NAVIGATING THE FUTURE WORKFORCE: THE IMPACT OF GENERATIVE AI ON FREELANCE OCCUPATIONS

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CERTIFICATE OF ORIGINALITY

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Abstract

The rapid diffusion of generative artificial intelligence (AI) tools such as ChatGPT is reshaping labor markets, raising concerns about job displacement, skill bias, and cross-occupational mobility. Using freelancer- and market-level transaction data from a leading global online freelancing platform and applying a Difference-in-Differences framework, this study investigates how the emergence of generative AI has affected demand across occupations. The results reveal a dual impact: writing-related work, particularly lower-value contracts, experienced significant declines in demand, while AI-related services and higher-value technology contracts expanded, reflecting both replacement and reinstatement effects. These patterns indicate a skill-biased impact of generative AI, with higher-skilled freelancers gaining access to more complex, higher-paying opportunities, while lower-skilled workers face shrinking demand. Further analysis shows that freelancers who explicitly integrate AI into their services consistently achieve higher earnings than non-adopters, underscoring the importance of adaptability in the new digital economy. Beyond within-occupation effects, the study identifies a cross-occupational dynamic: as generative AI lowers technical barriers, freelancers can reposition themselves in adjacent domains—such as writers transitioning into design-related work—demonstrating how absorptive capacity facilitates occupational mobility. Together, these findings contribute to research on skill-biased technological change and the future of work by showing how generative AI simultaneously displaces, reinstates, and redistributes opportunities, amplifying inequality while favouring skilled and adaptive freelancers.

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CHAPTER 1. INTRODUCTION

Over the past decade, we have witnessed a remarkable surge in technological advancements in the field of artificial intelligence (AI), and in the rapidly evolving landscape of artificial intelligence, one field has emerged as a captivating force: generative AI. With its ability to create new content, art, and even music, generative AI has captured the imagination of researchers, artists, and technology enthusiasts alike. This innovative branch of AI goes beyond mere automation and enters the realm of creativity, enabling machines to generate new and original outputs that mimic human-like qualities. Generative AI, at its core, aims to replicate the human capacity for imagination and creativity through computational means. It harnesses the power of advanced machine learning techniques to generate outputs that possess a semblance of originality, often surprising researchers with their ability to mimic human thought processes and artistic expression. From generating lifelike images and videos to composing music and crafting novels, generative AI has become a versatile tool, opening possibilities that were once confined to human creativity alone.

The development of artificial intelligence has seen significant milestones, with traditional natural language processing (NLP) models laying the foundation for more advanced systems like generative AI. Traditional NLP models, such as supervised sequence labelling, neural networks, and long short-term memory; are based on statistical methods and rule-based systems. These models have been instrumental in tasks like language translation, sentiment analysis, and information retrieval. These models typically rely on predefined rules and vast amounts of labeled data to perform their tasks, often requiring extensive manual intervention and fine-tuning (Graves, 2012). Generative AI, however, represents a paradigm shift from these traditional approaches. Unlike traditional NLP models that primarily focus on understanding and processing human language, generative AI models are designed to create. This creation can be in the form of text, images, music, or even complex designs (Hariharan, 2023). One of the most significant advancements in generative AI has been the development of models such as Generative Adversarial Networks (GANs) and Transformer-based models like GPT-3.

The distinction between traditional NLP and generative AI is marked by several key differences. Traditional NLP models are primarily concerned with the interpretation and manipulation of existing data. They are designed to understand language, extract information, and respond to queries based on pre-programmed rules or learned patterns from historical data (Jurafsky & Martin, 2021). These models often use architectures like Hidden Markov Models (HMMs), Conditional Random Fields (CRFs), or earlier forms of Recurrent Neural Networks (RNNs), which rely heavily on sequence-based processing and are limited by their capacity to handle long-range dependencies. In contrast, generative AI focuses on the creation of new data, aiming to generate outputs that are not just statistically coherent but also contextually rich and creatively original. Advanced architectures such as GANs and Transformers underpin these generative models. GANs, for instance, consist of two neural networks, a generator and a discriminator—that work in tandem to produce realistic outputs. Transformers, especially in models like GPT-3, utilize self-attention mechanisms to process and generate text, enabling them to understand and produce long sequences of data effectively (Vaswani et al., 2017). Furthermore, while traditional NLP models typically require large, labeled datasets to learn from, generative AI models often leverage unsupervised or semi-supervised learning techniques, allowing them to learn from vast, unlabeled datasets and making them more scalable and adaptable to various tasks without the need for extensive manual labeling (Brown et al., 2020). The outputs of traditional NLP models are generally deterministic and predictable, producing the same output given the same input, which can limit their ability to surprise or innovate. Conversely, generative AI models can produce a wide variety of outputs from the same input, adding a layer of creativity and originality, thus mimicking human-like creativity and innovation (Goodfellow et al., 2014; Radford et al., 2019).

As generative AI continues to evolve, its implications extend far beyond the realms of art and creativity, significantly influencing various sectors, including the labor market. The capabilities of generative AI to produce high-quality content have raised questions about its impact on jobs traditionally performed by humans, particularly in creative industries such as writing, graphic design, 3D modeling, and software development.

The labor market is a fundamental component of any economy, driving growth, innovation, and societal well-being. It encompasses all forms of employment, from manual labor to highly skilled professions, and serves as the mechanism through which labor resources are allocated and compensated. Labor market plays a huge role in overall economy performance as well as individuals' welfare: The dynamics of the labor market influence economic stability, consumer spending, and the overall standard of living (Nickell, 1997). Technological advancements have always played a crucial role in shaping the labor market, with each innovation bringing about new opportunities and challenges; meanwhile, the labor market has always been dynamic, adapting to technological advancements that change the nature of work. Historically, technological revolutions such as the Industrial Revolution and the advent of the internet have drastically altered labor market dynamics, leading to shifts in demand for different types of labor and the creation of new job categories (Autor, 2015; Brynjolfsson & McAfee, 2014). The emergence of generative AI might also have the potential to redefine the nature of work in many industries as it introduces new possibilities for automating creative and intellectual tasks, which were traditionally considered immune to automation (Bakhshi et al., 2015).

The introduction of generative AI presents both opportunities and challenges for workers in various fields. For instance, in the writing industry, generative AI tools can assist writers by drafting articles, creating marketing copy, or even generating entire books. While this can enhance productivity and provide valuable assistance, it also raises concerns about the potential displacement of human writers (Bessen, 2018). Focusing on the influence of generative AI on freelance work across a wide range of occupations, this research aims to provide a comprehensive understanding of its implications for the freelance economy and contribute to the ongoing discourse on the future of work in the age of AI. Specifically, the study seeks to address the following research questions:

- **RQ1:** How does the introduction of generative AI affect demand and earnings across freelance occupations?
- **RQ2:** Are these effects skill-biased within occupations?
- **RQ3:** Does generative AI enable cross-occupational mobility by lowering skill barriers?

By exploring these questions, this research aims to contribute to the literature on skill-biased technological change, the gig economy, and labor market transformations in the age of AI. It will offer insights into how generative AI is reshaping freelance occupations, not only by displacing certain jobs but also by creating new opportunities that potentially favor skilled workers and facilitate mobility across different sectors.

CHAPTER 2. LITERATURE REVIEW

2.1 The Impact of Automation and AI on Labor Markets

The evolution of automation and artificial intelligence has had profound impacts on labor markets globally. Historically, automation has driven significant shifts in employment patterns by mechanizing tasks that were previously manual, leading to increased productivity and economic growth. However, this transformation has also resulted in the displacement of certain job categories while creating new ones. For instance, Autor (2015) examines the history and future of workplace automation, highlighting how technological advancements have consistently altered job landscapes by replacing routine tasks with mechanized processes. Bessen (2018) further explores how AI, by enhancing productivity and generating new demand, affects job creation and displacement depending on the nature of demand.

Generative AI, however, goes beyond mere automation and has the potential to fundamentally reshape traditional perceptions of creative processes. Existing research has demonstrated the extensive capabilities of generative AI: Radford et al. (2019) highlight how language models can generate coherent and contextually relevant text, performing tasks that were once considered uniquely human. Similarly, Elgammal et al. (2017) demonstrate the transformative impact of Creative Adversarial Networks (CAN) on artistic expression by showing how these networks generate artistic works through learning and deviating from existing style norms. Thus, the profound potential of generative AI lies not only in mimicking but also in innovating within creative fields.

Traditional creative occupations, which have historically relied on human creativity and manual effort, are now witnessing a shift towards AI-driven processes. This shift not only challenges existing job roles but also opens new avenues for creative expression and productivity enhancement.

Due to the profound potential of generative AI, research has delved into the potential scope of generative AI's impact and the occupations that are more likely to be exposed to generative AI: Eloundou et al. (2023) investigated the impact of large language models (LLMs) in the context of the U.S. labor market and found that LLMs display characteristics resembling those of general-purpose technologies, suggesting significant economic, social, and policy consequences. Felten et al. (2023) discovered that highly educated, highly paid, white-collar occupations are most exposed to advances in generative AI. Thus, the rise of generative AI could have substantial implications for a wide variety of occupations within labor markets.

