Labor Market Signals: The Role of Large Language Models*

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Abstract

Large Language Models (LLMs) have the potential to transform the labor market, including hiring. This paper assesses their impact on signals that job-seekers send to potential employers and how this affects labor market matching. Through two field experiments, focusing on cover letters and involving job-seekers and recruiters, we document that LLMs enhance the quality of signals, particularly benefiting lower-quality applicants. However, these improvements do not translate into increased interview invitations because the improvements are concentrated in standardized, less influential sections of the cover letters. When recruiters are explicitly informed of candidates' use of LLMs, they place greater value on high-quality cover letters crafted without AI assistance. Our findings indicate that LLMs reduce the informativeness of signals, potentially leading to increased inefficiencies in labor market matching.

Key words: Large Language Models; Cover Letters; Labor Market; Matching; Signaling.

JEL codes: C93; J24; O33; M51

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1 Introduction

The labor market is undergoing rapid transformations, driven by technological innovation and evolving workplace practices. Recent research highlights the impacts of these developments on modern labor dynamics (Deming and Kahn, 2018; Englmaier et al., 2024; Deming et al., 2025). Among the emerging technologies, the rise of Large Language Models (LLMs) promises to have substantial implications for the future of work, with at least 80% of the U.S. jobs expected to be affected, and 23% of U.S. employees already using LLMs at work (Eloundou et al., 2023; The White House, 2022; Bick et al., 2025). However, relatively little attention has been given to how LLMs can influence labor market matching—the process through which job-seekers are matched to firms.

Labor market matching depends heavily on signals, such as CVs and cover letters, since firms cannot directly assess a job-seeker's productivity or fit (Spence, 1973). Cover letters, in particular, play a crucial role in many hiring processes, allowing job-seekers to showcase their soft skills such as their motivation, communication skills, and overall fit (ANP, 2023, 2024). Ex-ante, the effect of LLMs on such signals is not clear: on the one hand, LLMs can improve the underlying quality of the job-seeker's signal, for example by improving the writing quality (Noy and Zhang, 2023). On the other hand, LLMs can make texts more formulaic and less personalized (Shanahan, 2024), diminishing their effectiveness as a signal. Despite the uncertainty surrounding whether LLMs enhance or undermine job-seekers' employment prospects, more than half of all job-seekers use LLMs in their job applications (Criddle and Strauss, 2024). Do labor market signals written with LLM assistance help job-seekers get hired, and does this distort hiring decisions?

This paper answers this question through two pre-registered field experiments examining the impact of LLMs on labor market signals and analyzing both the perspectives of job-seekers and employers. The first experiment is conducted with job-seekers at two universities and recruiters from four multi-national companies with close to half a million employees. During the field experiment, some job-seekers were allowed to use ChatGPT when writing their cover letter, while others were not. Access to LLMs improves the quality of cover letters by more than 0.2 standard deviations, as evaluated by recruiters from the four firms who were blind to the two treatments. In line with Noy and Zhang (2023), Dell'Acqua et al. (2023), Caplin et al. (2024), and Brynjolfsson et al. (2025), the positive treatment effects are stronger for lower-quality applicants, thus reducing the dispersion in quality of the cover letters, hence reducing their value as a signal of the applicant's true ability.

We find that LLMs improve the least important aspects of the cover letter, which are also the least personalized sections. The most critical component—the job-seeker's motivation—is less generic and does not improve as a result of access to LLMs. As a result, the LLM-induced improvements in the cover letter do not increase the job-seeker's likelihood of being invited to the next stage of the recruitment process, an interview. Textual analysis of ChatGPT conversation histories reveals that job-seekers ask ChatGPT for help on their motivation section multiple times, however, ChatGPT does not improve this section significantly.

Recruiters' perceptions of LLM usage can affect the evaluation of labor market signals, with people having a preference for human over AI-generated content (Zhang and Gosline, 2023). To understand this, we conducted a second experiment where we employed 401 recruiters to evaluate a subsample of cover letters from the first experiment. Some were explicitly informed about whether a cover letter had been written with LLM assistance, while others were only told that some letters had been written with the assistance of LLMs without knowing which ones. When recruiters were explicitly informed about LLM usage, on average they do not rate cover letters differently. However, there is substantial heterogeneity: while the evaluation of low and medium-quality cover letters do not differ, recruiters evaluate high-quality cover letters written without LLM assistance more highly and are more likely to invite the applicant to the next stage of the recruitment process.

The two experiments illustrate how LLMs can affect labor market signaling. While LLMs raise the quality of cover letters—especially for weaker applicants—it decreases the letters' usefulness as a signal of the job-seeker's true ability. When recruiters learn that LLMs were used, they favor strong cover letters written without LLM assistance, resulting in a higher likelihood of those applicants being interviewed. By measuring the effect of LLMs on labor market signals and matching efficiency, our paper contributes to the literature on the role of new AI technologies on the labor market (Acemoglu and Restrepo, 2018, 2020; Bessen et al., 2025). Other studies have evaluated the role of technologies on employee-employer matches, including the internet (Autor, 2001) and algorithmic writing assistants, like Grammarly (Wiles et al., 2023; Wiles and Horton, 2023). To the best of our knowledge, we provide the first evidence on how LLMs affect labor market signaling and matching.

Compared with the other technological innovations, LLMs have greater capabilities (e.g., by generating text, rather than merely editing it) and their use is rapidly growing, meaning that they are likely to have a greater impact on the matching in the labor market.[1] While the writing assistants evaluated by Wiles et al. (2023) can improve the clarity of signals, for example by improving grammatical mistakes, LLMs can reduce the clarity of signals by making it harder for recruiters to evaluate the applicant's true abilities. We furthermore build on the insights of Wiles et al. (2023) by focusing on entry-level jobs: a domain where signals are scarce due to limited past work experience, yet with high stakes due to the path dependency of future jobs (Arellano-Bover, 2024). Our experimental findings further reveal that recruiters' perceptions—thus far overlooked in the literature—play an important role in the interplay between LLMs and hiring decisions. Therefore, our second experiment also contributes to the literature on the evaluation of human vs. AI-generated content (Liu et al., 2022; Weiss et al., 2022; Böhm et al., 2023; Zhang and Gosline, 2023; Kadoma et al., 2024; Bohren et al., 2024) by illustrating the implications on the labor market.

Additionally, our paper contributes to the growing body of evidence on the effects of generative AI and LLMs on productivity across a range of domains, including professional writing tasks (Noy and Zhang, 2023), law school exams (Choi and Schwarcz, 2024), coding tasks (Peng et al., 2023b), consulting (Dell'Acqua et al., 2023), customer support (Brynjolfsson et al., 2025), and business practices (Otis et al., 2024).[2] Unlike these settings, we focus on a personalized and persuasive writing task. This is a crucial distinction from existing studies, as LLMs may struggle with personalized persuasive writing due to their formulaic nature as a result of being instructed to replicate patterns from training data. Our results confirm this, as LLMs greatly improve non-personalized sections of the cover letter (e.g., introduction, conclusion), but do not improve the personalized sections (e.g., motivation). Textual analysis of conversations between the job-seeker and ChatGPT reveals that job-seekers repeatedly ask ChatGPT to improve the personalized sections, to no avail.

Lastly, we contribute to the literature on the role of signals in the labor market, which has been widely studied both theoretically and empirically (Spence, 1973; Kurlat

[1] LLMs have become ubiquitous in the workplace, with over 92% of Fortune 500 companies using ChatGPT (OpenAI, 2024), and 25% of the Dutch population using LLMs (Statistics Netherlands (CBS), 2024).

[2] Several other studies have studied LLMs and their implications. A non-exhaustive list includes Peng et al. (2023a); Cui et al. (2025); Toner-Rodgers (2024); Merali (2024); Carvajal et al. (2024); Capraro et al. (2024); Filippucci et al. (2024); Acemoglu (2024); Autor (2024).

and Scheuer, 2020; Bassi and Nansamba, 2021; Carranza et al., 2022). LLMs break down the separating equilibrium in the signaling model of Spence (1973), as the cost of using them does not differ by the applicant's ability. To nevertheless model and analyze the effects of LLMs on labor market signals and matching, we calibrate an assignment model with imperfect information using findings from our two experiments. Building on the existing matching literature (Teulings, 1995; Eeckhout and Kircher, 2018), we model the novel distortions introduced by LLM usage, incorporating experimentally observed asymmetries where LLMs disproportionately inflate signals from lower-ability workers. Our calibration exercise quantifies substantial welfare losses resulting from these distortions, estimating efficiency losses of up to 6%. These losses emerge because firms, anticipating inflated signals due to LLM use, discount all signals and make suboptimal hiring decisions.

The remainder of this paper is structured as follows. Sections 2 and 3 discuss the experimental design and results of the job-seeker experiment, while Section 4 describes the recruiter-side experiment. Section 5 presents the assignment model and quantification exercise, before Section 6 concludes.

2 Job-seeker Experiment: Design

To understand what effect LLMs have on cover letter quality, we recruited 137 students from two of the largest universities in the Netherlands, Tilburg and Utrecht University, to participate in a field experiment with four multi-national corporations: Philips, PwC, Rabobank, and VodafoneZiggo. The firms have a global workforce of over 480,000, and offer highly coveted positions. Each firm provided us with an entry-level job description, and two recruiters from their HR division.

During a university-wide career week, students signed up to our *Cover Letter Challenge*, by uploading a CV, filling in basic demographic information (which were used to stratify randomization), and indicating their preferred firm.[3] The event consisted of a 10-minute introduction, followed by 1 hour to write a cover letter to their preferred firm.[4] Students were informed that their cover letter and CV would be pseudonymized, and subsequently

[3] We focused on students who were in their last semester of either their bachelor or master degree, and who were actively looking for a job.

[4] Although job-seekers were told they only had a full hour to complete their cover letters, in reality the time constraint was not binding. Nevertheless, 83% finished their cover letter within 60 minutes.

shared with two independent recruiters of the firm they applied to. Recruiters evaluated the student's pseudonymized CV and Cover Letter against an evaluation criteria co-developed by the researchers in collaboration with the firms.[5] Recruiters evaluated five dimensions of the CV and cover letter individually, before assigning a final grade to the CV, cover letter, and complete application package. They subsequently indicated the likelihood of inviting the applicant to a job interview on a 5-point Likert scale.

Job-seekers were informed that they would receive personalized feedback on their cover letter and CV, and that the three best cover letters (as evaluated by the firms' recruiters) would receive 500, 300, and 200 Euros respectively. Furthermore, they were informed that recruiters could ask to be put in touch with high-quality applicants. Anecdotal evidence suggests that students highly valued the personalized feedback, and that this was their main motivation for participating.

Job-seekers were randomized across a control and treatment group. The control group were shown a 10-minute placebo guide on how to best use LinkedIn for the job search, and subsequently had 1 hour to write a cover letter. Students were informed that they would not have access to certain websites, including Large Language Models.[6] The treatment group were shown a 10-minute guide on how to improve prompt-writing on ChatGPT, before being asked to write a cover letter. Job-seekers in the treatment group were blocked from accessing the same websites as the control group, with the exception of Open AI's ChatGPT 3.5, which they were allowed to access through a free account provided by the researchers.[7] We tracked their browser history and ChatGPT conversation histories, which indicated that while 18% of applicants in the tontrol group (unsuccessfully) tried to access ChatGPT, 95% of applicants in the treatment group used ChatGPT to write their cover letter.

Randomization was stratified upon the job-seekers's university, their gender, whether they were a Bachelor or Master student, their GPA, and age. Appendix Table A1 shows that randomization was successful, as groups are balanced across stratified variables. We observe

[5]See Appendix B.1.3 for the evaluation criteria. In line with the evaluation criteria, recruiters used cover letters to understand an applicant's motivation, soft skills, and overall fit. These components play a large role for companies, as documented in the desired characteristics listed in the firm's job description. Among others: "Ambitious, proactive, analytical, good with figures, results-focused and flexible"; "Excellent communication and influencing skills, a customer first attitude, self starter with an entrepreneurial spirit, eager and ambitious";"Curious, flexible and driven by innovation"

[6]See Appendix B.1.1 for a list of blocked websites.

[7]At the time of the experiment, Spring 2024, GPT 3.5 was the most advanced free version.

that the ratings of CVs by the recruiters are higher in the Control than Treatment group (see Appendix Table A2), and hence control for the CV grade in our regressions, following Bruhn and McKenzie (2009). Since CVs were submitted before the experiment began, they could not have been influenced by the treatment.

Recruiters were blind to the two treatments and were told by their manager (who was our point of contact) that the purpose of the exercise was to test for the firm's internal consistency across recruiters - and were thus not told who the other recruiter within the firm would be. The recruiters were further told to identify high-quality candidates that they would be interested in interviewing for (future) open positions.

To estimate the effect of the use of ChatGPT on the perceived quality of an applicant's cover letter and likelihood of getting interviewed, we run the following OLS specification:

$$Y_i = \beta_0 + \beta_1 ChatGPT_i + \gamma X_i + \mu_{f,r} + \mu_s + \varepsilon_i \tag{1}$$

where $ChatGPT_i$ is an indicator equal to one if the individual is assigned to the ChatGPT treatment, and 0 otherwise. X_i is a vector of baseline covariates that were unbalanced at baseline and were used to stratify randomization (Bruhn and McKenzie, 2009). We include firm-by-recruiter fixed effects ($\mu_{f,r}$) and school-level fixed effects (μ_s). We cluster standard errors at the individual level since each applicant receives evaluations from multiple recruiters, creating potential correlation in the error terms across observations for the same individual.[8] Estimation is by OLS, except for when the outcome variable is *Likelihood of Interview* and *High Chance of Interview*, which are an ordered logit, and logit regression, respectively.

3 Job-seeker Experiment: Results

3.1 Main Treatment Effects

Table 1 presents the main results of the experiment, showing the effect of ChatGPT usage on various aspects of the quality of the cover letter and the likelihood of being invited to an interview, as evaluated by two independent recruiters. Outcome variables are stanardized

[8] Table A13 reports treatment effects without clustering.

(except for the logit regressions), and therefore treatment effects are reported in terms of standard deviations. Table 1 illustrates that the use of ChatGPT has a positive impact on the overall quality of the cover letter written by an applicant, improving its quality by 0.222 standard deviations on average, which is statistically significant at the 10% level (column 1). This improvement is primarily driven by enhancements in the introduction and closing sections of the cover letter, with treatment effects of 0.253 and 0.281 standard deviations, respectively, both significant at the 5% level (columns 3 and 6). The use of ChatGPT does not have a statistically significant treatment effect on the cover letter's layout, nor the sections discussing one's experience or motivation.

Table 1: Main Results: Effect of ChatGPT on Cover Letter

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Cover Letter			Likelihood of	High Chance of
	Total	Layout	Intro	Experience	Motivation	Closing	Interview	Interview
ChatGPT	0.222*	0.161	0.253**	0.075	0.150	0.281**	0.249	0.011
	(0.117)	(0.145)	(0.119)	(0.112)	(0.115)	(0.113)	(0.284)	(0.444)
Control Group Mean	0.000	0.000	0.000	0.000	0.000	0.000	2.799	0.278
Observations	274	274	274	274	274	274	274	274

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include strata variables and imbalanced baseline variables as controls, along with recruiter and school-level fixed effects. Standard errors are clustered at the individual level. Control mean refers to the mean value of the outcome in the control group. Robust standard errors are in parentheses. Column 1-7 refer to variables as described in Appendix B.1.3, while Column 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

While ChatGPT improves the evaluation of some aspects of the cover letters, it does not translate into a higher likelihood of being invited to the next phase of the recruitment process, a job interview. The causal estimate of the effect of LLM usage on a job-seeker's interview likelihood is positive but not statistically significant (column 7).[9] Appendix Figure A1 presents the marginal treatment effects, showing that they are not only statistically insignificant but also economically negligible, suggesting that LLMs usage by the job-seeker does not affect the quality of the match. Similarly, the probability of having a high chance of being invited to an interview (pre-registered as a *Likelihood of Interview* score greater than 3 on a 5-point scale) shows a marginally positive, but statistically insignificant effect (column 8).[10] This finding implies that the underlying matching between job-seekers and

[9]The interpretation of the coefficient is different compared with Column 1-6, as the regression is an ordered logit because the outcome variable is on a five-point scale.

[10]Appendix Tables A6 and A7 reproduce Table 1 using the Belloni et al. (2014) Double LASSO approach,

firms is unaffected by the usage of LLMs. Moreover, to assess whether recruiters themselves used LLMs to evaluate cover letters, we compared their ratings with those generated by ChatGPT. Using the same evaluation criteria, ChatGPT graded the cover letters as well (see Appendix A.1.5). We find that ChatGPT, unaware of which letters it had assisted in writing, consistently assigned higher scores to those it helped produce. This discrepancy confirms that our recruiters did not rely on LLMs for their evaluations, and highlights a concerning bias in addition to those documented in the literature already (Hoffman et al., 2017; Avery et al., 2023), given the increased use of algorithmic screening tools in recruitment (Eric Reicin, 2021; Institute for the Future of Work, 2022).

To understand why improvements in the cover letter's quality do not translate into higher interview chances, we examine the relative importance of different aspects of the cover letter in determining the likelihood of being invited to a job interview. Table 2 shows that the motivation section of the cover letter, and its layout, are the most important factors in determining interview likelihood (significant at the 1% level). However, our results in Table 1 indicate that ChatGPT does not significantly improve either section, which can explain why ChatGPT enhances the overall quality of a cover letter, but does not increase the likelihood of being invited to an interview.

and bootstrapped standard errors, with very similar results.

