Signaling in the Age of AI: Evidence from Cover Letters [*]

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Abstract

We study the impact of generative AI on labor market signaling using the introduction of an AI-powered cover letter writing tool on a large online labor platform. Our data track both access to the tool and usage at the application level. Difference-in-differences estimates show that access to the tool increased textual alignment between cover letters and job posts and raised callback rates. Time spent editing AI-generated cover letter drafts is positively correlated with hiring success. After the tool's introduction, the correlation between cover letters' textual alignment and callbacks fell by 51%, consistent with what theory predicts if the AI technology reduces the signal content of cover letters. In response, employers shifted toward alternative signals, including workers' prior work histories.

1 Introduction

Job seekers and college applicants increasingly turn to generative artificial intelligence (AI) tools like ChatGPT to edit résumés, craft cover letters, and prepare for interviews.[1] Despite the transformative potential of this technology for processes central to economic opportunities and social mobility, credible empirical evidence on how AI affects labor market signaling remains scarce.[2] The main obstacle is observability: outside of controlled lab settings, just as employers struggle to identify AI-assisted applications, so too do researchers. Current detection tools are error-prone and unreliable (Weber-Wulff et al. (2023)), making it difficult to assess AI assistance's real-world impact on hiring.

We overcome this challenge by studying the introduction of a generative AI cover letter writing tool on Freelancer.com, one of the world's largest online labor platforms. Freelancer connects international workers and employers to collaborate on short-term, skilled, and mostly remote jobs. On April 19, 2023, Freelancer introduced the "AI Bid Writer," a tool that automatically generates cover letters tailored to employers' job descriptions that workers can use or edit. The tool was available to a large subset of workers depending on their membership plans. Employers, as is typical in most real-world settings, could not observe which workers had access to the tool or whether a given cover letter was AI-assisted.

We use eight months of data from two leading skill categories, PHP and Internet Marketing, covering 5 million cover letters submitted to over 100,000 jobs.[3] We observe access to the tool and usage of the tool at the application level. We link access and usage information to the submitted cover letters and to callback and hiring outcomes to analyze the effect of generative AI at both the individual level and the market level. We also observe timestamps of workers' clicks on the AI tool and their application submissions, allowing us to measure the time they spent editing the AI-generated texts and examine the effect of human-AI interaction.

The tool's rollout and the granularity of the data enable us to answer fundamental questions raised by the widespread use of AI in job applications: (i) Does generative AI writing assistance improve an applicant's chances of receiving a callback? (ii) Does AI complement or substitute existing writing ability? (iii) As AI adoption grows, do employers rely less on cover letters as signals, and do other signals become more important? (iv) Does AI adoption affect overall hiring

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[1]This trend has received widespread media attention. Recent headlines include "AI is supposed to make applying to jobs easier—but it might be creating another problem" (NBC News, November 17, 2024) and "AI Is Taking Over College Admissions" (The Nation, October 11, 2024). In 2025, LinkedIn reported a 45 percent year-over-year increase in job applications, with generative AI widely believed to be a key driver of the surge ("Employers Are Buried in A.I.-Generated Résumés," The New York Times, June 21, 2025).

[2]Notable exceptions include Cowgill et al. (2024), who provide evidence on applicants' use of generative AI in a lab setting, and Wiles and Horton (2025), who study the effect of employers' use of generative AI tools to write job posts on an similar online labor platform.

[3]PHP, or Hypertext Preprocessor, is a widely used open-source scripting language designed for web development, enabling the creation of dynamic websites and applications.

rates? (v) Do workers revise the AI drafts and do their revisions matter for hiring outcomes?

The platform-native tool was adopted by a meaningful share of workers. In our sample, 84.9% of all bids were submitted by workers on membership plans with access to the tool. Following its launch, 62% of eligible users used it at least once in their applications, and 17% of all cover letters were written with its assistance. Studying the rollout of a tool that directly affected a sizable fraction of job applications allows us to examine not only the individual-level impact of generative AI but also its market-level consequences, including how it reshaped the informativeness of cover letters as a signal.

To measure how closely cover letters are tailored to job descriptions, we apply Term Frequency–Inverse Document Frequency (TF-IDF), a standard Natural Language Processing technique that captures the extent of keyword overlap between two texts. Using data from before the introduction of the AI writing tool, we show that our TF-IDF–based measure of cover-letter tailoring similarly predicts callbacks and awards—both across and within workers—providing complementary evidence that employers value cover letters that engage with job content.

We begin with a simple theoretical framework that generates predictions about the effects of AI on workers and on cover letters as a labor market signal. The model assumes that cover-letter quality is correlated with workers' underlying productivity and that generative AI raises cover-letter quality by a constant. We show that when generative AI becomes available to a subset of workers, the expected productivity conditional on a given level of cover-letter quality decreases, and the correlation between expected productivity and cover-letter quality also declines. We then extend the model to employers making multinomial choices among applicants. Numerical simulations show that workers with access to AI experience an increase in hiring probability while workers without access experience a decrease. Moreover, cover letters become less correlated with hiring after AI is introduced. We test these implications in the data, exploiting the introduction of the AI cover-letter writing tool.

We first examine the effect of gaining access to the generative AI tool on cover letter tailoring and on workers' chances of receiving a callback. We use a difference-in-differences design comparing workers with and without access. Identification of the causal effect of the platform-native AI writing tool is complicated by the release of GPT-4, a general-purpose generative AI technology, one month before the tool's launch. We address this by allowing for heterogeneous effects of GPT-4 by workers' treatment status—whether they were on membership plans that granted access to the platform-native tool. We formalize the identification assumptions within an econometric framework.

We find that access to the generative AI writing tool increased cover-letter tailoring by 0.16 standard deviations, while actual usage raised tailoring by 1.36 standard deviations. Applying the same design to callbacks as the outcome, we find that access to the generative AI tool increased the probability of receiving a callback by 0.43 percentage points, and usage raised it by 3.56 percentage points. The latter represents a 51% increase relative to the pre-rollout average callback rate of 7.02%.

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However, the results for callbacks are significant at the 10% level but not at the 5% level. A dynamic effect specification shows that the effect on callbacks tapered off after two months. These results suggest that generic or poorly matched cover letters present a significant barrier to receiving callbacks. In contrast, the estimates on actual awards are too imprecise to draw definitive conclusions.

Our second finding is that AI substitutes for, rather than complements, workers' pre-AI cover letter tailoring skills. We compute workers' average tailoring scores prior to the tool's introduction and study the heterogeneous effects of access to the tool by pre-existing writing ability. We find that workers who previously wrote more tailored cover letters experienced smaller gains in cover letter tailoring—indeed, the best writers gained half as much as the weakest ones. By enabling less skilled writers to produce more tailored cover letters, AI narrows the gap between workers with different initial abilities.

Because AI narrows differences across workers, the informativeness of cover letters as a signaling device might be reduced. We test this directly by looking at how the correlation between cover letter tailoring and hiring changed following the introduction of the AI tool. The correlation between cover-letter tailoring and receiving a callback fell by 51% after the launch of the AI tool, and the correlation with receiving an offer fell by 79%. Instead, employers shifted toward other signals less susceptible to AI influence, such as workers' past work experience. The correlation between callbacks and workers' review scores—the platform's proprietary metric summarizing past work experiences on the platform and determining the default ranking of applications—rose by 5%. These patterns suggest that as AI adoption increases, employers substitute away from easily manipulated signals like cover letters toward harder-to-fake indicators of quality. This shift may have important implications, including favoring established workers at the expense of newcomers trying to enter the market.

A natural question is whether the decline in cover-letter signaling, together with employers' partial shift toward alternative signals, affected overall market outcomes such as hiring, interviewing, and job completion. We find no evidence of changes in these outcomes following the tool's introduction, though we view this as a preliminary result that may not capture the broader impact of AI once it extends to aspects of the job application process beyond cover letters.

Finally, we examine the extent of human-AI interaction in our context. Although the tool auto-generates letters tailored to job posts, workers are free to edit the drafts. Using timestamps of workers' clicks on the AI tool and their subsequent application submissions, we construct a measure of editing time. We find that most AI-generated cover letters were submitted with little to no modification. However, workers with higher pre-AI writing ability tend to spend more time editing AI drafts. Examining the relationship between editing and outcomes, we show that—controlling for worker fixed effects—a one–standard deviation increase in editing time is associated with a 0.31 percentage point rise in the probability of receiving a job offer, equal to about 52% of the average offer rate among AI-assisted applications. These results indicate that

human revision enhances the effectiveness of AI-generated cover letters, contributing to a growing body of evidence on human–AI collaboration.

Related Literature Galdin and Silbert (2025) offer complementary evidence on the effects of generative AI on signaling in the same labor market. They use an LLM-based measure of cover letter quality and find, consistent with our results, that its correlation with application outcomes declined after AI tools became available. While we provide difference-in-differences evidence on the platform policy and evidence on human–AI interaction, they estimate an equilibrium model and perform counterfactual simulations.

Another closely related paper is Cowgill et al. (2024), who examine the impact of generative AI on job applications and startup pitches through a survey experiment. They find that generative AI reduces employers' and investors' screening accuracy. Our study explores similar questions in an online labor market, examining the effect of AI on actual hiring decisions. An additional important difference between the settings is that Cowgill et al. (2024) informed employers whether applicants used generative AI, whereas, in many real-world contexts—including ours—employers typically cannot discern whether an applicant received assistance from AI. As a result, our findings are not directly comparable.

In a similar labor market, Wiles et al. (2023) study the effect of a non-generative algorithmic writing assistance on employment through an experiment. The intervention they study focuses mostly on correcting spelling and grammar errors. They show that the tool improved treated workers' employment outcomes without affecting the employers' satisfaction. While we also investigate the role of AI—although of a different nature—in workers' employment outcomes, we are additionally able to speak to the market-level outcomes associated with the introduction of generative AI. Another related paper is Wiles and Horton (2025), who study generative AI assistance to employers for crafting job posts in a similar context and find that while the tool increased the number of job posts, it did not increase the number of matches. Our work is complementary to theirs as both sides of the labor market—firms and workers—increasingly adopt generative AI tools in matching.

Also related is work that examines the functioning of online labor markets and their broader economic implications. Horton (2010), Chen and Horton (2016), and Stanton and Thomas (2020) document how these markets operate, the behavioral responses of workers to wage changes, and the significance of platform-mediated employment. Stanton and Thomas (2025) provide evidence on the distributional consequences of gig platforms, showing how access to online markets affects both workers and firms, and highlighting heterogeneity in who ultimately benefits from platform participation. This focus on heterogeneous impacts complements theoretical and empirical work such as Horton et al. (2024) and Allman et al. (2025), who analyze frictions and signaling mechanisms in matching markets. Our paper extends this line of inquiry by examining how generative AI reshapes

the informativeness of signals on these platforms. More broadly, our contribution also connects to research on AI's impact on labor markets: Agrawal et al. (2019), Noy and Zhang (2023), Brynjolfsson et al. (2025), and Acemoglu (2025) show how AI affects productivity and innovation, while we highlight an alternative channel through labor market signaling. Also related is Brinatti et al. (2023), who use data from a global online labor platform to study wage determination in remote work.

Recent research highlights the disruptive effects of generative AI on worker behavior and employer decision-making. Dillon et al. (2025) show that generative AI reshapes productivity, information processing, and work patterns among knowledge workers. Studies closer to our context, such as Cao and Zhu (2025a), Cao and Zhu (2025b), and Chen et al. (2025), demonstrate how AI adoption changes labor market dynamics in distinct ways: Cao and Zhu (2025a) highlight fairness concerns in algorithmic decision-making and show that AI tools can exacerbate existing inequalities if not carefully designed; Cao and Zhu (2025b) document how the availability of AI writing assistance reshapes workers' incentives to invest in communication skills and alters the distribution of opportunities across applicants; and Chen et al. (2025) argue that widespread AI use may trap workers in a "mediocrity equilibrium," reducing incentives for effort and originality. Together, these studies underscore that the effects of AI adoption extend beyond productivity, fundamentally altering skill demand, redistributing opportunities, and influencing worker motivation. In contrast, our findings show that in the context of online labor markets, generative AI directly reshapes workers' ability to signal their suitability to employers through cover letters, a mechanism that also connects to the broader literature on human–AI interaction. In economics more broadly, Agarwal et al. (2023) study collaboration between AI and radiologists in medical diagnosis, while in computer science, Hosanagar and Ahn (2024) and Chakrabarty et al. (2025) demonstrate how human editing can improve the quality of LLM-generated texts. Together, these strands situate our contribution within both the literature on generative AI in labor markets and the broader study of human–AI collaboration.

In developing our model, we build most directly on the framework of Cowgill et al. (2024), who study how the introduction of generative AI affects the informativeness of job applications. Their analysis shows that when AI assistance becomes available, application materials become less revealing of underlying worker quality, reshaping how employers interpret signals in hiring. Our model is also similar to that of Frankel and Kartik (2019) in which quality can be interpreted as a natural action and access to AI gaming ability. Together, these papers highlight the central insight that new technologies or multidimensional private information can weaken the mapping between observed signals and underlying productivity, and our model applies this perspective to the case of AI-assisted cover letters.

Organization Section 2 describes the market and the rollout of the AI tool. Section 3 presents the data, our measure of cover letter tailoring, and tool adoption patterns. Section 4 presents

a simple theoretical framework that makes predictions about the effects of the AI tool. Section 5 studies the individual-level impact of generative AI on cover letters and hiring outcomes. Section 6 turns to market-level consequences, including those on cover letters as a screening device. Section 7 examines the human-AI interaction. Section 8 concludes.

2 Context

In this section, we describe the platform and the generative AI–powered cover-letter writing tool that constitute the focus of our analysis.

2.1 Freelancer.com

Our analysis employs data from Freelancer.com, which ranks among the world's largest online task-based labor markets both in terms of user base and the volume of posted jobs. Platforms like Freelancer.com, Upwork, and Fiverr serve as digital marketplaces that connect workers and employers worldwide, facilitating the exchange of remotely delivered tasks such as software development, sales and marketing support, and creative work—commonly referred to as "freelancing." Since its inception in 2009, the platform has attracted over 83 million users from 247 countries, regions, and territories, with over $1 billion in gross payments transacted.

On Freelancer.com, the matching process unfolds in five main steps. First, firms or individual employers seeking to outsource a task post a project— also referred to as a 'job' in this paper—on the platform. The employer describes the job and specifies a minimum budget, which is the lowest amount a worker can bid. Most jobs are fixed-budget rather than hourly. We interpret the minimum budget as a measure of the job's size, and in all subsequent analyses we normalize workers' wage bids by this minimum budget. Second, workers with skills matching the job requirements submit bids on these jobs. Bidding for jobs on Freelancer.com is free for workers; however, the number of bids a worker can submit each month is limited. Workers can increase their monthly bidding allowance by subscribing to one of the platform's membership plans (see https://www.freelancer.com/membership/). Each bid typically comprises two components: the proposed payment amount and a written job proposal, which serves as a cover letter outlining the worker's suitability for the task. Third, based on the set of submitted bids and the characteristics of the competing workers, the platform employs a recommendation algorithm (as a function of the volume and strength of a bidder's past reviews, referred to henceforth as the "bidder review score") to rank the bids for employers. Fourth, employers review the bids, displayed in order of ranking, and select the most appealing one, initiating the work process. Alternatively, employers may opt to leave the job unfilled if none of the bids meet their requirements. During this process, employers can and often reach out to a subset of bidders for a private conversation, which we refer to as a callback.

Finally, after the task is completed, both the worker and the employer rate each other's performance by assigning a star rating, which contributes to their respective reputations on the platform. Payments are handled through the platform and are typically divided into milestone payments.

2.2 The AI Bid Writer

On April 19, 2023, Freelancer.com launched the AI Bid Writer. With a single click, the tool automatically generates a cover letter tailored to the job description, thereby reducing the effort and time required for freelancers to bid. While the auto-generated cover letters are ready for immediate submission, freelancers are free to edit the text before submission.

