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# Large Language Models, Small Labor Market Effects

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## 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 3%), 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.

*JEL Codes:* J23, J24, J31, O33

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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 take-up 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 administrative panel data on earnings, hours, and occupations.<sup>1</sup> Our analysis proceeds in four parts.

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<sup>1</sup>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 analyzing 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; David, 1990).

However, despite substantial investments in AI chatbots, their overall impact on work remains modest: users report average time savings of 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, the lack of 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 adopters’ economic outcomes. Difference-in-differences estimates for earnings, hours, and wages are all precisely estimated zeros, with confidence intervals ruling out average effects larger than 1%. At the occupation level, estimates are similarly close to zero, generally excluding changes greater than 6%. These limited impacts persist in our quasi-experimental analysis based on employer policies, suggesting that the average causal effect is indeed negligible. A direct survey question—“*Have AI chatbots affected your labor earnings?*”—confirms that workers overwhelmingly report no impact on earnings as of November 2024. Moreover, difference-in-differences estimates show no differential trends over time and are not larger among adopters whose use is encouraged by employers, indicating that the limited impacts are not merely a very short-term phenomenon.

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 examine whether AI chatbots have affected broader workplace outcomes, potentially influencing even non-adopting workers. Comparing workplaces with high versus low rates of chatbot usage, we find no evidence that firms with greater adoption have experienced differential changes in total employment, wage bills, or retention of incumbent workers. 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 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 J.

**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). Finally, we draw firm-level data (e.g., annual revenue and employment) from the *Firm Statistics* (FIRM) Register. 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 I. 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).<sup>2</sup>

Employers’ encouragement is 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.<sup>3</sup> Notably,

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<sup>2</sup>Although outright bans are now rare, they persist in some occupations that involve sensitive data (e.g., financial advisors) or require high factual accuracy (e.g., legal professionals).

<sup>3</sup>Customized chatbots are typically versions of ChatGPT, tailored for workplace use through adjustments such as compliance with data security, training on internal data, and custom prompt creation. Often, these are thin wrappers around ChatGPT Enterprise or the OpenAI API. Appendix B.2.1 details the usage of AI chatbot products, showing that ChatGPT remains the dominant player. It also provides additional information on the characteristics of in-house chatbots.

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).

Which firms have adopted different AI chatbot initiatives? Table 1 shows that firms encouraging AI chatbot use tend to be slightly younger (each additional 10 years of age is associated with a 1.4 percentage point decrease in encouragement), more productive (a doubling of productivity corresponds to a 4.7 percentage point increase), and more likely to be privately owned (associated with a 4.1 percentage point increase), but not systematically larger than others.<sup>4,5</sup> Overall, however, chatbot initiatives are largely unrelated to observable firm characteristics, which account for just 1.3% of the within-occupation variation in encouragement—far less than the 10.6% explained by our 11 occupation categories alone. In other words, many otherwise comparable firms have adopted markedly different strategies toward AI chatbots, even for similar workers within the same occupation. We examine the implications of these divergent approaches in the sections that follow.

### **2.1.1 Employer Initiatives and Worker Outcomes**

Throughout the paper, we explore how the employer initiatives for AI chatbots relate to workers’ adoption and benefits from the tools. This analysis is motivated by the literature on “Productivity J-Curves,” which emphasizes that complementary organizational investments may be critical for realizing the gains from new technologies (Brynjolfsson and

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<sup>4</sup>Appendix Table B.1 shows that these correlations with firms’ characteristics are robust to controlling for worker characteristics.

<sup>5</sup>Younger and more productive firms are commonly found to adopt new technologies faster; see, e.g., Acemoglu et al. (2022), who document adoption patterns for a range of advanced technologies in 2019, including AI and robotics. One difference stands out: while larger firms are typically found to adopt new technologies faster, this pattern does not hold for AI chatbots, whose employer encouragement appears unrelated to firm size. This may reflect the low fixed costs associated with AI chatbots—many of which are free and relatively easy to start using. As shown in Column (7) of Table 1, however, larger firms are more likely to have their own AI chatbot.

Hitt, 2000; Brynjolfsson, Rock and Syverson, 2021). Moreover, because early adoption of AI chatbots was largely worker-driven, this analysis sheds light on the extent to which employers can move the needle and influence outcomes by also investing in the technology.

Specifically, we compare workers in the same occupations with similar characteristics and estimate how their adoption behaviors and reported benefits vary with employer initiatives for AI chatbots:

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

where  $Y_i$  is a chatbot-related outcome for worker  $i$ , such as use or reported benefits of AI chatbots for work;  $X_i$  is a vector of worker pre-determined characteristics, including age, gender, experience, and occupation fixed effects;<sup>6</sup> and  $\text{EmployerInitiative}_i$  captures employer-driven initiatives, such as encouraging employees to use AI chatbots. Appendix H presents a simple Roy-style model of chatbot adoption to help interpret the estimates in Equation (1). We draw on this framework in the discussions that follow.

Although employer initiatives are not assigned through a randomized design, our rich data on firms and workers allow us to examine the robustness of our findings to several potential confounders. Appendix F.1 presents these robustness checks. First, we show that all results hold when controlling for firm characteristics (Table 1), ensuring that differences across encouraged workplaces are not driven by variation in firm age, size, or productivity. Second, we show that the results are robust to controlling for workers' detailed task mixes within occupations, demonstrating that the effects of employer encouragement are not driven by differences in the types of tasks more amenable to AI chatbot use.<sup>7</sup> Together, these robustness checks help rule out confounding from observable factors and support the validity of our findings.

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<sup>6</sup>All worker characteristics are measured in 2022, before AI chatbots became available.

<sup>7</sup>We do not include task controls in our main specification, as task mix may itself be endogenous to chatbot adoption. Indeed, Section 3.2 shows that AI chatbots have created new job tasks for many workers.

Finally, although our main analysis relies on workers’ self-reports of employer initiatives, Appendix F.2 shows that the findings also hold when instead using coworker reports to measure employer initiatives. This robustness supports our interpretation of employer initiatives as workplace-level treatments.

## 2.2 Worker Adoption

Figure 2 shows how AI chatbot adoption varies with employer encouragement for a typical worker. The *Non-Encouraged* estimates highlight the bottom-up nature of chatbot adoption: even without employer encouragement, 47% of workers have used AI chatbots for work, and 8% use them daily. Despite this high baseline, the *Encouraged* estimates show that employer encouragement significantly boosts adoption, nearly doubling take-up rates to 83% for a typical worker. The relative impacts are even more pronounced for intensive use, with daily adoption rising to 21% when employers actively promote chatbot use.

Do employer initiatives influence which workers use AI chatbots? Figure 3 examines differences in adoption across demographic groups within occupations, estimated separately for settings with and without employer encouragement. The *Non-Encouraged* estimates reveal substantial adoption gaps across worker groups. For example, in workplaces without employer encouragement, women are about 12 percentage points less likely to have used AI chatbots than comparable men in the same occupation. Younger, less experienced, and higher-earning workers are also more likely to have adopted the tools.

Importantly, the demographic gaps in adoption are markedly smaller in workplaces where employers actively encourage chatbot use. In particular, the gender gap narrows from 12 to 5 percentage points in encouraged settings. Similarly, the age gap shrinks by approximately 40% when employers promote adoption. In contrast, the reduction in gaps is smaller among more experienced workers, suggesting that established work habits may

be more resistant to change—even when encouraged by employers.

Figures B.2–B.3 examine how other types of employer initiatives are associated with AI chatbot adoption, yielding two key insights.

First, firm-provided training programs are particularly effective, boosting overall adoption and reducing the gender gap in uptake to 3.6 percentage points.<sup>8</sup> The effectiveness of training aligns with findings from the 2023 survey round, in which 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 in workplaces where the tools are prohibited. Although employer bans are associated with a reduction in overall adoption to roughly one-third of the baseline rate, about 80% of the baseline gender gap remains. 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 show, using a vignette experiment, that the gap largely reflects male students continuing to use 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 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). Higher adoption rates among younger, less experienced, and higher-earning workers also replicate the patterns observed in our earlier round.<sup>9</sup> Bick, Blandin and Deming (2025) report

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<sup>8</sup>Figure B.3 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.

<sup>9</sup>For comparison, in our 2024 survey round, ChatGPT adoption rose 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).

similar adoption patterns among U.S. workers, and Otis et al. (2024a) show that gender gaps in Generative AI adoption are pervasive across contexts.

We contribute to this evidence by documenting that employer-driven initiatives to support AI chatbot adoption are now common and play an important role in shaping overall adoption rates and demographic disparities in usage.<sup>10</sup>

By contrast, earlier surveys found relatively low take-up rates of AI at the firm level. For example, Bonney et al. (2024) document that as of February 2024, only 5.4% of U.S. firms reported using AI, with adoption in the leading sector (Information) still below 20%.

Our survey provides the first comprehensive evidence on how employers are integrating Generative AI into the workplace. We find that employer initiatives—especially those focused on training—substantially increase adoption and help narrow demographic gaps in take-up. This finding aligns with Dillon et al. (2025), who document that firm effects are a primary driver of workers’ take-up of a randomized offer for Microsoft Copilot.

More broadly, the importance of employer initiatives for AI chatbot adoption echoes an extensive literature on the diffusion of general-purpose technologies, which stresses the need for complementary investments and coinvention (Bresnahan and Greenstein, 1996; David, 1990; Feigenbaum and Gross, 2024). In the sections that follow, we examine how employer investments in AI chatbots shape the tools’ effects on work processes and labor-market outcomes.

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<sup>10</sup>For instance, the rise of employer initiatives may explain much of the shift observed between the 2023 and 2024 surveys—namely, increased adoption and a narrowed gender gap—as most initiatives were implemented in the interim. One of the first in-house AI chatbots, DanskeGPT, was launched by Denmark’s largest bank in March 2024 (Danske Bank, 2024).

## 3 Work

### 3.1 Benefits for Users

What benefits do users report from AI chatbots? Figure 4 shows that workers primarily cite time savings in completing job tasks (Panel (a)), with an average of 25 minutes saved per day of use (Panel (b)). Additionally, nearly half of users report improvements in work quality and enhanced creativity from using AI chatbots. In contrast, increased job satisfaction is the least commonly reported benefit.<sup>11</sup>

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 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).

Appendix H presents a simple Roy model of chatbot adoption to interpret the differences between encouraged and non-encouraged users in Figure 4. The model shows that employer encouragement affects the average benefits reported by users through two distinct forces: a direct, individual-level effect of encouragement, and a selection effect arising from broader adoption. The selection effect tends to be more negative when users are more positively selected on their potential benefits and when employer encouragement primarily

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<sup>11</sup>Toner-Rodgers (2024) shows that other generative models—specifically those that generate materials designs rather than text—have profound impacts on the scientific discovery process for materials scientists, significantly enhancing their innovative capacity but also reducing their job satisfaction.

reduces adoption costs rather than increases user benefits. In this light, the consistently greater reported benefits in workplaces that encourage chatbot use, as shown in Figure 4, are especially noteworthy. They suggest that employer-led initiatives primarily work by enhancing the benefits of the tools—consistent with “Productivity J-curves”—and that these effects are large relative to any selection on worker-level gains from AI chatbot use.<sup>12</sup>

What is the economic significance of the reported benefits of AI chatbots? In Table 2, 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. In addition, 25% spend more time on the same tasks they initially saved time on, especially when employers actively encourage chatbot use. This pattern suggests that firm-led initiatives play an important role in enabling workers to expand task outputs in response to the task-specific productivity gains from chatbots.

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<sup>12</sup>Disentangling the individual-level causal effects from the selection effects would require additional assumptions (e.g., on the functional form of the adoption model à la Heckman (1979)) or alternative sources of variation (e.g., an instrument that shifts adoption costs without affecting perceived benefits). We do not attempt to separate these effects, as we view the bundled impact of employer encouragement as informative in itself—highlighting the average benefits of AI chatbots that may arise when employers actively invest in unlocking the tools’ potential.

## 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.

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.<sup>13</sup> 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 2.

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

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<sup>13</sup> *AI Integration* refers to embedding AI chatbots into workflows to automate or enhance tasks. For example, software developers report “fine-tuning AI coding assistants by providing feedback and project-specific examples,” legal professionals describe “developing organizational AI usage policies and guidelines,” and teachers mention “adapting exams and assignments to account for AI tool usage.” See Appendix C.2 for additional examples.

involving idea generation and data insights are present in all occupations but are less central, typically comprising 5%–20% of new tasks.<sup>14</sup>

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 employer initiatives for realizing the benefits of AI chatbots aligns with the concept of “Productivity J-curves,” where firm-based complementary investments are needed to unlock the potential of new technologies (Brynjolfsson, Rock and Syverson, 2021; David, 1990).

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 further underscores the importance of firm-led investments for driving workplace transformations from technological change (Brynjolfsson and Hitt, 2000; Brynjolfsson, Rock and Syverson, 2021).

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<sup>14</sup>More broadly, we may classify the new job tasks into “core AI use” (*AI Ideation*, *AI Content Drafting*, and *AI Data Insights*) and “implementation and oversight” (*AI Quality Review*, *AI Integration*, and *AI Ethics & Compliance*). Using this taxonomy, on average, 41% of the new tasks are related to core AI use, with the remaining 59% focused on enabling and managing the use of AI chatbots.

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.<sup>15,16</sup> How can we reconcile workers’ modest reported time savings with the substantial effects observed in RCTs?

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.

Relatedly, while RCTs often focus on jobs where AI chatbots are continuously applicable, the typical adopter in our data uses chatbots only every third to fourth day, diluting their overall time savings accordingly. On days when they do use the tools, however, average time savings still amount to just 6–7%, substantially below experimental estimates. Limited applicability may again be an important explanation: even on usage days, adopters spend only 5-6% of their work hours actively using AI chatbots (see Table B.2).<sup>17,18</sup>

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<sup>15</sup>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.

<sup>16</sup>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).

<sup>17</sup>Our time use estimates align with, but fall at the lower end of, the range reported by Bick, Blandin and Deming (2025).

<sup>18</sup>The time use estimates should be interpreted with caution, as we might not expect a 100% active utilization rate even in tasks where AI chatbots are directly applicable. For example, in the writing task studied by Noy and Zhang (2023), treated workers spent on average 3 minutes before pasting in a large block of text—presumably generated by ChatGPT. The workers then spend an additional 14 minutes manually editing and refining the output. In our data, adopters spend an average of 2.2% of their total

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.<sup>19</sup>

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.<sup>20</sup>

## 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

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work hours using AI chatbots—less than the time savings they report. This pattern is also consistent with Noy and Zhang (2023), where treated workers saved 10 minutes on average despite only 3 minutes of initial tool use.

<sup>19</sup>Another source of discrepancy between our time savings estimates and those from RCTs lies in the parameter of interest: whereas experiments typically identify Average Treatment Effects (ATE) for the study population, our estimates reflect self-reported time savings among users—closer to an Average Treatment Effect on the Treated (ATT). However, if workers adopt chatbots based on their expected individual benefits—such that users tend to derive greater gains than non-users—the modest time savings reported in our survey appear even more stark when contrasted with the larger effects found in RCTs.

<sup>20</sup>Edelman, Ngwe and Peng (2023) shows that self-reported time savings from AI chatbots—particularly Microsoft Copilot—may overstate actual productivity gains. This further reinforces the point that workers' productivity improvements from AI chatbots are modest, as our self-reported time savings estimates would then represent an upper bound on realized benefits. That said, overstated gains may not be the full story: Section 4.3 shows that workers' self-reported earnings effects closely align with our difference-in-differences estimates based on administrative data, reflecting that workers recognize that AI chatbots have not materially improved their earnings.

to administrative 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.<sup>21</sup> 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 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. Section 4.2.1 presents the results from these quasi-experimental analyses, which closely align with our main difference-in-differences estimates.

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<sup>21</sup>Appendix B.2.1 shows that ChatGPT remains the dominant AI chatbot to date.

#### 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. Our primary adoption measure is whether workers have used AI chatbots for work, but we also examine the effects of more intensive adoption (e.g., daily usage) and early adoption (based on responses to our 2023 survey round). We study impacts on log earnings, recorded hours, and wages, and also consider effects on extensive-margin employment.

**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:

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

where  $\lambda_{2m}$  are month fixed effects that control for seasonality in labor market outcomes. The parameters of interest,  $\beta_{\tau}$ , capture the differential changes in labor market outcomes for adopters, indexed to November 2022, the release of ChatGPT. Motivated by the greater work-related benefits when employers encourage AI chatbot use (Section 3), we further split the difference-in-differences estimates by whether adopters are encouraged. In both cases, we use all non-adopters as the comparison group and control for workers' pre-determined characteristics and seasonality.

**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:

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

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 Results

Figure 7 examines the labor earnings of adopters relative to non-adopters, before and after the introduction of AI chatbots.

Panel (a) begins by presenting the difference in means. The estimates show that adopters earn about 7% more than comparable non-adopters. Panel (b) splits adopters based on whether their usage is employer-encouraged, showing that encouraged users exhibit even larger earnings premia. However, leveraging the panel dimension of our administrative data reveals that these earnings differentials entirely predate the arrival of AI chatbots. When indexing differences to November 2022, the difference-in-differences estimates in Panel (c) show no differential changes for adopters following the introduction of AI chatbots. The estimates remain flat even among adopters whose employers actively encourage chatbot use.

The dynamic difference-in-differences in Figure 7.(c) reveal that adopters are on slightly stronger labor market trends. However, because these trends entirely predate AI chatbots, the pooled difference-in-differences in Figure 9.(a) (which control for pre-trends; see Equation (3)) are precise zeros, with confidence bands ruling out effects larger than 1%.

Figure 7 provides three key insights. First, one and a half years after their launch,

AI chatbots have had minimal average impact on adopters' earnings. The confidence intervals of our dynamic difference-in-differences estimates rule out changes larger than 2%, and our pooled difference-in-differences estimates rule out effects larger than 1%. Second, these effects show no differential trends after the introduction of AI chatbots, indicating that the minimal impacts are not merely a very short-term phenomenon.<sup>22</sup> Lastly, despite evidence in Section 3 that employer encouragement boosts work-related benefits of AI chatbots, we find no differential changes in earnings for adopters whose employers encourage their use.

While Figure 7 shows that adopters have not fared better in terms of earnings following the introduction of AI chatbots, this pattern could mask offsetting effects on wages and hours. Figure 8 examines this possibility by presenting separate estimates for workers' hourly wages, intensive-margin hours, and extensive-margin employment. Once again, we find no differential changes for adopters in any of these outcomes, even among those encouraged to use the tools.

Do the overall zero effects mask heterogeneous gains and losses across workers? To investigate this, Figure 9.(a) first estimates the effects of AI chatbots on worker earnings 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 9.(b) splits the difference-in-differences estimates according to workers' demographics, reported effects of AI chatbot use, usage intensity, 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

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<sup>22</sup>Section 4.3 shows that survey responses from November 2024 similarly report no earnings impacts of AI chatbots.

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 use them more intensively (i.e., daily users for work) or 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 differential 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,<sup>23</sup> we now isolate the variation in adoption associated with employer policies only (Figure 2). Table B.3 reports the corresponding “first stage” estimates, showing that encouragement increases adoption by 36.3 percentage points among otherwise similar workers.

Figure 10 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. Section F.2 further supports this conclusion by using coworkers’ reports to

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<sup>23</sup>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.

measure 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 2), the confidence bands in Section 4.2 are narrow enough to rule out a comparable effect on earnings. For example, our pooled estimate (“All” in Figure 9.(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 9.(a) 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 11 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 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 9 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 11 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 generally misperceiving their gains from AI chatbots.<sup>24</sup>

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 adaptations, 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 existing literature provides little evidence on whether adopters of AI chatbots have fared better in the labor market, and a core contribution of this paper is to fill that gap. While a host of studies document productivity effects within jobs, it remains unclear how these translate into workers’ earnings and hours, as high-quality microdata on such outcomes is rarely available. We address this limitation by leveraging the comprehensive administrative labor market data offered in the Danish setting.

Our key finding is that the adoption of AI chatbots has had no significant impact on workers’ earnings, recorded hours, or wages. Although the productivity gains from chatbot use are themselves modest—averaging 2.8% in time savings per user (see Section 3)—we

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<sup>24</sup>We do not have sufficient statistical power to detect comparable pass-through effects in our difference-in-differences estimates of administrative labor market outcomes (Section 4.2). As such, readers may wish to interpret our findings on the precise pass-through rates with some caution.

can rule out comparable effects on labor market outcomes. Our best estimate suggests that only about 3–7% of workers’ time savings are passed through to higher earnings, with greater elasticity at firms that actively encourage chatbot use.

