**WORKING PAPER** · NO. 2025-56

# Large Language Models, Small Labor Market Effects

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APRIL 2025

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# Large Language Models, Small Labor Market Effects*

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April 15, 2025

**Abstract**

We examine the labor market effects of AI chatbots using two large-scale adoption surveys (late 2023 and 2024) covering 11 exposed occupations (25,000 workers, 7,000 workplaces), linked to matched employer-employee data in Denmark. AI chatbots are now widespread—most employers encourage their use, many deploy in-house models, and training initiatives are common. These firm-led investments boost adoption, narrow demographic gaps in take-up, enhance workplace utility, and create new job tasks. Yet, despite substantial investments, economic impacts remain minimal. Using difference-in-differences and employer policies as quasi-experimental variation, we estimate precise zeros: AI chatbots have had no significant impact on earnings or recorded hours in any occupation, with confidence intervals ruling out effects larger than 1%. Modest productivity gains (average time savings of 2.8%), combined with weak wage pass-through, help explain these limited labor market effects. Our findings challenge narratives of imminent labor market transformation due to Generative AI.

*We thank David Autor, Matthew Notowidigdo, and seminar participants at INSEAD, Microsoft Research, and MIT Sloan for helpful comments and suggestions. This project received financial support from the Center for Applied Artificial Intelligence and the Polsky Center for Entrepreneurship and Innovation. Caspar Ringhof provided excellent research assistance.

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The emergence of AI chatbots marks the rise of Generative Artificial Intelligence (AI). By some measures, these technologies are already living up to the immense hype: AI chatbots have seen the fastest worker adoption of any new technology (Bick, Blandin and Deming, 2025; Humlum and Vestergaard, 2025), randomized controlled trials (RCTs) demonstrate substantial productivity gains for users (Brynjolfsson, Li and Raymond, 2025; Noy and Zhang, 2023), and case studies indicate notable effects on online labor market platforms (Teutloff et al., 2025). These effects on productivity and labor demand are remarkable in both magnitude—ranging from 15% to 50%—and speed, materializing within a few months.

However, the broader labor market implications of Generative AI remain unclear for at least three reasons. First, while workers have embraced AI chatbots for their low costs and ease of use, we lack evidence on whether firms are making meaningful investments in integrating these tools into workplace processes (Bonney et al., 2024). Second, RCTs show that the effects of AI chatbots can turn negative if applied to the wrong tasks (Dell'Acqua et al., 2023; Otis et al., 2024*b*), raising caution in extrapolating effects from controlled settings to the broader economy. Third, while studies have documented effects on productivity, it remains unclear how these translate into earnings and hours, as high-quality microdata on such outcomes is rarely available.

This paper addresses these gaps by conducting two large-scale surveys on AI chatbot adoption and linking the responses to matched employer-employee data in Denmark. Our dataset includes two survey rounds (late 2023 and 2024), each covering about 25,000 workers from 7,000 workplaces across 11 occupations exposed to AI chatbots, linked to monthly panel data on earnings, hours, and occupations.[1] Our analysis proceeds in three parts.

[1]Our list of occupations is accountants, customer support specialists, financial advisors, HR professionals, IT support specialists, journalists, legal professionals, marketing professionals, office clerks, software developers, and teachers.

First, we examine how firm-led investments in AI chatbots influence workers' take-up of the tools. Employers are now heavily invested in AI chatbots: most encourage their use, 38% deploy in-house models, and 30% of employees have received training.

These initiatives greatly boost adoption, nearly doubling take-up rates for the typical worker from 47% to 83%. The relative importance of employer encouragement becomes even more pronounced for more intensive usage. Notably, these efforts narrow demographic disparities in take-up: the gender gap in chatbot adoption shrinks from 11.9 to 5 percentage points when firms actively encourage use, with training initiatives proving particularly effective.

Second, we investigate how chatbot adoption affects work processes. While AI chatbots save time across all exposed occupations (for 64%–90% of users), their impact on work quality and job satisfaction varies. Notably, AI chatbots have created new job tasks for 8.4% of workers, including some who do not use the tools themselves. We examine how AI chatbots are reshaping work by by analyzing to workers' free-text descriptions of their new tasks. The role of task creation in shaping the impact of AI chatbots on work aligns with existing theories on how automation technologies reinstate labor demand (Acemoglu and Restrepo, 2019; Autor et al., 2024).

Importantly, the benefits from AI chatbots—time savings, quality improvements, creativity, task expansion, and job satisfaction—are 10%-40% greater when employers encourage their usage. This underscores the importance of firm-led complementary investments in unlocking the productivity potential of new technologies (Brynjolfsson, Rock and Syverson, 2021).

However, despite substantial investments in AI chatbots, their overall impact on work remains modest: users report average time savings of just 2.8% of work hours. This contrasts with the significant productivity gains—often exceeding 15%—documented by RCTs in our study occupations (Brynjolfsson, Li and Raymond, 2025; Noy and Zhang, 2023; Peng et al., 2023). Two key factors help explain this discrepancy. First, effect heterogeneity—while existing RCTs concentrate on occupations with the largest productivity gains from AI chatbots, our broader survey reveals that several exposed occupations see more modest gains. Second, firm-based complementary investments—many real-world workers do not operate under the same favorable conditions as those in experimental settings, limiting realized productivity gains. These findings caution against directly extrapolating productivity gains from controlled experiments to the broader economy.

In the third part of the paper, we examine the effects of AI chatbots on labor market outcomes. We link our survey data to administrative records on monthly earnings, hours, and occupations through June 2024—one and a half years after ChatGPT's launch. Using a difference-in-differences framework, we compare adopters and non-adopters before and after the arrival of AI chatbots and leverage employer policies to isolate quasi-exogenous variation in adoption.

Our main finding is that AI chatbots have had minimal impact on workers' economic outcomes. Difference-in-differences estimates for earnings and hours are all precisely estimated zeros, with confidence intervals ruling out average effects larger than 1%. At the occupation level, effects are similarly close to zero, generally ruling out changes greater than 6%. These limited impacts persist in the quasi-experimental analysis based on employer policies, suggesting that the average causal effect is indeed negligible. Moreover, a direct survey question—*"Have AI chatbots affected your labor earnings?"*—confirms that workers perceive no earnings impact as of November 2024.

While reported time savings from AI chatbots are modest, we have statistical power to rule out comparable earnings effects. Specifically, we estimate that only 3–7% of workers' productivity gains are passed through to higher earnings, with greater elasticity at firms that encourage chatbot use. These pass-through estimates align with, but fall at the lower end of, existing estimates (Card et al., 2018). In summary, the limited impacts of

AI chatbots on workers' earnings reflect a combination of modest productivity gains and weak pass-through to wages, although employer policies can enhance both.

As a final analysis, we assess whether AI chatbots have affected workplace outcomes, potentially influencing even non-adopting workers. Comparing workplaces with high versus low rates of AI chatbot usage, we find no evidence that firms with greater chatbot adoption have fared differently in total employment or wage bills. Direct survey responses from non-users confirm that they perceive no chatbot-related changes in earnings.

Overall, our findings challenge narratives of imminent labor market transformations due to Generative AI. While adoption has been rapid, with firms now heavily invested in unlocking the technological potential, the economic impacts remain small.

# 1 Data and Institutional Setting

Denmark offers an ideal setting for examining the labor market impacts of Generative AI.

First, Danish workers have been at the forefront of Generative AI adoption, with take-up rates comparable to those in the United States (Bick, Blandin and Deming, 2025; Humlum and Vestergaard, 2025; RISJ, 2024).

Second, Denmark's labor market is highly flexible, with low hiring and firing costs and decentralized wage bargaining—similar to that of the U.S.—which allows firms and workers to adjust hours and earnings in response to technological change (Botero et al., 2004; Dahl, Le Maire and Munch, 2013). In particular, most workers in our sample engage in annual negotiations with their employers, providing regular opportunities to adjust earnings and hours in response to AI chatbot adoption during the study period.

Third, Denmark has exceptional infrastructure for tracking the adoption of new technologies. In particular, every Dane has a digital mailbox that Statistics Denmark can use to distribute survey invitations. We use this infrastructure to conduct two large-scale, representative surveys on AI chatbot adoption, which we detail below.

Finally, our partnership with Statistics Denmark allows us to link these surveys to matched employer-employee data, providing a unique opportunity to analyze labor market effects such as changes in earnings, working hours, and job mobility.

Taken together, these factors make Denmark a prime setting for observing early labor market effects of Generative AI, with insights that may extend to other advanced economies—including the US—and an unparalleled data infrastructure to assess these impacts rigorously.

## 1.1 Data Sources

This paper builds on two large-scale surveys on AI chatbot adoption, conducted in November–December of 2023 and 2024. The first survey provided the dataset for Humlum and Vestergaard (2025), which documented adoption patterns of ChatGPT, the dominant AI chatbot. This paper extends that dataset in two key ways. First, we link survey responses to administrative labor market data after the introduction of ChatGPT, enabling us to assess impacts on earnings, work hours, and job mobility. Second, we introduce a second survey round in 2024 that (*i*) broadens the scope to include all AI chatbots, including in-house models, (*ii*) provides extensive data on firm-led adoption initiatives, and (*iii*) offers deeper insights into workers' actual usage and perceived benefits of these tools. Section 1.3 outlines the 2024 survey, which is the primary focus of this paper.

## 1.2 Occupations

Our surveys focus on 11 occupations that are particularly exposed to AI chatbots: *accountants, customer support specialists, financial advisors, HR professionals, IT support specialists, journalists, legal professionals, marketing professionals, office clerks, software developers, and teachers.* These occupations were selected based on three criteria: (*i*) they have at least one O*NET job task where AI chatbots can save time, as measured by the

"Direct Exposure (E1)" metric from Eloundou et al. (2024); (*ii*) they are captured by a well-defined set of ISCO codes; and (*iii*) they contain a sufficient number of workers for statistical analysis. Humlum and Vestergaard (2025) details the selection and empirical measurement of these occupations.

## 1.3 Survey Outline

Our 2024 survey is organized into the four blocks summarized below. The 2023 round followed a similar structure. The full questionnaires are in Appendix G.

**Block 1: Occupation and tasks.** Workers first select their occupation and report the importance of six representative tasks in their occupations.

**Block 2: Adoption.** Workers report their experiences with various AI chatbots, including the domains, frequency, and duration of usage.

**Block 3: Employer initiatives.** Workers are asked about any employer initiatives related to AI chatbots, including usage policies, in-house chatbots, and employee training.

**Block 4: Impact on work.** Workers are asked about their experienced benefits and estimated effects of AI chatbots.

## 1.4 Register Data

We use several administrative registers at Statistics Denmark. Our matched employer-employee data come from the *E-Income Register,* which records earnings, hours, occupation, and industry for all job spells in Denmark on a monthly basis from 2008 onward. This register is compiled by the Danish tax authorities and subsequently harmonized by Statistics Denmark into the *Employment Statistics of Employees* (BFL) dataset. We complement this with demographics data on individuals from the *Population Register*

(BEF), and wealth information for the *Personal Wealth Register* (FORMPERS). Because our survey was sent to workers identified in the register data by their (deidentified) social security numbers (*pnr*), all respondents can be matched to the register data.

## 1.5 Survey Sample

We invited 115,000 workers to participate in each of our survey rounds in 2023 and 2024. The registers at Statistics Denmark enabled us to target these invitations by occupation and workplace. In particular, for each of our 11 occupations, we conducted a workplace-based sampling procedure, first drawing a random set of workplaces within the occupations and then sampling all relevant workers for these workplaces. This sampling procedure maximizes the statistical power of the workplace-level analyses whilst keeping our sample representative. Appendix A.1 details the sampling protocol. We sent three reminders per survey round, two by e-mail and one by text. The invitation letters are in Appendix F. We received about 25,000 valid and complete responses to each of the survey. Appendix A.2 details our survey response rates. While our main analysis focuses on responses from the 2024 round, we use the 2023 round to examine the dynamics of our estimated effects.

### 1.5.1 Representativeness and Response Quality

Appendix A.2.1 conducts several checks on the representativeness and quality of our survey responses. These analyses extend the checks in Humlum and Vestergaard (2025) to the 2024 survey round. First, we ensure that our sample represents the population based on observables, including age, gender, experience, earnings, and wealth. Second, following Dutz et al. (2025), we use randomized participation incentives to show that our findings are also balanced on workers' latent willingness to participate in the survey. Finally, we cross-check that the survey responses align with variables that are also recorded in the administrative registers.

# 2 Adoption

## 2.1 Employer Initiatives

Figure 1, Panel (a) shows the prevalence of employer policies related to AI chatbot usage across our 11 occupations. Firms are now heavily invested in AI chatbots: about 43% of workers are explicitly encouraged to use them, another 21% are allowed, while only about 6% are explicitly prohibited from doing so. This marks a shift from early responses to ChatGPT, when many employers restricted its use due to concerns over data confidentiality and output accuracy (Humlum and Vestergaard, 2025).

Employers' encouragements are supported by substantial investments in tools and training. Panel (b) shows that 38% of firms have their own AI chatbots—most often customized versions—and Panel (c) shows that 30% of employees have participated in training courses on AI chatbot usage, with most of these courses organized by their employer. Notably, these firm-wide investments are prevalent in all 11 occupations but are particularly widespread in journalism and marketing and more limited in teaching. The widespread investments in AI chatbots at the workplace are consistent with their potential as a general-purpose technology (Eloundou et al., 2024).[2]

## 2.2 Worker Adoption

How do employer initiatives affect workers' adoption of these tools? To answer this question, we compare workers in the same occupations with similar characteristics and examine how their adoption behavior changes in response to employer initiatives:

$$Y_i = \gamma' X_i + \beta \times \text{EmployerInitiative}_i + \varepsilon_i, \tag{1}$$

[2]Appendix B.2.1 shows that ChatGPT remains the dominant product. Even when firms invest in their own AI chatbots, they often base them on GPT.

where $Y_i$ represents a worker outcome, such as the use of AI chatbots for work; $X_i$ is a vector of worker characteristics, including age, gender, experience, and occupation fixed effects; and $\text{EmployerInitiative}_i$ denotes an employer-driven initiative, such as encouraging employees to use AI chatbots.

While our main analysis relies on workers' self-reported employer initiatives, Section 5.1 demonstrates that our findings remain robust when using coworkers' responses in an instrumental variables strategy. This robustness supports our interpretation of employer initiatives as workplace-wide treatments. In addition, Figure B.2 shows that all results are robust to controlling for workers' detailed task mixes within occupations.[3]

Figure 2 shows that employer encouragement policies significantly boost adoption, nearly doubling take-up rates for the typical worker from 47% to 83%. The relative impact of employer encouragement becomes even more pronounced for more intensive usage. For example, the share of workers using AI chatbots daily rises from 8% to 21% when employers encourage their use.

Do employer initiatives influence which workers use AI chatbots? In Figure 3, we estimate demographic gaps in AI chatbot adoption within occupations, separately based on whether employers encourage chatbot use.

Employer encouragement significantly reduces demographic disparities in AI chatbot adoption. For instance, the gender gap in chatbot use shrinks from 11.9 to 5 percentage points when firms actively promote adoption. In contrast, such encouragement is less effective among more experienced workers, highlighting the difficulties in changing established work habits.

Figures B.3–B.4 show the effects of other employer initiatives on AI chatbot adoption, yielding two key insights.

First, firm-provided training programs are particularly effective, boosting overall

[3] We prefer not to control for task mixes in our main specification, as they may be endogenous to chatbot use. Indeed, Section 3.2 shows that AI chatbots have created new job tasks for many workers.

adoption and reducing the gender gap in uptake to 3.6 percentage points.[4] The effectiveness of training aligns with findings from the 2023 survey round, where women were significantly more likely to cite lack of training as a barrier to ChatGPT adoption (Humlum and Vestergaard, 2025).

Second, the gender gap in chatbot adoption persists even when employers prohibit the tools. Although employer bans reduce overall adoption to a third of its baseline rate, roughly 80% of the baseline gender gap remains in these workplaces. This pattern mirrors findings by Carvajal, Franco and Isaksson (2024), who document a similar gender gap in ChatGPT use among Norwegian bachelor's students and use a vignette experiment to show that the gap largely reflects male students using the tools even when explicitly banned.

## 2.3 Comparison to the Literature

The widespread adoption of AI chatbots and the substantial demographic gaps in usage are now well-documented facts in the literature. For example, our 2023 survey found that 39.8% of workers had used ChatGPT for work, with adoption rates 15.9 percentage points lower among women within occupations (Humlum and Vestergaard, 2025).[5] Bick, Blandin and Deming (2025) report similar adoption patterns among U.S. workers, and Otis et al. (2024*a*) show that the gender gap in Generative AI adoption is pervasive across contexts.

We contribute to this evidence by documenting that employer-driven adoption initiatives for AI chatbots are now common and play a crucial role in shaping overall adoption rates and demographic disparities in usage.[6]

[4]Figure B.4 shows that while training consistently reduces disparities across all usage intensities—including daily use—employer encouragement alone may widen the gender gap in frequent chatbot usage.

[5]For comparison, in our 2024 survey round, ChatGPT adoption has risen to 49.1%, with a gender gap of 12.3 percentage points (see Appendix B.2.2 for a comparison of the 2023 and 2024 adoption patterns).

[6]For instance, the rise of employer initiatives likely explains much of the shift between the 2023 and 2024 surveys—namely, increased adoption and a narrowed gender gap—as most initiatives were implemented in the interim. For example, one of the first in-house AI chatbots, DanskeGPT, was launched by Denmark's largest bank in March 2024 (Danske Bank, 2024).

By contrast, earlier surveys on AI have found relatively low take-up rates among firms. For example, Bonney et al. (2024) document 5.4% of US firms reported using AI as of February 2024, with adoption in the leading sector (Information) below 20%.

Our survey provides the first comprehensive evidence on how employers are integrating Generative AI into the workplace. We find that employer policies—especially those focused on training—substantially increase adoption and help narrow demographic gaps in take-up.

More generally, the importance of firm-wide complementary investments for the take-up of AI chatbots aligns with the literature on "Productivity J-Curves" in the diffusion of general-purpose technologies (Brynjolfsson, Rock and Syverson, 2021). In the following sections, we examine how the employer investments in AI chatbots influence the tools' impacts on work processes and labor market outcomes.

# 3 Work

## 3.1 Benefits for Users

What benefits do workers report from using AI chatbots? Figure 4 shows that workers primarily report time savings as a main benefit (Panel (a)), with an average saving of 25 minutes per day of use (Panel (b)). Additionally, nearly half of workers cite improved work quality and enhanced creativity as key advantages.[7] In contrast, increased job satisfaction is the least commonly reported benefit.

Table C.1 breaks down these benefits by occupation, revealing significant variation. For instance, marketing professionals are more than twice as likely as teachers to report that chatbots improve work quality (69.8% vs. 32.1%), while software developers are

[7]Toner-Rodgers (2024) show that other generative models—specifically ones that generate materials design rather than words—can profoundly impact the scientific discovery process for materials scientists. While we likewise find that AI chatbots support creativity, their primary reported benefit lies in saving time on content drafting.

more than twice as likely as journalists to report increased job satisfaction from chatbot use (30.5% vs. 12.6%). Despite these differences, AI chatbots help save time across all exposed occupations, with time savings reported by 64%–90% of users.

Importantly, the benefits from AI chatbots—time savings, quality improvements, creativity, task expansion, and job satisfaction—are all 10%-40% greater when employers encourage their usage. This highlights the importance of firm-based complementary investment for unlocking the work-related benefits of new technologies (Brynjolfsson and Hitt, 2000).

What is the economic significance of the reported benefits of AI chatbots? In Table 1, we combine workers' frequency of use (from Figure 2) with their reported time savings per day of usage (from Figure 4.(b)) to estimate time savings as a percent of total work hours. Average time savings from AI chatbots vary from 6.8% among marketing professionals whose employers encourage their use to 0.6% among teachers in schools that do not encourage their use. The larger time savings for encouraged workers reflect both that they use the AI chatbots more often and report greater time savings per day of use. Across our 11 occupations and employer policies, the average time savings amount to 2.8% of the total work hours of users.

How do workers allocate the time savings from AI chatbots? Figure 4.(c) shows that the vast majority (80%) reallocate this time to other job tasks, while fewer than 10% use it for additional breaks or leisure. Finally, 25% spend more time on the same tasks they saved time on, particularly when their employers actively encourage AI adoption. This suggests that firm-led investments play an important role in enabling workers to expand task outputs in response to task-specific productivity gains (Brynjolfsson, Rock and Syverson, 2021).

## 3.2 Workloads and Task Creation

Figure 5 examines how AI chatbots influence workloads. Notably, AI chatbots have created new workloads for 17% of users (Panel (a)), with 4.4 percentage points performing more of the same tasks, 10.9 percentage points taking on new tasks, and 1.7 percentage points doing both. Importantly, new workloads are 20-50% more pronounced in workplaces that encourage the use. This highlights the importance of firm-led initiatives for realizing workplace transformations from new technologies (Brynjolfsson, Rock and Syverson, 2021).

To further understand how AI chatbots affect the nature of work, we asked respondents to describe the new job tasks they perform as a result of AI chatbots. In Appendix C.2, we categorize the free-text responses into common new tasks associated with AI chatbots in each occupation. AI chatbots have generated new job tasks for workers across all 11 occupations, with 50% to 95% of these directly linked to AI use.

Figure 6 breaks down the composition of AI-related job tasks by occupation. The most common task relates to the integration of AI chatbots into the workplace, accounting for 15%–40% of all new tasks, with the highest shares observed in IT support and software development. This pattern highlights that we are currently in a phase where substantial resources are being devoted to adapting workflows to AI chatbots. It is consistent with firms being in the trough of a productivity J-curve (Brynjolfsson, Rock and Syverson, 2021) and helps contextualize the modest time savings we observe in Table 1.

The second most common task involves using AI for content drafting, which appears across most occupations. AI ethics and compliance issues are especially prominent in teaching—where educators increasingly need to detect AI-generated homework—and in the legal profession, where practitioners are formulating guidelines for chatbot use. Tasks involving idea generation and data insights are present in all occupations but are less central, typically comprising 5%–20% of new tasks.

Consistent with the finding that workloads from AI chatbots extend beyond tasks directly related to using them, Figure 5.(b) shows that 5% of non-users report new workloads stemming from AI chatbots. Specifically, Figure C.1.(b) shows that about 10%–15% of teachers who have not used AI chatbots report new workloads from the technology. In general, these new workloads for non-users consist almost entirely of novel tasks, with effects more pronounced in workplaces that encourage AI chatbot use.

Taken together, the widespread creation of new tasks, the spillovers to non-users, and the stronger effects in workplaces that encourage the tools all highlight the broader workplace transformations caused by AI chatbots.

### 3.3 Comparison to the Literature

The importance of task creation for the impact of AI chatbots on workloads supports key theoretical predictions for how automation technologies may reinstate the demand for labor in the production process (Acemoglu and Restrepo, 2019; Autor et al., 2024). Notably, across all occupations, workplaces that encourage AI chatbot use experience greater task creation from these tools. This underscores the importance of firm-led investments for driving workplace transformations from technological change (Brynjolfsson, Rock and Syverson, 2021).

That said, the average reported time savings of 2.8% for adopters may seem small compared to the substantial productivity gains—often exceeding 15%—documented by RCTs in our study occupations.[8,9] How can we reconcile workers' modest reported time savings with the substantial effects observed in RCTs?

[8] Noy and Zhang (2023) report time savings of 37% from ChatGPT in text writing tasks representative of marketing and HR professionals. Brynjolfsson, Li and Raymond (2025) estimate productivity effects of 15% from a GPT-based chat assistant among customer and IT support agents, with more pronounced effects for less experienced workers. Cui et al. (2024) estimate a 26% productivity gain from GitHub Copilot among software developers, while Peng et al. (2023) report a 58% increase.

[9] Our estimated productivity gains are closer to those of Acemoglu (2025), though for different reasons. While Acemoglu (2025) combines the experimental productivity estimates with a calibrated adoption curve, we measure both adoption and (self-reported) time savings directly. Bick, Blandin and Deming (2025) provide a thoughtful comparison between their survey-based estimates of productivity gains and the predictions of Acemoglu (2025).

First, our reported time savings are highest precisely in the occupations covered by RCTs, such as customer and IT support (Brynjolfsson, Li and Raymond, 2025), marketing and human resources (Noy and Zhang, 2023), and software development (Peng et al., 2023). In contrast, reported savings are about half as large among teachers, accountants, and financial advisors, whose tasks may be less suited to chatbot assistance. This occupational heterogeneity supports the concept of a "jagged frontier" of AI chatbot costs and benefits (Dell'Acqua et al., 2023), warranting caution against extrapolating productivity estimates across tasks or occupations.

Second, reported time savings are significantly higher when employers actively encourage chatbot use. For example, marketers and software developers whose employers promote AI chatbots report time savings of approximately 7%. In this sense, RCTs may capture the productivity effects of a well-coordinated and carefully managed adoption of these tools. While such estimates provide valuable insight into the workplace potential of AI chatbots, our survey indicates that many users do not operate under similarly favorable conditions. This highlights the need for caution when extrapolating productivity benefits from controlled settings onto the broader economy.

Our time savings estimates align more closely with those of Bick, Blandin and Deming (2025), who, in a nationally representative U.S. survey, find an average reported time savings of 5.4% among users. However, their study does not split the time savings by occupation or employer policies, limiting direct comparability to our estimates.[10]

[10] Edelman, Ngwe and Peng (2023) shows that self-reported time savings from AI chatbots (particularly Microsoft Copilot) may overstate actual savings. Three facts lend credibility to our self-reported benefit measures. First, as noted above, our reported time savings are modest—substantially below those found in existing RCTs and broadly in line with the survey-based estimates of Bick, Blandin and Deming (2025), though slightly lower. Second, as shown in Section 4, workers' self-reported earnings effects closely match our difference-in-differences estimates based on administrative data. Third, as we also show in that section, the relationship between self-reported time savings and earnings effects implies productivity–wage pass-through rates within the range of standard estimates in the literature.

