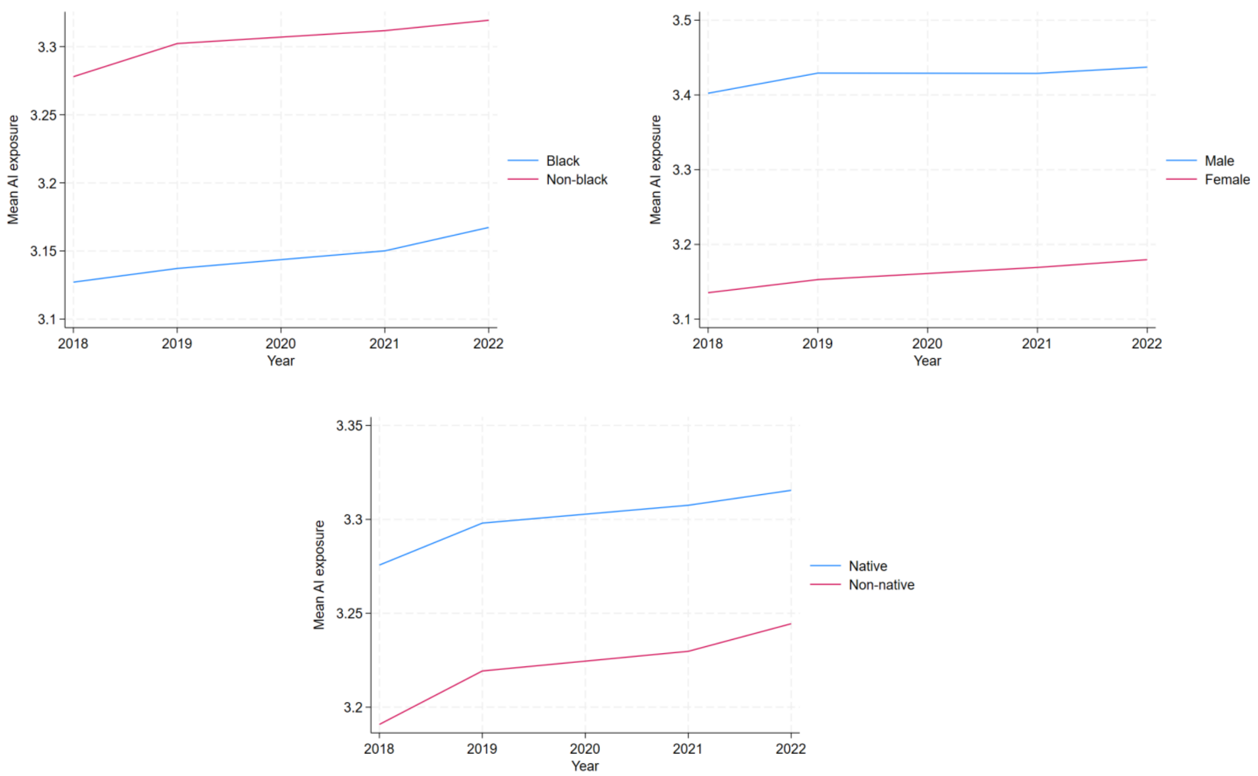
Figure 2(b) reveals the yearly trends of AI exposure for the two genders over the same period from 2018-2022, and results in a positive increase in mean AI exposure. Males represented by blue have a baseline of 3.40 in AI exposure at the year 2018, followed by a development of around 0.03 in AI exposure for the next year, remained stable till 2021, and finally reached 3.44 of mean AI exposure by 2022. The pink trend representing females in the graph maintains a median difference of 0.26[7] from males. Females have 3.13 of mean AI exposure initially, gradually growing to 3.18 in AI exposure by 2022. The difference between the trending lines reflects the prevalence of males in AI complementary fields, such as pilots or fire supervisors, which were occupations with exposure scores ranging up to 6.54 previously covered via [Data and measurements], whereas females concentrate on low AI exposure jobs, such as room attendants. This pattern supports the paper's findings that AI exposure exacerbates the income gap between genders.