Table 2: Determinants of Interview Likelihood

	(1) Likelihood of Interview
CL: Layout	0.525**
	(0.216)
CL: Intro	0.293
	(0.249)
CL: Experience	0.399
	(0.249)
CL: Motivation	0.823***
	(0.249)
CL: Closing	0.474
	(0.315)
Control Group Mean	2.799
Observations	274

Standard errors in parentheses

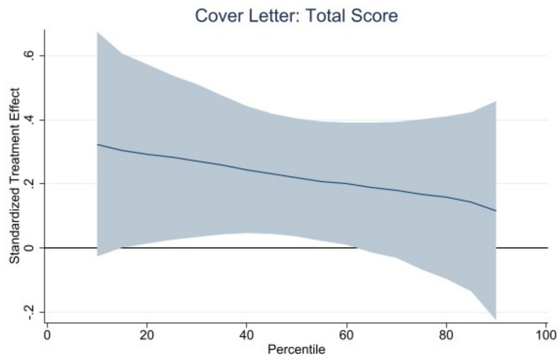
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Ordered Logit regression, regressing the likelihood of an interview to a job interview, on the sub-components of the cover letter and CV (described in Appendix B.1.3). Sub-components of the CV are omitted from the regression table, for visibility purposes. Standard errors are clustered at the individual level. Control mean refers to the mean value of the outcome in the control group. Robust standard errors are in parentheses. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

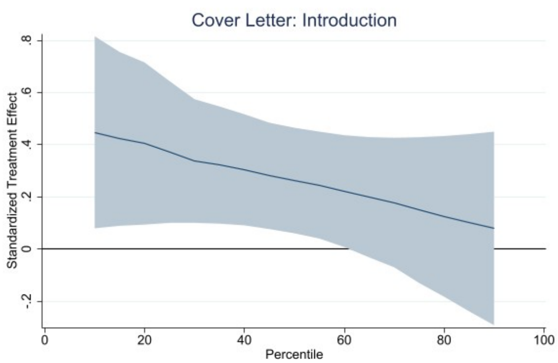
Decomposing the average treatment effects by the applicant's perceived ability, measured by the assigned grade on the cover letter, we find that the positive treatment effects of the use of LLMs on the cover letter quality are driven by lower-quality applicants, in line with the findings of Noy and Zhang (2023), Dell'Acqua et al. (2023), and Brynjolfsson

Figure 1. Quantile Regressions

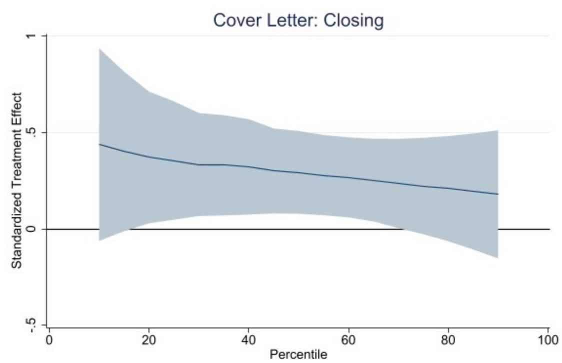
(a) Cover Letter: Total Score



(b) Cover Letter: Introduction



(c) Cover Letter: Closing



et al. (2025).[11] Figure 1 presents the standardized treatment effects of quantile regressions, illustrating a clear pattern of lower perceived ability applicants benefiting more from LLMs than their higher perceived ability counterparts. This trend is consistent across the overall cover letter score (Panel A), introduction (Panel B), and closing section (Panel C).[12]

For the total cover letter score (Panel A), the effect of ChatGPT is strongest at the lower end of the distribution, with a standardized treatment effect of 0.318 at the 10th percentile. The introduction section (Panel B) shows a particularly pronounced decline in

[11] We do not find any heterogeneous treatment effects by gender of the job-seeker, or by type of university degree, as discussed in Appendices A.1.2 and A.1.3.

[12] The pattern is also consistent for Layout, Motivation, and Experience, however magnitudes are not statistically significant. Results are available upon request.

treatment effect across percentiles, from 0.433 at the 10th percentile to 0.076 at the 90th percentile. The closing section (Panel C) exhibits a more gradual decline but maintains a positive effect across most of the distribution.

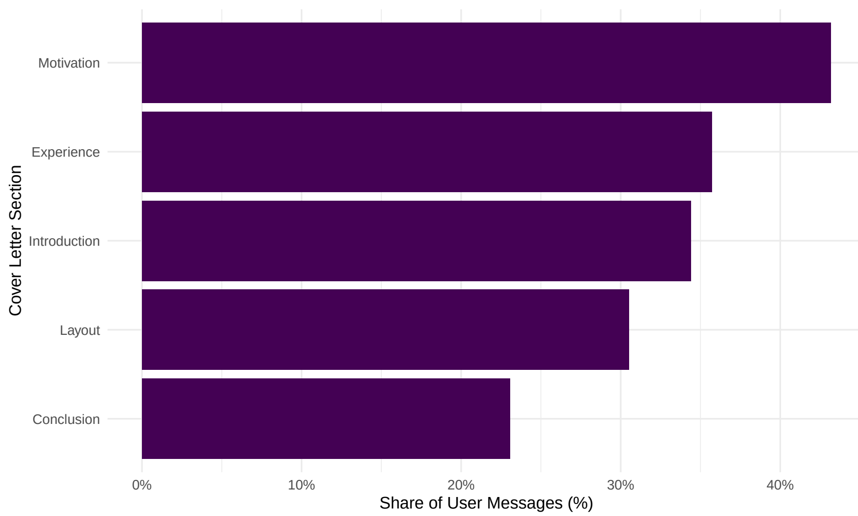
Since we find that perceived quality improves, but the likelihood of securing an interview remains unchanged—leaving matching unaffected—we examine how job-seekers interacted with ChatGPT, how access to ChatGPT affected their browsing history, and whether effective prompting enhanced ChatGPT's effect.

3.2 Analysis of ChatGPT Interactions

We begin by analyzing the conversations between job-seekers and ChatGPT to understand how they engaged with the model during the cover letter writing process. We developed a comprehensive text analysis framework that quantifies both the focus and nature of user interactions. Our methodology tracks mentions of the five key cover letter sections (Layout, Introduction, Experience, Motivation, and Conclusion), distinguishing between content-based interactions (where users seek substantive help with section content) and guidance-based interactions (where users ask for simple structural or formatting advice). For each conversation, we compute the percentage of total mentions per section and the ratio of content versus guidance requests. This allows us to understand both where users focus their attention and how they utilize ChatGPT. Appendix D provides the complete technical details of our methodology, with Appendix Table A38 and Figure A9 demonstrating substantial variation in user engagement, with the number of exchanges per conversation ranging from 1 to 16 messages (mean = 6.4, median = 5).

Figure 2. ChatGPT Prompts

(a) Distribution of messages across cover letter sections.



(b) Share of Content vs. Guidance Prompts per Cover Letter Section

Figure 2a shows how users target their messages across different sections during the cover letter writing process, showing that the Motivation and Experience sections dominate the conversations, accounting for 43.2% and 35.7% of total mentions respectively. In contrast, the Conclusion section receives notably less attention, with only 23.1% of mentions.[13] Therefore, the ineffectiveness of ChatGPT at improving the personalized sections of the cover letter is not due to job-seekers not asking for ChatGPT's advice on these sections. Figure A7 compares these patterns between applicants above and below the median CV rating, revealing consistent message distribution patterns regardless of applicant quality. Figure 2b reveals that across all sections, users predominantly engaged with ChatGPT for content-based assistance rather than guidance - suggesting applicants use ChatGPT for substantial changes to the cover letter's content, rather than small changes in its format. The only exception is in the layout, where users are much more interested in guidance rather than content-related assistance. This further underlines that LLMs differ from other technologies such as algorithmic writing assistants (Wiles et al., 2023; Wiles and Horton, 2023).

Second, we investigate whether ChatGPT complements or replaces other information tools. Table 3 reveals a significant substitution effect between ChatGPT usage and other online resources: job-seekers in the treatment arm conducted 51% fewer Google searches and visited 38% fewer websites compared to individuals in the control arm (Columns 1 and 2). This effect is particularly pronounced for searches related to grammar, which decrease by 84% among individuals with access to ChatGPT (Column 6). These findings suggest that ChatGPT was used as a comprehensive tool, potentially replacing the need for multiple online resources. The marked reduction in grammar-related searches indicates that users may rely on ChatGPT's language proficiency, reducing their dependence on external grammar tools, such as those evaluated in Wiles et al. (2023). This substitution effect highlights ChatGPT's capacity to streamline the writing process by consolidating various aspects of language assistance and information gathering into a single platform.[14]

Browser histories are not available for all job-seekers, with differential availability across experimental arms (see Appendix Table A10).[15] Appendix Table A12 presents Lee (2009) bounds to account for potential selection bias, confirming the robustness of our findings. The consistent negative treatment effects on websites visited across these bounds further support

[13] Percentages sum up to more than 100% as prompts could refer to multiple sections at once.

[14] Appendices A.1.8 and A.1.9 report the effects of LLM usage on the time taken to write a cover letter, as well as its complexity. No statistically significant results are found, expect for LLM usage increasing the average word length within cover letters.

[15] When collecting browser history and ChatGPT conversations, 18 computers did not contain any recorded history.

the conclusion that ChatGPT usage substantially alters online information-seeking behavior during the cover letter writing process.

Table 3: Browser History

	(1)	(2)	(3)	(4)	(5)	(6)
	# Websites Visited	# Google Searches	Searched: Firm	Searched: Cover Letter	Searched: Grammar	Searched: Translation
ChatGPT	-7.422***	-5.120***	-1.825	-1.140	-2.427***	-1.280
	(2.215)	(1.320)	(1.169)	(0.692)	(0.631)	(0.749)
Control Group Mean	19.351	10.000	5.281	2.368	2.895	2.175
Observations	119	119	119	119	119	119

Notes: Intention to Treat estimates. Column 1 reports treatment treatment effects on the total number of websites visited, while Column 2 refers to the number of google searches. Columns 3-6 refer to whether the subject searched the relevant topic. Treatment effects are reported from OLS regressions. Standard errors are clustered at the individual level. PD Lasso machine learning technique is used to select control variables (Belloni et al., 2014), along with firm and school-level fixed effects. Control mean refers to the mean value of the outcome in the control group. Robust standard errors are in parentheses. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

Lastly, we examine whether adherence to the ChatGPT training influenced cover letter quality, aiming to disentangle the effect of LLM usage from the guidance job-seekers received.[16] To assess the impact of training adherence, we use OpenAI's API to perform sentiment analysis on job-seekers' conversation histories with ChatGPT, measuring the extent to which they applied the suggested prompting techniques. Table 4 reports the normalized treatment effect of compliance with the ChatGPT training on cover letter quality. The results show no significant relationship between training adherence and cover letter scores. This suggests two possibilities: either improved prompting does not meaningfully enhance cover letter quality in this context, or our training was insufficiently effective in teaching techniques that translate into better outcomes.[17] These precisely estimated null results reinforce our confidence that the observed treatment effects are primarily driven by ChatGPT usage rather than the training itself.

[16] We initially planned to include a third experimental arm in which job-seekers received the same training as the control group but were also allowed to use ChatGPT for their cover letters. This treatment was pre-registered in the AEA RCT Registry (AEARCTR-0013355). However, due to power concerns, we dropped this arm before the experiment began.

[17] The training's content is similar to that recommended by OpenAI (see here, despite being developed independently, 10 months earlier.

Table 4: Effect of ChatGPT Training on Results

	(1)	(2)	(3)	(4)	(5)	(6)
	Cover Letter					
	Total	Layout	Intro	Experience	Motivation	Closing
ChatGPT Training Compliance	-0.001	0.021	0.046	-0.111	-0.010	0.046
	(0.100)	(0.115)	(0.084)	(0.070)	(0.099)	(0.107)
Control Group Mean	-0.056	-0.051	-0.090	0.009	-0.021	-0.094
Observations	82	82	82	82	82	82

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions. All regressions include strata variables and imbalanced baseline variables as controls, along with recruiter and school-level fixed effects. Standard errors are clustered at the individual level. Control mean refers to the mean value of the outcome in the control group. Robust standard errors are in parentheses. Columns 1-6 refer to variables as described in Appendix B.1.3. ChatGPT training compliance is a 10-point scale indicating whether individuals applied the ten techniques discussed for effective prompting, see B.1.2 ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

4 Recruiter Experiment: Perceptions of AI

The first experiment reveals that while job applicants benefit from using LLMs in their cover letters, the improvements are limited to the less critical sections. As a result, these enhancements do not significantly impact the likelihood of securing a job interview. However, it remains unclear if recruiters can detect AI-generated cover letters and what their attitudes towards LLM usage are. Strong preferences could bias hiring decisions, leading to outcomes based on the recruiters' perceptions rather than quality of the job-seeker's signal. This raises an important question: what happens to recruiters' evaluations of cover letters if they are explicitly informed that some applicants used LLMs? To address this, we run a second experiment with 401 recruiters on Prolific, examining the role of LLM disclosure and its potential influence on recruiters' decisions.[18]

[18] Among the recruiters, 65.3% are from the United Kingdom, while the remaining 34.7% come from various European countries: Germany, Italy, Portugal, Spain, France, the Netherlands, Ireland, the Czech Republic, Denmark, Finland, Switzerland, Belgium, Austria, and Sweden. All recruiters work in Human Resources, are fluent in English, and have been active on Prolific within the past 90 days.

4.1 Experimental Design

The recruiters are assigned to evaluate five pseudonymized cover letters, and are asked to evaluate each cover letter using the same grading rubric as recruiters in the job-seeker experiment.[19] The cover letters are drawn from the sample of cover letters that were written by job-seekers in the job-seeker experiment.[20] 84% of recruiters are employed either full- or part-time, 59% identify as female, with an average age of 37.[21] They are randomized across three treatments: *No Information*, *Partial Information*, and *Full Information*.

In the *No Information* treatment, recruiters are asked to evaluate the quality of the cover letters without receiving further information about the nature of the job-seeker experiment. This captures the naive setup, where recruiters are unaware of the two experimental arms, and hence are in the same situation as the recruiters in the job-seeker experiment (and real world). In *Partial Information*, recruiters are told that some cover letters were written with the assistance of ChatGPT, while others were not. In addition to evaluating the quality of the cover letters, recruiters in this treatment are asked to identify which cover letters are written with ChatGPT's assistance. In *Full Information*, recruiters are informed precisely which cover letters are written with the assistance of ChatGPT. This explores the scenario where applicants have to disclose LLM use in their application (which 49% of recruiters are in favor of), or if humans were able to diagnose the use of LLMs, and hence how recruiters respond to the use of LLMs by job-seekers.

By comparing *No Information* and *Partial Information*, we observe whether priming recruiters on the potential use of ChatGPT influences their perception of the cover letter's quality. In line with the fact that recruiters already believed that 61% of applicants use LLMs in their job applications, we find no differences between *No Information* and *Partial Information* (see Appendix A.2.6). Furthermore, in only 49% of cases in the *Partial In-*

[19]Recruiters are paid a fixed fee. This is in line with Carvajal et al. (2024), and several other recent studies that use unincentivized measures (Ameriks et al., 2020; Andre et al., 2022; Stango and Zinman, 2023), motivated by the literature finding limited differences between real-life behavior and related unincentivized measures (Brañas-Garza et al., 2021, 2023; Falk et al., 2023).

[20]Six cover letters are selected from both the control and treatment group in the job-seeker experiment. Cover letters are chosen such that for both treatment and control, two cover letters are from the bottom, middle, and top tercile of the total grade distribution. Furthermore, an even gender split was ensured, and all cover letters applied to the same job description. The average grades of the cover letters, as evaluated by the recruiters in the job-seeker experiment, are 5.90 vs. 5.85 for control and treatment groups ($p = 0.95$).

[21]A recruiter in our study had participated in 540 other studies on Prolific, took 20 minutes to complete the survey, and received an hourly payment of $13.21, on average.

formation treatment did recruiters correctly identify whether the cover letter was written with the assistance of LLMs, statistically indistinguishable from guessing ($p = 0.5114$).[22] This provides evidence that while recruiters are aware that applicants use LLMs in their job applications, they are unable to identify which applicant actually uses LLMs.[23]

To ease interpretation of results, we will therefore only compare the *Full Information* and *Partial Information* treatments, excluding the *No Information* group - as we are primarily interested in the response of recruiters when they know ChatGPT has been used, versus knowing specifically which applications have used ChatGPT.[24] We run the following OLS specification to estimate the treatment effect of *Full Information* on the recruiter's evaluation of the applicant's cover letter and likelihood of getting interviewed:

$$Y_{a,r} = \beta_0 + \beta_1 FullInfo_r + \gamma X_r + \mu_a + \varepsilon_{a,r} \tag{2}$$

where $Y_{a,r}$ is the outcome variable for the cover letter written by job applicant a, evaluated by recruiter r. $FullInfo_r$ is an indicator equal to one if the recruiter is assigned to the *Full Information* Treatment, and 0 if the recruiter is assigned to the *Partial Information* Treatment. We control for the recruiter's age and sex (X_r) and job applicant-level fixed effects (μ_a). We cluster standard errors at the recruiter level since each recruiter evaluates multiple cover letters, creating potential correlation in the error terms across observations from the same recruiter.[25] Estimation is by OLS, except for when the outcome variable is *Likelihood of Interview* and *High Chance of Interview*, which are an ordered logit, and logit regression, respectively.

[22] The ability to correctly detect LLM usage is uncorrelated with the recruiter's confidence at being able to detect LLM usage ($\rho = 0.0292, p = 0.7409$).

[23] Young recruiters (below the median age) are more confident in their ability to detect LLM usage than older applicants ($p = 0.0405$), however we detect no statistically significant difference in their actual ability to detect LLM usage ($p = 0.8700$). Male and female recruiters are statistically indistinguishable in both their confidence and ability to detect LLM usage ($p = 0.5106$ and $p = 0.5829$, respectively).

[24] Appendix A.2.6 reports the regression results of the regression comparing *No Information*, *Partial Information*, and *Full Information*.

[25] Table A31 reports treatment effects without clustering.

4.2 Results

Table 5 reports average treatment effects of the *Full Information* treatment on the quality of the cover letter and likelihood of inviting the candidate to an interview, separately for all cover letters (Panel A), cover letters written without the assistance of ChatGPT (Panel B), and cover letters written with the assistance of ChatGPT (Panel C). While the *Full Information* treatment does not result in a higher evaluation of the overall grade of the cover letter (Panel A, Column 1), recruiters do evaluate the Experience and Closing sections of the cover letter higher. Despite no difference in the evaluation of the overall quality of the cover letters, recruiters are more likely to invite job-seekers to the next stage of the recruitment process in the *Full Information* treatment, as indicated by the statistically significant increase in the likelihood, and high chance, of inviting the candidate to an interview (Panel A, Columns 7 and 8).

Table 5: Main Results: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Cover Letter			Likelihood of	High Chance of
	Total	Layout	Intro	Experience	Motivation	Closing	Interview	Interview
Panel A. All Cover Letters (N=1345)								
Full Info	0.09	0.12	0.10	0.12*	0.07	0.12*	0.22*	0.26**
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.11)	(0.12)
Control Group Mean	0.00	-0.00	-0.00	0.00	0.00	-0.00	3.37	0.50
*Panel B. Cover Letters Written **WITHOUT** ChatGPT Assistance (N=676)*								
Full Info	0.08	0.17*	0.12	0.11	0.12	0.14	0.38**	0.50***
	(0.08)	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.15)	(0.17)
Control Group Mean	0.00	-0.09	-0.02	-0.01	-0.02	0.00	3.35	0.50
*Panel C. Cover Letters Written **WITH** ChatGPT Assistance (N=669)*								
Full Info	0.09	0.06	0.07	0.13	0.03	0.09	0.07	0.05
	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.15)	(0.16)
Control Group Mean	-0.00	0.09	0.02	0.01	0.02	-0.00	3.39	0.51

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses, and are clustered at the recruiter-level. Column 1-7 refer to variables as described in Appendix B.1.3, while Column 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

Decomposing this overall treatment effect into cover letters that were written with and without ChatGPT assistance (which recruiters in the *Full Information* treatment were explicitly told, while this was not the case in the *Partial Information* treatment), we observe that the positive treatment effects are entirely driven by those cover letters written without the assistance of ChatGPT. Despite the average evaluation of the cover letter's quality not increasing (Panel B, Column 1), we document statistically significant increases in the likelihood of inviting the candidate to a job interview (Panel B, Columns 7 and 8). For cover letters that were written with ChatGPT assistance, we do not observe statistically significant effects when recruiters are informed that the cover letter was written with the assistance of ChatGPT. This indicates that recruiters are not penalizing applicants for using LLMs, but instead reward applicants that do not use them.[26]

Taking advantage of our experimental design, we can gain further insights into what sort of cover letters are evaluated differentially when recruiters are made aware of LLM usage. The cover letters selected from the job-seeker experiment were balanced across LLM usage vs. not, but also balanced in terms of their quality. For cover letters written both with and without the assistance of ChatGPT, two were chosen from the bottom, middle, and upper tercile, respectively. Hence we have comparable heterogeneity in the quality of cover letters. Appendix A.2.5 decomposes the average treatment effects from Table 5 for cover letters that scored in the lower and middle tercile, with no statistically significant effects of revealed LLM usage on the recruiters' evaluation of the quality of the cover letter. Nevertheless, recruiters are more likely to invite applicants with average-quality cover letters to an interview when informed that the cover letter was written without LLM assistance. This suggests that awareness of LLM usage influences recruitment decisions, specifically whether an applicant is invited for an interview. While the use of LLM itself does not directly affect hiring decisions or labor market outcomes, knowledge of its use may have negative consequences for job-seekers.

