AI and Freelancers: Has the Inflection Point Arrived?

Dandan Qiao
National University of Singapore
qiaodd@nus.edu.sg

Huaxia Rui
University of Rochester
huaxia.rui@simon.rochester.edu

Qian Xiong
Tsinghua University
xq20@mails.tsinghua.edu.cn

Abstract

Artificial intelligence (AI) has seen tremendous improvements in capabilities recently, yet how AI impacts different labor markets remains unclear. Leveraging the launch of ChatGPT, this study aims to elucidate how AI influences freelancers across different online labor markets (OLMs). Employing the Difference-in-Differences method, we discovered two distinct scenarios following ChatGPT's launch: 1) displacement effects in translation & localization OLM, reducing freelancers' work volume and earnings; 2) productivity effects in web development OLM, increasing freelancers' work volume and earnings. Theoretically, we developed a Cournot competition model to explain and identify that an inflection point exists for each occupation. Before this point, human workers benefit from AI enhancements; beyond this point, human workers would be replaced. Additional analyses across various occupations consistently demonstrate the two scenarios caused by AI. Further investigation into the progression from ChatGPT 3.5 to 4.0 reveals three evolving patterns of AI's effects, thereby reinforcing our inflection point conjecture.

Keywords: artificial intelligence, online labor market, jobs, ChatGPT, large language models

1. Introduction

Driven by the ever-growing memory and speed of computers, artificial intelligence (AI) has grown to permeate all walks of life. Recently, Large Language Models (LLMs) have emerged as a revolutionary advancement in the realm of AI, owing to their remarkable skills in simulating human-like abilities across a range of language-related tasks. ChatGPT, namely Chat Generative Pretrained Transformer, was the first to bring the application of LLMs to the general public, and it has rapidly become an indispensable tool for countless individuals and organizations. Since its launch on November 30, 2022, ChatGPT has reportedly amassed around 100 million active users monthly, setting a new record as the quickest-growing consumer app ever. Careers from different domains have been exposed to this popular AI tool, alarming people to rethink the "technology displacement" issue.

At the heart of the debate is the power of information technology (IT) to automate many tasks, thereby enhancing the productivity of human labor but also potentially leading to the substitution of labor by technology. Following Acemoglu and Restrepo (2019), we refer to the two opposing effects as the displacement effects and productivity effects. These countervailing forces compete to determine how technology finally influences the labor market. In this fruitful literature, technology itself, however, is treated as a black box, entering an economy's production function as a factor alongside human labor in an aggregated manner. This macroscopic approach is technology-agnostic and focuses on the long-term impact of any automation technology.

However, given the rapid development of the current wave of AI technologies, it is imperative to understand the more immediate effect of AI on the labor market as well, especially on the online labor markets (OLMs). Unlike full-time jobs that are more stable, freelance jobs are more susceptible to changes in market condition. We expect the impact of major AI innovations on jobs to first unfold on freelance markets. Several recent studies have demonstrated either the displacement or productivity effects of AI on OLMs (Demirci et al., 2023; Liu et al., 2023; Lysyakov & Viswanathan, 2022). However, these studies have not elucidated why the same AI innovations produce exactly the contrasting effects on different types of jobs. To address this issue, our research obtained a unique worker-level dataset across multiple occupations and introduced an inflection point conjecture to explain our empirical findings, enriching both empirical and theoretical insights into the future of work.

Specifically, we collected data from one of the most popular online labor platforms. Through a Difference-in-Differences (DiD) design, we observed two different scenarios that ChatGPT can impact freelancers in highly affected OLMs: 1) displacement effects for translation & localization OLM, featuring reduced work volume and earnings; 2) productivity effects for web development OLM, featuring increased work volume

URI: https://hdl.handle.net/10125/109062
978-0-9981331-8-8

and earnings. A series of robustness checks were also conducted to further test the validity of these findings.

To understand why AI affects freelancers differently, we have developed a Cournot competition model in which AI reduces both the market potential due to its displacement effect and the marginal cost due to its productivity effect. Despite its simplicity, the model implies the existence of an inflection point for each occupation. Before AI reaches the inflection point of an occupation, human labor can benefit from any progress in AI performance, experiencing productivity effects. However, once AI surpasses the inflection point, further improvement in AI performance will hurt human labor, showing the displacement effects.

To draw a more comprehensive picture for the impact of AI, we conducted additional empirical analysis to show how AI influences various categories of markets. The estimations continue to unveil two different scenarios that AI can bring to freelancers. We further consider the release of ChatGPT 4.0 as another improvement of AI, estimating the effects of both ChatGPT 3.5 and 4.0. The empirical findings reveal three patterns for the effects of these two AI upgrades: 1) both displacement effects; 2) transitioning from productivity to displacement effects; and 3) both productivity effects. The noticeable absence of a transition from a dominating displacement effect to a dominating productivity effect aligns with the inflection point conjecture, which suggests that once the displacement effect dominates, it cannot be reversed.

2. Literature review

2.1. Automation technology and labor market

In the past decades, automation technology has largely eliminated the demand for labor undertaking repeated and manual work. Such substitution has shifted the labor demand towards skilled and highly educated workers (Autor et al., 1998). Researchers have also acknowledged automation technology as an effective tool to augment human ability (Autor et al., 2003). These mixed effects give rise to an important research branch exploring the relations between automation technology and labor.

Economists have engaged in extensive theoretical deliberation to understand how automation technology might impact human labor. Some research utilizes economic models to describe the elasticity of substitution among different production factors, such as IT, labor, and capital (Dewan & Min, 1997; Zhang et al., 2015). Other research has extensively explored the role of technology in working processes. Notably, Autor et al. (2003) introduced the perspective of task composition to explain how computer technology affects the demand for human skills. Specifically, routine tasks, governed by explicit rules, are readily automated, whereas nonroutine tasks, lacking defined rules, primarily experience productivity effects with automation technologies.