Figure 2(c) exhibits the yearly trends of AI exposure between natives and immigrants, persistently evident from 2018-2022, yielding a positive increase in mean AI exposure. Natives represented by blue have a mean AI exposure of 3.275 in the index year 2018, subsequent by a rapid growth of 0.022 in 2019, and lastly gradually rising to 3.315 in 2022. Non-natives had a lower starting point of 3.19 in 2018, followed by an almost identical gradient in trends to natives until a rise of 0.015 in 2021, and reached 3.24 in 2022. The steeper rise of mean AI exposure between 2021 and 2022 indicates a reduction of the difference between natives and non-natives, proven by the change of the difference from 0.085 in 2018 to 0.07 in 2022, and this corresponds to the paper's evidence that inequality reduces at the mean exposure of 3.288.



Notes: The figures illustrate the yearly trends of AI exposure of different social groups. The sample originates from ACS data covering 2018, 2019, 2021, and 2022 from 4,276,327 observations.

Figure 2. Yearly trends of AI exposure

[7] calculated by median of AI exposure in male trend - median of AI exposure in female trend

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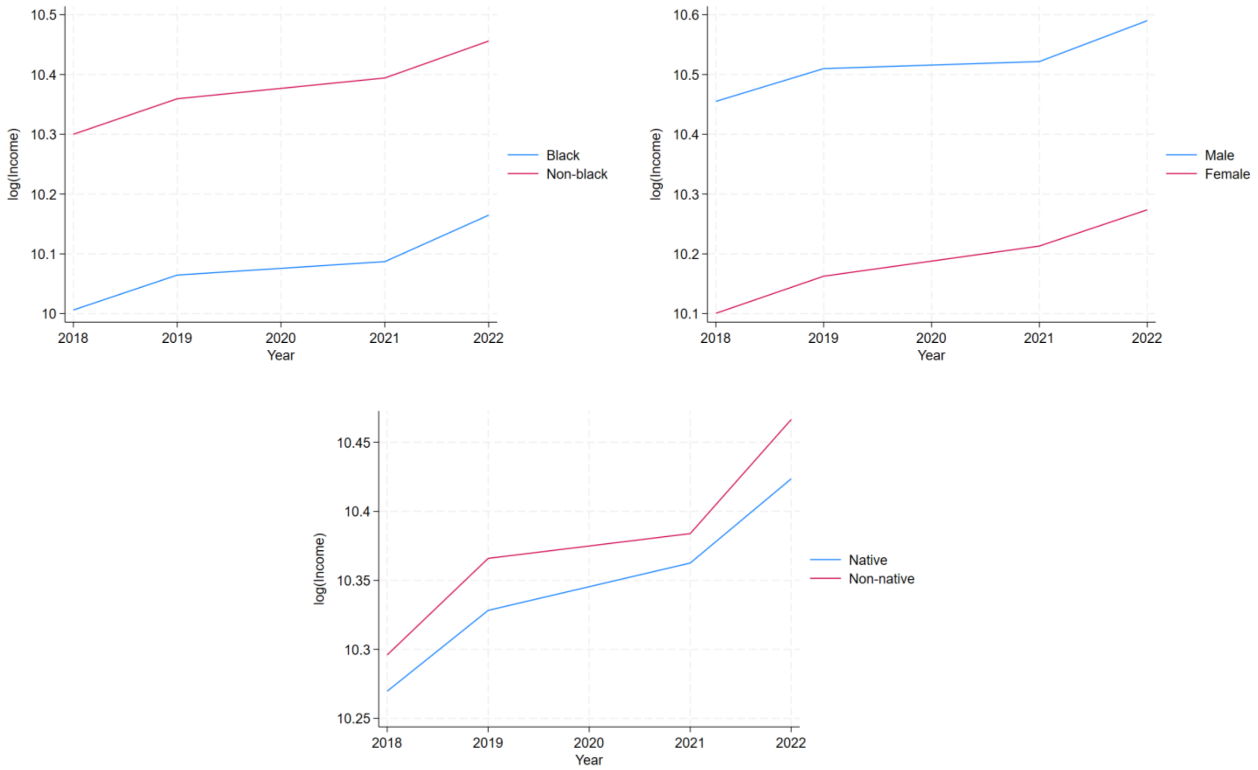
Figure 3 illustrates the annual trends[8] of log income for different social groups, ranging from 2018-2022. For Figure 3(a), which corresponds to 2(a), non-Black groups started from a log income of 10.3, who earned an advantage of 0.3 points of log income compared to the 10.0 baseline log income of black groups. The trends for both groups are almost parallel, with the same difference of a wide 0.3 points throughout the period and reaching 10.45 for non-black groups and 10.16 for black groups in 2020.