# 4 Labor Market Outcomes

Our preceding analysis shows that AI chatbots are now widespread, with adopters reporting time savings and other work-related benefits, especially in workplaces that encourage their usage. Have these changes affected workers' labor market outcomes, such as earnings or recorded work hours? To answer this question, we link the survey responses to matched employer-employee data on labor market outcomes (see Section 1.4 for details). We first outline our empirical strategy in Section 4.1 before presenting our results in the subsequent sections.

## 4.1 Empirical Strategy

Our primary analysis employs a difference-in-differences specification, comparing the labor market outcomes of adopters and non-adopters before and after the introduction of AI chatbots. A key concern in this analysis is that adopters may have fared differently in the labor market even without AI chatbots. We take three steps to address this issue.

First, we control for workers' pre-determined characteristics—including gender, age, and labor market experience—to ensure these factors do not drive our estimates (e.g., adopters being younger and naturally on upward earnings trajectories).

Second, we leverage our panel data to implement a difference-in-differences approach indexed to November 2022, the release date of ChatGPT.[11] This allows us to control for time-invariant differences between workers (e.g., high-ability adopters who would have earned more regardless) and examine whether adopters experienced differential changes after this date. Additionally, we assess whether adopters were on distinct labor market trends even before AI chatbots became available, enabling us to control for potential pre-existing differences.

Finally, to address unobserved confounding shocks (e.g., adopters facing sudden

[11] Appendix B.2.1 shows that ChatGPT remains the dominant AI chatbot to date.

setbacks or tailwinds in the labor market after November 2022), we leverage quasi-exogenous variation from the employer policies documented in Section 2.1. Specifically, we compare similar workers whose AI chatbot adoption differs due to employer-wide usage policies. Sections 4.2.1 and 5.1 present the results from these quasi-experimental analyses, which closely align with our main difference-in-differences estimates.

### 4.1.1 Regression Specifications

Let $Y_{it}$ denote a labor market outcome (e.g., earnings) for worker $j$ in month-year $t$, let $X_i$ represent a vector of workers' pre-determined characteristics (age, gender, experience, and occupation FEs), and let $A_i$ indicate whether the worker has adopted AI chatbots.

**Dynamic Difference-in-Differences.** To assess overall impacts, we employ a dynamic difference-in-differences specification that compares the monthly outcomes of adopters and non-adopters before and after the introduction of AI chatbots:

$$Y_{it} = \underbrace{\sum_{\tau} \lambda_{1\tau} X_i \mathbf{1}_{\{t=\tau\}}}_{\text{Pre-Determined Controls}} + \underbrace{\sum_{m} \lambda_{2m} \mathbf{1}_{\{m=m(t)\}}}_{\text{Seasonality}} + \underbrace{\sum_{\tau \neq 2022M11} \beta_\tau A_i \mathbf{1}_{\{t=\tau\}}}_{\text{Dynamic Diff-in-Diffs}} + \beta_0 A_i + \varepsilon_{it}, \quad (2)$$

where $\lambda_{2m}$ are month fixed effects. The parameters of interest, $\beta_\tau$, capture the differential changes in labor market outcomes for adopters, indexed to November 2022, the release of ChatGPT. In the quasi-experimental analysis of employer policies, we swap $A_i$ for an indicator of the policy considered, such that $\beta_\tau$ identifies the reduced-form effect of facing the policy.

**Pooled Difference-in-Differences.** To examine heterogeneous impacts across multiple dimensions, we use a pooled specification that compares the average outcomes of adopters and non-adopters before and after the introduction of AI chatbots:

$$Y_{it} = \underbrace{\sum_{\tau} \lambda_{1\tau} X_i \mathbf{1}_{\{t=\tau\}}}_{\text{Pre-Determined Controls}} + \underbrace{\sum_{m} \lambda_{2m} \mathbf{1}_{\{m=m(t)\}}}_{\text{Seasonality}} + \underbrace{\lambda_3 t + \lambda_4 A_i t}_{\text{Time Trends}} + \underbrace{\beta A_i \mathbf{1}_{\{t \geq 2022M11\}}}_{\text{Pooled Diff-in-Diff}} + \beta_0 A_i + \varepsilon_{it}, \tag{3}$$

where we add adopter-specific time trends to ensure our pooled difference-in-differences estimates are not driven by spurious trends in outcomes. The parameter of interest, $\beta$, captures the average differential change in the labor market outcomes of adopters after November 2022.

## 4.2 Earnings and Hours

Figure 7 presents dynamic difference-in-differences estimates for the impact of AI chatbot adoption on workers' earnings and work hours. The figure reveals three key results. First, one and a half year after their launch, AI chatbots have had minimal average impact on the earnings or hours of adopters. Our confidence intervals rule out changes larger than 2%.[12] Second, these effects show no differential trend after the arrival of AI chatbots, indicating that the minimal impacts are not just a very short-term phenomenon.[13] Finally, despite employer encouragements boosting the benefits of AI chatbots in Section 3, we find no differential impact on labor market outcomes for adopters whose employers encourage their use.[14] Figure D.2 similarly shows no differential impact on the extensive-margin employment of adopters.

Do the overall zero effects mask heterogeneous gains and losses across workers? To investigate this, Figure 8.(a) first estimates the effects of AI chatbots on worker earnings

[12]Figure D.1 reports the corresponding difference-in-means. It shows that adopters of AI chatbots do earn more than non-adopters, reflecting the selection patterns already documented in Section 2. However, because these earnings differences entirely predate the arrival of AI chatbots, the difference-in-differences estimates in Figure 7 are zero.

[13]Section 4.3 shows that survey responses from November 2024 similarly show no earnings impacts of AI chatbots.

[14]We further analyze the role of employer policies in Section 4.2.1.

separately for each of the 11 occupations in our sample. Notably, we do not find significant effects of AI chatbots in any occupation: the occupation-specific estimates are all close to zero, generally ruling out effects larger than 6%.

Further probing heterogeneous effects, Figure 8.(b) splits the difference-in-differences estimates according to workers' demographics, reported effects of AI chatbot use, and timing of adoption. The figure reveals three insights about the limited impacts of AI chatbots on labor market outcomes.

First, while chatbot adoption has been highly unequal across demographic groups—with younger men more likely to use the tools—we find no differential effects on their labor market outcomes. Second, while some workers do report substantial benefits from AI chatbots (e.g., daily time savings of more than an hour), we cannot detect significantly better labor market outcomes for these workers. Similarly, workers who report enhanced quality or creativity or new workloads from AI chatbot usage have not fared better in the labor market since their introduction. Finally, we find no evidence that AI chatbots have had differential impacts on workers who adopted them early (i.e., within the first year of ChatGPT's launch). The absence of effects even for early adopters aligns with our dynamic difference-in-differences estimates, which show no trend in outcomes following the arrival of AI chatbots and suggest that the minimal impacts may not be merely a short-term phenomenon.

### 4.2.1 Impacts of Employer Initiatives

The difference-in-differences results above show that adopters have not fared better in the labor market after the introduction of AI chatbots, even those who adopted early or report large benefits from their use. To ensure that these estimates are not confounded by unobserved shocks to adopters,[15] we now exploit that employer policies cause variation

[15]For example, workers experiencing unforeseen personal or professional setbacks may struggle to adopt new technology. Conversely, those who expect to succeed regardless may see little need for chatbot assistance.

in adoption among similar workers. Table B.1 reports the "first stage" effects of these policies, showing how encouragements raise adoption among otherwise similar workers.

Figure 9 shows the "reduced form" effects of employer encouragements on workers' labor market outcomes, with dynamic effects in Panel (a) and occupation-specific impacts in Panel (b). Across all of our occupations studied, workers who are encouraged to use AI chatbots have not fared differently in the labor market. These results support our conclusion that AI chatbots have had no causal effect on the labor market outcomes of adopters. This conclusion is further supported in Section 5.1, which uses coworkers' reports as instruments for employer encouragement.

## 4.3 Perceived Impacts

The absence of earnings impacts from AI chatbots may seem surprising, given that workers report work-related benefits in Section 3. While reported time savings are also modest (around 2%–4% for the average user; see Table 1), the confidence bands in Figure 7 are narrow enough to rule out a comparable effect on earnings. For example, our pooled estimate ("All" in Figure 8.(a)) rejects effects on earnings larger than 1%. More specifically, software developers and marketing professionals report time savings of approximately 7% when employers encourage AI chatbot use—effect sizes that Figure 8 also rules out for earnings.

To further investigate the earnings impacts, we directly asked workers: *"Have AI chatbots affected your labor earnings?"* If so, we followed up with, *"By how much?"* Figure 10 plots workers' responses against their estimated time savings, yielding four key insights.

First, workers overwhelmingly report that AI chatbots have not meaningfully affected their earnings: the average perceived earnings impact ranges from 0.04% to 0.2%, depending on whether their employer encourages their use. These estimates are an order of magnitude smaller than the reported time savings in Section 3 and fall within the confidence bands of the actual earnings effects in Section 4.2. Moreover, because these perceived earnings effects were collected in November 2024, they provide reassurance that the zero difference-in-differences estimates in Section 4.2 are not merely a consequence of a short post-treatment window ending in June 2024. The continued absence of meaningful effects in November 2024 aligns with the difference-in-differences estimates, which show no differential trend following the introduction of AI chatbots.

Second, the limited perceived earnings effects primarily reflect that about 97% of workers report no change in earnings due to AI chatbots—rather than large positive and negative effects canceling each other out (see Appendix D.2 for a detailed breakdown). This further supports our conclusion from Figure 8 that AI chatbots have not had significant heterogeneous impacts on labor market outcomes.

Third, workers' perceived earnings effects are only weakly correlated with their reported time savings. As the slopes in Figure 10 indicate, only 3–7% of their estimated time savings translate into earnings. This suggests that the limited labor market impacts result from a genuinely weak pass-through of time savings and other benefits, rather than from workers misperceiving their gains from AI chatbots.

Fourth and finally, all these effects—time savings, pass-through rates, and ultimately earnings impacts—are significantly larger when employers encourage AI chatbot use. This highlights the critical role of firm-led adaptions, not only in unlocking the work-related benefits of the technology (as documented in Section 3) but also in translating these benefits into labor market outcomes such as earnings.

## 4.4 Comparison to the Literature

The literature provides little evidence on how AI chatbots affect workers' labor market outcomes, and a core contribution of this paper is to fill that gap.

The closest existing evidence comes from case studies of specific labor markets, often online platforms for freelance work. These studies document remarkable shifts in labor demand following the launch of ChatGPT (Hui, Reshef and Zhou, 2024; Teutloff et al., 2025). For example, Teutloff et al. (2025) report that demand for substitutable freelance services, such as writing and translation, declined by 20–50% after ChatGPT. In contrast, we find no significant impact on labor market outcomes across our diverse set of 11 occupations. What might explain this difference? Our evidence points to four potential factors.

First, while freelance proofreading may be highly substitutable by AI chatbots, most exposed occupations do not fall into this extreme category.[16] Indeed, workers in our survey report only modest time savings from AI chatbots. This reiterates our observations from Section 3.3 that existing studies tend to concentrate on the occupations where the productivity effects from the tools are the largest.

Second, freelance work offers far less job security and rigidity, allowing productivity changes to pass through more quickly to labor market outcomes. In contrast, we find only a weak relationship between workers' time savings and earnings effects from AI chatbots. While the flexibility of freelance work makes it useful for identifying short-run changes in labor demand, our findings on the weak pass-through of productivity gains caution against extrapolating these effects to the broader labor market. Indeed, our pass-through estimates align more closely with existing literature, which suggests that about 5% to 15% of firm-level productivity gains are passed through to wages (Card et al., 2018). By comparison, we estimate an average pass-through of 7% when employers encourage AI chatbot use.

Finally, although existing studies document shifts in demand on specific platforms, it remains unclear how these shifts affect workers' total earnings and hours, as workers may adapt by reallocating their tasks. In our survey, most workers report using time saved

[16] Teutloff et al. (2025) show that the overall impacts of ChatGPT on freelance work are more mixed, with some complementary skills seeing increases.

by AI chatbots for other tasks, including new job responsibilities introduced by AI. A key advantage of our administrative data is that it allows us to measure workers' total earnings and hours, regardless of how they reallocate time in the labor market.

# 5 Further Analysis

Our earlier analysis shows that while AI chatbots are now widely used—saving users time and creating new job tasks, especially in workplaces that encourage their use—their overall impact on the labor market remains limited. In this final section, we present two additional analyses that support these conclusions.

First, in Section 5.1, we implement an instrumental variables (IV) strategy to strengthen our interpretation of employer encouragement as a workplace-wide policy. Specifically, we instrument an individual's encouragement with the leave-one-out average encouragement rate among their coworkers—that is, other employees in the same occupation and workplace. The IV estimates align with earlier OLS results.

Second, in Section 5.2, we examine whether AI chatbots have influenced broader workplace outcomes. Even if the benefits to individual users have not yet led to changes in their earnings or hours, employers might still be adjusting overall employment or wage bills in response to these tools.[17] Despite this possibility, we find no evidence that "high-adoption" workplaces have fared differently since the introduction of AI chatbots.

## 5.1 Coworker IV

### 5.1.1 Empirical Strategy

Our coworker IV design is based on the following idea: if reported encouragement reflects employer-wide policies—rather than idiosyncratic, worker-level variation—then coworkers

[17] If such adjustments are occurring, AI chatbots could also be affecting non-adopting coworkers, potentially violating the "no spillovers" assumption in our worker-level difference-in-differences analysis. Indeed, Section 3.2 showed that AI chatbots have already introduced new workloads for non-users, suggesting broader workplace changes.

should also report being encouraged to use AI chatbots. To operationalize this idea, we construct leave-one-out averages of coworkers' encouragement rates for each worker $i$ and use these leave-out means as instruments for worker $i$'s own reported encouragement:

$$\text{EmployerInitiative}_i = \pi' X_{j,-i} + \alpha \times \text{EmployerInitiative}_{j,-i} + \varepsilon_{1i} \tag{4}$$

$$Y_i = \gamma' X_{j,-i} + \beta \times \widehat{\text{EmployerInitiative}}_i + \varepsilon_{2i}, \tag{5}$$

where $\text{EmployerInitiative}_i$ denotes an employer-driven initiative, such as encouraging employees to use AI chatbots, and $X_{j,-i}$ denotes the leave-one-out mean of the characteristics $X$ of worker $i$'s coworkers—that is, other workers in the same occupation and workplace.

The coworker IV strategy is made possible by our workplace-based sampling design (described in Section 1.5), which ensures that most respondents have coworkers who also participated in the survey. To mitigate measurement error due to incomplete sample coverage, we apply an empirical shrinkage procedure to the leave-out encouragement rates, $\text{EmployerInitiative}_{j,-i}$ (see Appendix E.3 for details on this method). Importantly, our IV estimates are robust to using the raw leave-out means instead.

#### 5.1.2 Results

**First Stage.** Table E.1 reports the first-stage results from Equation (4). Coworker encouragements strongly predict an individual worker's own reported encouragement: the first-stage coefficient is approximately 1, with an F-statistic of 3,645. The strong correlation in reported employer encouragement at the workplace level supports our interpretation of these initiatives as centralized policies. Reassuringly, once the coworker encouragement rate is accounted for, coworkers' characteristics $X_{j,-i}$ do not predict worker $i$'s encouragement. This serves as a conditional balance test for the exogeneity of the employer usage policies.

**Adoption and Work.** Table 2 presents the IV estimates from Equation (5) and compares them to the OLS estimates shown in Figures 2-5. The IV results broadly align with our OLS estimates but with interesting differences.

The IV estimates for adoption (Panel a) are 1.5–2 times larger than the corresponding OLS estimates. Moreover, Figure E.1.(a) shows that employer encouragement—instrumented using coworker rates—can completely eliminate the gender gap in AI chatbot adoption.[18]

By contrast, the IV estimates for reported benefits among adopters (Panel b) are more attenuated. For instance, while Figure 4.(a) suggests that encouragement increases the share of workers reporting time savings by 10 percentage points, the corresponding IV estimate is 5.3 percentage points. Finally, Panel (b) indicates that the IV estimate for the creation of new tasks among adopters is roughly twice as large as the OLS estimate shown in Figure 5.

Taken together, these results suggest that workplace-wide encouragement (as captured by our IV strategy) can significantly boost chatbot adoption and prompt larger-scale work reorganization. However, the individual-level benefits—such as perceived time savings—appear more dependent on whether the worker personally feels encouraged, as captured by the OLS estimates.

**Labor Market Outcomes.** Figure E.2 revisits our analysis of how employer encouragement affects individual labor market outcomes, this time using the coworker IV to instrument for individual encouragement. The results confirm that employer encouragement policies have had no impact on workers' labor market outcomes.

A takeaway from our earlier analysis is that the modest labor market effects are partly due to weak pass-through from time savings to labor earnings—though this pass-through

[18]However, also consistent with the OLS estimates in Figure B.4, Figure E.1.(b) shows that encouragement alone may widen the gender gap in frequent chatbot usage.

is stronger when employers actively encourage chatbot use. Table E.2 replicates this result using the coworker IV. Pass-through remains modest (ranging from 2% to 6%), but is roughly three times higher when employers encourage chatbot use.

## 5.2 Workplace Outcomes

### 5.2.1 Empirical Strategy

To investigate the workplace impacts of AI chatbots, we shift our difference-in-differences analysis to the workplace level, comparing workplaces with high versus low adoption rates. Specifically, we run the regression models in Section 4.1.1, where $Y_{it}$ is now an outcome of workplace $j$ (e.g., total employment or wage bill), $X_i$ are the average pre-determined characteristics of its employees, and $A_i$ is the share of its employees who have adopted AI chatbots.

A concern for this analysis is that our survey may not cover all employees at workplace $j$, leading to measurement error in the survey-based adoption rates $A_i$, which could attenuate our difference-in-difference estimates. We take two steps to address this issue. First, as described in Section 1.5, we implement a two-stage sampling strategy that maximizes the coverage of our sampled workplaces—first drawing a random set of workplaces, then sampling all their employees. Second, as described in Appendix E.3, we apply an Empirical Bayes shrinkage procedure to correct for measurement error in the survey-based adoption rates. Notably, all our results remain robust when using the raw survey-based adoption rates.

### 5.2.2 Results

Figure 11 shows the impacts of AI chatbot adoption on total workplace earnings and employment hours. Panel (a) shows dynamic difference-in-differences, and Panel (b) shows the pooled difference-in-differences for each occupation. Across the board, workplaces with higher rates of AI chatbots adoptions have not fared differently. Scaling the point estimates with the standard deviation of workplace adoption rates (20pp after shrinkage; see Appendix E.3), we can rule out standardized effects larger than 1%.[19]

Finally, to further investigate potential labor market spillovers from AI chatbots, we also asked non-users directly whether AI chatbots have affected their earnings. Figure E.3 in Appendix E.2 provides the answers, showing 99.6% answers “No”. This solidifies our conclusion that—despite changing workloads, even for non-users—AI chatbots have not had meaningful spillover effects on labor market outcomes such as earnings.

# 6 Conclusion

Generative AI is heralded as the engine of a new industrial revolution (World Economic Forum, 2024), yet we lack evidence on its economic impacts outside laboratory settings and case studies (Brynjolfsson, Li and Raymond, 2025; Noy and Zhang, 2023).

This paper provides large-scale evidence on the labor market impacts of AI chatbots, the most widely adopted Generative AI tool to date. Our study is based on a series of extensive surveys on AI chatbot usage in 11 exposed occupations, linked to matched employer-employee data in Denmark.

Despite rapid adoption and substantial investments by both workers and firms, our key finding is that AI chatbots have had minimal impact on productivity and labor market outcomes to date. Moreover, we find no evidence of differential trends over time, suggesting that the limited effects are not merely a very short-run phenomenon. In this sense, our results echo Robert Solow’s famous observation about the IT revolution: *“You can see the computer age everywhere but in the productivity statistics”* (Solow, 1987).

However, our analysis sheds light on mechanisms through which Generative AI could

[19]The absence of effects on firm-level employment and wage bills stands in contrast with Eisfeldt et al. (2024), who show that firms with occupational compositions more exposed to AI chatbots experienced a rise in their stock prices following the release of ChatGPT. This simultaneous increase in market capitalizations, despite limited labor demand effects, suggests that we may currently be at the trough of a productivity J-curve—where investors anticipate current investments will affect economic outcomes in the longer run (Brynjolfsson, Rock and Syverson, 2021).

become transformative over time. First, consistent with Brynjolfsson, Rock and Syverson (2021), we find that firm-driven investments and workplace reorganizations are critical to unlocking AI's potential: Take-up rates and productivity benefits of AI chatbots are substantially higher when employers encourage usage, provide training, or deploy in-house models. Second, aligning with theoretical predictions for how automation technologies may reinstate labor demand (Acemoglu and Restrepo, 2019), we find that AI chatbots have created new job tasks—extending even to workers who do not use the tools directly—signaling broader workplace transformations. Finally, labor market rigidities appear to delay the economic impact, as productivity gains from AI chatbots translate only weakly into earnings growth, particularly in firms that do not actively promote their usage.

Still, we believe that the key finding in this paper will remain central to understanding the labor market effects of Generative AI. Any account of transformational change must contend with a simple fact: two years after the fastest technology adoption ever, labor market outcomes—whether at the individual or firm level—remain untouched.

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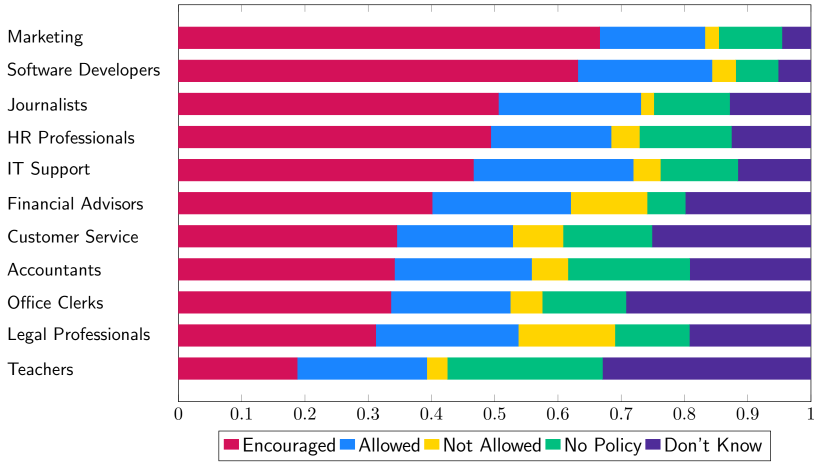
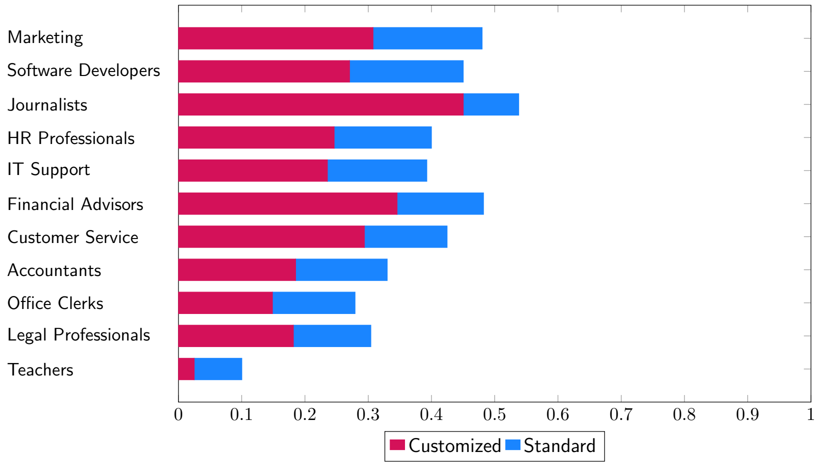
# Figures and Tables