Importantly, the overall impact of generative AI on labor markets remains contested. As noted in the broader literature on automation, new technologies often bring displacement effects—where automation substitutes for human labor—alongside reinstatement effects, where technological change creates new roles, tasks, and industries (Acemoglu & Restrepo, 2018; Bessen, 2018). Generative AI particularly exemplifies this tension: on the one hand, it may reduce demand for repetitive tasks such as writing or programming due to its advanced content generation capabilities; on the other hand, it may stimulate demand for new AI-related services such as prompt engineering, synthetic media creation, and AI-assisted design. Consequently, the net effect of generative AI on freelance work remains ambiguous and varies across occupations and task complexities. Understanding this balance between replacement and opportunity is therefore critical for assessing the evolving role of freelancers in the age of AI—a gap this research aims to address.

2.2 The Gig Economy and Online Freelancing

The gig economy, characterized by short-term contracts and freelance work, has become a significant component of the global labor market. It provides crucial income generation and employment opportunities, especially in regions with high unemployment or limited access to traditional job markets (Agrawal et al., 2013). In fact, it has already established itself as a vital part of the global workforce: In 2024, the gig economy was projected to encompass one-third of the world's workforce and generate $500 billion in gross revenue within five years (Jeff, 2024). A major driver of this growth is the flexibility and variety of employment opportunities it offers, making it an attractive option for workers seeking alternatives to traditional employment arrangements (Codagnone et al., 2016).

Looking ahead, the gig economy is poised for substantial expansion. By 2027, approximately 86.5 million people are expected to be freelancing in the United States, accounting for over half (50.9%) of the U.S. workforce. Moreover, by 2025, 36% of knowledge workers currently in full-time employment are considering transitioning to freelance work (The Upwork Team, 2025). These trends indicate that the freelance model is becoming a mainstream component of the labor market, especially among high-skilled professionals. With such significant growth potential, studying the gig economy is important not only because it offers insights into broader labor market transformations, but also because it is becoming a central pillar of the global employment landscape. Understanding how emerging technologies like generative AI interact with this evolving sector is therefore essential for anticipating the future of work.

A key component of the gig economy is the rise of online freelancing platforms, which have enabled a dynamic and accessible marketplace for services such as writing, marketing, graphic design, and software development (Kässi & Lehdonvirta, 2018). These platforms provide freelancers with global access to clients as well as task, spatial, and scheduling flexibility—further enhancing the adaptability that defines gig work (O'Neil, 2023). In addition, their reliance on digital infrastructure means that technological shifts can quickly and profoundly influence the availability and nature of freelance work (Graham et al., 2017). This dynamic environment makes online freelancing platforms an ideal setting for studying the labor market impacts of generative AI.

2.3 Productivity and Creativity Effects of Generative AI

Generative AI is reshaping freelance work, with pronounced effects in writing, graphic design, and software development. Some research has already shown the potential of generative AI on creating high quality content: For example, Reisenbichler et al. (2022) explore how natural language generation (NLG) can benefit content marketing by proposing a semi-automated approach using state-of-the-art NLG; they found that the machine-generated content, designed to perform well in search engines, is virtually indistinguishable from human-written SEO texts after human refinement. Moreover, this approach outperforms content created by human writers (including SEO experts) in search engine rankings, while also reducing production costs. Brand et al. (2023)

also provide valuable insights for querying large language models (LLMs) effectively in marketing research: By exploring the application of LLMs like GPT-3.5 in understanding consumer preferences, they demonstrate that GPT-3.5 generates survey responses consistent with economic theory and realistic willingness-to-pay estimates for products and features. Given the potential of generative AI to produce high-quality content, existing research has explored how users' utilization of generative AI impacts writing tasks, with a specific emphasis on enhancing productivity and creativity. For example, Noy and Zhang (2023) conducted a study on the productivity effects of ChatGPT and found that ChatGPT significantly increases average productivity by decreasing the time taken and increasing output quality. Furthermore, ChatGPT reduces inequality, primarily substituting for worker effort, and reshapes tasks by emphasizing idea-generation and editing over rough-drafting. Similarly, Chen and Chan (2023) compared two collaboration modalities with Large Language Models (LLMs) in advertising: as "ghostwriters" (generating content) and as "sounding boards" (providing feedback on human-created content). Interestingly, they found that using LLMs as sounding boards enhances the quality of ad copies for non-experts, while using them as ghostwriters is detrimental to expert users. Other research shows the effects of using generative AI from field experiment: Jia et al. (2023) provided evidence that AI's assistance in sequentially dividing labor tasks can enhance employee creativity and sales in a telemarketing field experiment. This enhancement occurs by enabling innovative script generation and fostering positive emotions among higher-skilled employees, while having a limited impact on lower-skilled employees. This body of literature suggests that generative AI can significantly enhance productivity and creativity, although the nature of the enhancement may depend on the specific tasks and the expertise of the users involved.

In the realm of software development, existing research also highlighted the potential of generative AI to enhance productivity: Peng et al. (2023) explored the potential of software developers using AI pair programmers such as GitHub Copilot on controlled experiment; the recruited software developers were asked to implement an HTTP server in JavaScript as quickly as possible. The treatment group, which had access to the AI pair programmer, completed the task 55.8% faster than the control group. Similarly, Quispe and Grijalba (2024) investigated the effects of ChatGPT on software development efficiency using novel data from the GitHub Innovation Graph AI. They found that tools like ChatGPT can substantially boost developer productivity. Specifically, ChatGPT availability had significant positive effects on the number of git pushes, repositories, and unique developers per 100,000 people, particularly for high-level, general-purpose, and shell scripting languages. Overall, literature supports the productivity and creativity enhancement effect of generative AI across different domains.

2.4 Skill-Biased Technological Change in the Age of Generative AI

Technological advancement has long played a critical role in reshaping the labor market by altering the demand for different skill levels. A key framework for understanding these shifts is Skill-Biased Technological Change (SBTC), which posits that technological innovations tend to favour workers with higher cognitive, analytical, or creative skills, while reducing demand for routine or manual labor. As new technologies emerge, they often complement high-skill workers but substitute for low- and medium-skill labor, leading to changes in wage structures, occupational demand, and employment inequality (Autor et al., 1998; Acemoglu, 2002).

A growing body of empirical research supports the SBTC hypothesis. Autor et al. (1998) found that the spread of computer technologies significantly increased demand for college-educated workers in the U.S., contributing to rising wage inequality. He argues that computers substituted for routine cognitive tasks while complementing abstract, non-routine problem-solving work. More recent evidence extends this pattern to online gig platforms: Guo et al. (2023) found that the growth of these platforms disproportionately increases local employment for high-skill workers, while the impact on low-skill employment remains limited. This suggests that even within the gig economy, technological change may exacerbate labor market inequalities unless accompanied by reskilling initiatives or policy interventions.

The rise of generative AI represents a novel and intensified phase of skill-biased change: Since generative AI goes beyond automation and expands into domains previously seen as uniquely human, this raises questions about who benefits and who is displaced. Just as earlier waves of computerization favoured those with advanced skills like technical or problem-solving capabilities, generative AI might also complement high-skill workers who has enough capabilities to adapt and integrate these tools into their workflows, while potentially displacing lower-skill workers whose tasks are more easily replicated or replaced. As a result, generative AI may further widen the gap between high- and low-skill workers, intensifying existing labor market inequalities.

2.5 Occupational Adaptation and Skill Realignment in the Generative AI Era

Building on the concept of SBTC, it is also crucial to consider why some workers and occupations adapt more effectively to generative AI than others. A useful lens for understanding this variation is absorptive capacity theory, which emphasizes an individual’s or organization’s ability to recognize the value of new information, assimilate it, and apply it to productive ends (Cohen & Levinthal, 1990; Zahra & George, 2002). In the context of generative AI, absorptive capacity helps explain the uneven occupational impacts of technological change: Workers who can leverage their existing knowledge to integrate and exploit new AI tools—particularly those with adjacent creative, linguistic, or conceptual skills—are more likely to benefit from these shifts. Conversely, workers whose skill sets are narrowly specialized or less aligned with AI-enabled workflows may face greater risk of displacement. This perspective frames generative AI not merely as a substitutive force, but as a catalyst for occupational evolution—rewarding those capable of reconfiguring their expertise and workflows around emerging technologies.

As generative AI reshapes skill demands across industries, its impact can be viewed as both a continuation and an intensification of earlier waves of technological change. Indeed, the rise of generative AI has the potential to profoundly impact both industrial production and society, acting as a significant driver for the fourth industrial revolution (Paukovits, 2023). During previous industrial revolutions, there was a notable shift from artisanal craftsmanship to factory-based production. For instance, an abundant supply of skilled artisans, particularly in metalworking, was a key factor driving Britain’s success during the early Industrial Revolution. These artisans’ skills could be readily adapted to developing the new machinery and manufacturing processes that began to appear in the mid-eighteenth century (Kelly et al., 2023). Just as earlier technological advancements led to significant shifts in the labor market—necessitating new skills and transforming existing roles—generative AI has the potential to significantly influence the skills required in the labor market today.