Figure 3(b) is similar to the last trend, demonstrating the gap between the log income of males and females in the U.S. The baseline of males states a log income of 10.45, a smooth side with little increase between 2019 to 2021, then approaching 10.6 by 2022. Females began with a log income of 10.10 and grew from 10.16 to 10.21 by the pandemic period, ultimately ending with 10.27. The general difference is around 0.3.

The next figure, Figure 3(c), displays a much shorter gap between trends, visually contrasting with other graphs. The non-natives have the log point around 10.30 in 2018, and the natives have a log point of around 10.27. There is rapid growth in log income for both groups under AI exposure; the gap between the trends in the year 2019 is 0.04. And by 2021, the gap between natives and non-natives is 0.02, which is a deduction of half for the earning gaps. However, the gap in log income rose to 0.04 again in 2022, which corresponds to the little increase for natives in AI exposure in the year. The general difference for natives and non-natives is 0.03.



Notes: The figures illustrate the yearly trends of log income of different social groups. The sample originates from ACS data covering 2018, 2019, 2021, and 2022 from 4,276,327 observations.

Figure 3. Yearly trends of log income

[8] 2020 is excluded due to the pandemic.

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4. Empirical analysis

4.1. Empirical strategies

In my empirical analysis, I first decompose the correlations of personal income, using the following specification:

$$\log(Income_{iobwt}) = \alpha AIExposure_o + X_{it}\beta + \gamma_b + \gamma_w + \gamma_t + u_{iobwt}, \quad (2)$$

where $Income_{iobwt}$ is the annual total personal income of individual i, with occupation o, birthplace b, workplace w, and year t, $AIExposure_o$ is the exposure of AI of occupation o, X_{it} is a vector of explanatory variables including race, gender, nativity, and age, γ_b is birthplace fixed effects, γ_w is workplace fixed effects, and γ_t is year fixed effects. u_{iobwt} is the error term. I cluster standard errors in a robust fashion. α is the core parameter of interest. If $\alpha > 0$, then personal income is positively associated with AI exposure.

In the second step, I examine how AI exposure affects income gaps. Specifically, I estimate the following specification:

$$\log(Income_{iobwt}) = \alpha AIExposure_o + X_{it}\beta + \delta AIExposure_o \times X_{it} + \gamma_b + \gamma_w + \gamma_t + u_{iobwt}, \quad (3)$$

where $AIExposure_o \times X_{it}$ is the interaction of AI exposure and an explanatory variable. β in equation (2) captures income gaps associated with X_{it}, and δ in equation (3) illustrates whether AI exposure increases or decreases income gaps. If β and δ are of the same sign, then AI exposure increases income gaps associated with X_{it}.

4.2. Empirical results

Table 3 presents the correlations of log personal income. In column (1), the regression coefficient is 0.0619, statistically significant at the 1% level. This indicates that increasing AI exposure by 1 unit (about one-third of the mean) raises the log points of personal income by 0.0619. In column (2), the regression coefficient is -0.0291, statistically significant at the 1% level. This indicates that black individuals in the US have 0.0291 less for personal income. In column (3), the regression coefficient is 0.0336, statistically significant at the 1% level. This indicates that being Male raises the log points of personal income by 0.0336. In column (4), the regression coefficient is -0.0159, statistically significant at the 1% level. This indicates that being native reduces the log points of personal income by 0.0159. In column (5), the regression coefficient is 0.0264, statistically significant at the 1% level. This indicates that increasing age by one unit raises the log points of personal income by 0.0264. Column (6) includes all explanatory variables in columns (1) through (5), and the coefficients are qualitatively similar.