Figure 1: Prevalence of Employer Initiatives for AI Chatbot Adoption

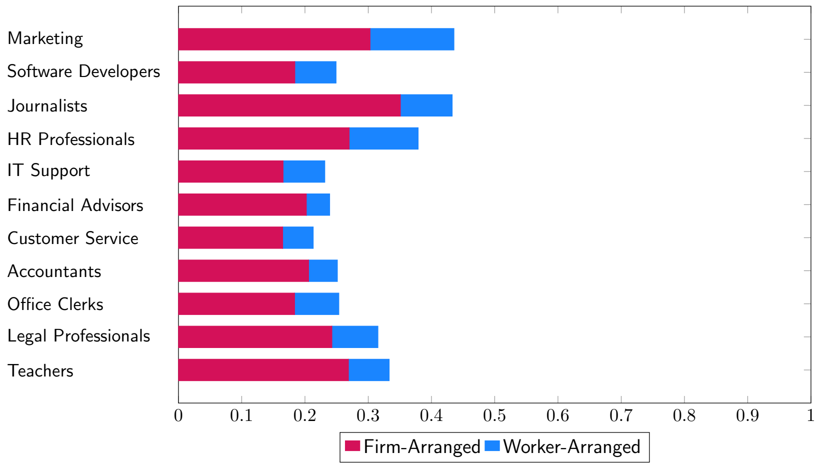
(a) Usage Policies




(b) In-House AI Chatbots

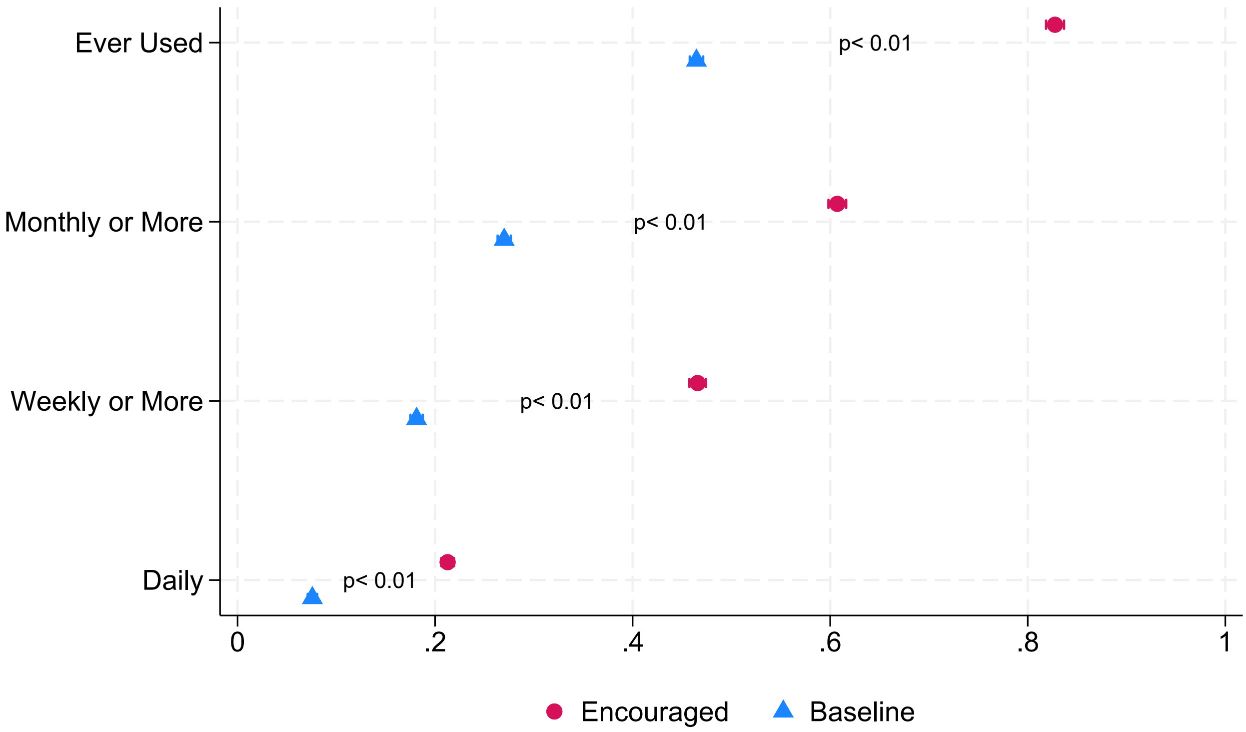



(c) Training in AI Chatbots



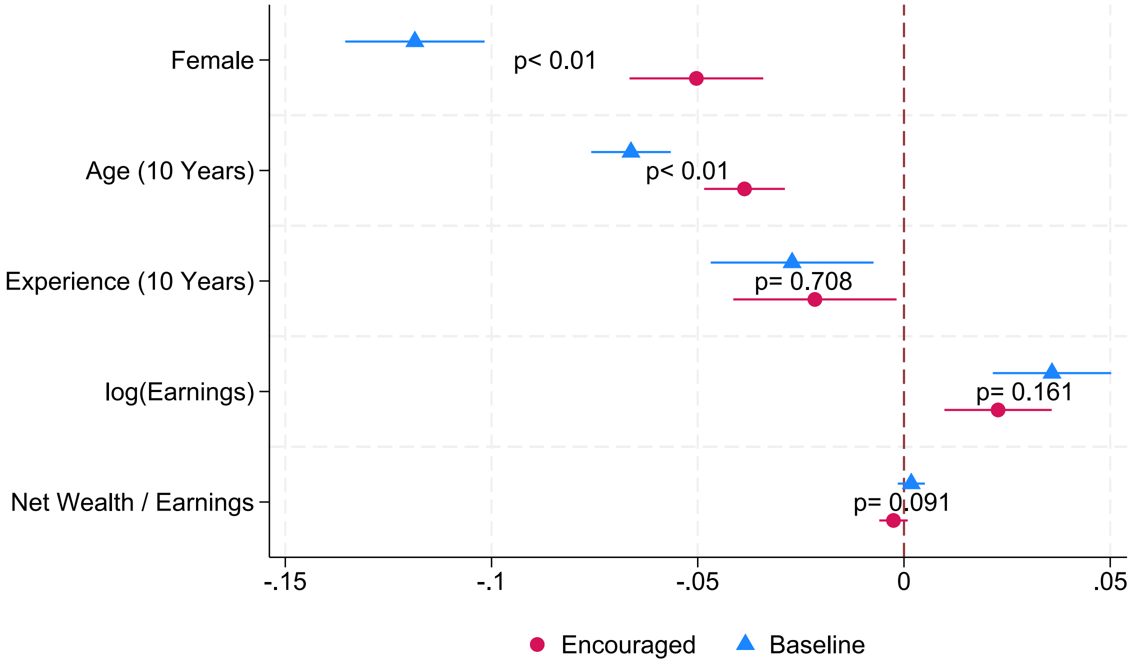

*Notes*: This figure shows the share of workers affected by various employer initiatives related to AI chatbot adoption. Panel (a) shows employers' policies on AI chatbot usage for work. Panel (b) indicates whether the employer has its own AI chatbot. Panel (c) reports whether workers have participated in AI chatbot training courses. Figure B.1 provides a workplace-level version of this graph, yielding similar results. *Sample*: All completed responses from the 2024 survey.

Figure 2: Importance of Employer Policies in AI Chatbot Adoption




*Notes*: This figure illustrates the impact of employer policies on workers' use of AI chatbots. The estimates are based on predicted values from Equation (1), varying employer usage policies (Encouraged = 1 vs. Encouraged = 0) while holding workers' characteristics $X$ at their mean values. Whiskers represent 95% confidence bands of the predicted values. The reported p-values test whether the coefficients differ between the two groups. *Sample*: All completed responses from the 2024 survey linked to registry data.

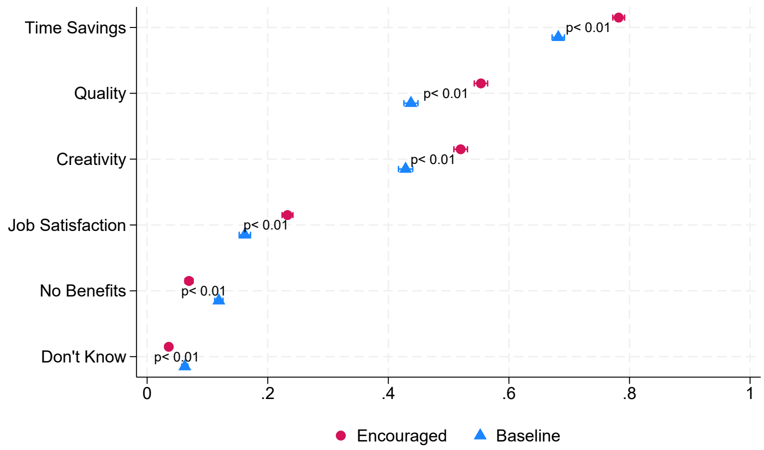
Figure 3: Influence of Employer Encouragement on Worker Gaps in AI Chatbot Adoption



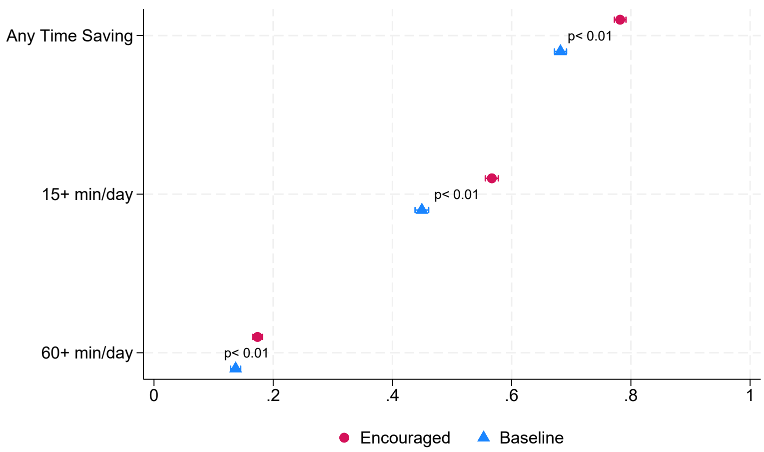

*Notes*: This figure illustrates the impact of employer usage policies on worker disparities in AI chatbot adoption. The estimates are obtained from a multivariate regression of AI chatbot adoption on worker characteristics $X$, controlling for occupation fixed effects, and are estimated separately based on employers' AI chatbot initiatives (Encouraged = 1 vs. Encouraged = 0). Whiskers represent 95% confidence intervals. The reported p-values test whether the coefficients differ between the two groups. *Sample*: All completed responses from the 2024 survey linked to registry data.

Figure 4: Benefits of AI Chatbots for Adopters

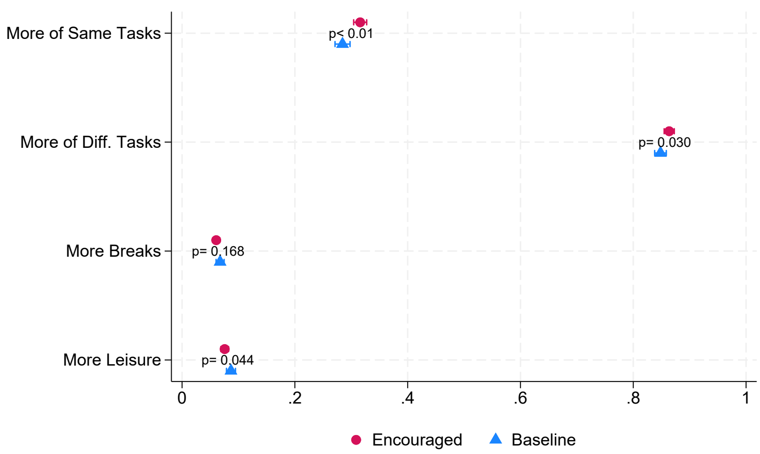
(a) Reported Benefits




(b) Estimated Time Savings




(c) Allocation of Time Savings

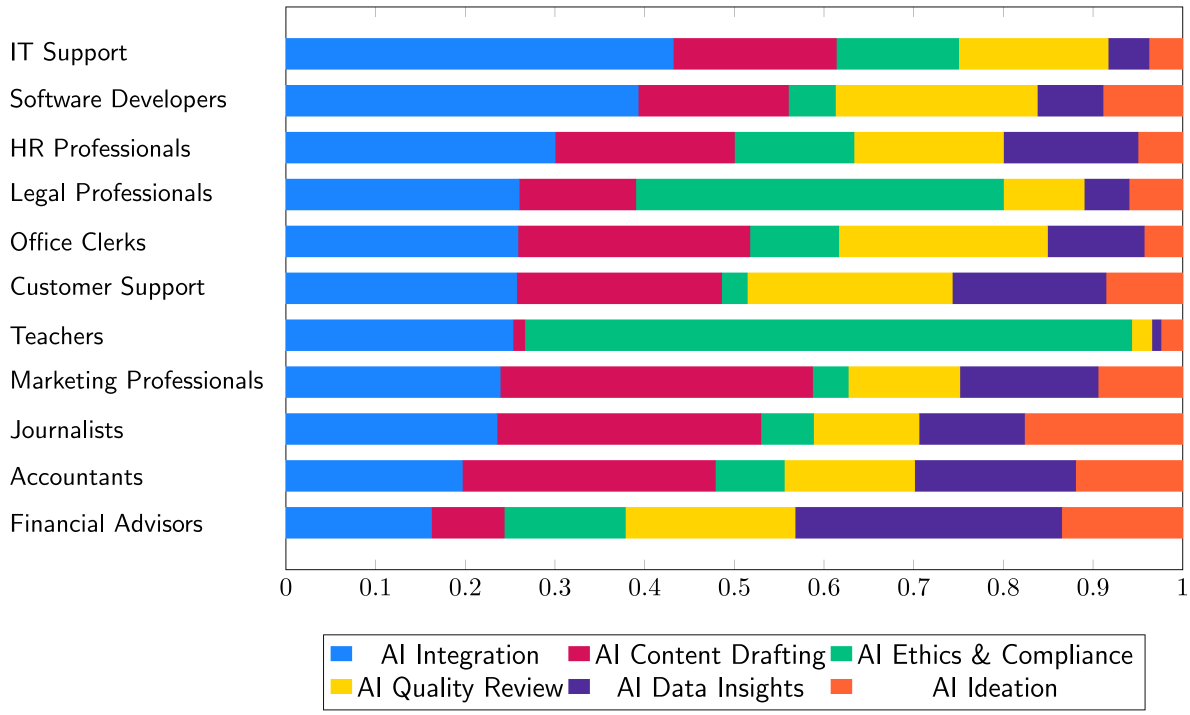



*Notes*: This figure illustrates how employer initiatives influence the benefits workers report from using AI chatbots. Panel (a) presents the share of adopters reporting various benefits, Panel (b) shows the share reporting different levels of time savings, and Panel (c) details how these workers allocate their saved time. The estimates are based on predicted values from Equation (1), varying employer usage policies (Encouraged $= 1$ vs. $= 0$) while holding workers' characteristics $X$ at their mean values. Whiskers represent 95% confidence bands of the predicted values. The reported p-values test whether the coefficients differ between the two groups. *Sample*: All completed responses from the 2024 survey linked to registry data.

Figure 5: New Workloads from AI Chatbots


*Notes*: This figure illustrates how employer initiatives influence the new workloads created by AI chatbots. Panel (a) presents results for adopters, while Panel (b) focuses on non-adopters (workers who have never used AI chatbots for work). Estimates are predicted values from Equation (1), varying employer usage policies (Encouraged = 1 vs. Encouraged = 0) while holding workers' characteristics $X$ at their mean values. Whiskers represent 95% confidence bands of the predicted values. The reported p-values test whether the coefficients differ between the two groups. *Sample:* All completed responses from the 2024 survey linked to registry data.

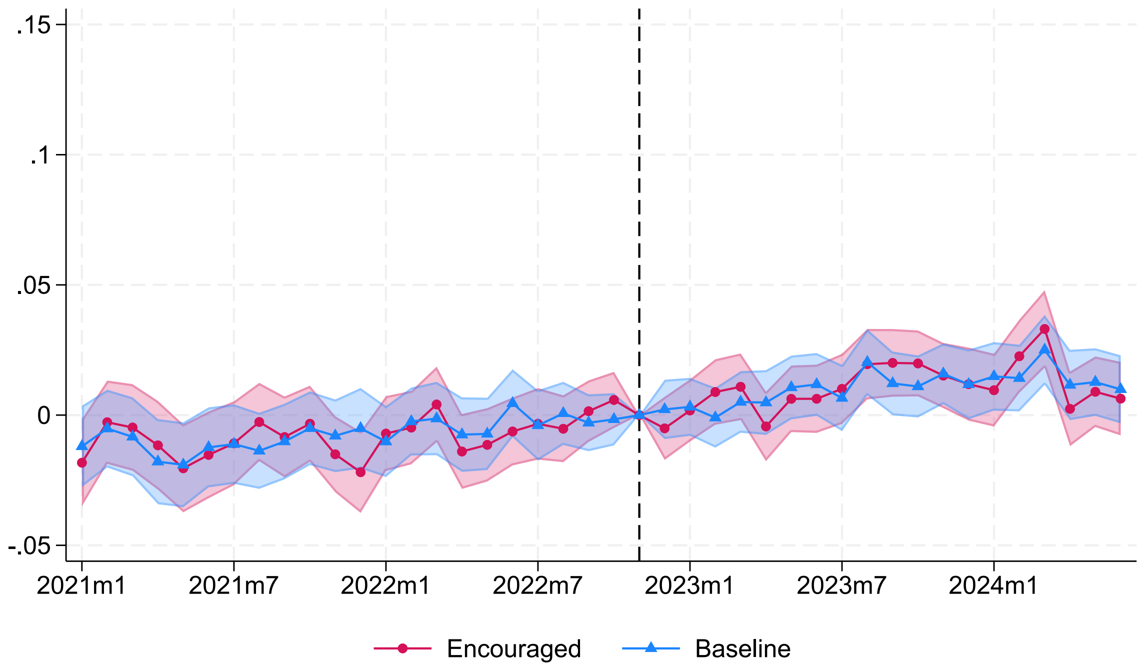
Figure 6: Composition of AI Tasks



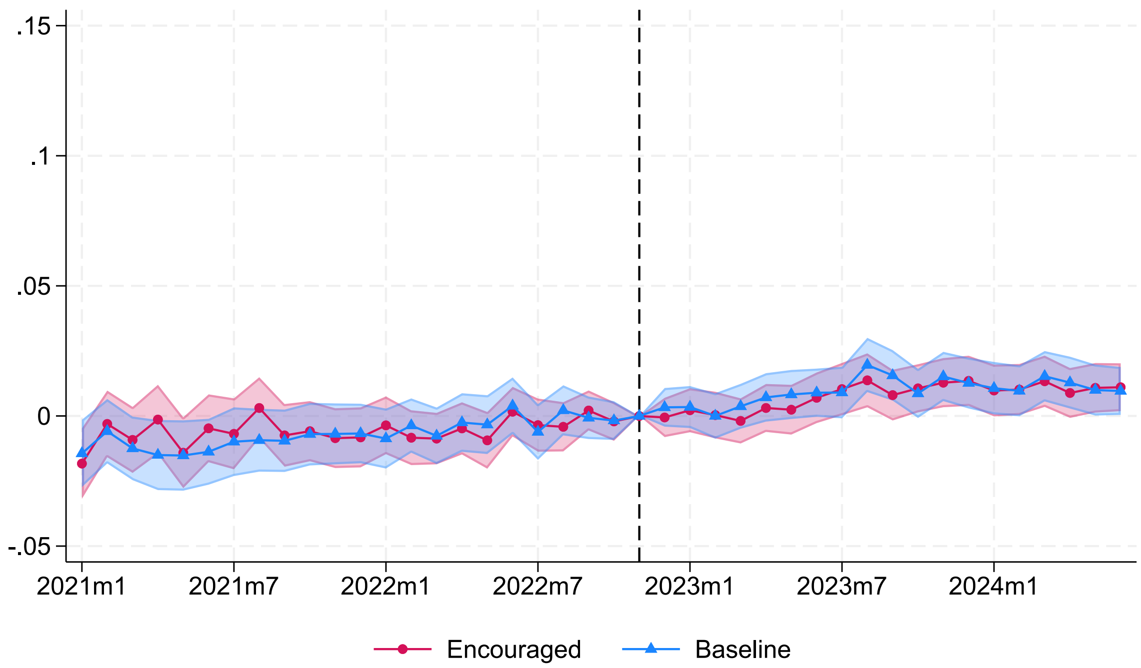

*Notes*: This figure shows the distribution of reported new job tasks across major task categories for each occupation. Appendix C.2 defines the categories. Tasks are ordered according to their average shares among the eleven occupations. Occupations are ordered according to their shares on *AI Integration*, the most frequent tasks across the occupations. *Sample*: All completed responses from the 2024 survey who reported new job tasks due to AI chatbots.

Figure 7: Have Adopters Fared Better in the Labor Market?
(Dynamic Difference-in-Differences)

(a) log Earnings



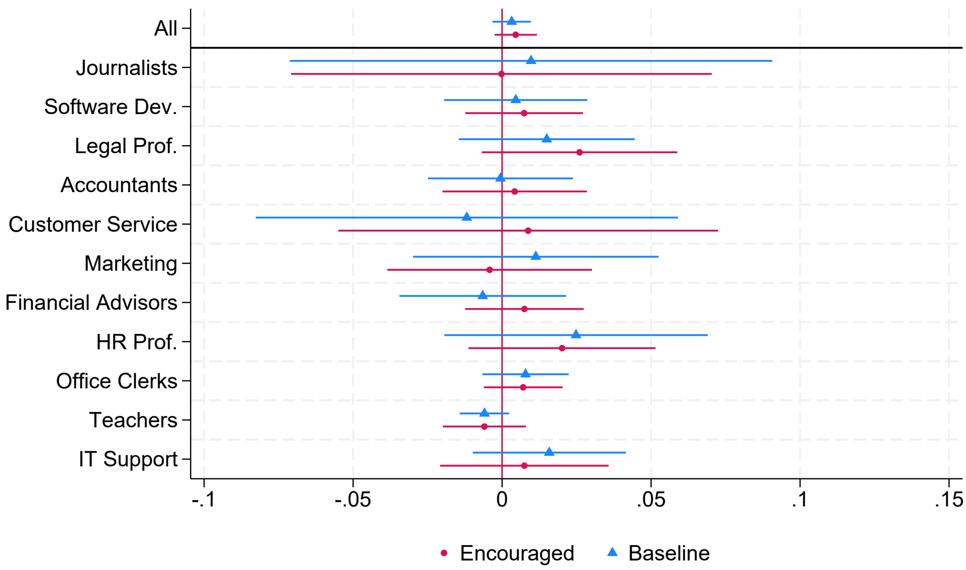

(b) log Hours



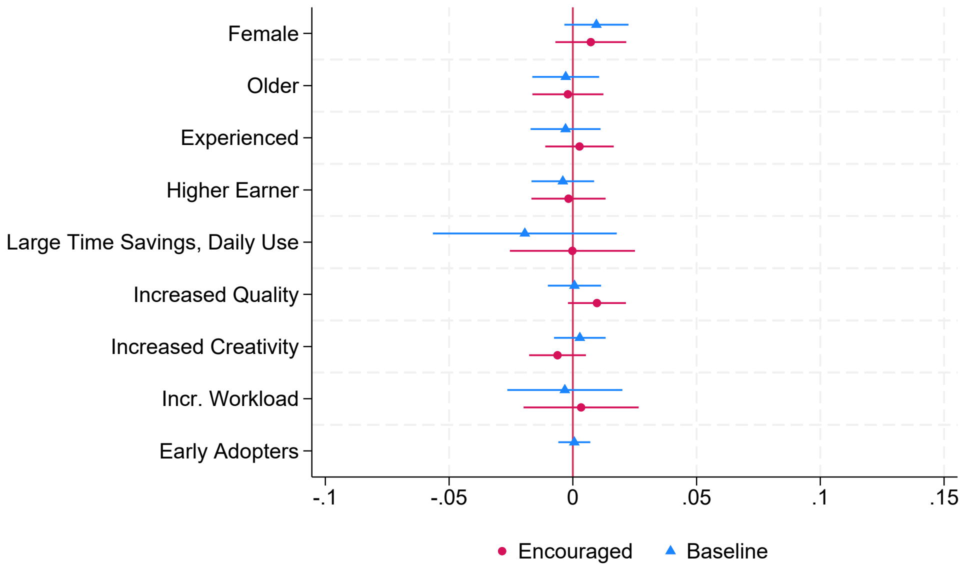

*Notes*: This figure presents the differential labor market outcomes of AI chatbot adopters relative to non-adopters, indexed to the launch of ChatGPT in November 2022. Effects are estimated separately for adopters whose employers encourage AI chatbot use ("Encouraged") and those without encouragement ("Baseline"), with all non-adopters serving as the control group in both cases. Estimates are based on the dynamic difference-in-differences specification in Equation (2). Shaded areas represent 95% confidence intervals. *Sample:* All completed responses from the 2024 survey linked to registry data.

Figure 8: How Do the Earnings Effects of Adoption Vary Across Workers?
(Pooled Difference-in-Differences)

(a) Occupation-Level Effects



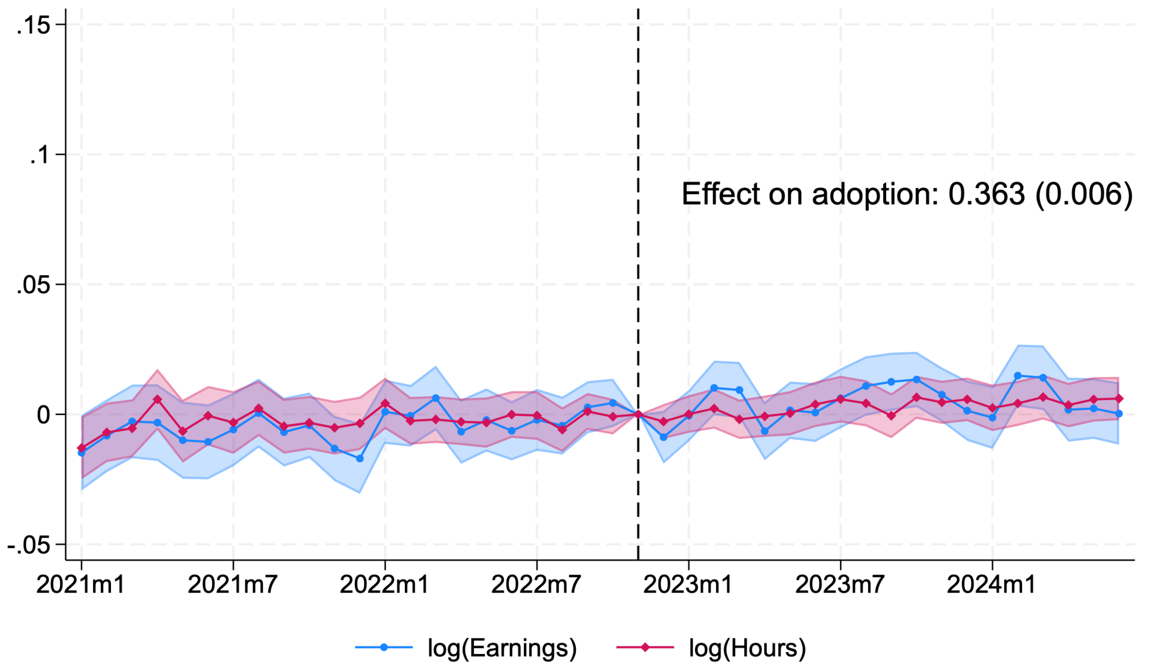

(b) Differential Effects by Worker Characteristics



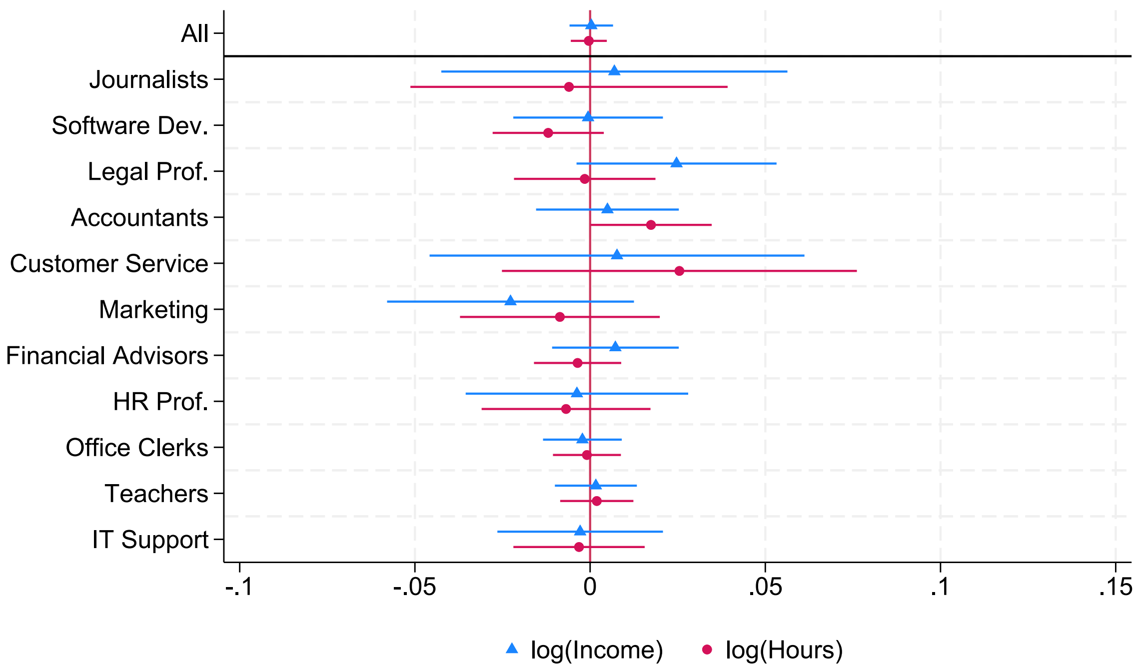

*Notes*: This figure presents the differential labor market outcomes of AI chatbot adopters relative to non-adopters, indexed to the launch of ChatGPT in November 2022. Effects are estimated separately for adopters whose employers encourage AI chatbot use ("Encouraged") and those without encouragement ("Baseline"), with all non-adopters serving as the control group in both cases. Estimates are based on the pooled difference-in-differences specification in Equation (3), with whiskers representing 95% confidence intervals. Panel (a) first shows a pooled estimate (*All*) and then reports impacts separately for each of our 11 study occupations. Panel (b) shows differential effects by workers' characteristics, estimated by interacting the regression model in Equation (3) with an indicator for the particular characteristic. These indicators are coded as follows: *Female* indicates women, *Older/Experienced/Higher Earner* indicates above-median age/experience/earnings within the occupation, *Large Time Savings, Daily Use* indicates daily users of AI chatbots with time savings exceeding 60 minutes per day (see Figures 2 and 4.(b)), *Increased Quality / Creativity* indicates reporting improved quality / creativity from using AI chatbots (see Figure 4.(a)). *Incr. Workload* indicates reporting new job tasks due to AI chatbots (see Figure 5). *Early adopters* are workers who had adopted ChatGPT in our 2023 survey round. (Because the 2023 round did not ask about employer encouragement, we can only report the average effect.) *Sample:* All completed responses from our surveys linked to registry data.

