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ABSTRACT

This study investigates how occupational AI exposure impacts employment at the intensive margin, i.e., the length of workdays and the allocation of time between work and leisure. Drawing on individual-level time diary data from 2004–2023, we find that higher AI exposure—whether stemming from the ChatGPT shock or broader AI evolution—is associated with longer work hours and reduced leisure time, primarily due to AI complementing human labor rather than replacing it. This effect is particularly pronounced in contexts where AI significantly enhances marginal productivity and monitoring efficiency. It is further amplified in competitive labor and product markets, where workers have limited bargaining power to retain the benefits of productivity gains, which are often captured by consumers or firms instead. The findings question the expectation that technological advancements alleviate human labor burdens, revealing instead a paradox where such progresses compromise work-life balance.

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1. Introduction

Artificial intelligence (AI) was initially conceived with the goal of making human work and life more interesting, fulfilling, and less laborious. Paired with other technological advances like automation, AI has the potential to boost productivity, enhance job satisfaction, and promote a healthier work-life balance. Nevertheless, empirical evidence regarding AI's impact on both work and leisure remains inconclusive. While much of the discussion has centered on AI's capacity to displace labor in some scenarios and generate new roles in others (e.g., Felten et al., 2019; Webb, 2019; Acemoglu et al., 2022; Kogan et al., 2023; Hampole et al., 2025), relatively little attention has been given to how AI reshapes work on the intensive margin—particularly its effects on work time, contracting efficiency, and the distribution of productivity gains. This paper aims to fill these gaps by analyzing the micro-level impacts of AI on time allocation, drawing on detailed individual-level time diaries collected from 2004 to 2023. Through this examination, we investigate how AI exposure influences work supply at the intensive margin and assess its broader implications for firm valuation and economic outcomes.

The relationship between occupation exposure to AI and work time is a priori ambiguous. For any given task, AI-driven automation and efficiency improvements should theoretically shorten task duration. Additionally, wealth creation boosted by technology should entice individuals to allocate more time from work to leisure, provided that leisure is a normal good. However, the classical principle-agent model (notably Holmstrom and Milgrom (1987)) provides a rich set of predictions in a setting where a worker optimally allocates his effort based on the production process, monitoring effectiveness and personal preferences. AI's impact on the potential to enhance productivity in diverse fields,[1] combined with its capacity to improve monitoring and productivity measurement, can result in heavier workloads and longer hours. This effect is expected to be more pronounced in competitive product markets,

[1] E.g., stock analysis (e.g., Gu et al., 2020; Lopez-Lira and Tang, 2023), legal practices (e.g., Casey and Niblett, 2016; Surden, 2019), music generation (e.g., Briot et al., 2017; Briot, 2021), and accounting (Commerford et al., 2022).

where businesses face escalating expectation from customers and pressures from competitors' enhanced capabilities; and in labor markets with relatively inelastic supply, where workers lack substantive bargaining power to adjust their schedules to their own advantage. Furthermore, AI's integration of real-time effort tracking and improved information availability frequently erodes the division between work and personal life, further contributing to extended working hours for some individuals.

Data from the American Time Use Survey (ATUS) provides a unique opportunity to test the hypotheses. The ATUS conducts a cross-sectional survey each year, with an average annual sample size of approximately 26,400 participants. Our sample spans two decades from 2004 to 2023. Respondents document their activities using detailed 24-hour diaries at 15-minute intervals, from which market-based work time, leisure time, and some special categories (such as education and entertainment) can be calculated, with reasonable variations for sensitivity checks (e.g., whether social activities at the workplace count as work or leisure). To attribute the changes in workday patterns to AI, we then measure each occupation's AI exposure based on the textual correlation between task descriptions and the content of AI-related patents using large language models. We further distinguish between complementarity and substitution relationships between AI and jobs.

The advent of ChatGPT toward the end of 2022 provides a natural experiment to test on how workers change time allocation when their jobs are disrupted or complemented by the new AI technology. Workers in occupations with higher exposure to generative AI experienced a significant increase in work hours and a decrease in leisure time following the introduction of ChatGPT. An interquartile increase in AI exposure is associated with a 3.15-hour increase in daily work time. This effect is particularly evident in occupations that are more complementary to generative AI and in regions where AI awareness is higher, as measured by Google search trends. Given that the general public was largely unprepared for exact timing of ChatGPT and even more for its advanced, "human like" capabilities,[2] the prolonged

[2]The surprise by the general public was evident from the comments on social media shortly after ChapGPT's launching. For instance, The *New York Times* article titled "A Conversation With Bing's Chatbot Left Me Deeply Unsettled," published on February 16, 2023, captured many of these reactions and reflected the broader

workday is likely to be attributable to the new technology. The fact that AI technology actually increases overall work hours challenges the conventional expectation that such technology enables people to finish work faster.

The same relationship holds for the entire sample period concerning occupational exposure to general AI technology. After accounting for personal characteristics, a set of alternative exposure measures to innovation, and saturated fixed effects—including occupation, industry $\times$ year, state $\times$ year, year-month, and day-of-week—an interquartile shift in occupational AI exposure corresponds to an additional 2.2 hours of work in the cross-section, or about 40% of that magnitude within occupations (i.e., when incorporating additional occupation fixed effects). Furthermore, the effect increases monotonically with the level of net complementarity in occupational AI exposure. This finding supports the hypothesis that AI-augmented productivity motivates workers to extend their working hours. The hypothesis is further supported by evidence that occupational complementarity to AI is positively correlated with wages, which are expected to rise to incentivize greater effort.

In addition, we provide evidence of AI's impact on performance monitoring, leveraging the rapid adoption of AI-driven monitoring in remote work during the 2020 pandemic as a natural laboratory. Remote workers with greater exposure to AI surveillance technologies work longer hours post-pandemic. In contrast, this effect is not observed among the self-employed, where the principal-agent problem does not apply, confirming the placebo effect.

Finally, we discover that despite higher compensation, greater AI exposure is associated with lower general welfare of workers, as evidenced by decreased employee satisfaction in Glassdoor ratings, consistent with stagnation of worker reservation utility despite productivity gains. Moreover, the extension of the working day is more pronounced when the labor market is competitive, reducing workers' bargaining power to extract rents from technology-enabled productivity gains; or when the product market is competitive, leading to most of the rents being passed on to consumers, leaving little for firms to share with workers. In both scenarios, the reservation utility of workers (reflecting overall welfare in equilibrium) fails to keep pace

public astonishment at the technology's capabilities.

with productivity gains during the AI boom, thereby undermining the income effect that would have otherwise induced more leisure and discouraged work. The combined results suggest that while AI-driven productivity gains promise greater efficiency, they have resulted in longer working hours and lower employee satisfaction, especially in competitive markets and for occupations with higher AI complementarity, challenging the conventional expectation that technology frees humans from prolonged workdays.

Our study contributes to the rapidly growing literature analyzing the impact of AI on the economy. A growing body of research (Autor, 2015; Felten et al., 2019; Webb, 2019; Acemoglu et al., 2022; Yang, 2022; Babina et al., 2024; Hampole et al., 2025) has uncovered various facets of AI's impact on businesses and employment, focusing primarily on the extensive margin, i.e., occupations disrupted and new opportunities created by AI. In contrast, this study centers on the intensive margin of workdays within the framework of a principal-agent model. Needless to say, we also build upon and contribute to the literature using time allocation surveys, which have predominantly examined general or cyclical trends and their heterogeneity across population subgroups.[3] Among studies built on time allocation survey, our study is unique through the lens of AI exposure.

The remainder of the paper is organized as follows: Section 2 develops a simple model within a principal-agent framework to provide theoretical guidance on the various ways AI technology can influence worker time allocation. Section 3 introduces the primary datasets used in our analyses, including patent data, occupation data, LinkedIn, Glassdoor, and the American Time Use Survey. Section 4 presents the empirical analyses and reports the results. Finally, Section 5 concludes.

[3] For instance, Aguiar et al. (2021) shows that younger men experienced the greatest decline in market work hours among all demographic groups over the last 15 years, reallocating their leisure to video gaming and other recreational computer activities. Aguiar and Hurst (2007) finds that the least educated adults experienced the largest increases in leisure. Aguiar et al. (2013) investigates how individuals reallocate their lost work hours during recessions.

2. Modeling Framework and Hypotheses

Theories addressing the principal-agent problem have inspired a large body of research, including many seminal papers. While this study is primarily empirical, we ensure that our analyses are well-informed by theoretical insights. In particular, we build on straightforward adaptations of the Holmstrom and Milgrom (1987) model of dynamic incentive contracts, which examines how risk-averse agents respond to compensation schemes that balance incentives, risk-sharing, and the timing of information disclosure in a continuous-time framework. This model offers predictions about the relationship between a worker's "effort" (interpreted as the number of work hours in our empirical context) and several key factors, including marginal productivity, the ease of effort monitoring, and the worker's bargaining power in capturing or preserving the rents from technology-driven productivity gains.

The simple model, presented in the Online Appendix A, features a risk-neutral principal, a risk-averse agent, and a production process following the standard Brownian motion in which effort and marginal productivity are multiplicative in determining the drift while noise is exogenously given. Under constant absolute risk aversion (CARA) utilities and a convex cost of effort for the agent, Holmstrom and Milgrom (1987) demonstrate that the optimal dynamic contract converges to a linear form in the aggregate: a lump-sum payment plus a share of the output, i.e., $\alpha + \beta X$. In this framework, the lump sum ensures the agent's reservation utility, $\underline{U}$ (shaped by the worker's relative bargaining power, which depends on the competitiveness of both the labor and product markets). The "sharecropping" coefficient, β, is inversely related to the agent's increasing marginal cost of effort, risk aversion, and output noise. Finally, the agent's effort level, in response to the incentive, is positively correlated with their marginal productivity and aligns in direction with the factors influencing β.