Assume two individuals in the US labor market with the same race, gender, age, and nativity, the first employed as a professional model representing occupation with low AI exposure (score of 1.42), another working as a software engineer with high AI exposure (score of 4.5), both are median in their field of work and earns the same high wage before the incoming of AI. After the rise of AI automation, as presented in the Table, there is a 0.0619 higher annual log income for high AI exposure employment ($p < 0.01$), which indicates that the software engineer will have a rocketing increase due to his occupation's alignment with AI capabilities, and the software engineer's wage will outrun the model even though they pay the same effort at work. Next, gender disparities are examined. Imagine two individuals of opposite genders in the US, with other factors ceteris paribus, and both people have the same occupation of a financial advisor, the male has an advantaged log point of 0.0336, demonstrating that there will be a distinguished income between the male and the female. Then it

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comes to races, for instance, simulate a black and a non-black salesman, because of racism in the country, the African American salesman has a -0.0291 shift in log income compared to the non-African American salesman, as the other salesman earns more than the black salesman, there is inequality in the industry. For nativity, assume two software engineers again, one migrated from India, where it is famous for producing programmers, and another local software engineer. Without considering other factors, the native worker affected by the log-point of -0.0159 will find himself disadvantaged in income compared to the Indian worker. At last, we presume two workers with only the difference of age in the workforce, the older worker gets a boosted annual income with a log point of 0.00264 for each additional year for his extra work experience in the industry, but this doesn't build inequality, as the younger individual will eventually age. When all variables are included, these effects remain robust but slightly reduced, reflecting how AI exposure amplifies income for those in complementary roles, yet demographic factors like race and gender enlarge disparities, as seen in A's lower income despite the same effort.

Table 3. Correlations of personal income

	(1)	(2)	(3)	(4)	(5)	(6)
			log(Income)			
AI exposure	0.619***					0.534***
	(0.000812)					(0.000769)
Black		-0.291***				-0.119***
		(0.00227)				(0.00200)
Male			0.336***			0.192***
			(0.00116)			(0.00104)
Native				-0.159***		-0.00723
				(0.00687)		(0.00594)
Age					0.0264***	0.0240***
					(3.93e-05)	(3.63e-05)
Birthplace FE	Y	Y	Y	Y	Y	Y
Workplace FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	3,678,242	3,678,242	3,678,242	3,678,242	3,678,242	3,678,242
R-squared	0.227	0.108	0.124	0.104	0.221	0.330

Notes: The sample covers 2018, 2019, 2021, and 2022. * Significant at 10%, ** 5%, *** 1%. Robust standard errors are provided in parentheses.

Table 4 examines the effects of AI on racial inequality; the interaction term AI exposure*Black is - reveals that black individuals earn less than non-black individuals under the boost from AI exposure. The results demonstrate that increased exposure to AI in the workplace worsens the income inequality between races; The coefficient for AI exposure*Black is -0.0286 ($p<0.01$), indicating that for each unit increase in AI exposure, Black individuals' log income increases by 0.0286 less than that of non-Black individuals. And at average AI exposure levels, this translates to a 9.40% larger income gap between Black and non-Black workers. AI adoption raises earnings in different degrees when it comes to different races, widening the racial pay gap and thereby widening the racial inequality. [9]

For Table 4, analyzing AI's effects on racial inequality. This time, consider a black and a non-Black individual in the US attending the same role of a data analyst in a firm using AI tools for predictive modeling. The interaction term AI exposure*Black (-0.0286, $p<0.01$) indicates that for each unit increase in AI exposure, Black individuals experience 0.0286 log points less income growth than non-Black individuals. This widens the racial income gap, where blacks have an initial disadvantage in their coefficients on log income (-0.0825) aggravated by AI, with the mean exposure of 3.288, the gap increases by 9.40%. Thus, AI boosts incomes overall but benefits non-Black workers

[9] The formula is Percentage Increase in Income Gap $= (\delta \times \text{AI exposure}) \times 100$, where δ is the coefficient of the interaction term AI exposure*Black (-0.0286) and AI exposure is the mean level (3.288). This yields $(-0.0286 \times 3.288) \times 100 \approx 9.40\%$.

more. By comparing only on race, the non-black data analyst will earn a higher wage than the black data analyst.