Figure 9: Have Employer Chatbot Policies Affected Workers' Outcomes? (Reduced Form)

(a) Labor Market Effects of Encouragement (Dynamic Diff-in-Diffs)




(b) Occupation-Level Effects of Encouragement (Pooled Diff-in-Diffs)



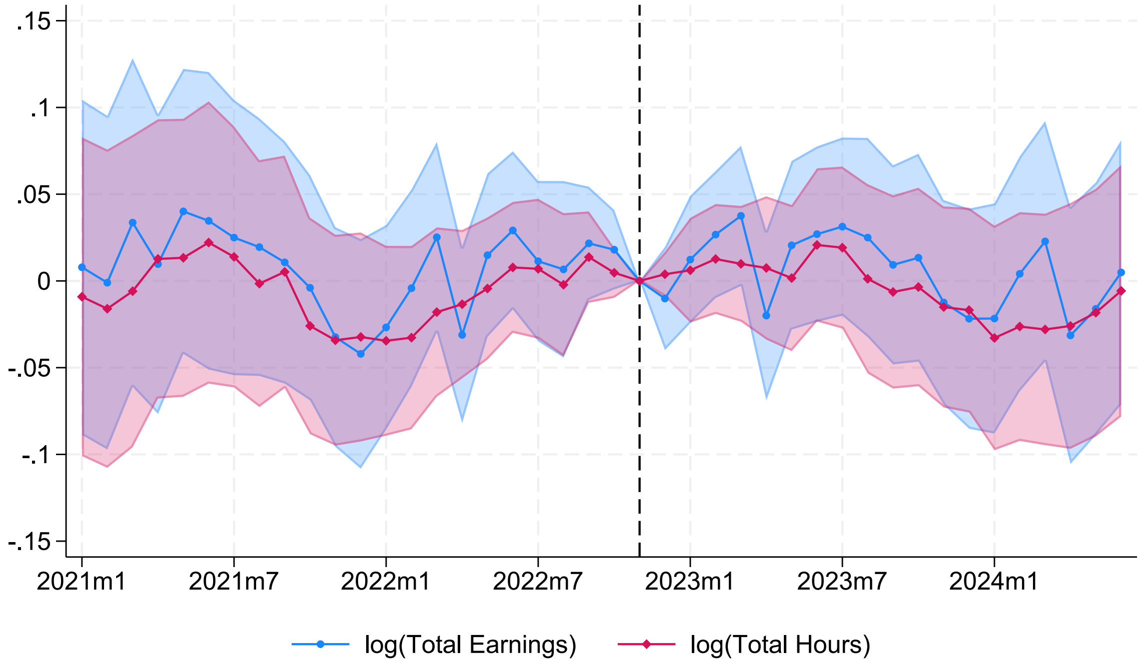

*Notes*: This figure presents the differential labor market outcomes of workers who are encouraged to use AI chatbots by their employers, compared to all other workers, indexed to the launch of ChatGPT in November 2022. Panel (a) is based on the dynamic difference-in-differences specification in Equation (2), with shaded areas representing 95% confidence intervals. The plot also reports the corresponding first-stage effect on adoption (0.363) from Table B.1. Panel (b) first shows a pooled estimate (*All*) and then reports impacts separately for each of our 11 study occupations. These effects are based on the pooled difference-in-differences specification in Equation (3), with whiskers representing 95% confidence intervals. *Sample:* All completed responses from the 2024 survey linked to registry data.

Figure 10: How Do Workers' Earnings Impacts Relate to Their Time Savings?

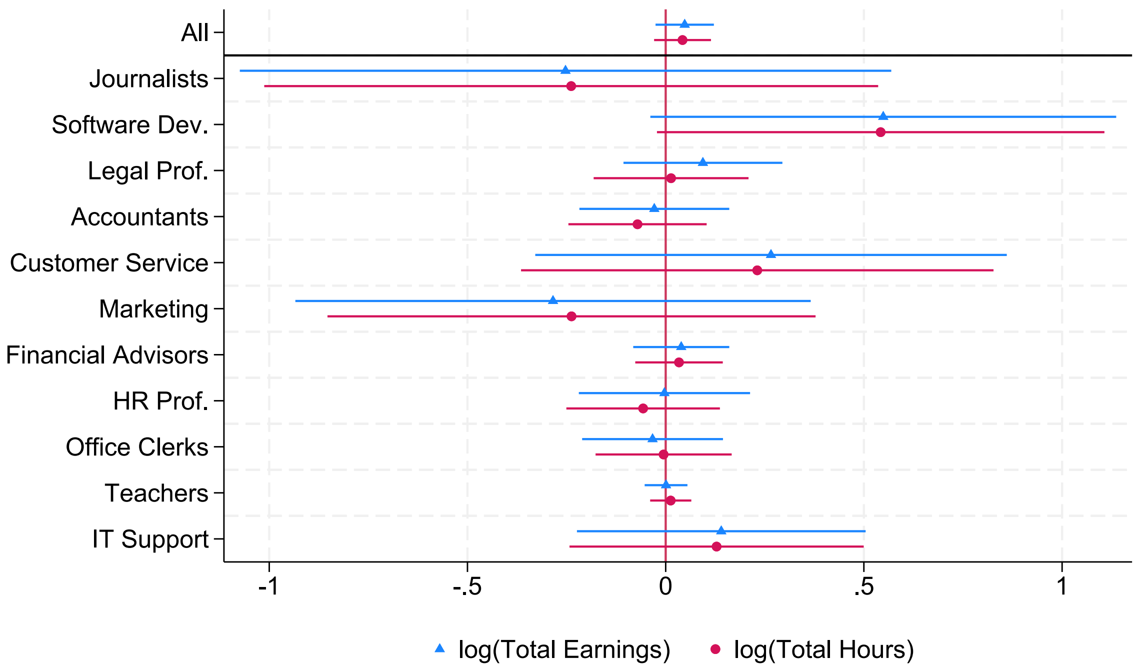

*Notes*: This figure presents a binned scatterplot of workers' perceived earnings impacts from AI chatbots against their estimated time savings from these tools, absorbing occupation fixed effects. The sample is divided based on whether employers encourage AI chatbot use. The regression line represents the line of best fit for each group, controlling for occupation fixed effects. *Sample*: All completed responses from the 2024 survey.

Figure 11: Have High-Adoption Workplaces Fared Differently?

(a) Workplace Outcomes




(b) Occupation-Level Effects




*Notes*: This figure presents the differential change in workplace outcomes by adoption rates, indexed to the launch of ChatGPT in November 2022. Adoption rates are measured as the share of employees who have used AI chatbots for work, adjusted for measurement error using an Empirical Bayes shrinkage procedure detailed in Appendix E.3. Panel (a) is based on the dynamic difference-in-differences specification in Equation (2), weighted by the number of respondents at the workplace; shaded areas indicate 95% confidence intervals. Panel (b) shows the effects separately by occupation, based on the pooled difference-in-differences specification in Equation (3), also weighted by the number of respondents at the workplace; whiskers indicate 95% confidence intervals. *Sample:* All completed responses from workplaces with at least two respondents from the 2024 survey linked to registry data.

Table 1: What Drives Workers' Time Savings from AI Chatbots?

| Occupation | Policy | Time Savings / Work Hours (1) | Time Saved Per Day Used / Daily Work Hours (2) | Days Used / Work Days (3) | Covariance (4) |
|---|---|---|---|---|---|
| Marketing Professionals | Encouraged | 0.068 | 0.109 | 0.513 | 0.012 |
| Marketing Professionals | Baseline | 0.046 | 0.087 | 0.386 | 0.012 |
| Software Developers | Encouraged | 0.065 | 0.093 | 0.566 | 0.012 |
| Software Developers | Baseline | 0.039 | 0.074 | 0.377 | 0.011 |
| HR Professionals | Encouraged | 0.042 | 0.081 | 0.403 | 0.009 |
| HR Professionals | Baseline | 0.026 | 0.074 | 0.235 | 0.009 |
| IT Support | Encouraged | 0.041 | 0.075 | 0.405 | 0.011 |
| IT Support | Baseline | 0.028 | 0.060 | 0.282 | 0.011 |
| Customer Service Rep. | Encouraged | 0.039 | 0.066 | 0.439 | 0.010 |
| Customer Service Rep. | Baseline | 0.020 | 0.050 | 0.238 | 0.008 |
| Legal Professionals | Encouraged | 0.033 | 0.074 | 0.335 | 0.008 |
| Legal Professionals | Baseline | 0.018 | 0.065 | 0.165 | 0.007 |
| Office Clerks | Encouraged | 0.029 | 0.065 | 0.308 | 0.009 |
| Office Clerks | Baseline | 0.015 | 0.047 | 0.176 | 0.007 |
| Journalists | Encouraged | 0.028 | 0.050 | 0.373 | 0.009 |
| Journalists | Baseline | 0.021 | 0.048 | 0.219 | 0.011 |
| Financial Advisors | Encouraged | 0.022 | 0.053 | 0.287 | 0.007 |
| Financial Advisors | Baseline | 0.015 | 0.040 | 0.177 | 0.008 |
| Accountants and Auditors | Encouraged | 0.022 | 0.055 | 0.281 | 0.006 |
| Accountants and Auditors | Baseline | 0.009 | 0.041 | 0.141 | 0.003 |
| Teachers | Encouraged | 0.010 | 0.049 | 0.138 | 0.003 |
| Teachers | Baseline | 0.006 | 0.044 | 0.087 | 0.002 |
| All | Encouraged | 0.036 | 0.070 | 0.368 | 0.010 |
| All | Baseline | 0.022 | 0.057 | 0.226 | 0.009 |

*Notes*: This table presents workers' time savings from AI chatbots, categorized by workers' occupations and employer policies. The table focuses on workers who have ever used AI chatbots for work. Column (1) reports the average time savings as a percentage of total work hours. The remaining columns decompose these time savings into three components: time savings per day of use (Column (2)), the share of workdays with AI chatbot usage (Column (3)), and the covariance between Columns (2) and (3) (Column (4)). These components satisfy the relationship: Column (1) = Column (2) $\times$ Column (3) + Column (4), which follows from the identity: $E[XY] = E[X]E[Y] + \mathrm{Cov}(X,Y)$. We code daily time savings as follows: 0–15 minutes/day as 7.5 minutes, 15–60 minutes as 37.5 minutes, and 60+ minutes as 90 minutes. We set daily work hours to 8, as nearly all sampled workers are full-time employees. *Sample*: The table is based on all completed responses from the 2024 survey that can be linked to the registry data.

Table 2: The Impact of Employer Encouragement on Adoption and Work (OLS vs. IV)

(a) Adoption

| | Ever Used | | Monthly or More | | Weekly or More | | Daily | |
|---|---|---|---|---|---|---|---|---|
| | OLS (1) | IV (2) | OLS (3) | IV (4) | OLS (5) | IV (6) | OLS (7) | IV (8) |
| Encouraged | 0.363 | 0.725 | 0.337 | 0.640 | 0.285 | 0.506 | 0.137 | 0.228 |
| | (0.007) | (0.022) | (0.007) | (0.022) | (0.007) | (0.021) | (0.005) | (0.017) |

(b) Reported Benefits

| | Time Savings | | Quality | | Creativity | | Job Satisfaction | |
|---|---|---|---|---|---|---|---|---|
| | OLS (1) | IV (2) | OLS (3) | IV (4) | OLS (5) | IV (6) | OLS (7) | IV (8) |
| Encouraged | 0.100 | 0.053 | 0.116 | 0.090 | 0.091 | 0.088 | 0.071 | 0.026 |
| | (0.008) | (0.031) | (0.009) | (0.033) | (0.009) | (0.031) | (0.007) | (0.025) |

(c) Allocation of Time Savings

| | More of Same Tasks | | More of Diff. Tasks | | More Breaks | | More Leisure | |
|---|---|---|---|---|---|---|---|---|
| | OLS (1) | IV (2) | OLS (3) | IV (4) | OLS (5) | IV (6) | OLS (7) | IV (8) |
| Encouraged | 0.031 | 0.035 | 0.016 | 0.037 | -0.007 | -0.016 | -0.011 | -0.010 |
| | (0.009) | (0.035) | (0.007) | (0.024) | (0.005) | (0.016) | (0.006) | (0.019) |

(d) New Workloads from AI Chatbots (Adopters)

| | Same Tasks | | New Tasks | | Same and New Tasks | |
|---|---|---|---|---|---|---|
| | OLS (1) | IV (2) | OLS (3) | IV (4) | OLS (5) | IV (6) |
| Encouraged | 0.016 | 0.018 | 0.045 | 0.106 | 0.008 | 0.014 |
| | (0.004) | (0.012) | (0.006) | (0.021) | (0.002) | (0.008) |

*Notes:* This table presents estimates of the impact of employer encouragement on AI chatbot adoption (Panel a), the reported benefits of adoption (Panel b), the allocation of time savings (Panel c), and new workloads resulting from chatbot use among adopters (Panel d). Odd-numbered columns report OLS regressions that control for worker characteristics using the specification in Equation (1). Even-numbered columns report IV regressions, instrumenting for *Encouraged* using leave-out coworker encouragement rates, as specified in Equations (4)–(5). Table E.1, Column (1), presents the corresponding first-stage estimates. The OLS coefficients correspond to the difference between the "Baseline" and "Encouraged" predicted values shown in Figures 2, 4(a,c), and 5(a), respectively. Standard errors, shown in parentheses, are clustered at the workplace level. *Sample*: The OLS columns are based on all complete responses from the 2024 survey that can be linked to the registry data, while IV columns are based on all complete responses from workplaces with at least two respondents from the 2024 survey that can be linked to the registry data.

# Online Appendix

# Large Language Models, Small Labor Market Effects

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# A Data and Institutional Setting

## A.1 Sampling Protocol

Our 2024 survey invited 115,000 workers across 11 occupations. Ideally, we would sample an equal number from each—i.e., 10,450 journalists, 10,450 software developers, etc. However, some occupations in Denmark employ fewer than 10,450 workers. To address this, we follow these steps:

1. If an occupation has fewer than 10,450 workers, we sample all available workers.
2. The remaining invitations are redistributed equally among the other occupations.
3. Workplaces are randomly selected for sampling, and if chosen, all relevant workers (i.e., those in the target occupation) within the workplace are included.
4. Large workplaces can distort the sample balance. To mitigate this, we apply individual-level sampling to the top 2.5% of workplaces (ranked by the number of employees in the relevant occupation), randomly selecting employees using the same sampling probability as in Step 3.
5. To precisely reach our target of 115,000 workers, we make final adjustments by randomly including or excluding workers, independent of their workplace.

The 2023 survey followed a similar protocol, with minor modifications; see Humlum and Vestergaard (2025) for details.

## A.2 Survey Sample

Table A.1 outlines how successive sample restrictions define our analysis sample. In total, we obtained about 25,000 complete and valid responses per survey round that can be linked to registry data. The attrition and response rates in our survey are comparable to those obtained in previous Danish surveys (Hvidberg, Kreiner and Stantcheva, 2023). While our main analysis focuses on responses from the 2024 round, we use the 2023 round to examine the dynamics of our estimated effects.

Table A.1: Sample Construction

| | *2024 Survey* | | *2023 Survey* | | | |
|---|---|---|---|---|---|---|
| | | | *Main Survey* | | *Follow-Up Only* | |
| | Individuals | Percent of invitees | Individuals | Percent of invitees | Individuals | Percent of invitees |
| 1. Invitees | 115,000 | 100.0 | 100,000 | 100.0 | 15,000 | 100.0 |
| 2. Respondents | 30,411 | 26.4 | 29,067 | 29.1 | 4,094 | 27.3 |
| 3. In target occupation(s) | 26,925 | 23.4 | 25,121 | 25.1 | 3,504 | 23.4 |
| 4. Complete responses | 25,241 | 21.9 | 18,109 | 18.1 | 2,561 | 17.1 |
| 5. Linked to registers | 24,796 | 21.6 | 17,907 | 17.9 | 2,559 | 17.1 |

*Notes*: This table outlines how successive sample restrictions define our analysis sample. We conducted two survey rounds in November 2023 and 2024, each inviting 115,000 workers to participate. The 2023 survey included both a main survey and a two-week follow-up, with 15,000 workers invited only to the follow-up. Row 2 reports the number of individuals who responded to the survey. Row 3 shows the respondents who were still employed in one of our 11 target occupations at the time of the surveys. Row 4 presents the respondents who fully completed the survey questionnaire. Row 5 indicates the complete responses that could be linked to registry data.

### A.2.1 Representativeness and Response Quality

In this section, we extend the checks of representativeness and response quality provided in Humlum and Vestergaard (2025) to include the 2024 survey round.

Table A.2 show that our survey respondents resemble our survey populations on observable characteristics.

Table A.2: Balance Table for Survey Respondents

| | *2024 Survey* | | | *2023 Main Survey* | | |
|---|---|---|---|---|---|---|
| | Population | Sampled | Responded | Population | Sampled | Responded |
| | (1) | (2) | (3) | (1) | (2) | (3) |
| Age | 42.93 | 42.94 | 46.11 | 42.41 | 42.40 | 45.38 |
| | (11.54) | (11.52) | (11.50) | (11.57) | (11.57) | (11.51) |
| Female | 0.56 | 0.56 | 0.56 | 0.52 | 0.52 | 0.49 |
| | (0.50) | (0.50) | (0.50) | (0.50) | (0.50) | (0.50) |
| log(Earnings) | 12.98 | 12.98 | 13.01 | 13.07 | 13.07 | 13.11 |
| | (0.70) | (0.70) | (0.64) | (0.58) | (0.59) | (0.53) |
| Experience | 6.11 | 6.11 | 7.24 | 6.05 | 6.05 | 7.12 |
| | (4.80) | (4.80) | (4.92) | (4.58) | (4.57) | (4.67) |
| Wealth / Earnings | 10.92 | 6.50 | 6.74 | 4.09 | 4.87 | 4.10 |
| | (2,148.09) | (286.36) | (204.16) | (157.40) | (262.31) | (39.57) |
| Observations | 284,439 | 115,000 | 25,241 | 283,806 | 100,000 | 18,109 |

*Notes*: This table compares the mean characteristics of workers in our population (Column 1), our sampled survey invitees (Column 2), and survey respondents with complete responses (Column 3) for each survey round. The *Sampled* columns correspond to line 1 of Table A.1. The *Responded* columns correspond to line 4 of Table A.1. *Population* columns (1) show a difference in the female share between the 2023 and 2024 survey rounds that warrants explanation. This difference arises from a slight modification to the sampling protocol in 2023, in which some sampled workplaces had only (a random) 50% of their relevant workers invited to the survey. This altered the weight each of our 11 occupations received in the invite population, leading to the shifts in gender share observed in columns (1). Importantly, and as expected, the gender composition of the survey population *within* each of our 11 occupations remains virtually unchanged between survey rounds, as does the total unweighted worker population (i.e., without reweighting occupations to reflect our sampling protocol). Since all analyses include occupation fixed effects, this change in occupational composition across survey rounds does not affect our results. Moreover, nearly all analyses in this paper rely on the 2024 survey round, which did not involve the sampling protocol modification. *Sample*: The table includes all individuals in our survey population.

Table A.2 shows that complete respondents (who form the basis of our main analysis sample) and partial respondents have similar characteristics and give similar responses to the survey (before partial respondents drop out).

Table A.3: Balance Table for Complete vs. Partial Responses

| | *2024 Survey* | | *2023 Main Survey* | |
|---|---|---|---|---|
| | Completed | Drop Out | Completed | Drop Out |
| | (1) | (2) | (1) | (2) |
| *Panel A: Characteristics* | | | | |
| Age | 46.11 | 44.46 | 45.38 | 45.00 |
| | (11.50) | (11.98) | (11.51) | (11.53) |
| log(Earnings) | 13.01 | 13.00 | 13.11 | 13.10 |
| | (0.64) | (0.71) | (0.53) | (0.53) |
| Experience | 7.24 | 6.52 | 7.12 | 6.88 |
| | (4.92) | (4.82) | (4.67) | (4.63) |
| Net Wealth/Earnings | 6.74 | 3.77 | 4.10 | 3.75 |
| | (204.16) | (10.08) | (39.57) | (16.43) |
| Female | 0.56 | 0.57 | 0.49 | 0.60 |
| | (0.50) | (0.49) | (0.50) | (0.49) |
| *Panel B: Adoption* | | | | |
| Used | 0.69 | 0.75 | 0.55 | 0.51 |
| | (0.46) | (0.43) | (0.50) | (0.50) |
| Used for Work | 0.49 | 0.58 | 0.40 | 0.38 |
| | (0.50) | (0.49) | (0.49) | (0.48) |
| Used for Core Task | 0.31 | 0.15 | 0.21 | 0.17 |
| | (0.46) | (0.35) | (0.41) | (0.38) |
| Observations | 25,241 | 1,773 | 18,109 | 7,012 |

*Notes*: This table compares the mean characteristics and adoption behaviors of workers who fully completed (Column 1) and partially completed (Column 2) our surveys. The *Completed* columns correspond to line 4 of Table A.1. Standard deviations are shown in parentheses. See the note of Table A.2 for an explanation of the difference in the female population shares between the 2023 and 2024 survey rounds. *Sample*: All individuals with partial survey responses.

Table A.4 shows that workers who are randomly offered a higher participation prize are more likely to take part in our surveys but do not systematically differ in their responses. Dutz et al. (2025) develop an econometric framework that uses this variation to reweight the sample based on workers' latent willingness to participate; see Humlum and Vestergaard (2025) for its application to our survey.