The release of the AI Bid Writer was unannounced beforehand, ensuring that its adoption was unaffected by pre-release anticipation. The tool is available exclusively to users subscribed to the Plus or higher membership tiers. The Plus plan costs \$8.95 per month and permits up to 100 bids, compared with 6 bids for free members and 50 bids for Basic members, who pay \$4.99 per month. Using the AI Bid Writer incurs no additional cost[4].

In our data, we observe workers' membership plans—and thus whether they had access to the AI Bid Writer—as well as whether they clicked on the tool's button for each bid submitted. Importantly, this information is not available to employers: they neither know workers' membership plans nor observe whether a cover letter was generated using the AI Bid Writer. This feature is essential for the interpretation of our results: cover letters that were customized with and without AI could appear similar to the employers, leading employers to reconsider the informational value contained in well-tailored cover letters. This inability to detect the use of AI tools is also a common feature in other real-world contexts, such as college applications.

The AI Bid Writer tool was not the only generative AI tool that workers had access to in the sample period. One alternative is GPT-4, a general-purpose AI tool that OpenAI released on March 14, 2023, just over a month before the launch of the AI Bid Writer. Compared to its predecessor GPT-3.5 (released prior to our sample period in November 30, 2022), GPT-4 exhibits substantially enhanced reasoning. GPT-4's gains in logical coherence, nuanced query interpretation, and adherence to complex, long-form instructions are well-documented in benchmark evaluations (OpenAI (2023)). Beyond raw reasoning, GPT-4 also shows advances on writing tasks, including cover-letter generation, and exhibits emergent theory-of-mind behavior that may support more audience-aware drafting (Deveci et al. (2023), Sikander et al. (2023), Kosinski (2023)).

We believe that the platform-native tool was comparable to GPT-4 in terms of the quality of the cover letters it produced. The main differences lay in cost and ease of use: while the AI Bid Writer was free for workers on qualifying membership plans, access to GPT-4 required a

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[4]Further information about the feature and its functionality is provided on Freelancer.com's support page: AI Bid Writer Overview (https://www.freelancer.com/support/job/ai-bid-writer).

$20 monthly subscription. In addition, the AI Bid Writer automatically reads the job posting and generates a cover letter with a single click, whereas freelancers using GPT-4 would need to copy and paste the job description into the OpenAI interface or develop a script to automate the process—potentially incurring additional costs through the ChatGPT API. Due to these advantages of the AI Bid Writer, the tool was used by a substantial set of workers (which we show in Section 3.3) despite the concurrent availability of other tools like GPT-4.

In our analyses, we explicitly account for the GPT-4 launch when estimating the effects of the platform-native AI writing tool. We discuss the assumptions in an econometric framework in Section 5.1.

3 Data Patterns

This section begins by presenting the data, sample restrictions, and summary statistics. We then describe our measure of cover letter tailoring and demonstrate that it predicts hiring outcomes. Next, we document adoption patterns of the AI Bid Writer tool and examine whether its launch coincided with changes in membership plan purchases or job postings.

3.1 Data Description and Sample Restrictions

Our analysis focuses on all bids submitted to jobs requiring skills categorized under "PHP" and "Internet Marketing" (two of the most popular skill categories) during the 240-day period period between January 19, 2023, and September 15, 2023. We exclude bids where the proposed wage exceeds 30 times the minimum job budget, as these outliers likely do not reflect typical bidding behavior. Finally, we omit jobs that received only a single bid, as these are likely direct offers.

The analytic sample comprises of 5,499,707 bids submitted by 264,082 unique bidders across a total of 106,714 jobs. Wage bids average 3.349 times the minimum job budget, reflecting a range of pricing strategies. At the bidder level, the average number of bids submitted during the sample period is 20.8, though this figure masks substantial heterogeneity. A minority of highly active bidders account for the majority of bids, reflecting a skewed distribution of activity. On average, bidders receive 0.11 awards in PHP and Internet Marketing jobs during the sample period. At the job level, the average job receives 51.5 bids, underscoring the competitive nature of the platform.

In Section 5, when examining the individual impact of the generative AI tool, we rely on a difference-in-differences specification examining the within-worker change in outcomes between the workers who had access to the AI tool versus those who did not. Consequently, we omit bids from individuals whose access to the AI tool changed during the sample period, as well as from those who were not active both before and after the intervention. These restrictions yield a final sample of 2,511,592 bids from 17,759 workers.

In Section 6, when examining the market-level impact of the generative AI tool, we employ the full sample of bids.

3.2 TF-IDF: a Measure of Cover Letter Tailoring

Because the AI Bid Writer automatically produces cover letters customized to job posts, it dramatically reduces the costs of tailoring applications. To measure cover letter tailoring, we focus on textual alignment, which captures the degree of overlap in keywords between a cover letter and a job description. The underlying assumption is that more tailored cover letters should exhibit greater textual similarity with the job posting, reflecting the freelancer's effort in addressing the specific requirements of the employer. On the contrary, generic cover letters which are re-used across jobs would exhibit lower textual similarity.

To quantify this, we utilize Term Frequency-Inverse Document Frequency (TF-IDF), a simple text vectorization technique that assigns weights to words based on their importance within a document while accounting for their overall prevalence across the corpus. Specifically, following a pre-processing step to remove stopwords, we construct TFIDF vectors for each job post and cover letter. Each element in the TFIDF vector represents the weighted frequency of a word within the text. The TFIDF score for a given word w in document d is computed as:

$$\text{TFIDF}(w,d) = \text{TF}(w,d) \times \text{IDF}(w)$$

where $\text{TF}(w,d)$ represents the term frequency of word w in document d, and $\text{IDF}(w)$ is the inverse document frequency, given by:

$$\text{IDF}(w) = \log\left(\frac{N}{1+n_w}\right)$$

where N is the total number of documents in the corpus, and n_w is the number of documents containing word w.

After computing the TFIDF vectors for both the job description and the bid proposal, we measure their cosine similarity to obtain a numerical representation of textual alignment. The cosine similarity between two TFIDF vectors, v_p (for the job description) and v_b (for the cover letter), is defined as:

$$\text{Cosine Similarity} = \frac{v_p \cdot v_b}{\|v_p\|\|v_b\|} \tag{1}$$

This measure ranges from 0 to 1, where a value closer to 1 indicates a higher degree of textual similarity between the job description and the cover letter, while a value near 0 suggests little to no overlap.

By constructing this textual alignment measure, we obtain a quantitative metric of how closely

Table 1: Cover Letter Tailoring and Bid Success

	Offer	
	(1)	(2)
Cover Letter Tailoring	0.0078***	0.0045***
	(0.0007)	(0.0009)
Wage	-0.0006***	-0.0005***
	(0.00003)	(0.00004)
Experience	-0.0140***	0.0045***
	(0.0003)	(0.0012)
Job FE	✓	✓
Bidder FE		✓
Outcome Mean	0.0068	0.0068
Outcome Std. Dev	0.0820	0.0820
N	1,005,483	1,005,483

Table notes: The table reports regression results where the dependent variable is an indicator for whether the bid is suceessful. Column (1) reports estimates controlling for job fixed effects, while Column (2) reports estimates additionally controlling for bidder fixed effects. Standard errors are reported in parentheses and clustered at the job level. Cover letter tailoring is measured as textual similarity—the cosine similarity between TF-IDF vectors of a job proposal and a job description. Wage is normalized as the wage bid divided by the minimum job budget. Experience is calculated as the ranking percentile of a platform-calculated bidder review score among bids on the job. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

a freelancer's cover letter mirrors the employer's job posting, allowing for an analysis of how cover letter quality evolves over time and in response to AI. This measure, while simple, has several advantages. First, it is highly computationally inexpensive. Second, it is largely insensitive to word count and is normalized by document length—hence, variation in the word counts of job descriptions or cover letters do not introduce bias. Third, it is insensitive to word order or sentence structure, and hence explicitly focuses on content similarity while ignoring stylistic variations.[5]

We validate that in the pre-rollout sample, our measure of textual similarity is significantly predictive of hiring. In Table 1, we regress the outcome of whether a bid is selected on the cover letter's textual similarity score, the worker's level of experience (captured by the review score), and the normalized wage (the bid amount divided by the minimum job budget). Accounting for job fixed effects, a one standard deviation increase in textual similarity (0.134) corresponds to an increase in absolute selection probability of 0.10 percentage points, or a 15.46% increase in the probability of being selected compared to the raw mean. This positive correlation is robust to the

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[5]Wiles et al. (2023) study the impact of an AI tool that primarily corrects spelling and grammar errors in a similar context.

inclusion of worker fixed effects. Together, these results support the interpretation of cover-letter tailoring as a labor-market signal—namely, that firms use it to form beliefs about otherwise unobservable worker attributes, such as productivity, interest in the job, or match-specific quality.

Appendix Table A1 includes examples of textual similarity scores for selected bids on a job. While our measure of textual alignment between cover letters and job postings captures the dimension most directly affected by the AI Bid Writer, we acknowledge that cover letters also vary along other important dimensions—such as style—that our measure does not capture. Assessing the impact of generative AI tools on these additional aspects of cover letters lies beyond the scope of this paper and is left for future work.

3.3 Tool Adoption Patterns

Figure 1: Worker Adoption Rates: Share of Bids Submitted with AI Assistance
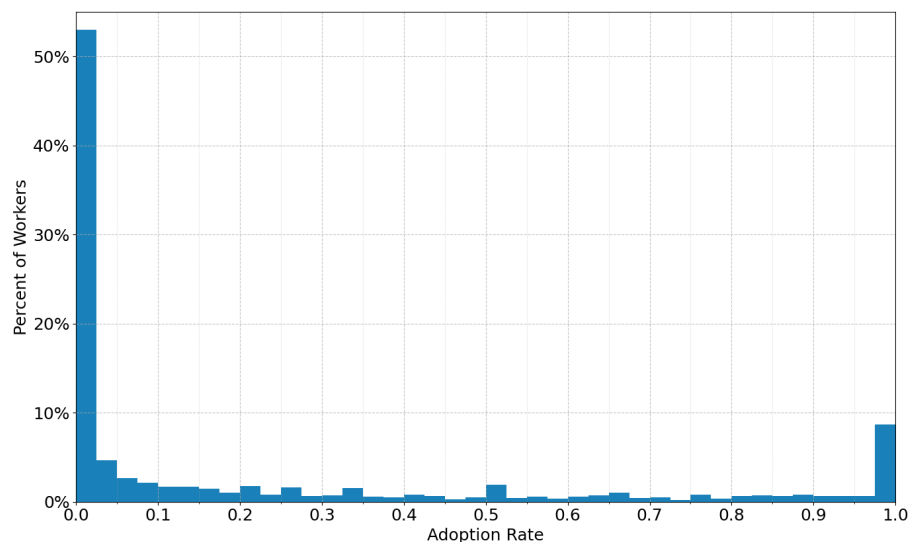

Figure Notes: Adoption rates are measured at the worker level as the fraction of bids submitted with the AI tool during the period when it was available. The sample is restricted to workers who had access to the tool.

Using data on workers' membership plans and per-application usage of the AI Bid Writer, we analyze adoption of the tool. We find that 61.9% of workers with access tried it at least once. Figure 1 presents the histogram of adoption rates among these users. The distribution is bimodal: about 39% of workers used the tool in fewer than 10% of their bids, while more than 17% relied on it in over 90% of their bids. This wide dispersion underscores the heterogeneous nature of AI adoption, with workers pursuing different strategies regarding when and how frequently to incorporate AI into their cover letters.

In the post-AI sample, about 19% of eligible bids—those submitted by workers with access to the tool—were written with assistance from the AI Bid Writer. Since these workers account for the vast majority of bids in our data, 16.71% of all bids were AI-assisted. This substantial adoption provides the basis for analyzing the market-level effects of AI in Section 6.

3.4 Trends in User Memberships and Job Postings

In this section, we examine whether the launch of the AI Bid Writer coincided with changes in membership plan purchases or in the number of projects posted.

The AI cover-letter writing tool was available to workers on the Plus and higher membership tiers. A potential concern is that workers might have adjusted their membership choices in response to the feature. About 85% of bids in our sample are submitted by workers on membership plans that include access to the tool. Figure 2a shows that the number of purchases and renewals of AI-eligible plans among workers in our data sample remained stable around the tool's introduction, aside from a seasonal dip during the summer weeks. Figure 2b plots the share of AI-eligible plans among all membership purchases, which is stable across the full sample. Together, this evidence suggests that the tool's introduction did not materially affect selection into membership tiers—consistent with the fact that the AI tool was only one of many benefits bundled into higher-tier plans, the most prominent being the larger number of bids workers could submit each month.

Figure 2: Purchases of Membership Plans with Access to AI Tool

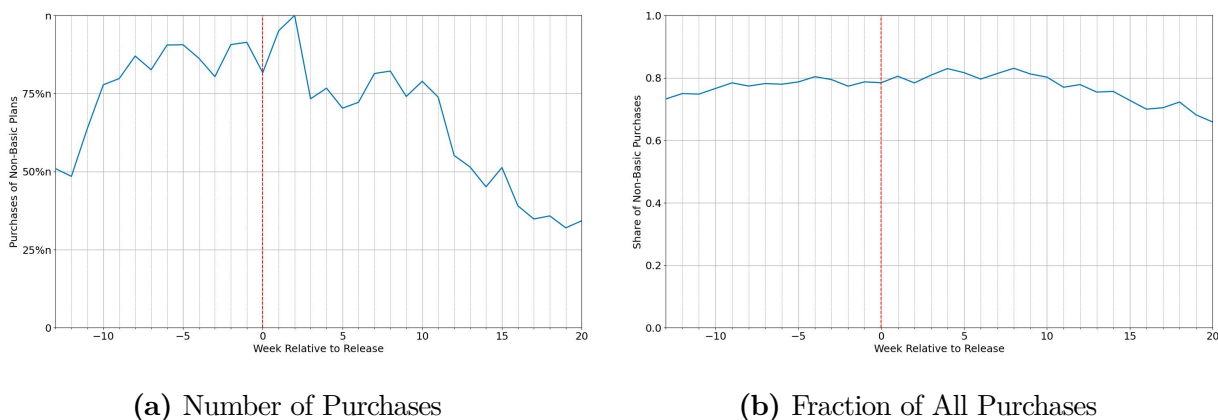(a) Number of Purchases

(b) Fraction of All Purchases

Figure Notes: The left panel reports the number of purchases and renewals of membership plans that provide access to the AI tool. The right panel reports the share of such plans relative to all membership plan purchases and renewals. Due to data confidentiality, the y-axis in panel (a) is normalized. The maximum value is shown as 'n', and other ticks represent fractions of n.

Another potential concern is that the rollout of the AI cover-letter tool might have coincided with changes in job postings. Figure 3 shows that the weekly number of new jobs in our sample

remained stable around the launch, with a decline only later in the summer months—a pattern consistent with the drop in membership purchases.[6]
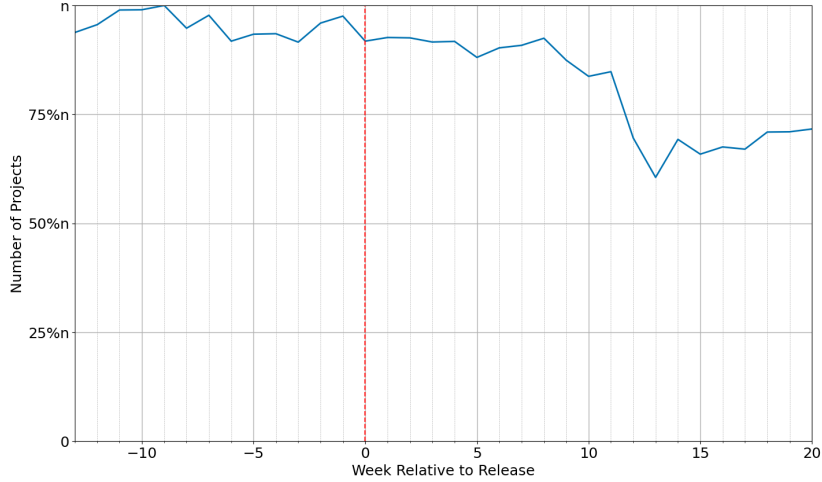
Figure 3: Weekly Number of Jobs Posted

Figure Notes: A job's week is defined as the week when its first bid was submitted. Due to data confidentiality, the y-axis is normalized. The maximum value is shown as 'n', and other ticks represent fractions of n.