What might explain the weak relationship between reported productivity gains and workers’ earnings? One possibility is that workers simply overestimate their actual benefits from the tools. Given that the reported time savings are already modest, this would reinforce the conclusion from Section 3.3 that realized gains are substantially lower than RCT estimates. Nevertheless, overstated gains may not be the full story: workers themselves recognize that only a small fraction of their reported time savings translates into higher earnings. Indeed, workers’ self-reported earnings effects closely align with our difference-in-differences estimates based on administrative data.

Are the weak wage pass-through rates from AI chatbot gains theoretically surprising? One benchmark is the competitive labor market model, in which wages equal marginal productivity and do not respond to firm-specific shocks. Under this model, workers’ productivity gains from chatbot adoption should pass through one-to-one into wages, while firm-level investments in the tools should have no effect on worker pay (Becker, 1964). Relative to this benchmark, it is surprising both that (i) workers’ adoption of AI chatbots has had such limited effects on wages, and (ii) employer investments appear to *increase* the pass-through to earnings.<sup>25</sup>

What might explain the limited effects of AI chatbots on earnings, especially when employers do not encourage their use? First, while chatbots may save time on existing tasks, these savings may not increase productivity on *marginal* tasks unless employers

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<sup>25</sup>As described in Footnote 24, our conclusions about differential pass-through by employer encouragement rely on workers’ self-reported earnings effects, as we lack the statistical power to detect comparable effects in the administrative labor market outcomes. Readers may therefore wish to interpret these conclusions about pass-through rates with caution. Nevertheless, Appendix F.2 shows that the self-reported pass-through estimates remain robust when using coworker reports to measure employer encouragement, helping to mitigate concerns that the higher pass-through effects observed in these workplaces simply reflect correlated reporting errors across variables.

adapt workflows accordingly. Consistent with this view, Section 3 shows that workers in encouraged settings are better able to take on more work in response to chatbot use.

Second, even if productivity increases, users of AI chatbots may be poorly positioned to bargain for higher pay when employers do not endorse the tools. The bottom-up nature of adoption—often occurring without managerial involvement—may create principal-agent frictions that weaken the link between productivity and pay.

More broadly, labor markets exhibit imperfections that both weaken the connection between individual productivity and pay and allow firm-level productivity shocks to affect wages (Kline, 2025; Manning, 2011). For example, Balke and Lamadon (2022) estimate pass-through rates of 26% for worker-specific and 10% for firm-specific productivity shocks using matched employer-employee data from Sweden. Similarly, Card et al. (2018) report firm-level pass-through estimates ranging from 5% to 15%, a range that encompasses our 7% estimate in encouraged settings. Such firm-level pass-through effects are often attributed to firms expanding along upward-sloping labor supply curves. In the following section, we directly examine the firm-level effects of chatbot adoption.

## 5 Broader Impacts

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 impact on adopters’ earnings and employment remains limited.

In this final section, we examine whether AI chatbots have influenced broader workplace outcomes. Even if the benefits to individual users have not yet translated into changes in their earnings or hours, employers may still be adjusting overall employment levels or wage bills in response to these tools. For instance, if AI chatbots reduce labor needs, high-adoption workplaces might slow hiring or even lay off workers. Conversely, if the tools enhance productivity and spur demand, these workplaces may instead expand

employment and increase wage bills. Such adjustments could also affect non-adopting workers, thereby violating the “no spillovers” assumption underlying our worker-level difference-in-differences analysis in Section 4.2. Indeed, Section 3.2 showed that AI chatbots have already created new workloads for non-users, indicating broader workplace changes.

## 5.1 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. We study these workplace relationships among employees within each occupation. For instance, we examine how the total wage bill for marketing professionals evolves in workplaces where a larger share of marketing professionals adopt AI chatbots. We also examine incumbent workers—those employed before the introduction of AI chatbots—whose outcomes we can track regardless of whether they remain with their original firms.

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 bias 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 G, we apply an Empirical Bayes shrinkage procedure to correct for measurement error in the survey-based adoption rates. Importantly, workplaces exhibit substantial variation in adoption rates even after

correcting for measurement error: the standard deviation across workplaces remains 20 percentage points after shrinkage. Notably, all our results remain robust when using the raw survey-based adoption rates.

## 5.2 Results

Figure 12 shows the impacts of AI chatbot adoption on total workplace wage bills 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 chatbot adoption have not fared differently. Scaling the point estimates with the standard deviation of workplace adoption rates (20pp after shrinkage; see Appendix G), we can rule out standardized effects larger than 1%.

The introduction of AI chatbots could also shift the composition of employment between incumbent workers and new hires. For instance, adopting and operating new tools may require hiring new workers who displace incumbents (Bessen et al., 2023), whereas assistance from the tools could instead help retain workers (Brynjolfsson, Li and Raymond, 2025). To explore these possibilities, Figure E.1 examines the impact of workplace adoption on incumbent workers—those employed before the introduction of AI chatbots—whose labor market outcomes we can track regardless of whether they remain with or separate from their initial firm.<sup>26</sup> Once again, we find no evidence that workers initially employed at high-adoption workplaces have been affected differently.

## 5.3 Perceived Impacts

While the analysis above shows that high-adoption workplaces have not experienced differential outcomes—even for non-adopting workers—AI chatbots could still affect non-users through other channels. For example, if chatbot availability constitutes a broader,

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<sup>26</sup>This analysis of incumbent workers resembles the research designs of Autor et al. (2014); Walker (2013).

economy-wide shock, it could affect earnings across entire occupations, regardless of individual or workplace adoption.

To assess this possibility, we directly asked non-users whether they perceive AI chatbots to have affected their earnings. Tellingly, Figure E.2 shows that 99.6% responded “No.” This finding reinforces our conclusion that—despite changes in workloads, even among non-users—AI chatbots have not caused broader impacts on labor market outcomes, such as equilibrium wages or hours.

## 5.4 Comparison to the Literature

We have limited evidence on how AI chatbots affect workplace outcomes, largely because firm-level data on Generative AI adoption remain scarce, and even fewer datasets link adoption to workplace economic outcomes.<sup>27</sup> We leverage our matched employer-employee links and comprehensive sample coverage to aggregate workers’ responses to the workplace level and assess their impacts in administrative labor market data.

The closest related evidence comes from online job postings. Eisfeldt et al. (2024) show that firms with occupational compositions more exposed to AI chatbots—based on pre-ChatGPT job postings—experienced stock price increases following the release of ChatGPT.<sup>28</sup> Schubert (2025) further shows that hiring for Generative AI skills, as listed in job postings, interacts with the demand for remote work. While these studies based on job postings suggest notable changes in firms’ labor demand immediately following the release of ChatGPT, we find no corresponding effects for high-adoption workplaces in administrative labor market data.<sup>29</sup>

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<sup>27</sup>The few existing surveys on Generative AI adoption all sample individual workers, whose responses cannot be linked at the workplace level (Blandin, Bick and Deming, 2025; Hartley et al., 2024; Pew, 2024). Bonney et al. (2024) survey AI adoption in U.S. firms as of February 2024 but do not specifically measure Generative AI or link adoption to subsequent changes in economic outcomes.

<sup>28</sup>This rise in market capitalization is consistent with firms being at an early stage of a productivity J-curve, where current investments are expected to yield economic returns over the longer term (Brynjolfsson, Rock and Syverson, 2021).

<sup>29</sup>While job postings offer a rich source of data, it is less clear how well they capture employees’ actual use of tools, particularly non-specialized ones like ChatGPT. First, although the emergence of Generative

At the broader market level, the closest existing evidence comes from case studies of online labor market 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 three factors.

First, while freelance proofreading may be highly substitutable by AI chatbots, most exposed occupations do not fall into this extreme category.<sup>30</sup> 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 manifest more quickly in labor market outcomes. In contrast, we find only a weak relationship between workers’ time savings and labor market 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 limited pass-through of productivity gains caution against extrapolating these effects to the broader labor market.

Finally, although existing studies document shifts in the demand for certain tasks on specific platforms, it remains unclear how these shifts affect workers’ total earnings and hours, as workers may reallocate their time across tasks. In our survey, most workers report using time saved by AI chatbots to perform other tasks, including new responsibilities

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AI skills in job postings is notable, it remains unclear how such listings correspond to employees’ actual use of AI chatbots (Schubert, 2025). Second, while Eisefeldt et al. (2024); Schubert (2025) rely on variation in firm-level *exposure* to AI chatbots *across* occupations (i.e., variation in hiring across jobs with different relevance to AI chatbots), our analysis instead examines variation in firm-level *adoption* of AI chatbots *within* occupations (i.e., variation in actual use of AI chatbots for the same relevant jobs).

<sup>30</sup>Teutloff et al. (2025) show that the overall impacts of ChatGPT on freelance work are more mixed, with some complementary skills seeing increases.

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 their time in the labor market.

## 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 administrative 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 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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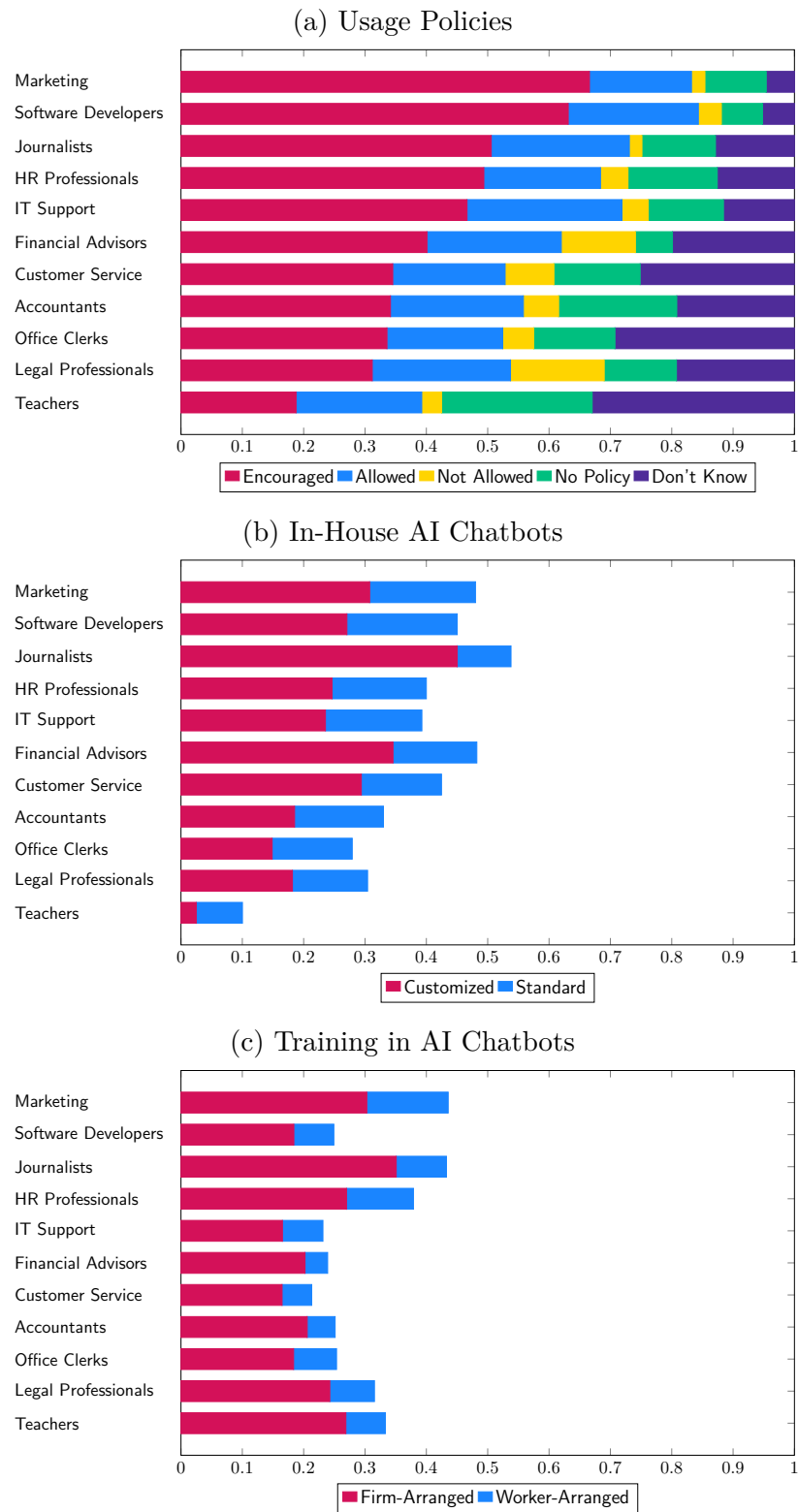
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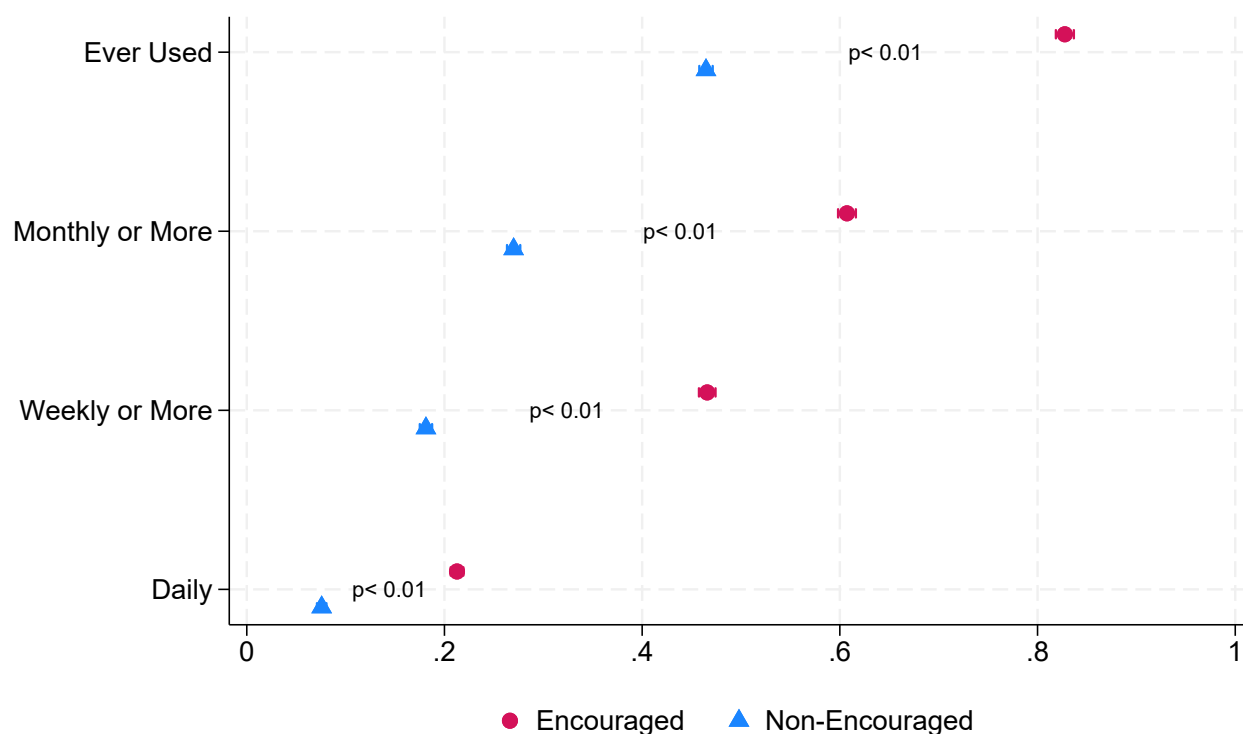
# Figures and Tables

Figure 1: Prevalence of Employer Initiatives for AI Chatbot Adoption



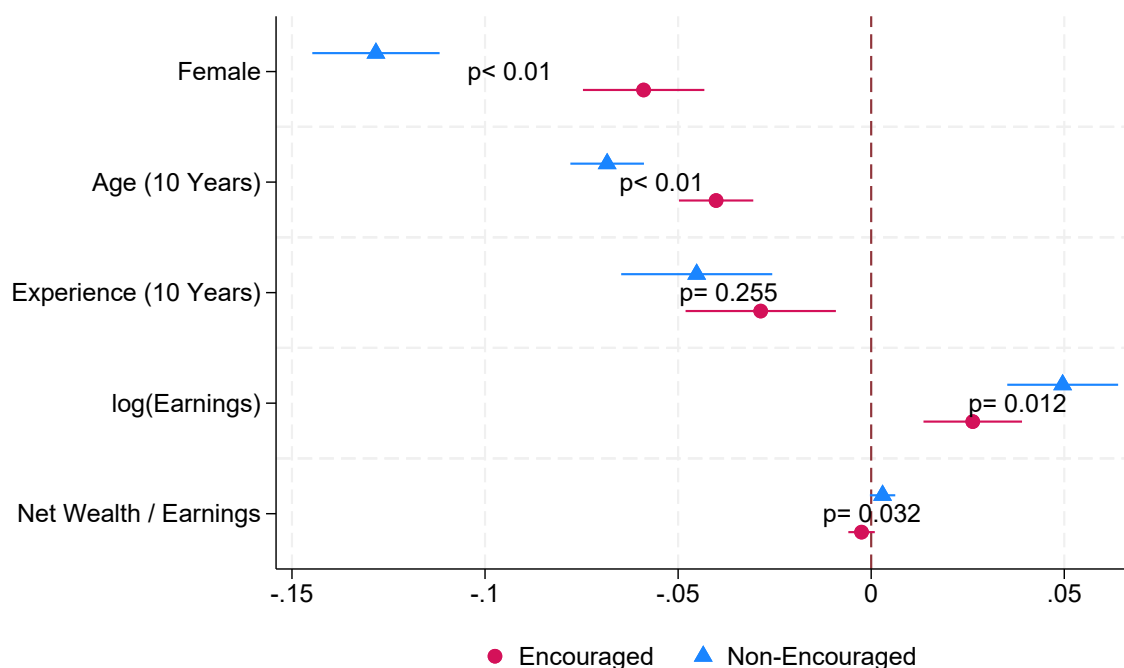
*Notes:* This figure shows the share of workers affected by various employer initiatives related to AI chatbot adoption. Panel (a) shows employers' policies on AI chatbot usage for work. Panel (b) indicates whether the employer has its own AI chatbot. Panel (c) reports whether workers have participated 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. Some confidence intervals are too narrow to be distinguished from the point estimates at this scale. 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.