Recently, academia's attention has shifted towards AI, due to its increasing role in our society. Researchers expand upon prior theoretical frameworks to enhance the understanding of AI-labor relations. Employing a task-based approach, Acemoglu and Restrepo (2019) argued that AI and robotics significantly displace human labor but noted potential countervailing factors that could mitigate this effect. Agrawal et al. (2019) delineated jobs into prediction and decision tasks, suggesting that AI's impacts on various job categories are ambiguous. These studies focus on the impact of general automation technology from a macro level and with a long-term horizon. However, they fall short of explaining the impact of a specialized technology (i.e. LLM or ChatGPT more specifically) from a micro level with a short-term horizon, which our research aims to address to provide more timely insights for many stakeholders, especially the workers in the labor market.

Empirical investigation based on real-world data is also necessary and critical to determine the actual scope and impact of automation technology on human labor. Existing empirical evidence, however, presents divergent findings. At the aggregate level, while some found net displacement effects (Chwelos et al., 2010), some found evidence for net productivity effects (Bresnahan et al., 2002). At the micro level, the impact often depends on different types of employers or workers (Lu et al., 2018; Zhang et al., 2023).

These dual effects are also present in labor markets following the advancement of AI (Lysyakov & Viswanathan, 2022; Xue et al., 2022). For instance, Xue et al. (2022) demonstrated that increasing AI applications positively impact the employment of non-academically trained workers, yet adversely affect academically trained employees. However, these studies primarily rely on data from single occupation or macro-level analysis, overlooking AI's heterogeneous impact across various labor markets. Our research, capitalizing on the advent of recent LLM technology, tackles this issue by examining a unique worker-level dataset across multiple occupations.

2.2. Large language models

Large Language Models represent a significant advancement in AI, designed to overcome the limitations of traditional machine learning (ML) systems that depend on supervised learning for language comprehension and lack generalization (Radford et al., 2019). LLMs are pretrained on extensive and generalpurpose internet data, enabling them to effectively mimic human language without explicit supervision. The pretraining process enables LLMs to assimilate linguistic information for text generation and handle diverse downstream applications (Brown et al., 2020).

This is known as "in-context learning" (Wies et al., 2023), where LLMs adapt to various tasks by integrating specific instructions or examples into their input without altering their internal structure (Brown et al., 2020; Radford et al., 2019). This closely mirrors the human approach to task processing, where understanding and action are derived directly from textual instructions.

The emergent abilities endowed by the pretraining process allow LLMs to affect various labor sectors. On one hand, LLMs can mimic human workers by interpreting and executing tasks from text-based instructions, challenging the need for humans in certain markets as cost-effective and high-quality alternatives (Eloundou et al., 2023). On the other hand, the evolution of LLMs aims to lower entry barriers into various labor sectors (Wies et al., 2023), potentially benefiting employees across diverse skill levels. While numerous debates and discussions have taken place, there remains a lack of comprehensive empirical investigation into the impact of LLMs on the labor market.

2.3. Online labor market

The online labor market (OLM) has grown tremendously in the past decades. By joining an OLM, workers can access job opportunities beyond national boundaries, actively participating in the global labor market instead of being confined to local demand (Kanat et al., 2018). These unique attributes of OLMs yield substantial social benefits, such as mitigating offline unemployment and enhancing the well-being of workers in developing countries (Huang et al., 2020).

However, the recent advancement of LLM, especially ChatGPT, has significantly shocked the OLM, posing a critical societal issue. On one hand, OLM's basis on AI-exposed digital platforms amplifies AI's impact. On the other hand, the inherently temporary nature of employment in OLMs makes online freelancers particularly vulnerable to AI-induced market disruptions (Horton, 2010). Several studies have investigated the short-term effects of LLM on the OLMs, which, however, revealed mixed effects.

The majority of these studies have underscored the displacement effects of LLM (Demirci et al., 2023; Hui et al., 2023; Liu et al., 2023). For example, Liu et al. (2023) found significant decreases in transaction volume for gigs and freelancers directly exposed to ChatGPT. Demirci et al. (2023) observed a 21% decline in job postings for writing and coding jobs post to the launch of ChatGPT. In contrast, some researchers have observed that this progress of LLM does not invariably harm freelancers. Yuan and Chen (2023), for instance, noted a general decline in demand for writing-related services, yet also identified a potential increase in demand for specific types of services, such as planning and review.

The mixed findings from these studies align with existing research on the impacts of previous AI tools on labor markets (Brynjolfsson et al., 2023; Xue et al., 2022). However, these studies primarily rely on empirical analyses for a limited set of job categories, and have yet to explain why the same AI innovations produce exactly the opposite effects on different types of jobs. Our research introduces the inflection point conjecture to theoretically explain our empirical findings and highlight the evolving relation between AI and freelancers across varying OLMs. Our findings hence could provide significant insights into the future of work, enhancing both empirical and theoretical contributions.

3. A tale of two markets

3.1. Empirical context

We use a popular online labor platform as our empirical context. Jobs on this platform cover a large variety, such as writing, programming, construction, and accounting. These jobs can be classified into fixed-price jobs and hourly-rated jobs. The fixed-priced job openings provide the total amount of compensation for the job, while the hourly-rated job openings provide a guide for the hourly price of the job and the estimated duration of the job. After a job is posted, freelancers can submit their proposals to the employer. The employer will review these applications and work proposals to select the most suitable freelancers for the job. There is also a negotiation process between freelancers and employers to determine the pricing, where freelancers can bid for the hourly rate or the entire project. After that, freelancers will proceed to perform the assigned projects. Upon completion, the employer releases the payment due and provides ratings and reviews based on the quality of the work.

The platform has a hierarchical freelancer classification system that categorizes all freelancers into different markets, based on the jobs they have taken and the skills listed in their profiles. This detailed system offers a clear portrayal of jobs necessitating specialized skills and corresponding workers in the corresponding market. Besides, the platform grants full access to the work history of its workers, such as job titles, job start and end dates, job prices, and ratings. This allows us to obtain rich worker-level transaction data related to distinct job categories. All recorded work histories represent deals that have been successfully transacted on the markets, reflecting the market equilibrium resulting from the interplay of demand and supply dynamics.

We utilize the launch of ChatGPT as an exogenous shock. Released on November 30, 2022, ChatGPT has exerted significant impacts across various tasks. It stands as the first generative AI tool to gain mainstream recognition, making it an ideal candidate for studying AI shocks. For this analysis, we focus on two highly affected job markets from the investigated freelance platform, i.e., translation & localization and web development, where LLMs have exhibited remarkable proficiency in performing relevant tasks.