Table A.4: Balance Table for Participation Prize Categories

| | *2024 Survey* | | | | | *2023 Main Survey* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Levels | Differences to 1000 DKK | | | p-value | Levels | Differences to 1000 DKK | | | p-value |
| | 1000 DKK | 2500 DKK | 5000 DKK | 10000 DKK | | 1000 DKK | 2500 DKK | 5000 DKK | 10000 DKK | |
| | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| *Panel A: Characteristics* | | | | | | | | | | |
| Age | 46.11 | -0.25 | -0.18 | -0.44 | 0.18 | 45.38 | -0.46 | -0.42 | -0.49 | 0.15 |
| | | (0.20) | (0.90) | (0.91) | | | (0.24) | (0.96) | (0.97) | |
| log(Earnings) | 13.01 | -0.00 | -0.01 | -0.01 | 0.48 | 13.11 | -0.03 | -0.00 | -0.01 | 0.04 |
| | | (0.01) | (0.11) | (0.11) | | | (0.01) | (0.06) | (0.06) | |
| Experience | 7.24 | -0.09 | -0.11 | -0.06 | 0.55 | 7.12 | -0.01 | -0.01 | -0.05 | 0.95 |
| | | (0.08) | (0.40) | (0.40) | | | (0.09) | (0.35) | (0.35) | |
| Net Wealth/Earnings | 6.74 | -1.96 | 0.62 | 0.94 | 0.50 | 4.10 | -0.05 | 0.87 | 0.38 | 0.55 |
| | | (1.71) | (36.33) | (35.44) | | | (0.27) | (0.42) | (0.42) | |
| Female | 0.56 | -0.02 | -0.00 | -0.02 | 0.04 | 0.49 | 0.00 | -0.01 | -0.00 | 0.41 |
| | | (0.01) | (0.03) | (0.04) | | | (0.01) | (0.04) | (0.04) | |
| *Panel B: Adoption* | | | | | | | | | | |
| Used | 0.69 | 0.00 | -0.00 | -0.01 | 0.69 | 0.55 | -0.02 | -0.01 | -0.01 | 0.40 |
| | | (0.01) | (0.03) | (0.03) | | | (0.01) | (0.03) | (0.03) | |
| Used for Work | 0.49 | -0.00 | -0.02 | -0.02 | 0.02 | 0.40 | -0.01 | -0.00 | -0.00 | 0.61 |
| | | (0.01) | (0.03) | (0.03) | | | (0.01) | (0.04) | (0.04) | |
| Used for Core Task | 0.31 | -0.00 | -0.01 | -0.00 | 0.75 | 0.21 | -0.01 | 0.00 | -0.00 | 0.59 |
| | | (0.01) | (0.03) | (0.03) | | | (0.01) | (0.04) | (0.04) | |
| Response Rate | 0.20 | 0.02 | 0.02 | 0.03 | 0.00 | 0.16 | 0.02 | 0.02 | 0.04 | 0.00 |
| | | (0.00) | (0.00) | (0.00) | | | (0.00) | (0.00) | (0.00) | |
| Observations | 5,787 | 6,351 | 6,432 | 6,671 | | 4,026 | 4,525 | 4,549 | 5,009 | |

*Notes*: This table shows that individuals assigned to different participation prize categories (1,000 DKK, 2,500 DKK, 5,000 DKK, and 10,000 DKK) have similar characteristics (Panel A) and adoption behaviors (Panel B) but differ in their rates of completed responses (last row). Column (5) reports $p$-values from a joint test of whether mean outcomes are equal across the four prize categories. The total number of observations corresponds to line 4 of Table A.1. See the note of Table A.2 for an explanation of the difference in the female population shares between the 2023 and 2024 survey rounds. *Sample*: All complete survey responses.

As an external validation of our survey responses, we cross-check variables workers' reported occupations with those recorded in the administrative registers. Table A.5 shows that the survey and registers agree on the occupation of 87% of our respondents.

Table A.5: Correlation Between Occupation in Survey vs. Register, $P(\text{Survey}|\text{Register})$

| | In Survey | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Journalists | Software Developers | Paralegals | Accountants and Auditors | Customer Service Rep. | Marketing Professionals | Financial Advisors | HR Professionals | Office Clerks | Teachers | IT Support | Observations |
| **Panel A: 2024 Survey** | | | | | | | | | | | | |
| Journalists | 0.98 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 325.00 |
| Software Developers | 0.00 | 0.86 | 0.00 | 0.00 | 0.01 | 0.01 | 0.00 | 0.00 | 0.01 | 0.00 | 0.08 | 2,799.00 |
| Paralegals | 0.01 | 0.03 | 0.81 | 0.02 | 0.00 | 0.00 | 0.02 | 0.02 | 0.07 | 0.01 | 0.01 | 2,106.00 |
| Accountants and Auditors | 0.00 | 0.02 | 0.01 | 0.86 | 0.01 | 0.01 | 0.02 | 0.01 | 0.05 | 0.00 | 0.01 | 2,793.00 |
| Customer Service Rep. | 0.00 | 0.02 | 0.01 | 0.01 | 0.79 | 0.03 | 0.00 | 0.01 | 0.09 | 0.01 | 0.01 | 631.00 |
| Marketing Professionals | 0.00 | 0.07 | 0.01 | 0.01 | 0.09 | 0.69 | 0.01 | 0.01 | 0.07 | 0.01 | 0.03 | 1,781.00 |
| Financial Advisors | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.96 | 0.00 | 0.01 | 0.00 | 0.00 | 1,243.00 |
| HR Professionals | 0.01 | 0.03 | 0.03 | 0.01 | 0.00 | 0.02 | 0.02 | 0.73 | 0.12 | 0.01 | 0.01 | 849.00 |
| Office Clerks | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.97 | 0.00 | 0.01 | 6,488.00 |
| Teachers | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 6,440.00 |
| IT Support | 0.00 | 0.13 | 0.00 | 0.00 | 0.02 | 0.02 | 0.00 | 0.00 | 0.03 | 0.00 | 0.79 | 1,470.00 |
| **Panel B: 2023 Survey** | | | | | | | | | | | | |
| Journalists | 0.97 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 555.00 |
| Software Developers | 0.00 | 0.87 | 0.00 | 0.00 | 0.01 | 0.02 | 0.00 | 0.00 | 0.01 | 0.00 | 0.08 | 3,185.00 |
| Paralegals | 0.01 | 0.03 | 0.79 | 0.02 | 0.01 | 0.00 | 0.01 | 0.02 | 0.08 | 0.01 | 0.01 | 2,518.00 |
| Accountants and Auditors | 0.00 | 0.02 | 0.01 | 0.85 | 0.01 | 0.01 | 0.02 | 0.02 | 0.05 | 0.00 | 0.01 | 2,710.00 |
| Customer Service Rep. | 0.01 | 0.03 | 0.01 | 0.01 | 0.79 | 0.04 | 0.01 | 0.01 | 0.07 | 0.01 | 0.01 | 869.00 |
| Marketing Professionals | 0.00 | 0.05 | 0.00 | 0.00 | 0.09 | 0.74 | 0.01 | 0.01 | 0.06 | 0.00 | 0.03 | 2,125.00 |
| Financial Advisors | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.95 | 0.00 | 0.02 | 0.00 | 0.00 | 1,918.00 |
| HR Professionals | 0.01 | 0.03 | 0.06 | 0.01 | 0.00 | 0.01 | 0.02 | 0.68 | 0.14 | 0.01 | 0.02 | 1,434.00 |
| Office Clerks | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.96 | 0.00 | 0.01 | 3,395.00 |
| Teachers | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 4,135.00 |
| IT Support | 0.00 | 0.15 | 0.00 | 0.00 | 0.02 | 0.02 | 0.00 | 0.01 | 0.03 | 0.00 | 0.76 | 2,277.00 |

*Notes*: This table presents the correlation between occupational codes reported in the survey and those recorded in the administrative data of Statistics Denmark. Each cell represents the probability of reporting the column occupation in the survey, conditional on having the row occupation registered with Statistics Denmark. The average agreement rate (diagonal elements) is 87%. *Sample*: All completed survey responses.

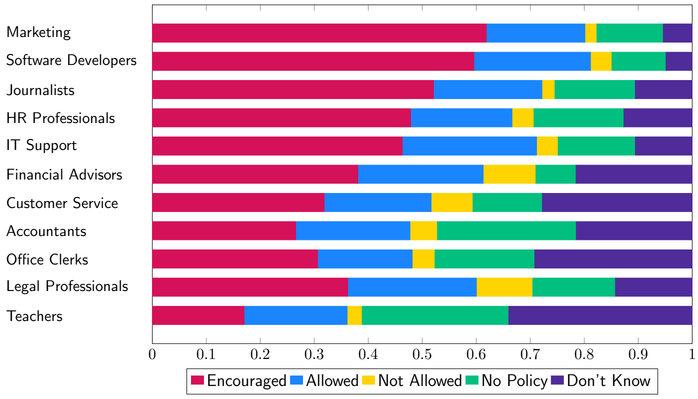
The disagreements in Table A.5 likely reflect measurement error in the registers because firms generally do not update occupational switches of existing employees (Groes, Kircher and Manovskii, 2015). Furthermore, some workers may have switched jobs between June 2024 (our latest month of register data) and November 2024 (the launch of our survey). Table A.5 shows the disagreements occur in cells that reflect likely switches, such as (IT Support, Software Developer). By contrast, the survey and register data agree on the occupation of 100% of our school teachers.

# B Adoption

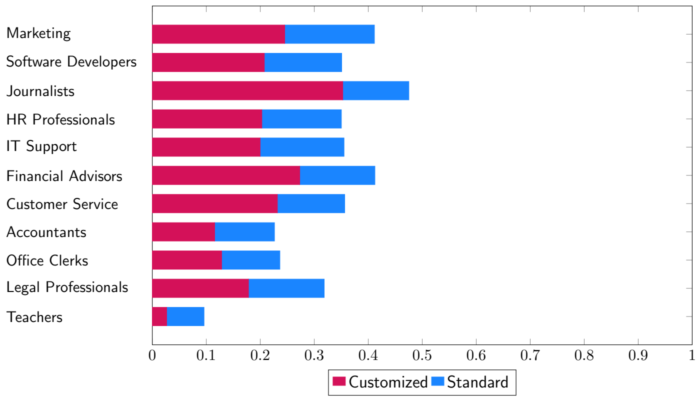
## B.1 Employer Initiatives

Figure B.1: The Prevalence of Employer Initiatives for AI Chatbot Adoption (Workplaces)

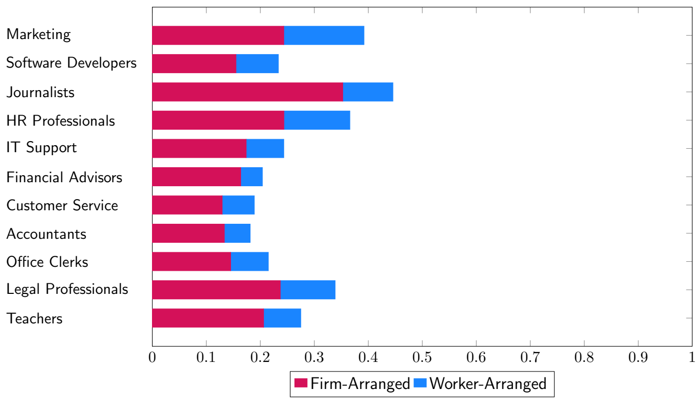
(a) Usage Policies




(b) In-House AI Chatbots




(c) Training in AI Chatbots




*Notes*: This figure shows the share of workplaces affected by various employer initiatives related to AI chatbot adoption. Workers in our sample have been reweighted so all workplaces have the same weight. Panel (a) shows employers' policies on AI chatbot usage for work. Panel (b) indicates whether the employer has its own AI chatbot. Panel (c) reports whether workers have participated in AI chatbot training courses. *Sample*: All completed responses from the 2024 survey.

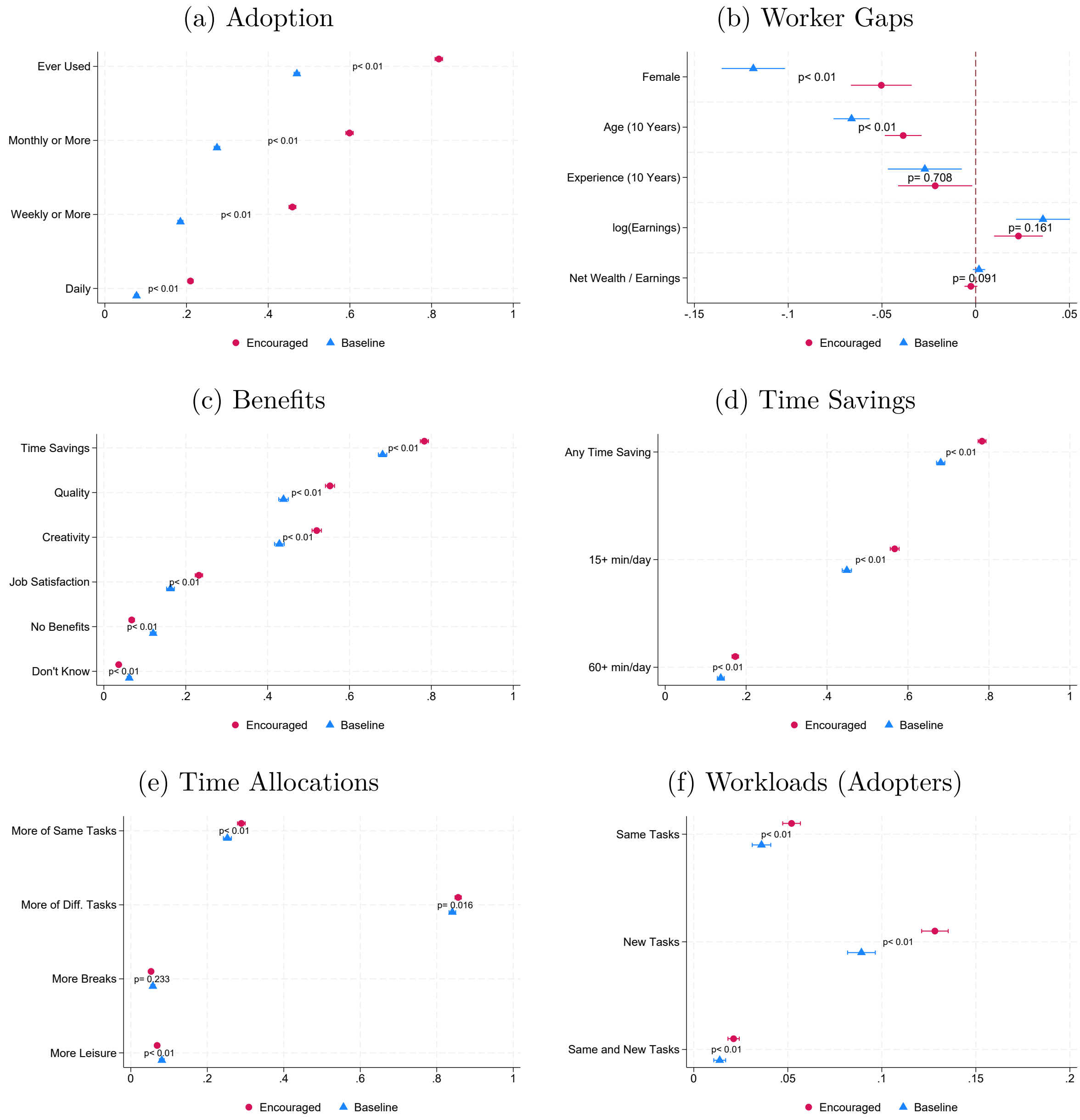
## B.2 Worker Adoption

Table B.1: Who Has Adopted AI Chatbots?

| | Ever Used | Monthly or More | Weekly or More | Daily |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Encouraged | 0.363*** | 0.337*** | 0.285*** | 0.137*** |
| | (0.006) | (0.006) | (0.005) | (0.004) |
| Female | -0.106*** | -0.130*** | -0.098*** | -0.041*** |
| | (0.006) | (0.006) | (0.006) | (0.004) |
| Age (10 Years) | -0.060*** | -0.051*** | -0.038*** | -0.017*** |
| | (0.004) | (0.004) | (0.003) | (0.003) |
| Experience (10 Years) | -0.040*** | -0.044*** | -0.044*** | -0.032*** |
| | (0.007) | (0.007) | (0.007) | (0.005) |
| log(Earnings) | 0.043*** | 0.018*** | 0.011** | -0.000 |
| | (0.005) | (0.005) | (0.005) | (0.004) |
| Net Wealth / Earnings | 0.002 | -0.001 | -0.001 | -0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Occupation FE's | ✓ | ✓ | ✓ | ✓ |
| Mean of Outcome | 0.596 | 0.392 | 0.285 | 0.126 |
| Observations | 24796 | 24796 | 24796 | 24796 |

*Notes*: This table compares workers within occupations and asks what characterizes those who have adopted AI chatbots for work. The columns vary by frequency of usage. *Encouraged* indicates that the employer actively encourages AI chatbot use for work (see definitions in the note of Figure 1 ). All other characteristics are based on register variables from 2022. *Experience* is the years of employment in the relevant occupation. *Earnings* are total labor income. *Net Wealth* is the sum of real assets, financial assets, and pension savings minus the sum of priority debt, other private debt, and public debt, winsorized at the 5th and 95th percentiles. The regressions control for occupation fixed effects. Standard errors in parentheses. *Sample*: The table is based on all complete responses from the 2024 survey that can be linked to the registry data.

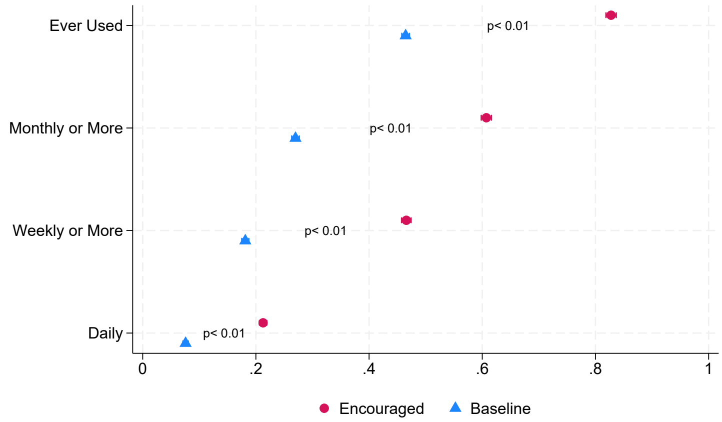
Figure B.2: The Impact of Employer Encouragement on Adoption and Work (Controlling for Workers' Task Mixes)



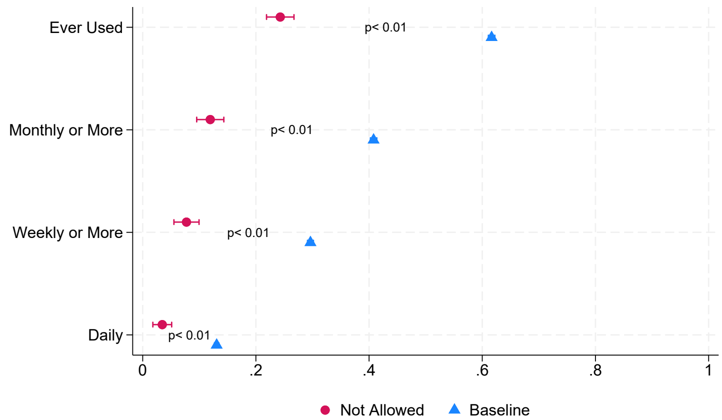

*Notes:* This figure shows that our main results on how employer encouragements affect adoption and work are robust to controlling for workers' detailed task specializations. The estimates are based on Equation (1), augmented with task importance fixed effects as additional controls. Task importances are derived from our survey, which asked workers to rate the importance of six representative O*NET job tasks in their occupations; see Appendix G and Humlum and Vestergaard (2025, SI6) for details. Panel (a) corresponds to Figure 2, Panel (b) to Figure 3, Panels (c), (d), and (e) to Figure 4, and Panel (f) to Figure 5.(a). The estimates shown are predicted values from Equation (1), now including task importance fixed effects, and vary employer usage policies (Encouraged = 1 vs. Encouraged = 0) while holding worker characteristics $X$ at their mean values. Whiskers represent 95% confidence bands of the predicted values. The reported p-values test whether the coefficients differ between the two groups. *Sample*: All completed responses from the 2024 survey linked to registry data.

Figure B.3: Importance of Employer Policies in AI Chatbot Adoption

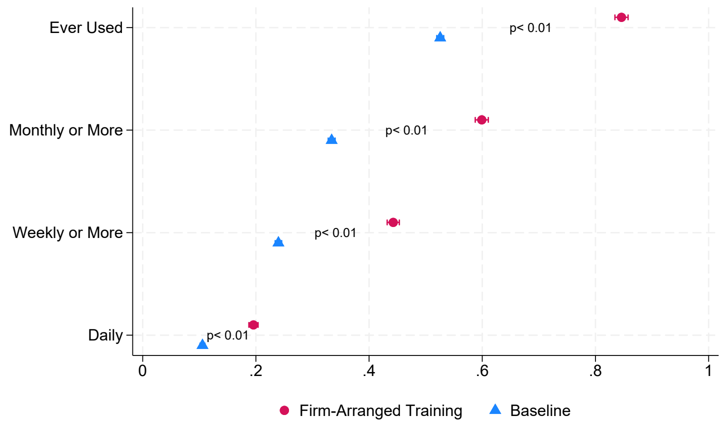
(i) Usage Policy: Encouraged




(ii) Usage Policy: Not Allowed




(iii) Firm-Arranged Training

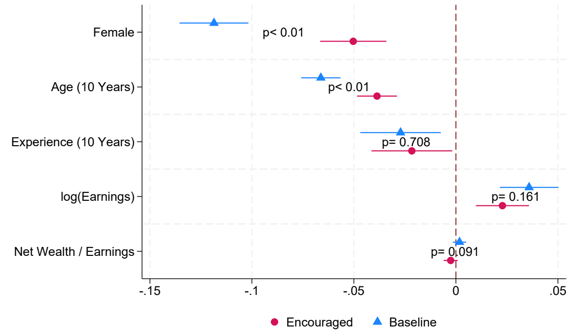



*Notes*: This figure illustrates the impact of employer policies on workers' use of AI chatbots. The estimates are based on predicted values from Equation (1), varying employer initiatives (EmployerInitiative = 1 vs. EmployerInitiative = 0) while holding workers' characteristics $X$ at their mean values. Panel (i) splits workers based on whether their employer encourages AI chatbot use, Panel (ii) splits workers based on whether their employer allows AI chatbot use, and Panel (iii) splits workers based on whether they have participated in firm-arranged AI chatbot training. Panel (i) is identical to Figure 1. Whiskers represent 95% confidence intervals. The reported p-values test whether the coefficients differ between the two groups. *Sample*: All completed responses from the 2024 survey linked to registry data.

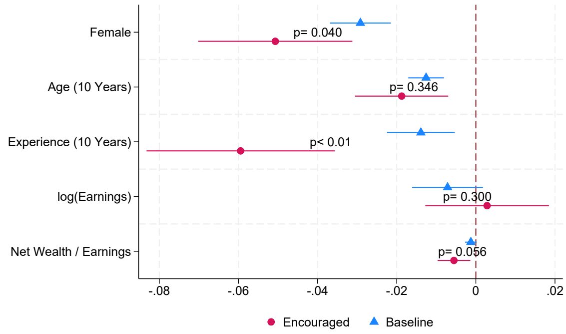
Figure B.4: Influence of Employer Initiatives on Worker Gaps in AI Chatbot Adoption

(i) Usage Policy: Encouraged

(a) Ever Used

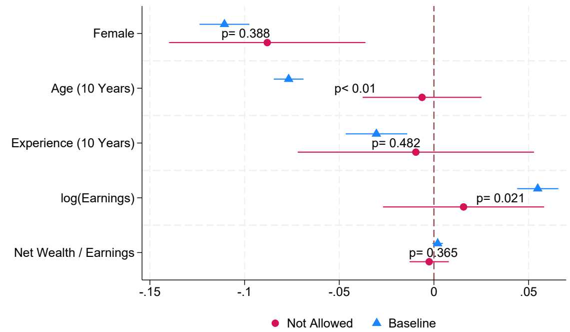



(b) Daily Use

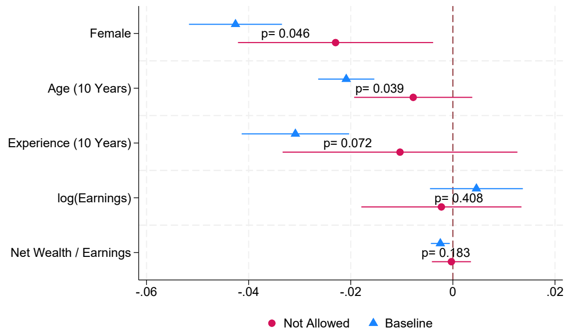



(ii) Usage Policy: Not Allowed

(a) Ever Used

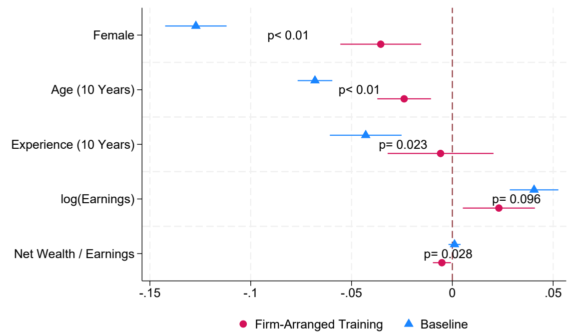



(b) Daily Use

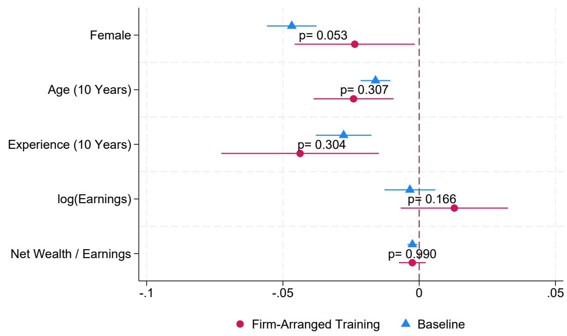



(iii) Firm-Arranged Training

(a) Ever Used




(b) Daily Use




*Notes*: This figure illustrates the impact of employer initiatives on worker disparities in AI chatbot adoption. The estimates are obtained from regressions of AI chatbot adoption on worker characteristics $X$, controlling for occupation fixed effects, and are estimated separately based on employers' AI chatbot initiatives. Panel (i) splits workers based on whether their employer encourages AI chatbot use, Panel (ii) splits workers based on whether their employer allows AI chatbot use, and Panel (iii) splits workers based on whether they have participated in firm-arranged AI chatbot training. For each of these, subpanels (a) predicts whether workers have ever used AI chatbots for work, while subpanbel (b) predicts whether workers use AI chatbots daily. Panel (i) is identical to Figure 3. Whiskers represent 95% confidence intervals. The reported p-values test whether the coefficients differ between the two groups. *Sample*: All completed responses from the 2024 survey linked to registry data.