4   The Signaling Model

In this section, we present a simple model that highlights the main forces at play when AI becomes available to a subset of job applicants. The model generates predictions about how the tool affects both workers who gain access and those who do not, as well as how it alters the role of cover letters as a signal. We test these predictions in the sections that follow.

4.1   Setup

Let i index workers and j index firms. The cover-letter tailoring of worker i when applying to firm j, denoted h_{ij}, depends on the worker's latent productivity q_i and access to the AI tool. Let $\rho_i \in \{0,1\}$ indicate AI access, with $\Pr(\rho_i = 1) = p \in (0,1)$, and let $A \geq 0$ denote the effect of the tool on cover-letter tailoring. We assume

$$h_{ij} = q_i + \rho_i A + \nu_{ij}, \tag{2}$$

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[6]This seasonal slowdown is a well-documented phenomenon in freelance markets. Numerous specialized media reports note this cyclical decline; see, for example, Robinson (2024), Goodwin (2025), and Vozza (2016).

where $\nu_{ij} \sim \mathcal{N}(0,\sigma^2)$ is an i.i.d. shock and $q_i \sim \mathcal{N}(\mu_0,\tau^2)$ represents worker productivity. We assume that q_i, ν_{ij} and a_i are independent, i.e. AI access is random and unrelated to productivity[7], and that $(q_i, \quad \rho_i, \quad \nu_{ij})$ are independent across workers. This model assumes full compliance: workers with access always use the tool. But one could easily adapt the model to one of random partial compliance.

The introduction of the AI tool corresponds to a shift from $A=0$ to $A>0$.

4.2   AI and the Expected Productivity

Employers do not value cover-letter quality per se; they value what h_{ij} reveals about q_i. We therefore characterize how observed quality maps into expected productivity. With the Gaussian prior for q, additive noise ν, and unobserved access ρ_i (Bernoulli with mean p), we have

$$\mathbb{E}[q_i \,|\, h_{ij}] = \mu_0 + \frac{\tau^2}{\tau^2+\sigma^2}\Big(h_{ij} - \mu_0 - Ag(h_{ij})\Big), \tag{3}$$

where

$$g(h_{ij}) = \mathbb{P}[\rho_i = 1 | h_{ij}] = \frac{1}{1+\frac{1-p}{p}\exp\left(\frac{-2A(h_{ij}-\mu_0)+A^2}{2(\tau^2+\sigma^2)}\right)}. \tag{4}$$

Appendix Section B.1 provides the derivation. The function $g(h_{ij})$ represents the possibility that the cover letter could be written with AI assistance. That possibility, multiplied by the technology's effect A, is the discounting that employers apply to cover letters when AI is available. Intuitively, higher-quality cover letters are more likely to be written with AI assistance ($g'(h)>0$). And if more workers have access to the tool—a higher p—the possibility that a given cover letter is assisted by AI is also higher.

Before the introduction of AI, when $A=0$, expected productivity rises linearly in cover letter quality, consistent with cover letters as a signaling tool. After AI becomes available to a subset of workers, it raises the cover letter quality for those workers. This has several implications:

(i) The availability of AI lowers the expected productivity at every cover letter quality level

$$\mathbb{E}[q \,|\, h; A>0] - \mathbb{E}[q \,|\, h; A=0] = -\frac{\tau^2}{\tau^2+\sigma^2}Ag(h) < 0, \forall h;$$

(ii) The availability of AI lowers the correlation between cover letter quality and expected productivity

$$\frac{\partial}{\partial h}\mathbb{E}[q_i | h; A>0] = \frac{\tau^2}{\tau^2+\sigma^2}\left[1 - \frac{A^2}{\tau^2+\sigma^2}g(h)\Big(1-g(h)\Big)\right] < \frac{\tau^2}{\tau^2+\sigma^2} = \frac{\partial}{\partial h}\mathbb{E}[q_i | h; A=0], \forall h.$$

[7]This formulation follows the cover-letter production function in Cowgill et al. (2024), with the modification that AI access at rollout is incomplete: only a subset of workers receive access, and for those workers the tool's effect is an additive shift of magnitude A.

4.3 Hiring Decision

In this section, we move beyond the effect of AI on expected worker productivity to examine its impact on hiring outcomes. To do so, we introduce a model of employer choice. We begin with a benchmark case in which employers' hiring decisions are independent across workers, and then extend to a more realistic setting that incorporates direct competition among workers.

Worker vs. the outside option Assume that a randomly drawn worker i applies to job j. Employer j observes the cover letter quality and decides whether to hire the worker or to select the outside option. Let the employer's utility from hiring worker i be

$$u_{ij} = \mathbb{E}[q_i \,|\, h_{ij}] + \varepsilon_{ij}, \tag{5}$$

where ε_{ij} are i.i.d. Type-I extreme value shocks. Employer's utility from the outside option is ε_{0j}, with mean 0. The worker's probability of being hired is a function of her cover letter quality

$$\mathbb{P}[\text{hire } i | h_{ij}] = \frac{\exp(\mathbb{E}[q_i \,|\, h_{ij}])}{1 + \exp(\mathbb{E}[q_i \,|\, h_{ij}])}. \tag{6}$$

Note that the probability of being hired is increasing in expected productivity. Hence, for a given cover letter quality h, the availability of AI ($A > 0$) lowers the hiring probability. There are also implications on the effect of AI on workers with and without access:

(i) At all productivity levels, access to AI assistance increases the worker's hiring probability. For sufficiently high-quality workers, the gain from AI decreases in the worker's quality.

(ii) At all productivity levels, workers without access to AI assistance experience a decrease in their hiring probability after AI becomes available. For sufficiently high-quality workers, the loss grows in the worker's quality.

Appendix Section B.1 provides the proofs. The results show that workers with access benefit from AI, with moderately productive workers gaining more than the most productive. By contrast, workers without access are negatively affected, as employers discount the quality of their cover letters.

Yet employers' hiring decisions are unlikely to be independent across workers. On the platform, each worker competes not only with the outside option but also with other workers. Once competition is introduced, some of the earlier results become parameter-dependent. In the next subsection, we extend the model to incorporate competition and present numerical simulations that generate predictions consistent with several patterns documented in the empirical analysis.

Competition between workers   For each task j, N applicants are randomly drawn. Employer j observes $\{h_{ij}\}_{i=1}^N$ and selects one of the workers or the outside option. Conditional on the vector $h_j = (h_{1j},...,h_{Nj})$, the multinomial logit choice probability is

$$\mathbb{P}[\text{hire } i|h_j] = \frac{\exp(\mathbb{E}[q_i \,|\, h_{ij}])}{1 + \sum_{k=1}^N \exp(\mathbb{E}[q_k \,|\, h_{kj}])}. \tag{7}$$

The ex-ante probability that worker i is hired, before the identities of her competitors are realized, integrates over the competitors' cover letters:

$$\mathbb{P}[\text{hire } i|h_{ij}] = \int \frac{\exp(\mathbb{E}[q_i \,|\, h_{ij}])}{1 + \sum_{k\neq i} \exp(\mathbb{E}[q_k \,|\, h_{kj}])} \prod_{k\neq i} f(h_{kj}) dh_{kj}, \tag{8}$$

where $f(\cdot)$ is the unconditional density of cover-letter quality for rivals (induced by the distributions of q, ρ, and ν).

We use numerical simulations to examine how introducing the AI tool changes hiring outcomes. Figure 4 plots the probability of being hired as a function of cover letter quality before and after the tool's introduction. After AI is introduced, the hiring probability becomes less sensitive to cover letter quality—the curve flattens, reflecting weaker signaling power.

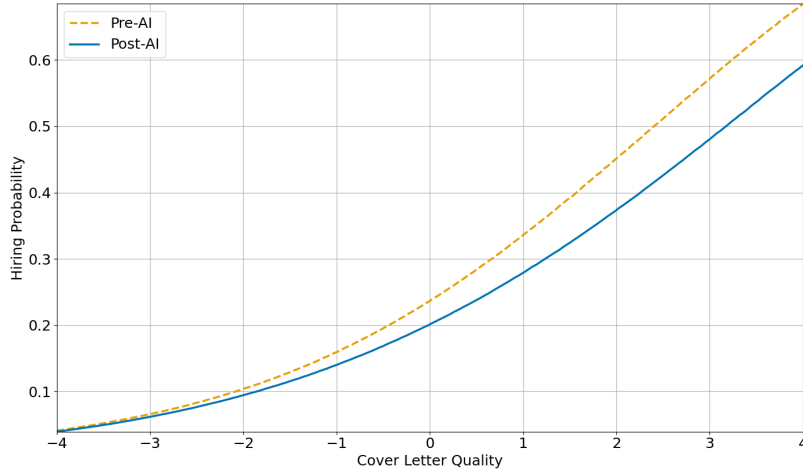**Figure 4:** Probability of Being Hired Pre- and Post- AI given Cover Letter Tailoring

Figure Notes: This numerical simulation was made using $\mu_0 = 0$, $\sigma^2 = 1$, $\tau^2 = 1$, $p = 0.5$, $N = 3$ and $A = 1$ (post-AI).

Figure 5 presents numerical results for hiring probabilities of the treatment group (workers with access) and the control group (workers without access). For this parameterization (reported below the figure), the patterns from the independent-choice case carry over: among treated workers, AI

raises hiring probabilities, though the gain diminishes with productivity q. Control workers, by contrast, face a decline in hiring probability, driven both by employers' discounting of their cover letters and by heightened competition from higher-quality letters submitted by treated workers. The loss is especially pronounced for high-productivity workers.

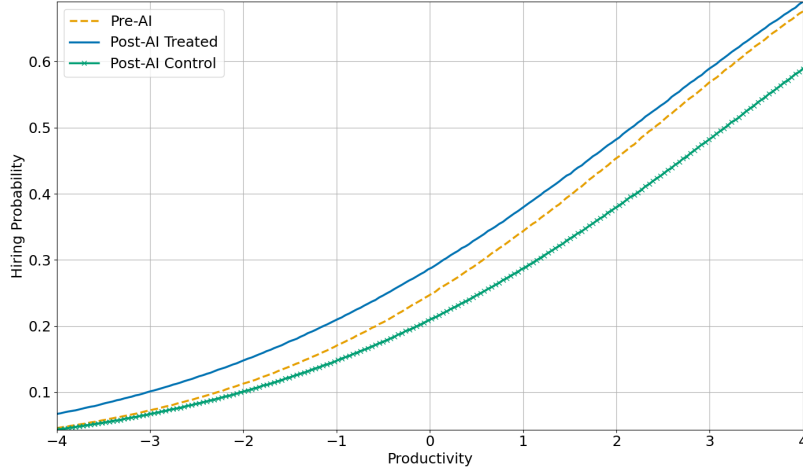**Figure 5:** Probability of Being Hired Pre- and Post-AI

Figure Notes: This numerical simulation was made using $\mu_0=0$, $\sigma^2=1$, $\tau^2=1$, $p=0.5$, $N=3$ and $A=1$ (post-AI).

Figure 6 plots the probability of being hired as a function of latent productivity q, before and after the tool's introduction. We evaluate this probability ex ante—that is, before it is known whether a worker has access to the tool—so the measure reflects average hiring chances across access states. For sufficiently low q, the hiring probability increases; for high q, it decreases. This pattern reflects two opposing forces: (i) the possibility of AI access, which raises expected cover-letter quality and thereby the probability of being hired; and (ii) the employers' discounting of cover letters, which reduces the hiring probability. For low-q workers, the first effect dominates, whereas for high-q workers, the second effect dominates.

In conclusion, our simple signaling model generates predictions at both the individual and market levels. At the individual worker level, the model predicts that workers with access experience an increase in hiring probability after AI is introduced whereas workers without access experience a decrease. At the market level, the model predicts a weakening of the correlation between cover-letter quality and hiring. We next test these predictions in the data, exploiting the introduction of the platform-native AI cover-letter writing tool.

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Figure 6: Probability of Being Hired Pre- and Post- AI given Productivity
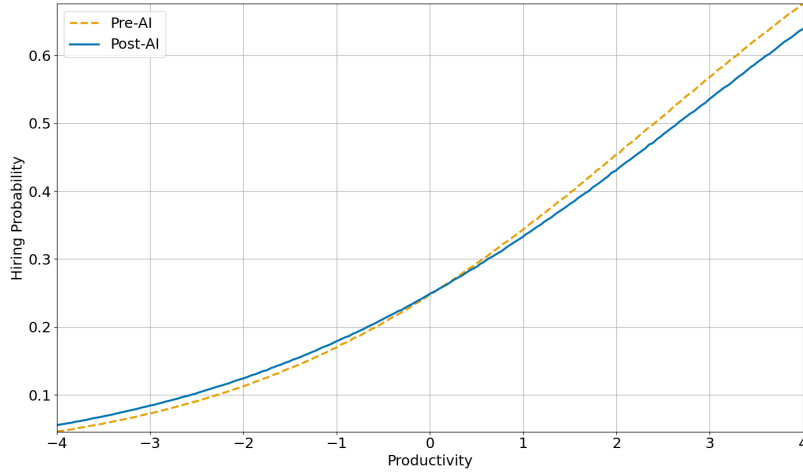

Figure Notes: This numerical simulation was made using $\mu_0=0$, $\sigma^2=1$, $\tau^2=1$, $p=0.5$, $N=3$ and $A=1$ (post-AI).

5   The Individual-Level Impact of Generative AI

In this section, we study the partial equilibrium effects of the generative AI writing tool. Using a two-way fixed effect specification, we compare the outcomes between workers who did and did not have access to the tool before and after the rollout of the tool. The outcomes we consider are the cover letter quality and the probability of receiving a callback.

5.1   Econometric Assumptions

In this subsection we address two identification challenges in our estimation: the introduction of GPT-4 during our sample period and potential SUTVA— Stable Unit Treatment Value Assumption— violations arising from the competitive nature of our setting. First, we explain how our research design accounts for the confounding factor introduced by GPT-4 and the assumptions required for identification. We then discuss how to interpret the estimates given that the tool's rollout generates market-level changes and competitive spillovers.

GPT-4 Introduction   As discussed in the introduction, we must account for the rollout of GPT-4. In a standard difference-in-differences design, identification comes from comparing two groups (treatment and control) before and after treatment implementation. However, pre-treatment exposure to an analogous external technology (GPT-4) can confound this comparison in our setting. To address this, we impose the following identification assumption: although the effect

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of GPT-4 may differ between treated and control workers, its impact stabilizes within one month of its introduction. In other words, we assume post-GPT parallel trends in the absence of the platform-native tool. We also assume no anticipation of the platform tool introduction.