The model can be extended to incorporate a general constant elasticity of substitution (CES) utility function, where the marginal utilities of consumption and leisure are interdependent. This framework allows for the examination of how the work-leisure allocation changes in response to external factors that influence the agent's reservation utility $\underline{U}$ via their best alternatives in the marketplace. When consumption and leisure are complements, or when the reservation utility is sufficiently high (limiting the principal's ability to increase β due to the agent's risk aversion), work time is expected to decrease as the reservation utility rises. Since leisure is a normal good, the agent places greater value on it as their welfare improves. Rising $\underline{U}$ allows the agent to allocate more time to leisure and less to work (while enjoying higher consumption), all else being equal.

The model offers tight guidance on how AI can influence optimal incentives and the equilibrium level of effort for several reasons. First, if AI enhances the marginal productivity of the agent—indicating that human and AI are complements in job tasks[4]—this increase in marginal productivity results in greater effort or longer working hours. Conversely, if human and AI are substitutes in the job,[5] the effect is reversed. It is worth noting that a principal-agent relationship is not required for this effect, as the same dynamic would apply to self-employed individuals.

Second, AI enhances work monitoring by providing better predictions or more precise signals of workers' efforts. This can occur through improved forecasting of market opportunities, ensuring that the right products are produced, or through more accurate assessment of workers' labor input using past and concurrent, own and peer data. Both mechanisms reduce the noise component (i.e., factors unrelated to workers' effort or actions), thereby increasing work hours. This effect operates in the same direction regardless of whether AI substitutes or complements labor, though it is significantly stronger when the worker acts as an agent (i.e., employed by someone else) rather than as a principal (i.e., self-employed).

[4] A burgeoning literature corroborates complementarity in a wide range of occupations: Armour et al. (2022) find that AI-enabled services augment the capabilities of human lawyers and generate new roles for legal experts. Brogaard et al. (2024) find that human floor traders compete better with the help from algorithmic traders. Cao et al. (2024) demonstrate the superiority of a "Man + Machine" stock analyst over either human or AI analysts. Wang et al. (2024) find evidence supporting that AI solutions complement human experience in medical coding tasks for healthcare systems.

[5] An equally large literature has expressed concerns over displacements of human labor during technology advancement: Kogan et al. (2023) estimate the wage disruption effect of labor-saving technologies. Cheng et al. (2024) discuss the effect of labor-replacing automation technologies on firms' financial outcomes. Hui et al. (2024) find that generative AI reduce the demand and wages for human labor in online labor market. Jiang et al. (Forthcoming) report that exposure to fintech leads to a decline in job postings and employment. Cao et al. (2024) highlight that AI outperforms humans in certain tasks like processing transparent data.

Third, market forces and competitive conditions determine the extent to which workers benefit from AI-enabled productivity gains. When AI complements human labor and enhances labor productivity, the degree to which these gains translate into worker welfare–through a combination of higher pay and lower work hours—depends on the relative bargaining power of workers vis-a-vis their employers. Workers in regions or occupations characterized by competitive labor markets have limited bargaining power and may see little material benefit, with most of the rents accruing to employers or shareholders. Moreover, the share of rents available for firms to split with their workers also depends on product market competition. In highly competitive markets, consumers emerge as the primary beneficiaries of AI-driven productivity gains through better-quality products, lower prices, and rising consumer expectations, leaving little surplus for firms to share with their workers. If AI substitutes human labor and reduces labor productivity, workers find themselves in an even weaker bargaining position.

The distribution of the rents impacts work hours via the income effect linked to workers' reservation utility. When workers are able to capture a significant portion of the gains, their reservation utility increases, leading to greater consumption of leisure (a normal good), which, in turn, suppresses work hours. Conversely, when workers receive only a small share of the gains, the income effect from reservation utility is limited, resulting in minimal impact on work hours. The distribution of productivity rents serves as a distinct channel through which AI influences work-life balance.

3. Data, Measurement, and Overview

3.1. American Time Use Survey (ATUS)

To study how workers allocate time in the advent of AI, this study uses the ATUS database (2004-2023) of the Bureau of Labor Statistics (BLS) as its primary dataset. The ATUS delivers comprehensive, nationally representative data detailing how Americans use their time, where they spend it, and who they spend it with. It is the only federal source covering both market work (e.g., employment) and non-market activities, such as childcare and volunteering. To date, the ATUS data has been extensively used to examine social issues related to trends in work and leisure, health, and equality (e.g., Aguiar et al., 2013, 2021; Alon et al., 2020; Doepke et al., 2023; Graff Zivin and Neidell, 2014; Krueger and Mueller, 2010).

The ATUS conducts a cross-sectional survey each year, with an average annual sample size of approximately 26,400 participants. The ATUS sample is drawn from the population of households that participated in the Current Population Survey (CPS). One eligible person (household members aged 15 or older) per household is selected to participate in ATUS. Following Aguiar et al. (2013), our sample consists of respondents aged between 16 and 65, excluding individuals who are not in the position to be employed, such as full-time students aged below 25 and those serving in the military.[6] The sample further excludes those hired by tech firms to focus on workers in AI-using firms rather than AI-inventing firms following the literature (Acemoglu et al., 2022; Babina et al., 2024).[7] As the ATUS survey does not specifically select respondents based on employment status, the unemployed remain in our sample as long as an occupation code is available - typically reflecting their most recent job.[8] Long-term unemployed individuals do not have relevant occupation affiliation, so their exclusion does not impact our analysis of work time across occupations with varying AI exposure. These criteria result in 123,603 unique individuals in the ATUS sample from 2004 to 2023, spanning four labor market statuses: employed - at work, employed - absent, unemployed - on layoff, and unemployed - looking.

The ATUS respondents are interviewed once to document their activities from the previous day, using 24-hour diaries divided into 15-minute intervals. These activities, classified into

[6]The military sector is defined using the Census industry code ("teio1icd") provided by ATUS, including national security and international affairs (9590) and armed forces (9600-9900).

[7]The tech sector is defined using the Census industry code ("teio1icd") provided by ATUS, including information (6470–6780), scientific and technical Services (7380-7460), and other professional, scientific, and technical services (7490). Details on this classification system can be found in Appendix A of the ATUS Data dictionary at https://www.bls.gov/tus/dictionaries/atusintcodebk23.pdf.

[8]The CPS survey of the ATUS respondents was collected two to five months before their ATUS interview. This allows us to retrieve the most recent employment information (i.e., occupation code, industry code) from the CPS survey for respondents who were employed during the CPS survey but became unemployed by the time of the ATUS interview.

over 400 distinct types, are grouped into four broad categories: basic survival (a fixed seven hours per day for critical survival functions such as sleeping and eating), market work (to be explained shortly), leisure, and others. Following previous literature (e.g., Aguiar et al., 2013, 2021; Boerma and Karabarbounis, 2021), our paper uses weekly hours as the unit of analysis, calculated by multiplying daily hours by seven (with a top cap of 168 hours).

Market work, or simply "work," comprises two components: (i) "Core" market work, which includes time spent on main jobs, overtime work, and work activities performed at home;[9] and (ii) ancillary activities, covering time spent on supplementary work-related tasks, such as security procedures and waiting related to work. In our analyses, "work" time includes "work, main job," "eating and drinking as part of job", "sports and exercise as part of job," "security procedures as part of job," "waiting associated with work-related activities," and "work-related activities, not elsewhere classified." Commuting and social activities at work are excluded but results are qualitatively similar with their inclusion. [10]

Leisure activities are broadly defined to include activities such as watching television and movies, engaging with recreational computing and video games, reading, sports, and various hobbies. Activities such as eating, sleeping, and personal care (ESP) may serve dual function of meeting essential biological needs and offering leisure value. Thus we consider the time above the seven hours for essential needs from these categories to be leisure activities. The residual category, "other," including the remaining time spent on home production (domestic responsibilities such as cleaning, maintenance, cooking, shopping, and gardening); childcare; education (personal academic pursuits, such as participating in classes or doing homework); job search activities (submitting resumes, conducting job interviews, and exploring employment opportunities); own medical care; civic activities (going to church or social club, volunteering, etc.); any unclassified activities.

Table 1 Panel A reports the summary statistics at the ATUS respondent level. Unless otherwise specified, all potentially unbounded variables are winsorized at the 1% extremes.

[9] Secondary jobs, if any, are excluded due to the lack of occupation-related information.

[10] Commuting and social activities at work include "socializing, relaxing, and leisure as part of job", and "travel related to work."

The average respondent allocates 34.9 hours to work and 55.5 hours to leisure per week. The variation is substantial, with standard deviations of 30.7 and 27.3 hours, respectively. In the residual category, the average person spends 1.7 hours on education, 1.6 hours on civic activities, 0.4 hours on own medical care, 0.1 hours on job search, 15.7 hours on home production, and 4.5 hours on child care. These time allocation estimates are consistent with previous studies (e.g., Aguiar et al., 2013, 2021).

ATUS also reports wages for each individual, which are expressed in 2023 constant dollars in our analyses. For workers paid hourly, the hourly wage is directly reported. For non-hourly workers, we estimate the hourly wage by dividing their weekly earnings by the total hours they typically work each week. The average hourly earnings in our sample are $27.8 in 2023 dollars.

[Insert Table 1 here.]

3.2. AI patents

Central to our analysis is measuring individual occupation's exposure to AI technologies. To carry out this task, we first collect a comprehensive sample of AI patents granted between 2000 and 2023 from the Artificial Intelligence Patent Dataset (AIPD). AIPD was publicly released by the United States Patent and Trademark Office (USPTO) in 2021. Giczy et al. (2022) provide a detailed description of their procedures to identify components of AI technologies from the universe of U.S. patents published between 1976 and 2020 using machine learning models. Pairolero et al. (2023) extends the data to identify U.S. patent documents published from 1976 through 2023 containing AI. AIPD provides model predictions for the probability of a patent being AI-related, and we classify one as an AI patent if the predicted probability exceeds the 86% threshold following Pairolero et al. (2023).