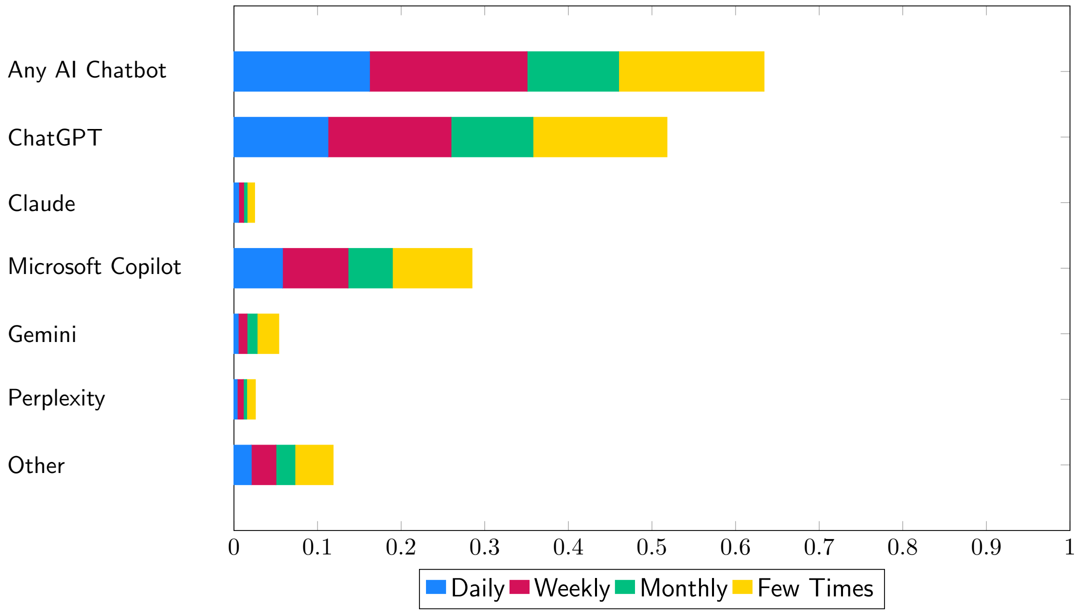
### B.2.1 AI Chatbot Products

While our main analysis focuses on the adoption of any AI chatbot, our survey also measures usage of specific products. This section provides details on product-level adoption.

The main takeaway is that ChatGPT remains the dominant tool. Figures B.5–B.7 show that approximately 80% of all adopters use ChatGPT, and its dominance holds across all occupations.

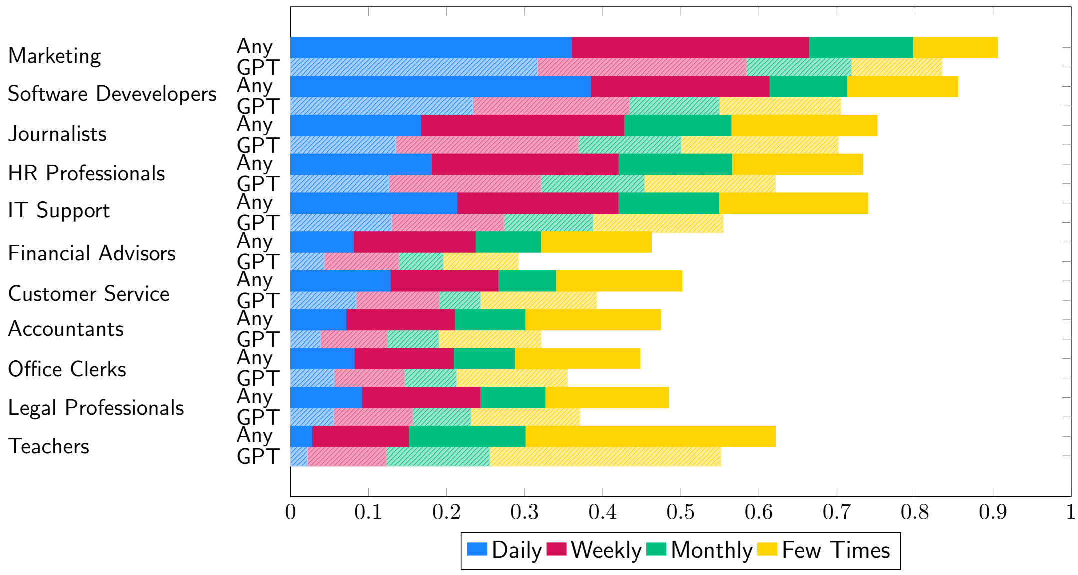
Table B.2 further reveals that users of other chatbots often multihome—that is, they also use ChatGPT. For example, 84% of daily Gemini users also use ChatGPT daily. An exception is Microsoft Copilot: only 39% of its daily users also use ChatGPT. Still, this figure is substantially higher than the overall share of daily ChatGPT users in the population (11%), suggesting that workers are generally not exclusive to a single chatbot—those who use one are more likely to use others as well.

Figure B.5: The Prevalence of AI Chatbot Products




*Notes:* This figure displays the share of workers who have used various AI chatbots for work, categorized by frequency of usage. *Sample:* All completed responses from our 2024 survey round.

Figure B.6: The Dominance of ChatGPT




*Notes:* This figure shows the share of workers in our study occupations who have used AI chatbots for work, distinguishing between those who have used any AI chatbot and those who have specifically used ChatGPT. *Sample:* All completed responses from our 2024 survey round.

Table B.2: Correlation Between AI Chatbot Product Usage, $P(\text{Column}|\text{Row})$

(a) Ever Used for Work

| | Any | ChatGPT | Claude | Copilot | Gemini | Perplexity | Other |
|---|---|---|---|---|---|---|---|
| Any | 1.00 | 0.82 | 0.04 | 0.45 | 0.09 | 0.04 | 0.19 |
| ChatGPT | 1.00 | 1.00 | 0.05 | 0.39 | 0.10 | 0.05 | 0.17 |
| Claude | 1.00 | 0.94 | 1.00 | 0.66 | 0.39 | 0.23 | 0.39 |
| Copilot | 1.00 | 0.72 | 0.06 | 1.00 | 0.11 | 0.05 | 0.16 |
| Gemini | 1.00 | 0.91 | 0.18 | 0.56 | 1.00 | 0.15 | 0.32 |
| Perplexity | 1.00 | 0.90 | 0.22 | 0.56 | 0.32 | 1.00 | 0.36 |
| Other | 1.00 | 0.73 | 0.08 | 0.39 | 0.15 | 0.08 | 1.00 |
| All Workers | 0.64 | 0.53 | 0.03 | 0.29 | 0.06 | 0.03 | 0.12 |

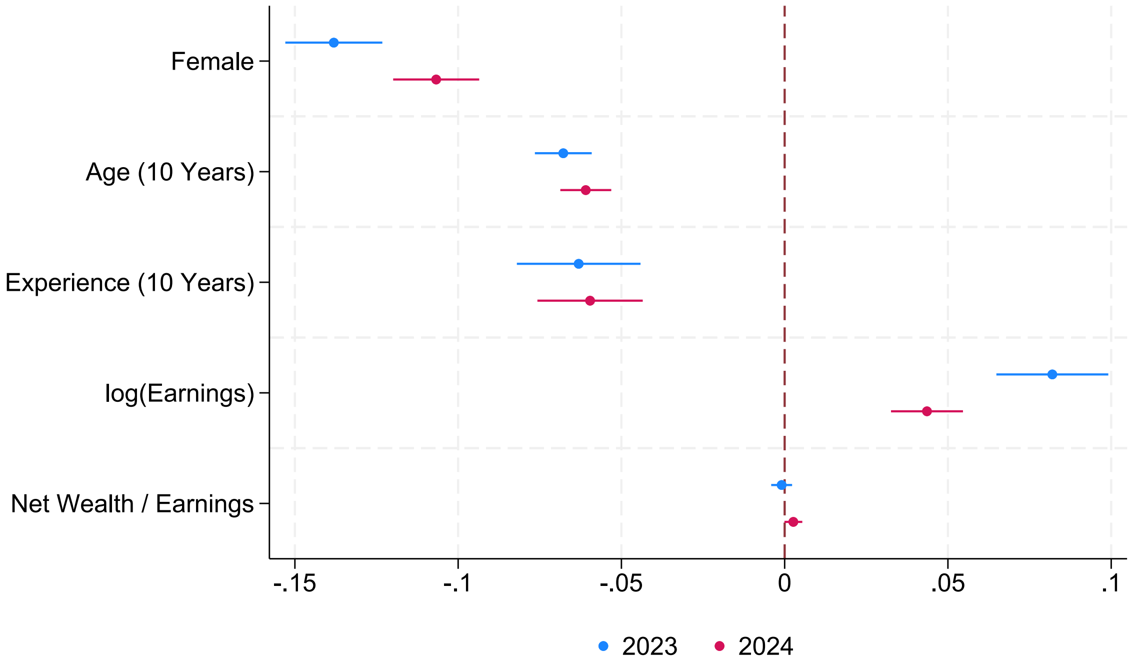
(b) Daily Use for Work

| | Any | ChatGPT | Claude | Copilot | Gemini | Perplexity | Other |
|---|---|---|---|---|---|---|---|
| Any | 1.00 | 0.69 | 0.03 | 0.36 | 0.03 | 0.02 | 0.13 |
| ChatGPT | 1.00 | 1.00 | 0.03 | 0.20 | 0.04 | 0.02 | 0.07 |
| Claude | 1.00 | 0.63 | 1.00 | 0.38 | 0.09 | 0.10 | 0.20 |
| Copilot | 1.00 | 0.39 | 0.04 | 1.00 | 0.04 | 0.01 | 0.08 |
| Gemini | 1.00 | 0.84 | 0.10 | 0.43 | 1.00 | 0.08 | 0.26 |
| Perplexity | 1.00 | 0.66 | 0.14 | 0.22 | 0.10 | 1.00 | 0.20 |
| Other | 1.00 | 0.38 | 0.05 | 0.21 | 0.06 | 0.04 | 1.00 |
| All Workers | 0.16 | 0.11 | 0.01 | 0.06 | 0.01 | 0.00 | 0.02 |

*Notes:* This table presents the correlation between the use of different AI chatbot products. Each cell represents the probability of using the column product, conditional on using the row product. Panel (a) reports probabilities for any work-related use, while Panel (b) focuses on daily work-related use. *All Workers* reports the unconditional usage rate of the chatbot in the given column, weighting all occupations equally. *Sample:* All completed survey responses from our 2024 survey round.

### B.2.2 Comparison to 2023 Survey

Figure B.7: Use of ChatGPT for Work (Nov '23, '24)




*Notes*: This figure presents estimates from a multivariate regression of ChatGPT usage for work on worker characteristics, controlling for occupation fixed effects. The regressions are estimated separately for the 2023 and 2024 survey rounds. *Sample*: All completed responses from the 2023 and 2024 survey rounds.

# C Work

## C.1 Benefits for Users

Table C.1: Perceived Benefits of AI Chatbots by Occupation

| Occupation | Time Savings (1) | Quality (2) | Creativity (3) | Job Satisfaction (4) | No Benefits (5) | Don't Know (6) |
|---|---|---|---|---|---|---|
| Accountants | .709 | .524 | .418 | .156 | .08 | .059 |
| Customer Service | .723 | .572 | .413 | .142 | .083 | .041 |
| Financial Adv. | .769 | .55 | .488 | .173 | .082 | .021 |
| HR Prof. | .844 | .638 | .623 | .253 | .028 | .03 |
| IT Support | .76 | .526 | .423 | .239 | .097 | .034 |
| Journalists | .67 | .394 | .467 | .126 | .137 | .042 |
| Legal Prof. | .783 | .544 | .45 | .204 | .083 | .027 |
| Marketing | .898 | .698 | .625 | .289 | .023 | .014 |
| Office Clerks | .689 | .563 | .489 | .185 | .073 | .067 |
| Software Dev. | .838 | .528 | .446 | .305 | .076 | .022 |
| Teachers | .637 | .321 | .458 | .132 | .15 | .071 |

*Notes*: This table presents the share of adopters who report various benefits from using AI chatbots for work, broken down by occupation and by whether their employer encourages AI chatbot use. *Sample*: All completed responses from the 2024 survey round.

## C.2 Workloads and Task Creation

Our survey includes free-text responses about the new tasks workers have recived due to AI chatbots. We categorize these responses into six broad AI-related categories, listed in Table C.2, as well as into more granular, occupation-specific subtasks.

Table C.2: Categories of New Tasks from AI Chatbots

| **Task** | **Description** |
|---|---|
| AI Ideation | Leveraging AI to spark or expand creative ideas—such as concepts, strategies, or solutions. The human selects and builds on the most promising suggestions. |
| AI Content Drafting | Using AI tools to generate initial drafts of text or media (e.g., documents, emails, code). The human professional prompts the AI, then edits and refines the output for accuracy and tone. |
| AI Quality Review | Reviewing AI-generated content for accuracy, clarity, and relevance. The human fact-checks, corrects errors, and ensures the output meets required standards. |
| AI Data Insights | Using AI to analyze data or documents and surface patterns, summaries, or key insights. The human then interprets and applies these findings to decisions. |
| AI Integration | Embedding AI into workflows to automate or enhance tasks. Professionals design prompts, refine workflows, correct outputs, and fine-tune systems based on feedback. |
| AI Ethics & Compliance | Ensuring AI use follows ethical, legal, and institutional standards. This includes setting guidelines, monitoring for bias or misuse, and reviewing outputs for compliance. |

*Notes:* This table describes our six broad categories of AI-related tasks.

Examples of occupation-specific tasks, along with their corresponding general task categories, include:

1. **Accountants:** Drafting financial statements and reports using AI for initial content

(*AI Content Drafting*), Analyzing financial data with AI tools to identify trends or anomalies (*AI Data Insights*)

2. **Customer Support:** Reviewing AI-suggested responses to ensure accuracy and proper tone (*AI Quality Review*), Training the AI customer service chatbot by feeding it new Q&As from resolved issues (*AI Integration*)
3. **Financial Advisors:** Analyzing market trends and client data with AI to inform advice (*AI Data Insights*)
4. **HR Professionals:** Drafting job postings, policy documents, or employee communications using AI (*AI Content Drafting*), Analyzing employee survey results or HR data with AI to gain insights (*AI Data Insights*)
5. **IT Support:** Generating technical troubleshooting guides and FAQs using AI (*AI Content Drafting*), Security and Compliance when Implementing AI (*AI Ethics & Compliance*)
6. **Journalists:** Using AI to draft article outlines, summaries, or initial news reports (*AI Content Drafting*), Brainstorming story ideas, angles, or interview questions with AI (*AI Ideation*)
7. **Legal Professionals:** Ensuring AI tools and outputs uphold legal ethics and confidentiality (*AI Ethics & Compliance*), Developing organizational AI usage policies and guidelines (*AI Integration*)
8. **Marketing Professionals:** Generating marketing copy, social media posts, or product descriptions with AI (*AI Content Drafting*)
9. **Office Clerks:** Drafting routine emails, letters, or documents using AI assistance, (*AI Content Drafting*), Performing quality control on AI-generated text and documents (*AI Quality Review*)
10. **Software Developers:** Implementing AI and writing prompts (*AI Implementation*)

11. **Teachers:** Detecting AI-generated homework (*AI Ethics & Compliance*), Integrating chatbots into lessons (*AI Integration*)

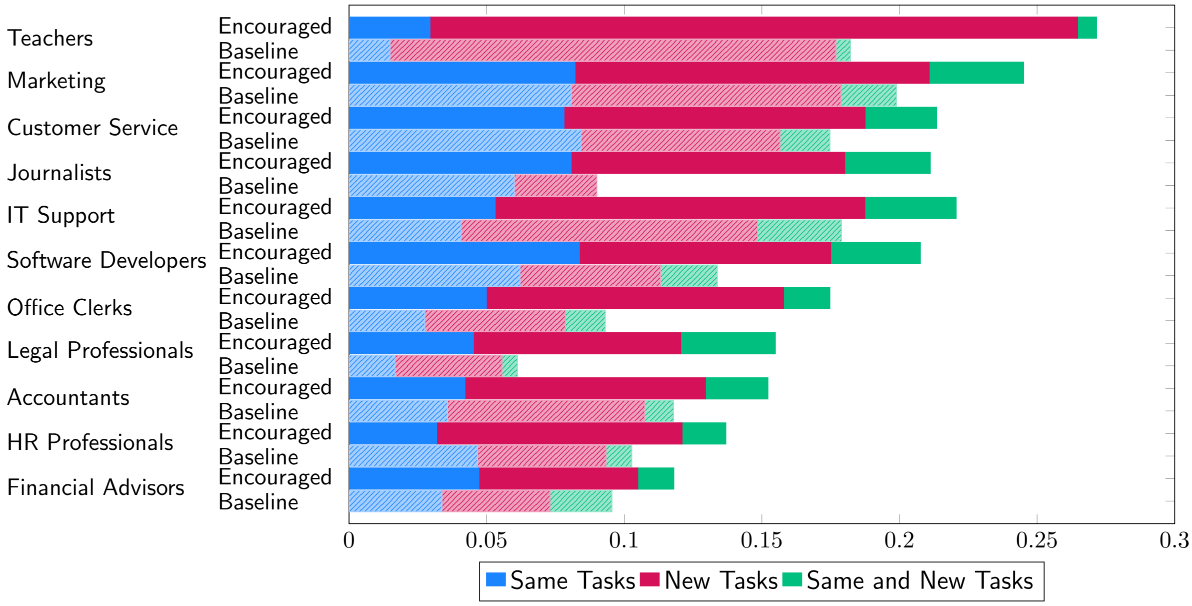
We also include a "non-AI" task category, which typically reflects new assignments for the worker that are not novel within the workplace or profession. Examples include "meeting with customers," "taking over tasks due to freed-up time," or the more ambiguous "handling more complex tasks GenAI cannot solve."

To categorize the free-text responses, we divided them between two independent coders. Each coder then cross-checked a random sample of the other's work, with near-complete agreement.

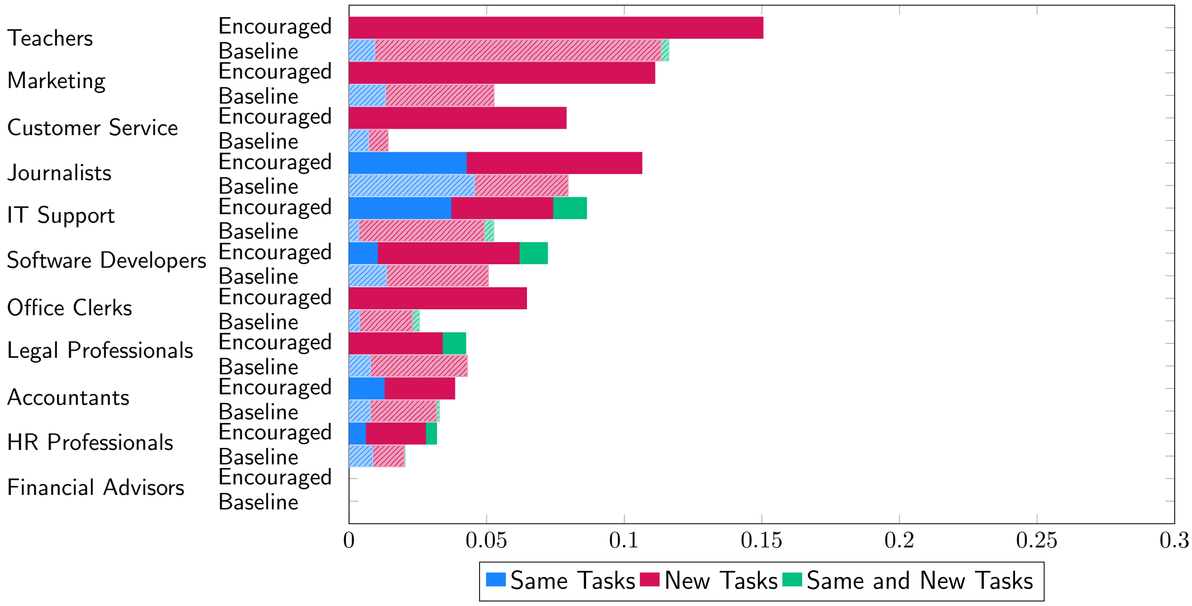
Figures C.1 illustrate that AI chatbots have led to the creation of new tasks across all 11 occupations in our study. Figure C.2 shows that 50% to 95% of these tasks are directly linked to AI use.

Figure C.1: Workloads from AI Chatbots

(a) Adopters

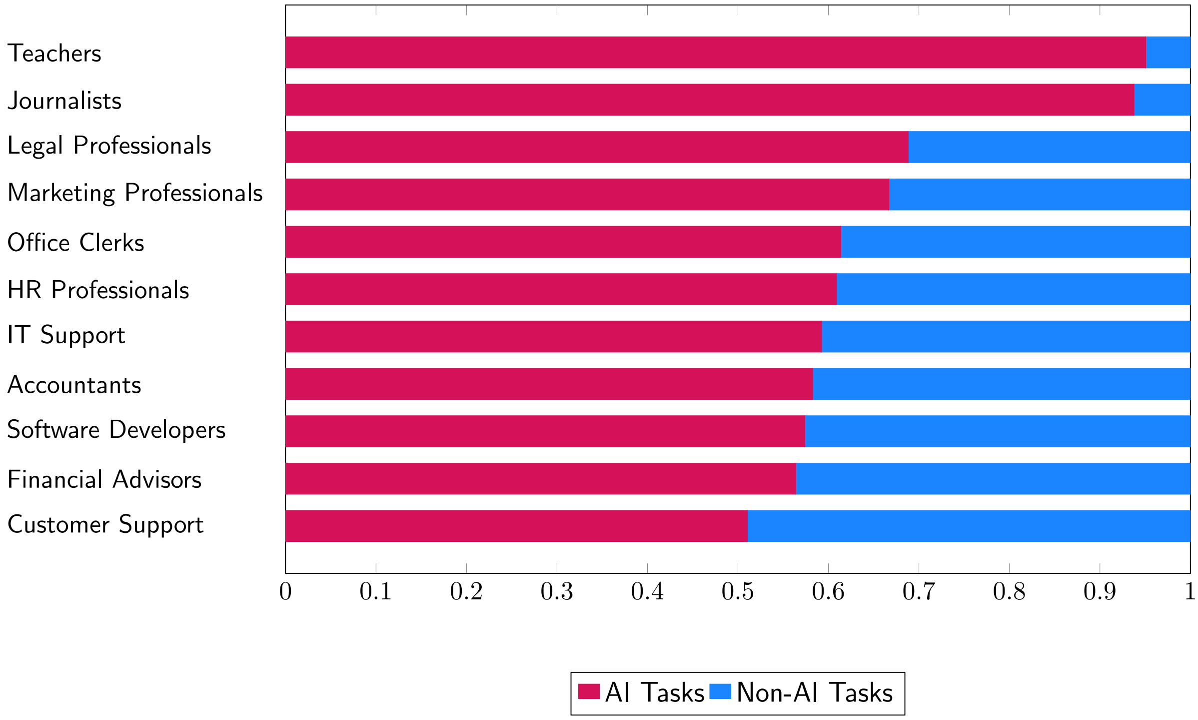



(b) Non-Adopters




*Notes*: This figure presents the share of workers who report increased workloads due to AI chatbots, distinguishing between additional tasks of the same type, new job tasks, or both. The responses are broken down by occupation and by whether employers encourage AI chatbot use. Panel (a) focuses on adopters (workers who have ever used AI chatbots for work), while Panel (b) examines non-adopters. *Sample*: All completed responses from the 2024 survey round linked to registry data.

Figure C.2: Composition of New Job Tasks

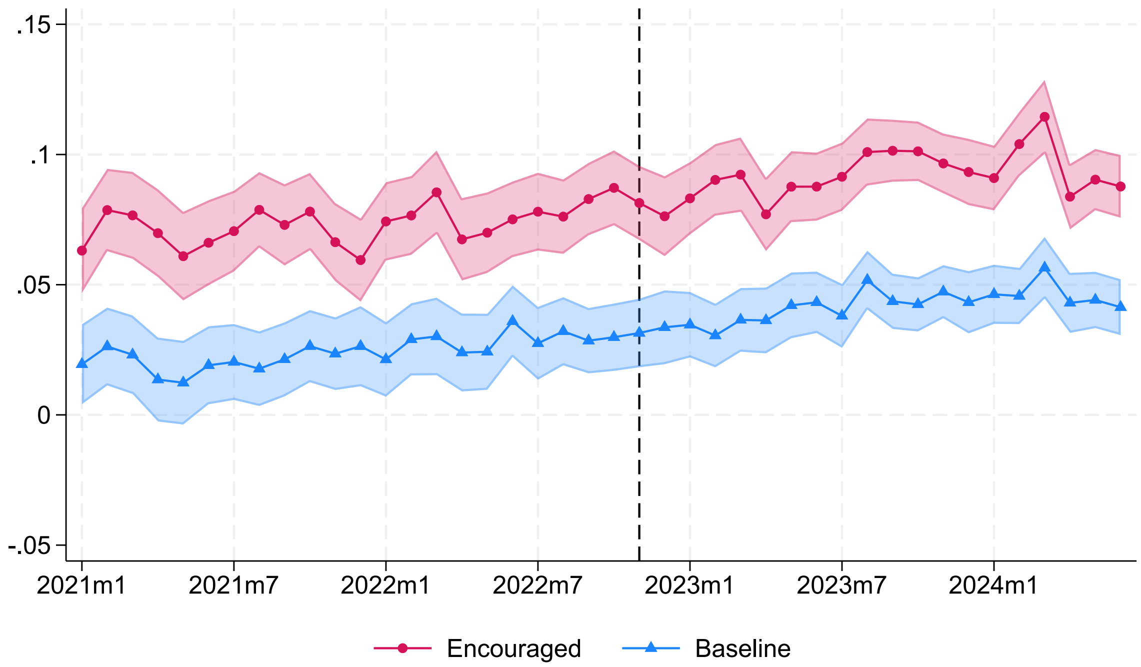



*Notes*: This figure shows the share of new job tasks that are directly linked to AI chatbot use. Occupations are ordered according to their shares of AI tasks *Sample*: All completed responses from the 2024 survey who reported new job tasks due to AI chatbots.