First, the capability of LLMs to manage a wide range of translation tasks has been validated in real-world settings (Popel et al., 2020). Researchers and practitioners have shown ChatGPT's competitiveness against popular translation tools like Google Translate and DeepL, and its excellent ability to generate contextually relevant content (Jiao et al., 2023). ChatGPT also exhibits above-average performance in some language exams than human beings (OpenAI, 2023). Therefore, we selected translation & localization OLM as one focus to investigate AI's impact.

Second, recent research has found that by using GitHub Copilot, a tool powered by OpenAI's generative AI model, web developers can implement an HTTP server in Javascript 55.8% faster than developers without access to this AI tool (Peng et al., 2023). Web development jobs involve multifaceted tasks, demanding a comprehensive skill set, such as programming proficiency, systematic planning, and design expertise. Although ChatGPT cannot autonomously finish all these tasks, it has been demonstrated to play a supportive role to human programmers, assisting in tasks like code debugging and function identification. Therefore, we chose web development OLM as another focus of our analysis.

Finally, we selected the construction design OLM as the comparison group, which has been demonstrated as one of the least impacted industries by ChatGPT (Eloundou et al., 2023). While endeavors to integrate ChatGPT into construction design software like 3D Max are emerging, these remain in the conceptual phase, and practical implementation for independent projects are far from being ready. Thus, freelancers in the construction design OLM can serve as a good control group.

Furthermore, we assessed the extent to which ChatGPT can impact the three markets by utilizing the AI Occupational Exposure Index (AIOE) introduced by Felten et al. (2023) and the Google Search Volume Index (SVI). Firstly, we mapped the three markets to the AIOE index by associating each market with the most related occupations in the AIOE database and then calculated the average AIOE index, as presented in Figure 1. Secondly, we obtained the Google SVI by co-searching ChatGPT and the name of a specific market, plotting the weekly time trend in Figure 2. These results demonstrate that construction design OLM is little impacted by ChatGPT, whereas web development OLM and translation & localization OLM are more significantly impacted, which supports our selection of the treated and the control markets for further analyses.

3.2. Data and variables

We identified workers in the three aforementioned OLMs by targeting individuals under the relevant "specialties" classification provided by the platform. In compliance with the platform's data retrieval limits, we obtained profiles and work histories of 6,743 workers from the construction design OLM, 7,582 workers from the translation & localization OLM, and 15,000 workers from the web development OLM. We then removed the inactive workers who had not accepted any job before November 1, 2022, and aggregated the data at the worker level on a monthly basis.

A worker in a specific market may possess multiple skills, enabling them to engage in jobs beyond their primary OLM. In this paper, we define jobs aligned with workers' primary labor market as "focal jobs", while others as "non-focal jobs". Keyword searching was used to identify freelancers' focal jobs. We then constructed all measurements based on the focal jobs accepted within a given month, rather than those completed. We excluded data from November and December 2022 to account for potential pre-launch impacts of ChatGPT and holiday effects. Hence, the study's time frame spans

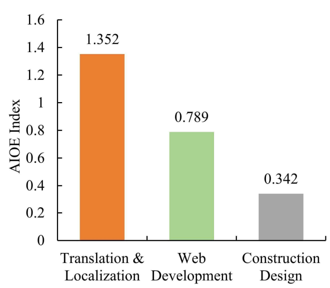

Figure 1. AIOE index comparison.

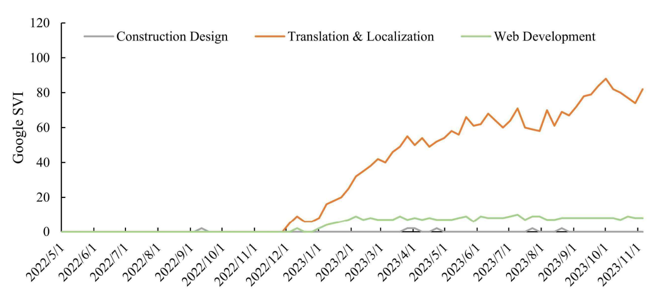

Figure 2. Weekly trend of Google SVI.

six months before and ten months after the shock, from May 1, 2022, to October 31, 2023. Table 1 provides definitions and descriptive statistics of key variables for the main analyses.

3.3. Identification strategy

To examine the impact of AI on freelancers, we used the following two-way fixed-effect DiD model for identification.

$$Y_{it} = \beta_0 + \beta_1 \times ChatGPT_{it} + \beta_2 \times X_{it} + \eta_i + \tau_t + \epsilon_{it} \quad (1)$$

In Equation (1), i and t index worker and month, respectively. The dependent variable Y_{it} measures worker i's transaction volume or earnings of worker i in month t. We used $\log(Fjobnum_{it})$ to measure the log-transformed number of focal jobs worker i accepts in month t. $Fjobratio_{it}$ is used to measure the ratio of accepted focal jobs to the total number of accepted jobs by worker i in month t. $\log(Fjobearn_{it})$ is used to measure worker i's total earnings from focal jobs in month t. The explanatory variable of interest is the binary variable $ChatGPT_{it}$ (i.e., $Treat_i \times After_t$) which equals 1 if worker i's main job category is the treated job category and the transaction activities under investigation occurred after ChatGPT's launch; otherwise, it equals 0. η_i captures worker-fixed effects, while τ_t captures time-fixed effects. X_{it} captures time-varying variables, such as worker i's tenure measured by the months up to month t since the registration.

To ensure workers in the treated and control groups are comparable, we used Propensity Score Matching (PSM) to improve the sample balance by accounting for workers' experience, total number of accepted focal jobs, wages (i.e., average price and hourly rate of focal jobs) and quality of work (i.e., the average rating of focal jobs). All these variables were calculated from the work record before ChatGPT's launch. We adopted a 1:1 nearest-neighbor matching strategy at the worker level and excluded observations falling outside of the common support region (Caliendo & Kopeinig, 2008).