Define the potential outcome $Y_{i,t}^g(d)$ as the outcome for worker i in period t under treatment status $d \in \{0,1\}$. The superscript g indicates the GPT-4 status, where $g=1$ if the period occurs after the introduction of the tool and $g=0$ otherwise. Let t^* denote the period in which the platform tool was rolled out (measured in months). GPT-4 was introduced in period t^*-1. Let $Y_{i,t}^g$ be the outcome we observe in the data. We impose the following assumptions:

Assumption 1 (**Post-GPT Parallel Trends**). *For all $s > t^*-1$,*

$$\mathbb{E}\Big[Y_{i,s}^1(0) - Y_{i,s-1}^1(0)\Big|Access_i=1\Big] - \mathbb{E}\Big[Y_{i,s}^1(0) - Y_{i,s-1}^1(0)\Big|Access_i=0\Big]=0,$$

Assumption 2 (**No Anticipation of the Tool**). *For all $t < t^*$ and $g \in \{0,1\}$,*

$$Y_{i,t}^g = Y_{i,t}^g(0).$$

The first assumption is equivalent to allowing the effect of GPT-4 on the treated and control groups to differ, but only through a level shift at the time of introduction. The second assumption states workers do not change their behaviour or outcomes in anticipation of the future implementation of the AI tool. A standard two-way fixed effects regression identifies

$$\mathbb{E}[Y_{i,t}^1 - Y_{i,t^*-1}^1 \,|\, Access_i=1] - \mathbb{E}[Y_{i,t}^1 - Y_{i,t^*-1}^1 \,|\, Access_i=0], \tag{9}$$

averaged over post-treatment periods. Under the canonical difference-in-differences framework (Assumptions 1, 2, and SUTVA), this specification would identify

$$\mathbb{E}[Y_{i,t}^1(1) - Y_{i,t}^1(0) \,|\, Access_i=1], \tag{10}$$

averaged over time.[8] However, in our competitive setting, treatment of one unit induces spillovers onto units that do not receive the treatment. The next subsection discusses this violation and its implications for interpreting our estimates.

SUTVA Violation   Our setting violates the Stable Unit Treatment Value Assumption (SUTVA): when one worker is treated, rivals' outcomes change because hiring is competitive. In addition, the introduction of the tool shifts the market—specifically, the salience of cover letter tailoring

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[8]See Appendix B.2 for a derivation.

changes after the tool becomes available. To clarify what the estimated coefficients are capturing, consider the following econometric model.

Let the outcome of interest be Y_{it}^g. Define the potential outcome $Y_{it}^g(d,m,c)$ as the outcome for worker i in period t under GPT-4 status $g \in \{0,1\}$, treatment status $d \in \{0,1\}$ market status m, and competition status c. The market status m captures general features such as the salience of cover-letter tailoring in firms' hiring decisions or overall propensity of firms to hire. The competition status c reflects the nature of competition regarding access to the tool—that is, whether the group the worker does not belong to (treatment or control) has access to the tool. Equation 9 shows what a standard two-way fixed effects regression identifies. Under this model, we can express that object through the following decomposition:
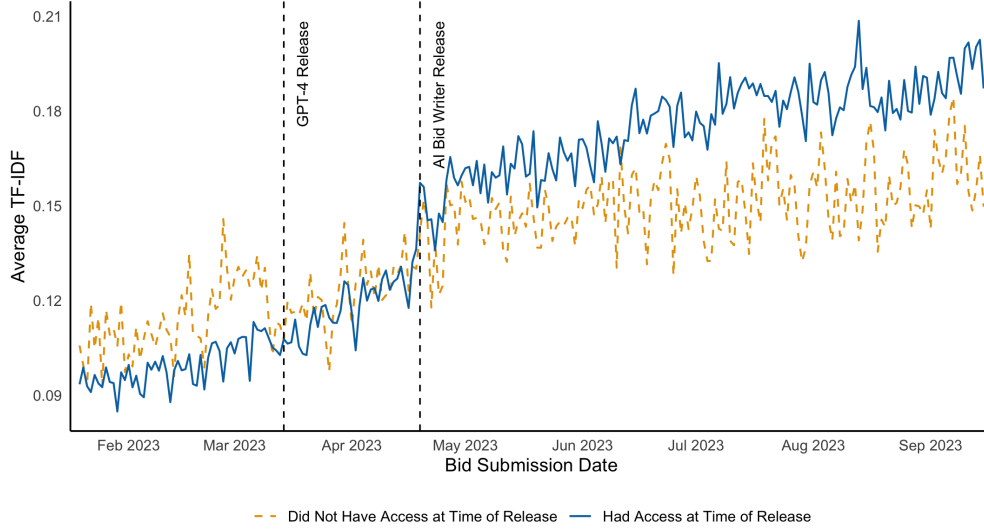
$$\underbrace{\mathbb{E}[Y_{i,t}^1(1,m_1,0) - Y_{i,t^*-1}^1(0,m_0,0)\,|\,\text{Access}_i=1] - \mathbb{E}[Y_{i,t}^1(0,m_1,1) - Y_{i,t^*-1}^1(0,m_0,0)\,|\,\text{Access}_i=0]}_{\text{Total Effect}} =$$

$$\underbrace{\mathbb{E}[Y_{i,t}^1(1,m_1,0) - Y_{i,t^*-1}^1(0,m_1,0)\,|\,\text{Access}_i=1] + \mathbb{E}[Y_{i,t}^1(0,m_1,1) - Y_{i,t^*-1}^1(0,m_1,1)\,|\,\text{Access}_i=0]}_{\text{Direct Effect}} \quad +$$

$$\underbrace{\mathbb{E}[Y_{i,t^*-1}^1(0,m_1,1) - Y_{i,t^*-1}^1(0,m_1,0)\,|\,\text{Access}_i=0]}_{\text{Competition Spillovers}} \quad +$$

$$\underbrace{\mathbb{E}[Y_{i,t^*-1}^1(0,m_1,0) - Y_{i,t^*-1}^1(0,m_0,0)\,|\,\text{Access}_i=1] + \mathbb{E}[Y_{i,t^*-1}^1(0,m_1,0) - Y_{i,t^*-1}^1(0,m_0,0)\,|\,\text{Access}_i=0]}_{\text{Market Shift Effect}}$$

where m_1 is the market status after the introduction of the tool and m_0 is the market status before the tool but under the presence of GPT-4. The first term is our object of interest: the effect of the platform on workers' outcomes while holding market conditions constant. The second term captures the indirect effect of a treated unit on the outcome of an untreated unit. This term highlights the zero-sum nature of our setting. Since workers compete for tasks, an increase in the probability of being hired for one group necessarily implies a decrease for the other (abstracting from market-level shifts). Because spillovers in this context are negative, the DiD coefficient provides a lower bound on the sum of the other two effects. Finally, the third term reflects aggregate market changes that coincided with the introduction of the tool. Note that this third term affects the results only insofar as aggregate shifts differentially impact the control and treatment groups.

5.2 The Impact of AI on Cover Letter Tailoring

We begin by examining the impact of access to the AI writing tool on textual similarity scores in cover letters. Figure 7 presents a visual comparison of average text similarity scores between bidders with and without access to the AI tool. Before the rollout of the AI tool and the rollout of GPT-4, the tailoring of cover letters written by workers with access followed a similar trend to

Figure 7: Time Series of Average Cover Letter Tailoring by Membership Status

Notes: Text similarity is computed as the cosine similarity between TF-IDF vectors of a job proposal and a job description.

those without access. However, after the rollout, the two lines diverged, with the former exhibiting a noticeable and sustained increase in similarity.

To formally estimate the effect, we employ a two-way fixed effects intention-to-treat (ITT) estimator, specified as follows:

$$y_{ijt} = \delta_i + \gamma_t + \beta \text{PostAI}_t \times \text{Access}_i + \lambda \text{PostGPT}_t \times \text{Access}_i + x_{ijt} + \epsilon_{ijt}$$

where the outcome y_{ijt} is text similarity score of the cover letter written by worker i at auction j in week t, δ_i captures worker fixed effects, γ_t represents week fixed effects, PostGPT_t is an indicator for whether the bid was submitted after the release of GPT-4 (March 14), PostAI_t is an indicator for whether the bid was submitted post platform tool rollout (April 19), Access_i is an indicator for whether the bidder had access to the tool at rollout, and x_{ijt} is a vector of additional controls including the experience level of the worker at the time of bidding (based on their platform-calculated review score) and the normalized wage bid (wage bid divided by the minimum job budget).

While the above specification recovers an intention-to-treat (ITT) effect of AI access on labor market outcomes, we additionally obtain the local average treatment effect (LATE). The need to estimate LATE arises from imperfect compliance: not all workers with access to the AI writing tool used it, and those who did use it did not necessarily do so for every auction. This non-compliance implies that the ITT estimate is a lower bound of the effect of AI usage, as it is an average over cases where the eligible workers used the tool and cases where the eligible workers did not use the tool.

To estimate the LATE, we instrument for AI usage with treatment using the below specification:

$$y_{ijt} = \delta_i + \gamma_t + \beta \text{AI Bid}_{ijt} + x_{ijt} + \lambda \text{PostGPT}_t \times \text{Access}_i + \epsilon_{ijt},$$

where the dependent variable, y_{ijt}, again represents textual similarity for bidder i on auction j in week t. The variable AI Bid_{ijt} is an indicator for whether the AI tool was used to write the bid. Observing usage of the AI tool at the application level is a key advantage of our paper. We instrument for AI Bid_{ijt} using $\text{PostAI}_t \times \text{Access}_i$, the interaction of AI tool access and the post-rollout period.

Table 2: Effect of AI on Cover Letter Tailoring

| | Cover Letter Tailoring | | | |
	(1) ITT	(2) LATE	(3) ITT	(4) LATE
AI	0.0270***	0.2112***	0.0220***	0.1832***
	(0.0032)	(0.0183)	(0.0032)	(0.0194)
Bidder FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓
$\text{PostGPT}_t \times \text{Access}_i$			✓	✓
Outcome Mean	0.1474	0.1474	0.1474	0.1474
Outcome Std. Dev.	0.1634	0.1634	0.1634	0.1634
N	2,511,592	2,511,592	2,511,592	2,511,592

Table notes: Cover letter tailoring is measured as textual similarity—the cosine similarity between TF-IDF vectors of a cover letter and a job description. Column (1) and (3) report the ITT (the coefficient of PostAI × Access in the two-way fixed effect specification) with and without the PostGPT × Access term, respectively. Column (2) and (4) report the LATE with and without the PostGPT × Access term, where we instrument for the usage of AI using Post × Access. Wage bids and experience levels are controlled for. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 2 contains the results from the above specifications, where columns (1) and (2) exclude the $\text{PostGPT}_t \times \text{Access}_i$ term. We find that across specifications, access to the AI tool significantly increased textual similarity scores. Examining column (3), using the ITT specification, the coefficient on the interaction term is 0.0220, which is 16.42% of the pre-rollout textual similarity standard deviation of 0.1340. Relative to the pre-rollout baseline average textual similarity score of 0.1082 among those with access, this corresponds to an overall increase of 20.33%. Because compliance is incomplete, our estimate of accessing the tool provides only a lower bound on the effect of actually using it.
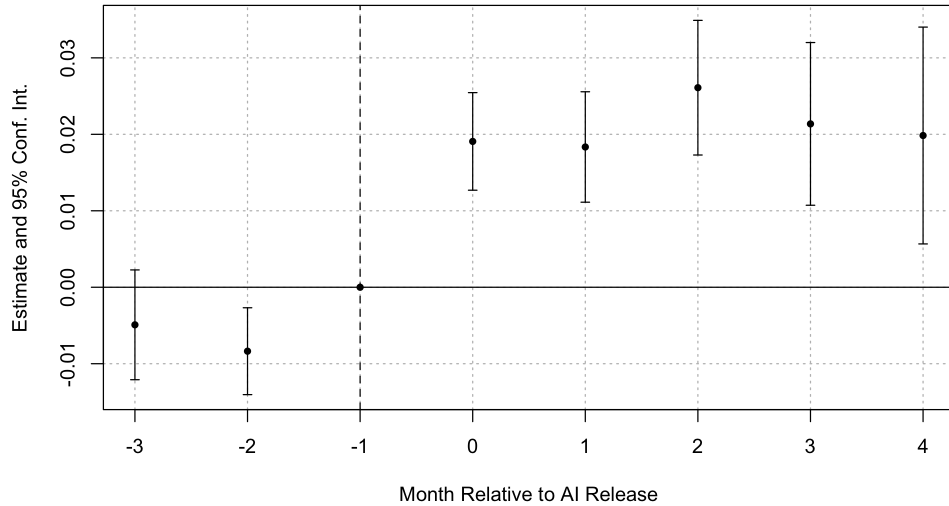
Employing the LATE specification in column (4), the coefficient on using AI bids is 0.1832, which is 136.72% the pre-rollout standard deviation in similarity scores of 0.1340. Relative to the baseline mean similarity score among the treated, these estimates suggest that using the AI Bid Writer is associated with increases of 169.32% in textual similarity.

To evaluate dynamic effects, we additionally perform the following ITT specification:

$$y_{ijt} = \delta_i + \gamma_t + \sum_{k \neq -1} \beta_k \mathbf{1}\{t = k\} \times \text{Access}_i + \text{PostGPT}_t \times \text{Access}_i + x_{ijt} + \epsilon_{ijt}$$

Figure 8 reports the results, suggesting a persistent and significant effect associated with having access to the tool.

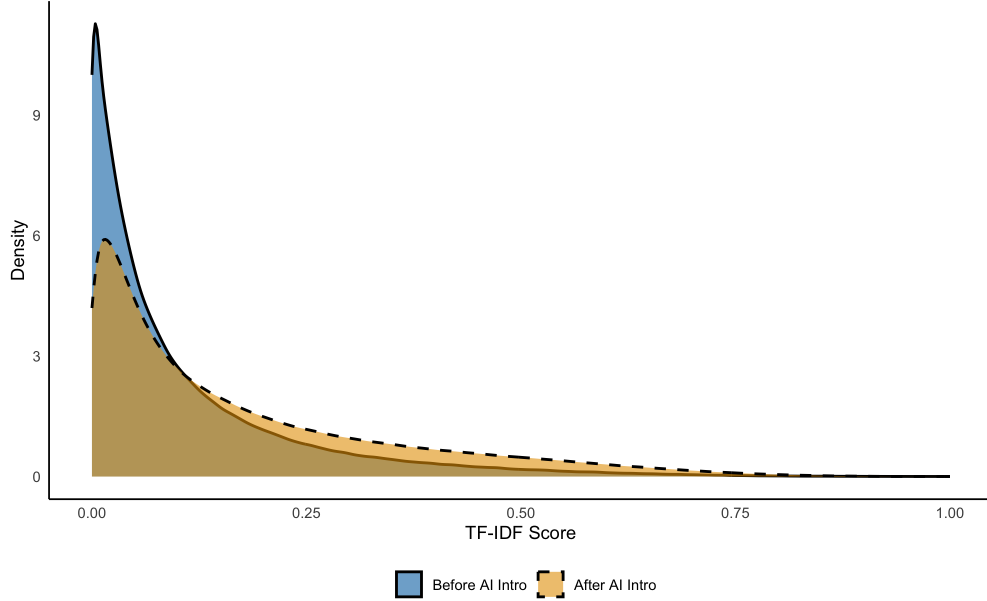**Figure 8:** Dynamic Effects of AI on Cover Letter Tailoring (ITT)

Notes: Cover letter tailoring is measured as text similarity – the cosine similarity between TF-IDF vectors of a job proposal and a job description. The above plots the coefficients and associated confidence intervals of the interactions between treatment and month indicators. Month 0 begins on April 19, 2023, the release of the tool, whereas Month -1 serves as the reference week. Standard errors are clustered at the bidder level.

Our analysis so far has focused on the average effect of AI on cover letter tailoring; however, AI could shift the distribution of the cover letter tailoring in meaningful ways. In Figure 9, we plot the distribution of cover letter tailoring for workers who had access to the tool before and after the tool's rollout. We note that the post-rollout sample includes both bids that used the tool and bids that did not, despite having access. Notably, we observe a significant decline in the percentage of cover letters exhibiting extremely low textual similarity scores. This makes intuitive sense as now the cost of tailoring is drastically reduced.

5.3 Does AI Complement or Substitute Pre-Existing Writing Ability?

The previous section found that the AI Bid Writer had a significant and positive impact on cover letter tailoring. However, the impact of generative AI assistance may vary across workers, for

Figure 9: Distribution of Cover Letter Tailoring Before and After AI Roll-out

Notes: Text similarity is computed as the cosine similarity between TF-IDF vectors of a job proposal and a job description. The sample is limited to bids by workers who had access to the tool, but is not limited to bids for which the tool was used.

instance, depending on their prior ability to craft relevant and tailored cover letters. On the one hand, workers who were already skilled at customizing cover letters may be better positioned to leverage the tool's capabilities. On the other hand, workers who previously wrote more generic cover letters may benefit more, since they have greater scope for improvement. Our unique data setting allows us to provide direct evidence on the nature of this heterogeneity.