These procedures result in a total of 905,667 AI patents granted from 2000–2023 that fall into one or more of eight categories classified in Pairolero et al. (2023): (i) machine learning, (ii) vision, (iii) natural language processing, (iv) speech, (v) evolutionary computation, (vi)

AI hardware, and (vii) knowledge processing, and (viii) planning and control. The literature has shown that only a small subset of patents have meaningful scientific and economic value. For example, about one quarter of patents were never cited, and less than 1% of the patents receive more than one hundred citations (Kogan et al., 2017). To focus on technologies that reshape the production process, we limit our analysis to the top 1% of the most important AI patents each year, identified by their adjusted forward citation counts. Based on the USPTO patent citation data, the adjusted forward citation count of a given AI patent is defined as its raw citation count divided by the average citation count of AI patents issued in the same year-quarter within the same CPC subclass (e.g., Kogan et al., 2017; Bloom et al., 2021; Lerner and Seru, 2022). The final sample used to construct occupational AI exposure contains 9,270 AI patents. Table 1 Panel B lists the number of AI patents every year in our sample and their average count of adjusted citations.

The textual information from the title and abstract of each AI patent allows us to extract information about the scope and content of the underlying innovations from text corpora. This information is then matched to occupations to assess the latter's exposure to AI.

3.3. Occupation data

The second step in completing the measurement involves retrieving job tasks from the Occupational Information Network (O*NET) database maintained by the US Department of Labor. O*NET outlines specific tasks performed in individual occupations identified by an 8-digit Standard Occupational Classification (SOC) code and annotated with descriptions of the occupation's job tasks.[11] For example, tasks associated with the occupation "data scientists" (SOC 15-2051.00) in 2023 entail "analyze, manipulate, or process large sets of data using statistical software," "create graphs, charts, or other visualizations to convey the results of data analysis using specialized software," and "propose solutions in engineering, the sciences, and other fields using mathematical theories and techniques."

[11] The O*NET database has been explored by studies in labor economics (e.g., Howell and Wolff, 1991; Autor and Dorn, 2013; Deming, 2017) and finance (e.g., Bates et al., 2024; Ma et al., 2016; Jiang et al., Forthcoming).

To track the evolution of job tasks, we leverage the historical releases of O*NET databases to create an annual panel of occupations spanning from 2000 to 2023.[12] Every year, the O*NET sample includes 900–1,100 occupations identified by the 8-digit SOC codes with job task information.

3.4. Supplemental data on employment: LinkedIn and Glassdoor

Two databases provide supplemental information on employment, workload, and compensation at the individual level, which is aggregated to the occupation × firm level. First, LinkedIn data from Revelio Lab contains information about education and employment at the user profile level in a structured resume-like format. The structure allows us to aggregate information at both the occupation and employer levels. With individuals' employment history updated through the end of 2023, we construct panels at the occupation × firm × year level, facilitating inference on the relationship between time allocation and firm outcomes.

Glassdoor, through Revelio Lab, provides extensive information about pay, workload, and employee reviews of their jobs and employers for nearly all major companies. Each employee review contains review text, the employee's ratings on several aspects of the firm, including overall satisfaction and work-life-balance (WLB), and information about the reviewer, such as her job title, tenure, employment status, and location.[13] Glassdoor also groups occupations into seven types: sales, finance, operation, marketing, administrative, scientist, and engineer. Following prior research (Green et al., 2019; Gornall et al., 2024), we retain only U.S.-based current employees, resulting in a final sample of 1,405,965 reviews across 4,334 firms.

Panel C reports the summary statistics of the job rating sample at the job type × firm level. The average overall job rating is 3.41, and the WLB rating is similar at 3.40. Total compensation averages \$108,300 (SD = \$51,710), with a median of \$99,060. Employment at the firm × job type level exhibits substantial dispersion, with a mean of 511.8 and a standard

[12] We describe the procedures and the O*NET data release we use to construct the annual panel of occupations' job tasks in Section B.1 in the online appendix.

[13] Prior studies have validated that the Glassdoor review data provide valuable insights into firm performance and broadly reflect the labor market, though they tend to overrepresent skilled occupations (e.g., Edmans, 2011; Green et al., 2019; Gornall et al., 2024).

deviation of 709.66.

3.5. Other data

The 2023 Best States to Work Index (BSWI) is obtained from Oxfam, a global organization dedicated to addressing poverty, inequality, and social injustice across more than 75 countries with over 80 years of experience. BSWI is constructed based on state policies in three dimensions: wages (40% of overall score); worker protections (35% of overall score); and rights to organize (25% of overall score).[14]

Finally, for a subset of analyses where we analyze firm performance, the sample firms are restricted to U.S. publicly listed firms with information retrieved from Compustat, CRSP, and related WRDS databases.

3.6. Measuring occupational AI exposure over time

3.6.1. Measuring AI exposure at the occupation-patent level

An accurate measure of occupational exposure to AI technology is essential for attributing changes in time allocation to AI. There have been a variety of exposure measures to a diverse set of technologies or innovations, e.g., AI exposure developed by Felten et al. (2018) and Webb (2019), generative AI exposure from Eisfeldt et al. (2023) and Hartley et al. (2024), software and robot exposure developed by Webb (2019), fintech exposure from Jiang et al. (Forthcoming), labor-saving and labor-augmenting technology exposure from Kogan et al. (2023). These measures typically analyze the micro-foundations of tasks and aggregate each task's exposure to the occupational level, using either equal weights or task importance. Ideally, the exposure measure captures both cross-sectional differences across occupations and time-series variations in AI exposure within each occupation.

Following Webb (2019) and Jiang et al. (Forthcoming), we develop the AI exposure measure by comparing the text of AI patents and the text of job descriptions. A potential approach,

[14] Data available at https://www.oxfamamerica.org/explore/issues/economic-justice/workers-rights/best-states-to-work/.

such as word embeddings, measures the overlap between two textual sources by calculating their cosine similarity (e.g., Hoberg and Phillips, 2016; Webb, 2019). However, we follow the recent trend in the literature (e.g., Lopez-Lira and Tang, 2023; Jha et al., 2024; Kim and Nikolaev, 2024) that leverages large language models, such as ChatGPT, to analyze unstructured textual data. ChatGPT, with its ability to process questions and generate natural language responses, offers several benefits over traditional methods. These benefits include greater flexibility in the expression of tasks, better understanding of the context, and more detailed language interpretations (de Kok, 2025). Specifically, we prompt ChatGPT to compare the textual description of a bundle of job tasks of an occupation to that of an AI patent. Section B.3.1 of the Online Appendix provides more details on the ChatGPT prompt setup, examples, and validation.

Our sample contains 9,270 AI patents from 2000 to 2023 and an average of 950 occupations, identified with the 8-digit SOC code, in a given year. In total, ChatGPT encodes 8.71 million pairs at the occupation (o) $\times$ patent (i) level, yielding the following two variables. The first one is an AI exposure score ($AI_{o,i}^{EXP}$), which presents a similarity score (ranging from 1 to 10) between the text description of an AI patent i and the bundled job tasks of occupation o. The average similarity score is 3.7. The second one is a complementarity classification ($AI_{o,i}^{COMP}$) following procedures of Kogan et al. (2023) and Jiang et al. (Forthcoming). It is a categorical variable (1 = complement, 0 = neutral, and -1 = substitute) that indicates whether a given AI patent primarily complements, substitutes, or is neutral to the tasks of an occupation. Among all occupation-patent pairs, 77.4% exhibit a complementary relationship, 19.4% show a substitute relationship, and 3.2% are natural. This proportion is almost identical to Kogan et al. (2023)'s finding that approximately 19.7% of the job tasks are susceptible to AI substitution.

3.6.2. Aggregating AI exposure to the occupation-year level

To measure the aggregate impact of a cluster of AI innovations on a given occupation's tasks, we sum up the individual impact of AI patents in a given period. That is, the annual AI exposure of a given occupation o in a year t, $AI_{o,t}^{EXP}$, is the sum of the exposure of occupation o to all AI patents i published during the 5-year period leading to year t as follows:

$$AI_{o,t}^{EXP} = \sum_{i \in I_t} AI_{o,i}^{EXP}, \tag{1}$$

where I_t represents the set of all AI patents i published between year $t-4$ and year t.

Three related AI exposure measures at the occupation level in the existing literature are from Webb (2019), Felten et al. (2019) and Hampole et al. (2025). Webb (2019) applies natural language processing algorithms to measure the overlap between text descriptions of job tasks and patents. Felten et al. (2019)'s AI exposure measure builds on the crowdsourced assessments between 1,800 respondents from Amazon's Mechanical Turk (mTurk) web service and the Frontier Foundation (EFF) AI Progress Measurement dataset AI across nine AI applications (such as speech recognition and image generation) from 2010 to 2015.

There are two main differences between our measure and the two earlier ones: First, both previous measures are time-invariant and are based on information at the end of their respective sample periods. Second, due to their research focus and the sample periods (mid- to late- 2010s), the AI technology in those contexts was mostly restricted to machine learning algorithms, and covers six of the eight AI technologies used in our sample. In comparison, Hampole et al. (2025) construct AI exposure measures at the occupation-firm level by identifying firms' adoption of AI applications from resumes and job postings provided by Revelio during the 2010 to 2023 period. This approach offers a more firm-specific perspective on AI exposure, though it is limited to occupation codes available in Revelio. While the O*NET database encompasses approximately 800 occupations at the SOC 6-digit level, Revelio assigns resumes to 335 SOC 6-digit codes.