3.4. Effects on translation & localization OLM

Our first analysis examines the effect of ChatGPT on translators, using the workers in the construction design OLM as the control group. Table 2 reports the DiD estimation results, and Table 3 presents the test for parallel trend. Overall, we find strong displacement effects of ChatGPT on translation & localization OLM, compared with construction design OLM. Regarding $\log(Fjobnum_{it})$, there is a significant decrease of 9.0% ($=1-e^{-0.094}$) in the absolute number of focal jobs accepted by workers after ChatGPT's launch. In terms of $Fjobratio_{it}$, the results show that workers also accept fewer focal jobs in the relative term. The coefficient of $ChatGPT_{it}$ for $\log(Fjobearn_{it})$ is negative and statistically significant as well, suggesting a decrease in worker's earnings from focal jobs by 29.7% ($=1-e^{-0.353}$). These results indicate that ChatGPT has equipped itself with adequate skills to understand language and handle translation, thereby exerting displacement effects on workers in this sector.

3.5. Effects on web development OLM

Our second analysis tests ChatGPT's effects on web developers, again using workers in the construction design OLM as the control group. The DiD estimation results and test for the parallel trend are presented in Table 2 and Table 3. Compared with construction design OLM, there is a significant increase on average in transaction volume for web developers after ChatGPT's launch by 6.4% ($= e^{0.062}-1$). This is also true in terms of relative transaction volume. Furthermore, the launch of $ChatGPT_{it}$ significantly increases the total monthly earnings by 66.5%($= e^{0.510}-1$). These results indicate that ChatGPT is unlikely to automate the process of web development but acts as an assistant to improve web developers' productivity. Web development jobs require diverse knowledge and careful planning. This makes ChatGPT hard to learn from internet text to become a qualified web developer, thereby exerting the productivity effects on web developers.

3.6. Inverse propensity score weighting

We additionally used Inverse Propensity Score Weighting (IPW) to account for the potential differences among workers in different OLMs (Kumar et al., 2019). We computed the propensity score for worker i, which is the logit probability that worker i is in the treated group (i.e., the translation & localization and web development OLMs) given his/her values of matching variables. We then computed the inverse probability weights and re-conducted the DiD analysis. The estimations, presented in Table 4, are consistent with the main results, confirming the robustness of our findings.

3.7. Control for market-specific time trend

The unobserved time-varying factor that affects different groups differently poses potential threats to the identification strategy of DiD. Therefore, we controlled market-specific time trends to account for unobserved variations, such as changes in market size. Table 5 reports the estimation results of ChatGPT's effects. These findings align with our main analyses, further reinforcing the robustness of our empirical analysis.

Table 1. Definitions and descriptive statistics of key variables.

Variables	Definitions	Count	Mean	Min	Max	Std. Dev.
$Fjobearn_{it}$	The total earnings of focal jobs accepted in month t by worker i	350752	391.753	0.000	294652.500	3206.490
$Fjobnum_{it}$	The number of focal jobs accepted in month t by worker i	350752	0.386	0.000	124.000	1.181
$Fjobratio_{it}$	The ratio of accepted focal jobs to all accepted jobs in month t by worker i	350752	0.192	0.000	1.000	0.382
$Fjobprice_{it}$	The average price per focal job accepted in month t by worker i	67136	1407.063	0.650	294652.500	5770.349
$Fjobrating_{it}$	The average rating of focal jobs accepted in month t by worker i	43610	4.872	1.000	5.000	0.448
$Fhourprice_{it}$	The average hourly rate of focal jobs accepted in month t by worker i	30249	27.346	3.000	500.000	20.784
$Tenure_{it}$	The number of months since worker i's registration up to month t	350752	40.632	0.000	280.000	35.707

Note: If worker i does not accept any focal jobs in month t, $Fjobprice_{it}$ and $Fhourprice_{it}$ will be recorded as a null value, and $Fjobratio_{it}$ will be recorded as zero.

Table 2. Effects of ChatGPT on translation & localization and web development OLMs.

	Translation & Localization OLM			Web Development OLM		
	(1)	(2)	(3)	(4)	(5)	(6)
	log(*Fjobnum*)	*Fjobratio*	log(*Fjobearn*)	log(*Fjobnum*)	*Fjobratio*	log(*Fjobearn*)
ChatGPT	-0.094*** (0.014)	-0.057*** (0.011)	-0.353*** (0.072)	0.062*** (0.011)	0.064*** (0.010)	0.510*** (0.065)
Observ.	36416	36416	36416	50224	50224	50224
Adj. R^2	0.469	0.272	0.344	0.357	0.213	0.269

Note: (1) *p<0.1, **p<0.05, ***p<0.01; (2) Clustered standard errors are in the parentheses; (3) We control for time-fixed effect, worker-fixed effect, and worker tenure. Unless otherwise noted, the same specifications are applied to the subsequent tables.

Table 3. Relative-time model: Effects of ChatGPT on translation & localization and web development OLMs.