Table 4. Effects of AI on racial inequality

	(1)	(2)	(3)	(4)
		log(Income)		
AI exposure	0.591***	0.618***	0.569***	0.538***
	(0.000878)	(0.000850)	(0.000779)	(0.000802)
Black	-0.0825***	-0.0287***	0.0850***	0.0275***
	(0.00995)	(0.00988)	(0.00912)	(0.00917)
AI exposure*Black	-0.0286***	-0.0469***	-0.0658***	-0.0461***
	(0.00295)	(0.00293)	(0.00273)	(0.00274)
Male	0.174***			0.191***
	(0.00112)			(0.00104)
Native		-0.148***		-0.00747
		(0.00636)		(0.00594)
Age			0.0239***	0.0241***
			(3.64e-05)	(3.63e-05)
Birthplace FE	Y	Y	Y	Y
Workplace FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	3,678,242	3,678,242	3,678,242	3,678,242
R-squared	0.234	0.229	0.324	0.330

Notes: The sample covers 2018, 2019, 2021, and 2022. * Significant at 10%, ** 5%, *** 1%. Robust standard errors are provided in parentheses.

Table 5 examines the effects of AI on gender inequality; The interaction term AI exposure*Male is 0.0124 ($p<0.01$), indicating that for each unit increase in AI exposure, male individuals' log income increases by 0.0124 more than that of female individuals. Suggesting that AI exposure widens the gender income gap. Results show a roughly 4.08% wider income gap between males and females under AI exposure. [10]

When it comes to gender, Table 5 presents the difference in income for males and females in the US with an interaction term AI exposure*Male (0.0124), revealing that American men earn 0.0124 more log points in income per unit of AI exposure than women, widening the gender income gap. Since males already have a baseline advantage of 0.133, the gap will expand by 4.03% at the mean exposure level, as the AI exposure boosts income by 0.582 log points. Proving that AI perpetuates unequal income growth between genders, possibly because men often occupy roles with higher AI exposure.

Table 5. Effects of AI on gender inequality

	(1)	(2)	(3)	(4)
		log(Income)		
AI exposure	0.582***	0.585***	0.565***	0.564***
	(0.00113)	(0.00113)	(0.00106)	(0.00106)
Male	0.133***	0.122***	0.383***	0.390***
	(0.00579)	(0.00579)	(0.00528)	(0.00529)
AI exposure*Male	0.0124***	0.0163***	0.0571***	0.0598***
	(0.00165)	(0.00165)	(0.00152)	(0.00152)
Black	-0.173***			-0.121***
	(0.00215)			(0.00200)
Native		-0.151***		-0.00779
		(0.00634)		(0.00594)
Age			0.0242***	0.0241***
			(3.63e-05)	(3.64e-05)

[10] The formula is Percentage Increase in Income Gap $= (\delta \times \text{AI exposure}) \times 100$, where δ is the coefficient of the interaction term AI exposure*Male (0.0124) and AI exposure is the mean level (3.288). This yields $(0.0124 \times 3.288) \times 100 \approx 4.08\%$.

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Table 5. (continued)

Birthplace FE	Y	Y	Y	Y
Workplace FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	3,678,242	3,678,242	3,678,242	3,678,242
R-squared	0.234	0.232	0.330	0.330

Notes: The sample covers 2018, 2019, 2021, and 2022. * Significant at 10%, ** 5%, *** 1%. Robust standard errors are provided in parentheses.

Table 6 examines the effects of AI on the nativity income gap; the interaction term AI exposure*Native is 0.109 ($p<0.01$), denoting that for each unit increase in AI exposure, native individuals' log income increases by 0.109 more than that of non-native individuals. AI exposure reduces the income gap between native and non-native individuals. A reduction of 35.84% in the income gap is derived from the interaction effect under AI exposure. [11] For example, there is a difference in income gap between the native software engineer and the Indian migrant software engineer in terms of nativity, where the primary Native coefficient (-0.509) marks that natives start with a lower income than B, with the positive interaction AI exposure*Native (0.109), natives gain 0.109 more log points per unit of exposure, individuals like the native programmer start lower but gain more, narrowing the gap. With the AI exposure coefficient (0.522) helping a 35.84% reduction in inequality at the mean exposure level between natives and non-natives represented by the local and the Indian.