Historically, artistic creation has been deeply rooted in manual skills and techniques. Artists were required to possess a high degree of proficiency in drawing, painting, and other traditional methods to produce visually compelling works. As digital tools and technologies evolved, the landscape of artistic creation began to shift. Digital art software and graphic design tools altered the process, enabling a broader range of individuals to engage in artistic endeavours without the need for extensive manual skills (Zylinska, 2020). The advent of text-to-image generative AI has further introduced a paradigm shift in the creation of visual content. Technologies such as Generative Adversarial Networks (GANs) and Transformer-based models have made it possible to generate high-quality images from textual descriptions. Notable examples include DALL-E, an AI model capable of generating images from text prompts, and GANs for text-to-image synthesis (Reed et al., 2016; Radford et al., 2021). This shift has significant implications for the skill sets required in the creative industry.

In the era of text-to-image generative AI, the ability to generate compelling artwork is increasingly influenced by one's proficiency in crafting detailed and imaginative prompts. Writing skills, particularly those related to descriptive and evocative language, have become crucial in leveraging these AI tools effectively. Existing research also showed the importance of prompt design in AI image generation: Oppenlaender (2022) highlights the intricate relationship between human creativity and prompt design within AI-generated visual art. He emphasizes that creativity extends beyond algorithmic processes, involving the skilful crafting of prompts by users. This perspective challenges the conventional notion of creativity as solely product-centric and underscores the importance of prompt engineering in shaping AI art. Similarly, McCormack et al. (2023) found that generative AI tools have the potential to democratize creativity by making art and design tasks more accessible to non-professional users. This democratization suggests that individuals without traditional artistic skills can now participate in and contribute to the creative process.

Recently, new image, video, and world models—such as Google Genie 3, Veo, and OpenAI Sora—have further expanded the creative possibilities of generative AI. These models, which enhance the ability to generate immersive environments and interactive media, build upon the capabilities of earlier generative tools by incorporating more advanced multi-modal input and output systems: Google Genie 3, for example, is designed to generate dynamic, navigable virtual worlds from text prompts, pushing the boundaries of interactive world models. In the video generation space, OpenAI's Sora 2 have emerged as one of the leading tools by enabling creators to turn prompts into short, synchronized audio-visual clips (Laurent, 2026; Gray, 2025). These innovations underscore the growing role of generative AI in reshaping not only traditional creative fields but also interactive media and virtual reality experiences. However, concerns about image and video quality, cost, and copyright issues persist, posing challenges to the widespread adoption of these technologies (McCormack et al., 2023).

Due to the importance of prompt engineering in AI-generated image, researches have highlighted the role of users to the quality of AI-generated image: Mei (2023) advocate for recognizing Generative AI users who actively shape the output through iterative processes—adjustment, refinement, selection, and arrangement; as these iterative processes highlight that the role of the human operator is not merely passive but rather central to the quality of the AI-generated art. Moreover, Zhou and Lee (2024) explored the implications of incorporating text-to-image generative AI into the human creative workflow. Their research indicates that text-to-image AI significantly enhances human creative productivity and increases the likelihood of receiving a favourite per view.

They further found that AI-assisted artists, who can produce more novel content ideas regardless of their overall novelty before adoption, create artworks that their peers evaluate more favourably. This result implies that ideation and likely filtering are necessary skills in the text-to-image process, highlighting the continued importance of human creativity in conjunction with AI capabilities.

The intersection of writing and design facilitated by generative AI presents unique opportunities and challenges for freelancers. Freelancers in the writing industry, who possess strong skills in crafting detailed and imaginative prompts, are well-positioned to transition into roles traditionally dominated by visual artists. This transition is supported by the growing body of literature on the gig economy and digital labor markets, which highlights the fluidity of skill sets and the potential for cross-disciplinary movement (Chui et al., 2016).

The potential for skill transfer from writing to design has significant economic and social implications. For the writing industry, this shift may mitigate the adverse effects of job displacement caused by AI-driven automation by opening new avenues for employment in the design sector. Conversely, the design industry may experience an influx of new talent with unique skills that blend linguistic creativity with visual aesthetics. This hybrid skill set could lead to innovative forms of artistic expression and new business opportunities (Berger & Frey, 2016).

CHAPTER 3. Research Design and Results

3.1 Research Context

The primary research context for this study was Upwork, one of the leading online freelancing platforms. Established in 2015 through the merger of two prominent freelancing platforms, Elance and oDesk, Upwork is currently one the largest online labour platform for freelancing and facilitates wide variety of freelance services, including writing, legal, software development, customer services, and more (Blyth et al., 2022). With over 18 million of skilled freelancers and 5 million clients from over 180 nations all over the world, Upwork exemplifies the global and dynamic nature of the gig economy (Shewale, 2024). Notably, the platform hosts a high volume of creative-sector work—such as IT, design, creative writing, and web development—and actively promotes a forward-looking image by incorporating terms like "digital nomad" and "Work 3.0" into its branding (Popiel, 2017). These features make Upwork an ideal setting for examining how generative AI is reshaping labor markets, particularly in creative and knowledge-intensive occupations.

In this study, I collect data about freelancer's complete work history from publicly accessible pages on Upwork, which includes details of each completed job, such as earned income and job specific information. Additionally, I also collect data about freelancers' various characteristics, such as their education, stated hourly rates, and overall work experience. The data collection was strictly limited to publicly visible information, which adheres to the platform's access restrictions.

I aggregated the data into a freelancer-month level panel dataset with the time period ranging from January 2022 to December 2023, this comprehensive structure enables a longitudinal analysis of how individual freelancers' activity and income evolve over time, especially around the emergence and proliferation of generative AI tools. To ensure the focus of this study remained on freelancers with active participation, freelancers with least one recorded job during the study's time frame are included in the dataset.

Freelancers in the dataset are categorized into three broad occupational groups: writing, technological and digital solutions, and customer service. For each freelancer, monthly job counts and income are recorded based on the start date of each job. These variables allow us to track occupational differences in exposure and adaptation to generative AI. Table 1 is a summary of main variable in the dataset by occupation.

Table 1: Descriptive statistics

Variable	**Writing**			**Customer Service**			**Technological Solution**		
	Mean	Std. Dev.	Min–Max	Mean	Std. Dev.	Min–Max	Mean	Std. Dev.	Min–Max
No. of freelancers	87,434	—	—	98,382	—	—	67,826	—	—
Monthly Jobs	0.38	1.21	0–186	0.14	0.64	0–42	0.45	1.35	0–87
Monthly Earning	171.4	1456.2	0–177757.7	52.8	529.4	0–6225.4	275.3	2050.6	0–38368.2
Total Hours Worked	2045.8	4328.9	0–69283	865.4	1965.2	0–10674	765.2	2867.2	0–29381
Total Jobs Worked	27.8	119.4	0–9206	10.6	32.3	0–2056	9.82	40.8	0–1864.2
Stated Hourly Wage	26.4	35.9	3-900	15.9	18.3	5-100	32.9	72.5	8-900

Notes: All monetary values are in USD.

Monthly Jobs variable represents the monthly number of jobs started by a freelancer, serving as a measure of their workload and activity level, *Monthly Earning* captures the monthly earnings of a freelancer, directly indicating their financial compensation for completed tasks. Other variables measure freelancer's characteristic: *Total Hours Worked* denotes the cumulative hours worked by a freelancer; *Total Jobs Worked* represents the cumulative number of jobs completed by a freelancer; *Stated Hourly Wage* measures the freelancer's expected hourly wage; *Education* indicates the freelancer's educational attainment, and is coded as follows: 0 for no formal education, 1 for a high school degree, 2 for an associate degree or diploma, 3 for a bachelor's degree, 4 for a master's degree, and 5 for a doctoral degree. These variables offer a comprehensive view of a freelancer's professional profile, enabling a detailed analysis of how generative AI influences various aspects of their work and economic outcomes. Together, these variables provide a multidimensional view of freelancers' professional profiles and economic outcomes, enabling robust analysis of how generative AI affects labor supply, income dynamics, and occupational adjustment across different skill groups.

3.2 Main results

In this section, I empirically examine the impact of generative AI on freelance labor markets. I begin by investigating how the introduction of generative AI tools—such as ChatGPT— has shifted demand across different occupational categories. This part focuses on the replacement and reinstatement effects of generative AI, particularly within writing-related and technology-related work.

Next, I explore the skill-biased impact of generative AI. Specifically, I examined whether generative AI disproportionately benefits skilled freelancers by increasing their relative demand and work opportunities. This analysis draws on actual market transaction data to evaluate how generative AI may reinforce or reshape occupational hierarchies based on skill level.

Finally, I extend the analysis to the cross-occupational effects of generative AI. Beyond its potential role in amplifying within-occupational disparities, generative AI may also facilitate mobility across occupational boundaries—allowing freelancers to apply their capabilities in adjacent or previously inaccessible domains. This part explores how AI technologies enable individuals to reposition themselves in the freelance labor market by leveraging adaptable and transferable skill sets.