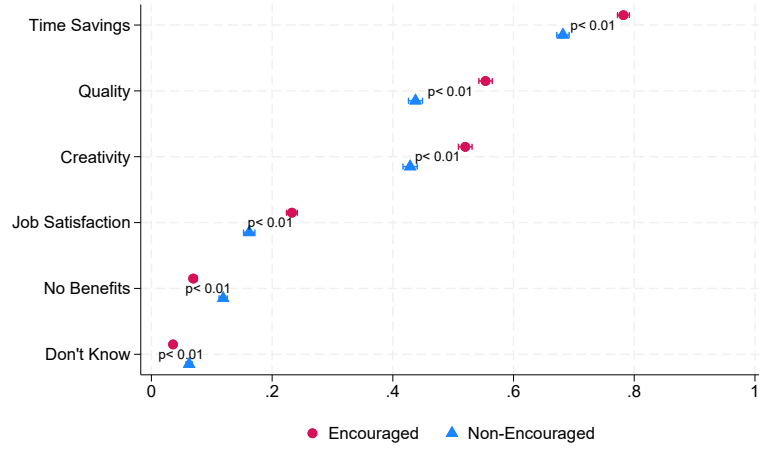
Figure 3: Influence of Employer Encouragement on Worker Gaps in AI Chatbot Adoption



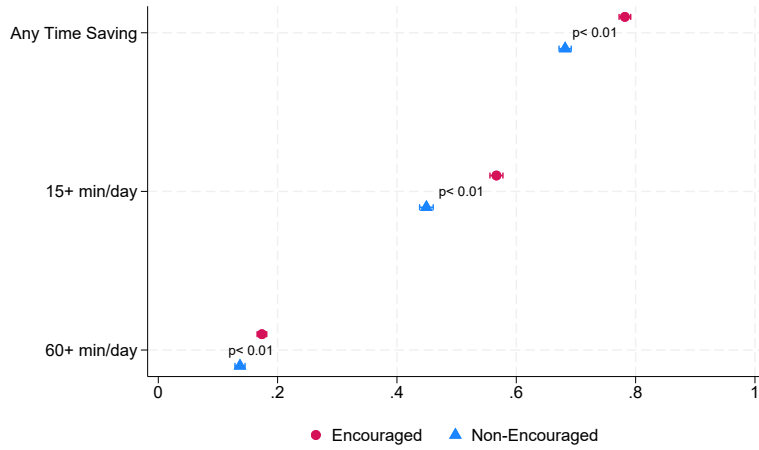
*Notes:* This figure illustrates the impact of employer usage policies on worker disparities in AI chatbot adoption. The estimates are obtained from a multivariate regression of AI chatbot adoption on worker characteristics  $X$ , controlling for occupation fixed effects, and are estimated separately 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

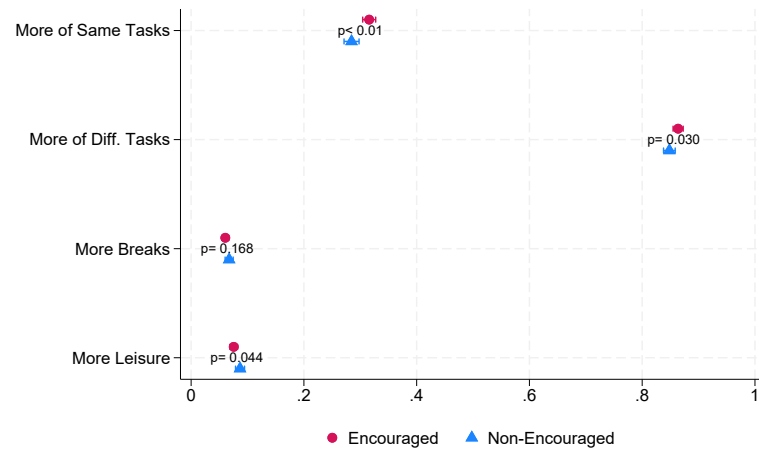
(a) Reported Benefits



(b) Estimated Time Savings



(c) Allocation of Time Savings



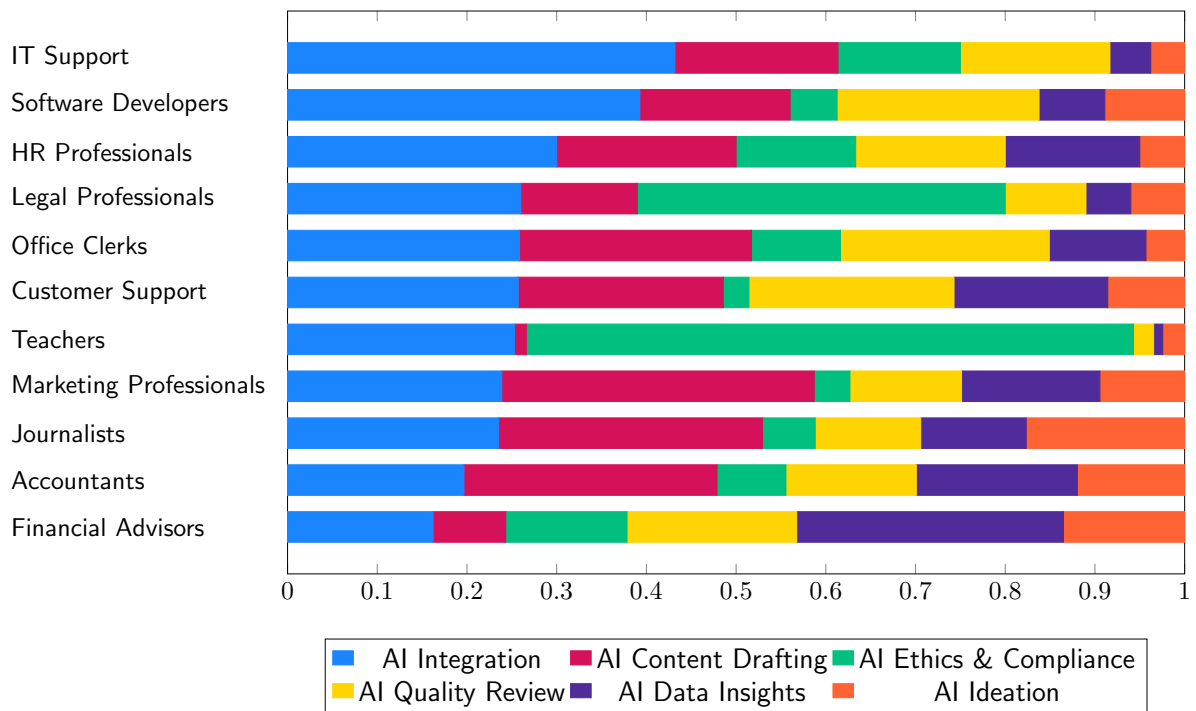
*Notes:* This figure illustrates how employer initiatives influence the benefits workers report from using AI chatbots. Panel (a) presents the share of adopters reporting various benefits, Panel (b) shows the share reporting different levels of time savings, and Panel (c) details how these workers allocate 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. Some confidence intervals are too narrow to be distinguished from the point estimates at this scale. 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



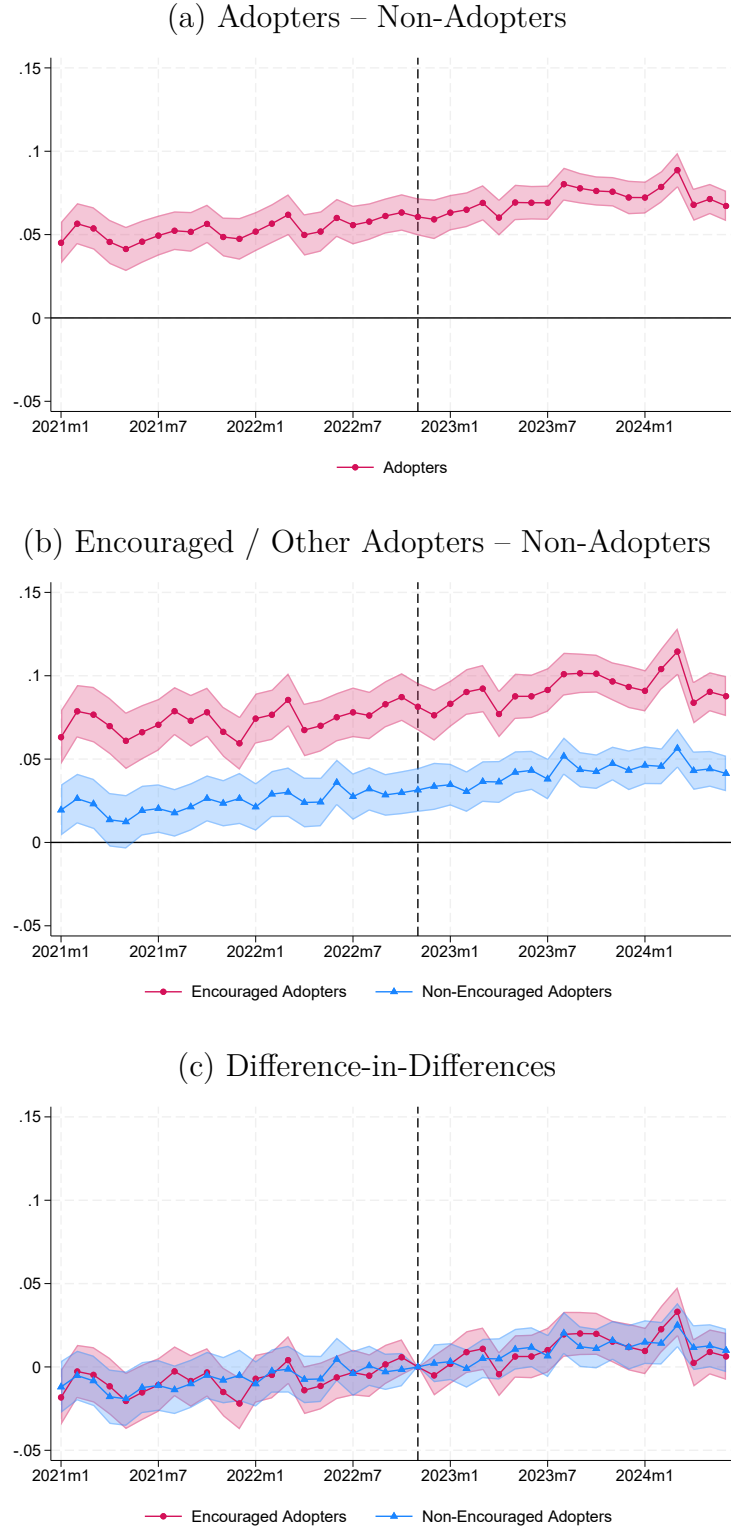
*Notes:* This figure illustrates how employer initiatives influence the new workloads created by AI chatbots. Panel (a) presents results for adopters, while Panel (b) focuses on non-adopters (workers who have never used AI chatbots for work). Estimates are predicted values from Equation (1), varying 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. Some confidence intervals are too narrow to be distinguished from the point estimates at this scale. 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



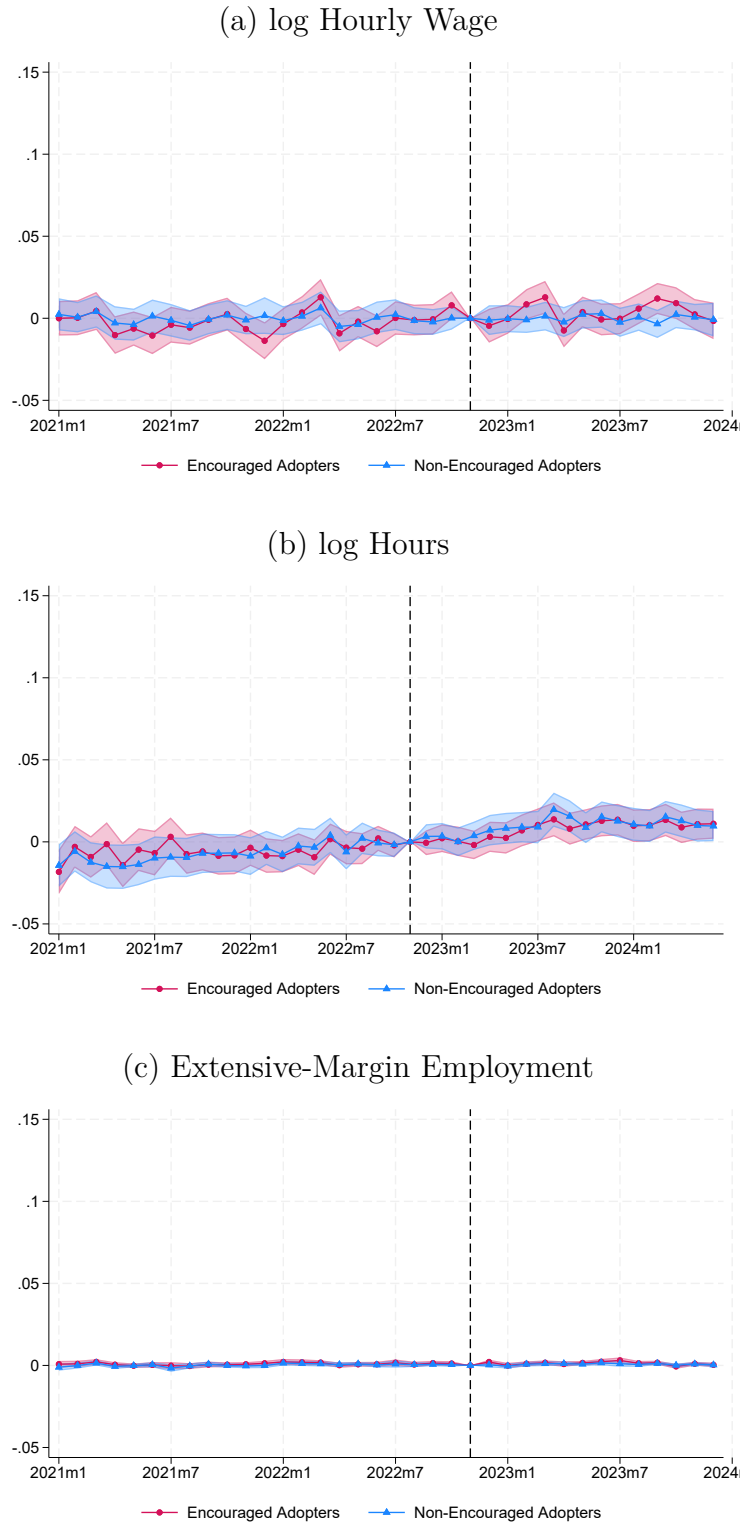
*Notes:* This figure shows the distribution of reported new job tasks across major task categories for each occupation. *AI Ideation* refers to “using AI to generate or expand creative ideas, such as concepts, strategies, or solutions,” *AI Content Drafting* refers to “using AI tools to produce initial drafts of text or media,” *AI Quality Review* refers to “reviewing and correcting AI-generated content for accuracy, clarity, and relevance,” *AI Data Insights* refers to “using AI to analyze data or documents and extract key patterns or insights,” *AI Integration* refers to “embedding AI into workflows to automate or enhance tasks,” and *AI Ethics & Compliance* refers to “ensuring AI use follows ethical, legal, and organizational standards.” See Appendix C.2 for details and occupation-specific examples. 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: Log Earnings Around the Launch of AI Chatbots



*Notes:* This figure shows the earnings gap between AI chatbot adopters and non-adopters, before and after the launch of ChatGPT in November 2022. Panel (a) reports the difference in log earnings between AI chatbot adopters and non-adopters, controlling for occupation fixed effects, pre-determined worker characteristics, and seasonality. Panel (b) splits adopters by whether their employers encourage chatbot use, keeping all non-adopters as the control group in both cases. Panel (c) presents the difference-in-differences that correspond to Panel (b), indexed to November 2022, the launch date for ChatGPT. The difference-in-difference estimates are based on the specification in Equation (2). Shaded areas represent 95% confidence intervals. *Sample:* All completed responses from the 2024 survey linked to registry data.

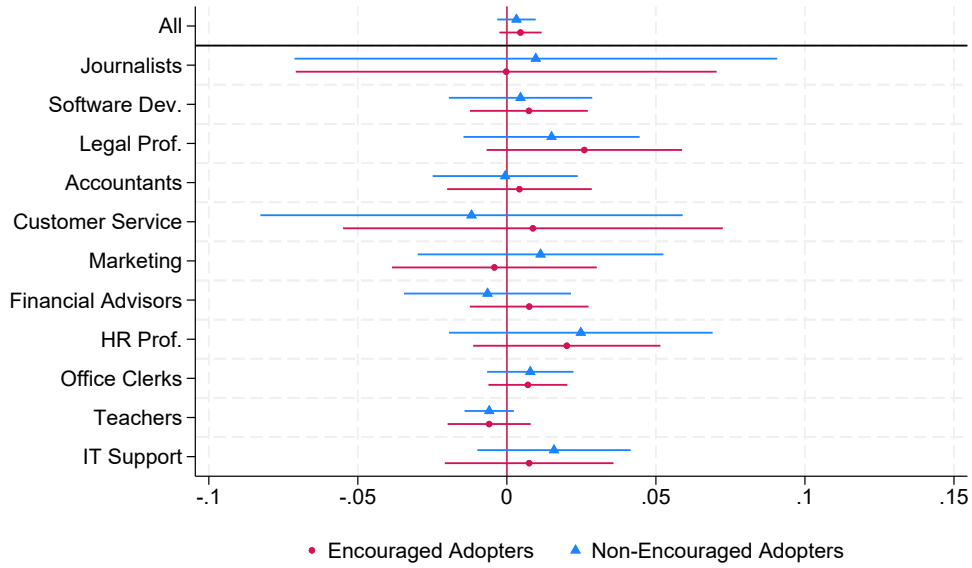
Figure 8: Labor Market Outcomes of Adopters Relative to Non-Adopters  
Difference-in-Differences



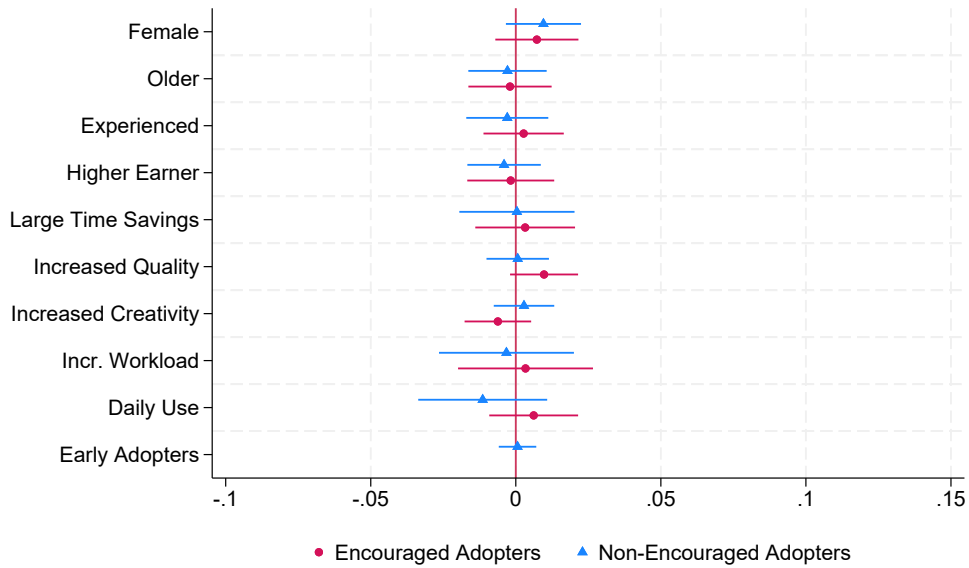
*Notes:* This figure presents the differential labor market outcomes of AI chatbot adopters relative to non-adopters, indexed to the launch of ChatGPT in November 2022. Effects are estimated separately for adopters whose employers encourage AI chatbot use (“Encouraged”) and those without encouragement (“Non-Encouraged”), 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 9: How Do the Earnings Effects of Adoption Vary Across Workers?  
Pooled Difference-in-Differences in Log Earnings

(a) Occupation-Level Effects



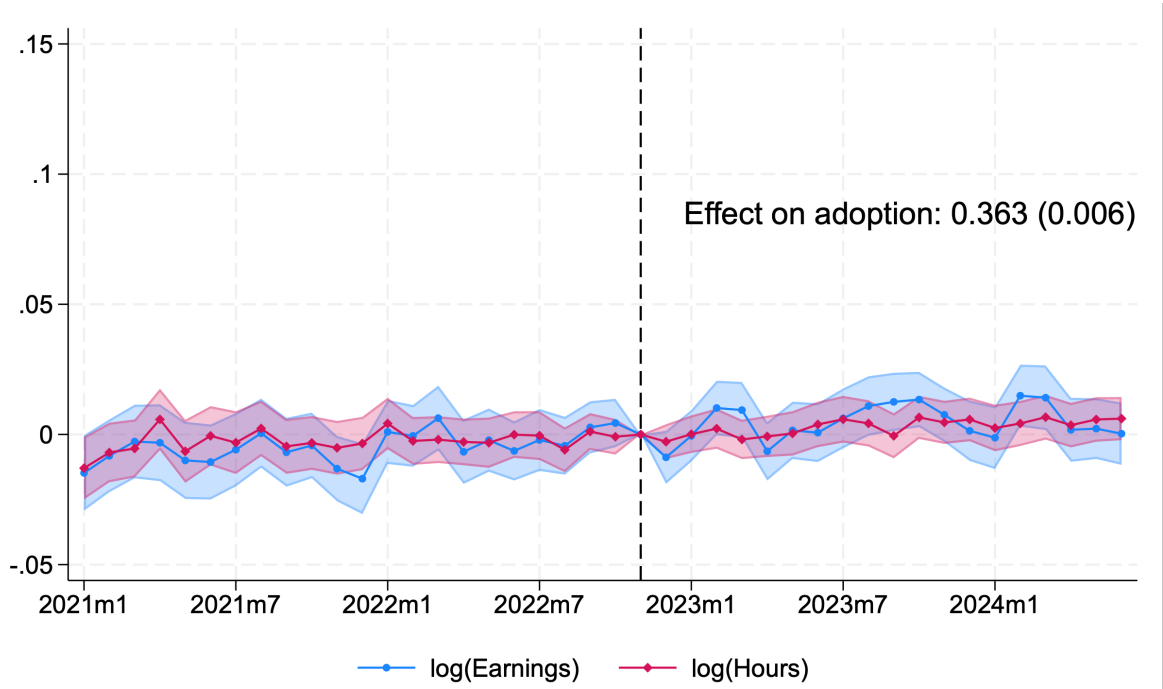
(b) Differential Effects by Worker Characteristics