Table 6. Effects of AI on native income gap

	(1)	(2)	(3)	(4)
	log(Income)			
AI exposure	0.522***	0.495***	0.522***	0.492***
	(0.00189)	(0.00190)	(0.00184)	(0.00185)
Native	-0.509***	-0.537***	-0.182***	-0.175***
	(0.00954)	(0.00952)	(0.00905)	(0.00904)
AI exposure*Native	0.109***	0.116***	0.0526***	0.0503***
	(0.00209)	(0.00209)	(0.00202)	(0.00202)
Male	-0.175***			-0.117***
	(0.00215)			(0.00200)
Black		0.176***		0.192***
		(0.00111)		(0.00104)
Age			0.0240***	0.0240***
			(3.64e-05)	(3.63e-05)
Birthplace FE	Y	Y	Y	Y
Workplace FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	3,678,242	3,678,242	3,678,242	3,678,242
R-squared	0.229	0.323	0.323	0.330

Notes: The sample covers 2018, 2019, 2021, and 2022. * Significant at 10%, ** 5%, *** 1%. Robust standard errors are provided in parentheses.

Given that AI exposure is shown to widen gender and racial income gaps while narrowing the nativity gap, these results highlight the importance of targeted interventions to address the uneven distribution of AI-driven economic benefits. For instance, implementing a progressive AI levy on high AI-exposure jobs. The tax could generate revenue that cushions displacement shocks in vulnerable occupations, and finance specialized AI training programs for disadvantaged groups, including Black individuals and women who face compounded disadvantages due to AI's

[11] The formula is Percentage Decrease in Income Gap $= (\delta \times \text{AI exposure}) \times 100$, where δ is the coefficient of the interaction term AI exposure*Native (0.109) and AI exposure is the mean level (3.288). This yields $(0.109 \times 3.288) \times 100 \approx 35.84\%$.

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intersectional impact on existing disparities. Similarly, regulations on AI industries could be enforced to execute comprehensive workforce retraining schemes and provide severance benefits to ease the immediate financial hardships during periods of unemployment. In further detail, the investments in education for girls and students of color could be expanded to emphasize training in AI cooperation or learning to be AI-resilient, such as skill-building of social intelligence or creative problem-solving, thereby reducing their exposure to income losses. Thirdly, for immigration policies, the observed reduction in the nativity gap (35.85%) highlights how AI can help level opportunities for non-native workers, by reinforcing skill-building initiatives for all residents, including immigrants, enabling them to benefit equally from AI, building a path to mutually beneficial outcomes, where a more skilled population enhances economic productivity and revenue from AI industries. Lastly, progressive taxation modifications could assist in reallocating the disproportionate redistribution of financial gains from AI by ensuring higher contributions from well-compensated AI sector occupations that support those facing widened gaps, thus promoting a broader societal sharing of technological benefits.

4.3. Discussion on policy responses

As evidence indicates, AI raises overall wages in complementary occupations but also amplifies income disparities across demographic groups and regions. To enhance social welfare, policies should aim to reduce the unequal distribution of these gains while continuing to support innovation.

One approach is to promote greater competition in AI markets by lowering barriers to entry. This would prevent excessive income concentration in a few firms and ensure broader access to AI tools. Stronger antitrust enforcement and open standards can help limit monopolistic behavior, while reducing excessive rents captured by businesses would allow productivity gains to be shared more equitably across firms and workers.

A distinct strategy is to expand subsidized training, particularly for individuals with lower incomes, as AI automation tends to benefit high-income workers disproportionately. Subsidies should prioritize training in AI-complementary skills—such as digital literacy, data analytics, and applied AI use—with targeted support for underrepresented groups, including African Americans, women, and other low-income populations. This would help counter rising inequality and raise aggregate productivity. Existing programs like the Workforce Innovation and Opportunity Act (WIOA) could be improved by adjusting funding allocations to ensure more equitable participation.