	Translation & Localization OLM			Web Development OLM		
	(1)	(2)	(3)	(4)	(5)	(6)
	log(*Fjobnum*)	*Fjobratio*	log(*Fjobearn*)	log(*Fjobnum*)	*Fjobratio*	log(*Fjobearn*)
$RelTime_{t-6}$	-0.036 (0.027)	-0.026 (0.024)	-0.155 (0.150)	-0.012 (0.022)	-0.009 (0.022)	-0.098 (0.145)
$RelTime_{t-5}$	0.005 (0.028)	0.035 (0.025)	0.250 (0.158)	-0.021 (0.023)	-0.010 (0.022)	-0.117 (0.145)
$RelTime_{t-4}$	-0.011 (0.025)	0.015 (0.024)	0.069 (0.145)	0.001 (0.021)	0.000 (0.022)	-0.046 (0.145)
$RelTime_{t-3}$	0.013 (0.025)	0.028 (0.023)	0.089 (0.140)	0.027 (0.022)	0.024 (0.021)	0.143 (0.145)
$RelTime_{t-2}$	0.005 (0.023)	0.027 (0.022)	0.165 (0.137)	0.013 (0.020)	0.005 (0.020)	0.102 (0.134)
$RelTime_{t}$	-0.077*** (0.026)	-0.025 (0.023)	-0.251* (0.149)	0.070*** (0.022)	0.077*** (0.021)	0.554*** (0.143)
$RelTime_{t+1}$	-0.079*** (0.024)	-0.033 (0.022)	-0.196 (0.135)	0.055*** (0.021)	0.052** (0.021)	0.432*** (0.134)
$RelTime_{t+2}$	-0.067*** (0.026)	-0.025 (0.022)	-0.170 (0.138)	0.066*** (0.022)	0.064*** (0.021)	0.504*** (0.143)
$RelTime_{t+3}$	-0.110*** (0.025)	-0.054** (0.022)	-0.352** (0.143)	0.044** (0.022)	0.060*** (0.021)	0.401*** (0.143)
$RelTime_{t+4}$	-0.096*** (0.025)	-0.040* (0.024)	-0.255* (0.148)	0.060*** (0.021)	0.070*** (0.021)	0.540*** (0.138)
$RelTime_{t+5}$	-0.095*** (0.027)	-0.042* (0.024)	-0.301** (0.147)	0.047** (0.023)	0.044** (0.022)	0.336** (0.150)
$RelTime_{t+6}$	-0.096*** (0.025)	-0.052** (0.022)	-0.276** (0.137)	0.068*** (0.021)	0.069*** (0.021)	0.566*** (0.137)
$RelTime_{t+7}$	-0.105*** (0.025)	-0.052** (0.023)	-0.364*** (0.140)	0.062*** (0.023)	0.056*** (0.022)	0.559*** (0.143)
$RelTime_{t+8}$	-0.134*** (0.025)	-0.063*** (0.022)	-0.372*** (0.135)	0.074*** (0.023)	0.091*** (0.022)	0.632*** (0.146)
$RelTime_{t+9}$	-0.123*** (0.025)	-0.053** (0.022)	-0.296** (0.135)	0.084*** (0.022)	0.071*** (0.022)	0.542*** (0.142)
Observ.	36416	36416	36416	50224	50224	50224
Adj. R^2	0.469	0.272	0.344	0.357	0.213	0.269

Note: *p<0.1, **p<0.05, ***p<0.01; *Rel Time*(σ), a binary variable, represents the relative month σ to the launch month of ChatGPT.

Table 4. Effects of ChatGPT on translation & localization and web development OLMs (Using IPW).

	Translation & Localization OLM			Web Development OLM		
	(1)	(2)	(3)	(4)	(5)	(6)
	log(*Fjobnum*)	*Fjobratio*	log(*Fjobearn*)	log(*Fjobnum*)	*Fjobratio*	log(*Fjobearn*)
ChatGPT	-0.041*** (0.008)	-0.016** (0.007)	-0.123*** (0.045)	0.035*** (0.006)	0.039*** (0.005)	0.283*** (0.038)
Observ.	92848	92848	92848	162480	162480	162480
Adj. R^2	0.459	0.278	0.345	0.372	0.218	0.264

Note: (1) *p<0.1, **p<0.05, ***p<0.01; (2) Clustered standard errors are in the parentheses.

Table 5. Effects of ChatGPT on translation & localization and web development OLMs (Controlling market-specific time trend).

	Translation & Localization OLM			Web Development OLM		
	(1)	(2)	(3)	(4)	(5)	(6)
	log(*Fjobnum*)	*Fjobratio*	log(*Fjobearn*)	log(*Fjobnum*)	*Fjobratio*	log(*Fjobearn*)
ChatGPT	-0.064*** (0.020)	-0.038** (0.016)	-0.277*** (0.104)	0.042** (0.017)	0.052*** (0.015)	0.382*** (0.103)
Observ.	36416	36416	36416	50224	50224	50224
Adj. R^2	0.469	0.272	0.344	0.357	0.213	0.269

Note: (1) *p<0.1, **p<0.05, ***p<0.01; (2) Clustered standard errors are in the parentheses; (3) We control for time-fixed effect, worker-fixed effect, market-specific time trend, and worker tenure.

4. The inflection point conjecture

4.1. Inflection point of AI and jobs

To explore why advancements in AI affect workers in various OLMs differently, we develop a micro model to analyze the role of AI in our empirical context. Consider a Cournot competition model with n workers each providing the same service with the same marginal cost of producing one unit of service within an occupation. Initially, there are three basic concepts for this model. First, an occupation represents a category of jobs within a marketplace, which in the context of this study is often referred to as an OLM. Second, a job is a concrete project or work posted on the freelance platform. Lastly, a task is the smallest cognitive unit required for the successful completion of a job. This model is based on the job that consists of multiple tasks.

Let the marginal cost be $(1-a)c$ where $c>0$ and $a\in[0, 1]$. We interpret a as the percentage of tasks that can be successfully completed by AI during the production of the service. So c represents a worker's marginal cost without using any AI assistance. Market demand for the service is determined by $p=S(a)-b\sum_i q_i$ where p is the price, q_i is the quantity of services provided by worker i, and $S(a)$ represents the market potential. S(a) is decreasing in a. For potential employers who are more AI literate, AI is more reliable and competent in their focal jobs, which makes them more inclined to substitute AI for human labor. As AI improves, i.e., an increase in a, more potential employers fall into that category, thereby reducing the market potential. Moreover, $S(a)$ is likely concave because technology adoption often accelerates as the technology matures. There are several possible mechanisms. First, as AI performance increases, more employers will use it which creates more word-of-mouth recommendations, hence more adoptions. Second, there is a positive externality from more employers using AI due to the dissemination of know-how and best practices. Third, innovative businesses will develop specialized software to facilitate the use of AI to aid specific occupations, as AI becomes increasingly powerful for that type of job. We impose the technical assumptions of $|S'(0)|<c$ and $|S'(1)|>c$ to avoid non-interesting cases.