A key limitation of our AI exposure measure, along with other technology exposure measures in the literature, is that textual similarity-based measures are non-directional – they are unable to distinguish between substitutive and complementary effects embedded in the exposure.[15] To decompose the substitutive and complementary effects of AI exposure, we construct an AI net complementarity exposure following the approach used for fintech complementarity in Jiang et al. (Forthcoming). Specifically, for a given SOC 8-digit occupation o in a year t, AI net complementarity ($AI_{o,t}^{COMP}$) is defined as the sum of the product of AI exposure and AI complementarity classification of occupation o with respect to AI patents i published during the five-year period ending in year t, as shown in the following equation:

$$AI_{o,t}^{COMP} = \sum_{i \in I_t} AI_{o,i}^{EXP} \cdot AI_{o,i}^{COMP} \tag{2}$$

To ensure that the values of AI exposure measures remain within a range below 10, we divide both $AI_{o,t}^{EXP}$ and $AI_{o,t}^{COMP}$ by 10,000.

3.6.3. Matching occupation-level AI exposure to the ATUS respondents

The ATUS data employs Census occupation classification codes, so we aggregate our AI exposure measures, derived from SOC 8-digit occupation codes, to the corresponding level for alignment with the ATUS data. Specifically, the occupation classification, "occ1990dd" developed by Dorn (2009), is utilized to aggregate the Census occupation codes to a balanced panel of occupations, which also serves as the occupational unit in the regressions.[16]

After aggregating $AI_{o,t}^{EXP}$ and $AI_{o,t}^{COMP}$ from the SOC 8-digit occupation to the SOC 6-digit occupation level, we merge the results with the "occ1990dd" occupation codes, using equal weights at each aggregation step.[17] Next, the raw scores of AI exposure measures are transformed into percentile ranks following the literature (e.g., Autor and Dorn, 2013; Webb,

[15] In papers focusing on the labor displacement effect of AI, e.g., Hampole et al. (2025), posit that the semantic similarity between AI applications and job tasks implies a disruptive or substitutive effect.

[16] The "occ1990dd" classification system has been widely employed in labor economics studies (e.g., Autor and Dorn, 2009, 2013; Webb, 2019). We aggregate the Census occupations codes to "occ1990dd" codes using crosswalks obtained from: https://www.ddorn.net/data.htm.

[17] We match the SOC 6-digit occupation codes to occ1990dd in three steps: (i) we first match the SOC 2000 code and SOC 2018 code to the SOC 2010 codes using the crosswalks provided by BLS at https://www.bls.gov/soc/soc_2000_to_2010_crosswalk.xls and https://www.bls.gov/soc/2018/soc_2010_to_2018_crosswalk.xlsx; (ii) We then use the crosswalk provided by Webb (2019) to map the SOC 2010 codes to the 2010 Census occupation codes; (iii) lastly, the 2010 Census occupation codes is matched to "occ1990dd" codes using the crosswalk provided by Autor (2015) at https://www.ddorn.net/data.htm.

2019). Specifically, for each year, we sort occupations based on their $AI_{o,t}^{EXP}$ or $AI_{o,t}^{COMP}$ and assign them a percentile rank ranging from 1 to 100.

For the interest of the readers, Table OA.2 of the Online Appendix lists top occupations grouped by AI exposure and AI net complementarity in 2023. On the top of the list of both $AI_{o,t}^{EXP}$ and $AI_{o,t}^{COMP}$ are computer and information system managers, bioinformatics technicians, operations research analysts and management analysts. Occupations with high $AI_{o,t}^{EXP}$ but low $AI_{o,t}^{COMP}$ include data entry keyers, tellers, and office machine operators, while those at the bottom – such as dancers, barbers, and meat packers – rank low in both dimensions.

Panel A of Figure 1 shows the time series of the raw scores of two AI exposure variables, $AI_{o,t}^{EXP}$ and $AI_{o,t}^{COMP}$ that summarize the occupations of the individuals in the ATUS survey from 2004 to 2023. Predictions of the average AI exposure measures are estimated using quadratic regressions weighted by ATUS weights.

[Insert Figure 1 here.]

Table 1 Panel A reports the summary statistics of the occupational AI exposure measures of ATUS respondents. The average $AI_{o,t}^{EXP}$ score is 0.66, while that of $AI_{o,t}^{COMP}$ is 0.47, indicating that AI innovations tend to have a more substantial complementary effect than a substitute effect on the labor market.

3.6.4. Validation of occupation-level AI exposure measures

To validate the occupation-level AI exposure score ($AI_{o,t}^{EXP}$) built with ChatGPT, we compare it to a measure calculated as the Term-Frequency-Inverse Document Frequency cosine similarity (TF-IDF) for a subset of patent-occupation pairs based on the 50 most influential AI patents from each year.[18] $AI_{o,t}^{EXP}$ scores show a correlation of 0.83 with the TF-IDF measure at the "occ1990dd" occupation $\times$ year level, demonstrating a strong alignment between the two measures and confirming the robustness of the GPT-derived measure.

[18] Section B.2.3 of the Online Appendix describes the TF-IDF textual analysis procedures.

The TF-IDF measure is not directional and therefore is not as effective in validating our measure of AI net complementarity exposure ($AI_{o,t}^{COMP}$). To address this issue, we compare $AI_{o,t}^{COMP}$ to the predicted wage growth attributed to AI complementarity and substitution estimated by Kogan et al. (2023).[19] In 2023, $AI_{o,t}^{COMP}$ exhibits a correlation of 0.60 with the overall wage growth related to AI. Breaking down the wage growth, $AI_{o,t}^{COMP}$ has correlations of -0.59 and 0.47 with the wage growth attributed to AI substitution and complementary components, respectively. Taken together, this evidence validates the reliability of our AI net complementarity measure.

3.6.5. Comparison with other occupation-level exposure measures

A growing literature has estimated and analyzed occupation exposure to a variety of technologies and innovations including AI. It is thus necessary to compare and distinguish AI exposure from the other exposure measures. Figure OA.1 of Online Appendix plots the AI exposure used in this study against six related occupational exposure measures: AI exposure developed by Felten et al. (2019), AI exposure and robot exposure developed by Webb (2019), routine task intensity (RTI) provided by Autor and Dorn (2013), offshorability exposure developed by Firpo et al. (2011) and standardized by Autor and Dorn (2013), and work-from-home (WFH) feasibility score provided by Dingel and Neiman (2020).

The first two panels of Figure OA.1 show a positive correlation between our AI exposure measure constructed using all AI patent filings from 2000 to 2023 and measures by Webb (2019) and Felten et al. (2019). Further, AI exposure is negatively correlated with routine-task intensity and a positive correlation with offshoring potentials and WFH feasibility.

[19] Using an open question-based approach, Kogan et al. (2023) ask ChatGPT about AI's potential to substitute or complement job tasks and yields time-invariant measures of different AI exposure components. They do not report the exposure but provide AI-related earnings changes of occupations with the highest complementarity (substitution) exposure in Online Appendix. Section B.2.4 of the Online Appendix provides more details about the validation procedures.

4. AI and Workday: Empirical Analyses

4.1. Event study: ChatGPT

The release of generative AI tools, notably ChatGPT in November 2022, marked a watershed moment for AI adoption in the workplace. Its immediate accessibility and versatility accelerated AI integration across industries and transformed business processes almost overnight. According to McKinsey (2024), 33% of respondents' organizations adopt generative AI right away in 2023 and that number increases to 65% in 2024.[20] The advent of generative AI was a transformative event—rather than a gradual progression—whose precise timing was unforeseen by its adopters. Such properties make it an ideal setting to study the impact of AI on workday.

The event study entails a difference-in-difference specification approach around the shock with time allocation variables from the ATUS data as dependent variables. The test sample covers 2022 to 2023, a relatively short range striding ChatGPT to capture the discrete change. The hypothesis is that the impact of AI adoption on work hours should be more prominent among occupations with greater sensitivity to generative AI. That is, the level of "treatment" is captured by the generative AI exposure of the occupation to which a worker is affiliated. The exposure construction follows Eisfeldt et al. (2023) who use a large language model to classify whether job tasks of occupations can be performed more effectively using ChatGPT based on task descriptions.[21] The regression, at the survey respondent level, with subscripts of i (individual), o (occupation), and t (year) level, is as follows:

$$Y_{i,o,t} = \beta_1 \cdot GenAI_o^{EXP} \cdot POST_t + \beta_2 \cdot X_{i,t} + \alpha + \epsilon_{i,o,t}. \tag{3}$$

The dependent variable is the number of weekly hours spent in a category (i.e., market work or leisure) of activities. $GenAI_o^{EXP}$ is generative AI exposure of the occupation in percentile

[20] https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai

[21] Section B.3 of the Online Appendix provides more details. Table OA.3 of the Online Appendix lists top occupations grouped by generative AI exposure measures.

rank. The $POST_t$ dummy equals one for the year 2023. The regression incorporates a set of individual-level controls including age, the number of children below 18, and a set of indicators for gender, educational attainment, marital status, and race. The regression further includes a battery of fixed effects, α, at the following levels: occupation, state $\times$ year, industry $\times$ year, year-month, and day-of-week.[22] These fixed effects filter out macro economic factors at both the industry and state levels, as well as seasonality and weekday effects. Following general practice in this literature (e.g., Aguiar et al., 2021), the linear regression is weighted by ATUS sample weights in order to recover the representativeness of the population. Standard errors are double clustered at the occupation and state level.