Since training is a long-term policy tool, short-term measures are also necessary to buffer disruptions. These include expanding wage insurance, unemployment benefits, or income tax credits, as well as relocation vouchers to support workers moving to regions with stronger AI-driven job growth. However, relocation policies risk creating brain drain in rural areas and increasing housing pressures in cities; thus, they should be paired with complementary housing reforms.

AI-specific levies or tax reforms can capture excess rents in AI-intensive industries. Revenues could then be redistributed through fiscal policy to fund training, social insurance, and other programs, ensuring that the benefits of AI are more broadly shared across society. However, this can be difficult to achieve in the U.S., as corporate lobbies and anti-tax political coalitions will impose strong opposition to tax hikes on higher earners or technology industries.

Another policy that is also considered difficult to achieve in the U.S. is to implement the reinforcement of immigrant skill-building initiatives, as evidence proves AI narrows the nativity wage gap from access to AI-complementary jobs for non-natives. This opportunity for equality potential could be used to generate social welfare gains and economic productivity, which could be achieved by retraining and providing equal access to programs for immigrants. However, this approach is controversial as immigration policies are one of the most debatable topics, and favoring immigrants instead of natives can bring dissatisfaction for natives.

5. Conclusion

In this paper, the effects of artificial intelligence (AI) are examined on inequality in the US. Following [5], I measure AI exposure at the occupation level. Using individual survey data from the 2018-2023 American Community Survey, I find that AI exposure is positively linked to personal income. In addition, AI exposure is positively associated with the income gap between the black and the non-black population and the income gap between males and females, and is negatively associated with the income gap between native and non-native residents.

This paper explores how AI exposure influences personal income and intensifies inequalities across race, gender, and nativity lines in the American labor market. The performance of AI exposure in jobs and its different degrees of boost to incomes for different races, genders, and natives or non-natives are investigated, and the question of how AI exposure changes income is addressed for its ability to transform occupations and to amplify existing social disparities. Policymakers and government agencies must understand these dynamics as unchecked AI adoption widens divides in society, and policy interventions might resolve the increasing inequality and even promote economic growth.

The findings reveal that higher AI exposure is strongly linked with increased personal income, where a unit rise is associated with a 0.619 log point gain, signifying that roles with AI automation are benefited. AI's impact on different groups varies, causing inequality by race and gender. Black individuals gain 0.0286 fewer log points per unit (9.40% larger disparity in mean exposure), and Male workers gain 0.0124 log points per unit (expanding gap by 4.08%). AI narrows the gaps of inequality at the same time, where the disadvantage is reduced by 35.84% between natives and non-natives. Native-born individuals in exposed roles experience faster income growth that offsets their baseline lower earnings compared to non-natives.

The paper still has limitations on its statistical measures and complete inferences of reasonable policies that the US government can employ. The analysis is based on ACS data during the years 2018-2022, excluding previous trends of AI development and inequality relationships. Besides, 2020 is a key year with its data precluded by the COVID-19 pandemic, resulting in the disability to trace the trend of log income and AI exposure with further accuracy. Moreover, the current data for 2023 and 2024. AI is a new and fast-developing field, and it may not fully capture the evolution of AI. The estimates of this paper, based only on the years 2018-2022, might misrepresent inequalities. Perfect policies are also difficult to develop or implement in the US, as political and institutional barriers in the US are likely to act as a barrier for the policy to be feasible. Lastly, this research is based only on the US, indicating that estimations and trends might not apply to other countries or economic bodies in the world.

As a result, the analysis can be extended by exploring other dimensions of inequality, such as race, more divided in comparing East and West Asians, Latin Americans, and American Indians. Regional variations can be considered as well, such as those between North and South states. Data from post-2023 can be analyzed, as AI develops annually, and evolving patterns of AI inequality might be concluded. Furthermore, comparative cross-national studies could assess whether the observed effects of AI on income disparities in the US hold globally. Such research would provide insights for designing international policies to control the unequal outcomes of AI automation. I leave this to future research.

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