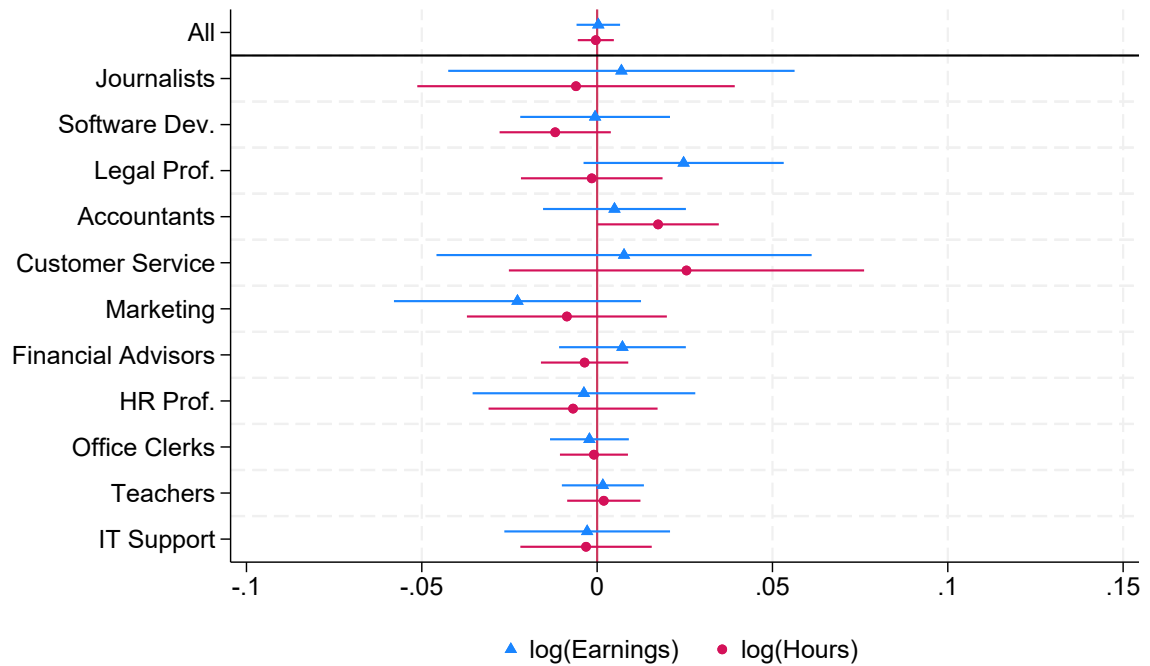
*Notes:* This figure presents the differential labor market outcomes of AI chatbot adopters relative to non-adopters, indexed to the launch of ChatGPT in November 2022. Effects are estimated separately for adopters whose employers encourage AI chatbot use (“Encouraged”) and those without encouragement (“Non-Encouraged”), 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* indicates users who report time savings exceeding 60 minutes per day of use (see Figure 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). *Daily Use* indicates users who report using AI chatbots for work on a daily basis (see Figure 2). *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 10: Have Encouragements Affected Workers' Outcomes? (Reduced Form)

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

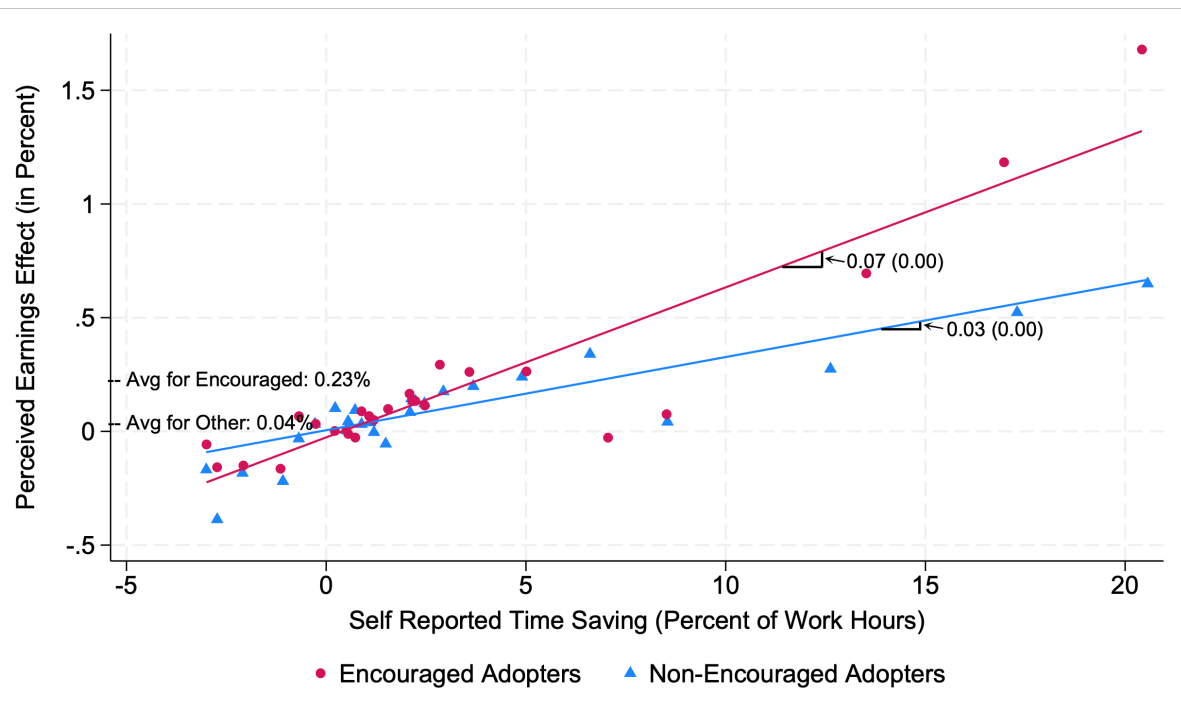


(b) Occupation-Level Effects of Encouragement (Pooled Diff-in-Diffs)



*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.3. 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 11: How Do Workers' Earnings Impacts Relate to Their Time Savings? (Binscatter)



*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 12: Have High-Adoption Workplaces Fared Differently?

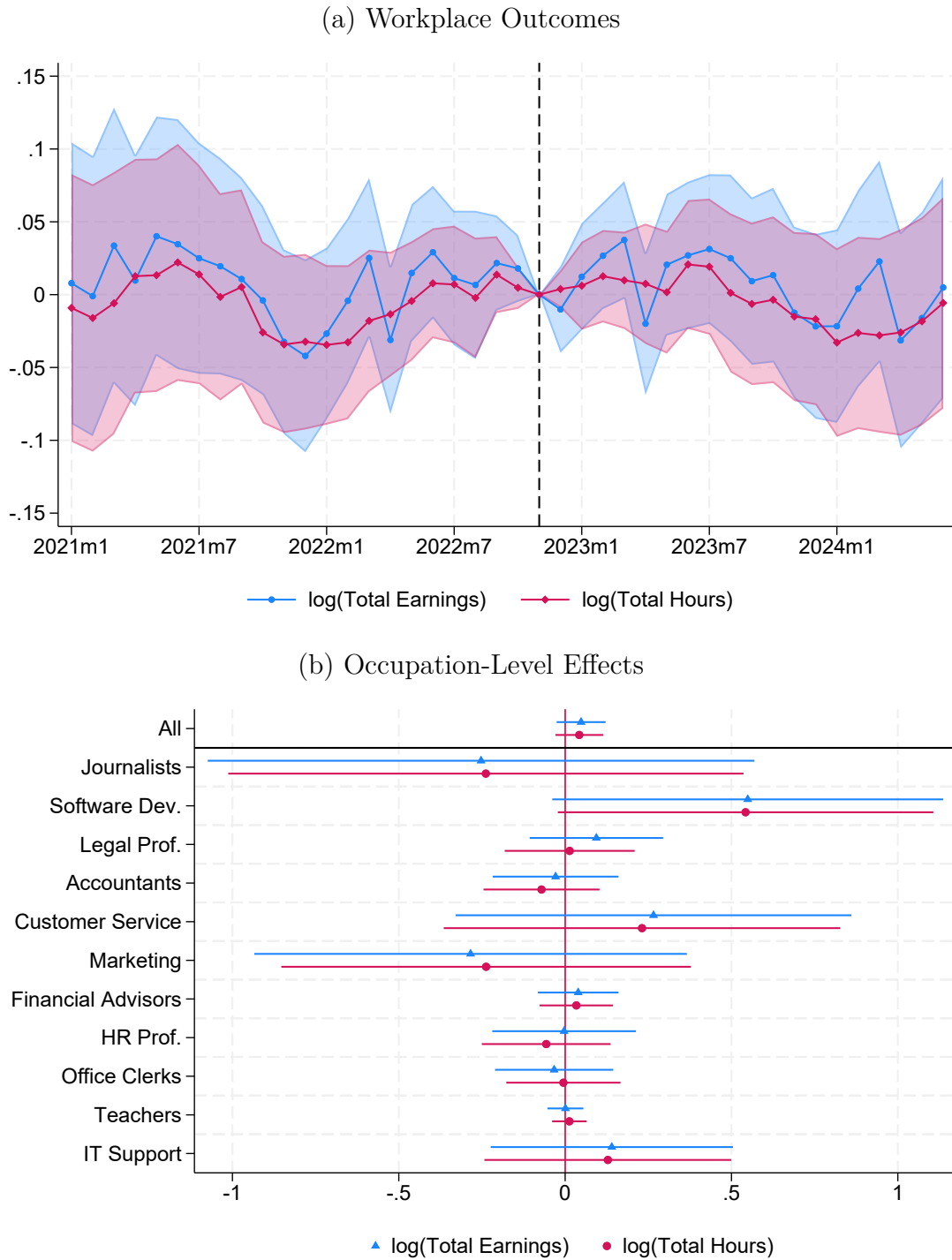


Table 1: Which Workplaces Have Adopted AI Chatbot Initiatives?

	Encouraged (1)	Allowed (2)	Not Allowed (3)	No Policy (4)	Don't Know (5)	Firm-Arranged Training (6)	In-House Chatbot (7)
Firm Age (10 Years)	-0.0140** (0.0044)	0.0030 (0.0021)	0.0028 (0.0026)	0.0038* (0.0016)	0.0044 (0.0025)	-0.0122** (0.0039)	-0.0091* (0.0043)
log(Firm Employment)	0.0036 (0.0048)	-0.0082*** (0.0023)	0.0036 (0.0023)	-0.0195*** (0.0022)	0.0204*** (0.0029)	-0.0048 (0.0043)	0.0362*** (0.0056)
log(Firm Labor Productivity)	0.0468** (0.0153)	0.0275*** (0.0077)	0.0051 (0.0051)	-0.0374*** (0.0077)	-0.0420*** (0.0084)	0.0765*** (0.0135)	0.0697*** (0.0176)
Private Firm	0.0414* (0.0168)	-0.0076 (0.0094)	-0.0141* (0.0072)	-0.0104 (0.0066)	-0.0092 (0.0096)	0.0257 (0.0144)	0.0554** (0.0180)
Occupation FE's	✓	✓	✓	✓	✓	✓	✓
Mean of Outcome	0.419	0.209	0.061	0.132	0.178	0.231	0.375
Within $R^2$	0.013	0.003	0.009	0.016	0.016	0.010	0.042
$R^2$	0.106	0.005	0.032	0.046	0.071	0.023	0.123
Observations	24184	24184	24184	24184	24184	24184	24184

*Notes:* This table examines which firm characteristics predict the adoption of various employer initiatives to promote AI chatbot use. Columns (1)–(5) report results for employer usage policies, while Columns (6)–(7) report results for in-house chatbots and firm-provided training. Firm characteristics are measured in 2021, our latest data year available. Labor productivity is measured as value added per full-time equivalent worker. The regressions control for whether the firm reports value added. The regressions also control for occupation fixed effects, and Table B.1 shows that the estimates are robust to adding controls for worker characteristics. Standard errors, reported in parentheses, are clustered at the firm level. *Sample:* The table is based on all completed responses from the 2024 survey that can be linked to the registry data.

Table 2: What Drives Adopters' Time Savings from AI Chatbots?

		Time Savings / Work Hours	Time Saved Per Day Used / Daily Work Hours	Days Used / Work Days	Covariance
Occupation		(1)	(2)	(3)	(4)
Marketing Professionals	Encouraged	.068	.109	.515	.012
Marketing Professionals	Non-Encouraged	.046	.087	.388	.012
Software Developers	Encouraged	.065	.093	.567	.012
Software Developers	Non-Encouraged	.039	.074	.378	.011
HR Professionals	Encouraged	.042	.081	.405	.009
HR Professionals	Non-Encouraged	.026	.074	.237	.009
IT Support	Encouraged	.041	.075	.407	.011
IT Support	Non-Encouraged	.028	.06	.283	.011
Customer Service Rep.	Encouraged	.039	.066	.439	.01
Customer Service Rep.	Non-Encouraged	.02	.05	.24	.008
Legal Professionals	Encouraged	.033	.074	.336	.008
Legal Professionals	Non-Encouraged	.018	.065	.166	.007
Office Clerks	Encouraged	.029	.065	.309	.009
Office Clerks	Non-Encouraged	.015	.047	.177	.007
Journalists	Encouraged	.028	.05	.374	.01
Journalists	Non-Encouraged	.021	.048	.221	.011
Accountants and Auditors	Encouraged	.022	.055	.282	.006
Financial Advisors	Encouraged	.022	.053	.288	.007
Financial Advisors	Non-Encouraged	.015	.04	.179	.008
Accountants and Auditors	Non-Encouraged	.009	.041	.143	.003
Teachers	Encouraged	.01	.049	.14	.003
Teachers	Non-Encouraged	.006	.044	.088	.002
All	Encouraged	.036	.07	.369	.01
All	Non-Encouraged	.022	.057	.227	.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:  $E[XY] = E[X]E[Y] + \text{Cov}(X, Y)$ . Occupations are sorted by their average time savings (Column (1)) among encouraged users. We code daily time savings (Column (2)) as follows: 0–15 minutes/day as 7.5 minutes, 15–60 minutes as 37.5 minutes, and 60+ minutes as 90 minutes. We code frequency of use (Column (3)) as follows: daily use is divided by 1; weekly use by 5 (corresponding to 5 workdays per week); monthly use by  $21\frac{2}{3}$  (corresponding to  $4\frac{1}{3}$  weeks per month); and use a few times by 65 (corresponding to 4 uses over 12 months). 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.

# Online Appendix

## Large Language Models, Small Labor Market Effects

Anders Humlum      Emilie Vestergaard  
University of Chicago    University of Copenhagen

<b>A Data and Institutional Setting</b>	<b>3</b>
A.1 Sampling Protocol . . . . .	3
A.2 Survey Sample . . . . .	4
<b>B Adoption</b>	<b>9</b>
B.1 Employer Initiatives . . . . .	9
B.2 Worker Adoption . . . . .	11
<b>C Work</b>	<b>20</b>
C.1 Benefits for Users . . . . .	20
C.2 Workloads and Task Creation . . . . .	21
<b>D Labor Market Outcomes</b>	<b>26</b>
D.1 Results . . . . .	26
D.2 Perceived Impacts . . . . .	27
<b>E Broader Impacts</b>	<b>29</b>
E.1 Results . . . . .	29
E.2 Perceived Impacts . . . . .	30
<b>F Robustness Analysis</b>	<b>30</b>
F.1 Additional Controls . . . . .	31
F.2 Coworker Encouragement . . . . .	34
<b>G Empirical Bayes Shrinkage</b>	<b>40</b>
G.1 Workplace Adoption Rates . . . . .	41
G.2 Coworker Encouragement Rates . . . . .	42

<b>H</b>	<b>Theoretical Framework</b>	<b>44</b>
H.1	Setup . . . . .	44
H.2	Predictions . . . . .	45
H.3	Discussion . . . . .	48
<b>I</b>	<b>Invitation Letter</b>	<b>49</b>
I.1	English Translation . . . . .	50
I.2	Original Danish Version . . . . .	52
<b>J</b>	<b>Survey Questionnaire</b>	<b>54</b>
J.1	English Translation . . . . .	55
J.2	Original Danish Version . . . . .	60

# 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

	<i>2024 Survey</i>		<i>2023 Survey</i>			
	Individuals	Percent of invitees	<i>Main Survey</i>		<i>Follow-Up Only</i>	
			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

	<i>2024 Survey</i>			<i>2023 Main Survey</i>		
	Population (1)	Sampled (2)	Responded (3)	Population (1)	Sampled (2)	Responded (3)
Age	42.93 (11.54)	42.94 (11.52)	46.11 (11.50)	42.41 (11.57)	42.40 (11.57)	45.38 (11.51)
Female	0.56 (0.50)	0.56 (0.50)	0.56 (0.50)	0.52 (0.50)	0.52 (0.50)	0.49 (0.50)
log(Earnings)	12.98 (0.70)	12.98 (0.70)	13.01 (0.64)	13.07 (0.58)	13.07 (0.59)	13.11 (0.53)
Experience	6.11 (4.80)	6.11 (4.80)	7.24 (4.92)	6.05 (4.58)	6.05 (4.57)	7.12 (4.67)
Wealth / Earnings	10.92 (2,148.09)	6.50 (286.36)	6.74 (204.16)	4.09 (157.40)	4.87 (262.31)	4.10 (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

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

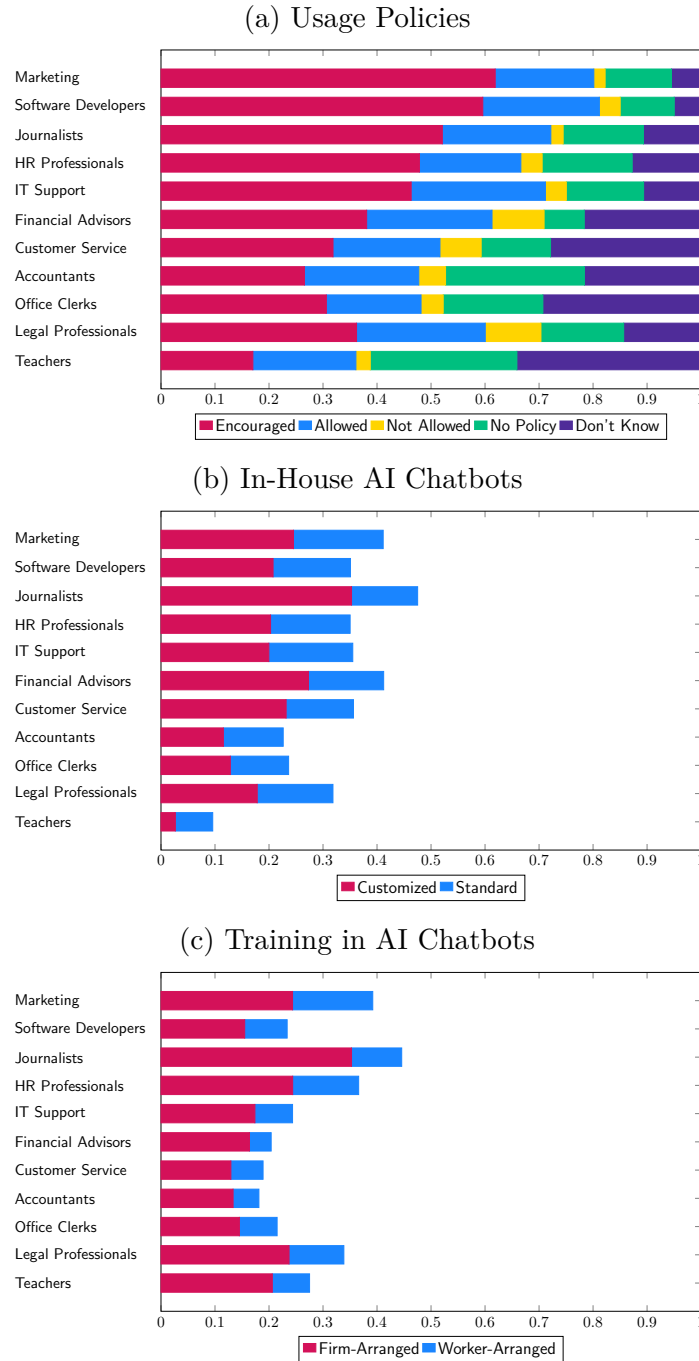
*Notes:* This table presents the correlation between occupational codes reported in the survey and those recorded in the administrative data of Statistics Denmark. Each cell represents the probability of reporting the column occupation in the survey, conditional on having the row occupation registered 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)



*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.