Table 2 reports the weighted linear regression results for equation (3) using ATUS data from 2022 to 2023. Column (1) reports the results for the full sample. Specifically, workers more exposed to generative AI experienced significantly increased work hours (Panel A) and reduced leisure hours (Panel B) following the introduction of ChatGPT. A one-percentile rank increase in generative AI exposure is associated with an increase of 0.063 hours in weekly work time and a decrease of 0.064 hours in leisure time following the introduction of ChatGPT. Consequently, comparing 2023 to 2022, an interquartile increase in generative AI exposure corresponds to an additional 3.15 hours (0.063×50 percentiles from the 25th to the 50th) of work and a reduction of 3.20 hours in leisure. Columns (2) and (3) present the results for subsamples divided into the top quartile and the remaining observations based on the extent to which generative AI complements the job tasks (see definition in Section B.3 of the Online Appendix). The magnitude of the top 25% is more than twice that of the rest, although the difference is not significant. Columns (4) and (5) present results for subsamples divided into the top quartile and the remaining observations based on local AI awareness, measured by state-level Google search trends for ChatGPT from November 30 to December 31, 2022.[23] Workers in regions within the top quartile of AI awareness demonstrate greater

[22]Industry is defined by the Census detailed industry code "trdtind1" used in ATUS (Refer to Appendix A of the ATUS Data dictionary at https://www.bls.gov/tus/dictionaries/atusintcodebk23.pdf). It identifies 51 unique industries.

[23]Figure OA.2 of the Online Appendix plots the Google search trend of AI and ChatGPT from 2010 to 2023, suggesting a peak in Google search of "ChatGPT" and "AI" in December 2022 following the release of

sensitivity in the relationship between generative AI exposure and work (or leisure) hours than the remaining observations, and the differences are significant at the 10% level.

[Insert Table 2 here.]

4.2. Occupation AI exposure and work time

Next we extend the event study to the full sample period based on measured occupational AI exposure (see Section 3.6 for more details). Figure 2 provides a diagnostic test. The figure illustrates the distributional effects of occupational AI exposure on the work-life balance in our sample, comparing 2004 and 2023. As AI exposure percentile ranks increase, individuals experience longer working hours (Panel A) and shorter leisure hours (Panel B), with this gap becoming more pronounced in 2023.

[Insert Figure 2 here.]

More formally, we estimate the relationship between occupational AI shocks and work time at the individual (i) respondent level, indexed by occupation (o) and year (t)s:

$$Y_{i,o,t} = \beta_1 \cdot AI^{EXP}_{o,t-1} + \beta_2 \cdot X_{i,t} + \epsilon_{i,o,t}. \tag{4}$$

where the dependent variables are weekly hours spent on market work and leisure. The key independent variable, $AI^{EXP}_{o,t-1}$, is the lagged occupational AI exposure, constructed as detailed in Section 3.6. Following general practice in the literature (e.g., Autor and Dorn, 2013; Webb, 2019), the raw exposure scores are transformed to percentile ranks in each year. The model specification incorporates additional covariates representing individual-level characteristics, including age, the number of children below 18, and a set of indicators for gender, educational attainment, marital status, and race. Fixed effects at the following levels are also included: occupation, state × year, industry × year, year-month, and day-of-week variations.

ChatGPT.

Following standard practice in the literature (e.g., Aguiar et al., 2021) to recover the population representativeness of the sample, the linear regression is weighted by ATUS sample weights. Unless otherwise stated, all potentially unbounded variables are winsorized at the 1% extremes. Standard errors are double-clustered by occupation and state.

Table 3 reports the weighted linear regression results for Equation (4) using ATUS data from 2004 to 2023. Columns (1)–(3) present the results for weekly work hours. We find that greater occupational AI exposure is associated with an increase in work hours. Specifically, in column (1) where all fixed effects are included except the occupation fixed effects, a one-percentile rank increase in occupational AI exposure is associated with an increase of 0.044 hours in weekly work time. Accordingly, an interquartile shift of one's occupational AI exposure percentile rank would increase her work hours by 2.20 per week on average. The cross-sectional relationship is both economically and statistically significant (at the 1% level). To alleviate concerns regarding cross-sectional relation potentially driven by confounding factors, the regression in column (2) further controls for other common occupation exposure measures in the literature, including robot exposure from Webb (2019), routine task index (RTI) from Autor and Dorn (2013), and offshorability exposure constructed by Firpo et al. (2011) and standardized by Autor and Dorn (2013), all in percentile ranks. The direction and magnitude of the coefficient for occupational AI exposure remains consistent (0.034, significant at the 1% level). To further mitigate the concern that the relation between AI exposure and time allocation could be driven by occupation-level unobserved heterogeneity, column (3) incorporates occupation fixed effects. The direction of the coefficient for occupational AI exposure remains consistent, albeit at a smaller magnitude (0.018, significant at the 10% level).

[Insert Table 3 here.]

Columns (4)–(6) of Table 3 present the results for weekly leisure hours. We find that leisure hours decrease as occupational AI exposure increases. Specifically, column (4) indicates that a one-percentile rank increase in occupational AI exposure is associated with a decrease of

0.033 hours in weekly leisure time (significant at the 1% level). Consequently, an interquartile increase of one's occupational AI exposure percentile rank would reduce her leisure hours by 1.65 per week on average. Such a negative impact of occupational AI exposure on leisure hours remains consistent with additional occupational exposure measures including robot exposure, RTI, and offshorability score, and standardized and represented in percentile ranks (column (5)) and with occupation fixed effects (column (6)). Combined results suggest that time allocation to the residual category (which includes personal care, education, etc.) slightly decreases.

Table OA.4 of the Online Appendix reports the results of a series of robustness tests using alternative specifications. In column (1), the dependent variable of market work hours includes time spent on commute, work-related travels, and social and leisure activities at work. Columns (2)–(3) incorporate an additional indicator for part-time workers. Columns (4)–(5) do not control for race indicators. Columns (6) through (13) analyze a variety of subsamples. Specifically, columns (6)–(7) exclude currently unemployed individuals. Columns (8)–(9) exclude those who are surveyed on weekends. Columns (10)–(11) exclude workers in absence, those who are currently employed but are absent from work on the survey date. Finally, columns (12)–(13) only include workers who are compensated on an hourly basis (with greater flexibility in adjusting their work hours). Across all alternative specifications, the key coefficients for the impact of occupational AI exposure on work and leisure hours are significant and consistent with Table 3, confirming robustness.

Table OA.5 in the Online Appendix examines the effect of occupational AI exposure on different types of leisure activities, distinguishing between those that involve a digital screen and those that do not. For example, screen-based leisure activities include recreational computer use, gaming, watching TV, etc., while non-screen-based leisure activities encompass listening to music, reading, sports, traveling, etc. Columns (1) and (2) indicate that the previously documented decline in total leisure time is primarily driven by a reduction in non-screen-based activities, whereas time spent on screen-based leisure remains unaffected by occupational AI exposure. Columns (3) to (6) further disaggregate non-screen-based activities into recreation (e.g., relaxing, listening to music, traveling), socializing, leisure components of eating, sleeping, and personal care (ESP), and other activities (e.g., hobbies, reading, sports). The results suggest that the decline in non-screen leisure can be attributed primarily to reductions in solitary activities, particularly recreation and the leisure aspects of ESP.

Finally, we investigate how occupational AI exposure influences time allocation in activities other than work or leisure. Table OA.6 in the Online Appendix summarizes the findings. Specifically, time spent on civic activities significantly increases as AI exposure increases, while time allocated to education and own medical care also decreases, albeit insignificantly. Hence, AI does not contribute to the secular decline in devotion to social work and community engagement, a phenomenon known as "bowling alone."[24] In contrast, the coefficients of home production and childcare are not statistically significant. In other words, when work hours increase, workers tend to cut back on personal activities - such as leisure, education, and self medical care - while maintaining their family responsibilities.

4.3. Testing model predictions

4.3.1. Marginal productivity: AI complementarity vs. substitution and wage effect

A. Workday with technology complementarity

Technology can influence labor in two primary ways: substitution, where it replaces job tasks, and complementarity, where advancements in capital—such as improved tools—enhance workers' marginal productivity (e.g., Acemoglu, 1998; Acemoglu and David, 2011; Acemoglu and Restrepo, 2019). Thus, the overall effect shown in 3 invites a bifurcation. To decompose general AI exposure, we use ChatGPT to classify each AI patent as complementary, substitutive, or neutral to the tasks of an occupation based on its textual descriptions. The AI net complementarity exposure at the occupation level, $AI_{o,t}^{COMP}$, is defined as the difference between exposure to complementary and substitutive AI patents over the past five years, transformed

[24] The term was coined by the book *Bowling Alone: The Collapse and Revival of American Community* (2000) by Robert D. Putnam.

to percentile ranks by year. That is, we rank occupations by their net complementarity scores to AI technology (with low complementarity indicating a strong substitution effect). Further details on this variable can be found in Section 3.6.

Table 4 presents the weighted linear regression results for the impact of AI net complementarity exposure based on Equation (4), replacing $AI^{EXP}_{o,t-1}$ with $AI^{COMP}_{o,t-1}$. The dependent variables are weekly work hours in columns (1)–(4) and weekly leisure hours in columns (5)–(8). Column (1) shows that, controlling for fixed effects at the levels of state $\times$ year, industry $\times$ year, year-month and day-of-week, a one-percentile rank increase in AI net complementarity is associated with an increase of 0.055 hours in weekly work time (significant at the 1% level). That is, an interquartile increase in AI net complementarity is associated with an additional 2.75 work hours per week, equivalent to 7.89% of the sample mean (34.9 hours). Such a positive relationship between AI net complementarity exposure and work hours remains consistent when additional occupational exposure measures, including robot exposure, RTI, and offshorability, are included (column (2)) with occupation fixed effects (column (3), significant at the 5% level), and additionally controlled for the general AI exposure orthogonalized from AI complementarity (column (4), significant at the 10% level).

[Insert Table 4 here.]