Table 6 reports treatment effects on high quality cover letters, as identified by recruiters in the job-seeker experiment. Panel A documents large positive treatment effects on both the quality of the cover letter, and the likelihood of being invited to a job interview, as a result of the *Full Information* treatment. Decomposing the positive treatment effects of Panel A (where only Column 3 is marginally insignificant, at $p = 0.105$) across cover letters that were

[26] Appendix A.2.2 decomposes treatment effects by the gender of the recruiter, as well as their age. The positive treatment effects are primarily driven by female and older recruiters.

written with and without the assistance of ChatGPT highlights a stark contrast. Informing recruiters that a (high-quality) cover letter was written with the assistance of ChatGPT did not have a statistically significant effect on the evaluation of the cover letter, or the likelihood of inviting the applicant to a job interview, see Panel C. However, informing recruiters that the (high-quality) cover letter was written without the assistance of ChatGPT increases the rating of the cover letter by 0.24 standard deviations (Panel B, Column 1). All dimensions of the cover letter are evaluated more positively (Columns 2-6), which subsequently translate into large and highly significant increases in the likelihood of inviting the candidate to a job interview (Columns 7-8). Therefore, recruiters reward, high-quality cover letters when they are certain that they are written independently, without LLM assistance.

Further support comes from the finding that recruiters in the *Full Information* treatment place more importance on the CV in case the cover letter was of high quality and written with the assistance of ChatGPT (see Appendix Table A15), which implies that recruiters feel the need to put in additional effort (in the form of time needed to read the CV) to evaluate the applicant's true ability. This can be rationalized by their inability to credit a high-quality cover letter to the applicant's ability when they know the cover letter is written with LLM assistance.

In summary, we observe that recruiters are unable to correctly identify the use of LLMs in job applications: they perform no better than chance. Combined with the observation that recruiters believe that over 60% of job applicants use LLMs in their job applications, recruiters' evaluations of cover letters do not change after they are primed that some applicants may use LLMs when writing their cover letters. However, when recruiters are informed which job-seekers used LLMs, their evaluations of the quality of the cover letter, and likelihood to invite the applicant to a job interview, adjust. Disclosing LLM usage has no effect on the perceived quality of low- and medium-quality cover letters, but recruiters evaluate high-quality cover letters more positively when these are not written with the assistance of LLMs. This sizable increase in perceived quality also translates into a far greater likelihood of inviting the job applicant to an interview.

Table 6: Main Results: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation - Upper Tercile

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Cover Letter			Likelihood of	High Chance of
	Total	Layout	Intro	Experience	Motivation	Closing	Interview	Interview
Panel A. All Cover Letters (N=449)								
Full Info	0.18**	0.25***	0.15	0.20**	0.18**	0.16*	0.36**	0.49**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.16)	(0.19)
Control Group Mean	0.14	0.11	0.11	0.15	0.09	0.09	3.56	0.55
Panel B. Cover Letters Written ***WITHOUT*** *ChatGPT Assistance (N=230)*								
Full Info	0.24**	0.36***	0.22*	0.22*	0.25**	0.26**	0.63***	0.82***
	(0.11)	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.24)	(0.30)
Control Group Mean	0.27	0.11	0.19	0.28	0.18	0.26	3.67	0.60
Panel C. Cover Letters Written ***WITH*** *ChatGPT Assistance (N=219)*								
Full Info	0.12	0.15	0.08	0.18	0.11	0.06	0.09	0.20
	(0.13)	(0.12)	(0.14)	(0.13)	(0.13)	(0.13)	(0.22)	(0.26)
Control Group Mean	-0.01	0.11	0.02	0.02	0.01	-0.09	3.45	0.51

Notes: Intention to Treat estimates, for the upper tercile quality cover letters, as evaluated by recruiters in the job-seeker experiment. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses and are clustered at the recruiter-level. Column 1-7 refer to variables as described in Appendix B.1.3, while Column 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

5 Assignment Model with Imperfect Information and LLMs

Our experiments highlight the effects of LLMs at a specific moment and under an exogenous adoption rate of this new technology. To better understand potential efficiency losses arising from the use of LLMs during the application process, we run a calibration exercise. We apply the introduction of LLMs to a static one-to-one assignment model with imperfect information, where firms cannot directly observe workers' true abilities and instead rely on noisy signals. Based on our findings from the first experiment, we introduce LLMs as a new signal-enhancing technology, which disproportionately improves the signals of lower-ability workers, creating a non-linear shift in the distribution of signals (cover letter) received by firms. Firms form Bayesian estimates of worker abilities based on these signals, and matches are determined by positive assortative matching based on these estimates. Our exercise shows that while LLMs may improve signals for some workers, the resulting non-linear distortion introduces additional uncertainty for the firms, ultimately reducing aggregate matching efficiency relative to scenarios with either perfect information or symmetric noise.

The static economy consists of a continuum of workers, indexed by their quality s and distributed with CDF G_s, and a continuum of firms, indexed by their quality x and distributed with CDF G_x. We assume that both G_s and G_x admit densities denoted by g_s and g_x and have positive and bounded supports $\mathcal{S} := [\underline{s}, \overline{s}]$ and $\mathcal{X} := [\underline{x}, \overline{x}]$. The value of a match between a worker of type s and a firm of type x is given by $f(x, s)$ which satisfies Assumption 1:

Assumption 1. We assume that f is increasing, concave in both arguments, and features complementarity:[27]

$$f(x', s') - f(x, s') \geq f(x', s) - f(x, s) \; \forall s' \geq s \; \forall x' \geq x \tag{3}$$

Equation (3) means that an incremental gain in the value of a match to having a higher x (x' instead of x) is higher when s is higher (s' instead of s). The reverse is also true: having a higher s increases the value of a match when x is also higher. As such, our model implies a degree of complementarity between firms and workers, meaning that the best firms will be matched with the best workers, and the worst firms with the worst workers.

We assume that firms do not observe workers' true abilities. Instead, each worker sends a noisy signal of her ability to all firms. After observing these signals, the firms form a positive assortative matching based on the estimated worker qualities, denoted by $\tilde{s}$. The assignment in this economy is given by a function $x = \sigma(\tilde{s})$, which matches each worker s to a firm x according to the firm's estimate $\tilde{s}$. In equilibrium, all firms and workers must be matched one-to-one.[28] Hence, the assignment of a firm x to an estimated worker quality $\tilde{s}$ is deterministic and expressed by $x = \sigma(\tilde{s}) = G_x^{-1}(G_{\tilde{s}}(\tilde{s}))$ where $G_{\tilde{s}}$ is the distribution of estimated qualities of all workers. All randomness in matching then stems purely from the noise in the workers' signal, which causes the estimated $\hat{s}$ to deviate from the true worker

[27]This definition of complementarity is also known as weak supermodularity, and is equivalent to a non-negative cross derivative when it exists: $f_{xs} \geq 0$.

[28]Consequently, σ must be *measure-preserving*, ensuring an equal mass of workers and firms. See Appendix E for further details on the derivation of the assignment rule.

quality. In other words, conditional on the specific signal generated by a job-seeker, their matching to a particular firm is deterministic. Intuitively, this corresponds to a setting where each worker sends a single application (containing their noisy signal) to all firms, and neither the application nor vacancy-posting process generates additional costs in our model.

We make the following assumptions about the signals. A fraction p of workers sends a noisy linear signal, with the noise having zero mean and being uncorrelated with the worker's true ability. This fraction represents the portion of the population who either do not have access to, or choose not to adopt, LLM technology. In contrast, a fraction $1-p$ of the population has access to a technology (LLMs) that improves the quality of their signals.[29] These workers send a nonlinear signal that is increasing in their true ability. Consider a worker of true quality s. With probability p, the worker does not use LLM technology to enhance the signal. The signal y observed by firms is thus given by

$$y = \begin{cases} y_1 = s + e & \text{with probability } p, \\ y_2 = h(s+e) & \text{with probability } 1-p. \end{cases} \tag{4}$$

In our first experiment with job-seekers, we find that LLMs primarily improve the signals of low-ability workers while leaving high-ability workers' signals essentially unaffected. Motivated by this, we impose the following assumption on the function h.

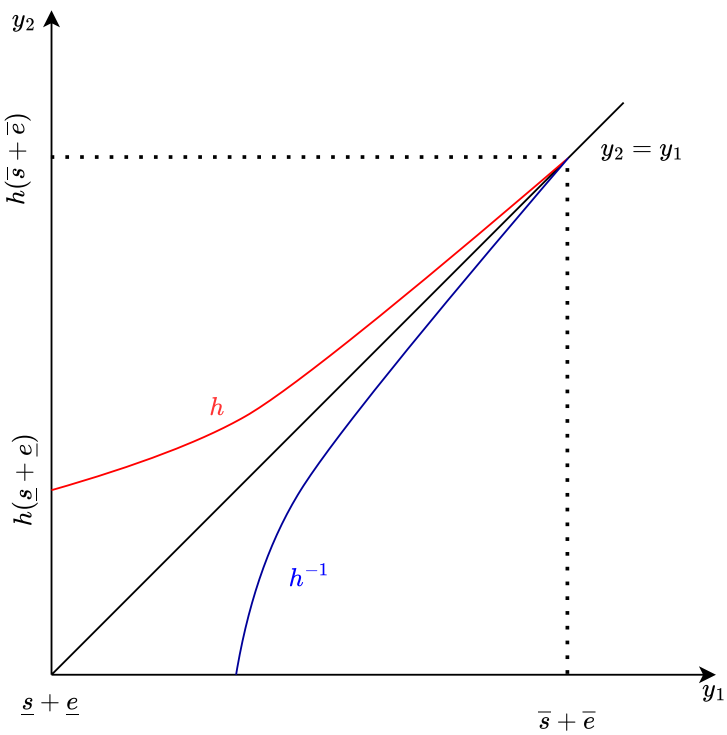
Assumption 2. $y_2 = h(y_1)$ is a continuous function that satisfies

1. $h(y_1) \geq y_1$ for all y_1
2. $0 < h'(y_1) < 1$ for all y_1
3. $\overline{y} := h(\overline{s} + \overline{e}) = \overline{s} + \overline{e}$

Assumption 2 implies that the technology used to increase the value of signals improves low-quality signals by a higher amount than high-quality ones, as we observed in the job-seeker experiment. An illustration h is shown in Figure 3.

[29]For simplicity, we assume that the probability of adopting the technology is independent of s and x.

Figure 3. Illustration function h



An important feature of this information structure is that firms only observe signal y from workers without knowing whether the signal is augmented by LLMs or not. This is supported by our second experiment, where we find that recruiters are no better than chance at identifying whether a job application package was written with LLM assistance or not.

From the signal y, firms form a Bayesian estimate of the worker's ability $\tilde{s}(y) = \mathbb{E}[s|Y = y]$ without knowing whether the signal was generated by LLMs or not. That is, unless the signal takes a value less than a lower bound $\underline{y}_2 := h(\underline{s} + \underline{e})$, in which case the firm can know with certainty that the signal was not generated with the assistance of LLMs (see Figure 3). For all other signal values, the law of total expectation is used to decompose firms' estimates on the job-seekers' quality:

$$\tilde{s}(y) = p\mathbb{E}[s|Y_1 = y] + (1 - p)\mathbb{E}[s|Y_2 = y] \tag{5}$$

Equation (5) shows that without additional knowledge about whether or not LLMs has been used, firms assign their prior probability of p to it not being used, and $1-p$ to it being used. We denote the first expectation in Equation (5) by $\hat{s}(y) := \mathbb{E}[s|Y_1 = y]$. This expectation coincides with the estimate of a workers' ability in the absence of LLMs, i.e. when LLMs are not used by any job applicant and the firms know this.

Since h is monotonic and thus invertible, the second conditional expectation is equivalent to $\mathbb{E}[s|Y_1 = h^{-1}(y)] = \hat{s}(h^{-1}(y))$.[30] Therefore, the estimate of workers' ability can be written as:

$$\tilde{s}(y) = \begin{cases} \hat{s}(y) & , \text{ for } y \leq \underline{y}_2 \\ p\hat{s}(y) + (1-p)\hat{s}(h^{-1}(y)) & , \text{ for } y \geq \underline{y}_2 \end{cases} \tag{6}$$

Since $h^{-1}(y) \leq y$ we have the following inequality

$$\tilde{s}(y) < \hat{s}(y), \quad \underline{y}_2 \leq y < \overline{y} \tag{7}$$

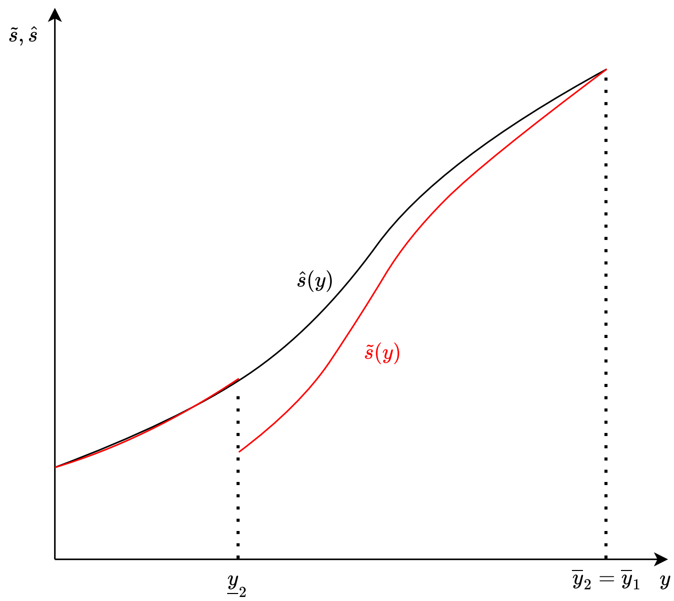
which, as illustrated in Figure 4, shows that for the range of signal values where the signal could have been augmented by LLMs ($\underline{y}_2 \leq y < \overline{y}$), firms form a lower estimate of workers' ability than the case where all signals are generated without LLM assistance.

For the range of signal values where firms cannot ascertain whether the signal was augmented by LLMs, they form a universally lower estimate of worker ability compared to the case without LLM assistance. This occurs because firms' Bayesian estimates incorporate the possibility of augmentation, effectively discounting the observed signal, leading to less informative signals. Consequently, while LLMs improve the quality of lower signals, they introduce a new form of uncertainty, which can negatively affect firms' perceptions of worker ability within this range.

[30] To see this, consider $\mathbb{E}[s|Y_2 = y] := \int s g_{s|y_2}(s|y)\mathrm{d}s$, and the CDF of y_2 can be written as $G_{y_2}(x) = \Pr\{Y_2 \leq x\} = \Pr\{h(s+e) \leq x\} = \Pr\{y_1 \leq h^{-1}(x)\} = G_{y_1}(h^{-1}(x))$. Similarly $G_{y_2|s}(x|s) = G_{y_1}(h^{-1}(x)|s)$. Then by Bayes' rule:

$$g_{s|y_2}(s|y) = \frac{g_{y_2|s}(y|s)g_s(s)}{g_y} = \frac{g_{y_1|s}(h^{-1}(y)|s)g_s(s)}{g_{y_1}(h^{-1}(y))} \equiv g_{s|y_1}(s|h^{-1}(y))$$

Figure 4. Comparison of $\tilde{s}$ and $\hat{s}$



The total value in this economy with imperfect information and LLMs is given by,

$$V_L = \int_{\mathcal{S}} \int_{\mathcal{S}} f(G_x^{-1}(G_{\tilde{s}}(\tilde{s})), s) \mathrm{d}G_{\tilde{s}|s}(\tilde{s}|s) \mathrm{d}G_s(s) \tag{8}$$

Proposition 1. *The total value in the economy with imperfect information and LLMs is lower than the total value of an economy with only imperfect information.*

Proposition 1 states that the aggregate value in the economy with imperfect information and LLMs (V_L) is at most equal to the value in the economy with imperfect information without LLMs.[31] This result reflects the fact that while LLMs can enhance the signals for some workers, the ambiguity created by the inability of firms to distinguish augmented signals from non-augmented ones leads to systematically lower worker ability estimates for certain signal ranges. This downward bias in estimates causes suboptimal matches, particularly due to the concavity and complementarity of the match value function f, thereby reducing overall output. Hence, since LLMs reduce individual disparities in signals, their aggregate effect may still fail to surpass the output of the imperfect information economy without LLM assistance.

[31] See Appendix E for details and proof.

5.1 Calibration

To quantify the efficiency losses as a result of LLMs with imperfect information, we calibrate parameters of the model and simulate the output losses. We assume a CES function for the value generated by the match of a firm and a worker, following Eeckhout and Kircher (2018), $f(x, s) = [\alpha x^{\rho} + (1-\alpha)s^{\rho}]^{1/\rho}$. Table 7 reports the parameters and the moments used in the calibration.

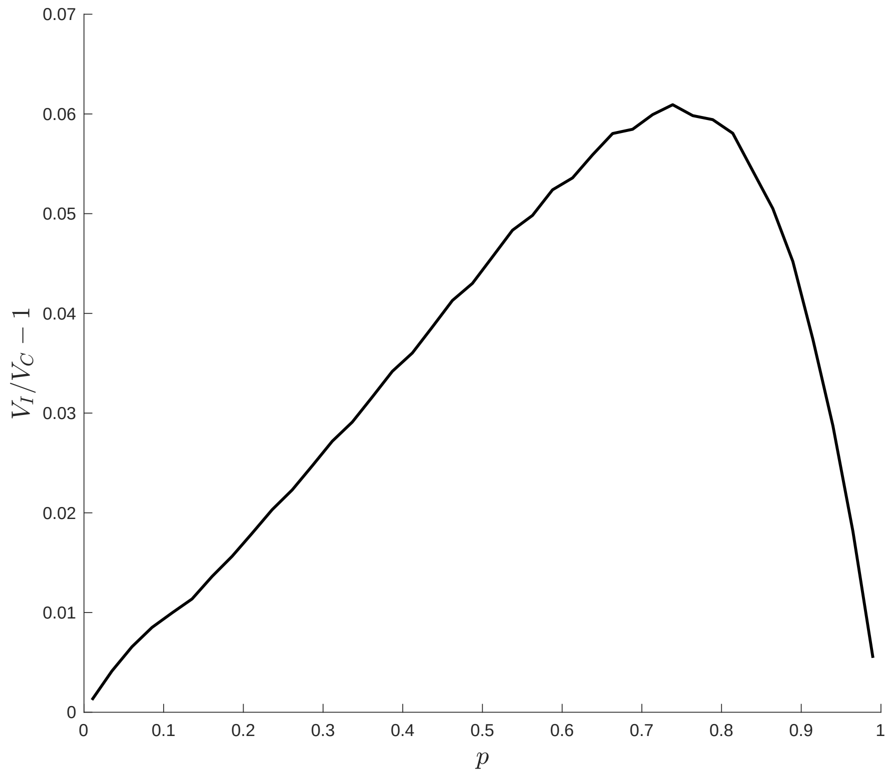
Figure 5 plots the efficiency loss as a result of LLMs on the vertical axis, as a percentage with respect to the efficiency in the case of positively assortative matching (PAM) with imperfect information but *without* LLMs (denoted by V_I). On the horizontal axis, p (the proportion of job-seekers that do *not* us LLMs) ranges from 0 to 1. Efficiency losses can amount to 6%, when approximately 30% of job-seekers use LLMs. In the job-seeker and recruiter experiments, the proportion of cover letters written with LLM assistance were 47% and 50%, respectively, which would result in approximately 4% efficiency losses. Figure 5 shows that the LLM-induced misallocation is not symmetric with respect to the proportion of job-seekers that use LLMs. Instead, once LLM adoption exceeds 30%, matching efficiency improves much more slowly than it deteriorated when LLM usage approached 30%. These results indicate that while LLM usage introduces moderate inefficiencies, these losses are not negligible.