To explore whether the impact of the AI writing tool differs based on a worker's pre-AI writing ability, we augment our baseline ITT specification by interacting AI Bid$_{it}$ with a worker's pre-AI writing ability q_i as shown below:

$$y_{ijt} = \delta_i + \gamma_t + \beta_1 \text{Post AI}_t \times \text{Access}_i + \beta_2 \text{Post AI}_t \times \text{Access}_i \times q_i + x_{ijt} + \epsilon_{ijt}.$$

The pre-AI writing ability q_i is measured as the average of the text similarity of worker i's cover letters before the introduction of the AI writing tool. We standardize q_i to have mean 0 and standard deviation 1. We report the results in Table 3.

We find that the AI tool *substitutes* for workers' pre-existing writing ability. Workers who wrote better cover letters experienced smaller improvements in cover letter tailoring after gaining access to the AI tool compared to those who previously struggled to do so. The top writer experienced, on average, a 27.23% smaller gain compared to the worst writer with treatment. By enabling less skilled writers to produce more relevant cover letters, AI narrows the gap between

Table 3: Heterogeneous Effect of AI on Cover Letter Tailoring

	Cover Letter Tailoring	
	(1)	(2)
$\text{Post}_t \times \text{Access}_i$	0.0268***	0.0218***
	(0.0032)	(0.0032)
$\text{Post}_t \times \text{Access}_i \times \text{Pre-AI Ability}_i$	-0.0073*	-0.0073*
	(0.0031)	(0.0031)
Bidder FE	✓	✓
Month FE	✓	✓
Outcome Mean	0.1474	0.1474
Outcome Std. Dev.	0.1634	0.1634
N	2,511,592	2,511,592

Table notes: The table reports OLS regression results with text similarity (TFIDF) as the outcome. Heterogeneous effects are based on the worker's average TFIDF (ranges from 0 to 1) in the period before the AI tool was introduced. Column (2) additionally controls for a PostGPT × Treat term. Wage bids and experience levels are controlled for. Standard errors are reported in parentheses and clustered at the bidder level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

workers with differing initial abilities. This suggests that the tool may dilute the informational value of cover letters, a hypothesis we formally test in Section 6.

5.4 The Impact of AI on Callbacks

Having established that AI improves the tailoring of workers' cover letters, we now use the same specifications to study the impact of AI on a key labor market outcome, the probability of receiving a callback. In our setting, as in most labor markets, employers often reach out to a subset of the bidders for a private conversation before making the final hiring decision, which we refer to as a callback. We observe which cover letters resulted in a callback and use that as the outcome variable.
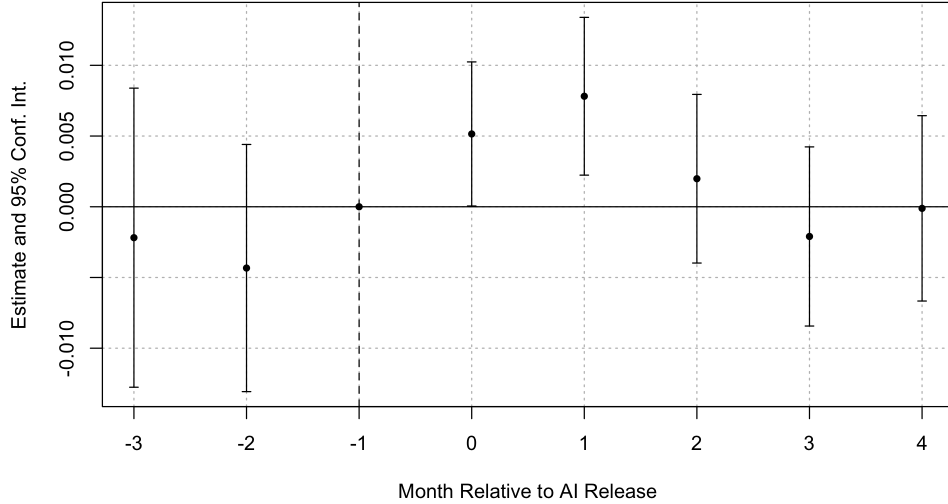
Table 4 shows that access to the AI Bid Writer increases the probability of receiving a callback by 0.43 percentage points (ITT). Relative to the 7.02% baseline callback rate among the treated, this amounts to an increase of about 6%. When we instrument for usage (LATE), the implied effect rises to 3.56 percentage points (51% of the baseline rate), which reflects the returns for the subset of workers who employed the tool.

Figure 10 plots the coefficients and confidence intervals from the dynamic ITT specification. We find that AI access significantly increases the probability of receiving a callback during the first two months after the tool's introduction, but the effect subsequently tapers off. By contrast, no such tapering is observed in the dynamic effects of AI on cover-letter tailoring. One possible interpretation is that, after two months, employers became more adept at recognizing AI-generated

Table 4: Effect of AI on Callbacks

| | Callback | | | |
	(1) ITT	(2) LATE	(3) ITT	(4) LATE
AI	0.0087***	0.0683***	0.0043*	0.0356*
	(0.0017)	(0.0144)	(0.0020)	(0.0170)
Bidder FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓
$\text{PostGPT}_t \times \text{Access}_i$			✓	✓
Outcome Mean	0.0707	0.0707	0.0707	0.0707
Outcome Std. Dev.	0.2564	0.2564	0.2564	0.2564
N	2,511,592	2,511,592	2,511,592	2,511,592

Table notes: A callback is defined as being chatted with by the employer after submitting a bid. Column (1) and (3) report the ITT (the coefficient of PostAI × Access in the two-way fixed effect specification) with and without the PostGPT × Access term, respectively. Column (2) and (4) report the LATE with and without the PostGPT × Access term, where we instrument for the usage of AI using Post × Access. Wage bids and experience levels are controlled for. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 10: Dynamic Effects of AI on Callbacks (ITT)

Notes: A callback is defined as being chatted with by the employer after submitting a bid. The above plots the coefficients and associated confidence intervals of the interactions between treatment and month indicators. Month 0 begins on April 19, 2023, the release of the tool, whereas Month -1 serves as the reference week. Standard errors are clustered at the bidder level.

cover letters—a change not captured by our textual similarity measure.

We consider the 51% increase in the probability of receiving a callback to be substantial, and comparable in magnitude to effects documented in prior work on the determinants of callback rates.

For instance, Bertrand and Mullainathan (2004) find that changing a job applicant's name from an African American–sounding name to a white-sounding name raises the callback rate by about 50%. Our results suggest that generic cover letters represent an important barrier to receiving callbacks. Tools that help workers quickly customize their cover letters enable them to better signal interest in the project and convey alignment with the role, thereby increasing their chances of passing the initial screening stage and being invited to interview. At least at the individual level, workers clearly benefit from the AI writing tool because it increases their chances of advancing toward employment.

6   The Market-Level Impact of Generative AI

An important advantage of our setting is that the AI tool was adopted in a substantial share of applications, allowing us to analyze market-level impact. In this section, we examine how the tool's introduction affected the signaling power of cover letters, as well as that of past work experience—a signal unaffected by AI. We conclude by presenting patterns in overall match rates.

6.1   The Signaling Power of Cover Letters

As previously shown, the AI writing tool had a larger impact on workers who previously wrote more generic cover letters. In other words, the AI writing tool substitutes from workers' existing ability. Therefore, AI potentially weakens the relationship between workers' innate ability and the cover letters that they produce, making cover letters a less informative signal. We now formally test this hypothesis by examining how the correlation between cover letter text similarity and hiring decisions changes after the release of the tool.

Our approach follows the specification:

$$y_{ijt} = \delta_i + \gamma_t + \beta_1 \text{Cover Letter Tailoring}_{ijt} + \beta_2 \text{PostAI}_t \times \text{Cover Letter Tailoring}_{ijt} + x_{ijt} + \epsilon_{ijt},$$

where y_{ijt} is the outcome (either selection or interview) of the application by worker i for job j in week t, and x_{ijt} includes the wage bid and worker's reputation ranking.

As Table 5 shows, before the introduction of the AI tool, the textual similarity of the cover letter strongly predicts the worker's chances of receiving an interview and receiving an offer. However, after the tool was introduced, that predictive power decreases. The correlation between cover letter tailoring and callback rates decreases by 50.51%. The correlation between cover letter tailoring and whether the worker receives an offer decreases by 78.57%. Appendix Tables A2 and A3 report robustness checks: one specification without bidder fixed effects and another that includes the interaction between Post GPT$_t$ and Cover Letter Tailoring$_{ijt}$. In both cases, the estimates remain of similar magnitude.

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Table 5: Signaling Power of Cover Letters: Pre vs. Post AI

	Interview	Offer
Cover Letter Tailoring$_{ijt}$	0.0485***	0.0056***
	(0.0027)	(0.0007)
Post$_t$×Cover Letter Tailoring$_{ijt}$	-0.0245***	-0.0044***
	(0.0030)	(0.0007)
Bidder FE	✓	✓
Month FE	✓	✓
Outcome Mean	0.0647	0.0053
N	5,499,707	5,499,707

Table notes: Wage bids and experience levels are controlled for. Standard errors are reported in parentheses and clustered at the bidder level. *** p < 0.01, ** p < 0.05, * p < 0.1.

To evaluate whether these effects are persistent, we additionally perform the following specification:

$$y_{ijt}=\delta_i+\gamma_t+\sum_{k\neq-1}\beta_k\mathbf{1}\{t=k\}\text{Cover Letter Tailoring}_{ijt}+\text{PostGPT}_t\times\text{Cover Letter Tailoring}_{ijt}+x_{ijt}+\epsilon_{ijt},$$

where t is month, y_{ijt} is whether the cover letter by worker i for job j in month t received a callback, q_{ijt} is the cover letter tailoring, and x_{ijt} includes the usual controls. Figure 11 presents the coefficients on month indicators times textual similarity scores, which are significantly negative in several months following the rollout of AI Bid Writer, suggesting that having a higher TF-IDF is less advantageous post AI-rollout. In Appendix Figure A1, we present the same specification without bidder fixed effects.

A similar pattern holds when examining being hired as the outcome, as shown in Figure 12, where textual similarity has a persistently reduced correlation with hiring in the months following the rollout of the tool. In Appendix Figure A2, we additionally present the results without controlling for bidder fixed effects. Together, these findings suggest a weakening of the signaling value of well-tailored cover letters. Despite only a minority of bids utilizing AI-generated proposals, the tool's availability disrupts the traditional link between cover letter tailoring and intrinsic bidder ability, reducing employers' reliance on textual similarity as a key hiring signal.

6.2 The Signaling Power of Past Work Experiences

The weakening of cover letters as a signaling device naturally raises the question of which alternative signals employers use to evaluate applicants. If generative AI reduces the informational content of written applications, then employers are likely to shift toward other observable and relatively harder-to-manipulate indicators of worker quality. On Freelancer.com, the most salient alternative

Figure 11: Post AI Roll-out, Cover Letters Persistently Less Predictive of Callback
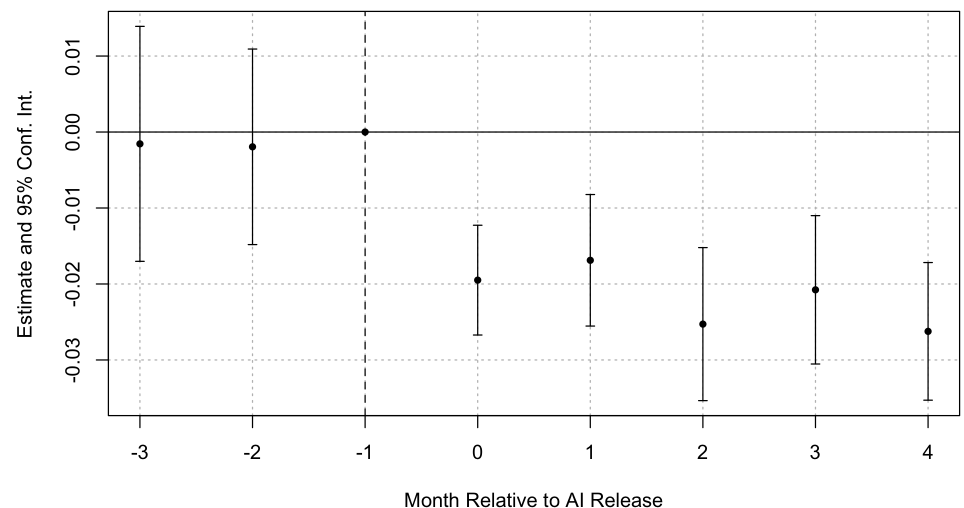

Figure Notes: Bidder fixed effects are controlled for. Interaction term event study coefficients on Month × Textual Similarity with interview as the outcome. Wages, experience levels, bidder, and month FEs are controlled for. Coefficients clustered at the bidder level.

Figure 12: Post AI Roll-out, Cover Letters Persistently Less Predictive of Hiring
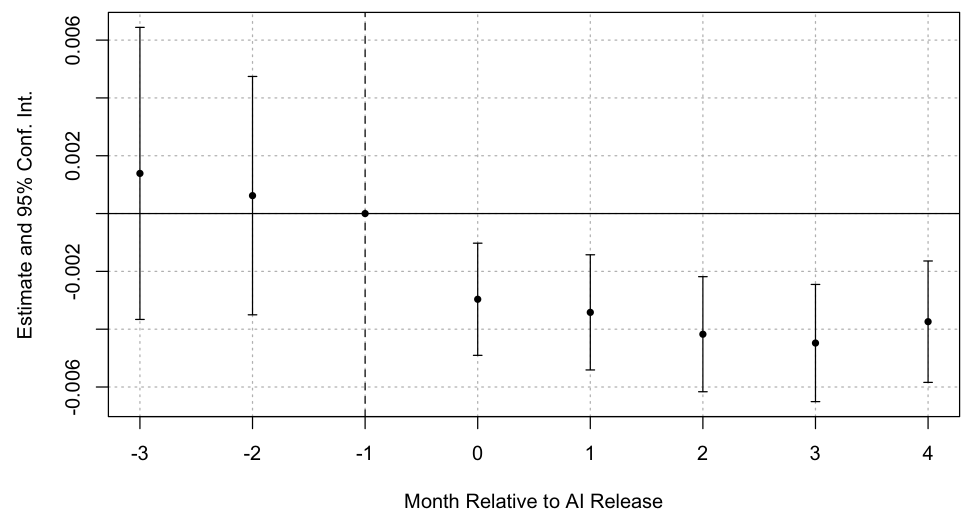

Figure Notes: Interaction term event study coefficients on Month × Textual Similarity with being hired as the outcome. Wages, experience levels, bidder, and month FEs are controlled for. Standard errors clustered at the bidder level.

is the review score—a platform-determined summary measure based on the volume and quality of a worker's past reviews. Crucially, this score governs the default ordering of applications as presented to employers. In practice, therefore, the bid score not only aggregates prior performance but also shapes the attention set of employers by determining which applicants appear most prominently at the top of the list.

To assess whether employers indeed substituted toward this signal, we re-estimate our baseline specification replacing cover letter tailoring with bid score rank percentile as the key regressor. The results are presented in Table 6. We find that, following the rollout of the AI tool, the predictive power of bid score rank percentile for interviews increases substantially. Specifically, the correlation between rank percentile and the probability of being interviewed rises by roughly 5% percent relative to the pre-period. By contrast, we detect no corresponding increase in the predictive power of rank percentile for ultimate hiring decisions. This divergence suggests that employers increasingly rely on platform-determined ranks when forming shortlists of candidates to engage with, but that final hiring outcomes continue to depend on additional factors beyond platform-calculated rankings.