On the leisure side, a higher AI net complementarity exposure is associated with significantly shorter leisure hours. Column (4) shows that a one-percentile rank increase in AI net complementarity is associated with a reduction of 0.043 hours in weekly leisure time (significant at the 1% level). The negative relationship remains consistent when additional controls and/or refined fixed effects as those in the "Work" regressions in the same table.

Overall, the magnitude and significance of the coefficients on $AI^{COMP}_{o,t-1}$ are greater than those of $AI^{EXP}_{o,t-1}$ presented in Table 3. Moreover, AI exposure that is not related to complementarity has no impact on time allocation. The combined evidence suggests that the documented extended workday results from AI's complementarity to human work. In other words, people end up having longer workdays precisely when AI makes them more productive (and presumably saves them time on given tasks). The seeming paradox echoes Jevons (1865), which predicted that improvements in engine technology—and hence energy efficiency—would lead to increased demand for and consumption of energy (coal at the time). Labor is another factor of production that could apply the logic: When task productivity improves, the demand for additional tasks increases, along with heightened expectations for both quality and expediency, fostering a culture of "always-on" and "ever-better."

B. Wage effect

We further explore the complementary or substitution effects of AI technologies on workers through wage. If AI exposure improves worker productivity, wages should increase (holding market competition constant). Conversely, if AI exposure leads to a substitution effect that reduces wages, exposed workers may be compelled to work more in order to maintain their total earnings. We test these two competing hypotheses by re-estimating Equation (4) using wages from the ATUS as the dependent variable.

Table 5 presents the results. The dependent variable is wage measured as 100 times the natural logarithm of hourly wages in 2023 constant dollars. The main explanatory variable is occupational AI exposure in columns (1)–(3) and AI net complementarity in columns (4)–(6). Consistent with prior studies built on time-invariant AI exposure measures (e.g., Felten et al., 2019; Kogan et al., 2023), we find that greater AI exposure is associated with increased wages. Specifically, in column (1), a one-percentile increase in AI exposure is associated with an increase of hourly wages by 0.25%, significant at the 1% level. The positive relationship remains consistent with specifications using additional occupational exposure measures (column 2), albeit with smaller magnitude and significance, even with occupation fixed effects (column 3, significant at the 10% level). Also, a one-percentile increase in AI net complementarity increases hourly wages by 0.35%, significant at the 1% level (column (4)). The positive relationship remains consistent with specifications using additional occupational exposure measures (column (5)) and occupation fixed effects (column (6), significant at the 5% level). Overall, the wage analysis suggests that working individuals, on average, experience positive financial gains from the complementarity of AI technology in their work.

[Insert Table 5 here.]

4.3.2. Performance monitoring: AI surveillance

Computerized workplace surveillance emerged in the 1980s (U.S. Congress, Office of Technology Assessment, 1987) and saw an unprecedented acceleration in 2020, driven by the shift to remote and hybrid work necessitated by COVID-19.[25] Advancements in technology related to datafication, sensorization, and computer vision, along with supporting infrastructure such as cybersecurity, enable employers to obtain increasingly accurate measures of real effort, with less contamination from noise in performance metrics. Such improvements, in the framework of a principal-agent model, are expected to elicit greater effort from workers.

The 2020 COVID shock provides a pivotal moment to examine the effect of monitoring on the workday using ATUS data from 2015 to 2023. Since remote work, outside of the strictest lockdown periods, may be an endogenous choice, we screen the sample based on ex-ante work-from-home (WFH) feasibility, as developed by Dingel and Neiman (2020), using job characteristics *pre-pandemic*. For this study, remote workers are classified as those in the 65 occupations that do not require essential in-person duties, defined as having a WFH score of one in Dingel and Neiman (2020).

Among the individuals belonging to occupations that can, ex ante, accommodate remote work, their reception to the AI surveillance technology shock in 2020 depends on the occupations' exposure to the new technology. Such an exposure could be constructed analogous to our main AI exposure measures. More specifically, we prompt ChatGPT to assess how AI surveillance technology enhances monitoring for each of the 65 occupations based on the six key dimensions in organizational control – restricting, recommending, recording, rating, replacing, and rewarding following (Kellogg et al., 2020).[26] With the resulting exposure mea-

[25] https://www.wsj.com/articles/youre-working-from-home-but-your-company-is-still-watching-you-11587202201?mod=Searchresults_pos20&page=1.

[26] Section B.4 of the Online Appendix describes the detailed procedures for measuring AI surveillance exposure of all occupations. Table OA.7 of the Online Appendix lists top occupations grouped by AI surveillance exposure.

sure, AI_o^{SUR}, and resorting to the event year of 2020, we are able to conduct the following difference-in-difference estimation on observations indexed by individual (i), occupation (o), and year (t):

$$Y_{i,o,t} = \beta_1 \cdot AI_o^{SUR} \cdot Post_t + \beta_2 \cdot X_{i,t} + \alpha + \epsilon_{i,o,t}. \tag{5}$$

The dependent variable is the number of weekly hours allocated to a specific activity category, such as market work or leisure. The regression includes the same set of individual-level controls as in our baseline regressions, along with a rich set of fixed effects. Since performance monitoring is a defining feature of a principal-agent setup and becomes moot in the absence of delegation, this hypothesis naturally lends itself to a placebo test: While AI surveillance technology is expected to elicit greater worker effort in equilibrium, the effect should be null for the self-employed.

Table 6 presents the weighted linear regression results for equation (5). Columns (1)–(2) report results for work hours, while columns (3)–(4) correspond to leisure hours. Additionally, the odd-numbered columns represent the sample of employees, whereas the even-numbered columns capture the self-employed (who comprise approximately 6.67% of respondents). For individuals employed by a "principal," a one-percentile increase in AI surveillance exposure is associated with a 0.043-hour increase in weekly work hours post-2020 relative to their own past level (significant at the 5% level), which translates to 2.15 additional hours in a workweek for an inter-quartile variation. In contrast, the self-employed—who act as their own "agents"—confirm a placebo effect, both economically and statistically.

[Insert Table 6 here.]

4.3.3. Reservation utility: Employee welfare and market competition

A. Employee welfare: Evidence from Glassdoor reviews

The relationship between technology-enabled productivity gains and workday length can also operate through the impact of these gains on workers' reservation utility, as agents reoptimize the allocation between work (and consequently, consumption) and leisure to adjust to a new welfare level determined within a competitive marketplace. At this new equilibrium, the effect of productivity gains—even when accompanied by higher compensation—on worker welfare remains a priori ambiguous, as factors such as self-motivation, fulfillment, and work-life balance play a critical role in shaping overall job satisfaction. To evaluate this relationship within the context of AI exposure, we leverage employee reviews from Glassdoor (via Revelio, as detailed in Section 3). Our analysis focuses on two key metrics: overall job satisfaction and Work-Life Balance (WLB) ratings for both public and private firms. These metrics are measured at the job type (k) $\times$ firm (i) $\times$ year (t) level, with both rating scales ranging from one (worst) to five (best).

The main explanatory variable, lagged AI exposure at the job type $\times$ firm level, is constructed in two steps. First, occupational AI exposure is aggregated to the job type $\times$ firm level, using employment weights from Linkedin. Second, a three-year moving average is applied to the job type AI exposure to account for the gradual adaptation to labor market disruptions (Jiang et al., Forthcoming). All specifications control for employment (natural logarithm), firm $\times$ job type fixed effects, and job type $\times$ year fixed effects.

Table 7 shows that greater AI exposure is associated with lower employee satisfaction, aligning with occupation-level evidence that AI exposure overall leads to extended work hours and decreased leisure time, despite the fact that wage increases with productivity and work hours. Based on the coefficients in column (1) and (4), an inter-quartile increases in a firm's general AI exposure and AI net complementarity exposure are associated with 4.3 and 3.8 basis point reduction in employees' overall satisfaction rating, respectively (relative to the average rating of 3.40). A qualitatively similar but more statistically significant relationship (at the 5% level) is observed for the work-life balance (WLB) rating. An inter-quartile increase in a firm's general AI exposure corresponds to a 5.6 basis point decrease in the WLB rating (relative to the average rating of 3.41).

[Insert Table 7 here.]

The negative association strengthens to 6.9 basis points when AI complementarity exposure serves as the main explanatory variable. Additionally, in column (3) and (6), the same inter-quartile increase is associated with a 2.2 and 5.5 basis point rise in average annual compensation, respectively, consistent with our previous findings at the occupation level. While these effects may appear modest in isolation, the clear lack of worker welfare improvement from AI is, in itself, a disappointment, particularly given that these technologies are intended to better serve humanity.

B. Worker bargaining power: Labor market competition

Whether reservation utility increases depends on the bargaining power of the agent (worker) relative to the principal (employer). In an uncompetitive labor market, workers will capture a larger share of the surplus generated by AI-enhanced productivity. The income effect, driven by an increase in reservation utility, leads workers to work less—relative to the level justified by increased productivity alone. Therefore, the effect documented in Table 3 and Table 4 is expected to be weaker in a less competitive labor market.

The labor economics literature readily supplies two proxies for labor market competition, which is the inverse of the bargaining power of employers relative to workers. The first is the labor market concentration at the state level, based on the argument that labor market concentration is a good proxy for firms' monopsony power in labor markets (e.g. Azar et al., 2020, 2022; Benmelech et al., 2022; Rinz, 2022). Building on this literature, the labor market concentration in this study is measured using the Herfindahl-Hirschman Index (HHI) calculated as the sum of the squared employment shares of public firms headquartered in the same state based on Compustat data. Higher HHI indicates greater labor market concentration, which is positively associated with firms' pricing power in the labor market. The second is the 2023 Best States to Work Index (BSWI) provided by Oxfam which assesses the labor-friendliness of state policies. Accordingly, we utilize the two proxies to examine the heterogeneity impact of AI net complementarity on work and leisure hours. The proxy for higher bargaining power of workers relative to firms, *I(Worker Power vs. Firm)*, equals one if the lagged labor market HHI is in the bottom quartile or the BSWI is in the top quartile, and zero otherwise. We then interact each of these two indicators with the AI net complementarity measure.