Table 7: Calibration Parameters

Parameter	Source	Value
Production Function	Eeckhout and Kircher (2018)	$\alpha = 0.5; \rho = 0.5$
Distribution of Worker Type	Teulings (1995)	$N(5.59, 1.29)$
Distribution of Firms Type	Teulings (1995)	$N(0, 1)$
Slope of h function	Experiment #1	0.61

Notes: From the control group's cover letters in Experiment #1, we have $\mathbb{E}[y_1] = 5.59$ and $Var[y_1] = 2.61$. Since $y_1 = s + e$ and e is assumed to have 0 mean, we get $E[s] = 5.59$, which we use to calibrate the moments of the workers' type distribution. To get the slope of the h function we first calculate the quantile treatment effect (Figure 1) for each 5-th percentile, then we regress the percentiles on the treatment effects and a constant. The slope of the h function is then one minus the estimated slope coefficient, which is -0.39.

Figure 5. Sensitivity of Misallocation to p



6 Conclusion

The emergence of Large Language Models has the potential to significantly impact productivity and reshaped labor market dynamics. LLMs are widely adopted, with Bick et al. (2025) documenting that nearly 40% of the US working-age population is using them, and 23% of employees using them at least once at work in the last week. However, their influence on labor market signals and subsequent matching efficiency remains largely unexplored. This paper addresses this gap by conducting two field experiments involving job-seekers and recruiters, the findings of which inform a calibration exercise of an assignment model with incomplete information and LLM usage.

In our job-seekers' experiment, we find that access to OpenAI's ChatGPT improves the average quality of cover letters. However, these gains do not translate to improved chances of receiving a job interview, as the ChatGPT-induced improvements are limited to less critical and personalized sections of the cover letter.[32] To understand how recruiters perceive job-seekers' use of this technology, our second experiment asked recruiters to evaluate cover letters while varying the degree of disclosure regarding whether ChatGPT was used. On average, we find no significant difference in evaluations based on the degree of disclosure. However, high-quality cover letters written without ChatGPT were evaluated more positively when recruiters were aware of this, suggesting that recruiters place a premium on high-quality applications when it is evident that the cover letter was written without LLM assistance.

Combined, our experimental results reveal important non-linearities in how LLMs impact job applicants. Lower-ability candidates clearly benefit from LLM assistance, whereas applicants already producing high-quality cover letters experience little improvement or may even be disadvantaged if recruiters become cautious about AI-generated content. These nuanced effects inform our model, which examines the broader welfare implications of widespread LLM adoption under conditions consistent with our experimental observations. Within this model and calibration, we find that LLM usage consistently reduces overall welfare by distorting labor market matching: lower-ability applicants appear more skilled than they are, placing them in roles demanding higher qualifications, while genuinely high-quality applicants become mismatched into positions for which they are overqualified. Although some firms seeking lower-skilled employees might occasionally benefit from this misalignment, the net effect is a reduction in aggregate welfare relative to a baseline scenario with imperfect information but no LLM assistance.

The findings from the two experiments and calibration are important, given that generative AI is still in its early stages, with limited regulation and uncertain future norms. However, if regulations mandating explicit disclosure of AI use—such as those currently being studied by the European Union—become widespread, the conditions in our *Full Information* treatment may resemble future reality.[33] Insights from this paper are likely to extend beyond the labor market, to situations in which a decision-maker cannot fully observe an applicant's ability. One such example is university admission essays. Universities have taken different approaches to the use of LLMs in admissions applications, ranging from bans to guidance on how to use them.[34] While the domain is different from our setting, the un-

[32] An analogy can be drawn to *grade inflation*, as a result of which the signal (in this case, one's grades) are less informative.

[33] Several academic journals and university admissions teams already require AI disclosure.

[34] The University of Michigan Law School bans AI tools in their applications, while Arizona State University

derlying characteristics—applicants submitting written texts outlining their motivation and qualification, and evaluators not knowing whether LLMs were used or not—are very similar. As such, our findings, in particular the heterogeneous effects of LLM assistance on the signal's quality and the importance of recruiters' knowledge and perception of LLM usage, can extend to other contexts. This is particularly important during the transitional phase we find ourselves in with LLMs, where models are constantly improving, and individuals and firms are still understanding use cases, best practices, and policies in response to them.

Given the accelerating capabilities of generative AI—our study employs the freely accessible ChatGPT 3.5, which is already outdated by newer, more advanced models—our results likely represent a conservative estimate of the technology's future impact. Therefore, the impact of generative AI on labor market signals and matching presents numerous promising avenues for future research, as our results suggest that the winners and losers can depend on the user's innate ability, perceptions of evaluators, and disclosure policies.

Law School allows applicants to use them as long as they disclose them, and Georgia Tech offers AI guidance to applicants (The Guardian, 2023).

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Online Appendix to:

Labor Market Matching in the Time of LLMs

by Kian Abbas Nejad, Giuseppe Musillo, Till Wicker, and Niccolò Zaccaria

A Figures and Tables

A.1 Job-seeker Experiment

A.1.1 Balance Table

Table A1: Balance Table: Demographics

		(1)		(2)	(1)-(2)
		Control		***Treatment***	Pairwise t-test
Variable	N	Mean/(SD)	N	Mean/(SD)	P-value
Dutch Speaker	72	0.236	65	0.200	0.613
		(0.428)		(0.403)	
GPA	72	7.505	65	7.557	0.644
		(0.669)		(0.639)	
English Ability	72	6.069	65	6.138	0.597
		(0.738)		(0.788)	
Masters Student	72	0.528	65	0.585	0.507
		(0.503)		(0.497)	
Age	72	23.597	65	23.123	0.457
		(4.023)		(3.347)	
Econ or Business Degree	72	0.750	65	0.738	0.878
		(0.436)		(0.443)	
Tilburg University	72	0.722	65	0.677	0.567
		(0.451)		(0.471)	
Female	72	0.486	65	0.538	0.544
		(0.503)		(0.502)	

Notes: Dutch speaker is a dummy variable equal to one if the student self-reports that they speak Dutch. GPA is on a scale from 0-10, and self-reported. English ability is on a scale from 1-7. Masters student is a dummy variable if the student is enrolled in a masters program. Age is the student's age. Econ or Business Degree is a dummy variable if the student is enrolled at Tilburg's School of Economics and Management, or Utrecht's School of Economics. Tilburg University is a dummy equal to one if the student is enrolled at Tilburg University. Female is a dummy equal to one if the student identifies as a female.

Table A2: Balance Table: CV Evaluation

		(1)		(2)	(1)-(2)
		Control		***Treatment***	Pairwise t-test
Variable	N	Mean/(SD)	N	Mean/(SD)	P-value
CV Grade	144	5.777	130	5.428	0.075*
		(1.567)		(1.663)	
CV: Layout	144	0.017	130	-0.019	0.768
		(0.997)		(1.007)	
CV: Education	144	0.107	130	-0.119	0.062*
		(1.000)		(0.991)	
CV: Experience	144	0.102	130	-0.113	0.077*
		(0.960)		(1.034)	
CV: Extra Curricular	144	0.081	130	-0.089	0.161
		(0.944)		(1.055)	

Notes: The sub-components of the CV are described in more detail in Appendix B.1.3. Evaluations of the sections are on a scale from 0-10.

A.1.2 Heterogeneity - By Gender

Table A3: Heterogeneous Results: Men vs. Women

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Cover Letter				Likelihood of	High Chance of
	Total	Layout	Intro	Experience	Motivation	Closing	Interview	Interview
ChatGPT	0.155	0.256	0.196	0.059	-0.030	0.211	0.194	0.047
	(0.176)	(0.208)	(0.191)	(0.153)	(0.185)	(0.193)	(0.354)	(0.522)
Female	-0.022	0.109	0.001	-0.026	-0.205	0.078	0.127	0.207
	(0.170)	(0.180)	(0.177)	(0.170)	(0.159)	(0.197)	(0.414)	(0.617)
ChatGPT*Female	0.123	-0.215	0.072	0.058	0.335	0.170	0.035	-0.087
	(0.236)	(0.276)	(0.239)	(0.222)	(0.237)	(0.244)	(0.577)	(0.875)
Control Group Mean	0.000	0.000	0.000	0.000	0.000	0.000	2.799	0.278
Observations	274	274	274	274	274	274	274	274

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include strata variables and imbalanced baseline variables as controls, along with recruiter and school-level fixed effects. Standard errors are clustered at the individual level. Control mean refers to the mean value of the outcome in the control group. Robust standard errors are in parentheses. Column 1-7 refer to variables as described in Appendix B.1.3, while Colummn 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). Female is a dummy variable equal to one if the job-seeker identifies as a female, and zero otherwise. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

A.1.3 Heterogeneity - By Economics Degree vs. Not

Table A4: Heterogeneous Results: Econ vs. Non-Econ degree

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Cover Letter			Likelihood of	High Chance of
	Total	Layout	Intro	Experience	Motivation	Closing	Interview	Interview
ChatGPT	0.267	0.360	0.152	-0.085	0.238	0.408	0.083	-0.298
	(0.247)	(0.259)	(0.197)	(0.296)	(0.267)	(0.256)	(0.669)	(0.886)
Econ/Business Degree	0.078	-0.067	-0.033	-0.077	0.229	0.231	0.904*	0.861
	(0.221)	(0.220)	(0.191)	(0.267)	(0.220)	(0.230)	(0.508)	(0.785)
ChatGPT*Econ/Business	-0.066	-0.279	0.107	0.228	-0.130	-0.150	0.128	0.451
	(0.282)	(0.303)	(0.252)	(0.323)	(0.292)	(0.287)	(0.724)	(1.009)
Control Group Mean	0.000	0.000	0.000	0.000	0.000	0.000	2.799	0.278
Observations	274	274	274	274	274	274	274	274

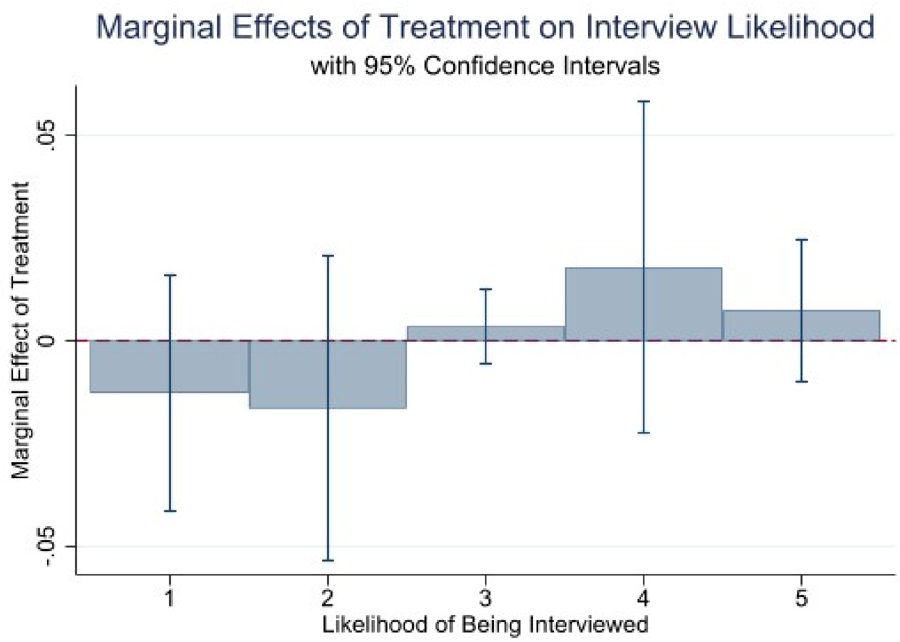
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include strata variables and imbalanced baseline variables as controls, along with recruiter and school-level fixed effects. Standard errors are clustered at the individual level. Control mean refers to the mean value of the outcome in the control group. Robust standard errors are in parentheses. Column 1-7 refer to variables as described in Appendix B.1.3, while Colummn 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). Econ/Business is a dummy variable equal to 1 if students are enrolled in Tilburg University's School of Economics and Management, or the Utrecht School of Economics. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

A.1.4 Marginal Treatment Effects: Likelihood of Interview

Figure A1. Marginal Treatment Effects: Likelihood of Interview



A.1.5 ChatGPT as a Recruiter

Table A5: ChatGPT as the Recruiter

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ChatGPT as the Recruiter							
	Cover Letter						Likelihood of	High Chance of
	Total	Layout	Intro	Experience	Motivation	Closing	Interview	Interview
ChatGPT	0.303***	0.252***	0.298*	0.212*	0.312**	0.440***	0.120	-0.099
	(0.108)	(0.090)	(0.151)	(0.121)	(0.131)	(0.137)	(0.085)	(0.112)
Control Group Mean	-0.156	-0.142	-0.148	-0.117	-0.151	-0.220	-0.071	0.009
Observations	137	137	137	137	137	137	137	137

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include strata variables and imbalanced baseline variables as controls, along with recruiter and school-level fixed effects. Standard errors are clustered at the individual level. Control mean refers to the mean value of the outcome in the control group. Robust standard errors are in parentheses. Column 1-7 refer to variables as described in Appendix B.1.3, while Colummn 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

A.1.6 Robustness: Double Lasso (Belloni et al., 2014)

Table A6: Double Lasso regression

	(1)	(2)	(3)	(4)	(5)	(6)
				Cover Letter		
	Total	Layout	Intro	Experience	Motivation	Closing
ChatGPT	0.218**	0.170	0.223**	0.094	0.129	0.296**
	(0.111)	(0.138)	(0.114)	(0.105)	(0.112)	(0.117)
Control Group Mean	0.000	0.000	0.000	0.000	0.000	0.000
Observations	274	274	274	274	274	274

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions. All regressions use the PD Lasso technique to identify controls, along with recruiter and school-level fixed effects. Standard errors are clustered at the individual level. Control mean refers to the mean value of the outcome in the control group. Robust standard errors are in parentheses. Column 1-6 refer to variables as described in Appendix B.1.3. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

A.1.7 Robustness: Bootstrap

Table A7: Bootstrap (200 reps)

	(1)	(2)	(3)	(4)	(5)	(6)
				Cover Letter		
	Total	Layout	Intro	Experience	Motivation	Closing
ChatGPT	0.222*	0.161	0.253**	0.075	0.150	0.281**
	(0.118)	(0.144)	(0.121)	(0.108)	(0.120)	(0.115)
Control Group Mean	0.000	0.000	0.000	0.000	0.000	0.000
Observations	274	274	274	274	274	274

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions. All regressions include strata variables and imbalanced baseline variables as controls, along with recruiter and school-level fixed effects. Standard errors are clustered at the individual level, and bootstrapped with 200 repetitions. Control mean refers to the mean value of the outcome in the control group. Robust standard errors are in parentheses. Column 1-6 refer to variables as described in Appendix B.1.3. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

A.1.8 Time Taken

Another dimension along which job-seekers using ChatGPT and not using ChatGPT could differ is the time taken to write the cover letter. If ChatGPT substitutes ones own writing, job-seekers can write cover letters more quickly. On the contrary, if job-seekers use ChatGPT to complement their own writing, the whole process can take longer. Table A8 reports average treatment effects for the time taken to write cover letters, with the use of ChatGPT reducing the amount of time job-seekers spent writing a cover letter by 2 minutes on average, a result which is not statistically significant. This null result is robust to winsorizing individuals that wrote for more than 60 and 75 minutes, the recommended time job-seekers had.

Table A8: Time Taken to Write Cover Letter

	(1)	(2)	(3)
		Time Taken	
	No wins.	Wins. 75 min	Wins. 60 min
ChatGPT	-2.120	-1.568	-0.327
	(1.815)	(1.679)	(1.422)
Control Group Mean	57.13	56.62	54.88
Observations	132	132	132

Notes: Intention to Treat estimates from OLS regressions. All regressions include strata variables and imbalanced baseline variables as controls, along with recruiter and school-level fixed effects. Standard errors are clustered at the individual level. Control mean refers to the mean value of the outcome in the control group. Robust standard errors are in parentheses. Time taken is the amount of time students took to write the cover letter. Columns 2 and 3 winsorize the time taken at 75 and 60 minutes, respectively. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

A.1.9 Length and Complexity of Cover Letter

Using LLMs as a writing aid can also impact the length and complexity of the cover letter, which in turn can influence the evaluations of their components. Table A9 reports average treatment effects of the LLM intervention on the cover letter's number of words, entropy, and average word length. The use of ChatGPT does not influence the length of the cover letter nor its entropy (a proxy for complexity), however the average word length increases significantly as a result of the use of ChatGPT.

Table A9: Length, Entropy, and Word Length

	(1) Length of Cover Letter	(2) Entropy	(3) Average Word Length
ChatGPT	0.163	0.100	0.476***
	(0.193)	(0.166)	(0.169)
Control Group Mean	0.000	0.000	0.000
Observations	137	137	137

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Intention to Treat estimates from OLS regressions. All regressions include strata variables and imbalanced baseline variables as controls, along with recruiter and school-level fixed effects. Standard errors are clustered at the individual level. Control mean refers to the mean value of the outcome in the control group. Robust standard errors are in parentheses. Length of the Cover Letter is the standardized number of words in the cover letter. Entropy is defined as Entropy $= -\sum_i p_i \log_2(p_i)$, where p_i is the frequency of character i in the cover letter. Average word length is the standardized average number of letters of words in the cover letter. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

A.1.10 Browser History

Balance Table: Those with vs. without browser history

Table A10: Balance Table: Browser History

	(1)		(2)		(1)-(2)
	Has Browser History		***No Browser History***		Pairwise t-test
Variable	N	Mean/(SD)	N	Mean/(SD)	P-value
Cover Letter Grade	119	-0.049 (1.070)	18	0.083 (0.960)	0.621
CV Grade	119	5.636 (1.670)	18	5.500 (1.727)	0.749
Assignment to Treatment	119	0.521 (0.502)	18	0.167 (0.383)	0.005***
Speaks Dutch	119	0.202 (0.403)	18	0.333 (0.485)	0.211
GPA	119	7.570 (0.640)	18	7.263 (0.695)	0.063*
English Proficiency	119	6.118 (0.750)	18	6.000 (0.840)	0.542
Masters Student	119	1.546 (0.500)	18	1.611 (0.502)	0.609
Age	119	23.101 (3.583)	18	25.167 (4.148)	0.027**
Econ/Business Degree	119	0.748 (0.436)	18	0.722 (0.461)	0.818
At Tilburg University	119	0.689 (0.465)	18	0.778 (0.428)	0.447
Female	119	0.521 (0.502)	18	0.444 (0.511)	0.548

Notes: Cover Letter and CV Grade are the average cover letter and CV grades, as evaluated by the recruiters. Assignment to Treatment is a dummy equal to one if the student was assigned to the ChatGPT treatment. Dutch speaker is a dummy variable equal to one if the student self-reports that they speak Dutch. GPA is on a scale from 0-10, and self-reported. English ability is on a scale from 1-7. Masters student is a dummy variable if the student is enrolled in a masters program. Age is the student's age. Econ or Business Degree is a dummy variable if the student is enrolled at Tilburg's School of Economics and Management, or Utrecht's School of Economics. Tilburg University is a dummy equal to one if the student is enrolled at Tilburg University. Female is a dummy equal to one if the student identifies as a female.