Table B.1: Which Workplaces Have Adopted AI Chatbot Initiatives?

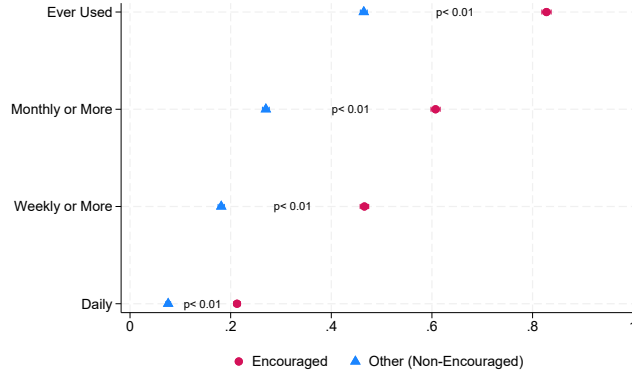
<b>Panel A: Within Occupations (Table 1)</b>							
	Encouraged (1)	Allowed (2)	Not Allowed (3)	No Policy (4)	Don't Know (5)	Firm-Arranged Training (6)	In-House Chatbot (7)
Firm Age (10 Years)	-0.0140** (0.0044)	0.0030 (0.0021)	0.0028 (0.0026)	0.0038* (0.0016)	0.0044 (0.0025)	-0.0122** (0.0039)	-0.0091* (0.0043)
log(Firm Employment)	0.0036 (0.0048)	-0.0082*** (0.0023)	0.0036 (0.0023)	-0.0195*** (0.0022)	0.0204*** (0.0029)	-0.0048 (0.0043)	0.0362*** (0.0056)
log(Firm Labor Productivity)	0.0468** (0.0153)	0.0275*** (0.0077)	0.0051 (0.0051)	-0.0374*** (0.0077)	-0.0420*** (0.0084)	0.0765*** (0.0135)	0.0697*** (0.0176)
Private Firm	0.0414* (0.0168)	-0.0076 (0.0094)	-0.0141* (0.0072)	-0.0104 (0.0066)	-0.0092 (0.0096)	0.0257 (0.0144)	0.0554** (0.0180)
Occupation FE's	✓	✓	✓	✓	✓	✓	✓
Mean of Outcome	0.419	0.209	0.061	0.132	0.178	0.231	0.375
Within <sup>2</sup>	0.013	0.003	0.009	0.016	0.016	0.010	0.042
<sup>2</sup>	0.106	0.005	0.032	0.046	0.071	0.023	0.123
Observations	24184	24184	24184	24184	24184	24184	24184
<b>Panel B: Within Occupations, Worker Controls</b>							
Firm Age (10 Years)	-0.0135** (0.0045)	0.0026 (0.0021)	0.0029 (0.0026)	0.0039* (0.0016)	0.0041 (0.0025)	-0.0119** (0.0039)	-0.0088* (0.0043)
log(Firm Employment)	0.0035 (0.0047)	-0.0081*** (0.0023)	0.0037 (0.0023)	-0.0197*** (0.0022)	0.0206*** (0.0028)	-0.0050 (0.0043)	0.0362*** (0.0055)
log(Firm Labor Productivity)	0.0415** (0.0145)	0.0251** (0.0077)	0.0051 (0.0050)	-0.0363*** (0.0077)	-0.0355*** (0.0077)	0.0716*** (0.0131)	0.0640*** (0.0170)
Private Firm	0.0396* (0.0167)	-0.0094 (0.0092)	-0.0140* (0.0071)	-0.0098 (0.0067)	-0.0064 (0.0094)	0.0238 (0.0144)	0.0533** (0.0178)
Worker Controls	✓	✓	✓	✓	✓	✓	✓
Occupation FE's	✓	✓	✓	✓	✓	✓	✓
Mean of Outcome	0.419	0.209	0.061	0.132	0.178	0.231	0.375
Within $R^2$	0.024	0.006	0.010	0.018	0.039	0.017	0.053
$R^2$	0.116	0.008	0.033	0.047	0.093	0.029	0.133
Observations	24184	24184	24184	24184	24184	24184	24184

*Notes:* This table examines which firm characteristics predict the adoption of various employer initiatives to promote AI chatbot use. Columns (1)–(5) report results for employer usage policies, while Columns (6)–(7) report results for in-house chatbots and firm-provided training. Firm characteristics are measured in 2021, our latest data year available. Labor productivity is measured as value added per full-time equivalent worker. The regressions control for whether the firm reports value added. Panel A controls for occupation fixed effects (corresponding to Table 1), whereas Panel B additionally controls for worker characteristics. Standard errors, reported in parentheses, are clustered at the firm level. *Sample:* The table is based on all completed responses from the 2024 survey that can be linked to the registry data.

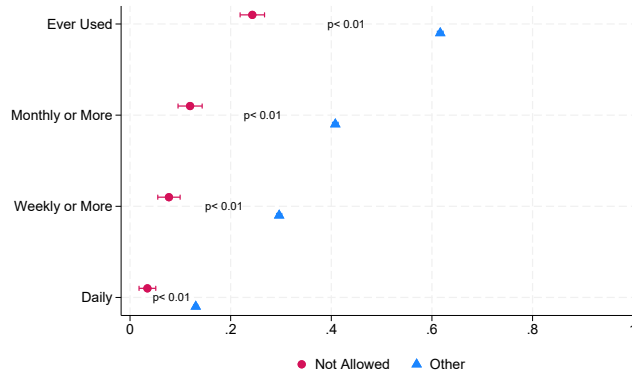
## B.2 Worker Adoption

Figure B.2: Importance of Employer Policies in AI Chatbot Adoption

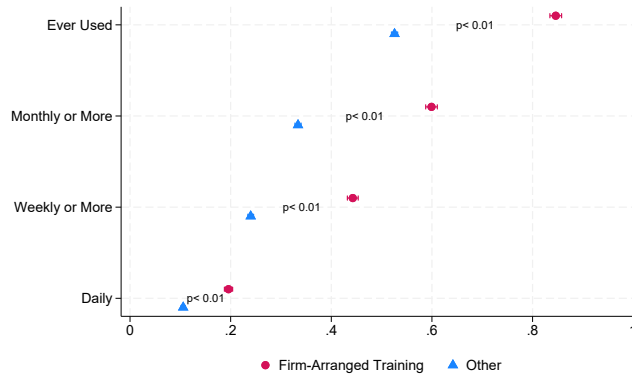
### (i) Usage Policy: Encouraged



### (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.3: Influence of Employer Initiatives on Worker Gaps in AI Chatbot Adoption

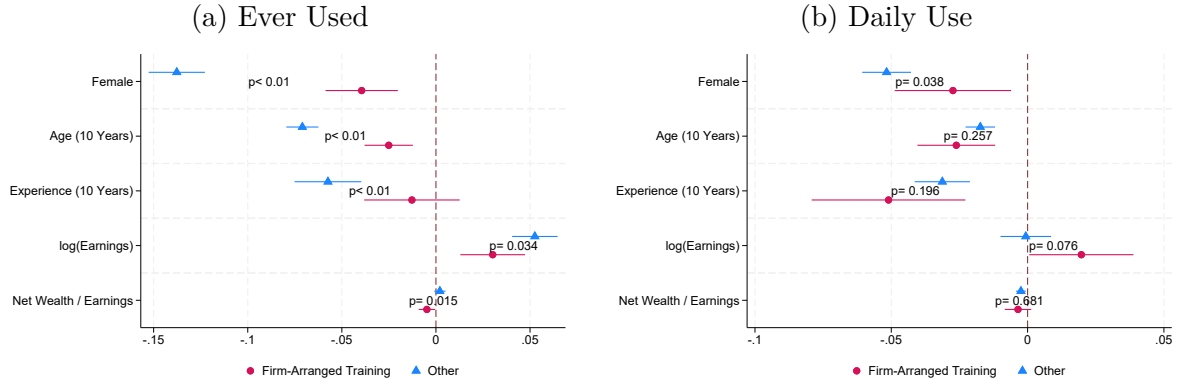
(i) Usage Policy: Encouraged



(ii) Usage Policy: Not Allowed



(iii) Firm-Arranged Training



*Notes:* This figure illustrates the impact of employer 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 subpanels (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.

Table B.2: Decomposition of Adopters' Time Use with AI Chatbots

		Time Use / Work Hours	Time Used Per Day Used / Daily Work Hours	Days Used / Work Days	Covariance
Occupation		(1)	(2)	(3)	(4)
Software Developers	Encouraged	.053	.074	.567	.011
Software Developers	Non-Encouraged	.033	.06	.378	.01
Marketing Professionals	Encouraged	.049	.076	.515	.01
Marketing Professionals	Non-Encouraged	.036	.062	.388	.011
Customer Service Rep.	Encouraged	.035	.058	.439	.01
Customer Service Rep.	Non-Encouraged	.014	.04	.24	.005
IT Support	Encouraged	.034	.06	.407	.009
IT Support	Non-Encouraged	.023	.051	.283	.008
HR Professionals	Encouraged	.031	.056	.405	.009
HR Professionals	Non-Encouraged	.016	.049	.237	.004
Legal Professionals	Encouraged	.027	.057	.336	.007
Legal Professionals	Non-Encouraged	.01	.044	.166	.003
Journalists	Encouraged	.025	.048	.374	.007
Journalists	Non-Encouraged	.013	.038	.221	.005
Office Clerks	Encouraged	.023	.054	.309	.006
Office Clerks	Non-Encouraged	.012	.044	.177	.004
Accountants and Auditors	Encouraged	.018	.044	.282	.006
Accountants and Auditors	Non-Encouraged	.007	.038	.143	.002
Financial Advisors	Encouraged	.016	.038	.288	.005
Financial Advisors	Non-Encouraged	.01	.031	.179	.005
Teachers	Encouraged	.009	.052	.14	.002
Teachers	Non-Encouraged	.005	.043	.088	.001
All	Encouraged	.029	.056	.369	.008
All	Non-Encouraged	.016	.046	.227	.006

*Notes:* This table presents workers' time use with 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 used as a percentage of total work hours. The remaining columns decompose this time use into three components: time use 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:  $E[XY] = E[X]E[Y] + \text{Cov}(X, Y)$ . We code daily time savings (Column (2)) as follows: 0–15 minutes/day as 7.5 minutes, 15–60 minutes as 37.5 minutes, and 60+ minutes as 90 minutes. We code frequency of use (Column (3)) as follows: daily use is divided by 1; weekly use by 5 (corresponding to 5 workdays per week); monthly use by  $21\frac{2}{3}$  (corresponding to  $4\frac{1}{3}$  weeks per month); and use a few times by 65 (corresponding to 4 uses over 12 months). 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 B.3: Who Has Adopted AI Chatbots?

	Ever Used (1)	Monthly or More (2)	Weekly or More (3)	Daily (4)
Encouraged	0.363*** (0.006)	0.337*** (0.006)	0.285*** (0.005)	0.137*** (0.004)
Female	-0.106*** (0.006)	-0.130*** (0.006)	-0.098*** (0.006)	-0.041*** (0.004)
Age (10 Years)	-0.060*** (0.004)	-0.051*** (0.004)	-0.038*** (0.003)	-0.017*** (0.003)
Experience (10 Years)	-0.040*** (0.007)	-0.044*** (0.007)	-0.044*** (0.007)	-0.032*** (0.005)
log(Earnings)	0.043*** (0.005)	0.018*** (0.005)	0.011** (0.005)	-0.000 (0.004)
Net Wealth / Earnings	0.002 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.003*** (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.

### B.2.1 AI Chatbot Products

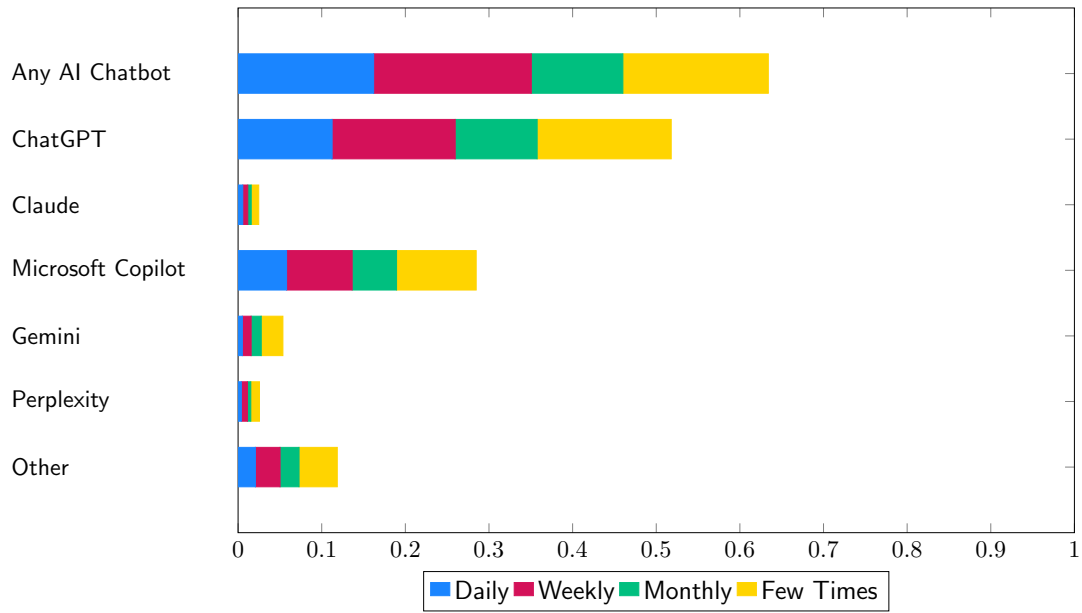
While our main analysis focuses on the adoption of any AI chatbot, our survey also measures usage of specific products. This section provides details on product-level adoption.

The main takeaway is that ChatGPT remains the dominant tool. Figures B.4–B.6 show that approximately 80% of all adopters use ChatGPT, and its dominance holds across all occupations.

Table B.4 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.

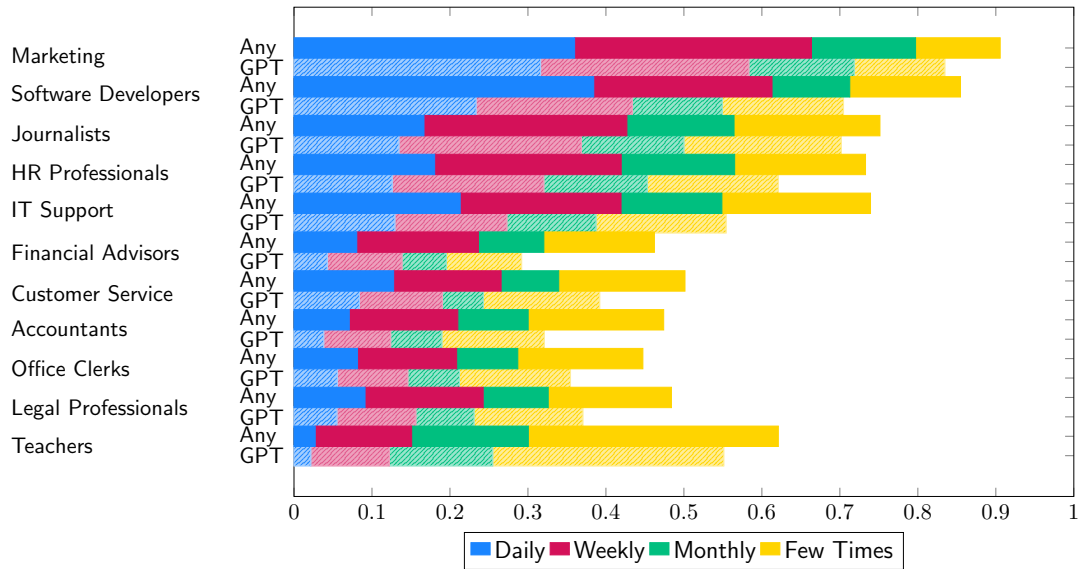
Table B.5 characterizes workers’ use of AI chatbot products based on whether their employers provide an in-house chatbot. The patterns of daily and weekly usage in Panels (a) and (b) are especially informative about ongoing, active use. The table shows that even customized in-house chatbots are most often versions of ChatGPT. These are typically thin wrappers around ChatGPT Enterprise or the OpenAI API, adapted for workplace use through features such as data security compliance, training on internal data, and custom prompt creation.

Figure B.4: 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.5: 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.4: 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.

Table B.5: AI Chatbot Product Usage by Availability of In-House Chatbots

## (a) Daily Use for Work

	Any	ChatGPT	Claude	Copilot	Gemini	Perplexity	Other
Customized In-House Chatbot	0.25	0.16	0.01	0.08	0.01	0.01	0.06
Standard In-House Chatbot	0.22	0.13	0.01	0.12	0.01	0.00	0.02
No In-House Chatbot	0.13	0.10	0.00	0.04	0.00	0.00	0.01
All Workers	0.16	0.11	0.01	0.06	0.01	0.00	0.02

## (b) Weekly Use for Work

	Any	ChatGPT	Claude	Copilot	Gemini	Perplexity	Other
Customized In-House Chatbot	0.52	0.36	0.02	0.18	0.02	0.02	0.14
Standard In-House Chatbot	0.47	0.30	0.01	0.28	0.02	0.01	0.04
No In-House Chatbot	0.29	0.24	0.01	0.10	0.01	0.01	0.02
All Workers	0.35	0.26	0.01	0.14	0.02	0.01	0.05

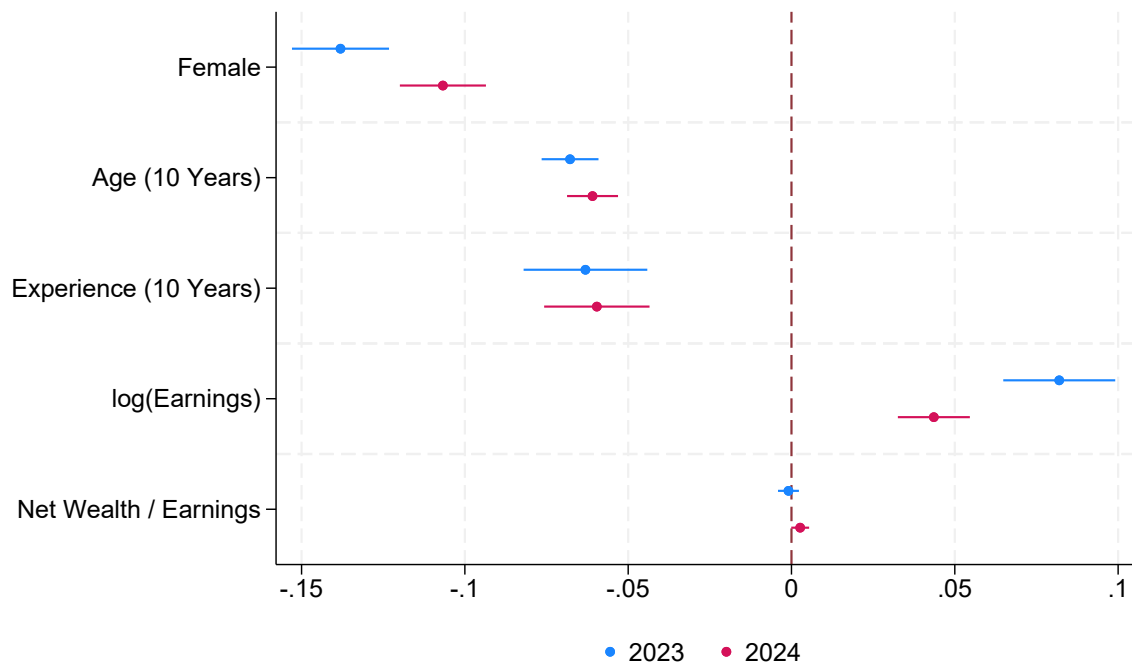
## (c) Ever Used for Work

	Any	ChatGPT	Claude	Copilot	Gemini	Perplexity	Other
Customized In-House Chatbot	0.80	0.63	0.04	0.34	0.07	0.03	0.29
Standard In-House Chatbot	0.80	0.59	0.03	0.54	0.06	0.03	0.11
No In-House Chatbot	0.59	0.52	0.02	0.24	0.06	0.03	0.07
All Workers	0.64	0.53	0.03	0.29	0.06	0.03	0.12

*Notes:* This table reports usage rates of different AI chatbot products among adopters, split by whether their employers offer their own in-house chatbot. Panel (a) presents daily usage rates, Panel (b) focuses on weekly usage rates, while Panel (c) shows rate of any usage for work. *Sample:* All completed survey responses from our 2024 survey round.