Table 6: Power of Rank Percentile: Pre vs. Post AI

	Interview	Offer
Rank Percentile$_{ijt}$	0.2223***	0.0044***
	(0.0037)	(0.0004)
Post AI$_t \times$ Rank Percentile$_{ijt}$	0.0116***	-0.0001
	(0.0024)	(0.0004)
Month FE	✓	✓
Bidder FE	✓	✓
Outcome Mean	0.0647	0.0053
N	5,499,707	5,499,707

Table notes: Rank Percentile is calculated as $1 - \frac{BidRank}{Number of Bids}$, with $BidRank$ being determined by a platform-specific score. Wage bids are controlled for. Standard errors are reported in parentheses and clustered at the bidder level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To assess the robustness of these findings, we estimate a dynamic event-study specification interacting month indicators with bid score. The results, visualized in Figure 13, corroborate the regression estimates: employers generally placed greater weight on bid scores in evaluating which applicants to interview following the tool's release. Taken together, these results are consistent with the view that the introduction of generative AI diminished the utility of cover letters and may have prompted employers to fall back on reputation-based signals already embedded in the platform's ranking algorithm. While this shift helped sustain screening efficiency in the short run, it also raises distributional concerns: established workers with stronger review histories may benefit disproportionately from such a reallocation of attention, while new entrants with weaker

track records may find it increasingly difficult to break into the market.

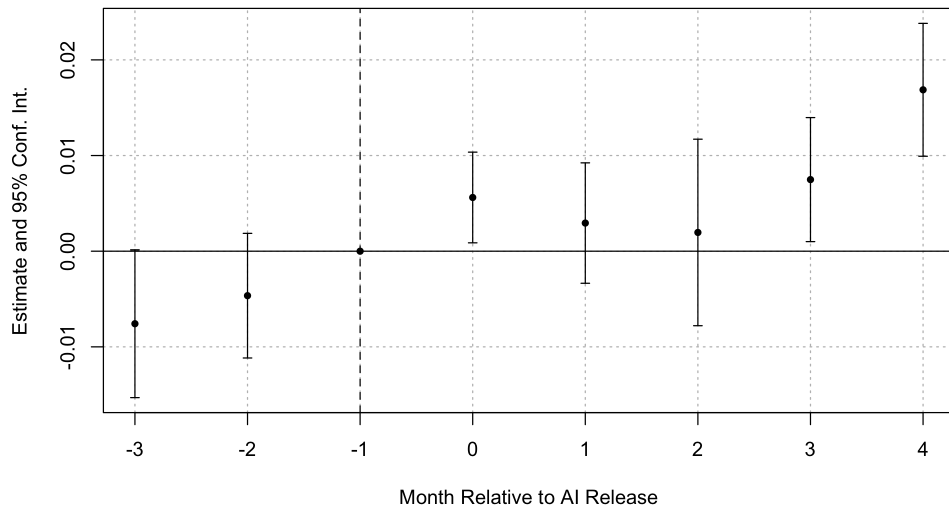**Figure 13:** Post AI Roll-out, Bid Score More Predictive of Interviewing

Figure Notes: Interaction term event study coefficients on Month $\times$ Rank Percentile with being interviewed as the outcome. Rank Percentile is calculated as $1 - \frac{BidRank}{NumberofBids}$, with $BidRank$ being determined by a platform-specific score. Wages, bidder, and month FEs are controlled for.

6.3 Overall Hiring Rates

A natural question that arises from the preceding analysis is whether the decline in the signaling value of cover letters, combined with employers' partial substitution toward alternative signals, ultimately affected overall market outcomes such as hiring, interviewing, and job completion rates. Figure 14 addresses this directly by plotting the share of jobs that resulted in at least one interview, an award, or a successful completion before and after the introduction of the AI tool. Notably, across all three measures we find no discernible changes. The share of jobs with at least one interview remains stable, as do the probabilities of job award and eventual completion.

The absence of aggregate effects on hiring outcomes may appear surprising given the substantial reallocation of informational content documented in Sections 6.1 and 6.2. However, this pattern is consistent with the interpretation that while AI disrupted one channel of signaling—cover letters—employers successfully shifted toward others, particularly past reputation scores, which partially substituted for the diminished informativeness of written applications. In this sense, the market may have adjusted to maintain equilibrium matching rates, despite changes in the informational environment.

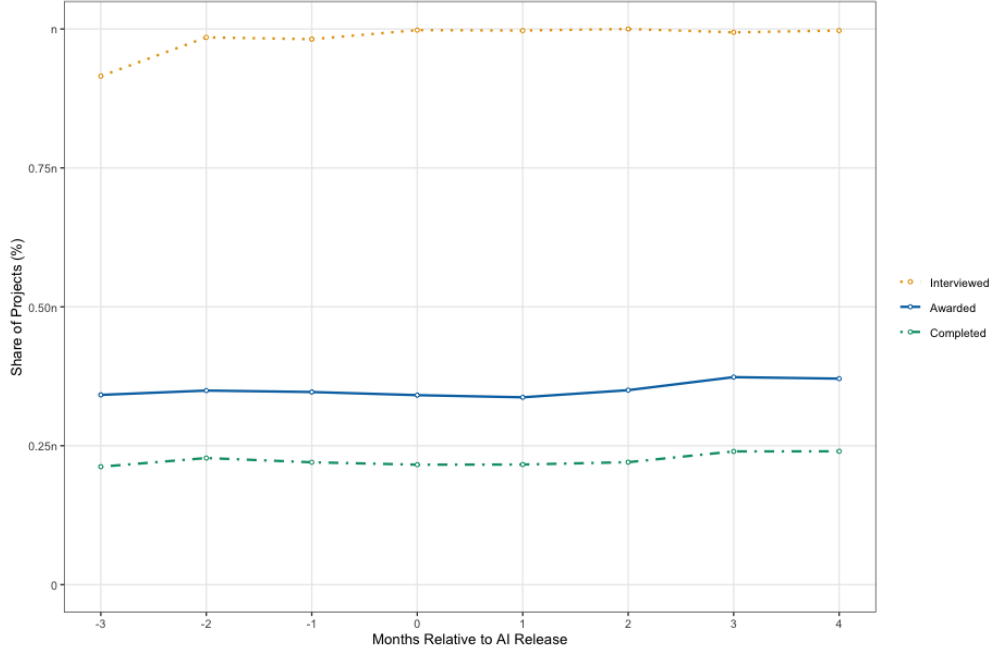**Figure 14:** Share of jobs Interviewing, Awarding, and Completing

Figure Notes: The above figure plots the percentage of jobs such that i) the employer engaged in at least one interview ii) the employer awarded the job iii) the employee successfully completed the job. A total of 106,714 jobs are represented. Due to data confidentiality, the y-axis is normalized. The maximum value is shown as 'n', and other ticks represent fractions of n.

We view this result as preliminary and emphasize two important caveats. First, our analysis focuses on the immediate aftermath of the AI tool's release, when cover letters remained one of several signals available to employers. Over time, as AI tools become more sophisticated and begin to erode additional dimensions of signaling, employers may find themselves with fewer credible indicators on which to rely. Second, our setting involves short-term freelance jobs where past reviews and platform-calculated rankings are readily available and highly salient. In other labor markets—such as those for first-time job seekers or college admissions—alternative signals may be weaker or absent, leaving fewer substitutes when written applications lose their informational value.

Taken together, our findings suggest that the immediate equilibrium impact of AI on hiring rates is limited, but this should not be interpreted as evidence that the technology is innocuous for market-level matching. Rather, it may reflect employers' ability to substitute toward other signals in the short run, which can generate distributional consequences: workers with more experience on the platform tend to hold higher bid scores. Whether such substitutability will persist as AI adoption spreads more broadly across application components remains an open question.

7 Human-AI Interaction

In the final section of the paper, we leverage unique data that capture worker interactions with the generative AI cover-letter writing tool in a real-world setting. We examine the extent to which workers edit the AI-generated drafts, the factors that shape their editing effort, and whether that effort influences hiring outcomes.

7.1 Do Workers Edit the AI-Generated Output?

While the AI tool aligns the content of the letter with the job requirements, workers are free to further customize the letters. We first document whether workers edit the output generated by the AI tool or simply submit it unchanged.

To measure editing, we use the elapsed time between when a worker clicked the AI cover-letter generation tool and when the application was submitted, interpreting this duration as editing time. Since this measure is only available for bids that used the tool, our analysis is restricted to AI-assisted applications.

Figure 15 shows the distribution of editing times. The majority of AI-assisted cover letters appear to be submitted with little or no modification: over 75% were finalized within one minute of clicking the tool. By contrast, a small share of workers invested more effort in customization, with roughly 5% of bids submitted at least five minutes after the AI draft was generated.

We next examine which types of workers invest effort in editing the tool's output. Specifically, we estimate a worker-level regression of the average time between clicking the tool and submitting a bid on the worker's average pre-period TF-IDF score. The goal is to assess how workers with different levels of cover-letter writing skill interact with AI: conditional on using the tool, do stronger writers simply accept the output, or do they devote more time to tailoring it?

Table 7 reports the results. The coefficient is positive and highly significant, indicating that higher pre-AI writing ability is associated with greater editing effort. To gauge the magnitude, moving from the 10th to the 90th percentile of pre-period cover-letter tailoring between treated workers (a difference of 0.23) corresponds to an increase of about 0.69 minutes in average editing time. Relative to the bid-level distribution, this increase represents roughly 59% of the mean (1.17 minutes) or about 0.20 standard deviations. These findings highlight heterogeneity in how workers engage with AI: more skilled writers invest additional effort in customizing their letters. Appendix Figure A3 illustrates this pattern. Workers below the median in pre-AI writing ability show a pronounced concentration of editing times between 0 and 1 minute, suggesting they often accept the AI output with minimal changes, whereas those above the median spread their editing effort over longer durations.
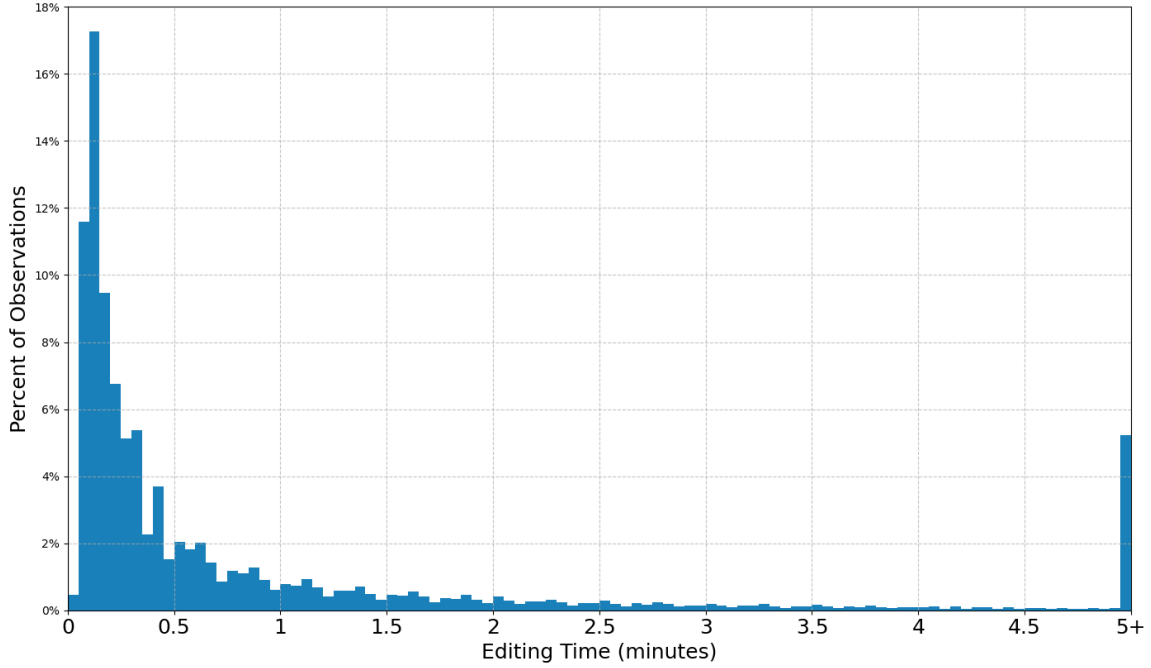
Figure 15: Histogram of Time Spent Editing

Figure notes: Bid-level histogram. Each observation represents the time, in minutes, between activating the tool and submitting the bid. Observations of 5 minutes or more are grouped in the final bin labeled "5+".

Table 7: Determinants of Time Spent Editing AI-Generated Output

	Average Editing Time (Minutes)
Average pre–AI TF-IDF	3.036***
	(0.605)
Constant	1.235***
	(0.084)
N	2,462

Table notes: The unit of observation is a worker. The outcome variable is the worker's mean TF–IDF score (ranging from 0 to 1) in the period prior to the AI tool's introduction. Editing time is measured as the number of minutes between activating the tool and submitting a bid. Average editing time refers to a worker's mean editing time across bids. The sample consists of all post-rollout bids that used the tool and had an editing time of less than 60 minutes. Standard errors, clustered at the worker level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7.2 Is Workers' Editing Effort Consequential?

Having documented patterns in how workers interact with the tool, we now examine whether workers' time spent editing influences hiring outcomes, namely the likelihood of receiving a callback and the likelihood of receiving a job offer.

To this end, we regress indicators for whether a bid received a callback or an offer on the time that worker spent editing the AI-generated cover letters. We control for worker fixed effects, as well as normalized wages and review score rank percentiles.

Table 8: Effects of Time Spent Editing AI-Generated Output on Hiring Outcomes

	Offer	Callback
Time spent editing (minutes)	0.000885***	0.001840***
	(0.000195)	(0.000351)
N	192,930	192,930
Worker FE	✓	✓
Outcome mean	0.006	0.068

Table notes: All regressions include a constant and controls for normalized wage and rank percentile. Offer is a bid-level indicator equal to 1 if the bid won the job and 0 otherwise. Callback is a bid-level indicator equal to 1 if the worker who submitted the bid was interviewed for the task and 0 otherwise. Time spent editing is measured in minutes from the moment the worker activated the tool to the moment the bid was submitted. The sample consists of all post-rollout bids that used the tool and had an editing time of less than 60 minutes. Standard errors, clustered at the worker level, are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The results are reported in Table 8. Column (1) reports results using job offer as the dependent variable. The coefficient on editing time is positive and highly significant: spending more minutes tailoring a cover letter after using the tool increases the probability of winning. A one–standard deviation increase in editing time (3.5 minutes) is associated with a 0.31 percentage-point higher probability of winning, or about 52% of the average win rate among AI-assisted bids (0.6%).

For callbacks (Column 2), the coefficient on editing time is likewise positive and highly significant. A one–standard deviation increase corresponds to a 0.64 percentage-point higher probability of chatting, roughly 9% of the average chat rate among AI-assisted bids (6.8%).

These results underscore the importance of how workers interact with AI. Section 5 showed that access to the AI tool increased the likelihood of receiving a callback, at least in the first two months. Here we add another layer of nuance: spending more time refining one's cover letter after adopting the tool is associated with higher probabilities of both receiving a callback and ultimately winning the job. However, these results should not be interpreted as evidence of a causal relationship: the decision to spend more time editing a cover letter is unlikely to be random

and may correlate with unobserved bid characteristics that employers find appealing. Further work is needed to more fully understand human–AI interaction in the context of job applications.

8   Conclusion

This study provides empirical evidence on the labor market consequences of AI-assisted job applications. While AI tools allow freelancers to produce more polished and tailored applications with less effort, our findings suggest that they fundamentally reshape how employers interpret cover letters. The widespread adoption of AI-assisted writing diminishes the informational value of cover letters, weakening their role as a hiring signal. In response, employers place greater weight on alternative signals, such as past work experience, that are less susceptible to AI. We find no evidence that this shift in signaling has affected overall hiring rates. Finally, we show that although most workers submit AI-generated drafts with minimal revision, within a worker, more time spent editing is associated with higher hiring success.