Each worker maximizes profit $\pi_i = pq_i - (1-a)cq_i = S(a)q_i - bq_i^2 - b\sum_{j\neq i} q_j q_i - (1-a)cq_i$, which yields the first-order condition:

$$\frac{\partial \pi_i}{\partial q_i}=S(a)-(1-a)c-2bq_i-b\sum_{j\neq i} q_j=0$$

$$\Leftrightarrow q_i^*=\frac{S(a)-(1-a)c-b\sum_{j\neq i} q_j}{2b}$$

We can solve for the Nash equilibrium as:

$$q_i^*=\frac{S(a)-(1-a)c}{(n+1)b}$$

Hence, the price, profit, and revenue in equilibrium are:

$$p^*=S(a)-\frac{n}{n+1}(S(a)-(1-a)c)>0,\ \pi_i^*=q_i^*\frac{S(a)-(1-a)c}{n+1}=b\cdot\left(q_i^*\right)^2$$

$$r_i^*=\pi_i^*+(1-a)cq_i^*=b\cdot\left(q_i^*\right)^2+(1-a)cq_i^*$$

To obtain comparative statics, we take the derivative of q_i^* and π_i^* with respect to a:

$$\frac{\partial q_i^*}{\partial a}=\frac{S'(a)+c}{(n+1)b},\ \frac{\partial \pi_i^*}{\partial a}=2bq_i^*\frac{S'(a)+c}{(n+1)b}$$

Define the inflection point as the unique solution $a^*\in(0,1)$ of the equation $S'(a)+c=0$. Furthermore, for comparative statics of a worker's revenue, take the derivative of r_i^* with respect to a:

$$\frac{\partial r_i^*}{\partial a}=\left(2bq_i^*+(1-a)c\right)\frac{\partial q_i^*}{\partial a}-cq_i^*$$

$$=\left(2\frac{S(a)-(1-a)c}{n+1}+(1-a)c\right)\frac{S'(a)+c}{(n+1)b}-c\frac{S(a)-(1-a)c}{(n+1)b}$$

Hence,

$$\frac{\partial r_i^*}{\partial a}<0 \Leftrightarrow S'(a)+c<(n+1)c\cdot\frac{S(a)-(1-a)c}{2S(a)+(n-1)(1-a)c}$$

Since $q_i^*>0\Leftrightarrow S(a)-(1-a)c>0$, the right-hand-side is positive. Therefore, $\partial r_i^*/\partial a<0$ if $S'(a)+c<0\Leftrightarrow a>a^*$. Note that $a<a^*$ does not imply $\partial r_i^*/\partial a>0$. However, with some technical assumptions on the shape of $S(a)$, it is possible to obtain another threshold $\tilde{a}\in(0, a^*)$ such that $\partial r_i^*/\partial a>0$ if and only if $a<\tilde{a}$. In summary, we obtain the following proposition:

Proposition 1 (Inflection Point): A worker's job volume (q_i^*) and profit (π_i^*) increase in a when $a<a^*$ but decreases in a when $a>a^*$. Moreover, a worker's revenue (r_i^*) also decreases in a when $a>a^*$.

This conjecture theoretically explains the tale of the two markets shown previously. ChatGPT manages most tasks in translation jobs, such as word translation, grammar correction, and localization. In contrast, its capabilities in web development are more limited, confined to code checking and function identification. Web developers are still indispensable. Therefore, ChatGPT's launch primarily exerts displacement effects on the translation & localization OLM but productivity effects on the web development OLM.

4.2. Analyses of additional job markets

We further obtained transaction data from additional markets to examine AI's heterogeneous effects across various OLMs. Beyond job categories included in our main analysis, we selected one specific OLM for each additional category on this platform. We employed the same methodology as the main analyses. The results for different models, presented in Table 6, unveil two different effects of AI, demonstrating that different occupations have different inflection points.

4.3. Advance from ChatGPT 3.5 to 4.0

We further considered the release of ChatGPT 4.0 on March 14, 2023, as the second upgrade of AI, estimating the effects of both ChatGPT 3.5 and 4.0 for the aforementioned eleven OLMs. The following two-way fixed-effect DiD model is used for estimation.

$$Y_{it} = \beta_0 + \beta_{1,1} \times ChatGPT\,3.5_{it} + \beta_{1,2} \times ChatGPT\,4.0_{it} + \beta_2 \times X_{it} + \eta_i + \tau_t + \epsilon_{it} \quad (2)$$

In Equation (2), the binary variable $ChatGPT\,3.5_{it}$ ($ChatGPT\,4.0_{it}$) equals 1 if worker i's main job category is the treated markets and the transaction activities under investigation occurred after the launch of ChatGPT 3.5 (ChatGPT 4.0); otherwise, it equals 0.

According to our inflection point conjecture, we anticipate only three possible outcomes: 1) continuous productivity: AI remains below the inflection point after both upgrades. 2) from productivity to displacement: AI does not reach the inflection point after the first upgrade but surpasses it following the second upgrade. 3) continuous displacement: AI has surpassed the inflection point with the first upgrade and continues to exceed it after the second upgrade. The results presented in Table 7 corroborate the three effect combinations, as no market undergoes a transition from displacement to productivity effects. This finding strengthens our model, showing that once AI crosses the inflection point of a job, it cannot revert to being below the inflection point with further AI upgrades.

Table 6. Effects of ChatGPT on different OLMs.

Category	Specific OLM	log(*Fjobnum*)	*Fjobratio*	log(*Fjobearn*)
Translation	Translation & Localization Services	-0.094***	-0.057***	-0.353***
Writing	Professional & Business Writing	-0.079***	-0.057***	-0.390***
IT & Networking	Information Security & Compliance	0.055**	0.052**	0.292*
Web, Mobile & Software Development	Web Development	0.062***	0.064***	0.510***
Customer Service	Community Management & Tagging	0.094***	0.073***	0.661***
Accounting & Consulting	Financial Planning	0.098***	0.079***	0.575***
Legal	Corporate & Contract Law	0.122***	0.072***	0.515***
Admin Support	Project Management	0.126***	0.100***	0.770***
Data Science & Analytics	Data Mining & Management	0.153***	0.102***	0.895***
Sales & Marketing	Marketing, PR & Brand Strategy	0.258***	0.176***	1.601***
Design & Creative	Photography	0.311***	0.167***	1.499***

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

Table 7. Effects of ChatGPT 3.5 and 4.0 on different OLMs.