## B.2.2 Comparison to 2023 Survey

Figure B.6: 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 received 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:** Brainstorming budget plans or tax strategies with AI suggestions (*AI Ideation*), Drafting financial statements and reports using AI for initial content (*AI Content Drafting*), Reviewing AI-generated financial outputs for accuracy and

completeness (*AI Quality Review*), Analyzing financial data with AI tools to identify trends or anomalies (*AI Data Insights*), Ensuring AI-driven accounting processes comply with financial regulations and standards (*AI Ethics & Compliance*)

2. **Customer Support:** Using AI to draft responses to common customer queries or emails (*AI Content Drafting*), Reviewing AI-suggested responses to ensure accuracy and proper tone (*AI Quality Review*), Analyzing customer interactions with AI to identify common pain points and FAQs (*AI Data Insights*), Creating and refining prompts for AI chatbots to handle customer questions (*AI Integration*), Training the AI customer service chatbot by feeding it new Q&As from resolved issues (*AI Integration*), Ensuring the AI chatbot adheres to customer privacy and service guidelines (*AI Ethics & Compliance*)
3. **Financial Advisors:** Brainstorming investment strategies or portfolio ideas using AI insights (*AI Ideation*), Generating draft financial plans and investment recommendations with AI assistance (*AI Content Drafting*), Reviewing AI-suggested investment recommendations for accuracy and client suitability (*AI Quality Review*), Analyzing market trends and client data with AI to inform advice (*AI Data Insights*), Ensuring AI-driven financial advice complies with regulations and ethical standards (*AI Ethics & Compliance*)
4. **HR Professionals:** Brainstorming employee training, development, or wellness program ideas using AI (*AI Ideation*), Drafting job postings, policy documents, or employee communications using AI (*AI Content Drafting*), Reviewing AI-generated candidate evaluations or HR reports for accuracy and bias (*AI Quality Review*), Analyzing employee survey results or HR data with AI to gain insights (*AI Data Insights*), Integrating AI tools for resume screening, interview scheduling, and answering candidate inquiries in recruitment (*AI Integration*), Ensuring AI recruitment and evaluation tools are fair, unbiased, and legally compliant (*AI Ethics & Compliance*)

5. **IT Support Specialists:** Generating technical troubleshooting guides and FAQs using AI (*AI Content Drafting*), Validating AI-proposed solutions to ensure they resolve issues without risk (*AI Quality Review*), Crafting effective queries/prompts for AI tools to diagnose IT issues (*AI Integration*), Integrating AI assistants into support systems to automate routine help requests (*AI Integration*)
6. **Journalists:** Brainstorming story ideas, angles, or interview questions with AI (*AI Ideation*), Using AI to draft article outlines, summaries, or initial news reports (*AI Content Drafting*), Fact-checking and editing AI-generated content to ensure accuracy and clarity (*AI Quality Review*), Summarizing research materials or interview transcripts for quick insight with AI (*AI Data Insights*), Ensuring AI-generated content abides by journalistic ethics and standards (*AI Ethics & Compliance*)
7. **Legal Professionals:** Brainstorming legal arguments, interpretations, or negotiation strategies with AI (*AI Ideation*), Drafting contracts, briefs, or other legal documents with AI providing initial content (*AI Content Drafting*), Reviewing AI-generated legal documents or analyses for accuracy and compliance (*AI Quality Review*), Using AI to research and summarize case law, statutes, or legal documents (*AI Data Insights*), Developing organizational AI usage policies and guidelines (*AI Integration, AI Ethics & Compliance*), Ensuring AI tools and outputs uphold legal ethics and confidentiality (*AI Ethics & Compliance*)
8. **Marketing Professionals:** Brainstorming campaign themes, slogans, or creative concepts with AI (*AI Ideation*), Generating marketing copy, social media posts, or product descriptions with AI (*AI Content Drafting*), Reviewing AI-created marketing content for quality and brand consistency (*AI Quality Review*), Analyzing consumer data and campaign results with AI to derive marketing insights (*AI Data Insights*)
9. **Office Clerks:** Drafting routine emails, letters, or documents using AI assistance (*AI Content Drafting*), Performing quality control on AI-generated text and doc-

uments (*AI Quality Review*), Using AI to extract information from documents or summarize data for reports (*AI Data Insights*), Ensuring no confidential information is inappropriately shared with AI tools (*AI Ethics & Compliance*)

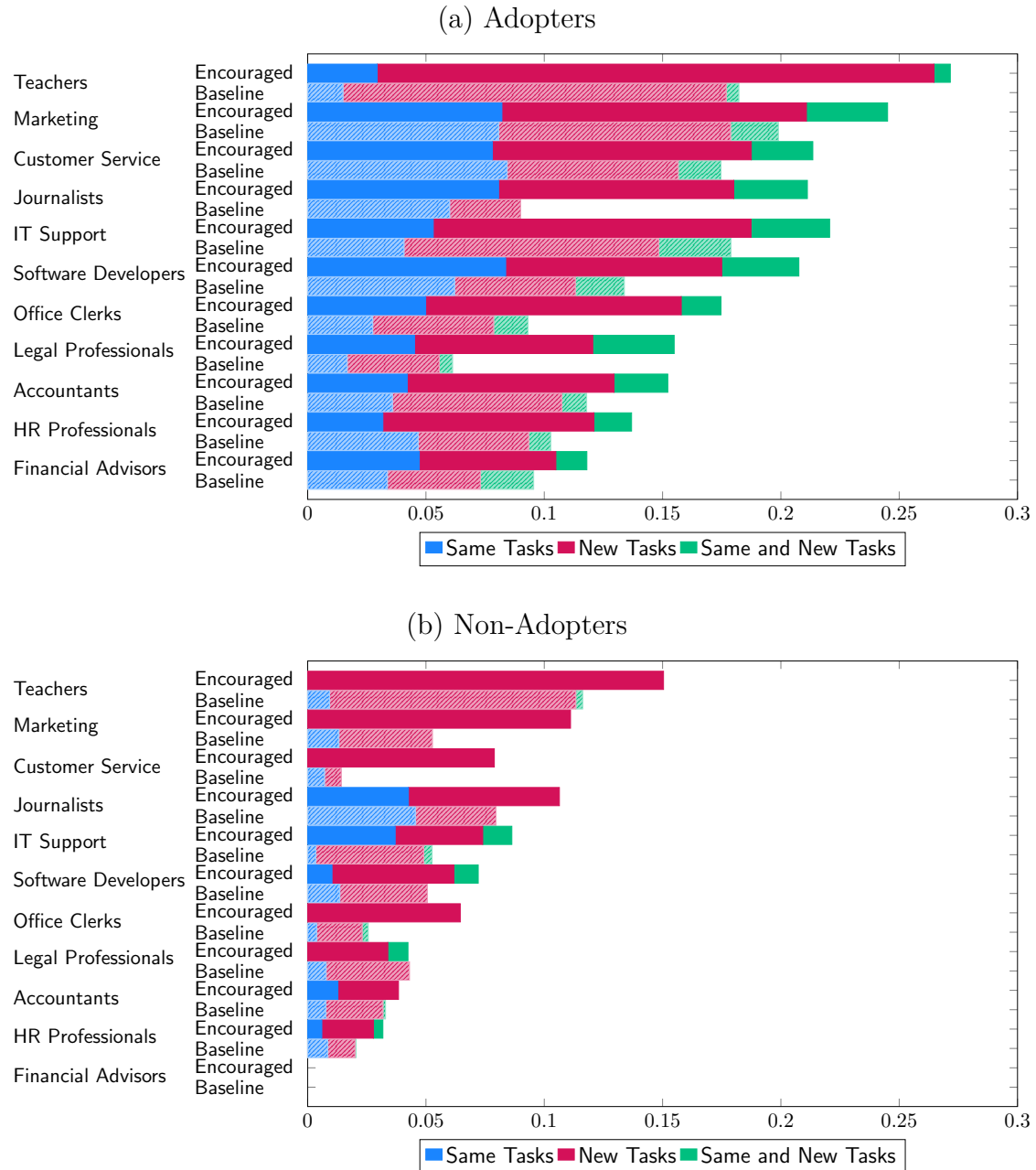
10. **Software Developers:** Using AI to generate code snippets, boilerplate code, or documentation (*AI Content Drafting*), Reviewing and testing AI-generated code to ensure correctness and security (*AI Quality Review*), Formulating specific prompts to guide AI in debugging or coding tasks (*AI Integration*), Fine-tuning the AI coding assistant by providing feedback and project-specific examples (*AI Integration*), Writing prompts for code generation (*AI Integration*)
11. **Teachers:** AI-assisted development of new course material and lesson plans (*AI Ideation*), Personalizing learning materials or feedback using AI insights from student performance (*AI Data Insights*), Adapting exams and assignments to account for AI tool usage (*AI Integration*), Integrating chatbots into lessons (*AI Integration*), Detecting AI-generated homework submissions (*AI Ethics & Compliance*)

For all broad categories, we include an “Other” subtask for each occupation (e.g., *AI Integration, Other*) to ensure that every broad category is represented across all occupations. In addition, we include a “non-AI” task category, which typically captures new assignments for the worker that are not novel within the broader 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.

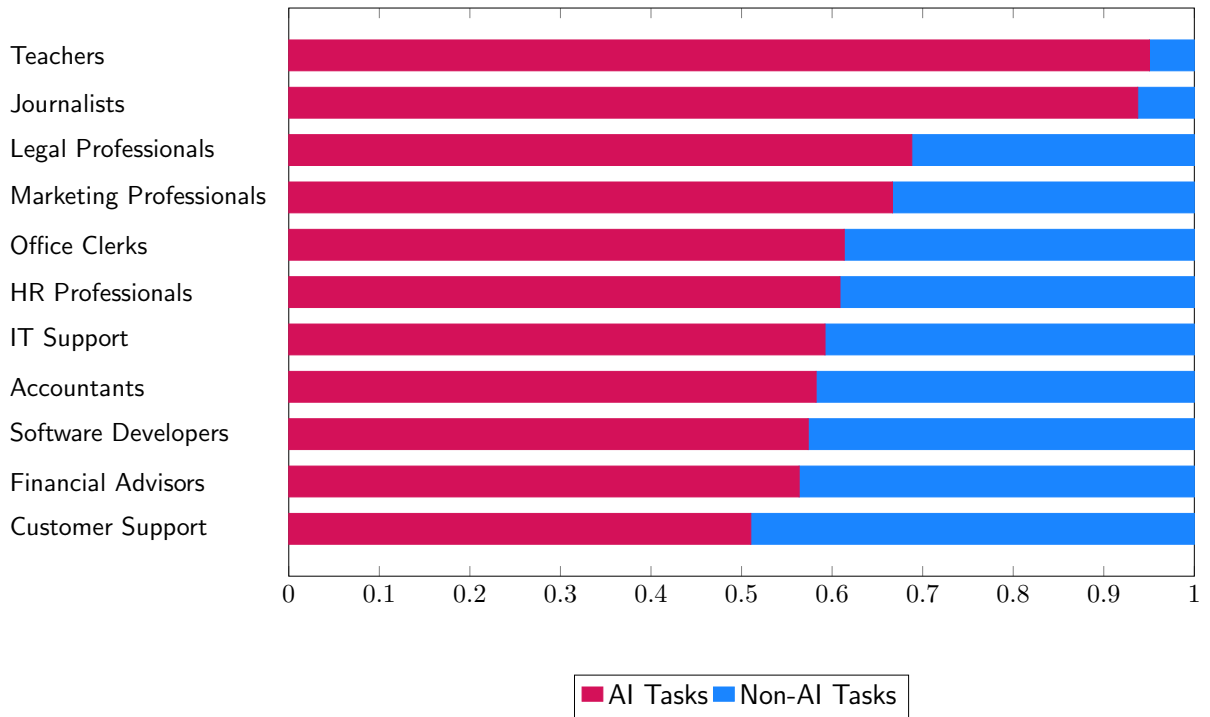
Figures C.1 illustrate that AI chatbots have led to the creation of new tasks across all 11 occupations in our study. Figure C.2 shows that 50% to 95% of these tasks are directly linked to AI use.

Figure C.1: Workloads from AI Chatbots



*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

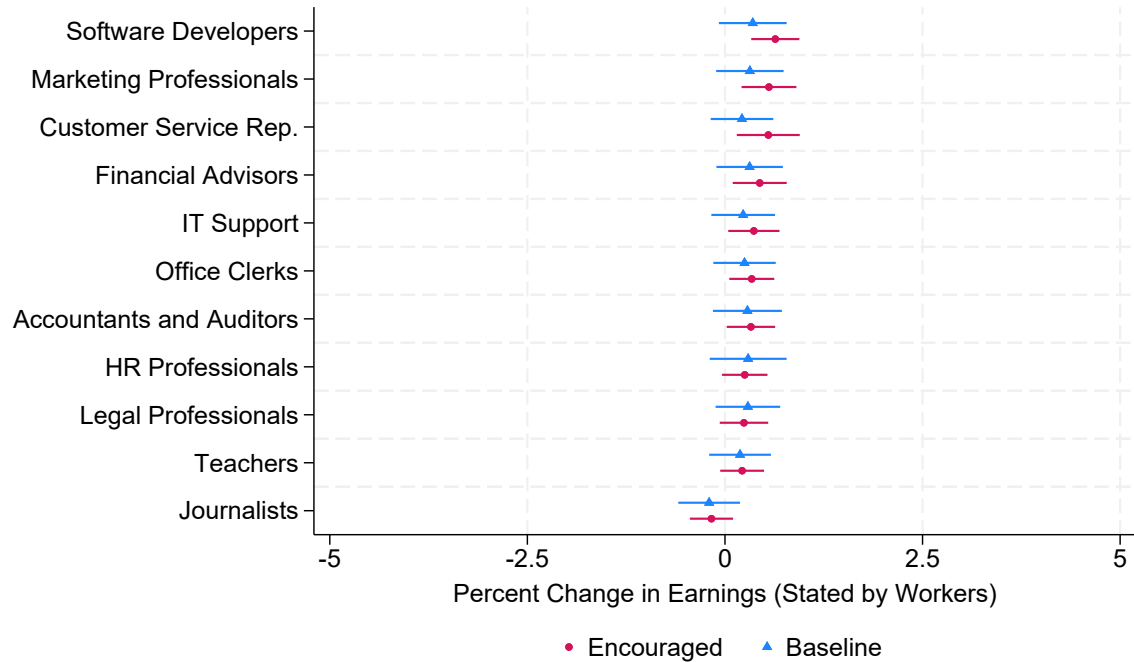
### D.1 Results

Table D.1: Pass-Through of Time Savings to Administrative Earnings and Wages

*Notes:* This table reports estimates of the pass-through rate from workers' perceived time savings due to AI chatbots to their actual earnings. The estimates are obtained by interacting the regression model in Equation (3) with workers' time savings. Estimates are reported separately based on whether employers encourage chatbot use (Encouraged = 0 or 1). *Sample:* The table is based on all complete responses from the 2024 survey that can be linked to the registry data.

## D.2 Perceived Impacts

Figure D.1: 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.2: Decomposition of Perceived Earnings Effects of AI Chatbots Among Adopters

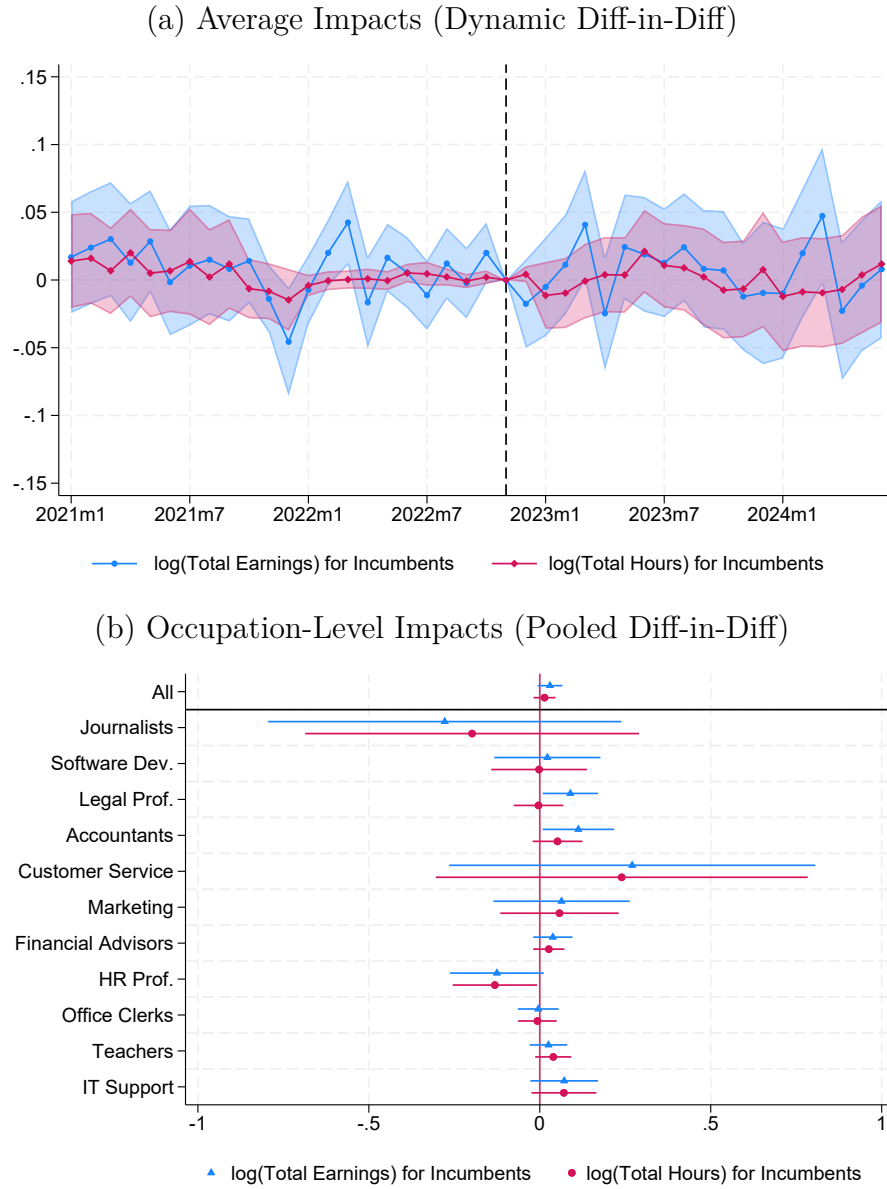
Occupation	Policy	Average Impact (in %) (1)	Share of Impacts			Conditional Average Impacts (in %)		
			Decreased Earnings (2)	Unchanged Earnings (3)	Increased Earnings (4)	Decreased Earnings (5)	Unchanged Earnings (6)	Increased Earnings (7)
Journalists	Baseline	-.118		.994			0	
Journalists	Encouraged	-.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 Broader Impacts

### E.1 Results

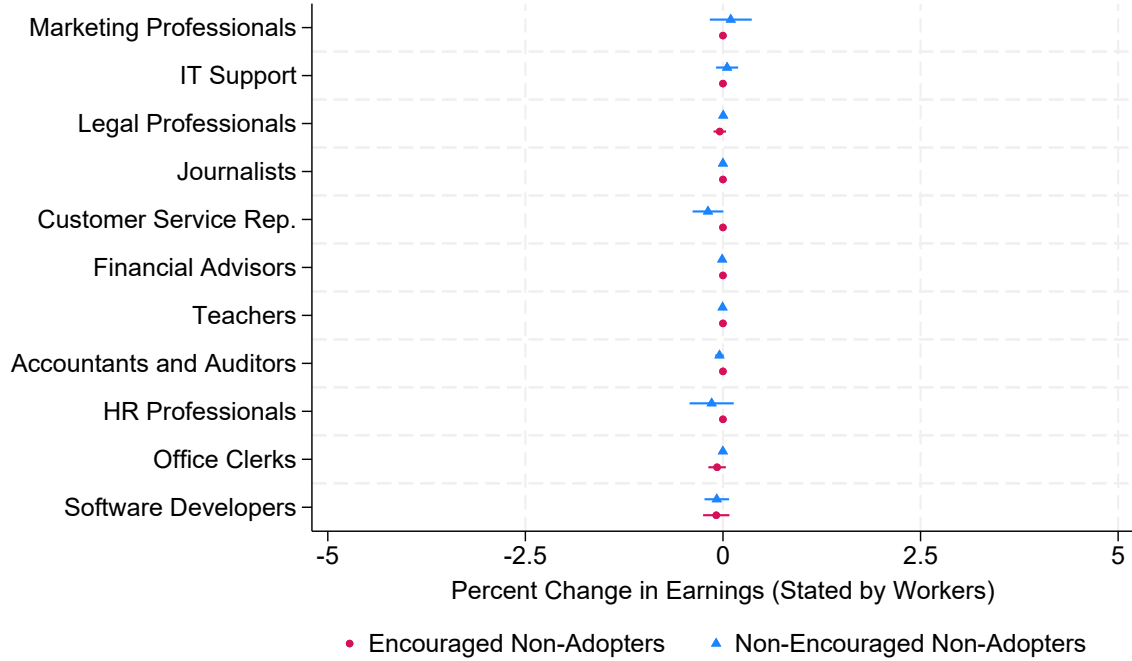
Figure E.1: Incumbent Worker Outcomes by Adoption Rates (Dynamic Diff-in-Diff)



*Notes:* This figure shows changes in incumbent workers' outcomes by adoption rates, indexed to the launch of ChatGPT in November 2022, at the workplace-occupational level. Incumbent workers are defined as those employed continuously from January to November 2022, leading up to the arrival of ChatGPT. Adoption rates are measured as the share of employees in a worker's initial workplace who have used AI chatbots for work, adjusted for measurement error using the Empirical Bayes shrinkage procedure described in Appendix G. The standard deviation of workplace adoption rates within occupations, after shrinkage, is 20 percentage points. Panel (a) is based on the dynamic difference-in-differences specification in Equation (2), weighted by the number of respondents at each 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 each workplace; whiskers indicate 95% confidence intervals. *Sample:* All completed responses from workplaces with at least two respondents in the 2024 survey linked to registry data.