3.2.1 Displacement Effect on Writing Occupation

To estimate the average treatment effect of generative AI on the labor market, I employ a difference-in-differences (DID) model. This econometric approach is well-suited for assessing causal effects by comparing the changes in outcomes over time between a treatment group and a control group, in a natural experiment induced by the emergence of generative AI. The model specification is:

$$log(1 + y_{it}) = \beta * Treat_i * Post_t + u_i + t_t + \epsilon_{it}$$

y_{it} is the main outcome of interest, which is freelancer i's monthly number of jobs and monthly income, $log(1 + y_{it})$ is the log-transformed dependent variable to handle the skewness and zero values in the main outcome of interest, β is the main variable of interest and represents the average treatment effect (ATE). It quantifies the differential impact of generative AI on the treated group compared to the control group, after accounting for time-specific effects and individual heterogeneity. $Treat_i$ is a binary variable that is equal to 1 if freelancer i works in treated occupation, and 0 otherwise; $post_t$ is another binary variable that equals 1 for the post-treatment period. u_i are the individual fixed effects that capture unobserved heterogeneity across different freelancers and account for any characteristics specific to each freelancer that remain constant over time, and t_t are time fixed effects that account for unobserved time-specific factors that affect the outcome but are common to all freelancers, The error term in the model is denoted by ϵ_{it}, accounting for unobserved factors affecting the outcome variable. This approach allows for a robust comparison, accounting for individual and time-specific heterogeneity, thus providing a clear estimate of the impact of generative AI on completed jobs in the selected occupation.

To estimate the displacement and reinstatement impact of generative AI on the labor market, I firstly focus on the writing occupation as the treatment group. This choice is driven by the direct influence of AI tools like ChatGPT, with the ability to generate coherent and contextually relevant text, on writing tasks. In contrast, customer service freelancers were selected as the control group, as their work requires significant human interaction and empathy, making it less likely to be directly influenced by ChatGPT (Lazzaro, 2024). The treatment time is set for November 2022, corresponding to the release of ChatGPT. Therefore, the post-treatment period begins in December 2022. By comparing the changes in outcomes of interest between these two groups over time, I aim to isolate the effect of ChatGPT on the freelance writing market.

Table 2: Writing occupation DID results

Variable	$\log(1 + \text{Jobs}_{\text{it}})$	$\log(1 + \text{Income}_{\text{it}})$
$\text{Treat}_{\text{i}} * \text{Post}_{\text{t}}$	-0.0180^{***}	-0.1004^{***}
	(0.003)	(0.0147)
Unit fixed Effects	Included	Included
Month Fixed Effects	Included	Included
#Observations	185816	185816

Notes: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The result, as shown in table 2, indicates that freelancers in the writing occupation experienced approximately 1.8% drop in monthly completed jobs and approximately 10.0% drop in monthly income. This significant decline suggests that generative AI is disrupting the freelance writing market. As AI tools become more capable of producing high-quality written content, they likely reduce the demand for human writers, leading to fewer job opportunities and lower incomes. This trend highlights the broader economic displacement caused by AI, where traditional roles are increasingly being replaced by automated systems (Brynjolfsson & McAfee, 2014; Frey & Osborne, 2017; Acemoglu & Restrepo, 2019).

To ensure the validity of the Difference-in-Differences (DID) approach, it is crucial to test for the parallel trends assumption. This assumption posits that, in the absence of the treatment, the treated and control groups would have followed similar trends over time. Testing for parallel trends involves examining whether the pre-treatment trends in the outcome variable are statistically indistinguishable between the treatment and control groups.

For this analysis, I performed a parallel trends test using data from the pretreatment period. The null hypothesis (H0) for this test is that the linear trends of the treatment and control groups are parallel.

Table 3: Writing occupation parallel trends test

Variable	F-statistic	P-value	Conclusion
$\log(1 + \mathrm{Jobs_{it}})$	0.24	0.6257	No significant divergence in trends
$\log(1 + \mathrm{Income_{it}})$	0.00	0.9768	No significant divergence in trends

Table 3 indicate that we fail to reject the null hypothesis of parallel trends. This result suggests that there is no significant difference in the pre-treatment trends of the outcome variable between the treatment and control groups, supporting the validity of the parallel trends assumption. Therefore, the DID model is robust and provides reliable estimates of the treatment effect.

To further explore the heterogeneity impact of generative AI on labor market, I employ a Difference-in-Differences-in-Differences (DDD) model. This approach allows for a nuanced analysis by examining how the treatment effect varies across different freelancer characteristics. The model specification is:

$$log(1 + y_{it}) = \beta_1 * Treat_i * Post_t + \beta_2 * Treat_i * Var_i$$
$$+\beta_3 * Post_t * Var_i + \beta_4 * Treat_i * Post_t * Var_i + u_i + t_t + \epsilon_{it}$$

Var_i is freelancer i's characteristic. β_1 captures the basic treatment effect, β_2 measures the interaction between the treatment group and freelancer's characteristic and β_3 measures the interaction between the post-treatment period and freelancer's characteristic. β_4 is the coefficient of interest, representing the triple interaction effect, which indicates how the treatment effect varies by freelancer's characteristic.

I code the freelancer characteristics as binary to have a detailed examination of how different profiles of freelancers are affected by the advent of generative AI. The variables Total Hours, Total Jobs, and Total Earnings are each coded as 1 if the freelancer's respective value is above the average, and 0 if below. This binary coding helps to distinguish freelancers with higher levels of experience from those with lower levels. Additionally, the Education variable is coded as 1 if the freelancer holds at least a bachelor's degree, and 0 otherwise, thus identifying freelancers with higher educational attainment.

Table 4: Writing occupation DDD results

Variable	$\log(1 + \mathrm{Jobs}_{\mathrm{it}})$
$\mathrm{Treat}_{\mathrm{i}} * \mathrm{Post}_{\mathrm{t}}$	-0.0251^{***}
	(0.0055)
$\mathrm{Treat}_{\mathrm{i}} * \mathrm{Post}_{\mathrm{t}} * edu$	0.0110^{*}
	(0.0066)
Unit fixed Effects	Included
Month Fixed Effects	Included
#Observations	185816

Notes: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4 indicates that freelancers with higher levels of education experienced a smaller decline in completed jobs and income compared to their less-educated counterparts. This result underscores the buffering effect of educational attainment in the face of technological disruptions. Higher education often equips individuals with advanced cognitive and technical skills, enhancing their adaptability in evolving job markets (Goldin & Katz, 2008). Additionally, educated individuals tend to learn and adapt quickly to new technologies, maintaining their productivity (Bresnahan et al., 1999). Overall, the protective effect of higher education highlights the importance of continuous learning and skill development in a rapidly changing technological landscape.

Table 5: Writing occupation DDD results

Variable	$\log(1 + \mathrm{Jobs}_{it})$		
$\mathrm{Treat}_i * \mathrm{Post}_t$	-0.0077 **	0.0017	-0.0040
	(0.0039)	(0.0024)	(0.0035)
$\mathrm{Treat}_i * \mathrm{Post}_t * Var$	-0.0199^{***}	-0.0537^{***}	-0.0422^{***}
	(0.0063)	(0.0075)	(0.0071)
Unit Fixed Effects	Included	Included	Included
Month Fixed Effects	Included	Included	Included
#Observations	185816	185816	185816
Heterogeneity by	Stated Hourly Wage	Total Jobs	Total Hours

Notes: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Interestingly, table 5 also indicates that freelancers with higher stated hourly wages, more total jobs, and more total hours experienced a greater decrease in monthly jobs. This phenomenon may be attributed to the increased competition and cost sensitivity in the market brought about by generative AI as high-wage freelancers might find it harder to compete with the more cost-effective solutions enabled by AI (Agrawal, Gans, & Goldfarb, 2018). Furthermore, more experienced freelancers might offer services that, while traditionally in high demand, are more generic and therefore more susceptible to automation by generative AI tools (Acemoglu & Restrepo, 2019). These tools efficiently perform routine, predictable tasks at lower cost, thus making freelancers who mainly rely on generic tasks more susceptible to displacement. Hence, this highlights the importance for freelancers to offer cost-effective and innovative services to remain competitive in an AI-driven market.

After analysing freelancer-level data, I extend the analysis to market-level data for deeper insights. Specifically, I aggregate job posting data into submarket-month units to examine market demand dynamics. Upwork has a three-layer classification of occupations, and I follow the finest level of sub-occupations in this analysis and assign each posted job to one of the occupations based on job posting information. For the treatment group (writing), there are 19 submarkets - such as article & blog writing, ghost writing- while the control group (customer service) has 8 submarkets. This classification enables a detailed comparison of AI's impact on market demand and supply within the writing industry versus the less-impacted customer service sector. By analysing these submarket-level variations, I can explore how generative AI influences market competition across different segments.

To explore how generative AI affects both market demand and supply, I construct two outcome variables at the submarket-month level for the DID analysis. First, to capture demand-side dynamics, I use $Posting_{it}$ as the outcome variable to represent the total number of job postings in submarket i at time t. A decline in postings would indicate reduced demand for freelance services in that submarket. Second, to capture supply-side responses, I use $Biding_{it}$ to represent the total number of freelancer bids submitted for jobs posted in submarket i at time t. This reflects the level of competition or freelancer interest in available opportunities. These measures together allow for a more comprehensive understanding of how generative AI reshapes labor market dynamics—capturing both the opportunities created and the pressures faced by freelancers.