Lee Bounds (2009) Calculation

There is differential 'attrition' of the browser history across treatments. In the Control group, we have the browser history for 79.17% of the sample. In the Treatment group, we have the browser history for 95.38% of the sample. The differential attrition rate is 95.38% - 79.17% = 16.22%. This is equal to 16.22% / 95.38% = 17.00% of the Control Group sample.

To get a lower bound, we trim the top 17.00% of the control group (for each outcome variable). To get an upper bound, we trim the bottom 17.00% of the control group (for each outcome variable).

Table A11: Probability of Not Having Browser History

	(1) No Browser History
ChatGPT	-0.137**
	(0.053)
Control Group Mean	0.208
Observations	137

Notes: Intention to Treat estimates from OLS regressions. All regressions include strata variables and imbalanced baseline variables as controls, along with recruiter and school-level fixed effects. Control mean refers to the mean value of the outcome in the control group. Robust standard errors are in parentheses. No Browser History is a dummy variable equal to 1 if we were unable to obtain the browser history of the student, and zero otherwise. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

Table A12: Browser History

	(1) # Websites Visited	(2) # Google Searches	(3) Searched: Firm	(4) Searched: Cover Letter	(5) Searched: Grammar	(6) Searched: Translation
Panel A. Lee (2009) Upper Bound						
ChatGPT	-2.220	-1.939*	1.327*	0.545	-0.958**	0.486
	(1.425)	(0.906)	(0.552)	(0.363)	(0.317)	(0.268)
Control Group Mean	19.351	10.000	5.281	2.368	2.895	2.175
Observations	110	110	111	111	112	110
Panel B. Lee (2009) Lower Bound						
ChatGPT	-9.484***	-6.341***	-1.825	-1.140	-2.427***	-1.280
	(2.247)	(1.365)	(1.169)	(0.692)	(0.631)	(0.749)
Control Group Mean	19.351	10.000	5.281	2.368	2.895	2.175
Observations	112	111	119	119	119	119

Notes: Intention to Treat estimates. Column 1 reports treatment treatment effects on the total number of websites visited, while Column 2 refers to the number of google searches. Columns 3-6 refer to whether the subject searched the relevant topic. Treatment effects are reported from OLS regressions. Standard errors are clustered at the individual level. All regressions include strata variables and imbalanced baseline variables as controls, along with recruiter and school-level fixed effects. Control mean refers to the mean value of the outcome in the control group. Robust standard errors are in parentheses. Panels A and B correct for Lee (2009) bounds, as explained in Appendix A.1.10. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

A.1.11 No Clustered Standard Errors

Table A13: Main Results: Effect of ChatGPT on Cover Letter

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Cover Letter			Likelihood of	High Chance of
	Total	Layout	Intro	Experience	Motivation	Closing	Interview	Interview
ChatGPT	0.222**	0.161	0.253**	0.075	0.150	0.281***	0.249	0.011
	(0.095)	(0.116)	(0.099)	(0.098)	(0.100)	(0.092)	(0.259)	(0.414)
Control Group Mean	0.000	0.000	0.000	0.000	0.000	0.000	2.799	0.278
Observations	274	274	274	274	274	274	274	274

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include strata variables and imbalanced baseline variables as controls, along with recruiter and school-level fixed effects. Standard errors are robust. Control mean refers to the mean value of the outcome in the control group. Robust standard errors are in parentheses. Column 1-7 refer to variables as described in Appendix B.1.3, while Column 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

A.2 Recruiter Experiment

A.2.1 Balance Table

Table A14: Balance Table: Demographics and Duration

	(1)		(2)		(3)		(1)-(2)	(1)-(3)	(2)-(3)
	No Info		***Partial Info***		***Full Info***		Pairwise t-test		
Variable	N	Mean/(SD)	N	Mean/(SD)	N	Mean/(SD)	P-value		
Duration (mins)	132	20.290	132	19.230	137	20.224	0.409	0.959	0.448
		(10.066)		(10.733)		(10.736)			
Intro Duration (mins)	132	3.202	132	3.120	137	3.297	0.854	0.833	0.715
		(3.312)		(3.932)		(4.013)			
Age	132	36.879	132	37.697	137	35.911	0.556	0.479	0.200
		(11.072)		(11.499)		(11.324)			
Female	132	0.598	132	0.598	137	0.562	1.000	0.547	0.547
		(0.483)		(0.492)		(0.498)			
Full-/Part-time	132	0.826	132	0.833	137	0.861	0.871	0.424	0.525
		(0.381)		(0.374)		(0.347)			
Student	132	0.250	132	0.174	137	0.248	0.133	0.973	0.139
		(0.435)		(0.381)		(0.434)			

Notes: Duration is the total number of minutes that the recruiter spent on the experiment, while Intro Duration captures the duration in minutes that the recruiter spent on the introduction. Age is the recruiter's age. Female is a dummy equal to one if the student identifies as a female. Full-/Part-time is a dummy variable equal to one if the recruiter is employed in full- or part-time employment. Student is a dummy equal to one if the recruiter is a student.

A.2.2 Only Partial and Full

Table A15: Additional Results

	(1) Want to See CV	(2) Time Taken
Panel A. All Cover Letters		
Full	0.19	0.01
	(0.15)	(0.07)
Control Group Mean	4.33	-0.00
Observations	1345	1345
Panel B. Cover Letters Written ***WITHOUT*** *ChatGPT Assistance*		
Full	0.05	0.00
	(0.18)	(0.10)
Control Group Mean	4.34	0.04
Observations	676	676
Panel C. Cover Letters Written ***WITH*** *ChatGPT Assistance*		
Full	0.34*	0.01
	(0.18)	(0.08)
Control Group Mean	4.31	-0.04
Observations	669	669

Notes: Intention to Treat estimates from OLS regressions. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses. Column (1) reports the recruiter's need to see the CV (on a 7-point Likert scale), while Column (2) reports the normalized time taken by the recruiter to read and evaluate the cover letter. Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

A.2.3 Recruiters Heterogeneity

Table A16: Female Recruiters: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Cover Letter			Likelihood of	High Chance of
	Total	Layout	Intro	Experience	Motivation	Closing	Interview	Interview
Panel A. All Cover Letters (N=780)								
Full	0.15*	0.16*	0.23**	0.14	0.16*	0.18*	0.19	0.20
	(0.09)	(0.10)	(0.10)	(0.09)	(0.10)	(0.10)	(0.15)	(0.16)
Control Group Mean	-0.03	-0.03	-0.05	-0.04	-0.05	-0.04	3.38	0.51
*Panel B. Cover Letters Written **WITHOUT** ChatGPT Assistance (N=396)*								
Full	0.18	0.23*	0.25**	0.15	0.24*	0.20	0.38*	0.50**
	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)	(0.20)	(0.22)
Control Group Mean	-0.07	-0.15	-0.11	-0.06	-0.11	-0.06	3.34	0.50
*Panel C. Cover Letters Written **WITH** ChatGPT Assistance (N=384)*								
Full	0.13	0.10	0.21*	0.14	0.09	0.17	-0.01	-0.08
	(0.11)	(0.11)	(0.12)	(0.11)	(0.11)	(0.11)	(0.20)	(0.21)
Control Group Mean	0.01	0.11	0.01	-0.03	0.00	-0.03	3.43	0.53

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses. Column 1-7 refer to variables as described in Appendix B.1.3, while Column 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. Sample consists of only female recruiters. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

Table A17: Male Recruiters: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation

	(1) Total	(2) Layout	(3) Intro	(4) Cover Letter Experience	(5) Motivation	(6) Closing	(7) Likelihood of Interview	(8) High Chance of Interview
Panel A. All Cover Letters (N=565)								
Full	0.00	0.05	-0.10	0.07	-0.05	0.04	0.30	0.36*
	(0.10)	(0.11)	(0.10)	(0.10)	(0.10)	(0.09)	(0.18)	(0.20)
Control Group Mean	0.05	0.04	0.08	0.07	0.08	0.07	3.35	0.49
Panel B. Cover Letters Written ***WITHOUT*** *ChatGPT Assistance (N=280)*								
Full	-0.05	0.08	-0.10	0.04	-0.05	0.07	0.38	0.47*
	(0.12)	(0.13)	(0.12)	(0.13)	(0.13)	(0.12)	(0.25)	(0.26)
Control Group Mean	0.11	0.01	0.14	0.07	0.11	0.10	3.36	0.50
Panel C. Cover Letters Written ***WITH*** *ChatGPT Assistance (N=285)*								
Full	0.06	0.03	-0.10	0.10	-0.05	0.02	0.21	0.26
	(0.13)	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.23)	(0.26)
Control Group Mean	-0.01	0.06	0.03	0.07	0.05	0.04	3.34	0.48

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses. Column 1-7 refer to variables as described in Appendix B.1.3, while Column 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. Sample consists of only male recruiters. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

Table A18: Old Recruiters: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Cover Letter			Likelihood of	High Chance of
	Total	Layout	Intro	Experience	Motivation	Closing	Interview	Interview
Panel A. All Cover Letters (N=620)								
Full	0.17	0.20*	0.23*	0.23**	0.15	0.23**	0.41**	0.45**
	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)	(0.11)	(0.17)	(0.18)
Control Group Mean	-0.00	-0.03	-0.06	-0.04	0.01	-0.01	3.34	0.49
*Panel B. Cover Letters Written **WITHOUT** ChatGPT Assistance (N=298)*								
Full	0.20	0.26	0.24	0.23*	0.22	0.30**	0.56**	0.54**
	(0.14)	(0.15)	(0.16)	(0.14)	(0.15)	(0.15)	(0.25)	(0.25)
Control Group Mean	-0.00	-0.11	-0.06	-0.05	-0.02	-0.02	3.34	0.49
*Panel C. Cover Letters Written **WITH** ChatGPT Assistance (N=322)*								
Full	0.15	0.15	0.22	0.22*	0.09	0.17	0.29	0.36
	(0.13)	(0.13)	(0.14)	(0.13)	(0.13)	(0.13)	(0.22)	(0.25)
Control Group Mean	-0.00	0.04	-0.07	-0.03	0.05	0.00	3.35	0.49

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses. Column 1-7 refer to variables as described in Appendix B.1.3, while Column 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. Sample consists of only recruiters above the median age. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

Table A19: Young Recruiters: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Cover Letter			Likelihood of	High Chance of
	Total	Layout	Intro	Experience	Motivation	Closing	Interview	Interview
Panel A. All Cover Letters (N=725)								
Full	0.01	0.04	-0.03	0.00	-0.00	0.02	0.06	0.14
	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)	(0.15)	(0.17)
Control Group Mean	0.00	0.03	0.06	0.04	-0.01	0.01	3.40	0.52
*Panel B. Cover Letters Written **WITHOUT** ChatGPT Assistance (N=378)*								
Full	-0.00	0.11	0.03	0.01	0.05	0.03	0.25	0.46**
	(0.09)	(0.10)	(0.10)	(0.10)	(0.11)	(0.10)	(0.20)	(0.23)
Control Group Mean	0.00	-0.07	0.02	0.03	-0.02	0.02	3.36	0.51
*Panel C. Cover Letters Written **WITH** ChatGPT Assistance (N=347)*								
Full	0.02	-0.03	-0.09	-0.01	-0.06	0.01	-0.15	-0.19
	(0.10)	(0.10)	(0.11)	(0.11)	(0.10)	(0.10)	(0.19)	(0.22)
Control Group Mean	0.00	0.15	0.11	0.05	-0.00	-0.00	3.44	0.53

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses. Column 1-7 refer to variables as described in Appendix B.1.3, while Column 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. Sample consists of only recruiters below the median age. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

A.2.4 Partial Information Only - Perceptions of Recruiters

In this section, we replicate Table 5 among recruiters in the *Partial Information* treatment, with the independent variable being the recruiter's belief of whether the cover letter was written with or without the assistance of LLMs. While the independent variable is not exogenous and hence causality cannot be claimed, the results provide suggestive evidence that recruiters do not punish or reward the perceived use of LLMs when they are not certain.

Table A20: Partial Info Only: Effect of Perception About ChatGPT Usage on Cover Letter Evaluation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Cover Letter			Likelihood of	High Chance of
	Total	Layout	Intro	Experience	Motivation	Closing	Interview	Interview
Thinks CL Written With GPT	0.03	0.15*	0.07	-0.05	-0.08	0.08	-0.02	-0.06
	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.08)	(0.17)	(0.20)
Control Group Mean	-0.06	-0.12	-0.08	-0.03	-0.02	-0.08	3.32	0.49
Observations	660	660	660	660	660	660	660	660

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (when recruiters thought the cover letter was not written with LLM assistance). Robust standard errors are in parentheses. Column 1-7 refer to variables as described in Appendix B.1.3, while Column 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. Sample consists of only recruiters in the *Partial Information* treatment. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

A.2.5 Tercile Heterogeneity

Table A21 reports treatment effects for cover letters in the lower tercile. The evaluations of the recruiters in the recruiter-side experiment are similar to those of recruiters in the job-seeker Experiment, as the average evaluation of these cover letters is below the mean, indicated by the negative value of the standardized control group mean (referring to the *Partial Info* treatment). Cover letters written with the assistance of ChatGPT are scored higher than those without (comparing the Control Group Means in Panels B vs. C), in line with the findings from Figure 1 which illustrates that the positive treatment effects of ChatGPT assistance on a cover letter's quality are primarily driven by lower-quality applicants. Furthermore, complete information on whether the applicant used ChatGPT or not does not impact either the evaluation of the quality of the cover letter (Columns 1 - 6), nor the likelihood of inviting the candidate to a job interview (Columns 7-8). Therefore, revealing the LLM assistance status of the applicant does not have an effect on the recruiters' evaluations of the low-quality cover letters.

Table A21: Main Results: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation - Lower Tercile

	(1) Total	(2) Layout	(3) Intro	(4) Cover Letter Experience	(5) Motivation	(6) Closing	(7) Likelihood of Interview	(8) High Chance of Interview
Panel A. All Cover Letters (N=449)								
Full Info	0.01	0.04	0.09	0.04	-0.02	0.07	0.07	0.08
	(0.10)	(0.11)	(0.10)	(0.10)	(0.11)	(0.10)	(0.19)	(0.22)
Control Group Mean	-0.35	-0.35	-0.31	-0.31	-0.33	-0.34	2.98	0.37
*Panel B. Cover Letters Written **WITHOUT** ChatGPT Assistance (N=223)*								
Full Info	-0.09	-0.00	0.03	-0.03	-0.10	0.01	-0.06	-0.01
	(0.13)	(0.15)	(0.14)	(0.13)	(0.14)	(0.14)	(0.26)	(0.32)
Control Group Mean	-0.49	-0.52	-0.45	-0.48	-0.42	-0.53	2.83	0.32
*Panel C. Cover Letters Written **WITH** ChatGPT Assistance (N=226)*								
Full Info	0.12	0.09	0.13	0.12	0.07	0.15	0.21	0.15
	(0.13)	(0.14)	(0.13)	(0.12)	(0.14)	(0.12)	(0.27)	(0.29)
Control Group Mean	-0.21	-0.19	-0.17	-0.15	-0.24	-0.16	3.12	0.42

Notes: Intention to Treat estimates, for the lower tercile quality cover letters, as evaluated by recruiters in the job-seeker experiment. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses. Column 1-7 refer to variables as described in Appendix B.1.3, while Column 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

Focusing next on the medium-quality cover letters - those which were graded in the middle tercile of the job-seeker experiment - Table A22 highlights heterogeneity in the evaluations of cover letters written with and without the assistance of LLMs. The perceived quality of the cover letter is unchanged as a result of *Full Information*, as the average grade of the cover letter is the same for both types of cover letters (see the Control Group Mean in Panels B and C), and the treatment effects are indistinguishable in Columns 1-6 across Panels A-C. Despite evaluating the cover letters as equally good, recruiters were statistically significantly more likely to recommend the applicant to the next step of the application process. This can be seen by comparing Columns 7 and 8 across Panels B and C. Informing recruiters that a cover letter was written without the assistance of ChatGPT statistically significantly increased the likelihood and chance of inviting the applicant to a job interview. Similarly, informing the recruiter that a cover letter was written with the assistance of ChatGPT reduced the likelihood of inviting the applicant to a job interview, albeit not statistically significantly. This suggests that recruiters place a premium on applications that did not use ChatGPT, even if the cover letters are deemed to be of comparable, average quality.