## E.2 Perceived Impacts

Figure E.2: 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.

## F Robustness Analysis

Sections 2 and 3 examine how employer encouragement affects workers' adoption and benefits of AI chatbots. This section assesses the robustness of our results to potential confounding factors. First, in Section F.1, we show that our findings are robust to controlling for a wide range of observable firm and worker characteristics, mitigating concerns that omitted variables drive the results. Second, in Section F.2, we compare individual-level and coworker-wide measures of encouragement. We find strong alignment between the two, supporting our interpretation of employer encouragement as a workplace-level treatment.

## F.1 Additional Controls

This section evaluates the robustness of the relationships between employer encouragement of AI chatbots and workers' adoption and reported benefits. We leverage the richness of our data to examine potential confounders on both the firm and worker sides.

On the firm side, we show that all results remain robust when controlling for firm characteristics (Table 1), ensuring that observed differences across workplaces are not driven by variation in firm age, size, or productivity. On the worker side, we show that the results are similarly robust to controlling for workers' detailed task mixes within occupations, ensuring that the effects of employer encouragement are not merely driven by differences in task types more amenable to AI chatbot use.<sup>31</sup>

Table F.1 and Figure F.1 summarize these robustness checks, showing that our estimates of the impact of employer encouragement on chatbot adoption and perceived benefits remain virtually unchanged after accounting for firm characteristics and worker task mixes.

The robustness of our estimates to the inclusion of this rich set of controls provides reassurance that observable confounders are not driving the results. Moreover, Oster (2019) and Altonji, Elder and Taber (2005) provide conditions under which the stability of coefficients to the inclusion of observable controls can also help rule out selection on *unobservables*.

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<sup>31</sup>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 J and Humlum and Vestergaard (2025, SI6) for details.

Table F.1: Encouragement, Adoption, and Work (Additional Controls)

(a) Adoption (Figure 2)								
	Ever Used		Monthly or More		Weekly or More		Daily	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Encouraged	0.365	0.347	0.337	0.321	0.283	0.268	0.136	0.129
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)
Worker characteristics controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm characteristics controls		✓		✓		✓		✓
Worker task mix controls		✓		✓		✓		✓
(b) Reported Benefits (Figure 4.(a))								
	Time Savings		Quality		Creativity		Job Satisfaction	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Encouraged	0.098	0.099	0.115	0.112	0.094	0.094	0.071	0.069
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)
Worker characteristics controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm characteristics controls		✓		✓		✓		✓
Worker task mix controls		✓		✓		✓		✓
(c) Allocation of Time Savings (Figure 4.(c))								
	More of Same Tasks		More of Diff. Tasks		More Breaks		More Leisure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Encouraged	0.033	0.026	0.013	0.010	-0.008	-0.009	-0.014	-0.015
	(0.009)	(0.010)	(0.007)	(0.008)	(0.005)	(0.005)	(0.006)	(0.006)
Worker characteristics controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm characteristics controls		✓		✓		✓		✓
Worker task mix controls		✓		✓		✓		✓
(d) New Workloads from AI Chatbots for Adopters (Figure 5.(a))								
	Same Tasks		New Tasks		Same and New Tasks			
	(1)	(2)	(3)	(4)	(5)	(6)		
Encouraged	0.016	0.016	0.046	0.040	0.008	0.008		
	(0.004)	(0.004)	(0.005)	(0.005)	(0.002)	(0.002)		
Worker characteristics controls	✓	✓	✓	✓	✓	✓		
Firm characteristics controls		✓		✓		✓		
Worker task mix controls		✓		✓		✓		

*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 our main estimates from Equation (1), corresponding to the differences between the “Encouraged” and “Non-Encouraged” predicted values shown in Figures 2, 4.(a,c), and 5.(a). Even-numbered columns report specifications where we augment controls for firms’ characteristics and workers’ detailed task mixes. Robust standard errors are shown in parentheses. *Sample:* All complete responses from the 2024 survey that can be linked to the registry data.

Figure F.1: Employer Encouragement and Worker Gaps in Adoption (Figure 3)



*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). Panel (a) presents our main specification from Figure 3, while Panel (b) adds controls for firm characteristics (Table 1) and workers' detailed task mixes. 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.

## F.2 Coworker Encouragement

A recurring theme in our analysis is the relationship between employer encouragement and workers' use of AI chatbots.

While our main analysis relies on workers' self-reports of employer encouragement, this section examines whether the results change when using coworker reports instead. This helps clarify whether the estimated effects reflect workplace-level treatments or individual-targeted interventions.

### F.2.1 Empirical Strategy

To operationalize these ideas, we construct leave-one-out averages of coworkers' reported employer encouragement for each worker  $i$ :

$$\text{Encouraged}_{j,-i} = \frac{1}{N_{j(i)} - 1} \sum_{k \in j(i) \setminus i} \text{Encouraged}_k, \quad (4)$$

where  $N_{j(i)}$  denotes the number of workers in the same workplace-occupation cell  $j(i)$  as worker  $i$ .

The coworker measurements are 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,  $\text{Encouraged}_{j,-i}$  (see Appendix G for details on this method). Importantly, our results in Section F.2.2 are robust to using the raw leave-out means instead.

Table F.2 shows that coworker encouragement strongly predicts 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.

Table F.2: Relationship Between Self- and Coworker-Reported Encouragement

	Encouraged (1)
Coworker Encouragement (EBS)	1.181*** (0.020)
Coworker Female Share	-0.016 (0.011)
Coworker Age	0.001 (0.001)
Coworker Potential Experience	-0.001 (0.001)
Occupation FEs	✓
F-Stat (Partial)	3644.56
Observations	16974

*Notes:* This table reports the relationship between workers' self-reported employer encouragement and those reported by their coworkers, estimated using the specification in Equation (5). Standard errors (in parentheses) are clustered at the workplace level. *F-Stat (Partial)* reports the F-statistic on the partial effect of Coworker Encouragement (EBS). *Sample:* The table is based on all completed responses from workplaces with at least two respondents from the 2024 survey linked to registry data.

In Section F.2.2, we estimate how employer encouragement affects the impact of AI chatbots, contrasting the effects of workers' self-reported encouragement with those of their coworkers'. To ensure the effects are measured on comparable scales, and not attenuated by measurement error, we present 2SLS estimates for the impact of coworker-reported employer encouragement:

$$\text{Encouraged}_i = \pi' X_{j,-i} + \alpha \times \text{Encouraged}_{j,-i} + \varepsilon_{1i} \quad (5)$$

$$Y_i = \gamma' X_{j,-i} + \beta \times \widehat{\text{Encouraged}}_i + \varepsilon_{2i}, \quad (6)$$

where  $X_{j,-i}$  denotes the leave-one-out mean of the characteristics  $X$  of worker  $i$ 's coworkers.

Table F.2 reports estimates of Equation (5).

### F.2.2 Results

**Adoption and Work.** Table F.3 and Figure F.2 compare the effects of self- and coworker-reported employer encouragement on AI chatbot adoption and associated benefits. The results broadly align, but with interesting differences.

The impact of coworker-reported encouragement on adoption (Panel (a)) is 1.5–2 times larger than the effect of self-reported encouragement. Furthermore, Figure F.2.(b) shows that coworker encouragement can entirely eliminate the gender gap in AI chatbot adoption. By contrast, coworker encouragement has a more muted effect on reported benefits among adopters (Panel (b)). For example, self-reported encouragement increases the share of workers reporting time savings by 10 percentage points, whereas the effect of coworker encouragement is only 5.3 percentage points. Finally, Panel (d) shows that coworker encouragement has roughly twice the effect of self-reported encouragement on the creation of new tasks among adopters, as compared to the effects shown in Figure 5.

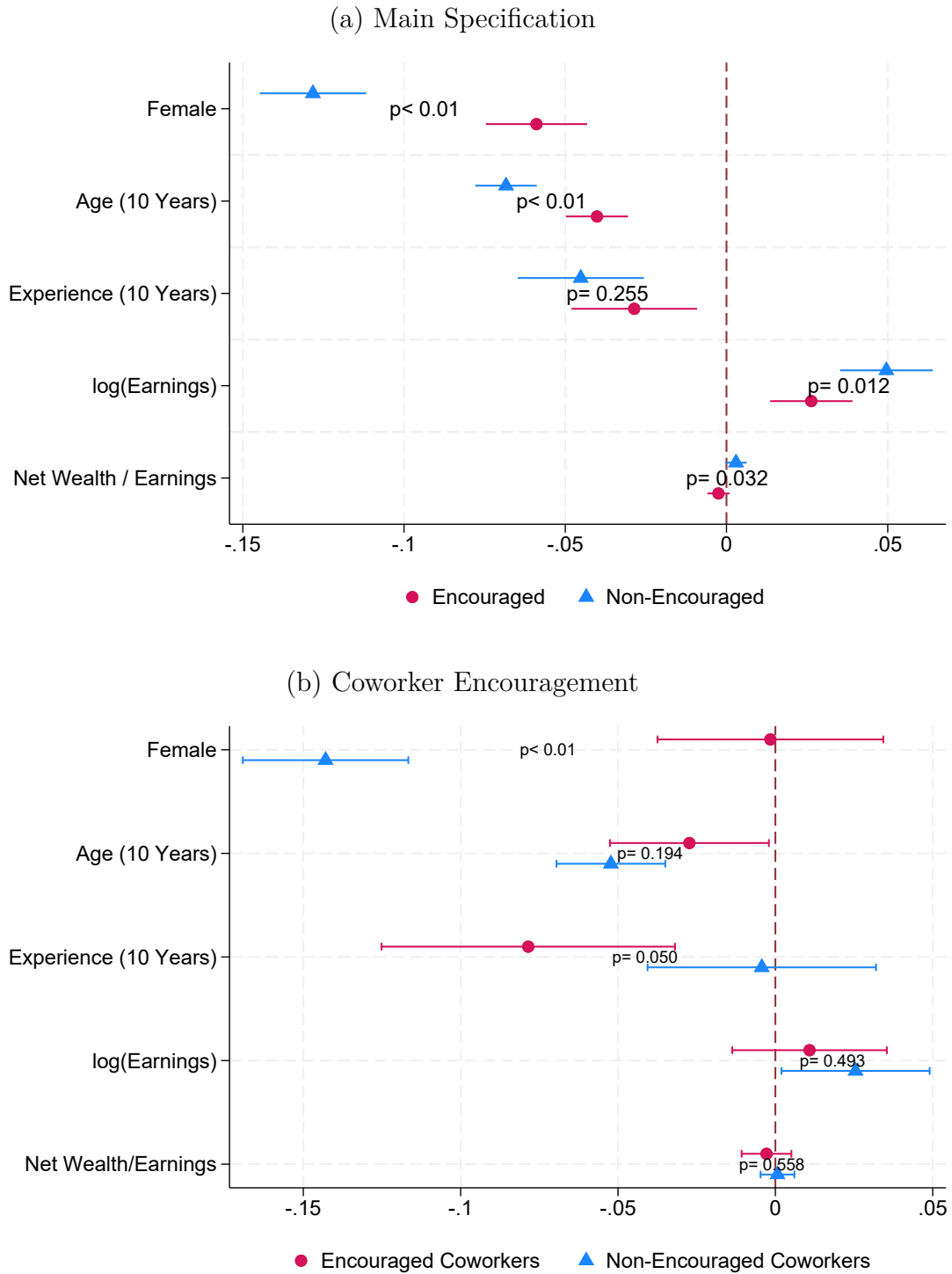
Taken together, these results suggest that workplace-wide encouragement (captured by coworker reports) significantly boosts chatbot adoption and leads to broader organizational changes that induce task creation. However, individual-level benefits—such as perceived time savings—appear more sensitive to whether workers personally feel encouraged, as measured by self-reports.

Table F.3: Encouragement, Adoption, and Work (Own vs. Coworker Reports)

(a) Adoption								
	Ever Used		Monthly or More		Weekly or More		Daily	
	Own (1)	CWs (2)	Own (3)	CWs (4)	Own (5)	CWs (6)	Own (7)	CWs (8)
Encouraged	0.363 (0.007)	0.725 (0.022)	0.337 (0.007)	0.640 (0.022)	0.285 (0.007)	0.506 (0.021)	0.137 (0.005)	0.228 (0.017)
(b) Reported Benefits								
	Time Savings		Quality		Creativity		Job Satisfaction	
	Own (1)	CWs (2)	Own (3)	CWs (4)	Own (5)	CWs (6)	Own (7)	CWs (8)
Encouraged	0.100 (0.008)	0.053 (0.031)	0.116 (0.009)	0.090 (0.033)	0.091 (0.009)	0.088 (0.031)	0.071 (0.007)	0.026 (0.025)
(c) Allocation of Time Savings								
	More of Same Tasks		More of Diff. Tasks		More Breaks		More Leisure	
	Own (1)	CWs (2)	Own (3)	CWs (4)	Own (5)	CWs (6)	Own (7)	CWs (8)
Encouraged	0.031 (0.009)	0.035 (0.035)	0.016 (0.007)	0.037 (0.024)	-0.007 (0.005)	-0.016 (0.016)	-0.011 (0.006)	-0.010 (0.019)
(d) New Workloads from AI Chatbots (Adopters)								
	Same Tasks		New Tasks		Same and New Tasks			
	Own (1)	CWs (2)	Own (3)	CWs (4)	Own (5)	CWs (6)		
Encouraged	0.016 (0.004)	0.018 (0.012)	0.045 (0.006)	0.106 (0.021)	0.008 (0.002)	0.014 (0.008)		

*Notes:* This table presents estimates of the impact of employer encouragement on: AI chatbot adoption (Panel a), 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 (“Own”) show the impact of self-reported encouragement, estimated using the specification in Equation (1). Even-numbered columns (“CWs”) show the impact of coworker-reported encouragement, estimated using the specifications in Equations (5)–(6). The “Own” coefficients correspond to the difference between “Encouraged” and “Non-Encouraged” predicted values shown in Figures 2, 4.(a,c), and 5.(a), respectively. Standard errors (in parentheses) are clustered at the workplace level. *Sample:* “Own” columns use all complete responses from the 2024 survey that can be linked to registry data. “CWs” columns include complete responses from workplaces with at least two linked respondents in the 2024 survey.

Figure F.2: Encouragement and Worker Gaps in Adoption (Own vs. Coworker Reports)

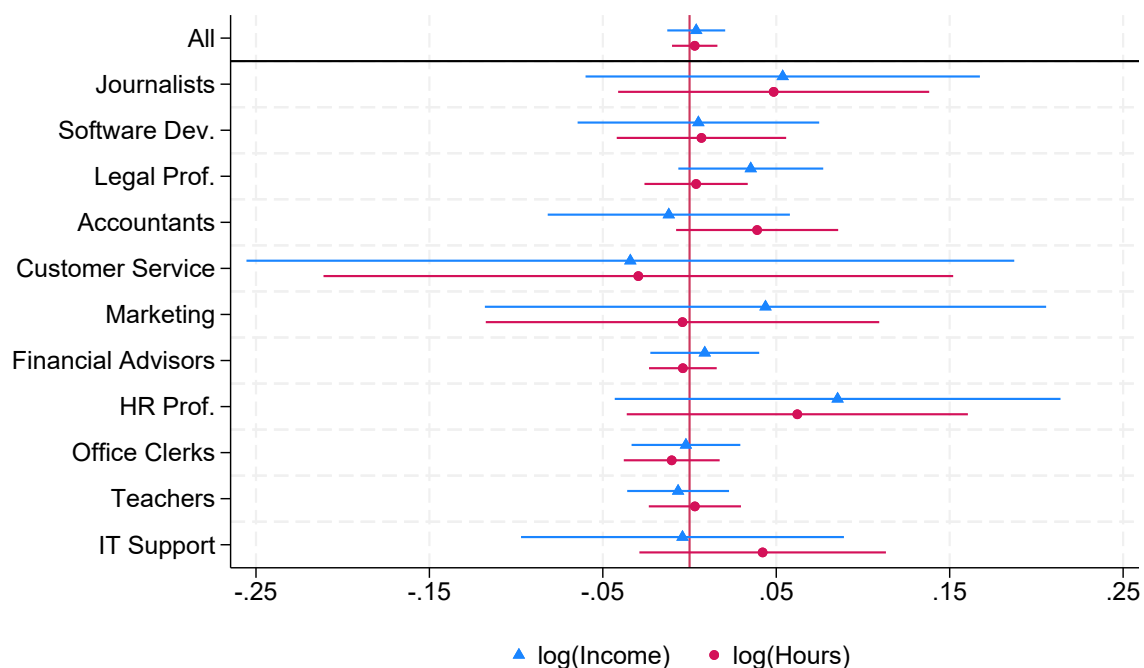


*Notes:* This figure presents the impact of coworker encouragement on worker disparities in AI chatbot adoption. The estimates are obtained from a multivariate regression of AI chatbot adoption on worker characteristics  $X$ , controlling for occupation-fixed effects, and all interacted with an indicator for employer encouragement. In Panel (b), we instrument these interaction effects using the corresponding interactions with our coworker encouragement variable. 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.

**Labor Market Outcomes.** Figure F.3 revisits our analysis of how employer encouragement affects individual labor market outcomes, this time using coworker reports to measure encouragement. The results confirm that employer encouragement policies have had no measurable impact on workers' labor market outcomes.

A key takeaway from our earlier analysis is that the modest labor market effects are partly explained by weak pass-through from time savings to labor earnings—though pass-through is somewhat stronger when employers actively encourage chatbot use. Table F.4 replicates this result using coworker reports to measure encouragement. Pass-through remains modest (ranging from 2% to 6%) but is approximately three times higher when employers are reported to encourage chatbot use.

Figure F.3: Have Encouragements Affected Workers' Outcomes? (Coworker Reports)



*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 encouragement rates described in Section F.2.1. *Sample:* All completed responses from the 2024 survey linked to registry data.