Online labor platforms provide a unique data opportunity to study the growing use of AI in job applications. At the same time, important differences from conventional labor markets mean that further research is needed to assess whether these findings generalize more broadly. As AI technologies continue to advance, ongoing research will be essential to understand their implications for labor market signaling and screening.

References

Acemoglu, Daron, "The simple macroeconomics of AI," *Economic Policy*, 2025, *40* (121), 13–58.

Agarwal, Nikhil, Alex Moehring, Pranav Rajpurkar, and Tobias Salz, "Combining human expertise with artificial intelligence: Experimental evidence from radiology," Technical Report, National Bureau of Economic Research 2023.

Agrawal, Ajay, Joshua S Gans, and Avi Goldfarb, "Artificial intelligence: the ambiguous labor market impact of automating prediction," *Journal of Economic Perspectives*, 2019, *33* (2), 31–50.

Agrawal, Ajay K, Joshua S Gans, and Avi Goldfarb, "Ai adoption and system-wide change," Technical Report, National Bureau of Economic Research 2021.

Alekseeva, Liudmila, José Azar, Mireia Giné, Sampsa Samila, and Bledi Taska, "The Demand for AI Skills in the Labor Market," May 2021. Available at SSRN: 3470610.

Allen, Ryan T. and Prithwiraj (Raj) Choudhury, "Algorithm-Augmented Work and Domain Experience: The Countervailing Forces of Ability and Aversion," *Organization Science*, January 2022, *33* (1), 149–169.

Allman, Maxwell, Itai Ashlagi, Amin Saberi, and Sophie H. Yu, "From Signaling to Interviews in Random Matching Markets," https://arxiv.org/abs/2501.14159 January 2025.

Altonji, Joseph G and Charles R Pierret, "Employer learning and statistical discrimination," *The quarterly journal of economics*, 2001, *116* (1), 313–350.

Bertrand, Marianne and Sendhil Mullainathan, "Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination," *American economic review*, 2004, *94* (4), 991–1013.

Brinatti, Agostina, Javier Cravino, Alberto Cavallo, and Andres Drenik, "The International Price of Remote Work," May 2023. Working paper.

Brynjolfsson, Erik, Danielle Li, and Lindsey Raymond, "Generative AI at work," *The Quarterly Journal of Economics*, 2025.

Cao, Jingman and Yuting Zhu, "AI for Fairness? The Role of Generative Tools in Shaping Freelancer Success," August 2025. Available at SSRN: 5346514.

___ **and** ___ , "When AI Writes Alike: Implications for Efficiency on Matching Platforms," August 2025. Job Market Paper.

Chakrabarty, Tuhin, Philippe Laban, and Chien-Sheng Wu, "Can ai writing be salvaged? mitigating idiosyncrasies and improving human-ai alignment in the writing process through edits," in "Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems" 2025, pp. 1–33.

Chen, Daniel L. and John J. Horton, "Are Online Labor Markets Spot Markets for Tasks? A Field Experiment on the Behavioral Response to Wage Cuts," *Information Systems Research*, 2016, *27* (2), 403–423.

Chen, Yvonne Jie, Jie Gong, Jin Li, and Zibo Zhao, "Better Technology, Worse Motivation: GenAI's Mediocrity Trap," May 2025. Available at SSRN: 5208163; Last revised: 19 June 2025.

Cowgill, Bo, Pablo Hernandez-Lagos, and Nataliya Langburd Wright, "Does AI Cheapen Talk? Theory and Evidence From Global Entrepreneurship and Hiring," *Theory and Evidence From Global Entrepreneurship and Hiring (July 26, 2024). Columbia Business School Research Paper*, 2024, (4702114).

Deveci, Can Deniz, Jason Joe Baker, Binyamin Sikander, and Jacob Rosenberg, "A comparison of cover letters written by ChatGPT-4 or humans," *Dan Med J*, 2023, *70* (12), A06230412. Randomized non-inferiority trial; free article on PubMed (PMID: 38018708).

Dillon, Eleanor W., Sonia Jaffe, Nicole Immorlica, and Christopher T. Stanton, "Shifting Work Patterns with Generative AI," Working Paper 33795, National Bureau of Economic Research May 2025.

Frankel, Alex and Navin Kartik, "Muddled Information," *Journal of Political Economy*, 2019, *127* (4), 1739–1776.

Galdin, Anaıs and Jesse Silbert, "Making Talk Cheap: Generative AI and Labor Market Signaling," Technical Report, Working Paper 2025.

Galdin, Anaïs Soledad and Jesse Silbert, "Equilibrium Provision of Information in Two-Sided Markets: Evidence from an Online Job Platform." PhD dissertation, Princeton University 2024.

Gans, Joshua S, "How will Generative AI impact communication?," *Economics Letters*, 2024, *242*, 111872.

Goodwin, Tom, "How to Survive the Summer Slowdown as a Freelancer," https://freelancernews.co.uk/finding-freelance-work/how-to-survive-the-summer-slowdown-as-a-freelancer/ April 2025. Accessed 2025-08-28.

Hendrycks, Dan, Tom Mazeika, Siddhartha Kadavath, Aman Arora, Vivek Gupta, Austin Jones, Yuning Doron, Jacob Steinhardt, Mohammad Bashir, Alexander Turner, Ashley Prost, Suzanne Ibarraran, Jason Phang, Hessam Khan, Benjamin Vuong, Jacob Zhang, Amanda Miller, Emily Zhai, Henry Wu, Chong Tao, Adrian Glaese, David Krueger, Jonathan Ho, Liane Baker, Federico Vecchi, John Schulman, Clemens Chainsurprise, Christian Carmichael, Aditya Ramesh, Rishabh Thoppilan, Tom Brown, and Dario Amodei, "Measuring Massive Multitask Language Understanding," arXiv preprint arXiv:2009.03300 2020.

Horton, John and Shoshana Vasserman, "Job-seekers send too many applications: Experimental evidence and a partial solution," *Manuscript, MIT*, 2021.

Horton, John J., "Online Labor Markets," in Amin Saberi, ed., *Internet and Network Economics: 6th International Workshop, WINE 2010, Stanford, CA, USA, December 13-17, 2010. Proceedings*, Vol. 6484 of *Lecture Notes in Computer Science* Springer Berlin Heidelberg December 2010, pp. 515–522.

Horton, John J, "Buyer uncertainty about seller capacity: Causes, consequences, and a partial solution," *Management Science*, 2019, *65* (8), 3518–3540.

_ , **Ramesh Johari, and Philipp Kircher**, "Sorting through Cheap Talk: Theory and Evidence from a Labor Market," Technical Report, National Bureau of Economic Research 2024.

Horton, John J., William R. Kerr, and Christopher T. Stanton, "Digital Labor Markets and Global Talent Flows," in George J. Borjas and Richard B. Freeman, eds., *High-Skilled Migration to the United States and Its Economic Consequences*, University of Chicago Press, May 2017, pp. 71–108.

Hosanagar, Kartik and Daehwan Ahn, "Designing human and generative AI collaboration," *arXiv preprint arXiv:2412.14199*, 2024.

Hui, Xiang, Oren Reshef, and Luofeng Zhou, "The short-term effects of generative artificial intelligence on employment: Evidence from an online labor market," *Organization Science*, 2024, *35* (6), 1977–1989.

Kosinski, Michal, "Theory of Mind May Have Spontaneously Emerged in Large Language Models," arXiv preprint arXiv:2302.02083 2023. version v1, PDF: https://arxiv.org/vc/arxiv/papers/2302/2302.02083v1.pdf.

Lavi, Dor, Volodymyr Medentsiy, and David Graus, "consultantbert: Fine-tuned siamese sentence-bert for matching jobs and job seekers," *arXiv preprint arXiv:2109.06501*, 2021.

Noy, Shakked and Whitney Zhang, "Experimental evidence on the productivity effects of generative artificial intelligence," *Science*, 2023, *381* (6654), 187–192.

OpenAI, "GPT-4 Technical Report," Technical Report, OpenAI 2023.

Otis, Nicholas, Rowan Clarke, Solene Delecourt, David Holtz, and Rembrand Koning, "The uneven impact of generative AI on entrepreneurial performance," 2024.

Ramanath, Rohan, Hakan Inan, Gungor Polatkan, Bo Hu, Qi Guo, Cagri Ozcaglar, Xianren Wu, Krishnaram Kenthapadi, and Sahin Cem Geyik, "Towards deep and representation learning for talent search at linkedin," in "Proceedings of the 27th ACM international conference on information and knowledge management" 2018, pp. 2253–2261.

Rambachan, Ashesh and Jonathan Roth, "A more credible approach to parallel trends," *Review of Economic Studies*, 2023, *90* (5), 2555–2591.

Robinson, Cheryl, "Entrepreneurs, Experiencing The Summer Slowdown? Here's How To Cope," https://www.forbes.com/sites/cherylrobinson/2024/07/23/entrepreneurs-experiencing-the-summer-slowdown-heres-how-to-cope/ July 2024. Accessed 2025-08-28.

Sikander, Binyamin et al., "ChatGPT-4 and Human Researchers Are Equal in Writing Introductions Regarding Publishability, Readability, and Content Quality," *PLoS / PubMed Central*, 2023.

Singh, Amit, Catherine Rose, Karthik Visweswariah, Vijil Chenthamarakshan, and Nandakishore Kambhatla, "PROSPECT: a system for screening candidates for recruitment," in "Proceedings of the 19th ACM international conference on Information and knowledge management" 2010, pp. 659–668.

Spence, Michael, "Job market signaling," in "Uncertainty in economics," Elsevier, 1978, pp. 281–306.

Stanton, Christopher T. and Catherine Thomas, "The Gig Economy Beyond Local Services and Transportation," *CESifo Forum*, September 2020, *21* (3), 21–26.

___ **and** ___ , "Who Benefits from Online Gig Economy Platforms?," *American Economic Review*, June 2025, *115* (6), 1857–1895.

Vozza, Stephanie, "How to Use a Summer Slowdown to Advance Your Career," https://www.fastcompany.com/3062058/how-to-use-a-summer-slowdown-to-advance-your-career July 2016. Accessed 2025-08-28.

Weber-Wulff, Debora, Alla Anohina-Naumeca, Sonja Bjelobaba, Tomáš Foltỳnek, Jean Guerrero-Dib, Olumide Popoola, Petr Šigut, and Lorna Waddington, "Testing of detection tools for AI-generated text," *International Journal for Educational Integrity*, 2023, *19* (1), 1–39.

Wiles, Emma and John J Horton, "Generative ai and labor market matching efficiency," *Available at SSRN 5187344*, 2025.

___ , **Zanele T Munyikwa, and John J Horton**, "Algorithmic writing assistance on jobseekers' resumes increases hires," Technical Report, National Bureau of Economic Research 2023.

Zhao, Jing, Jingya Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, and Mohammed Korayem, "Embedding-based recommender system for job to candidate matching on scale," *arXiv preprint arXiv:2107.00221*, 2021.

Zhu, Chen, Hengshu Zhu, Hui Xiong, Chao Ma, Fang Xie, Pengliang Ding, and Pan Li, "Person-job fit: Adapting the right talent for the right job with joint representation learning," *ACM Transactions on Management Information Systems (TMIS)*, 2018, *9* (3), 1–17.

Appendix

A   Tables and Figures

Table A1: Example Similarity Scores

Brief: I need to add a horizontal scrolling section to a WordPress website. User is scrolling vertical (up & down) while content is moving left and right. Solution: Plain HTML/CSS/JS is ok. Even better if we can use class/ID on the WPBakery Page Builder row to activate. Has to work on the demo site. I have some examples that can be copied (CSS and JS methods). Demo site: [LINK REDACTED]

Proposal Text	Similarity Score	AI Bid Writer
Hello! I understand that you need to add a horizontal scrolling section to your WordPress website, but the user needs to be able to scroll up and down while content is moving left and right. I also check the attached url with reference and I can make this perfectly. My name is Sandeep and I am a Full Stack Developer with over 7+ years of experience in the industry. I specialize in larger web applications and software development, as well as larger website builds. My solution is to use class/ID on the WPBakery Page Builder row to activate the section. This method works on the demo site and doesn't require any modifications to the site's code. If you are interested in my services please feel free to take a look at my portfolio or contact me directly for more information. Thank you for your consideration!	0.541	Yes
Hello I am a senior Web and Mobile app developer and I have worked on many jobs similar to this one. I understand that you need to add a horizontal scrolling section to your wordpress website, but instead of just moving from left to right, the content needs to move from left to right while the user is still able to scroll up and down through the section. My skillset allows me to tackle jobs like this and bring the user an exciting experience. I am confident that my expertise can help bring this job to success. If given the chance, I would love to work on this site with you! Please don't hesitate to reach out if you have any questions or would like more information about me or my skillset. Thank you for your consideration!	0.354	Yes
Hi, I can help u to add Vertical Scrolling function to ur WP Website I checked the demo site and found that It's easy task for my team because we had 10 + years experience in it Plz chat now bro !	0.339	No
"Hi Joshua M.! Because of my considerable experience in website development, I believe I would be a wonderful fit for this position. I have examined every detail, and everything appears doable, but if you could start the chat, I have a few questions. Here's what I can bring to your job: 1) Top-notch experience 2) Knowledge of best practices for data security 3) 24/7 communication: I will keep you updated with job's status and consistent updates 4) Someone who cares about helping you succeed and bring more value to your organization I am looking forward to hearing more about your exciting job!"	0.001	No

Table notes: A selection of four written proposals on an example job. Similarity Score is the measure of cover letter quality, computed as the cosine similarity between the TF-IDF vectors of the job description and the proposal. AI Bid Writer indicates whether the bid was written with the help of the platform-native AI tool.

Table A2: Signaling Power of Cover Letters: Pre vs. Post AI

	Interview	Offer
Cover Letter Tailoring$_{ijt}$	0.0409***	0.0082***
	(0.0045)	(0.0009)
Post$_t \times$Cover Letter Tailoring$_{ijt}$	-0.0193***	-0.0063***
	(0.0042)	(0.0009)
Month FE	✓	✓
Outcome Mean	0.0647	0.0053
N	5,499,707	5,499,707

Table notes: Wage bids and experience levels are controlled for. Standard errors are reported in parentheses and clustered at the bidder level. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A3: Signaling Power of Cover Letters: Pre vs. Post AI

	Interview	Offer
Cover Letter Tailoring$_{ijt}$	0.0512***	0.0062***
	(0.0034)	(0.0010)
Post$_t \times$Cover Letter Tailoring$_{ijt}$	-0.0213***	-0.0038***
	(0.0034)	(0.0009)
Bidder FE	✓	✓
Month FE	✓	✓
Outcome Mean	0.0647	0.0053
N	5,499,707	5,499,707

Table notes: Wage bids, experience levels and Post GPT$_t \times$Cover Letter Tailoring$_{ijt}$ are controlled for. Standard errors are reported in parentheses and clustered at the bidder level. *** p < 0.01, ** p < 0.05, * p < 0.1.

Figure A1: Post AI Roll-out, Cover Letters Persistently Less Predictive of Callback
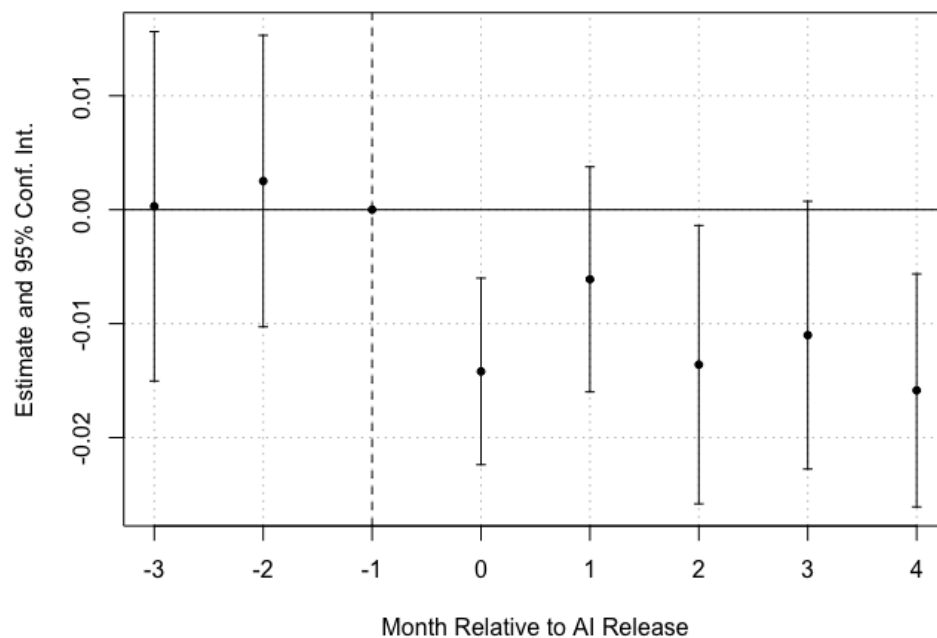

Figure Notes: Interaction term event study coefficients on Month $\times$ Textual Similarity with interview as the outcome. Wages, experience levels, and month FEs are controlled for. Standard errors clustered at the bidder level.