Table A22: Main Results: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation - Medium Tercile

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Cover Letter			Likelihood of	High Chance of
	Total	Layout	Intro	Experience	Motivation	Closing	Interview	Interview
Panel A. All Cover Letters (N=447)								
Full Info	0.07	0.06	0.05	0.12	0.07	0.12	0.24	0.19
	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.09)	(0.17)	(0.20)
Control Group Mean	0.21	0.25	0.21	0.17	0.24	0.26	3.57	0.59
Panel B. Cover Letters Written ***WITHOUT*** *ChatGPT Assistance (N=223)*								
Full Info	0.09	0.15	0.09	0.14	0.20	0.13	0.55**	0.61**
	(0.13)	(0.13)	(0.14)	(0.13)	(0.13)	(0.12)	(0.26)	(0.30)
Control Group Mean	0.21	0.14	0.21	0.16	0.17	0.27	3.53	0.57
Panel C. Cover Letters Written ***WITH*** *ChatGPT Assistance (N=224)*								
Full Info	0.05	-0.04	0.00	0.09	-0.08	0.09	-0.06	-0.23
	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)	(0.12)	(0.25)	(0.28)
Control Group Mean	0.22	0.36	0.21	0.18	0.32	0.25	3.61	0.60

Notes: Intention to Treat estimates, for the middle tercile quality cover letters, as evaluated by recruiters in the job-seeker experiment. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses. Column 1-7 refer to variables as described in Appendix B.1.3, while Column 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

A.2.6 Recruiter Experiment results: No, Partial, Full Info

Whole Sample

Table A23: Main Results: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation

	(1) Total	(2) Layout	(3) Intro	(4) Cover Letter Experience	(5) Motivation	(6) Closing	(7) Likelihood of Interview	(8) High Chance of Interview
Panel A. All Cover Letters (N=2005)								
Partial	-0.01	-0.03	0.00	-0.01	-0.02	-0.03	-0.08	-0.12
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.12)	(0.13)
Full	0.07	0.09	0.10	0.10	0.05	0.08	0.13	0.14
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.13)	(0.13)
t-test Partial vs. Full	0.12	0.03	0.08	0.03	0.19	0.03	0.08	0.03
Control Group Mean	-0.00	-0.00	0.00	0.00	-0.00	-0.00	3.40	0.53
*Panel B. Cover Letters Written **WITHOUT** ChatGPT Assistance (N=1004)*								
Partial	-0.03	-0.10	-0.01	-0.02	-0.04	-0.06	-0.16	-0.21
	(0.08)	(0.09)	(0.09)	(0.08)	(0.09)	(0.08)	(0.16)	(0.18)
Full	0.05	0.07	0.11	0.08	0.08	0.08	0.21	0.29*
	(0.08)	(0.09)	(0.08)	(0.08)	(0.09)	(0.08)	(0.16)	(0.17)
t-test Partial vs. Full	0.25	0.02	0.10	0.13	0.08	0.05	0.03	0.01
Control Group Mean	0.02	-0.02	-0.01	-0.00	0.00	0.03		0.54
*Panel C. Cover Letters Written **WITH** ChatGPT Assistance (N=1001)*								
Partial	0.01	0.04	0.02	0.00	0.01	0.01	-0.01	-0.04
	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)	(0.15)	(0.17)
Full	0.09	0.11	0.09	0.12	0.03	0.09	0.05	0.01
	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.16)	(0.17)
t-test Partial vs. Full	0.31	0.41	0.40	0.11	0.92	0.28	0.82	0.80
Control Group Mean	-0.02	0.02	0.01	0.00	-0.00	-0.03	3.38	0.52

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (No Information). Robust standard errors are in parentheses. Column 1-7 refer to variables as described in Appendix B.1.3, while Column 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

Table A24: Overall Additional Results: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation

	(1) Importance of CV	(2) Time Taken To Read CL
Panel A. All Cover Letters (N=2005)		
Partial	-0.26*	-0.03
	(0.15)	(0.07)
Full	-0.07	-0.02
	(0.17)	(0.07)
t-test Partial vs. Full	0.10	0.84
Control Group Mean	4.46	0.03
*Panel B. Cover Letters Written **WITHOUT** ChatGPT Assistance (N=1004)*		
Partial	-0.07	-0.01
	(0.17)	(0.10)
Full	-0.02	-0.00
	(0.19)	(0.09)
t-test Partial vs. Full	0.75	0.97
Control Group Mean	4.35	0.05
*Panel C. Cover Letters Written **WITH** ChatGPT Assistance (N=1001)*		
Partial	-0.45**	-0.05
	(0.18)	(0.08)
Full	-0.13	-0.04
	(0.19)	(0.07)
t-test Partial vs. Full	0.04	0.80
Control Group Mean	4.57	0.01

Notes: Intention to Treat estimates from OLS regressions. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (No Information). Robust standard errors are in parentheses. Column (1) reports the recruiter's need to see the CV (on a 7-point Likert scale), while Column (2) reports the normalized time taken by the recruiter to read and evaluate the cover letter. Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

Lower Tercile

Table A25: Main Results: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation

	(1) Total	(2) Layout	(3) Intro	(4) Cover Letter Experience	(5) Motivation	(6) Closing	(7) Likelihood of Interview	(8) High Chance of Interview
Panel A. All Cover Letters (N=669)								
Partial	0.04	0.02	-0.01	0.05	0.00	-0.03	0.07	-0.05
	(0.10)	(0.11)	(0.10)	(0.10)	(0.11)	(0.09)	(0.20)	(0.22)
Full	0.04	0.06	0.07	0.08	-0.02	0.04	0.12	0.03
	(0.11)	(0.11)	(0.10)	(0.10)	(0.11)	(0.10)	(0.20)	(0.23)
t-test Partial vs. Full	1.00	0.67	0.36	0.72	0.74	0.47	0.90	0.76
Control Group Mean	-0.40	-0.39	-0.30	-0.36	-0.35	-0.34	2.92	0.38
*Panel B. Cover Letters Written **WITHOUT** ChatGPT Assistance (N=333)*								
Partial	0.14	0.06	0.03	0.09	0.13	0.06	0.26	0.21
	(0.14)	(0.14)	(0.13)	(0.13)	(0.14)	(0.13)	(0.27)	(0.32)
Full	0.04	0.05	0.06	0.06	0.02	0.06	0.20	0.20
	(0.14)	(0.14)	(0.13)	(0.13)	(0.14)	(0.14)	(0.26)	(0.33)
t-test Partial vs. Full	0.59	0.97	0.74	0.93	0.54	0.80	0.82	0.96
Control Group Mean	-0.62	-0.59	-0.47	-0.55	-0.55	-0.58		0.28
*Panel C. Cover Letters Written **WITH** ChatGPT Assistance (N=336)*								
Partial	-0.06	-0.02	-0.04	-0.00	-0.13	-0.11	-0.13	-0.25
	(0.13)	(0.13)	(0.13)	(0.11)	(0.13)	(0.12)	(0.26)	(0.28)
Full	0.04	0.06	0.09	0.10	-0.07	0.03	0.04	-0.10
	(0.13)	(0.14)	(0.13)	(0.12)	(0.13)	(0.11)	(0.27)	(0.28)
t-test Partial vs. Full	0.49	0.51	0.29	0.48	0.84	0.35	0.62	0.69
Control Group Mean	-0.18	-0.19	-0.13	-0.17	-0.16	-0.09	3.19	0.47

Notes: Intention to Treat estimates, for the lower tercile quality cover letters, as evaluated by recruiters in the job-seeker experiment. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses. Column (1) reports the recruiter's need to see the CV (on a 7-point Likert scale), while Column (2) reports the normalized time taken by the recruiter to read and evaluate the cover letter. Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

Table A26: Overall Additional Results: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation

	(1) Importance of CV	(2) Time Taken To Read CL
Panel A. All Cover Letters (N=669)		
Partial	-0.18	0.11
	(0.22)	(0.11)
Full	-0.12	0.02
	(0.22)	(0.08)
t-test Partial vs. Full	0.85	0.40
Control Group Mean	4.29	-0.07
Panel B. Cover Letters Written ***WITHOUT*** *ChatGPT Assistance (N=333)*		
Partial	0.31	0.08
	(0.26)	(0.15)
Full	0.21	0.08
	(0.26)	(0.11)
t-test Partial vs. Full	0.71	0.91
Control Group Mean	3.99	-0.01
Panel C. Cover Letters Written ***WITH*** *ChatGPT Assistance (N=336)*		
Partial	-0.72***	0.15
	(0.27)	(0.15)
Full	-0.48*	-0.04
	(0.27)	(0.09)
t-test Partial vs. Full	0.48	0.16
Control Group Mean	4.59	-0.12

Notes: Intention to Treat estimates, for the lower tercile quality cover letters, as evaluated by recruiters in the job-seeker experiment. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses. Column (1) reports the recruiter's need to see the CV (on a 7-point Likert scale), while Column (2) reports the normalized time taken by the recruiter to read and evaluate the cover letter. Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

Middle Tercile

Table A27: Main Results: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation

	(1) Total	(2) Layout	(3) Intro	(4) Cover Letter Experience	(5) Motivation	(6) Closing	(7) Likelihood of Interview	(8) High Chance of Interview
Panel A. All Cover Letters (N=668)								
Partial	-0.02	0.01	0.04	-0.01	-0.01	-0.00	-0.13	-0.03
	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.09)	(0.18)	(0.20)
Full	0.05	0.07	0.10	0.10	0.05	0.11	0.11	0.17
	(0.10)	(0.09)	(0.10)	(0.10)	(0.10)	(0.09)	(0.18)	(0.20)
t-test Partial vs. Full	0.42	0.48	0.57	0.21	0.42	0.16	0.20	0.37
Control Group Mean	0.22	0.21	0.17	0.16	0.23	0.23	3.62	0.59
Panel B. Cover Letters Written ***WITHOUT*** *ChatGPT Assistance (N=333)*								
Partial	-0.07	-0.11	-0.00	-0.07	-0.05	0.01	-0.29	-0.20
	(0.13)	(0.13)	(0.14)	(0.12)	(0.13)	(0.12)	(0.25)	(0.28)
Full	0.02	0.04	0.10	0.06	0.15	0.14	0.24	0.41
	(0.13)	(0.13)	(0.14)	(0.13)	(0.13)	(0.12)	(0.26)	(0.29)
t-test Partial vs. Full	0.41	0.18	0.39	0.26	0.05	0.18	0.04	0.04
Control Group Mean	0.26	0.22	0.21	0.21	0.20	0.23		0.62
Panel C. Cover Letters Written ***WITH*** *ChatGPT Assistance (N=335)*								
Partial	0.05	0.14	0.11	0.05	0.04	-0.01	0.04	0.17
	(0.12)	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)	(0.25)	(0.30)
Full	0.09	0.10	0.11	0.14	-0.04	0.08	-0.01	-0.07
	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)	(0.11)	(0.24)	(0.29)
t-test Partial vs. Full	0.73	0.73	0.97	0.51	0.50	0.48	0.87	0.45
Control Group Mean	0.17	0.20	0.12	0.11	0.26	0.24	3.55	0.57

Notes: Intention to Treat estimates, for the middle tercile quality cover letters, as evaluated by recruiters in the job-seeker experiment. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses. Column (1) reports the recruiter's need to see the CV (on a 7-point Likert scale), while Column (2) reports the normalized time taken by the recruiter to read and evaluate the cover letter. Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

Table A28: Overall Additional Results: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation

	(1) Importance of CV	(2) Time Taken To Read CL
Panel A. All Cover Letters (N=668)		
Partial	-0.35*	-0.01
	(0.20)	(0.10)
Full	-0.21	-0.05
	(0.22)	(0.09)
t-test Partial vs. Full	0.41	0.62
Control Group Mean	4.55	0.02
Panel B. Cover Letters Written ***WITHOUT*** *ChatGPT Assistance (N=333)*		
Partial	-0.34	0.09
	(0.24)	(0.14)
Full	-0.41	-0.07
	(0.28)	(0.10)
t-test Partial vs. Full	0.76	0.18
Control Group Mean	4.62	-0.01
Panel C. Cover Letters Written ***WITH*** *ChatGPT Assistance (N=335)*		
Partial	-0.34	-0.12
	(0.25)	(0.11)
Full	-0.02	-0.04
	(0.27)	(0.12)
t-test Partial vs. Full	0.17	0.49
Control Group Mean	4.49	0.05

Notes: Intention to Treat estimates, for the middle tercile quality cover letters, as evaluated by recruiters in the job-seeker experiment. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses. Column (1) reports the recruiter's need to see the CV (on a 7-point Likert scale), while Column (2) reports the normalized time taken by the recruiter to read and evaluate the cover letter. Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

Upper Tercile

Table A29: Main Results: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation

	(1) Total	(2) Layout	(3) Intro	(4) Cover Letter Experience	(5) Motivation	(6) Closing	(7) Likelihood of Interview	(8) High Chance of Interview
Panel A. All Cover Letters (N=668)								
Partial	-0.06	-0.11	-0.03	-0.07	-0.05	-0.05	-0.17	-0.27
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.17)	(0.20)
Full	0.11	0.14	0.12	0.12	0.12	0.11	0.18	0.22
	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)	(0.09)	(0.17)	(0.19)
t-test Partial vs. Full	0.05	0.00	0.11	0.02	0.06	0.10	0.08	0.01
Control Group Mean	0.18	0.18	0.13	0.20	0.12	0.10	3.66	0.62
*Panel B. Cover Letters Written **WITHOUT** ChatGPT Assistance (N=338)*								
Partial	-0.16	-0.25**	-0.05	-0.08	-0.20*	-0.22*	-0.43*	-0.55*
	(0.11)	(0.13)	(0.13)	(0.12)	(0.12)	(0.11)	(0.26)	(0.30)
Full	0.08	0.10	0.17	0.13	0.05	0.04	0.21	0.26
	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)	(0.11)	(0.24)	(0.31)
t-test Partial vs. Full	0.03	0.00	0.05	0.05	0.03	0.02	0.01	0.00
Control Group Mean	0.43	0.33	0.25	0.34	0.36	0.45		0.72
*Panel C. Cover Letters Written **WITH** ChatGPT Assistance (N=330)*								
Partial	0.04	0.03	-0.00	-0.05	0.10	0.12	0.07	-0.02
	(0.13)	(0.13)	(0.14)	(0.13)	(0.13)	(0.13)	(0.24)	(0.26)
Full	0.14	0.18	0.07	0.11	0.20	0.17	0.14	0.18
	(0.12)	(0.13)	(0.13)	(0.12)	(0.12)	(0.13)	(0.24)	(0.27)
t-test Partial vs. Full	0.53	0.29	0.71	0.18	0.62	0.85	0.98	0.47
Control Group Mean	-0.06	0.04	0.03	0.06	-0.11	-0.24	3.40	0.51

Notes: Intention to Treat estimates, for the upper tercile quality cover letters, as evaluated by recruiters in the job-seeker experiment. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses. Column (1) reports the recruiter's need to see the CV (on a 7-point Likert scale), while Column (2) reports the normalized time taken by the recruiter to read and evaluate the cover letter. Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

Table A30: Overall Additional Results: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation

	(1) Importance of CV	(2) Time Taken To Read CL
Panel A. All Cover Letters (N=668)		
Partial	-0.24	-0.19*
	(0.19)	(0.10)
Full	0.12	-0.03
	(0.21)	(0.10)
t-test Partial vs. Full	0.05	0.05
Control Group Mean	4.54	0.14
Panel B. Cover Letters Written ***WITHOUT*** *ChatGPT Assistance (N=338)*		
Partial	-0.18	-0.18
	(0.25)	(0.15)
Full	0.11	-0.03
	(0.26)	(0.15)
t-test Partial vs. Full	0.21	0.23
Control Group Mean	4.44	0.17
Panel C. Cover Letters Written ***WITH*** *ChatGPT Assistance (N=330)*		
Partial	-0.31	-0.20*
	(0.25)	(0.11)
Full	0.13	-0.03
	(0.27)	(0.12)
t-test Partial vs. Full	0.13	0.12
Control Group Mean	4.64	0.11

Notes: Intention to Treat estimates, for the upper tercile quality cover letters, as evaluated by recruiters in the job-seeker experiment. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses. Column (1) reports the recruiter's need to see the CV (on a 7-point Likert scale), while Column (2) reports the normalized time taken by the recruiter to read and evaluate the cover letter. Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

A.2.7 No Clustered Standard Errors

Table A31: Main Results: Effect of Knowledge About ChatGPT Usage on Cover Letter Evaluation

	(1) Total	(2) Layout	(3) Intro	(4) Cover Letter Experience	(5) Motivation	(6) Closing	(7) Likelihood of Interview	(8) High Chance of Interview
Panel A. All Cover Letters (N=1345)								
Full Info	0.09*	0.12**	0.10*	0.12**	0.07	0.12**	0.22**	0.26**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.10)	(0.12)
Control Group Mean	0.00	-0.00	-0.00	0.00	0.00	-0.00	3.37	0.50
*Panel B. Cover Letters Written **WITHOUT** ChatGPT Assistance (N=676)*								
Full Info	0.08	0.17**	0.12	0.11	0.12*	0.14**	0.38***	0.50***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.14)	(0.17)
Control Group Mean	0.00	-0.09	-0.02	-0.01	-0.02	0.00	3.35	0.50
*Panel C. Cover Letters Written **WITH** ChatGPT Assistance (N=669)*								
Full Info	0.09	0.06	0.07	0.13*	0.03	0.09	0.07	0.05
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.14)	(0.16)
Control Group Mean	-0.00	0.09	0.02	0.01	0.02	-0.00	3.39	0.51

Notes: Intention to Treat estimates. Column 1-6 report treatment effects from OLS regressions, while columns 7 and 8 report multinomial logit and logit regressions, respectively. All regressions include controls for the recruiter's age and sex, as well as job-applicant fixed effects. Standard errors are clustered at the recruiter level. Control mean refers to the mean value of the outcome in the control group (Partial Information). Robust standard errors are in parentheses. Column 1-7 refer to variables as described in Appendix B.1.3, while Column 8 refers to a dummy if the Likelihood of Being Invited to an Interview is greater than three (on a five-point scale). Panel A reports treatment effects for all cover letters, while Panels B and C report treatment effect for cover letters written without LLM, and with LLM assistance, respectively. ***, ** and * represent significant differences at the 1, 5 and 10% level, respectively.

B Experiment Logistics

B.1 Job-seeker Experiment

B.1.1 Blocked Websites

OpenAI, in bold, is the only domain page that is blocked in the Control group, but not in the Treatment group.

B.1.2 Training Materials

The training material for the Control group can be found here.
The training material for the Treatment group can be found here.

OpenAI	Perplexity	Gemini
Falcon LLM	Google Gemini	Huggingface
Mistral	Llama	Claude
Anthropic	CopyAI	Anyword
Sudowrite	Writer	Writesonic
Rytr	Jasper AI	Simplified
Wordai	Grammarly	Careerflow AI
Resume IO	Kickresume	Teal HQ
Google Drive	Google Mail	Dropbox
Onedrive	SurfDrive	Rezi AI Cover Letter Builder
Jobscan	Coverletter Copilot	Microsoft Copilot
Myperfectresume	Coverdoc AI	AI Apply
Lazyapply	Zety	Aicoverlettergenerator
Coverletter-ai	Easycoverletter	Master Interview AI
There's an AI for that		

Table A32: List of Blocked Domain Names

B.1.3 Evaluation Criteria

	Low (0-4)	Medium (4-7)	High (7-10)
Layout, Writing Quality, and Clarity	Not professional in appearance; poor formatting; No flow or order to the way things are discussed; spelling and grammar errors; confusing sentences or main points	Letter generally looks clear and professional; Generally able to follow organization and flow; very few mistakes in spelling and grammar; some connection between the narrative and the position, but not maximized	Professional appearance; clean fonts and formatting; Clear organization; clean and consistent layout; free of grammar, spelling errors; overall narrative that clearly connects main points
Introduction	Does not cover basic info; weak link to the body of the cover letter; no link between the applicant and the position.	Conveys basic information in an unengaging form. Links to the main part of the cover letter, but not very effectively.	Covers basic information, offers an engaging and gripping way into the body of the letter and clearly connects the person to the position.
Relevant Experiences and Demonstration of Skills	not enough/ too much information in key areas; background, education and experience not fully explained; more questions raised than answered; all assertions without foundation or specifics to support them.	background, education and experience laid out but not connected to the position; Vague but inconsistent narrative.	Clear narrative; outlines background, education and experience fully and with specifics that connect directly to the position.
Motivation for Role and Alignment with Job	Little discussion of their motivation, the company, or how they would fit into existing organization.	Decent, but not always coherent motivation for the role; some good connections between the position and the applicant; some research done about the firm, but not that much.	focus on how they fit the job and will be effective members of the organization; outlines motivation in a coherent manner; strong understanding of the role, the organization, and how they would fit within the organization.
Closing	Not a strong closing statement; repetitive or wandering; no clear 'final message' to the reader and how they fit the job as outlined.	Has a sense of a closing statement but unenthusiastic or unconvincing; tries to convey too much, making it confusing; no succinct final message.	Strong closing statement of purpose; clearly outlines how their background, education and experience have prepared them for this specific position (without being repetitive).