Specific OLM	*ChatGPT* 3.5 ($\beta_{1,1}$)		*ChatGPT* 4.0 ($\beta_{1,2}$)	
	log(*Fjobnum*)	log(*Fjobearn*)	log(*Fjobnum*)	log(*Fjobearn*)
Translation & Localization Services	-0.074***	-0.293***	-0.025*	-0.075
Professional & Business Writing	-0.045**	-0.236**	-0.043***	-0.193*
Information Security & Compliance	0.106***	0.472**	-0.064*	-0.225
Web Development	0.061***	0.496***	0.001	0.017
Community Management & Tagging	0.101**	0.731**	-0.008	-0.087
Financial Planning	0.124***	0.624***	-0.032	-0.060
Corporate & Contract Law	0.126***	0.561**	-0.005	-0.058
Project Management	0.086***	0.602***	0.050*	0.211
Data Mining & Management	0.124***	0.702***	0.036	0.242*
Marketing, PR & Brand Strategy	0.213***	1.253***	0.056*	0.436**
Photography	0.207***	0.984***	0.130***	0.643***

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

5. Heterogeneous analysis

5.1. Freelancer location

ChatGPT was developed by the American AI research organization OpenAI. This analysis examines whether U.S. freelancers are more or less affected by ChatGPT compared to those in other regions. We introduced US_i as the moderator variable, defined as 1 if freelancer i resides in the United States, and 0 otherwise. As shown in Table 8, freelancer location does not significantly affect ChatGPT's impact on the translation & localization OLM, while U.S. web developers experience greater productivity effects. Freelancer location, a supply-side factor related to whether a freelancer can easily leverage ChatGPT for productivity enhancement, should not matter much in markets where the displacement effect dominates. In contrast, U.S. web developers are likely to have better access to and greater familiarity with ChatGPT, which, in turn, amplifies the productivity effect they experience.

5.2. Freelancer experience

Experienced workers could be more aware of market dynamics and potential threats (Dunne et al. 2005), potentially reacting differently to ChatGPT's launch compared to their less experienced counterparts.

We defined the moderator variable *Experienced*$_i$ as 1 if the number of focal jobs accepted by freelancer *i* before the release is above the median, and 0 otherwise. Table 9 reports the estimation results. We find an elevated negative effect of ChatGPT on experienced translators compared with less experienced translators. ChatGPT's proficiency in translation may diminish the competitive advantage of experience. Therefore, experienced translators who previously grabbed a larger market share can no longer do so in the post-ChatGPT world, and hence are more heavily impacted. Alternatively, experienced translators might be more alert to the looming challenges in the translation & localization OLM, thereby consciously choosing to exit the market. In contrast, we find no heterogeneity between experienced and less experienced web developers, indicating that the productivity boost by ChatGPT is less dependent on freelancer's experience.

Table 8. Heterogeneous analysis of freelancer's location.

	Translation & Localization OLM			Web Development OLM		
	(1)	(2)	(3)	(4)	(5)	(6)
	log(*Fjobnum*)	*Fjobratio*	log(*Fjobearn*)	log(*Fjobnum*)	*Fjobratio*	log(*Fjobearn*)
*US*ChatGPT*	0.015 (0.054)	-0.020 (0.254)	0.004 (0.038)	0.096** (0.047)	0.493* (0.286)	0.072* (0.039)
ChatGPT	-0.095*** (0.014)	-0.347*** (0.075)	-0.057*** (0.012)	0.056*** (0.012)	0.487*** (0.067)	0.060*** (0.010)
*US*After*	0.007 (0.031)	0.168 (0.192)	0.023 (0.025)	-0.007 (0.028)	0.076 (0.166)	0.002 (0.023)
Observ.	36416	36416	36416	50224	50224	50224
Adj. R^2	0.469	0.344	0.272	0.357	0.269	0.213

Note: (1) *p<0.1, **p<0.05, ***p<0.01; (2) Clustered standard errors are in the parentheses.

Table 9. Heterogeneous analysis of freelancer's experience.

	Translation & Localization OLM			Web Development OLM		
	(1)	(2)	(3)	(4)	(5)	(6)
	log(*Fjobnum*)	*Fjobratio*	log(*Fjobearn*)	log(*Fjobnum*)	*Fjobratio*	log(*Fjobearn*)
*Experienced *ChatGPT*	-0.102*** (0.028)	-0.241* (0.144)	-0.052** (0.022)	0.009 (0.023)	-0.042 (0.132)	-0.015 (0.019)
ChatGPT	-0.044*** (0.015)	-0.235*** (0.081)	-0.031** (0.014)	0.058*** (0.012)	0.530*** (0.076)	0.071*** (0.012)
*Experienced *After*	0.008 (0.020)	0.006 (0.111)	0.023 (0.016)	-0.024 (0.017)	-0.052 (0.097)	0.006 (0.014)
Observ.	36416	36416	36416	50224	50224	50224
Adj. R^2	0.470	0.344	0.273	0.357	0.269	0.213

Note: (1) *p<0.1, **p<0.05, ***p<0.01; (2) Clustered standard errors are in the parentheses.

6. Discussions and conclusion

This paper contributes both empirically and theoretically to our understanding of AI-labor relations. On the empirical side, this research first demonstrates the existence of two scenarios, i.e., displacement effects and productivity effects, which are widespread across varying OLMs. We further categorize these OLM, based on the job content and the predominant effects. Specifically, writing-related OLMs (e.g., professional & business writing OLM) are particularly susceptible to displacement effects. Consulting-related OLMs (e.g., international & immigration law OLM) typically provide specialized advice to support clients' decision-making, which may increasingly face displacement effects as ChatGPT's capabilities and knowledge base expand. Programming-related OLMs (e.g., web development OLM), where ChatGPT performs well, currently experience productivity effects. However, ChatGPT has the potential to replace programmers and eventually lead to displacement effects in the future. In contrast, OLMs related to operation (e.g., project management OLM) and creativity (e.g., photography OLM) require significant human interaction, specialized knowledge, or creative thinking, in which ChatGPT is less proficient. Therefore, these markets are likely to continue experiencing significant productivity effects.

On the theoretical front, we proposed the inflection point conjecture that contrasts the effect of AI progress on workers in two distinct stages. Before AI capabilities cross the inflection point of an occupation, workers always benefit from AI progress, but after AI capabilities cross the inflection point, workers become worse off whenever AI improves. Compared with previous macroscope research on AI-labor relation, our model is developed at a micro level and incorporates the intrinsic nature of LLMs and job features.