Figure A2: Post AI Roll-out, Cover Letters Persistently Less Predictive of Hiring
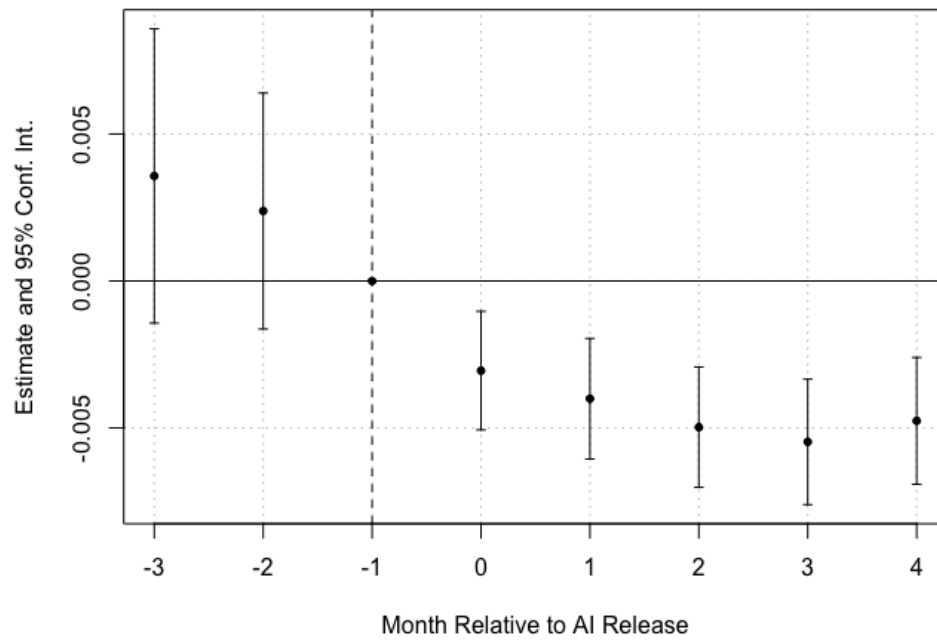

Figure Notes: Interaction term event study coefficients on Month $\times$ Textual Similarity with being hired as the outcome. Wages, experience levels, and month FEs are controlled for. Standard errors clustered at the bidder level.

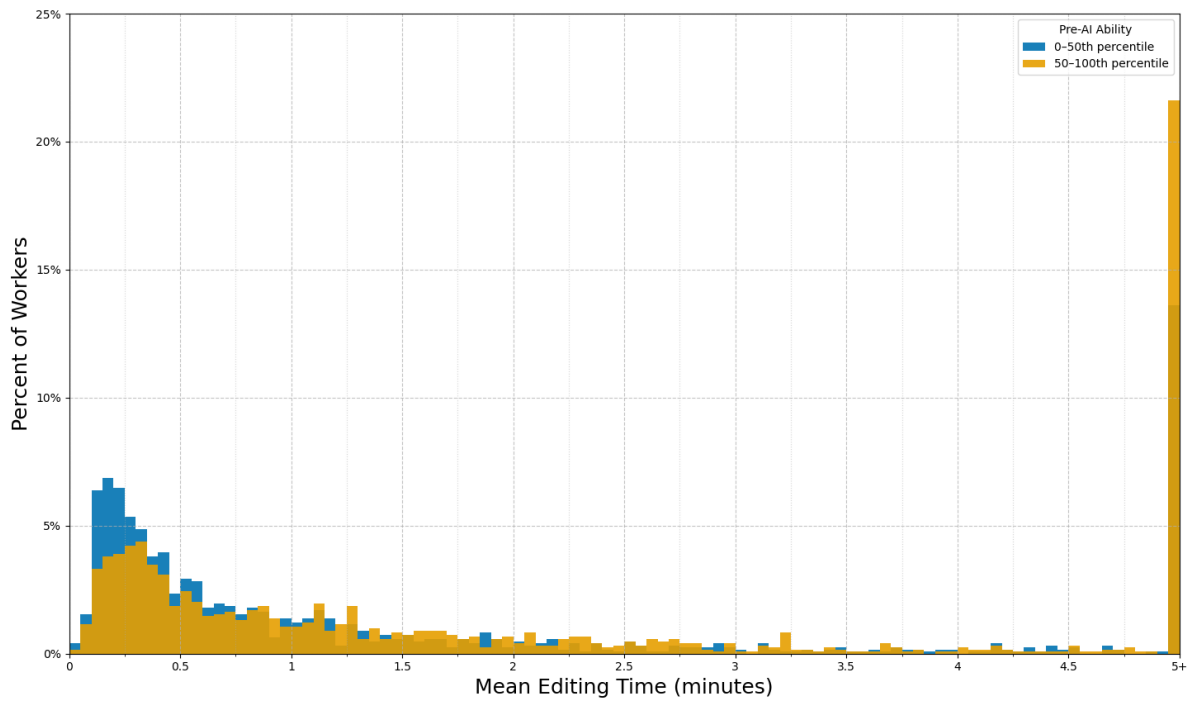**Figure A3:** Histogram of Mean Time Spent Editing

Figure notes: Worker-level histogram. Each observation represents a worker's average time, in minutes, between activating the tool and submitting a bid. Observations of 5 minutes or more are grouped in the final bin labeled "5+".

B Proofs and Derivations

B.1 Screening Model

- Here we derive equations 3 and 4. By the law of total expectations:

$$\mathbb{E}[q_i\,|\,h_{ij}]=\mathbb{E}[q_i\,|\,h_{ij},\rho_i=0]\mathbb{P}[\rho_i=0|h_{i,j}]+\mathbb{E}[q_i\,|\,h_{ij},\rho_i=1]\mathbb{P}[\rho_i=1|h_{i,j}]$$

$$\mathbb{E}[q_i\,|\,h_{ij}]=(\mu_0+\frac{\tau^2}{\tau^2+\sigma^2}(h_{ij}-\mu_0))(1-g(h_{ij}))+(\mu_0+\frac{\tau^2}{\tau^2+\sigma^2}(h_{ij}-\mu_0-A))g(h_{ij})$$

$$\mathbb{E}[q_i\,|\,h_{ij}]=\mu_0+\frac{\tau^2}{\tau^2+\sigma^2}(h_{ij}-\mu_0-Ag(h_{ij}))$$

which is equation 3. Let be f_1 be the p.d.f. of cover letter quality conditional on having access to AI ($h\sim\mathcal{N}(\mu_0+A,\tau^2+\sigma^2)$) and f_0 the p.d.f. conditional on not having access to the tool ($h\sim\mathcal{N}(\mu_0,\tau^2+\sigma^2)$). Bayes rule implies:

$$\mathbb{P}[\rho_i=1|h_{i,j}]=\frac{pf_1(h_{ij})}{pf_1(h_{ij})+(1-p)f_0(h_{ij})}$$

Rearranging the terms gives us:

$$\mathbb{P}[\rho_i=1|h_{i,j}]=\frac{1}{1+\frac{1-p}{p}\psi(h_{ij})}$$

where we define $\psi(h_{ij}):=\frac{f_0(h_{ij})}{f_1(h_{ij})}$.

$$\psi(h_{ij})=\frac{f_0(h_{ij})}{f_1(h_{ij})}=\exp\left\{\frac{-(h_{ij}-\mu_0)^2+(h_{ij}-\mu_0-A)^2}{2(\tau^2+\sigma^2)}\right\}=\exp\left\{\frac{-2A(h_{ij}-\mu_0)+A^2}{2(\tau^2+\sigma^2)}\right\}$$

This gives us 4. □

- Now we move to prove the results from subsection 4.3. Let $\Lambda(h,A):=\mathbb{E}[q|h;A]$. Let $A^*>0$ be the effect of AI. We have

$$\Lambda(q+A^*+\nu,A^*)-\Lambda(q+\nu,0)=\frac{\tau^2}{\tau^2+\sigma^2}(A^*(1-g(q+A^*+\nu)))>0,\forall(q,\nu)$$

Define $l(x):=\frac{\exp\{x\}}{1+\exp\{x\}}$. Probability of being hired given h and A is $l(\Lambda(h,A))$. The probability of being hired conditional on productivity q and on being treated is:

$$\mathbb{P}[\text{hire}\quad i|q;\rho_i=1;A=A^*]=\int_\nu l(\Lambda(q+A^*+\nu,A^*))\phi(\nu)d\nu$$

where $\phi(\nu)$ is the pdf of ν. The change in probability of being hired from $A=0$ to $A=A^*$ is:

$$\mathbb{P}[\text{hire} \quad i|q;\rho_i=1;A=A^*]-\mathbb{P}[\text{hire} \quad i|q;\rho_i=1;A=0]=$$

$$\int_\nu l(\Lambda(q+A^*+\nu,A^*))\phi(\nu)d\nu-\int_\nu l(\Lambda(q+\nu,0))\phi(\nu)d\nu=$$

$$\int_\nu \left[\underbrace{l(\Lambda(q+A^*+\nu,A^*))-l(\Lambda(q+\nu,0))}_{>0}\right]\phi(\nu)d\nu>0$$

Since $l(\cdot)$ is a strictly increasing function and $\Lambda(q+A^*+\nu,A^*)>\Lambda(q+\nu,0)$ the integrand is positive a.s., hence the integral is >0. The result for the control group is analogous. $\square$

Finally, consider the following definitions:

$$\Delta(q):=\mathbb{P}[\text{hire} \quad i|q;\rho_i=1;A=A^*]-\mathbb{P}[\text{hire} \quad i|q;\rho_i=1;A=0]$$

$$\alpha(q,\nu):=\Lambda(q+A^*+\nu,A^*)$$

$$\beta(q,\nu):=\Lambda(q+\nu,0)$$

$$m(q,\nu):=l(\alpha(q,\nu))-l(\beta(q,\nu))$$

$$\kappa:=\frac{\tau^2}{\tau^2+\sigma^2},V:=\tau^2+\sigma^2$$

Claim B.1 (Monotonicity). *Fix q. There exists ν_q that is decreasing in q such that for all $\nu>\nu_q$, $\frac{\partial m(q,\nu)}{\partial q}<0$.*

Proof. We have:

$$\frac{\partial \alpha(q,\nu)}{\partial q}=\kappa\left(1-\frac{(A^*)^2}{V}g(q+A^*+\nu;A^*)(1-g(q+A^*+\nu;A^*))\right)$$

$$\frac{\partial \beta(q,\nu)}{\partial q}=\kappa$$

which gives us:

$$\frac{\partial m(q,\nu)}{\partial q}=\kappa\left[l'(\alpha)\left(1-\frac{(A^*)^2}{V}g(q+A^*+\nu;A^*)(1-g(q+A^*+\nu;A^*))\right)-l'(\beta)\right]$$

where $l'(x)>0$ and is strictly decreasing for $x>0$.

Let $\nu_q=-\frac{\mu_0}{\kappa}+\mu_0-q$. For any $\nu>\nu_q$ we have $\beta(q,\nu)>0$ (and $\alpha(q,\nu)>0$, consequently).

Then, if $\left(1-\frac{(A^*)^2}{V}g(q+A^*+\nu;A^*)(1-g(q+A^*+\nu;A^*))\right)\geq 0$:

$$\frac{\partial m(q,\nu)}{\partial q}\leq\kappa\left[l'(\beta)\left(1-\frac{(A^*)^2}{V}g(q+A^*+\nu;A^*)(1-g(q+A^*+\nu;A^*))\right)-l'(\beta)\right]$$

$$=-\kappa\left[l'(\beta)\frac{(A^*)^2}{V}g(q+A^*+\nu;A^*)(1-g(q+A^*+\nu;A^*))\right]<0$$

And the result follows immediately if $\left(1-\frac{(A^*)^2}{V}g(q+A^*+\nu;A^*)(1-g(q+A^*+\nu;A^*))\right)<0$ □

Claim B.1 implies that, by dominated convergence, there is a $\hat{q}$ such that

$$\forall q>\hat{q}, \Delta'(q)<0.$$

The result for the control group is analogous. □

B.2 Econometric Assumptions

- Let $\Delta_t^g:=\mathbb{E}[Y_{i,t}^g|\text{Access}_i=1]-\mathbb{E}[Y_{i,t}^g|\text{Access}_i=0]$, and $\hat{\Delta}_t^g$ the sample version. Also, let $\mathcal{T}_p$ be the number of periods under the platform tool. Consider the following standard two-way fixed effect regression:

$$Y_{i,t}^g=\delta_i+\gamma_t+\beta\text{PostAI}_t\times\text{Access}_i+\lambda\text{PostGPT}_t\times\text{Access}_i+\epsilon_{i,t}$$

The estimator $\hat{\beta}$ can be written as[9]:

$$\hat{\beta}=\frac{\sum_{t\geq t^*}\hat{\Delta}_t^1}{\mathcal{T}_p}-\hat{\Delta}_{t^*-1}^1$$

Under LLN, this converges to

$$\frac{\sum_{t\geq t^*}\Delta_t^1}{\mathcal{T}_p}-\Delta_{t^*-1}^1$$

Under assumptions 1, 2 and SUTVA this is equivalent to

$$\frac{\sum_{t\geq t^*}\mathbb{E}[Y_{i,t}^1(1)-Y_{i,t}^1(0)|\text{Access}_i=1]}{\mathcal{T}_p}$$

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[9]By Frisch-Waugh-Lovell, the OLS coefficient on $\text{Access}_i\times\text{PostAI}_t$ equals the slope from regressing the residualized $Y_{i,t}^g$ on the residualized $\text{Access}_i\times\text{PostAI}_t$ after partialling out $(\delta_i,\gamma_i,\text{PostGPT}_t\times\text{Access}_i)$. In a balanced panel, this reduces to the average post difference $\frac{\sum_{t\geq t^*}\hat{\Delta}_t^1}{\mathcal{T}_p}$ minus the GPT-4 baseline $\hat{\Delta}_{t^*-1}^1$.

In our case (with 1 and 2, but without SUTVA) this is equivalent to:

$$\frac{\sum_{t \geq t^*} \mathbb{E}[Y_{i,t}^1(1,m_1,0) - Y_{i,t}^1(0,m_1,0)|\text{Access}_i = 1]}{\mathcal{T}_p} +$$

$$\frac{\sum_{t \geq t^*} \mathbb{E}[Y_{i,t^*-1}^1(0,m_1,1) - Y_{i,t^*-1}^1(0,m_1,0)|\text{Access}_i = 0]}{\mathcal{T}_p} +$$

$$\frac{\sum_{t \geq t^*} \mathbb{E}[Y_{i,t^*-1}^1(0,m_1,0) - Y_{i,t^*-1}^1(0,m_0,0)\,|\,\text{Access}_i = 1] + \mathbb{E}[Y_{i,t^*-1}^1(0,m_1,0) - Y_{i,t^*-1}^1(0,m_0,0)\,|\,\text{Access}_i = 0]}{\mathcal{T}_p}$$