Figure A2. Cover Letter Evaluation Criteria

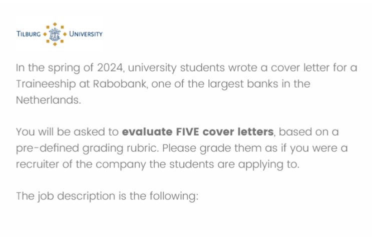
	Low (0-4)	Medium (4-7)	High (7-10)
Layout, Writing Quality, and Clarity	Not professional in appearance; poor formatting; No flow or order to the way things are discussed; spelling and grammar errors; confusing sentences or main points.	CV generally looks clear and professional; Generally able to follow organization and flow; very few mistakes in spelling and grammar; descriptions are generally clear.	Professional appearance; clean fonts and formatting; Clear organization; clean and consistent layout; free of grammar, spelling errors; effective use of CV phrasing.
Education	Below-average student, or from a subject not related to position they are applying for.	Average student, however does not belong to the top share of their cohort.	One of the top students in their cohort, as part of a demanding and relevant degree.
Experience	No or little relevant work / internship, or leadership experience.	Some relevant work / internship, or leadership experience, however it could be more.	Strong relevant work / internship, or leadership experience, for example through work experience or student associations.
Extra-curricular	No evidence of involvement in extra-curricular activities.	Some involvement in extra-curricular activities.	Strong involvement in extra-curricular activities.

Figure A3. CV Evaluation Criteria

B.2 Recruiter Experiment

Figure A4. Cover Page

(a) No Info



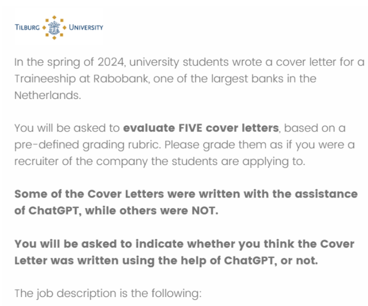
TILBURG UNIVERSITY

In the spring of 2024, university students wrote a cover letter for a Traineeship at Rabobank, one of the largest banks in the Netherlands.

You will be asked to **evaluate FIVE cover letters**, based on a pre-defined grading rubric. Please grade them as if you were a recruiter of the company the students are applying to.

The job description is the following:

(b) Partial Info



TILBURG UNIVERSITY

In the spring of 2024, university students wrote a cover letter for a Traineeship at Rabobank, one of the largest banks in the Netherlands.

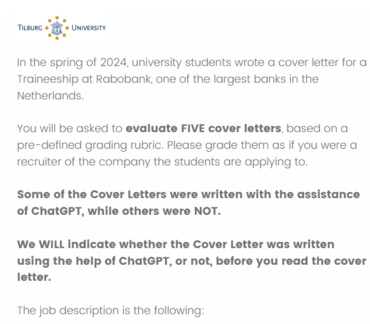
You will be asked to **evaluate FIVE cover letters**, based on a pre-defined grading rubric. Please grade them as if you were a recruiter of the company the students are applying to.

Some of the Cover Letters were written with the assistance of ChatGPT, while others were NOT.

You will be asked to indicate whether you think the Cover Letter was written using the help of ChatGPT, or not.

The job description is the following:

(c) Full Info



TILBURG UNIVERSITY

In the spring of 2024, university students wrote a cover letter for a Traineeship at Rabobank, one of the largest banks in the Netherlands.

You will be asked to **evaluate FIVE cover letters**, based on a pre-defined grading rubric. Please grade them as if you were a recruiter of the company the students are applying to.

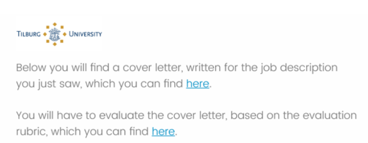
Some of the Cover Letters were written with the assistance of ChatGPT, while others were NOT.

We WILL indicate whether the Cover Letter was written using the help of ChatGPT, or not, before you read the cover letter.

The job description is the following:

Figure A5. Cover Letter Page

(a) No Info

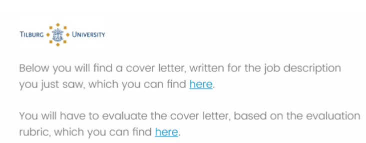


TILBURG UNIVERSITY

Below you will find a cover letter, written for the job description you just saw, which you can find here.

You will have to evaluate the cover letter, based on the evaluation rubric, which you can find here.

(b) Partial Info

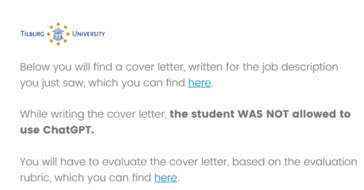


TILBURG UNIVERSITY

Below you will find a cover letter, written for the job description you just saw, which you can find here.

You will have to evaluate the cover letter, based on the evaluation rubric, which you can find here.

(c) Full Info



TILBURG UNIVERSITY

Below you will find a cover letter, written for the job description you just saw, which you can find here.

While writing the cover letter, **the student WAS NOT allowed to use ChatGPT.**

You will have to evaluate the cover letter, based on the evaluation rubric, which you can find here.

C Recruiter Insights on the Labor Market

The recruiter-side survey was also used to gain further insights into recruiters' perceptions of LLMs, and cover letters. These are outlined below:

Recruiters were asked to evaluate the sub-components of the cover letter (Layout, Introduction, Experience, Motivation, Conclusion) on a scale of 1-5, where 1 indicated the most personalized part of the cover letter, while 5 indicated the least personalized part of the cover letter.

Table A33: Personalization of Cover Letter Components

Cover Letter Component	Degree of Personalization
Layout	3.72
Introduction	2.46
Experience	2.44
Motivation	2.24
Conclusion	4.15

This indicates that the most personalized sections of the cover letter are the Motivation and Introduction. The least personalized section is the Conclusion.

Recruiters were also asked, on a five-point Likert scale, the degree to which they agree or disagree with the following statements: "It is acceptable for job applicants to use LLMs in their application"; "Job applicants should disclose LLM usage in their applications"; "The use of LLMs (e.g., ChatGPT) in a cover letter improves their grammar"; "The use of LLMs (e.g., ChatGPT) in a cover letter increases its originality and personalization". The results are presented in the table below:

Table A34: Agree-ability with Statements

	1 Strongly Disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly Agree	Average Value
Acceptable to Use	7.48%	24.19%	18.95%	40.40%	8.98%	3.19
Should Disclose Usage	8.23%	16.46%	26.1%8	27.68%	21.45%	3.38
LLM improves Grammar	2.74%	11.22%	17.21%	48.13%	20.70%	3.73
LLM increases originality	24.19%	38.40%	20.45%	13.72%	3.24%	2.33

Recruiters were asked on a five-point Likert scale how confident they were that they could detect LLM usage by job applicants. The results are presented in the Table below:

Table A35: Recruiter Confidence Detecting Use of LLMs in Cover Letters

	Not	Slightly	Moderately Confident	Very	Extremely	Average Value
Confident Detect LLM Use	5.51%	34.09%	42.61%	15.54%	2.26%	2.75

Recruiters were also asked about their attitudes towards applicants using LLMs in their cover letters:

Table A36: Recruiter perceptions about Use of LLMs in Cover Letters

	Very Negative	Negative	Neutral	Positive	Very Positive	Average Value
LLM Use in Cover Letter	7.29%	23.87%	44.72%	21.86%	2.26%	2.88

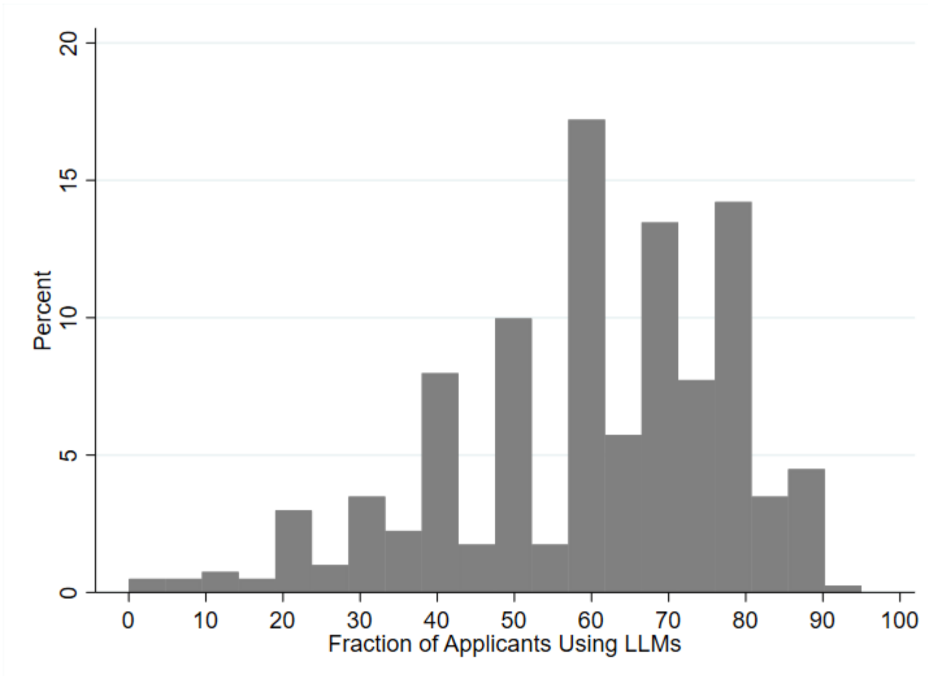
Recruiters were asked whether they thought LLMs like ChatGPT would have a smaller or greater impact on the quality of job applications, compared with Algorithmic Writing Assistants like Grammarly, which were empirically evaluated by Wiles et al. (2023).

Table A37: Impact of LLMs vs. Algorithmic Writing Assistants

	Far Smaller	Somewhat Smaller	Equally-sized	Somewhat Larger	Far Larger	Average Value
Impact of LLMs vs. AWA	3.99%	7.98%	19.20%	48.13%	20.70%	3.74

Lastly, recruiters were asked what percentage of applicants they think currently use LLMs in their job applications. The mean was 60.63%, with a wide distribution as illustrated by Figure A6.

Figure A6. Histogram of Recruiter's Perception on LLM Use Among Applicants



D ChatGPT Conversation Analysis

This section details our methodology for analyzing conversations between users and ChatGPT during cover letter writing. To perform sentiment analysis on the conversations between job-seekers and ChatGPT, we use OpenAI API research using model *gpt-4o-mini* to to classify and quantify the nature of these conversations to gain insights into user behavior and preferences. This approach allows for nuanced classification beyond simple keyword matching, capturing the contextual intent behind each user interaction.

Specifically, we focused our analysis on the five key components of the cover letter, and for each of these sections, user messages were classified into one of three categories:

1. **None**: The message does not pertain to the specific section.

2. **Content**: The user seeks or discusses substantive content related to the section. For example, a content-based message from a user is "write a cover letter to apply for a HR traineeship at ziggo with a formal writing".

3. **Guidance**: The user requests advice on formatting, wording, structure, or other structural aspects of the section. An example for a guidance-based interaction from the user is "Check the grammar, readability, and spelling of this text".

We developed a Python script that interfaces with the OpenAI API to automate the classification process. For each user's message to ChatGPT, the OpenAI API research model was asked the following:

```
{
    "role": "system",
    "content": "You are a helpful assistant that classifies user messages about cover letters.
    We have 5 sections:
    1) LAYOUT
       Definition:
       The Layout of a cover letter refers to its overall visual and structural presentation.
       This includes the use of clean and professional fonts, consistent formatting, organized sections, and a visually appealing arrangement that enhances readability.
```

```
    A well-designed layout ensures that the cover letter appears polished and professional, facilitating a clear flow of information without distractions from grammatical or formatting errors.

    Key Elements:
    - Professional appearance with clean fonts and appropriate font sizes.
    - Consistent formatting, including margins, spacing, and alignment.
    - Logical organization that guides the reader through the content smoothly.
    - Absence of spelling and grammar errors.
    - Clear and uncluttered presentation that enhances readability.

2) INTRODUCTION
    Definition:
    The Introduction of a cover letter serves as the opening paragraph that captures the reader's attention and sets the tone for the rest of the letter. It provides essential information about the applicant, such as their name, the position they are applying for, and a brief overview of their qualifications. A strong introduction engages the reader, establishes a connection between the applicant and the position, and smoothly transitions into the main body of the cover letter.

    Key Elements:
    - Clear statement of intent, specifying the job being applied for.
    - Brief overview of relevant qualifications or experiences.
    - Engaging hook or statement that grabs the reader's attention.
    - Connection between the applicant and the position or organization.
    - Smooth transition to the subsequent sections of the cover letter.

3) EXPERIENCE
    Definition:
```

```
    The Experience section of a cover letter details the applicant's relevant background, education, and work history. It highlights specific skills, accomplishments, and qualifications that align directly with the requirements of the position. This section provides concrete examples and evidence to support the applicant's suitability for the role, demonstrating how their past experiences have prepared them to contribute effectively to the organization.

    Key Elements:
    - Comprehensive overview of relevant work history and educational background.
    - Specific examples of skills and accomplishments that match the job requirements.
    - Clear connection between past experiences and the needs of the position.
    - Use of metrics or tangible outcomes to illustrate achievements.
    - Logical and coherent narrative that showcases the applicant's qualifications.

4) MOTIVATION
    Definition:
    The Motivation section explains the applicant's reasons for seeking the position and their interest in the organization. It conveys enthusiasm and a genuine desire to contribute to the company's goals. This section demonstrates the applicant's understanding of the role and the organization, highlighting how their personal and professional aspirations align with the company's mission and values. A well-articulated motivation reinforces the applicant's commitment and fit for the position.

    Key Elements:
    - Clear explanation of why the applicant is interested in the role and the company.
```

```
    - Insight into how the applicant's goals and values align with the organization's mission.
    - Demonstrated understanding of the company's industry, culture, and objectives.
    - Expression of enthusiasm and commitment to contributing to the organization.
    - Specific reasons that distinguish the applicant from other candidates.

5) CONCLUSION
   Definition:
   The Conclusion of a cover letter serves as the closing paragraph that reinforces the applicant's interest in the position and summarizes their qualifications. It provides a final opportunity to leave a positive impression, restate the key points that make the applicant a strong candidate, and outline the next steps. A compelling conclusion includes a call to action, such as requesting an interview, and expresses gratitude for the reader's time and consideration.

   Key Elements:
   - Summarization of key qualifications and fit for the position.
   - Restatement of enthusiasm and interest in the role and organization.
   - Clear call to action, such as requesting an interview or follow-up.
   - Expression of gratitude for the reader's time and consideration.
   - Professional and confident closing statement that leaves a lasting impression.

CONTENT vs. GUIDANCE:
 - 'content' means the user is seeking or discussing substantive help with that section (e.g., actively asking to write or describe it).
 - 'guidance' means the user is asking for advice about wording, formatting, synonyms, or other structural or minor clarifications regarding that section.

```

```
    Output EXACTLY in JSON with these keys: layout, introduction, experience,
     ↪  motivation, conclusion.
    Allowed values for each are: 'none', 'content', 'guidance'.
    No extra fields, no extra commentary."
}
```

This allowed us to have information on whether for each message the user was asking particular help on each section, and whether this help was content or guidance-based.

D.1 Additional Tables and Figures

Table A38: Summary Statistics for Number of User Messages

Agent	Mean	Median	Variance	SD	Min	Max
User	6.416667	5	19.22695	4.384855	1	16

Figure A7. Section-wise message distribution by CV rating. Comparison of message allocation patterns between users with above and below median CV ratings. Share expressed as percentage of total mentions.

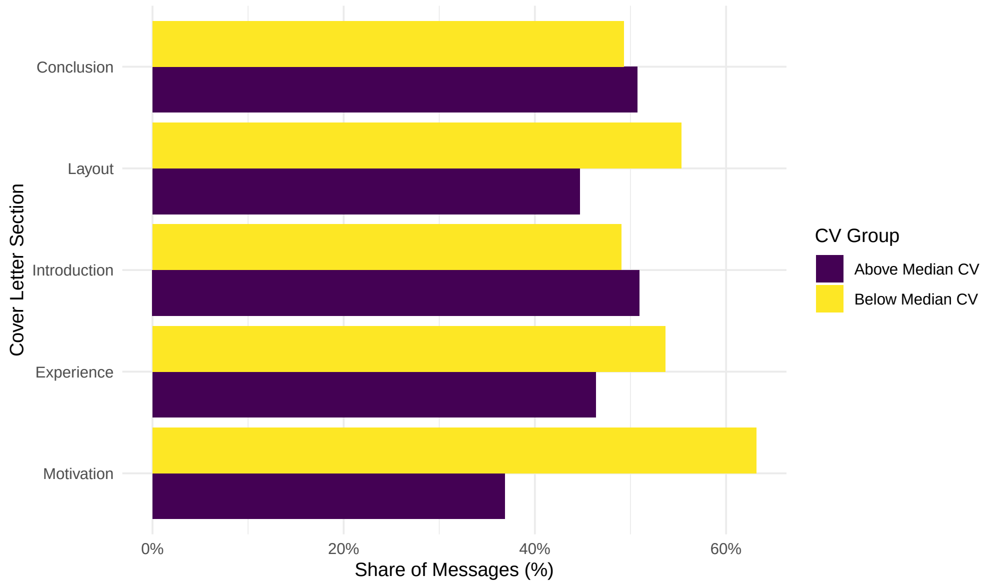


Figure A8. Content provision versus guidance requests in cover letter writing. The figure shows the share of messages dedicated to providing information versus requesting assistance. Share of messages expressed as percentage of total messages.