Table 6: Writing Occupation market-level DID results

Variable	$\log(1 + \mathrm{Posting_{it}})$	$\log(1 + \mathrm{Bid_{it}})$
$\mathrm{Treat_i} * \mathrm{Post_t}$	-0.1213^{***}	0.0228^{***}
	(0.033)	(0.0063)
Unit fixed Effects	Included	Included
Month Fixed Effects	Included	Included
#Observations	648	648

Notes: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6 indicate an approximately 12.1% drop in the total number of job postings and a 2.3% increase in bidding activity for writing-related tasks on the platform. This decline underscores a contraction in overall demand for human-written content, likely driven by generative AI's ability to efficiently perform routine or formulaic writing tasks.

A parallel trends test from table 7 supports the robustness of these DID results.

Table 7: Writing Occupation market-level parallel-trend test

Variable	F-statistic	P-value	Conclusion
$\log(1 + \text{Jobs}_{it})$	0.56	0.5698	No significant divergence in trends
$\log(1 + \text{Biding}_{it})$	0.13	0.7258	No significant divergence in trends

These findings reinforce the displacement effect of generative AI, highlighting its role in reducing demand for human labor in the writing industry. At the same time, the modest increase in bidding activity suggests a rise in freelancer supply—possibly due to higher productivity or perceived efficiency gains from using generative AI tools, which enable freelancers to bid on more jobs. This growing mismatch between rising supply and falling demand intensifies competition, contributing to the decline in earnings and job completions for freelancers in the writing occupation.

3.2.2 Reinstatement Effect on Technological and Digital Solutions

The previous section demonstrated that the writing occupations—due to the nature of tasks that can be efficiently automated by generative AI—are primarily affected by the technology's displacement effect, resulting in a notable decline in labor demand. In response, freelancers are increasingly compelled to adapt—not only to secure contracts, but also to maximize their potential returns. One avenue for such adaptation lies in transitioning toward roles that are more cognitively demanding and less easily automated. For instance, programming and software development often require advanced problem-solving, analytical thinking, and domain-specific expertise, and as a result, tend to command premium wages (Deming, 2017). When effectively integrated, generative AI tools can augment productivity in these complex tasks, lowering entry barriers and enabling freelancers to pursue high-value opportunities. Building on this idea, the following analysis explores how freelancers in technological and digital solutions services sector may benefit from the adoption of generative AI through increased job opportunities.

In this analysis, I continue to use customer service freelancers as the control group, since their work is less likely to be directly influenced by generative AI. Treatment group is defined as technological and digital solutions, a broad occupational category that includes software programming (e.g., web development, mobile development, video game development) as well as tasks directly related to AI (e.g., chatbot development, AI integration, generative AI modelling, and machine learning). By comparing this treatment group to the customer service group, I aim to understand how generative AI is reshaping job opportunities, productivity, and income in sectors closely aligned with emerging technologies. This approach allows for a nuanced understanding of the heterogeneous impacts of generative AI across different types of freelance work.

Table 8: Technological and digital solution occupation DID results

Variable	$\log(1 + \text{Jobs}_{\text{it}})$	$\log(1 + \text{Income}_{\text{it}})$
$\text{Treat}_\text{i} * \text{Post}_\text{t}$	0.0162^{***}	0.0386^{***}
	(0.0006)	(0.0048)
Unit fixed Effects	Included	Included
Month Fixed Effects	Included	Included
#Observations	166208	166208

Notes: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8 shows that freelancers in technological and digital solutions service occupation experiences approximately 1.6% increase in monthly completed jobs and 3.9% increase in monthly income. These findings suggest growing demand for AI-related services, consistent with broader trends in AI adoption across industries. As businesses seek to leverage AI for efficiency, innovation, and competitive advantage, they increasingly turn to freelancers with expertise in these domains.

This trend aligns with existing literature, which posits that technological change creates demand for specialized skills (Autor, 2015; Bessen, 2018). The observed income gains also highlight the premium placed on advanced technical skills in the AI economy (Manyika et al., 2017), reinforcing the value of reskilling and upskilling in response to evolving technological landscapes.

To ensure the robustness of DID result, I conducted a parallel trends test.

Table 9: Technological and digital solution occupation parallel-trend test

Variable	F-statistic	P-value	Conclusion
$\log(1+\ \mathrm{Jobs_{it}})$	1.23	0.2666	No significant divergence in trends
$\log(1+\ \mathrm{Income_{it}})$	0.57	0.4485	No significant divergence in trends

Table 9 supports the validity of the DID strategy, indicating that treatment and control groups followed similar pre-treatment trends.

To further explore heterogeneity, I utilize the same DDD approach to identify which freelancer profiles benefit most from the advent of AI technologies, thereby providing insights into how skills and experience levels influence adaptability and success in the AI-enabled freelance market.

Table 10: Technological and digital solution occupation DDD results

Variable		$\log(1+\ \mathrm{Jobs_{it}})$	
$\mathrm{Treat_i} * \mathrm{Post_t}$	0.0027^{**}	0.0027^{***}	0.0012
	(0.0011)	(0.0007)	(0.0008)
$\mathrm{Treat_i} * \mathrm{Post_t} * edu$	-0.0006	-0.0033^{**}	0.0021^{*}
	(0.0013)	(0.0015)	(0.0012)
Unit Fixed Effects	Included	Included	Included
Month Fixed Effects	Included	Included	Included
#Observations	166208	166208	166208
Heterogeneity by	Education	Total Jobs	Total Earnings

Notes: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 11: Technological and digital solution occupation DDD results

Variable	$\log(1+\ \mathrm{Income}_{\mathrm{it}})$			
$\mathrm{Treat_i} * \mathrm{Post_t}$	0.0184^{**}	0.0204^{***}	0.0081	0.0099^{*}
	(0.0011)	(0.0054)	(0.0060)	(0.0054)
$\mathrm{Treat_i} * \mathrm{Post_t} * edu$	-0.0025	-0.0230^{**}	0.0178^{*}	0.00192^{*}
	(0.0103)	(0.0120)	(0.0096)	(0.0098)
Unit Fixed Effects	Included	Included	Included	Included
Month Fixed Effects	Included	Included	Included	Included
#Observations	166208	166208	166208	166208
Heterogeneity by	Education	Total Jobs	Total Earnings	Total hours

Notes: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 10 and table 11 reveal intriguing insights: Freelancers with higher education levels do not necessarily benefit more from generative AI. This could reflect the nature of AI tools, which often embed advanced knowledge and lower the marginal value of formal education in certain technical tasks. In contrast, freelancers with higher total earnings and more total hours worked tend to benefit significantly more. This trend suggests that those freelancers who are already successful and heavily engaged in their freelance activities may have better resources and skills to integrate AI tools into their workflows, thereby enhancing their productivity and income further; furthermore, their established client base and extensive experience may also provide a competitive edge when leveraging these new technologies (Agrawal, Gans, & Goldfarb, 2018). Interestingly, freelancers with a higher number of total jobs experience a lesser benefit, possibly because their work often involves more generic tasks that are easier to complete but more susceptible to automation by generative AI, reducing the advantages they gain compared to those freelancers engaged in more specialized or complex tasks.

To complement the freelancer-level analysis, I also examined job posting data and job biding data at the submarket-month level for technological and digital solutions services.

Table 12: Technological and digital solution occupation market-level DID results

Variable	$\log(1 + \text{Posting}_{it})$	$\log(1 + \text{Bid}_{it})$
$\text{Treat}_i * \text{Post}_t$	0.1162^{***}	0.0188^{***}
	(0.039)	(0.0070)
Unit fixed Effects	Included	Included
Month Fixed Effects	Included	Included
#Observations	864	864

Notes: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

As shown in table 12, in contrast to the writing occupation, the number of job postings for technological and digital solutions has increased by approximately 11.6% following the emergence of generative AI. This upward trend suggests a clear reinstatement effect, in which technological advancement not only displaces certain types of work but simultaneously creates new, often higher-value roles that require adaptation and upskilling. The expansion in job postings indicates that generative AI may act as a catalyst for labor demand in emerging service categories, offering freelancers fresh opportunities to specialize and capture value in an evolving technological landscape.

Additionally, bidding activity within these occupations has also risen by approximately 1.9%, reflecting a growing pool of new freelancers entering occupation or existing freelancers in the occupation being more productive. This rise may be driven by two factors: First, the attractiveness of AI-enhanced roles with higher earnings potential; and second, the greater accessibility of these jobs due to generative AI tools that can assist with complex tasks. However, this rising supply may also signal increasing competition, suggesting that while generative AI enables new types of work, securing these opportunities still demands acquiring relevant technical skills and maintaining adaptability.

Overall, the results in this section highlight the reinstatement effect of generative AI in the freelance market, particularly in technical occupations, underscoring the importance of adaptability, continuous learning, and technology integration in maintaining a competitive edge. As AI reshapes the structure of labor demand, freelancers who can align their skills with emerging opportunities stand to benefit the most in the evolving digital economy.