Table 8 reports weighted linear regression results for the heterogeneity effect of AI net complementarity on work and leisure hours by labor market competition. For both indicators for labor market competition, lower labor market competition (higher bargaining power on the labor side) is associated with a smaller increase in work hours and a smaller decrease in leisure hours relative to the level of AI net complementarity. Specifically, at a given level of AI net complementarity, a worker in the bottom quartile of labor market concentration or the top quartile of BSWI experiences 0.024 and 0.014 (column (1) and (column (3)) fewer work hours per week (both significant at the 5% level), respectively. Notably, in more labor friendly states, as measured by labor market concentration or BSWI index, the positive relationship between AI net complementarity and work hours is weakened by more than 50%. Moreover, at a given level of AI net complementarity, a worker in the bottom quartile of labor market concentration or the top quartile of BSWI increases leisure hours by 0.011 and 0.09 (column (3) and (4)) per week (both significant at the 5% level), respectively, given a level of AI net complementarity. Taken together, the results suggest that the positive (negative) relationship between AI net complementarity and work (leisure) hours attenuates with greater bargaining power of employees.

[Insert Table 8 here.]

C. Producer bargaining power: Product market competition

Parallel to labor market competition, a firm's product market power determines how productive surplus is split between firms and the consumer of their products or services. The more pricing power of firms relative to consumers, the more surplus eventually accrues to labor as there is more to split with their employers. The level of surplus distributed to labors is expected to mitigate the impact of AI net complementarity on a worker's work and leisure hours due to the income effects. Accordingly, we examine the degree to which product market power of firms relative to consumers influences the relationship between AI net complementarity and work and leisure hours. We adopt two measures for product market power, provided by Hoberg and Phillips (2016). One is firm-level product similarity that assesses how closely a firm's product descriptions in its 10-K filings match those of industry peers. The other is the firm-level HHI, defined as the sum of the squared market shares of firms in the same 10-K text-based industry using Compustat sales data. Higher HHI indicates greater market concentration, which is positively associated with firms' pricing power, while higher product similarity suggests a higher level of competition, thus, negatively impacting firms' pricing power (Hoberg and Phillips, 2016).

To measure the product market power of firms in a given market, we calculate the average of product similarity and HHI of each Census industry, weighted by Compustat sales.[27] The indicator for high pricing power of firms in an industry relative to consumers, *I(Firm Power vs. Consumer)*, is set to one if the lagged product similarity is in the bottom quartile or if the product HHI is in the top quartile, and zero otherwise. Each of these two indicators are interacted with occupational AI net complementarity.

Table 9 presents the weighted linear regression results for the heterogeneity effect of AI net complementarity on work and leisure hours by product market power. Higher product market power of firms, measured using product similarities or product HHI, mitigates the positive relationship between AI net complementarity and work hours by 0.016 and 0.021 per week (column (1) and column (2)), significant at the 10% level, respectively. Moreover, higher product market power of firms mitigates the negative relationship between AI net complementarity and leisure time, indicated by the positive coefficients for the interaction between AI net complementarity and each of the product market power indicators. Specifically, at a given level of AI net complementarity, a worker in the industry where firms have a greater pricing power (i.e., bottom quartile worker in product market competition) based on product similarities and product HHI experience 0.024 and 0.031 more leisure hours per week, respectively (both significant at the 1% level). Overall, we find evidence confirming the prediction that

[27] We first calculate the sales-weighted product market competition proxies at the NAICS 3-digit industry level, and then match them to the corresponding Census industry code "trdtind1" using the crosswalk provided by BLS at https://www2.census.gov/programs-surveys/demo/guidance/industry-occupation/census-2012-final-code-list.xls.

as firms have greater pricing power relative to consumers, workers gain more surplus, which reduces the impact of AI technologies on work-life-balance. In other words, the increase in work hours relative to leisure hours is more pronounced when the product market is more competitive.

[Insert Table 9 here.]

5. Conclusion

The extensive individual-level time diary data (ATUS) collected over the past two decades offers a unique setting to examine the nuanced relationship between occupational AI exposure and workers' time allocation. Our analysis reveals a consistent pattern: workers in occupations with higher AI exposure end up working longer hours and enjoying less leisure time. This effect is particularly pronounced in contexts where AI significantly enhances marginal productivity and monitoring efficiency. It is further amplified in competitive labor and product markets, where workers' limited bargaining power fails to keep up with productivity gains, with rents often accruing to firms or consumers.

Historically, technological advancements like the Industrial Revolution and automation initially increased work hours as productivity demands rose and labor shifted to factory-based systems. Over time, however, productivity gains and social reforms reduced work hours, especially in developed economies, enabling improved work-life balance. Such a historical trend has contributed to the expectation for AI technologies. Our findings challenge the prevailing goal and assumption that technology progress improves lives including alleviating human labor burdens. Instead, they uncover a paradox where AI-driven productivity gains and enhanced monitoring efficiency extend workdays, especially in contexts with limited opportunities for workers to share in the benefits. To achieve a world where humans work less and enjoy greater well-being, deliberate policy interventions, equitable distribution of productivity gains, and cultural shifts prioritizing leisure and quality of life are essential. By shedding light on AI's impact on work-life dynamics from a principal-agent framework, this study contributes to the broader discussion on the socio-economic consequences of emerging technologies.

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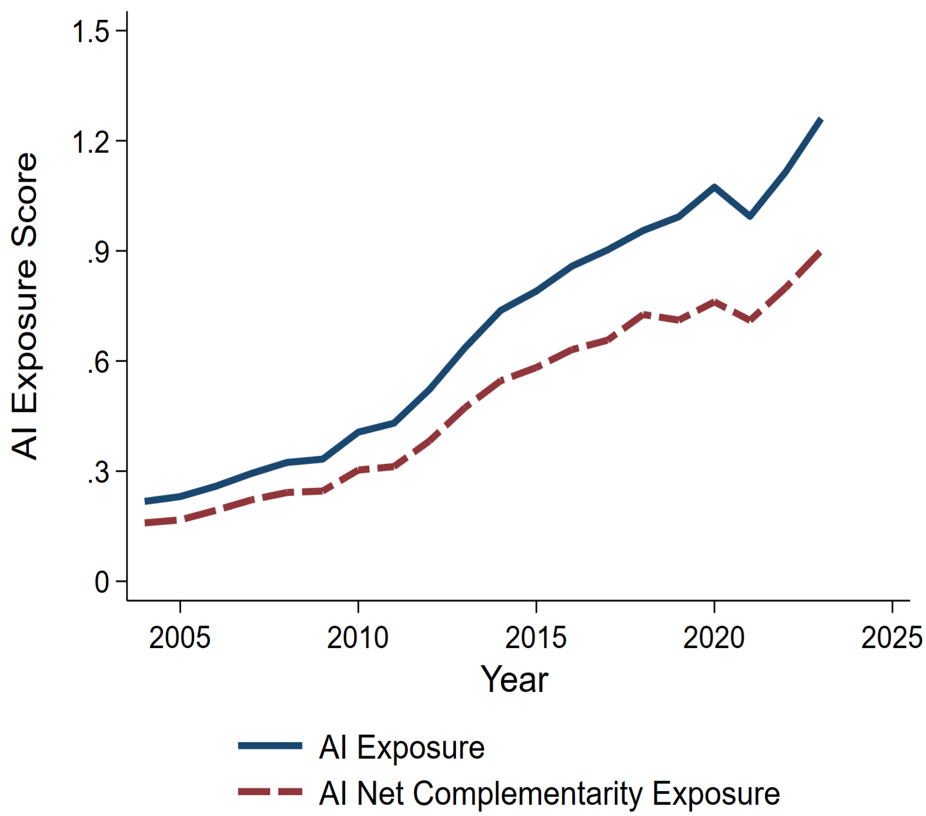
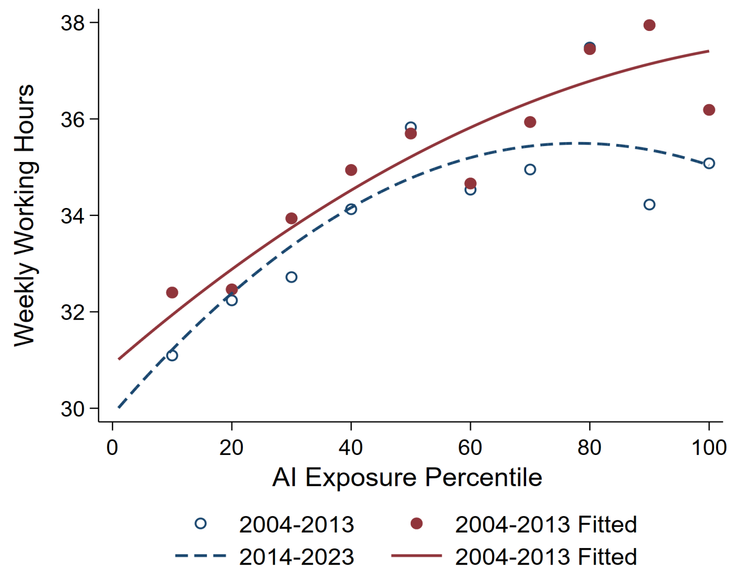
Figure 1. AI Exposure Over Time