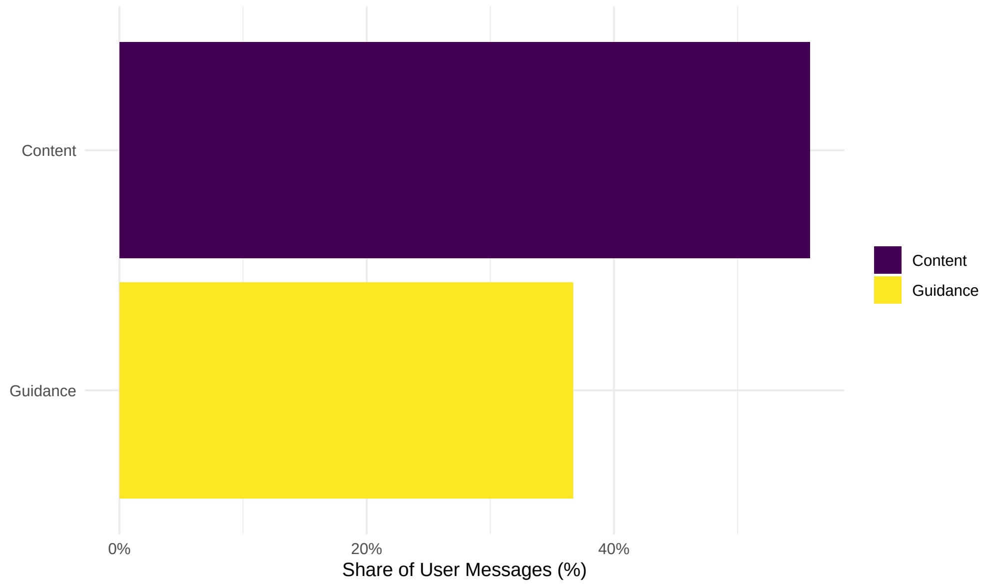
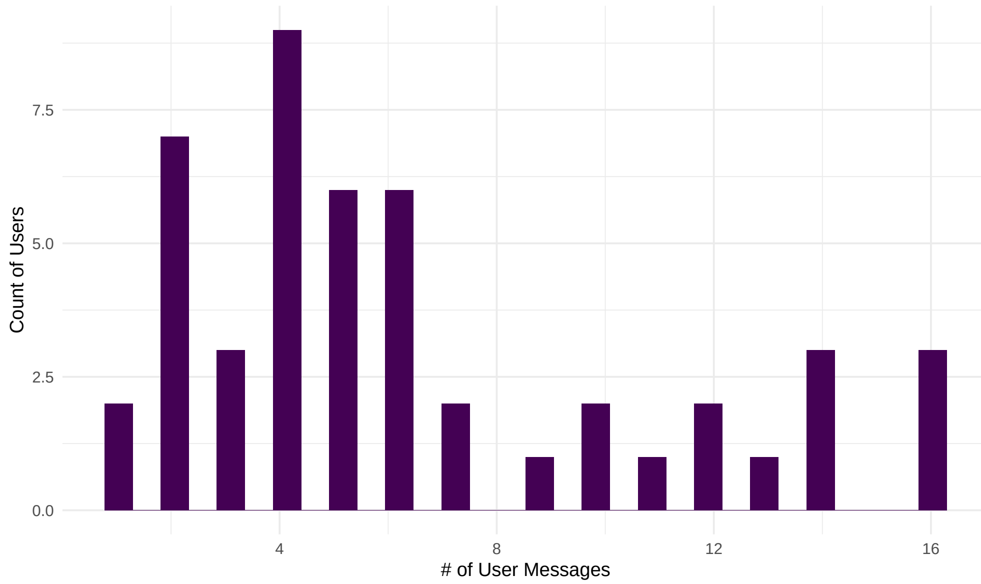


Figure A9. Distribution of total messages in cover letter writing sessions. The histogram shows the frequency distribution of the number of messages exchanged between users and ChatGPT during cover letter writing sessions.



E Model Details and Proofs

This section provides further details on the model. In addition to providing a proof of proposition 1 in the main text; we provide proofs of some properties of assignment models in the case of a continuum of agents. Many of these properties—such as uniqueness of assortative matching and optimality of positive assortative matching with supermodularity—are well-known in the case of discrete number of agents. We provide details on the extentions of these results to the case of continuum of agents; to our knowledge we are the first to do so.

E.1 Perfect Information Economy

The static economy consists of a continuum of workers, indexed by their quality s and distributed with CDF G_s, and a continuum of firms, indexed by their quality x and distributed with CDF G_x. We assume that both G_s and G_x admit densities denoted by g_x and g_s and have positive and bounded supports $\mathcal{S} := [\underline{s}, \overline{s}]$ and $\mathcal{X} := [\underline{x}, \overline{x}]$. The value of a match between a worker of type s and a firm of type x is given by $f(x, s)$ which satisfies Assumption 1:

Assignment in the economy without information frictions is defined by a function $x = \sigma(s)$, which matches each worker s with a firm x. In equilibrium, all firms and workers must be matched with each other, and matches are one-to-one: as explained above, there are no multi-worker firms or multi-firm workers. Therefore, the key property of σ is that, when considered as a set transformation, it must match an equal mass of workers and firms, in other words, σ must be a *measure-preserving* transformation. Given an assignment function σ, the aggregate value (or welfare) in this economy with perfect information is given by

$$V_P = \int_{\mathcal{S}} f(\sigma(s), s)\mathrm{d}G_s(s) \tag{9}$$

The monotonically-increasing assignment function that assigns top firms with top workers and bottom firms with bottom workers is known as *positively assortative matching* (PAM). PAM essentially matches the top $q = G_x(x)$ quantile of firms with the top $q = G_s(s)$ quantile of workers, and thus is given by $x = \sigma_P(s) = G_x^{-1}(G_s(s))$. Lemma 1 shows that PAM is unique in that it is the only monotonically-increasing measure-preserving transformation from the set of workers to the set of firms.

Lemma 1. *PAM is the only monotonically-increasing assignment function.*

Proof of Lemma 1. The relevant probability spaces are $(\mathcal{S}, \mathcal{B}_s, P_s)$ and $(\mathcal{X}, \mathcal{B}_x, P_x)$ where $\mathcal{B}_s, \mathcal{B}_x$ are the Borel σ-algebras of $\mathcal{S}, \mathcal{X}$, and P_s,P_x are the probability measures associated with distribution functions G_s, G_x.

An assignment function, as explained in the main text, is a function $\sigma : \mathcal{S} \to \mathcal{X}$ that assigns each worker $s \in \mathcal{S}$ to a firm $x \in \mathcal{X}$. Considered as a set transformation, it is a mapping from $\mathcal{B}_s$ to $\mathcal{B}_x$ that assigns groups of workers $S \subset \mathcal{S}$ to groups of firms $X \subset \mathcal{X}$. In equilibrium, an assignment transformation must be measure-preserving, i.e.

$$P_s\big\{\sigma^{-1}(B)\big\} = P_x\{B\} \ \forall B \in \mathcal{B}_x \tag{10}$$

Consider the sets $B = (\underline{x}, t)$ of the Borel σ-algebra $\mathcal{B}_x$, for any $\underline{x} < t \leq \overline{x}$. If σ is monotonically increasing, i.e. $\sigma(t') > \sigma(t) \ \forall t' > t$, this implies that:

$$P_s\big\{\sigma^{-1}((\underline{x}, t))\big\} = P_s\big\{(\underline{s}, \sigma^{-1}(t))\big\} = G_s(\sigma^{-1}(t)). \tag{11}$$

Where we used the fact that $\sigma^{-1}(\underline{x}) = \underline{s}$, since otherwise $\underline{x}$ or $\underline{s}$ will be unmatched, violating preservation of measure. Then Equation (10) gives:

$$G_s(\sigma^{-1}(t)) = G_x(t)$$

implying that σ must be PAM: $\sigma(t) = G_x^{-1}(G_s(t))$.

When dealing with monotonically-decreasing assignments, Equation (11) becomes

$$P_s\big\{\sigma^{-1}((\underline{x}, t))\big\} = P_s\big\{(\sigma^{-1}(t), \overline{s})\big\} = 1 - G_s(\sigma^{-1}(t)) \tag{12}$$

which leads to *negative assortative matching*: $G_x^{-1}(1 - G_s(t))$ being the unique monotonically-decreasing assignment. ■

In the context of discrete distributions Becker (1973) has shown that under the assumption of complementarity, PAM is the optimal assignment that maximizes Equation (9). We briefly extend this to the case of a continuum of workers and firms.

Lemma 2. *The positive assortative matching $\sigma_P(s) = G_x^{-1}(G_s(s))$ is optimal.*

Proof of Lemma 2. The relevant probability space is $(\mathcal{S}, \mathcal{B}_s, P_s)$ where $\mathcal{B}_s$ is the Borel σ-algebra of $\mathcal{S}$, and P_s is the probability measure associated with distribution function G_s.

For this proof we use the rearrangement inequality theorem of Burchard and Hajaiej (2006), who extend the results of Crowe et al. (1986), Almgren and Lieb (1989), and Brock (2000). This theorem, a generalization of the Hardy-Littlewood inequality, states that if f is a supermodular function, the following inequality holds for any measurable functions u, v:

$$\int_{\mathcal{S}} f(u(s), v(s)) \mathrm{d}P_s \leq \int_0^1 f(\overline{u}(z), \overline{v}(z)) \mathrm{d}z \tag{13}$$

where $\overline{u}(s)$ is the unique non-increasing rearrangement of $u(s)$ defined as:

$$\overline{u}(z) := \sup\left\{t \geq 0 : \rho_u(t) \geq z\right\}$$

where $\rho_u(t) = P_s(\{s \in \mathcal{S} : u(s) > t\})$ is the distribution function of u (a similar definition holds for $\overline{v}(s)$).

Intuitively, a non-increasing rearrangement of a function u is function $\overline{u}$ whose level sets have the same measure as u but are re-arranged in a decreasing order. For more information on rearrangements and related inequalities see Burchard (2009).

In our case, $u(s) = G_x^{-1}(G_s(s))$ and $v(s) = s$. Thus

$$\rho_u(t) = P_s(\{s \in \mathcal{S} : G_x^{-1}(G_s(s)) > t\}) = P_s(\{s \in \mathcal{S} : s > G_s^{-1}(G_x(t))\}) \tag{14}$$

$$= 1 - G_x(t) \tag{15}$$

$$\rho_v(t) = P_s(\{s \in \mathcal{S} : s > t\}) = 1 - G_s(t) \tag{16}$$

So

$$\overline{u}(z) = \sup\{t \geq 0 : 1 - G_x(t) \geq z\} = G_x^{-1}(1 - z) \tag{17}$$

$$\overline{v}(z) = \sup\{t \geq 0 : 1 - G_s(t) \geq z\} = G_s^{-1}(1 - z) \tag{18}$$

so the rearrangement inequality states

$$\int_{\mathcal{S}} f(\sigma_P(s), s)\mathrm{d}G_s(s) \leq \int_0^1 f(G_x^{-1}(1 - z), G_s^{-1}(1 - z))\mathrm{d}z \tag{19}$$

Let I denote the rightmost integral. With a simple change of variable $z = 1 - G_s(s)$ we obtain

$$I = -\int_{\overline{s}}^{\underline{s}} f(G_x^{-1}(G_s(s)), s)\mathrm{d}G_s(s) = \int_{\underline{s}}^{\overline{s}} f(G_x^{-1}(G_s(s)), s)\mathrm{d}G_s(s) \tag{20}$$

which shows that u, v are their own nonincreasing rearrangements, thus proving the optimality of PAM. ■

E.2 Imperfect Information without LLMs

Consider now an economy where firms cannot directly observe the quality of each worker and instead observe a signal y_1

$$y_1 = s + e \tag{21}$$

where e is the signal error with mean 0, distributed with CDF G_e on support $\mathcal{E} = [\underline{e}, \overline{e}]$. Here e reflects the fact that job-seekers' signal cover letter) does not fully reflect their relevant skills and abilities. Having received a signal y_1, firms form their Bayesian estimates of the hidden worker type as $\hat{s}(y_1) = \mathbb{E}[s|y_1]$ (which has the same support $\mathcal{S}$ as the true distribution of workers).

Implicit in the signal Equation (21) is the assumption that signal values are independent of firm qualities and only depend on the worker quality. That is, we assume each worker only produces one signal, which is then observed by all firms. More intuitively this is the scenario where each worker producer one job application package and sends it to all firms (costs of job applications and posting vacancies are irrelevant to our framework).

After all firms have observed each worker's signal, they form a positive assortative matching based on estimated worker qualities $\hat{s}$. Thus the assignment of firms to estimated worker qualities is deterministic and given by $x = \sigma_I(\hat{s}) = G_x^{-1}(G_{\hat{s}}(\hat{s}))$, while the randomness in matching between firm and true worker qualities stems purely from the randomness in worker quality estimates due to the imperfect signal. Given a worker of type s, they will be matched according to their estimated quality $\hat{s}$ and so the expected output from the matches with this worker will be:

$$\mathbb{E}[f(\sigma_I(\hat{s}), s)|s] = \int_{\mathcal{S}} f(G_x^{-1}(G_{\hat{s}}(\hat{s})), s)\mathrm{d}G_{\hat{s}|s}(\hat{s}|s)$$

This implies that the total output in this economy with PAM and imperfect information is given by:

$$V_I = \int_{\mathcal{S}}\int_{\mathcal{S}} f(G_x^{-1}(G_{\hat{s}}(\hat{s})), s)\mathrm{d}G_{\hat{s}|s}(\hat{s}|s)\mathrm{d}G_s(s) \tag{22}$$

The assignment given by σ_I is positively assortative with respect to the distribution of workers' quality estimates $\hat{s}$ and by Proposition 2 it is the optimal assignment between workers and firms given the information constraints. However, as asserted by Lemma 3, aggregate value in this economy with imperfect information is at most equal to the economy with perfect information.

Lemma 3. *$V_I \leq V_P$*

Proof of Lemma 3. With the concavity of f, Jensen's inequality shows that the value of the economy under imperfect information (V_I) is at most equal to that of the perfect information economy (V_P):

$$V_I \leq \int_{\mathcal{S}} f(\tilde{\sigma}(s), s)\mathrm{d}G_s(s) \leq \int_{\mathcal{S}} f(\sigma_P(s), s)\mathrm{d}G_s(s) = V_P \tag{23}$$

where $\tilde{\sigma}(s) = \mathbb{E}\big[G_x^{-1}(G_{\hat{s}}(\hat{s}))|s\big] \neq \sigma_P(s)$ for all s a.s. and the second inequality follows from Proposition 2. ■

Due to the randomness in matching between firms and true worker qualities s, some firms and workers will be better off in the scenario with imperfect information compared to the perfect information case. However there will be aggregate losses due to concavity and complementarity of f: such a random matching will assign some lower-quality firms with some higher-quality workers and vice versa, thus deviating from the first-best assignment of σ_P. Because of the complementarity, these two cannot cancel out in the aggregate, resulting in net losses.

A completely random assignment will be the case in which there is no information of the form (21), i.e. workers do not produce any CVs or cover letters to provide information about their skills to the firms. Total value of this *random* assignment economy is given by

$$V_R = \int_{\mathcal{S}} \int_{\mathcal{X}} f(x, s) \mathrm{d}G_x(x) \mathrm{d}G_s(s) \tag{24}$$

where workers and firms are assigned to each other based on their (independent) distributions. Lemma 4 shows that total value in such an economy is at most equal to the imperfect information economy with informative signals.

Lemma 4. $V_R \leq V_I$

Proof of Lemma 4. Recal V_R is given by

$$V_R = \int_{\mathcal{S}} \int_{\mathcal{X}} f(x, s) \mathrm{d}G_x(x) \mathrm{d}G_s(s)$$

Using Jensen's inequality we get

$$V_R \leq \int_{\mathcal{S}} f(x_m, s) \mathrm{d}G_s(s) =: I$$

where $x_m := \mathbb{E}[x]$ is the mean firm quality. The integral I can be simply re-written in a comparable form to V_I.

$$I = \int_{\mathcal{S}} \int_{\mathcal{S}} f(x_m, s) \mathrm{d}G_{\hat{s}|s}(\hat{s}|s) \mathrm{d}G_s(s) \tag{25}$$

In equation (25), we have the total value of an economy with the same information structure as that of V_I, but all workers are matched with the mean firm. Since σ_I is the positive assortative matching and by Proposition 2 is the optimal assignment given the joint distribution of $\hat{s}$ and s, then we must have $V_R \leq V_I$. ■

E.3 Imperfect Information with LLMs

With the details of the signal with imperfect information and LLM usage given in the main text, we can provide the proof of Proposition 1.

Proof of Proposition 1. Since $\tilde{s}$ is a function of y, total value can be rewritten as an integral with respect to the conditional distribution of signal values y

$$V_L = \int_{\mathcal{S}} \int_{\mathcal{Y}} f(G_x^{-1}(G_{\tilde{s}}(\tilde{s}(y))), s)\mathrm{d}G_{y|s}(y|s)\mathrm{d}G_s(s) \tag{26}$$

where $\mathcal{Y} = [\underline{y}, \overline{y}] = [\underline{s} + \underline{e}, \overline{s} + \overline{e}]$. The conditional distribution $G_{y|s}$ can be written, using law of total probability, as

$$\begin{aligned} G_{y|s}(x|s) &= \Pr\{y \leq x|s\} = p \Pr\{s + e \leq x|s\} + (1-p)\Pr\{h(s+e) \leq x|s\} && (27)\\ &= pG_{y_1|s}(x|s) + (1-p)G_{y_1|s}(h^{-1}(x)|s) && (28) \end{aligned}$$

So we have the decomposition $V_L = V_{A,1} + V_{A,2}$ where

$$\begin{aligned} V_{A,1} &= \int_{\mathcal{S}} \int_{\mathcal{Y}} p \cdot f(G_x^{-1}(G_{\tilde{s}}(\tilde{s}(y))), s)\mathrm{d}G_{y_1|s}(y|s)\mathrm{d}G_s(s) && (29)\\ V_{A,2} &= \int_{\mathcal{S}} \int_{\mathcal{Y}} (1-p) \cdot f(G_x^{-1}(G_{\tilde{s}}(\tilde{s}(y))), s)\mathrm{d}G_{y_1|s}(h^{-1}(y)|s)\mathrm{d}G_s(s) && (30) \end{aligned}$$

With a change of variables $y_1 := h^{-1}(y)$ the second integral becomes

$$\begin{aligned} V_{A,2} &= \int_{\mathcal{S}} \int_{\mathcal{Y}} (1-p) \cdot f(G_x^{-1}(G_{\tilde{s}}(\tilde{s}(y))), s)g_{y_1|s}(h^{-1}(y)|s)(h^{-1})'(y)\mathrm{d}y\mathrm{d}G_s(s) && (31)\\ &= \int_{\mathcal{S}} \int_{\mathcal{Y}} (1-p) \cdot f(G_x^{-1}(G_{\tilde{s}}(\tilde{s}(h(y)))), s)g_{y_1|s}(z|s)(h'(z))^{-1}h'(z)\mathrm{d}z\mathrm{d}G_s(s) && (32)\\ &= \int_{\mathcal{S}} \int_{\mathcal{Y}} (1-p) \cdot f(G_x^{-1}(G_{\tilde{s}}(\tilde{s}(h(y_1)))), s)\mathrm{d}G_{y_1|s}(y_1|s)\mathrm{d}G_s(s) && (33) \end{aligned}$$

By concavity of f,

$$V_L \leq \int_{\mathcal{S}} \int_{\mathcal{Y}} f(\sigma_A(y), s)\mathrm{d}G_{y_1|s}(y|s)\mathrm{d}G_s(s) =: I \tag{34}$$

Where

$$\sigma_A(y) = pG_x^{-1}G_{\tilde{s}}(\tilde{s}(y)) + (1-p)G_x^{-1}G_{\tilde{s}}(\tilde{s}(h(y)))$$

Note that V_I also can be written as

$$V_I = \int_{\mathcal{S}} \int_{\mathcal{Y}} f(\sigma_I(y), s)\mathrm{d}G_{y_1|s}(y|s)\mathrm{d}G_s(s) \tag{35}$$

where $\sigma_I(y) = G_x^{-1}(G_{\hat{s}}(\hat{s}(y)))$. Note that since the integral I in (34) is with respect to the joint distribution of y_1 and s, it provides an upper bound on the value of the economy with AI in terms of an economy without AI (but with imperfect information in terms of y_1) with a different assignment function σ_A. However since σ_I is the unique monotonically-increasing 1-to-1 assignment in such an economy and $\sigma_A \neq \sigma_I$ a.s., we have by Proposition 2 that V_I must be larger than V_L. ■