3.2.3 Skill Biased Impact of Generative AI

The findings from the previous section suggest that the replacement and reinstatement effects of generative AI are not uniform across occupations—writing-related jobs have declined, while demand for AI-related services has increased. It is therefore essential to assess whether these shifts affect all freelancers equally or whether they disproportionately benefit certain groups based on skill level. This inquiry draws on the economic literature on skill-biased technological change (SBTC), which argues that technological advancements often complement highly skilled labor while substituting for routine or low-skilled labor (Autor et al., 1998; Acemoglu & Autor, 2011). Given the capabilities of generative AI tools, it might display similar skill-biased effects within the freelance economy.

To better understand how generative AI affects freelancers with different skill levels, I use job contract values as a proxy for skill complexity. This assumption is grounded in the literature on skill-biased technological change, where tasks that require complex problem-solving and higher cognitive skills are typically associated with higher compensation. Higher-value contracts often demand greater expertise—such as creativity, analytical thinking, or strategic communication—and are more likely completed by highly skilled freelancers (Autor, Levy, & Murnane, 2003; Acemoglu & Autor, 2011). In contrast, lower-value contracts typically involve more routine or easily automated tasks accessible to a broader pool of workers (Bessen, 2015). This distinction provides a framework for assessing the skill-biased impact of generative AI.

In this study, I categorize work with earnings of $1,200 or more per contract as high-value (HV) work, and work with earnings between $250 and $500 as low-value (LV) work. Using the same DID framework, I estimate how outcomes change across treatment and control occupations before and after the emergence of generative AI. I define the outcome variable as freelancer i's monthly income, separately for high-value and low-value contracts: I use $HVIncome_{it}$ to denote freelancer i's monthly income from high value jobs, and $LVIncome_{it}$ to denote freelancer i's monthly income from low value jobs.

Firstly, start with writing occupation, considering two distinct subgroups of monthly income from high and low value jobs, as two treatment groups and juxtaposing them with customer service occupation from the control group:

Table 13: Writing occupation skill-biased DID results

Variable	$\log(1 + \text{HVIncome}_{it})$	$\log(1 + \text{LVIncome}_{it})$
$\text{Treat}_i * \text{Post}_t$	0.0132^{***}	-0.1581^{***}
	(0.0042)	(0.0521)
Unit fixed Effects	Included	Included
Month Fixed Effects	Included	Included
#Observations	185816	185816

Notes: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 13 reveals a clear divergence: Freelancers' high-value work earning has increased by approximately 1.3%, while freelancers' low-value work earning has declined by approximately 15.8% within writing occupations. This suggests that although freelancers in the writing occupation experienced an overall drop in earnings, the decline is largely concentrated in lower-value contracts. High-value contracts, in contrast, appear to have partially compensated for the loss, highlighting a redistribution rather than a uniform decline.

Next, I extend the analysis to the technological and digital solution sector:

Table 14: Technological and digital solution occupation skill-biased DID results

Variable	$\log(1 + \text{HVIncome}_{\text{it}})$	$\log(1 + \text{LVIncome}_{\text{it}})$
$\text{Treat}_\text{i} * \text{Post}_\text{t}$	0.1031^{***}	-0.0226^{***}
	(0.0298)	(0.0069)
Unit fixed Effects	Included	Included
Month Fixed Effects	Included	Included
#Observations	166208	166208

Notes: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

A similar pattern emerges in table 14: Freelancers earned more from high-value work, while their earning from low-value work has declined. This implies the increase on income in the technological and digital solutions sectors was largely contributed by the rise of high value works. Since previous literature has noted that workers with higher skill levels or greater cognitive capabilities are more likely to secure complex, higher-value contracts, whereas those with lower skill levels typically complete routine or lower-value tasks (Autor et al., 2003). So, the overall results support that generative AI disproportionately favours higher-skilled workers, as the opportunities it creates are largely concentrated in tasks requiring advanced cognitive and technical capabilities. The decline in lower-value work, meanwhile, suggests that routine or less complex tasks—even in technical fields—are becoming less competitive or are increasingly automated. Together, these results provide further evidence of a skill-biased shift in the freelance economy catalysed by generative AI.

To further investigate the potential skill-biased nature of generative AI, I complemented the above analysis with a specific examination of freelancers engaged in AI-related work within the writing occupation. Some freelancers have begun to proactively indicate that they incorporate generative AI into their work or offering related AI services, for example: Some freelancers indicate that they offered AI related services such as “AI Content Proofreader & editor”, “GTP-4 writing” in their profile page, I classifies those workers who actively embrace generative AI as “AI adopters”; Conversely, freelancers who do not venture into such areas are classified as “Non-adopters”.

Treating these two distinct subgroups of writing occupation as separate treatment groups and comparing them against a common control group of customer service occupation:

Table 15: AI adopters versus non-adopters DID results

Variable	$\log(1 + \text{Income}_{it})$ AI adopters	$\log(1 + \text{Income}_{it})$ Non- adopters
$\text{Treat}_i * \text{Post}_t$	0.0342^{***}	-0.1469^{***}
	(0.0092)	(0.0421)
Unit fixed Effects	Included	Included
Month Fixed Effects	Included	Included
#Observations	20032	156784

Notes: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The results from table 15 show that freelancers who integrated generative AI into their work saw approximately 3.4% increase in monthly income, whereas those who did not adopt AI experienced approximately 14.7% decline in monthly income. The fact that AI adopted freelancers consistently earn more, might imply that freelancers capable of integrating AI tools into their services may access more complex, higher-paying opportunities; This indicates that AI-related work may often coincide with high-skill tasks, potentially amplifying the earning capacity of freelancers engaged in these areas.

In summary, the results demonstrate that generative AI is contributing to a skill-biased reorganization of the freelance labor market. While lower-value work becomes increasingly vulnerable to automation or price competition, highly skilled freelancers with the capacity to offer higher-value, AI-integrated services appear to thrive in the evolving landscape.

3.2.4 Cross-Occupational Mobility in the Age of Generative AI

Having examined the within-occupation skill-biased effects of generative AI, I now turn to the cross-occupation dimension of this technological shift. Rather than focusing solely on disparities within a single field, this perspective investigates whether freelancers in certain occupations are better positioned to leverage generative AI to transition into adjacent—and sometimes lucrative—domains. fields. Such cross-occupational shifts illustrate how emerging technologies can redefine the domain of expertise and reshape labor dynamics more broadly.

A useful conceptual framework for understanding this phenomenon is absorptive capacity—the ability to recognize the value of new information, assimilate it, and apply it effectively (Cohen & Levinthal, 1990). Freelancers with a cognitive foundation in one domain may be well-positioned to adopt generative AI tools that enable them to operate effectively in a different, previously unrelated, domain. In this way, generative AI can serve as a bridge, lowering technical barriers and facilitating skill translation across domains.

Taking 3D content generation as a motivating example, the growing demand for 3D worlds and virtual environments across industries is accelerating the need for more efficient workflows and innovative design approaches. Traditionally, 3D designs required artists to master domain-specific skills such as topology, geometry, and digital sculpting (Tang et al., 2025). However, with the emergence of generative AI, individuals trained in art history can now use these tools to create immersive virtual worlds in specific historical contexts—without needing deep expertise in 3D modeling or coding. In this case, descriptive knowledge and historical insight—once largely confined to academic or educational settings—become valuable assets in digital design, illustrating how AI can blur traditional occupational boundaries.

Hence this section examines how generative AI not only intensifies inequality within occupations but also reconfigures opportunities across the freelance labor market by favoring workers with adaptable or complementary skills. In this research, I examine the occupational mobility of freelancers originally working in writing who have transitioned into design-related roles—facilitated by the application of AI tools.

The dataset utilized for this study meticulously records specific information about each freelancer's completed job, including a detailed list of required "skills and expertise" for each job. After collecting list of writing related and design related “skills and expertise”, I was able to classify freelancers’ completed jobs into either writing-related or design-related. This allows me to explore how generative AI empowers freelancers in the writing occupation to transition their skills into design-related roles. This occupational shift can reveal broader trends in the labor market, showcasing how individuals are responding to technological advancements by branching out into new areas of expertise.

Table 16: Writing job DID results

Variable	$\log(1 + \text{Writingjobs}_{it})$	$\log(1 + \text{Writingincome}_{it})$
$\text{Treat}_i * \text{Post}_t$	-0.0220^{***}	-0.1034^{***}
	(0.003)	(0.0146)
Unit fixed Effects	Included	Included
Month Fixed Effects	Included	Included
#Observations	185816	185816

Notes: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 17: Design job DID results

Variable	$\log(1 + \text{Designgjobs}_{it})$	$\log(1 + \text{Designincome}_{it})$
$\text{Treat}_i * \text{Post}_t$	0.0079^{***}	0.0385^{***}
	(0.0011)	(0.0067)
Unit fixed Effects	Included	Included
Month Fixed Effects	Included	Included
#Observations	185816	185816

Notes: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 16 and table17 shows a notable shift in the types of jobs completed by writing freelancers. While the number of writing jobs has decreased by approximately 2.2% and the associated income has decreased by approximately 10.3%, the number of design jobs has increased by approximately 0.79% and design income has increased by approximately 3.8%.