Table F.4: Pass-Through of Time Savings to Earnings (Own vs. Coworker Encouragement)

	Baseline		Encouraged	
	Own (1)	CWs (2)	Own (3)	CWs (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 "Own" coefficients correspond to the slopes of the best-fit lines in Figure 11. The "CWs" estimates instrument Encouraged using the coworker encouragement rates described in Section F.2.1. *Sample:* The table is based on all complete responses from the 2024 survey that can be linked to the registry data.

## G 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:

$$x_i \mid p_i \sim \text{Binomial}(n_i, p_i), \quad p_i \sim \text{Beta}(\alpha_0, \beta_0). \quad (7)$$

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:

$$\bar{p} = \frac{1}{m} \sum_{i=1}^m \frac{x_i}{n_i}, \quad s^2 = \frac{1}{m} \sum_{i=1}^m \left( \frac{x_i}{n_i} - \bar{p} \right)^2. \quad (8)$$

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:

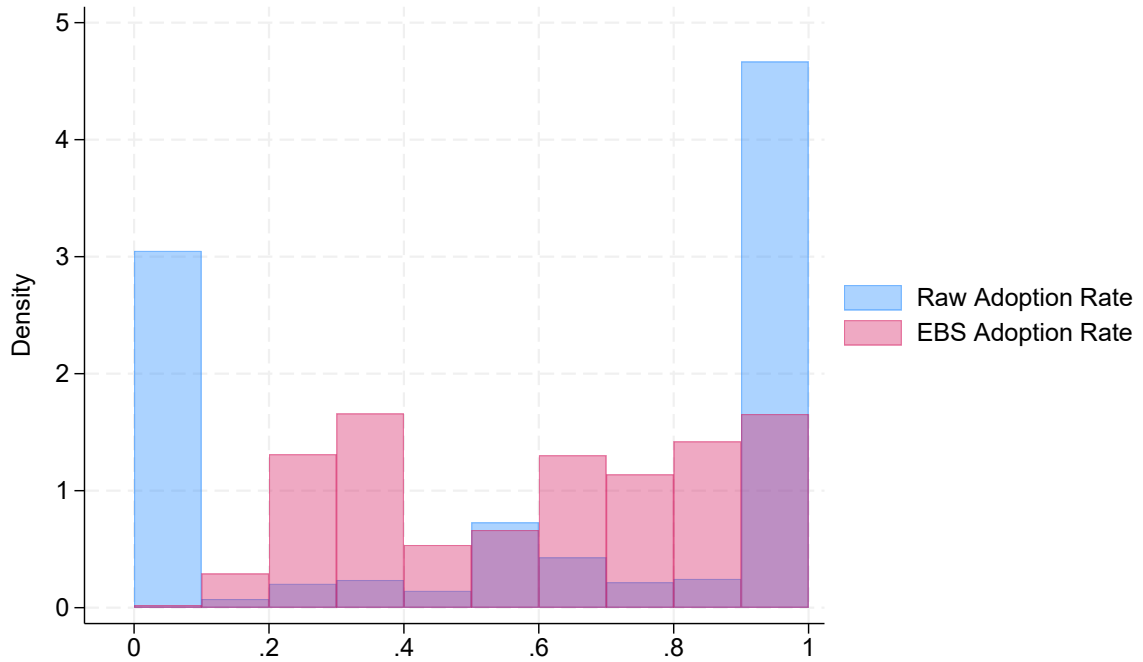
$$\mathbb{E}[p_i \mid x_i] = \frac{\alpha_0 + x_i}{\alpha_0 + \beta_0 + n_i}.$$

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

## G.1 Workplace Adoption Rates

Figure G.1 compares the raw and adjusted distributions of workplace adoption rates, while Table G.1 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 remain robust when using the raw workplace adoption rates instead.

Figure G.1: 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 G. *Sample:* All completed responses from our 2024 survey round linked to registry data.

Table G.1: Workplace Adoption Rates (Empirical Bayes Shrinkage)

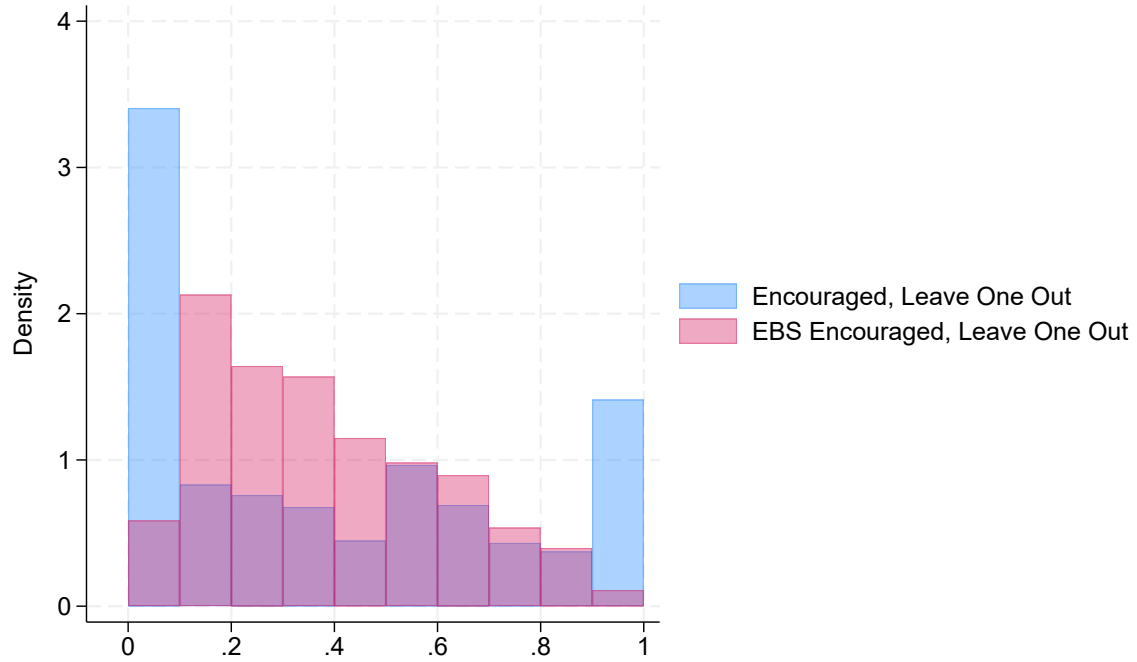
	p25	p50	p75	sd
Journalists	0.71	0.83	0.83	0.14
Software Developers	0.90	0.90	0.93	0.12
Legal Professionals	0.28	0.70	0.70	0.24
Accountants	0.25	0.25	0.73	0.24
Customer Service Rep.	0.27	0.50	0.74	0.24
Marketing Professionals	0.97	0.97	0.97	0.19
Financial Advisors	0.29	0.48	0.65	0.21
HR Professionals	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 G. *Sample:* All completed responses from our 2024 survey round linked to registry data.

## G.2 Coworker Encouragement Rates

Figure G.2 compares the raw and adjusted distributions of coworker encouragement rates, while Table G.2 presents summary statistics for the adjusted rates of workplaces. The typical standard deviation within occupations is 17 percentage points. Importantly, our results in Section F.2.2 remain robust when using the raw coworker encouragement rates instead.

Figure G.2: 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 G. *Sample:* All completed responses from our 2024 survey round linked to registry data.

Table G.2: 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 G. *Sample:* All completed responses from our 2024 survey round linked to registry data.

## H Theoretical Framework

Sections 2 and 3 examine how employer initiatives are associated with workers' adoption of AI chatbots and the benefits reported by users. In this section, we introduce a simple theoretical framework to interpret these empirical patterns. We posit a Roy (1951) style selection model of chatbot adoption, in which employer initiatives may shift both the costs and benefits of adoption. We use the model to analyze how these shifts affect workers' adoption decisions and the benefits they report from using the tools.

### H.1 Setup

Worker  $i$  derives benefits  $B_i$  from using AI chatbots:

$$B_i = \alpha_b + \beta_b \times i, \quad (9)$$

where individuals  $i \sim \mathcal{U}([0, 1])$  are drawn uniformly from the unit interval and sorted by their individual benefits, such that  $\beta_b \leq 0$ . While we assume linear functional forms for analytical simplicity, our predictions also hold under more general monotonicity assumptions.<sup>32</sup>

The worker also incurs a cost  $C_i$  of adopting chatbots:

$$C_i = \alpha_c + \beta_c \times i, \quad (10)$$

where  $\beta_c \geq 0$  if workers who benefit more from AI also face lower adoption costs.<sup>33</sup>

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<sup>32</sup>The key assumption underlying the predictions in Section H.2 is that adoption exhibits positive selection on benefits ( $B_i$ ), meaning that employer encouragement induces adoption among workers with marginally lower idiosyncratic benefits (i.e., higher  $i$ ).

<sup>33</sup>A common finding from RCTs is that AI chatbots tend to yield greater benefits for less experienced (and thus typically younger) workers (Brynjolfsson, Li and Raymond, 2025; Dell'Acqua et al., 2023; Noy and Zhang, 2023). If these workers also find it easier to adopt new tools, then  $\beta_c \geq 0$ .

## H.2 Predictions

We conceptualize employer encouragement  $E \in \{0, 1\}$  as shifting workers' costs and benefits of using AI chatbots through the parameters  $\alpha_c$  and  $\alpha_b$ :

$$\alpha = \alpha_0 + \alpha_1 E. \quad (11)$$

Figure H.1 illustrates these shifts; formal derivations are provided in the paragraphs below.

**Adoption rates.** Figure 2 shows how employer encouragement is associated with greater chatbot adoption by workers. In the Roy model outlined above, workers adopt AI chatbots if their perceived benefits exceed the associated adoption costs ( $B_i \geq C_i$ ). The resulting adoption rate is given by:

$$i^*(E) = \frac{\alpha_b - \alpha_c}{\beta_c - \beta_b}, \quad (12)$$

where  $0 < \alpha_b - \alpha_c < \beta_c - \beta_b$ , corresponding to the empirically relevant case in which adoption rates lie between 0 and 1.

Equation (12) implies that employer initiatives which raise benefits ( $\alpha_b$ ) or reduce adoption costs ( $\alpha_c$ ) increase adoption, with stronger effects when  $\beta_c - \beta_b$  is small—i.e., when workers are relatively homogeneous in their net benefits of using AI chatbots.

In this light, the fact that employer encouragement in Figure 2 is associated with a *doubling* of adoption rates suggests that these employer initiatives are powerful relative to the amount of individual heterogeneity in net benefits.

**Benefits for users.** Figure 4 shows that employer encouragement is associated with greater average benefits reported by users. The average benefit among users is:

$$\bar{B}(E) = \mathbb{E}[B_i(\alpha) \mid i \leq i^*(\alpha)] = \gamma \alpha_c + (1 - \gamma) \alpha_b, \quad (13)$$

where  $\gamma = \frac{\beta_b}{2(\beta_b - \beta_c)} \geq 0$ . Equation (13) provides two key insights about how employer encouragement relates to reported user benefits.

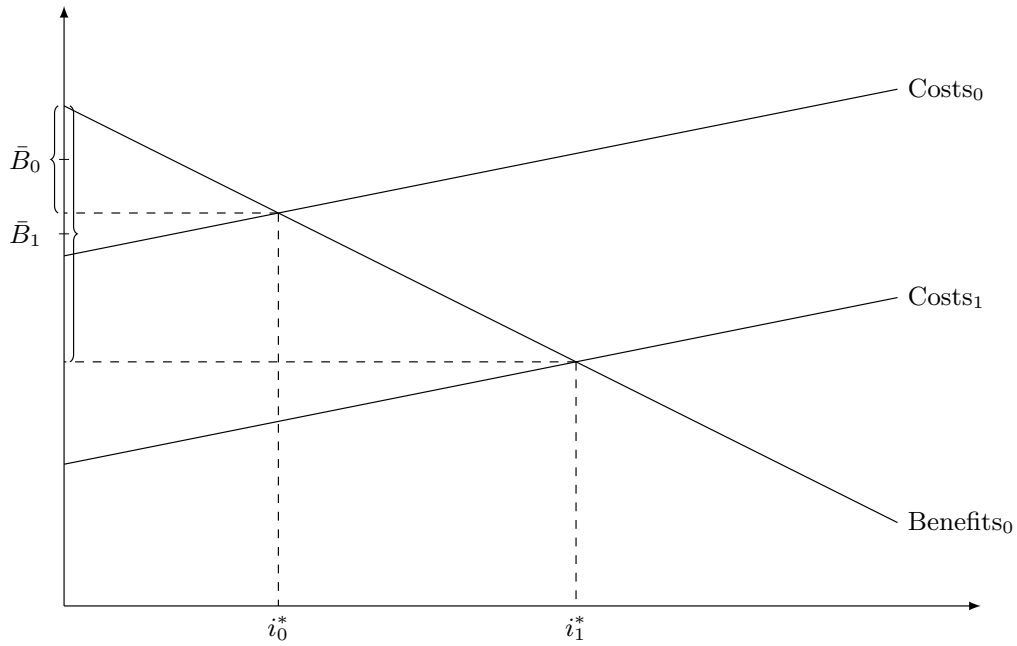
First, employer initiatives that reduce adoption costs ( $\alpha_c$ ) *lower* the average benefit among users due to a *selection effect*: lower costs induce adoption by workers with lower idiosyncratic benefits (i.e., higher  $i$ ). This negative selection effect,  $\gamma$ , is stronger when workers are more homogeneous in their net benefits from using AI chatbots (i.e., when  $\beta_c - \beta_b$  is small, so that employer initiatives generate larger increases in adoption; cf. Equation (12)) but more heterogeneous in their gross benefits from the tools (i.e., when  $\beta_b$  is large in absolute value, implying that marginal users have lower idiosyncratic benefits).

Second, employer initiatives that increase benefits ( $\alpha_b$ ) have two offsetting effects on average reported benefits. On the one hand, a higher  $\alpha_b$  directly raises each user's individual benefit  $B_i$ . On the other hand, it expands adoption, drawing in users with lower idiosyncratic benefits (i.e., higher  $i$ ), thereby triggering the same negative selection effect as a reduction in  $\alpha_c$ . The net effect of an increase in  $\alpha_b$  on the average reported benefits among users  $\bar{B}$  is positive if and only if  $\gamma < 1$ . This condition is more likely to hold when workers are relatively homogeneous in their gross benefits from the tools  $B_i$  but more heterogeneous in their adoption costs  $C_i$ .

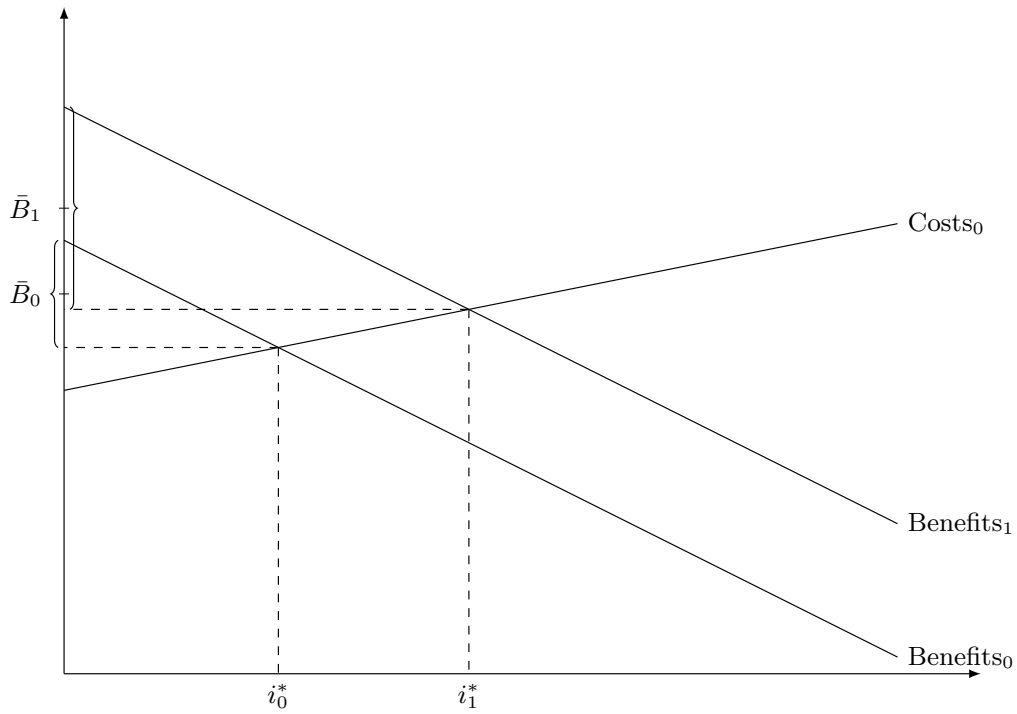
In summary, the average reported benefits among users provide a lower bound on the causal effect of employer encouragement on *individual* benefits, due to the presence of a negative *selection* effect. In this light, the fact that Figure 4 shows higher reported benefits among users in encouraged settings is striking. It suggests two things: (i) employer encouragement primarily raises perceived benefits ( $\alpha_b$ ), as reductions in adoption costs ( $\alpha_c$ ) would only generate the negative selection effect; and (ii) the employer-induced increases in benefits outweigh the adverse selection effect—implying that employer initiatives are powerful relative to degree of individual heterogeneity ( $\gamma < 1$ ).

Figure H.1: The Impact of Employer Initiatives on Adoption Rates and Reported Benefits

(a) Lower Costs



(b) Higher Benefits



*Notes:* This figure illustrates how employer initiatives affect adoption rates ( $i^*$ ) and average reported benefits among users ( $\bar{B}$ ). Panel (a) shows the impact of initiatives that reduce adoption costs ( $\alpha_c$ ), while Panel (b) depicts the impact of initiatives that enhance benefits ( $\alpha_b$ ). Lower adoption costs ( $\alpha_c$ ) unambiguously increase adoption rates and reduce average reported benefits due to a negative selection effect. In contrast, initiatives that raise benefits ( $\alpha_b$ ) also increase adoption, but their impact on average reported benefits is theoretically ambiguous and, at most, equal to their individual-level effect.

### H.3 Discussion

The preceding section examines the implications of workers self-selecting into chatbot adoption based on their individual benefits. Beyond this margin of selection, at least two additional forms of selection may be at play.

First, firms that choose to encourage chatbots may be the ones with the greatest benefits from the tools—even absent any encouragement initiatives—introducing potential reverse causality between employer encouragement and reported benefits. In the framework above, this corresponds to  $E$  being positively related to  $\alpha_{ob}$ . Second, employers may target their encouragement toward employees who are expected to benefit the most individually. This would resemble a “rotation” of the cost and benefit schedules in Figure H.1, rather than simple vertical shifts.

Section F addresses both of these additional selection margins empirically. First, Section F.1 examines whether employers select into encouragement based on their underlying benefits from chatbot use. We show that the effects of encouragement remain robust when controlling for a range of firm- and worker-level characteristics, including firm age, size, and productivity, as well as workers’ detailed task mixes and other attributes. These robustness checks show that the association between employer encouragement and reported benefits is not driven by observable confounders.

Second, Section F.2 implements a “coworker encouragement” design, using the average encouragement reported by a worker’s colleagues to measure workplace-wide encouragement rates. Because coworker encouragement rates capture only *workplace*-level variation, this approach helps address potential bias arising from employers targeting encouragement toward *individual* employees with the highest idiosyncratic benefits. As shown in Table F.3 and Figure F.2, the findings remain largely robust when using coworker encouragement as the source of variation.

# **I 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 50, followed by the original Danish version on page 52.

## Invitation Letter – English Translation



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](http://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](mailto: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

## Invitation Letter – English Translation

### 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-undersogelse>.

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](mailto:databeskyttelse@dst.dk).



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](http://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](mailto: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

## Invitation Letter – Danish Version

### 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 Statistik 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/persondatabase-skyttelse/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-undersogelse> 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](mailto:databeskyttelse@dst.dk)

## J 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 55, with the original Danish version on page 60.

## 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

## Survey Questionnaire – English Translation

### 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

## Survey Questionnaire – English Translation

### **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

## Survey Questionnaire – English Translation

### 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

## Survey Questionnaire – English Translation

### 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

## Survey Questionnaire – Danish Version

### 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

## Survey Questionnaire – Danish Version

### 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.