# D Labor Market Outcomes

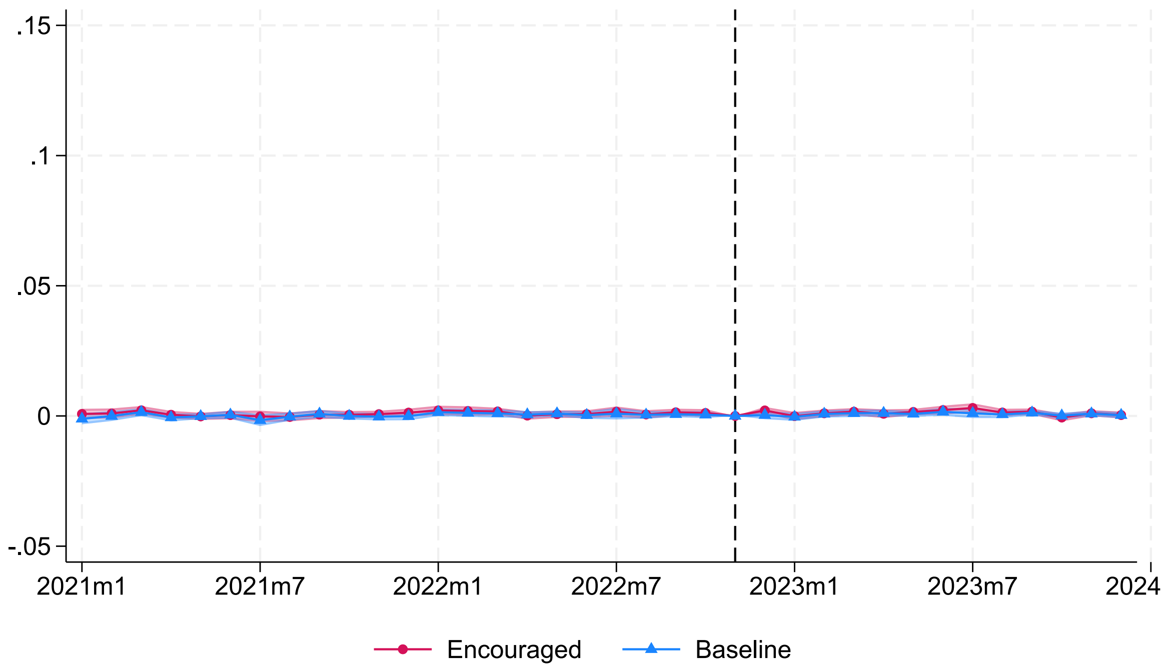
## D.1 Earnings and Hours

Figure D.1: log Earnings (Adopters – Non-Adopters)




*Notes*: This figure presents the difference in means of log earnings between AI chatbot adopters and non-adopters. The specification is the difference in means that corresponds to Equation (2). It controls for occupation fixed effects, predetermined worker characteristics, and seasonality. Effects are estimated separately for adopters whose employers encourage AI chatbot use ("Encouraged") and those without encouragement ("Baseline"), with all non-adopters serving as the control group in both cases. Shaded areas represent 95% confidence intervals. *Sample:* All completed responses from the 2024 survey linked to registry data.

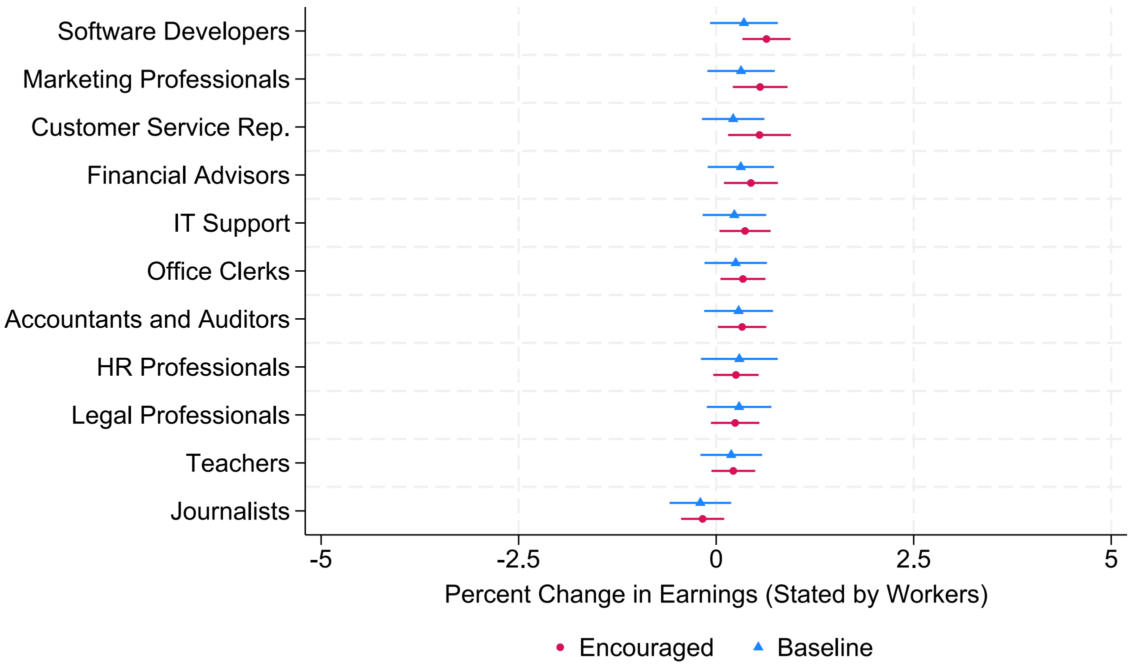
Figure D.2: Have Adopters Fared Better in the Labor Market?
Extensive Margin Employment (Dynamic Difference-in-Differences)




*Notes*: This figure presents the differential change in extensive margin employment of AI chatbot adopters relative to non-adopters, indexed to the launch of ChatGPT in November 2022. Extensive margin employment is defined as having positive hours and earnings. We end the plot in 2023 because the preliminary version of the *BFL* data available for 2024 does not distinguish between missing values and true zeros. Nevertheless, the point estimates for 2024 remain close to zero (within ±0.5%). Effects are estimated separately for adopters whose employers encourage AI chatbot use ("Encouraged") and those without encouragement ("Baseline"), with all non-adopters serving as the control group in both cases. Estimates are based on the dynamic difference-in-differences specification in Equation (2). Shaded areas represent 95% confidence intervals. *Sample:* All completed responses from the 2024 survey linked to registry data.

## D.2 Perceived Impacts

Figure D.3: Perceived Earnings Effects of AI Chatbots Among Adopters




*Notes*: This figure displays the average perceived earnings impact of AI chatbots among adopters, categorized by workers' occupations and whether their employers encourage AI chatbot use. Whiskers represent 95% confidence intervals. *Sample*: All completed responses from the 2024 survey round linked to registry data.

Table D.1: Decomposition of Perceived Earnings Effects of AI Chatbots Among Adopters

| | | | Share of Impacts | | | Conditional Average Impacts (in %) | | |
|---|---|---|---|---|---|---|---|---|
| Occupation | Policy | Average Impact (in %) (1) | Decreased Earnings (2) | Unchanged Earnings (3) | Increased Earnings (4) | Decreased Earnings (5) | Unchanged Earnings (6) | Increased Earnings (7) |
| Journalists | Baseline | -.118 | | .994 | | | 0 | |
| Journalists | Encouraged | -.159 | | .983 | | | 0 | |
| Software Developers | Baseline | .092 | .008 | .974 | .015 | -12.187 | 0 | 12.5 |
| Software Developers | Encouraged | .428 | | .96 | .037 | | 0 | 11.944 |
| Legal Professionals | Baseline | .031 | | .978 | | | 0 | |
| Legal Professionals | Encouraged | .057 | | .987 | .009 | | 0 | 10.5 |
| Accountants and Auditors | Baseline | 0 | .004 | .915 | .004 | -13.75 | 0 | 13.75 |
| Accountants and Auditors | Encouraged | .126 | | .973 | .015 | | 0 | 10 |
| Customer Service Rep. | Baseline | -.11 | .013 | .913 | | -9.167 | 0 | |
| Customer Service Rep. | Encouraged | .303 | | .942 | .041 | | 0 | 7.25 |
| Marketing Professionals | Baseline | .112 | | .956 | .023 | | 0 | 7.25 |
| Marketing Professionals | Encouraged | .37 | .006 | .955 | .038 | -16.5 | 0 | 12.422 |
| Financial Advisors | Baseline | .022 | | .964 | | | 0 | |
| Financial Advisors | Encouraged | .214 | | .979 | .019 | | 0 | 11.667 |
| HR Professionals | Baseline | 0 | | .964 | | | 0 | |
| HR Professionals | Encouraged | .071 | | .986 | | | 0 | |
| Office Clerks | Baseline | .015 | .002 | .901 | .003 | -7.143 | 0 | 8.462 |
| Office Clerks | Encouraged | .113 | | .978 | .014 | | 0 | 10.403 |
| Teachers | Baseline | -.007 | .001 | .975 | .001 | -9.167 | 0 | 4 |
| Teachers | Encouraged | .041 | | .992 | .007 | | 0 | 7.188 |
| IT Support | Baseline | .039 | .006 | .981 | | -4 | 0 | |
| IT Support | Encouraged | .172 | | .974 | .02 | | 0 | 11.25 |

*Notes*: This table decomposes the average perceived earnings impact (in percent) of AI chatbots among adopters (Column 1) into contributions from workers reporting decreased earnings (Columns 2 and 5), unchanged earnings (Columns 3 and 6), and increased earnings (Columns 4 and 7). Responses are categorized by workers' occupations and whether their employers encourage AI chatbot use. Empty cells represent fewer than five individuals and are blanked out in accordance with confidentiality rules. *Sample*: All completed responses from the 2024 survey round linked to registry data.

# E Further Analysis

## E.1 Coworker IV

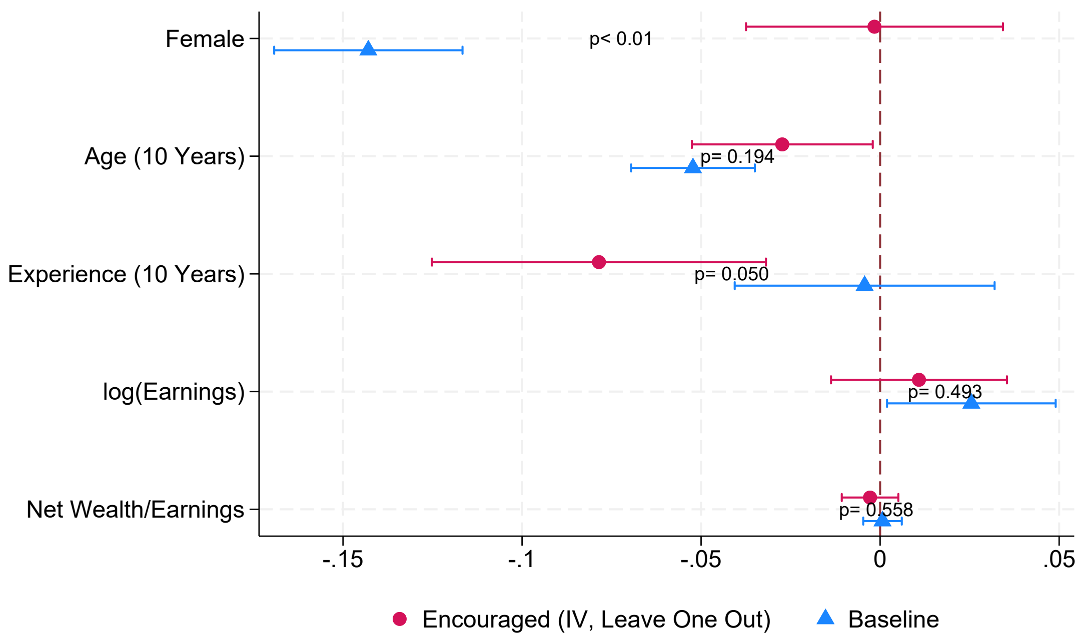
Table E.1: First Stages of Coworker Instruments for Employer Initiatives

| | Encouraged | Allowed | Not Allowed | No Policy | In-House Chatbot | Firm-Arranged Training |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Coworker IV (Leave Out, EBS) | 1.181*** | 1.291*** | 2.025*** | 1.302*** | 1.170*** | 1.200*** |
| | (0.020) | (0.083) | (0.096) | (0.109) | (0.018) | (0.015) |
| Coworkers Share Female | -0.016 | -0.018 | -0.008 | 0.015 | -0.016 | -0.009 |
| | (0.011) | (0.011) | (0.007) | (0.010) | (0.011) | (0.010) |
| Coworkers Age | 0.001 | 0.002 | 0.001* | -0.001 | 0.002* | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Coworkers Potential Experience | -0.001 | -0.002 | -0.001 | 0.001 | -0.002 | -0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Occupation FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| First Stage F-Stat | 3644.56 | 240.084 | 445.274 | 143.19 | 4387.586 | 6333.773 |
| Observations | 16974 | 16974 | 16974 | 16974 | 16974 | 16974 |

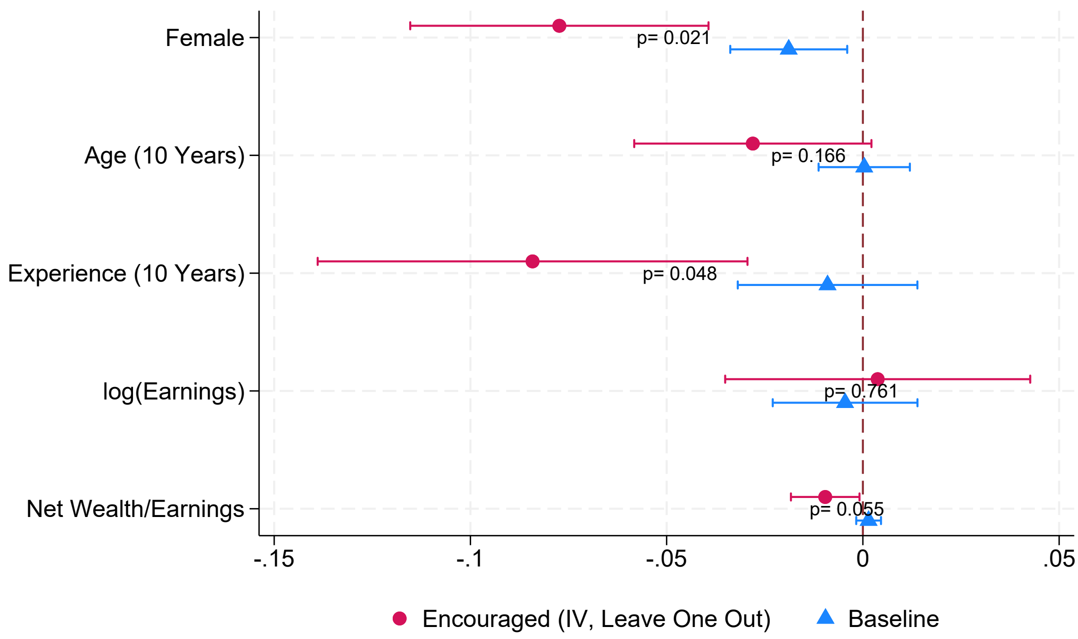
*Notes:* This table presents estimates of the first-stage regression of our coworker IV for employer initiatives, using the specification in Equation (4). Standard errors, shown in parentheses, are clustered at the workplace level. *Sample*: The table is based on all completed responses from workplaces with at least two respondents from the 2024 survey linked to registry data.

Figure E.1: The Influence of Employer Encouragement on Worker Gaps in AI Chatbot Adoption (Coworker IV)

(a) Ever Used

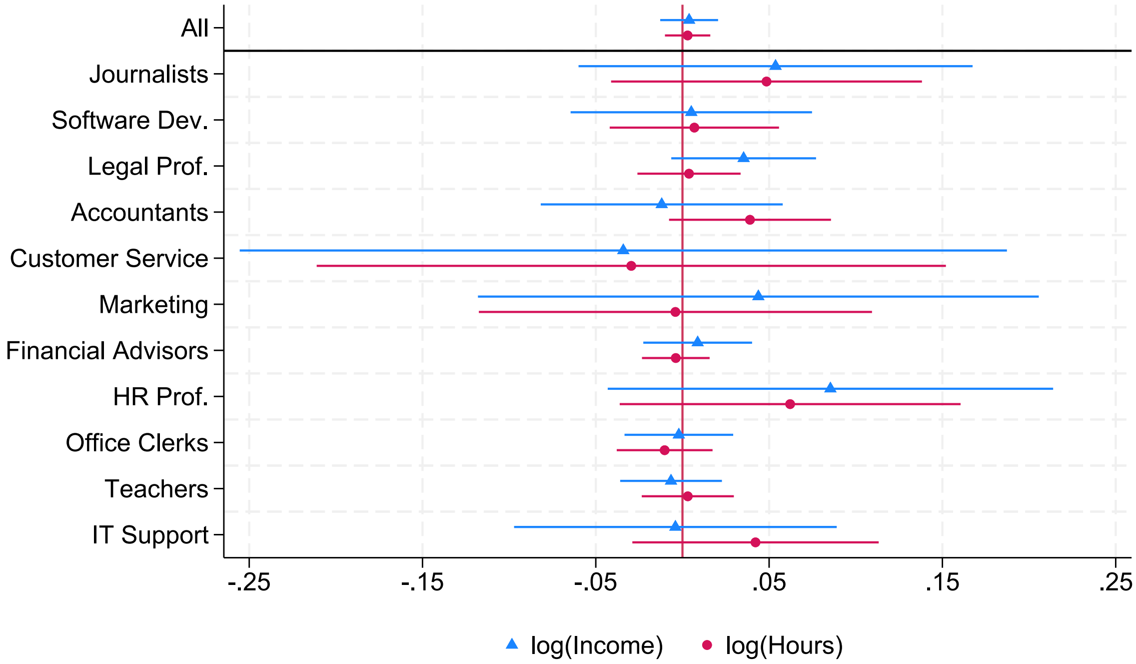



(b) Daily Use




*Notes*: This figure presents IV estimates of the impact of employer encouragement on worker disparities in AI chatbot adoption. The estimates are obtained from a multivariate regression of AI chatbot adoption on worker characteristics $X$, controlling for occupation-fixed effects, and all interacted with an indicator for employer encouragement. Our IV strategy instruments these interaction effects using the corresponding interactions with our coworker IV. The point estimates show predicted adoption rates for an average worker, $\bar{X}$, when Encouraged $= 0$ or $1$, respectively. Whiskers denote 95% confidence intervals. Reported p-values test whether the coefficients differ between the two groups. *Sample*: All completed responses from the 2024 survey linked to registry data.

Figure E.2: Have Employer Chatbot Policies Affected Workers' Outcomes? (Coworker IV)




*Notes*: This figure presents the differential labor market outcomes of workers who are encouraged to use AI chatbots by their employers, compared to all other workers, indexed to the launch of ChatGPT in November 2022. The figure is based on the pooled difference-in-differences specification in Equation (3), with whiskers representing 95% confidence intervals. The estimates come from a 2SLS specification where we instrument all effects of Encouraged using the corresponding coworker instruments described in Section 5.1. *Sample:* All completed responses from the 2024 survey linked to registry data.

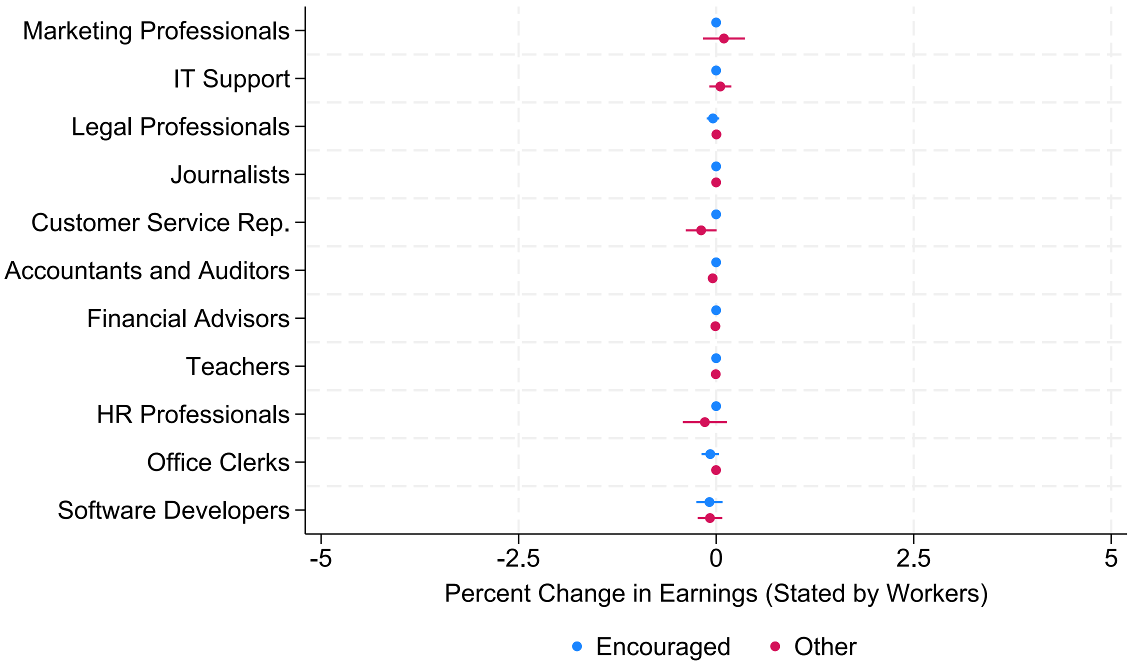
Table E.2: Pass-Through of Time Savings to Earnings (OLS vs. Coworker IV)

| | Baseline | | Encouraged | |
|---|---|---|---|---|
| | OLS | IV | OLS | IV |
| | (1) | (2) | (3) | (4) |
| Pass-through rate | 0.031 | 0.018 | 0.066 | 0.059 |
| | (0.005) | (0.032) | (0.003) | (0.016) |

*Notes:* This table reports estimates of the pass-through rate from workers' perceived time savings due to AI chatbots to their perceived earnings impacts. Estimates are reported separately based on whether employers encourage chatbot use (Encouraged = 0 or 1). The OLS coefficients correspond to the slopes of the best-fit lines in Figure 10. The IV estimates instrument Encouraged using the coworker instruments described in Section 5.1. *Sample*: The table is based on all complete responses from the 2024 survey that can be linked to the registry data.

## E.2 Workplace Outcomes

Figure E.3: Average Effect of AI Chatbots on Earnings (Non-Users of AI Chatbots for Work)




*Notes*: This figure shows workers' average perceived earnings impacts from AI chatbots, broken down by their occupations and whether employers encourage AI chatbot use. The figure focuses on workers who have not used AI chatbots for work. *Sample*: All completed responses from the 2024 survey.

## E.3 Empirical Bayes Shrinkage

We estimate workplace rates of adoption and encouragement using Empirical Bayes shrinkage with a Beta-Binomial model; see Walters (2024) for a detailed introduction to Empirical Bayes methods. The shrinkage is performed separately for each occupation, allowing underlying adoption rates to vary systematically across occupations.

We assume the adoption rate at each workplace, $p_i$, follows a Beta prior:

$$x_i \mid p_i \sim \text{Binomial}(n_i, p_i), \quad p_i \sim \text{Beta}(\alpha_0, \beta_0). \tag{6}$$

The Beta prior captures workplace-level variation. We estimate $\alpha_0, \beta_0$ via Method of

Moments, matching the Beta distribution's first two moments to observed data:

$$\bar{p} = \frac{1}{m}\sum_{i=1}^{m}\frac{x_i}{n_i}, \quad s^2 = \frac{1}{m}\sum_{i=1}^{m}\left(\frac{x_i}{n_i} - \bar{p}\right)^2. \tag{7}$$

From the Beta mean and variance formulas:

$$\alpha_0 = \frac{\bar{p}(1-\bar{p})}{s^2} - 1, \quad \beta_0 = \alpha_0\frac{1-\bar{p}}{\bar{p}}.$$

With these, we compute the posterior mean:

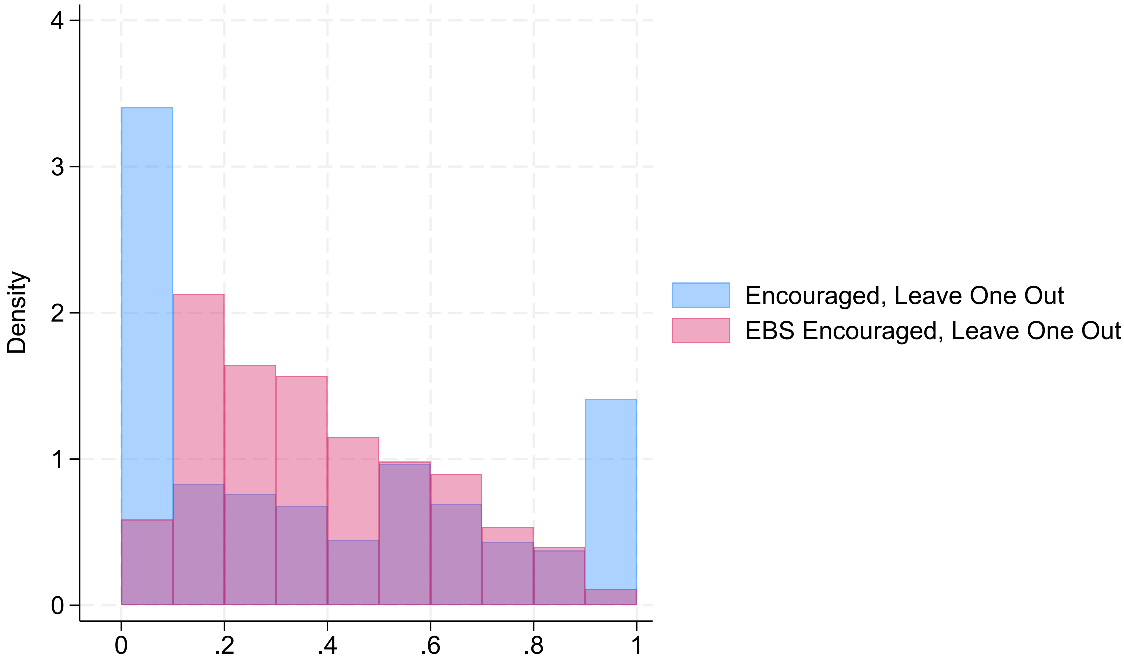
$$\mathbb{E}[p_i \mid x_i] = \frac{\alpha_0 + x_i}{\alpha_0 + \beta_0 + n_i}.$$

This shrinks estimates toward the overall mean, especially for small $n_i$.