The decrease in writing jobs and income could be attributed to the increasing capability of generative AI in producing high-quality written content, reducing the demand for human writers: Generative AI tools like GPT-3 have significantly enhanced the automation of writing tasks, leading to a reduction in opportunities for freelance writers (Eloundou et al., 2023). Conversely, the increase in design jobs and income highlights the adaptability and skill transfer potential of freelancers within the gig economy.

Writing freelancers, who inherently possess strong skills in crafting detailed and imaginative prompts, are now leveraging these skills to succeed in design-related roles. The advent of generative AI, particularly text-to-image models such as Midjourney, has enabled these freelancers to apply their writing skills in new, creative ways within the design field. The ability to generate high-quality visual content from textual descriptions has opened new opportunities for freelancers to expand their services beyond traditional writing tasks.

This skill transfer is facilitated by the foundational overlap between effective prompt engineering and creative design processes. Writing freelancers, with their proficiency in descriptive and evocative language, are well-suited to creating detailed prompts that guide AI tools in generating compelling visual content. This shift not only mitigates the negative impact of AI-driven automation on writing jobs but also introduces a new avenue for employment and income growth within the design sector.

Table 18: Design job percentage DID results

Variable	$\log(1 + \ Pecdesignjobs_{it})$
$\mathrm{Treat_i} * \mathrm{Post_t}$	0.0053^{***}
	(0.0005)
Unit fixed Effects	Included
Month Fixed Effects	Included
#Observations	185816

Notes: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To further substantiate the shift in occupational roles among writing freelancers following the advent of generative AI, an additional analysis was conducted using the percentage of monthly design jobs as the dependent variable: Specficially, $Pecdesignjobs_{it}$ represents the proportion of design jobs completed by freelancer i in month t, relative to their total completed jobs in the same period. The results corroborate the initial findings, showing a significant increase in the proportion of design-related work performed by writing freelancers.

The findings from table 18 are consistent with previous research that highlights the transformative potential of generative AI in democratizing creativity and enabling cross-disciplinary skill transfer (Oppenlaender, 2022; McCormack et al., 2023). This convergence of skills broadens the scope of opportunities available to writing freelancers, enabling them to transition into design roles that traditionally required a different set of expertise, thereby enhancing their resilience and competitiveness in the digital labor market.

In summary, the emergence of generative AI has facilitated a significant occupational shift for writing freelancers, allowing them to successfully transition into design-related roles by leveraging their writing skills for creative and innovative applications in the design industry. This occupational shift also indicates a broader trend where freelancers must continuously evolve their skill sets to keep pace with technological advancements and maintain their market relevance. By transitioning to design-related roles, writing freelancers demonstrate an adaptive response to the pressures of automation, leveraging their creative capabilities in new and emerging fields.

To enhance the reliability of the Difference-in-Difference DID results, I also examine the parallel trends assumption. Table 19 further confirm the robustness of the results.

Table 19: Design job percentage parallel-trend test

Variable	F-statistic	P-value	Conclusion
$\log(1 + \text{Writingjobs}_{it})$	0.02	0.8958	No significant divergence in trends
$\log(1 + \text{Writingincome}_{it})$	0.00	0.9705	No significant divergence in trends
$\log(1 + \text{Designjobs}_{it})$	2.13	0.1446	No significant divergence in trends
$\log(1 + \text{Designincome}_{it})$	1.92	0.1656	No significant divergence in trends
$\log(1 + \text{Pecdesignjobs}_{it})$	0.50	0.4812	No significant divergence in trends

3.3 Online Experiment

To further support the hypothesis of skill transfer facilitated by generative AI, I conducted an online experiment to explore how the emergence of generative AI impacts the interaction between writing and drawing skills. In this study, I enrolled a group of 65 skilled professionals with college education and allocate each of them incentivized writing and drawing task. Participants are asked to imagine and describe their perfect day at the beach, they are required to write a short passage and draw a sketch style drawing that describes the activities, people, and surroundings that would make their day perfect, they are told that their writing and drawing must describe the exact same imaginary scene. After participants finish their writing and drawing, I manually copy and paste each participant's writing as prompts into Midjourney, a generative AI tool that can produce high-quality image based on natural language prompts, to produce AI-generated images. I made all the AI-generated images to be sketch style to make sure that the drawing style of human drawing and AI-generated images are the same. So overall, each participants have one piece of writing, one piece of drawing they draw by hand, and one piece of AI-generated drawing that we manually created based on their writing. I recruited two experienced writing professionals and two experienced art professionals to access the quality of writing and drawing; each piece of output is seen by two evaluators. I observed a strong level of consensus among evaluators, with a correlation of 0.75 between writing grades, 0.77 between hand-drawn images, and 0.72 between AI-generated images.

Figure 1 displays the descriptive statistics for the grades and average grades assigned by two evaluators. Writing grades were assessed on a scale ranging from 1 to 7, while both drawing and AI-generated image grades were evaluated on a scale from 1 to 14. Notably, we observed that AI-generated images in general gain higher scores compared to hand-drawn counterparts. Specifically, the mean for average drawing grades is 3.354, with score spanning from a minimum of 1 to a maximum of 9. Conversely, the mean for average AI-generated image grades stands at 9.162, with scores ranging from a minimum of 6.5 to a maximum of 11. Figure 2 and figure 3 shows the grading distribution for drawing and AI-generated image.

	Mean	SD	MIN	MAX	Writing_1	Writing_2	Writing_Avg	Drawing_1	Drawing_2	Drawing_Avg	AIGC_1	AIGC_2	AIGC_Avg
Writing_1	3.431	1.380	1	7	1.000								
Writing_2	3.646	1.576	1	7	0.747	1.000							
Writing_Avg	3.538	1.382	1	7	0.925	0.943	1.000						
Drawing_1	3.369	2.058	1	10	0.048	-0.017	0.014	1.000					
Drawing_2	3.338	1.890	1	10	-0.099	-0.190	-0.158	0.775	1.000				
Drawing_Avg	3.354	1.860	1	9	-0.024	-0.106	-0.072	0.947	0.937	1.000			
AIGC_1	9.354	1.243	7	11	0.620	0.639	0.674	0.150	0.108	0.138	1.000		
AIGC_2	8.969	1.392	6	11	0.674	0.743	0.761	0.119	0.010	0.071	0.720	1.000	
AIGC_Avg	9.162	1.222	6.5	11	0.699	0.748	0.776	0.144	0.061	0.110	0.919	0.936	1.000

Figure 1

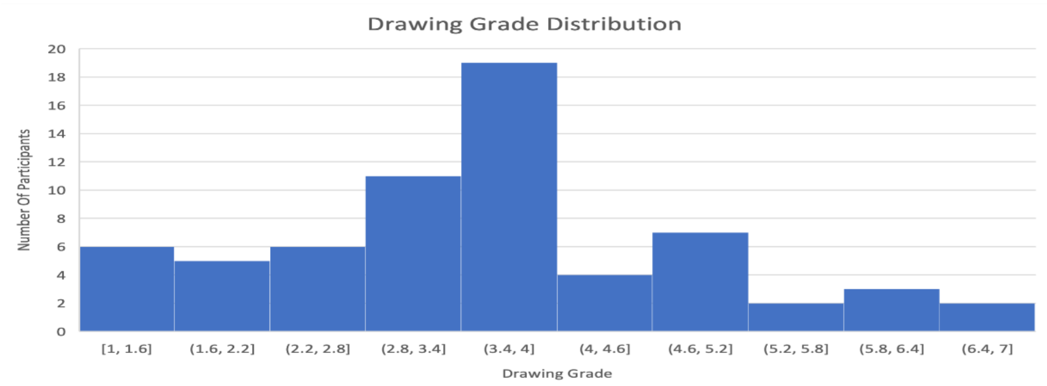

Figure 2

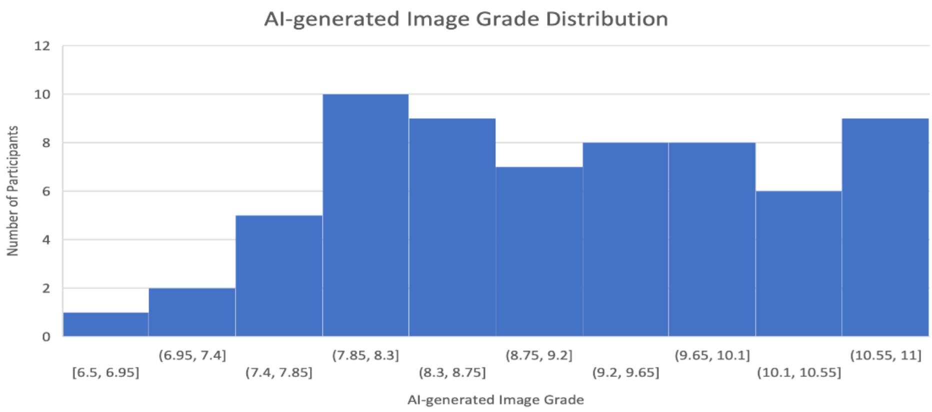

Figure 3

3.3.1 Skill Relationships

The analysis of skill relationships has revealed intriguing dynamics influenced by the emergence of generative AI. The correlation of -0.072 between participants' writing and drawing skills reveals a tenuous connection between these two abilities. This divergence underscores that while some succeed or struggle in both disciplines, many showcase a blend of skills – excelling in one skill but not the other. This shows that excellence in one skill does not automatically translate to excellence in the other.