Our findings have important practical implications for the future of work. From the workers' perspective, our study highlights AI's dual role. We observe declines in specific markets, prompting workers to reconsider their career paths. Meanwhile, we encourage workers to collaborate with AI to enhance productivity and seize opportunities in thriving markets. It is also advisable for platforms to undertake strategic resource reallocations, such as creating new AI-based job markets. These adjustments will help platforms maintain a competitive edge in a rapidly evolving digital economy.

7. References

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *J. Econom. Perspect.*, 33(2), 3-30.

Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial intelligence: The ambiguous labor market impact of automating prediction. *J. Econom. Perspect.*, 33(2), 31-50.

Autor, D. H., Katz, L. F., & Krueger, A. B. (1998). Computing inequality: Have computers changed the labor market? *Quart. J. Econom.*, 113(4), 1169-1213.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quart. J. Econom.*, 118(4), 1279-1333.

Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *Quart. J. Econom.*, 117(1), 339-376.

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., & others. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems*, 33, 1877-1901.

Brynjolfsson, E., Li, D., & Lindsey, R. (2023). Generative AI at work. *Preprint, submitted April 23*, https://arxiv.org/abs/2304.11771.

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *J. Econom. Surveys*, 22(1), 31-72.

Chwelos, P., Ramirez, R., Kraemer, K. L., & Melville, N. P. (2010). Research note—does technological progress alter the nature of information technology as a production input? New evidence and new results. *Inform. Systems Res.*, 21(2), 392-408.

Demirci, O., Hannane, J., & Zhu, X. (2023). Who is AI replacing? The impact of generative AI on online freelancing platforms. *Working Paper*. https://papers.ssrn.com/abstract=4602944.

Dewan, S., & Min, C. K. (1997). The substitution of information technology for other factors of production: A firm level analysis. *Management Sci.*, 43(12), 1660-1675.

Dunne, T., Klimek, S. D., & Roberts, M. J. (2005). Exit from regional manufacturing markets: The role of entrant experience. *International Journal of Industrial Organization,* 23(5-6):399–421.

Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2023). GPTs are GPTs: An early look at the labor market impact potential of large language models. *Preprint, submitted March 17*, https://doi.org/10.48550/arXiv.2303.10130.

Felten, E. W., Raj, M., & Seamans, R. (2023). Occupational heterogeneity in exposure to generative AI. *Working Paper*. https://papers.ssrn.com/abstract=4414065.

Horton, J. J. (2010). Online labor markets. In Saberi A. (Eds.), *Internet and Network Economics*. Springer, Berlin Heidelberg.

Huang, N., Burtch, G., Hong, Y., & Pavlou, P. A. (2020). Unemployment and worker participation in the gig economy: Evidence from an online labor market. *Inform. Systems Res.*, 31(2), 431-448.

Hui, X., Reshef, O., & Zhou, L. (2023). The short-term effects of generative artificial intelligence on employment: Evidence from an online labor market. *Working Paper*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4527336.

Jiao, W., Wang, W., Huang, J. T., Wang, X., & Tu, Z. (2023). Is ChatGPT a good translator? A preliminary study. *Preprint, submitted January 20*, https://doi.org/10.48550/arXiv.2301.08745.

Kanat, I., Hong, Y., & Raghu, T. S. (2018). Surviving in global online labor markets for IT services: A geo-economic analysis. *Inform. Systems Res.*, 29(4), 893-909.

Kumar, A., Mehra, A., & Kumar, S. (2019). Why do stores drive online sales? Evidence of underlying mechanisms from a multichannel retailer. *Inform. Systems Res.*, 30(1), 319-338.

Liu, J., Xu, X., Li, Y., & Tan, Y. (2023). "Generate" the future of work through AI: Empirical evidence from online labor markets. *Preprint, submitted August 9, https://doi.org/10.48550/arXiv.2308.05201*.

Lu, S. F., Rui, H., & Seidmann, A. (2018). Does technology substitute for nurses? Staffing decisions in nursing homes. *Management Sci.*, 64(4), 1842-1859.

Lysyakov, M., & Viswanathan, S. (2022). Threatened by AI: Analyzing users' responses to the introduction of AI in a crowd-sourcing platform. *Inform. Systems Res.*, 34(3), 1191-1210.

OpenAI. (2023). GPT-4 technical report. *Preprint, submitted March 15*, https://doi.org/10.48550/arXiv.2303.08774.

Peng, S., Kalliamvakou, E., Cihon, P., & Demirer, M. (2023). The impact of AI on developer productivity: Evidence from GitHub Copilot. *Preprint, submitted February 13*, https://doi.org/10.48550/arXiv.2302.06590.

Popel, M., Tomkova, M., Tomek, J., Kaiser, Ł., Uszkoreit, J., Bojar, O., & Žabokrtskỳ, Z. (2020). Transforming machine translation: A deep learning system reaches news translation quality comparable to human professionals. *Nature Communications*, 11(1), 4381.

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., Sutskever, I., & others. (2019). Language models are unsupervised multitask learners. *OpenAI Blog*, 1(8), 9.

Wies, N., Levine, Y., & Shashua, A. (2023). The learnability of in-context learning. *Preprint, submitted March 14*, https://doi.org/10.48550/arXiv.2303.07895.

Xue, M., Cao, X., Feng, X., Gu, B., & Zhang, Y. (2022). Is college education less necessary with AI? Evidence from firm-level labor structure changes. *Journal of Management Information System*s, 39(3), 865-905.

Yuan, Z., & Chen, H. (2023). The impact of ChatGPT on the demand for human content generating and editing services: Evidence from an online labor market. *ICIS 2023 Proceedings*. https://aisel.aisnet.org/icis2023/techandfow/techandfow/1.

Zhang, D., Cheng, Z., Mohammad, H. A. Q. H., & Nault, B. R. (2015). Research commentary—information technology substitution revisited. *Inform. Systems Res.*, 26(3), 480-495.

Zhang, D., Peng, G., Yao, Y., & Browning, T. R. (2023). Is a college education still enough? The IT-labor relationship with education level, task routineness, and artificial intelligence. *Inform. Systems Res.* Forthcoming.