### E.3.1 Coworker Encouragement Rates

Figure E.4 compares the raw and adjusted distributions of coworker encouragement rates, while Table E.3 presents summary statistics for the adjusted rates of workplaces. The typical standard deviation within occupations is 17 percentage points. Importantly, our results in Section 5.1.2 remain robust when using the raw coworker encouragement rates instead.

Figure E.4: Coworker Encouragement Rates (Raw vs. Shrinkage)




*Notes:* This figure compares the raw and adjusted distributions of coworker encouragement rates. The adjusted estimates are derived using an Empirical Bayes shrinkage procedure, as described in Section E.3. *Sample:* All completed responses from our 2024 survey round linked to registry data.

Table E.3: Coworker Encouragement Rates (Empirical Bayes Shrinkage)

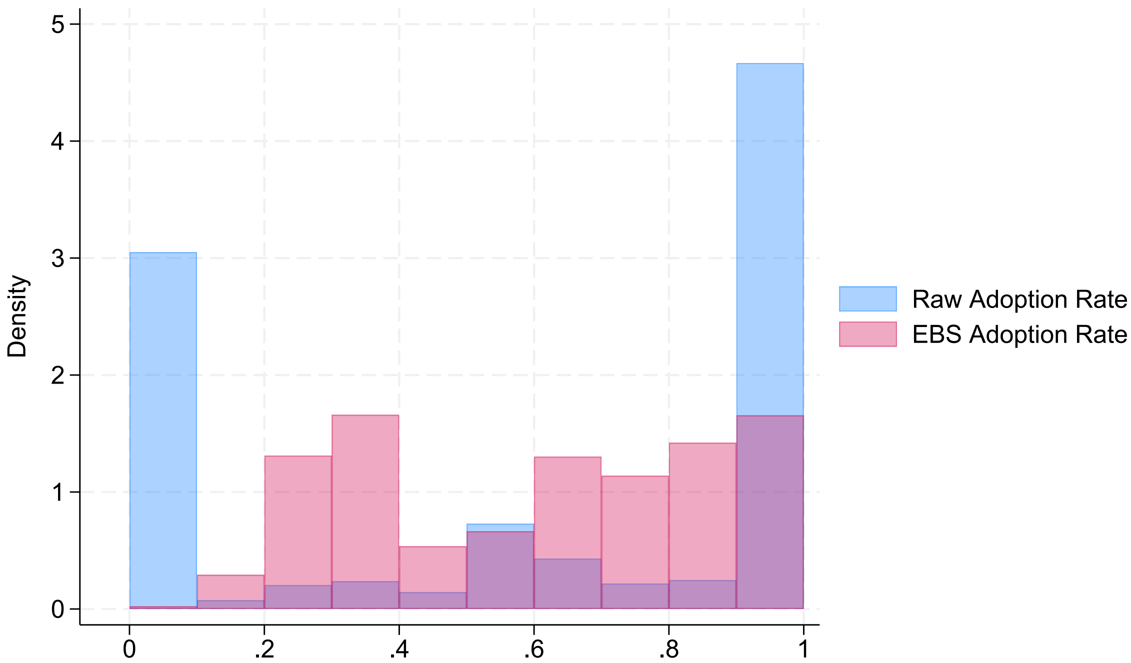
| | p25 | p50 | p75 | sd |
|---|---|---|---|---|
| Journalists | .414 | .457 | .58 | .138 |
| Software Developers | .53 | .68 | .768 | .16 |
| Legal Professionals | .092 | .178 | .465 | .23 |
| Accountants | .289 | .409 | .555 | .181 |
| Customer Service Rep. | .291 | .358 | .466 | .116 |
| Marketing Professionals | .607 | .823 | .869 | .18 |
| Financial Advisors | .196 | .35 | .605 | .237 |
| HR Professionals | .289 | .509 | .737 | .244 |
| Office Clerks | .232 | .31 | .448 | .149 |
| Teachers | .116 | .157 | .243 | .11 |
| IT Support | .359 | .48 | .593 | .162 |
| All | .310 | .428 | .575 | .173 |

*Notes:* This table presents summary statistics for the adjusted distributions of coworker encouragement rates, categorized by occupation. The adjusted estimates are derived using an Empirical Bayes shrinkage procedure, as described in Section E.3. *Sample:* All completed responses from our 2024 survey round linked to registry data.

### E.3.2 Workplace Adoption Rates

Figure E.5 compares the raw and adjusted distributions of workplace adoption rates, while Table E.4 presents summary statistics for the adjusted rates of workplaces. The typical standard deviation within occupations is 20 percentage points. Notably, our results in Section 5.2.2 remain robust when using the raw workplace adoption rates instead.

Figure E.5: Workplace Adoption Rates (Raw vs. Shrinkage)




*Notes:* This figure compares the raw and adjusted distributions of workplace adoption rates. The adjusted estimates are derived using an Empirical Bayes shrinkage procedure, as described in Section E.3. *Sample:* All completed responses from our 2024 survey round linked to registry data.

Table E.4: Workplace Adoption Rates (Empirical Bayes Shrinkage)

| | p25 | p50 | p75 | sd |
|---|---|---|---|---|
| Journalists | 0.71 | 0.83 | 0.83 | 0.14 |
| Software Developers | 0.90 | 0.90 | 0.93 | 0.12 |
| Legal Professionals | 0.28 | 0.70 | 0.70 | 0.24 |
| Accountants | 0.25 | 0.25 | 0.73 | 0.24 |
| Customer Service Rep. | 0.27 | 0.50 | 0.74 | 0.24 |
| Marketing Professionals | 0.97 | 0.97 | 0.97 | 0.19 |
| Financial Advisors | 0.29 | 0.48 | 0.65 | 0.21 |
| HR Professionals | 0.54 | 0.92 | 0.92 | 0.30 |
| Office Clerks | 0.31 | 0.38 | 0.63 | 0.18 |
| Teachers | 0.51 | 0.63 | 0.69 | 0.13 |
| IT Support | 0.58 | 0.88 | 0.88 | 0.22 |
| All | 0.51 | 0.68 | 0.79 | 0.20 |

*Notes:* This table presents summary statistics for the adjusted distributions of workplace adoption rates, categorized by occupation. The adjusted estimates are derived using an Empirical Bayes shrinkage procedure, as described in Section E.3. *Sample:* All completed responses from our 2024 survey round linked to registry data.

# F Invitation Letter

This section includes the invitation letter for our survey. We sent three reminders: two via email (Digital Post) and one via text message (SMS).

The section below focuses on our 2024 survey round. The invitation letter for the 2023 round follows the same format and is documented in Humlum and Vestergaard (2025).

The English translation begins on page 36, followed by the original Danish version on page 38.

November 2024

# Artificial intelligence and your job tasks

**Dear [name]**

Statistics Denmark is inviting you to participate in a research project about AI chatbots and your job tasks. You can participate by clicking the link below and completing the questionnaire.

**AI chatbots use artificial intelligence to read and write text**. You have been selected because you work in an occupation where AI chatbots may be relevant.

**Your responses are important** for research on new technology in the labor market. Everyone who completes the questionnaire will automatically participate in a lottery with **a prize of [X,XXX] DKK tax-free**.

Statistics Denmark is conducting the survey on behalf of researchers at the University of Copenhagen and the University of Chicago. The questionnaire takes **about 10 minutes** to complete.

**Start the survey [url]**

Or access www.dst.dk/ditsvar and enter your response code **[code]**.

**Statistics Denmark handles your data confidentially.** Results are presented in a way that prevents individual answers from being identified, and the data is used solely for statistical and scientific purposes.

Participation is voluntary. If you do not wish to participate, you can indicate this here: [refusal_link]

**If you have any questions**, you can e-mail info@dstsurvey.dk or call on 7777 7708 (every day between 9am and 4pm). Please provide your response code when contacting us.

Best regards,

Marie Fuglsang
Head of Division, DST Survey

Anders Humlum
Assistant Professor, University of Chicago

**Information about Statistics Denmark's surveys and your rights**

### Who is invited to Statistics Denmark's surveys?

Anyone residing in Denmark may be invited to participate in one of Statistics Denmark's surveys. Participants are randomly selected. Our surveys aim to reflect the opinions and attitudes of the entire population, across gender, age, education, and place of residence.

### Why is Statistics Denmark allowed to contact you?

Statistics Denmark can use its statistical production and related activities to carry out tasks under the rules for revenue-financed activities. This is stipulated in §1, section 3, no. 5, of the Act on Statistics Denmark.

### How do we process your information?

The responses you provide in the survey are handled in accordance with the European General Data Protection Regulation (GDPR) and the Danish Data Protection Act.

The University of Copenhagen is the data controller for this survey. You can read more about the data controller and find contact information here: https://informationssikkerhed.ku.dk/persondatabeskyttelse/publikation-af-videnskab/

Statistics Denmark is the data processor and is responsible for data collection on behalf of the data controller.

Your responses will only be used for statistical and scientific purposes in this survey. Your answers will be deleted or archived in accordance with applicable laws when they are no longer needed for the study.

You can read more about how we process your data at: https://www.dst.dk/privatlivspolitik-i-en-frivillig-undersoegelse.

If you have any other questions regarding the processing of your personal data, you are welcome to contact Statistics Denmark's Data Protection Officer at databeskyttelse@dst.dk.

Invitation Letter – Danish Version

November 2024

# Kunstig intelligens og dine arbejdsopgaver

**Kære [navn]**

Danmarks Statistik inviterer dig til at deltage i et forskningsprojekt om AI chatbots og dine arbejdsopgaver. Du deltager ved at klikke på nedenstående link og svare på spørgeskemaet.

**AI chatbots bruger kunstig intelligens til at læse og skrive tekst**. Du er blevet udvalgt til at deltage i denne undersøgelse, fordi du arbejder i et erhverv, hvor det kan være relevant at bruge AI chatbots.
**Dine svar er vigtige** for forskning i ny teknologi på arbejdsmarkedet. Alle der gennemfører spørgeskemaet, deltager automatisk i lodtrækningen om **en præmie på [X.XXX] kr. skattefrit**.

Danmarks Statistik gennemfører spørgeskemaet for forskere på Københavns Universitet og University of Chicago. Det tager **ca. 10 minutter** at besvare spørgeskemaet.

**Start undersøgelsen [url]**

Eller gå ind på www.dst.dk/ditsvar og tast svarkoden **[kode]**

**Danmarks Statistik behandler dine svar fortroligt.** Vi formidler resultaterne på en måde, så ingen kan se, hvad den enkelte har svaret og data anvendes alene til statistiske og videnskabelige formål.

Det er frivilligt at deltage. Ønsker du ikke at deltage, kan du tilkendegive det: [refusal_link]

**Har du spørgsmål**, kan du skrive til info@dstsurvey.dk eller ringe på tlf. 7777 7708 (alle dage ml. kl. 9-16). Oplys venligst din svarkode ved henvendelse.

Med venlig hilsen

Marie Fuglsang
Kontorchef, DST Survey

Anders Humlum
Adjunkt, University of Chicago

**Information om Danmarks Statistiks undersøgelser og dine rettigheder**

### Hvem bliver inviteret til Danmarks Statistiks undersøgelser?

Alle, der har bopæl i Danmark, har mulighed for at blive inviteret til at deltage i en af Danmarks Statistiks undersøgelser. Udvælgelse af personer til undersøgelsen sker tilfældigt. I vores undersøgelser er det vigtigt at kende meninger og holdninger fra hele befolkningen på tværs af køn, alder, uddannelse og bopæl.

### Hvorfor må Danmarks Statistik kontakte dig?

Danmarks Statistiks kan bruge den statistiske produktion og afledte aktiviteter til at udføre opgaver efter reglerne for indtægtsdækket virksomhed. Det følger af § 1, stk. 3, nr. 5, i lov om Danmarks Statistik.

### Hvordan behandler vi oplysninger om dig?

De svar, du afgiver ved deltagelse i spørgeskemaundersøgelsen, bliver behandlet i overensstemmelse med reglerne i den europæiske databeskyttelsesforordning (GDPR) og den danske databeskyttelseslov.

Københavns universitet er dataansvarlig for undersøgelsen. Du kan læse mere om den dataansvarlige og finde kontaktoplysninger her: https://informationssikkerhed.ku.dk/persondatabeskyttelse/publikation-af-videnskab/

Danmarks Statistik er databehandler og står for dataindsamlingen på vegne af den dataansvarlige.

Dine svar bruges udelukkende til statistiske og videnskabelige formål i denne undersøgelse. Dine svar slettes eller arkiveres efter gældende lovgivning, når oplysningerne ikke længere har et formål i undersøgelsen.

På linket https://www.dst.dk/privatlivspolitik-i-en-frivillig-undersoegelse kan du læse mere om, hvordan vi behandler oplysninger om dig.

Har du andre spørgsmål til behandling af dine personoplysninger, er du velkommen til at kontakte Danmarks Statistiks databeskyttelsesrådgiver på databeskyttelse@dst.dk

# G Survey Questionnaire

This section contains our survey questionnaire. The questionnaire follows a common structure for the different occupations but with job tasks and titles tailored to each specific occupation.

For the sake of brevity, the questionnaire below focuses on one occupation (journalism), listing one of their six job tasks (write commentaries, columns, or scripts).

The section below focuses on our 2024 survey round. The survey questionnaire for the 2023 round follows a similar format and is documented in Humlum and Vestergaard (2025).

The English translation starts on page 41, with the original Danish version on page 46.

# Survey Questionnaire – English Translation

**1. Introduction**

AI chatbots use artificial intelligence to read and write text. You have been selected to participate in this survey because you work in a profession where AI chatbots may be relevant.
Your participation is important regardless of your knowledge of chatbots or artificial intelligence.

**Block 1: Occupation and tasks**

**2.a Occupation**

Are you employed in [journalism]?

- Yes
- No

**2.b Occupation [if 2.a='No']**

Are you employed in one of the following areas?
If you are employed in multiple areas, please select your primary work area.

- HR work
- IT support
- Office and secretarial work
- Customer support
- Legal work
- Marketing
- Auditing and accounting work
- Software development
- Teaching
- Financial consulting
- I am not employed in any of the above work areas

**3. Task Importance** [if 2.b!= 'I am not employed in any of the above work areas'; all tasks]
We will first ask about some typical work tasks among [journalists].
For each task, please assess how **important the task is for your work**.
Extremely important means that the task is critical for performing your current job.
[Write commentaries, columns, or scripts]

- Not important
- Slightly important
- Important
- Very important
- Extremely important

**Block 2: Adoption**

**4. Awareness of AI chatbots**

AI chatbots use artificial intelligence to read and write text. We will now ask about your experiences with AI chatbots.
Had you heard of the following chatbots before this survey?
Mark all tools you had heard of before this survey.

- ChatGPT (developed by OpenAI)
- Claude (developed by Anthropic)
- Copilot (developed by Microsoft)
- Gemini (developed by Google)
- Perplexity (developed by Perplexity AI)
- Other AI chatbots
- Had not heard of AI chatbots before this survey

**5. Prior Use of AI Chatbots** [if 4 = 'Yes']
Have you used the following AI chatbots?
[ChatGPT / Claude / Copilot / Gemini / Perplexity / Other AI chatbots]

- Yes, only for work
- Yes, only for leisure
- Yes, for work and leisure

**6.a Purposes of Prior Use** [if 5='Yes, only for leisure' or 'Yes, for work and leisure']
How often have you used the following AI chatbots **for leisure**?
[ChatGPT / Claude / Copilot / Gemini / Perplexity / Other AI chatbots]

- Never
- A few times
- Monthly
- Weekly
- Daily

**6.b Purposes of Prior Use** [if 5='Yes, only for work or 'Yes, for work and leisure']
How often have you used the following AI chatbots **for work**?
[ChatGPT / Claude / Copilot / Gemini / Perplexity / Other AI chatbots]

- Never
- A few times
- Monthly
- Weekly
- Daily

**6.c Purposes of Prior Use** [if 5='Yes, only for work or 'Yes, for work and leisure' for any option]
Have you used an AI chatbot to perform the following work tasks?

- [Job task 1-6]
- None of the above

**7. Time use on AI chatbots** [if 5='Yes, only for work or 'Yes, for work and leisure' for any option]
Think back to the days when you used AI chatbots for your work. How much time did you spend using AI chatbots on average?

- Less than 15 minutes per day
- Between 15 minutes and an hour per day
- More than an hour per day

**8. Paid subscription** [if 5='Yes, only for work or 'Yes, for work and leisure' for 'ChatGPT']
Do you have an active Plus subscription for ChatGPT?

- Yes
- No

**Block 3: Employer Initiatives**

**9. Employer policies**
What is your employer's policy regarding the use of AI chatbots?

- Allowed and encouraged
- Allowed but not encouraged
- Not allowed
- No policy
- Don't know

**10. In-house AI chatbot**
Does your workplace have its own AI chatbot?

- Yes, a custom-designed product
- Yes, a standard product
- No
- Don't know

**11.a Training courses**
Have you participated in courses on using AI chatbots?

- Yes
- No

**11.b Training courses** [if 11.a = 'Yes']
Was your AI chatbot course organized by your employer?

- Yes
- No

## Block 4: Effects of AI chatbots

**12. Benefits from AI chatbots**

Have you experienced any of these benefits from using AI chatbots in your work?
Please select all that apply.

- Saved time at work
- Improved work quality
- Increased creativity
- Higher job satisfaction
- Have not experienced benefits
- Don't know

**13. Time savings from AI chatbots** [if 12='Saved time at work']

Think back to the days when you used AI chatbots for your work. How much time did you save using AI chatbots on average?

- Less than 15 minutes per day
- Between 15 minutes and an hour per day
- More than an hour per day

**14.a Earnings impact of AI chatbots**

Have AI chatbots affected how much you earn today?

- I earn more today as a result of AI chatbots
- AI chatbots have not affected my income
- I earn less today as a result of AI chatbots

**14.b Earnings impact of AI chatbots** [if 14.a=' I earn more today as a result of AI chatbots']

How much have AI chatbots increased your earnings?

- Under 5 percent
- Between 5 and 15 percent
- Over 15 percent

**14.c Earnings impact of AI chatbots** [if 14.a=' I earn less today as a result of AI chatbots']

How much have AI chatbots reduced your earnings?

- Under 5 percent
- Between 5 and 15 percent
- Over 15 percent

**15. Allocation of time savings from AI chatbots**

If AI chatbots save time on a task, do you expect to:

- Complete more of the same tasks
- Spend more time on other tasks
- Take more breaks
- Take more leisure time

**16. Workloads from AI chatbots**

Do you find that AI chatbots have increased your workload?

- Yes, more of the same job tasks
- Yes, new types of job tasks
- No

**17. New job tasks** [if 16='Yes, new types of job tasks']

What types of new tasks have you experienced after using AI chatbots?

- [open text field]

**18. End of survey**

Thank you for participating in the survey.

If you win one of the prizes, you will be notified directly in your e-Boks.

Survey Questionnaire – Danish Version

**1. Introduction**
AI chatbots bruger kunstig intelligens til at læse og skrive tekst. Du er blevet udvalgt til at deltage i denne undersøgelse, fordi du arbejder i et erhverv, hvor det kan være relevant at bruge AI chatbots. Din deltagelse er vigtig uanset dit kendskab til chatbots eller kunstig intelligens.

**Block 1: Occupation and tasks**

**2.a Occupation**
Er du beskæftiget med [journalistik]?

- Ja
- Nej

**2.b Occupation** [if 2.a='Nej']
Er du beskæftiget inden for et af følgende områder?
Hvis du er beskæftiget indenfor flere områder, vælg da dit primære arbejdsområde.

- HR-arbejde
- IT-support
- Kontor- og sekretærarbejde
- Kundesupport
- Juridisk arbejde
- Marketing
- Revisions- og regnskabsarbejde
- Softwareudvikling
- Undervisning
- Økonomisk rådgivning
- Jeg er ikke beskæftiget inden for ovenstående arbejdsområder

**3. Task Importance** [if 2.b!= 'Jeg er ikke beskæftiget inden for ovenstående arbejdsområder'; all tasks]
Vi vil først spørge ind til nogle typiske arbejdsopgaver blandt [journalister].
Til hver opgave bedes du vurdere, hvor **vigtig opgaven er for dit arbejde**.
Ekstremt vigtig betyder, at opgaven er kritisk for varetagelsen af dit nuværende job.
[Skrive kommentarer, klummer eller artikler]

- Ikke vigtig
- Lidt vigtig
- Vigtig
- Meget vigtig
- Ekstremt vigtig

**Block 2: Adoption**

**4. Awareness of AI chatbots**

AI chatbots bruger kunstig intelligens til at læse og skrive tekst. Vi vil nu spørge ind til dine erfaringer med AI chatbots.
Havde du hørt om følgende chatbots før denne undersøgelse?
Markér alle værktøjer, du havde hørt om før denne undersøgelse.

- ChatGPT (udviklet af OpenAI)
- Claude (udviklet af Anthropic)
- Copilot (udviklet af Microsoft)
- Gemini (udviklet af Google)
- Perplexity (udviklet af Perplexity AI)”
- Andre AI chatbots
- Havde ikke hørt om AI chatbots før denne undersøgelse

**5. Prior Use of AI Chatbots** [if 4 = ’Ja’]
Har du benyttet følgende AI chatbots?
[ChatGPT / Claude / Copilot / Gemini /Perplexity / Andre AI chatbots]

- Ja, kun til arbejde
- Ja, kun til fritid
- Ja, til arbejde og fritid

**6.a Purposes of Prior Use** [if 5=’Ja, kun til fritid’ or ’Ja, til arbejde og fritid’]
Hvor ofte har du benyttet følgende AI chatbots **til fritid**?
[ChatGPT / Claude / Copilot / Gemini /Perplexity / Andre AI chatbots]

- Aldrig
- Et par gange
- Månedligt
- Ugentligt
- Dagligt

**6.b Purposes of Prior Use** [if 5=’Ja, kun til arbejde or ’Ja, til arbejde og fritid’]
Hvor ofte har du benyttet følgende AI chatbots **til arbejde**?
[ChatGPT / Claude / Copilot / Gemini /Perplexity / Andre AI chatbots]

- Aldrig
- Et par gange
- Månedligt
- Ugentligt
- Dagligt

**6.c Purposes of Prior Use** [if 5='Ja, kun til arbejde or 'Ja, til arbejde og fritid' for any option]
Har du benyttet en AI chatbot til at udføre følgende arbejdsopgaver?

- [Arbejdsopgave 1-6]
- Ingen af ovennævnte

**7. Time use on AI chatbots** [if 5='Ja, kun til arbejde or 'Ja, til arbejde og fritid' for any option]
Tænk tilbage på de dage, hvor du har brugt AI chatbots til dit arbejde. Hvor meget tid brugte du med AI chatbots i gennemsnit?

- Mindre end 15 minutter per dag
- Mellem 15 minutter og en time per dag
- Mere end en time per dag

**8. Paid subscription** [if 5='Ja, kun til arbejde or 'Ja, til arbejde og fritid' for 'ChatGPT']
Har du et aktivt Plus-abonnement på ChatGPT?

- Ja
- Nej

**Block 3: Employer Initiatives**

**9. Employer policies**
Hvad er din arbejdsgivers politik ift. brugen af AI chatbots?

- Tilladt og tilskyndet
- Tilladt men ikke tilskyndet
- Ikke tilladt
- Ingen politik
- Ved ikke

**10. In-house AI chatbot**
Har din arbejdsplads sin egen AI chatbot?

- Ja, et specialdesignet produkt
- Ja, et standardprodukt
- Nej
- Ved ikke

**11.a Training courses**
Har du deltaget i kurser om brugen af AI chatbots?

- Ja
- Nej

**11.b Training courses** [if 11.a = 'Ja']
Var dit kursus i AI chatbots arrangeret af din arbejdsgiver?

- Ja
- Nej

**Block 4: Effects of AI chatbots**

**12. Benefits from AI chatbots**
Har du oplevet nogle af disse fordele ved brugen af AI chatbots i dit arbejde?
Markér gerne flere

- Sparet tid i arbejdet
- Forbedret kvalitet af arbejdet
- Øget kreativitet
- Højere arbejdsglæde
- Har ikke oplevet fordele
- Ved ikke

**13. Time savings from AI chatbots** [if 12='Sparet tid i arbejdet']
Tænk tilbage på de dage, hvor du har brugt AI chatbots til dit arbejde. Hvor meget tid sparede AI chatbots dig i gennemsnit?

- Mindre end 15 minutter per dag
- Mellem 15 minutter og en time per dag
- Mere end en time per dag

**14.a Earnings impact of AI chatbots**
Har AI chatbots påvirket hvor meget du tjener i dag?

- Jeg tjener mere i dag som følge af AI chatbots
- AI chatbots har ikke påvirket min indtjening
- Jeg tjener mindre i dag som følge af AI chatbots

**14.b Earnings impact of AI chatbots** [if 14.a=' Jeg tjener mere i dag som følge af AI chatbots']
Hvor meget har AI chatbots øget din indtjening?

- Under 5 procent
- Mellem 5 og 15 procent
- Over 15 procent

**14.c Earnings impact of AI chatbots** [if 14.a=' Jeg tjener mindre i dag som følge af AI chatbots']
Hvor meget har AI chatbots reduceret din indtjening?

- Under 5 procent
- Mellem 5 og 15 procent
- Over 15 procent

**15. Allocation of time savings from AI chatbots**
Hvis AI chatbots sparer tid i løsningen af en opgave, forventer du så, at
- Løse flere af samme opgaver
- Bruge mere tid på andre opgaver
- Tage flere pauser
- Tage mere fritid

**16. Workloads from AI chatbots**
Oplever du, at AI chatbots har øget din arbejdsmængde?
- Ja, flere af de samme arbejdsopgaver
- Ja, nye slags arbejdsopgaver
- Nej

**17. New job tasks** [if 16='Ja, nye slags arbejdsopgaver']
Hvilke slags nye arbejdsopgaver oplever du at have fået efter brugen af AI chatbots?
- [Fritekstfelt]

**17. End of survey**
Mange tak for at deltage i undersøgelsen.
Hvis du vinder en af præmierne, vil du få direkte besked i din e-Boks.