The correlation of 0.78 between the quality of writing and AI-generated images shows the bridging role played by generative AI. This strong correlation implies that individuals skilled in writing can generate high-quality AI-generated images by using their writing inputs as prompts.

More importantly, the observation of a significant gap between the quality of hand-drawn images and AI-generated images underscores the magnitude of the change, reflected by an average correlation of 0.11 between drawing and AI-generated image as determined by two evaluators, and both evaluators' assessed correlations are below 0.15. This divergence highlights the quality difference between participants' hand-drawn and AI-generated images, implying that participants' proficiency in hand-drawn images does not necessarily translate directly to creating equally high-quality AI-generated images. More broadly speaking, generative AI enables individuals to utilize their strength in one skill to enhance their skill in a previous different domain, implying that the boundaries between previously distinct skill gets blur, and the transformative influence of one skill upon another comes to the forefront.

3.3.2 Relative Standing

The exploration of grade gain and relative ranking change continues to unveil the transformative influence of generative AI on competitive dynamics. I found a pattern where individuals with unbalanced skill sets experience more significant shifts in their relative rankings, reinforcing the notion that AI-driven creativity can reshape the competitive landscape.

I divide participants into three distinct groups: Group 1, characterized by strong writing skills but weaker drawing abilities; Group 2, displaying a balanced proficiency in both writing and drawing; and Group 3, showcasing strong drawing skills but less proficiency in writing. The analysis of participants' grade gain in AI-generated image compared to drawing reveals intriguing insights.

Participants in Group 1, with a proficiency in writing but limitations in drawing, on average moves up in ranking 18.75 compared to group 2 ($p < 0.001$). This outcome highlights that generative AI's emergence can considerably alter individuals' competitive standings, particularly for those with specific skill imbalances, implying how the emergence of generative AI enables participants to channel their strengths in one skill to overcome weaknesses in a previously distinct skill.

Conversely, participants in Group 3, excelling in drawing but having weaker writing abilities, on average moves down in ranking 30.53 compared to group 2 ($p < 0.001$). This outcome highlights while drawing skills remain valuable, the emergence of generative AI empowers those with superior writing abilities to effectively narrow the gap, altering individuals' competitive standing in the contest.

These trends are equally mirrored in the grade gain data: Group 1 participants achieve an average grade gain 1.57 points higher than Group 2 ($p < 0.001$), while Group 3 participants experience an average grade gain 2.85 points lower than Group 2 ($p < 0.001$).

These findings further corroborate the hypothesis that generative AI can lead to significant shifts in individual's relative rankings especially for individuals with unbalanced skill sets, as individuals can strategically leverage their strengths to excel in new domain. This insight resonates across diverse contexts, shedding light on the profound impact of generative AI on the dynamics of contest.

3.3.3 Altered Rules

Generative AI enables individuals to harness strong skills in one domain to succeed in previously distinct domain, showcasing generative AI's potential to redefine the competition's rule. We observed that participants' average AI-generated image scores rise by 0.70 ($p < 0.001$) for each unit increase in their average writing scores, while drawing's impact on AI-generated image remains much lower ($p = 0.035$).

This shift is underscored by a significant change in predictor importance. In traditional way of drawing, writing's role in predicting drawing was minimal, yet after the emergence of generative AI, writing emerges as a vital predictor of drawing ability, signifying the technology's substantial influence.

These findings suggest that while traditional hand-made drawing have emphasized technical drawing skills, after the emergence of generative AI, linguistic play a crucial role in producing high-quality AI-generated images. This shift indicates generative AI introduces new criteria for the contest.

More broadly speaking, the emergence of generative AI allows individuals with strengths in one area (e.g. writing) to leverage those skills to excel in another (e.g. drawing), this has the potential to broaden the pool of participants who can engage in the competitions. Individuals who might have felt excluded due to limitations in drawing skills can also generate compelling visual content by using their writing abilities. Generative AI opens a new era where the barriers of contests become lower for individuals with multidimensional skill set, potentially reshaping the way training and preparation are undertaken.

CHAPTER 4. GENERAL DISCUSSION

4.1 Theoretical and Practical Implications

From a theoretical standpoint, this research contributes to the understanding of technological change and its effects on labor markets. The finding that writing freelancers experienced a decrease in jobs completed and income post-generative AI suggests a displacement effect due to automation (Acemoglu & Restrepo, 2019). This indicates that certain skills, particularly those related to traditional writing tasks, may become less valuable as AI tools can perform these tasks more efficiently. Conversely, the observed increase in jobs completed and income for freelancers in technology sectors, an area that requires more advanced cognitive skills, highlights the complementary nature of generative AI for specific occupations. This supports the idea that generative AI's replacement and reinstatement effects do not apply equally to all categories of work. This research also illustrates the potential skill-biased impact of generative AI by showing that generative AI may have biased impact against low-skill freelancers. Lastly, this study extends beyond skill-biased effect and explores how generative AI influences skill transfer and labor dynamics. Historically, technological advancements have led to significant shifts in labor markets, necessitating new skills and transforming existing roles. This study extends this narrative by demonstrating that generative AI facilitates a novel form of skill transfer, where freelancers traditionally engaged in writing can leverage their descriptive skills to succeed in design-related roles. This aligns with theories of skill-biased technological change, which posit that technological advancements disproportionately benefit workers with certain skill sets (Autor, 2015).

Practically, the findings have several implications for freelancers, platform operators, and policymakers. For freelancers, the research underscores the need for freelancers to explore new fields where their existing skill sets can be readily applied. For instance, writing freelancers, who are experiencing a decline in writing jobs demand due to generative AI, can leverage their descriptive language skills in emerging roles such as prompt engineering in design roles. Platform operators like Upwork can use these insights to provide various resources to help freelancers learn about AI technologies and how to integrate them into their services. Moreover, highlighting the potential for skill transfer can attract more freelancers to the platform, promoting a diverse talent pool that can meet varied client needs. For policymakers, the study suggests a need for supportive measures that facilitate continuous learning and skill development in the workforce. This is crucial for ensuring that workers can adapt to new technological realities and for mitigating the adverse effects of job displacement caused by automation.

To put this work into larger context, generative AI forms the foundation for agentic AI, a more advanced type of AI that not only generates content but also performs tasks and makes autonomous decisions (Oracle, 2025). While generative AI automates creative work, agentic AI takes this a step further by handling more complex, decision-based roles. In the future era of agentic AI, the findings from this research highlights that workers will need to adapt by actively utilizing their transferable skills to succeed in new roles, particularly those that are newly created and require high-level cognitive abilities. This evolution emphasizes the importance of continuous reskilling and adaptability in an AI-driven labor market.

4.2 Limitations and Directions for Future Research

A key limitation of this study is that it primarily captures the immediate effects of generative AI on freelance labor markets. The main empirical analysis focuses on the period shortly after the introduction of tools such as ChatGPT, which allows for clear identification of short-term displacement, reinstatement, and redistribution effects. However, the long-term impact of generative AI on labor —such as whether freelancers adapt, reskill, or become dependent on AI support—are outside the scope of this study and are largely unexplored in the existing literature.

Building on this research, I found two future research directions that might yield fruitful outcome. The first direction can examine whether non-native freelancers benefit or suffer when using AI to polish their job applications. Through a large-scale field experiment on a global freelance platform, I randomly submit three versions of otherwise identical job applications: a native-like version, a non-native version, and an AI-polished version. By comparing callback and positive response rates, this design allows causal identification of the effect of AI-assisted writing. To open the "black box," I further plan to use large language models to evaluate applications for perceived sincerity and "AI-likeness," alongside textual fingerprinting methods. This approach not only identifies what happens but also why, offering new insights into how AI-mediated communication shapes hiring outcomes.

The second study will shift focus to the long-term consequences of human–AI collaboration for skill development and cognitive dependence. Specifically, the research question is: Does sustained reliance on AI assistance enhance or erode independent creative capacity, and what are the broader market-level consequences? This project begins with a three-month $N = 1$ longitudinal experiment in which I systematically track the reinforcing and withdrawal effects of AI-assisted work on my own skill set. I then plan to construct an agent-based model (ABM) calibrated with parameters from this experiment to simulate how widespread reliance on AI might reshape labor markets over time. This "theoretical calculator" bridges micro-level behavioral patterns and macro-level labor dynamics, enabling exploration of whether AI ultimately promotes inclusive growth or exacerbates skill polarization.

Together, these projects extend beyond the immediate, short-term lens of the current study to develop a broader, integrated research agenda on AI and labor. By combining real-world field experiments with computational simulations, they offer a pathway to understanding not only how AI is reshaping freelance work today, but also how it may redefine the trajectory of skills and inequality in the economy.

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