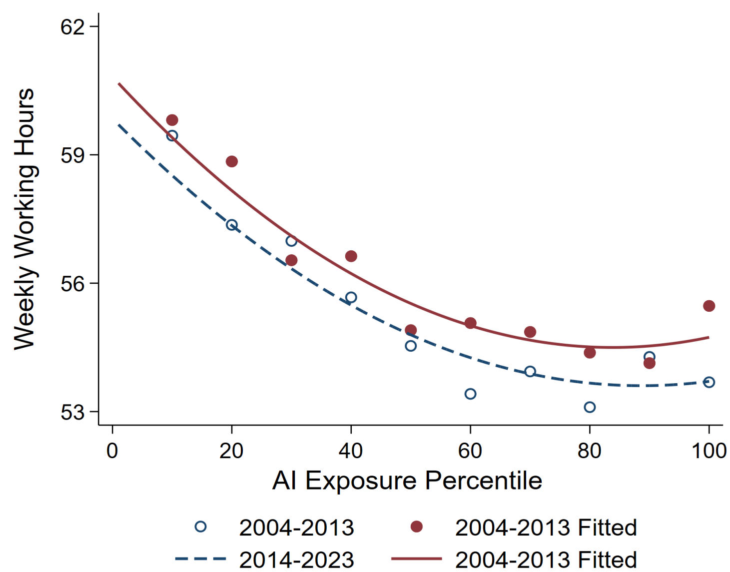
The figure plots the average occupational artificial intelligence (AI) exposure of ATUS respondents over time. The average is calculated using ATUS survey weights. Two AI exposure measures are constructed by the authors using AI patents published in the five years ending in a given year from 2000 to 2023: (i) average AI exposure based on the overlap of job tasks of occupations and AI patents (blue line) and (ii) average AI net complementarity exposure (red dotted line). Section B.2 describes the variable construction.

Figure 2. AI Exposure and Workday

A: Weekly Work Hours



B: Weekly Leisure Hours



The figure plots the average weekly hours allocated to work (Panel A) and leisure (Panel B) over occupation-level AI exposure in percentile rank. The time allocation variables are derived from the American Time Use Survey (ATUS) for the periods 2004–2013 and 2014–2023, weighted using ATUS sampling weights. Blue scatters and the blue dotted line represent data from 2004–2013, while red scatters and the red line correspond to 2014–2023. The scatters depict binned averages across 10-percentile groups, while the lines represent fitted values from quadratic regressions. Annual AI exposure of occupations is constructed by the authors using AI patents published in a five-year rolling window. The raw score for AI exposure is transformed into percentile ranks by year following the literature (e.g., Autor and Dorn, 2013; Webb, 2019).

Table 1: Summary Statistics

The table reports the summary statistics. Panel A describes the individual-level variables in the ATUS sample from 2004 to 2023. The time spent on activities is from the ATUS, expressed in hours per week. An individual's total time endowment, after subtracting off 49 hours for biological eating, sleeping, and personal care needs (ESP), is 119 hours per week. Market work includes time spent on main jobs, overtime work, and ancillary work activities. Leisure includes entertainment like recreational computing and video games, hobbies and leisure components of ESP. Home production includes household chores, grocery shopping, caring for other adults, etc. Education refers to one's own education like attending courses. Civic includes going to church, volunteering, etc. Job search activities include submitting resumes and conducting job interviews. Hourly wages are in 2023 dollars. The time-varying exposure measures at the "occ1990dd" occupation level, including AI exposure (AI^{EXP}) and AI net complementarity exposure (AI^{COMP}), are constructed by the authors and transformed into percentile ranks by year, as described in Section 3.6. Panel B summarizes the top 1% most cited AI patents every year from 2000 - 2023 based on the adjusted forward citations that are used to construct AI exposure measures. Adjusted forward citations are defined as raw citations over the average citations of AI patents granted within the same year-quarter and CPC subclass (Kogan et al., 2017). Panel C summarizes employee ratings and AI exposure at the firm-job type level from 2008 to 2023. Employees' ratings on overall satisfaction and work-life-balance (WLB) are from Glassdoor. AI exposure at the firm-job type-year level is constructed in two steps. First, occupational AI exposure is aggregated to the firm-job type level, using employment weights from Linkedin employment history; second, a three-year moving average is applied.

Panel A: Occupation Exposure, Time Allocation and Wages at the Individual Level

VARIABLES	N (1)	Mean (2)	Std (3)	P25 (4)	P50 (5)	P75 (6)
Weekly Hours						
Market work	123,603	34.88	30.72	0	43.28	59.50
Leisure	123,603	55.54	27.28	36.17	50.75	72.92
Education	123,603	1.70	7.70	0	0	0
Civic	123,603	1.61	5.90	0	0	0
Own medical care	123,603	0.37	2.08	0	0	0
Job Search	123,603	0.08	0.86	0	0	0
Home production	123,603	15.67	17.37	2.33	9.92	23.33
Child care	123,603	4.48	11.15	0	0	1.75
Hourly earnings ($)	104,400	27.73	17.72	15.01	22.30	34.93
I(Female)	123,603	0.48	0.50	0	0	1
I(Married)	123,603	0.55	0.50	0	1	1
No. Children	123,603	0.83	1.13	0	0	2
Age	123,603	40.06	13.15	29	40	51
Indicator for Educational Attachment						
I(Less than high school)	123,603	0.11	0.31	0	0	0
I(High school)	123,603	0.28	0.45	0	0	1
I(Some college education)	123,603	0.27	0.44	0	0	1
I(Bachelor's)	123,603	0.22	0.41	0	0	0
I(Master's and above)	123,603	0.13	0.33	0	0	0
AI^{EXP} - score	123,603	0.66	0.38	0.32	0.59	0.92
AI^{EXP} - percentile	123,603	54	29.11	29	60	80
AI^{COMP} - score	123,603	0.47	0.38	0.18	0.35	0.73
AI^{COMP} - percentile	123,603	55.61	28.12	29	60	81
$GenAI^{EXP}$ - score	8,131	0.37	0.24	0.16	0.36	0.54
$GenAI^{EXP}$ - percentile	8,131	60.84	25.61	43	65	81
AI^{SUR} - score	10,600	7.07	0.48	6.74	7.00	7.45
AI^{SUR} - percentile	10,600	45.87	26.66	23	37	70

Panel B: AI Patents Used for the AI Exposure Construction		
Year	No. AI Patents	No.Adjusted Citations
2000	100	7.21
2001	111	7.28
2002	114	7.41
2003	124	9.15
2004	137	9.99
2005	130	9.34
2006	186	10.10
2007	173	9.77
2008	190	11.01
2009	218	12.22
2010	300	11.70
2011	315	13.22
2012	398	15.04
2013	446	16.39
2014	492	17.07
2015	480	17.36
2016	514	19.02
2017	555	19.79
2018	556	21.07
2019	705	20.69
2020	750	20.79
2021	741	21.30
2022	762	19.53
2023	771	24.93

Panel C: Summary Statistics at the Job Type × Firm Level						
VARIABLES	N (1)	Mean (2)	Std (3)	P25 (4)	P50 (5)	P75 (6)
Rating (overall)	103,165	3.41	1.04	3.00	3.50	4.00
Rating (WLB)	103,165	3.40	1.04	2.91	3.50	4.00
Total Compensation ($000)	103,165	108.30	51.71	79.52	99.06	124.44
AI^{EXP} - percentile	103,165	69.40	13.50	61.61	71.37	79.13
AI^{COMP} - percentile	103,165	71.40	13.73	64.57	73.75	80.79
Employment	103,165	511.80	709.66	52.00	191.00	620.00

Table 2: Event Study: Introduction of ChatGPT

The table reports the weighted linear regressions using the ATUS sample weights (Aguiar et al., 2021) that examine the heterogeneity effect of occupational exposure to generative AI on work-life balance based on individual responses to the ATUS survey from 2022 to 2023. The occupations are uniquely identified by "occ1990dd" codes from Dorn (2009). The dependent variable is weekly hours spent on market work in Panel A and leisure in Panel B. In each panel, column (1) presents the results for the full sample. Columns (2)–(3) present the results for subsamples defined using generative AI complementarity exposure at the occupation level, developed following Kogan et al. (2023). Columns (4)–(5) present the results for subsamples defined using the state-level Google search trend of ChatGPT from November 30 to December 31, 2022. The main explanatory variable, $GenAI^{EXP}$, is generative AI exposure measure at the occupation level, constructed following Eisfeldt et al. (2023) and transformed to percentile ranks following the literature (e.g., Autor and Dorn, 2013; Webb, 2019). $POST$ dummy equals one for the year 2023. All specifications include individual-level controls including age, the number of children, and a series of indicator variables for gender, educational attainment, marital status, and race, and fixed effects at the following levels: occupation, state × year, industry × year, year-month, and day-of-week. Standard errors are double clustered by occupation and state. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Work					
DV	Weekly Work Hours$_{i,o,t}$				
		$GenAI_o^{COMP}$		State-level Google Search of ChatGPT$_s$	
Sample	Full Sample	Top 25%	Bottom 75%	Top 25%	Bottom 75%
	(1)	(2)	(3)	(4)	(5)
$GenAI_o^{EXP} \times POST_t$	0.063**	0.178**	0.088*	0.161**	0.053*
	(2.12)	(2.02)	(1.82)	(3.59)	(1.77)
Individual Characteristics	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
year-month FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes
Observations	8,094	3,394	4,692	1,830	6,190
R^2	0.340	0.478	0.315	0.410	0.363
Adjusted R^2	0.298	0.427	0.250	0.294	0.313

Panel B: Leisure					
DV	Weekly Leisure $\text{Hours}_{i,o,t}$				
		$GenAI_o^{COMP}$		State-level Google Search of ChatGPT_s	
Sample	Full Sample	Top 25%	Bottom 75%	Top 25%	Bottom 75%
	(1)	(2)	(3)	(4)	(5)
$GenAI_o^{EXP} \times POST_t$	-0.064*	-0.175*	-0.089	-0.178***	-0.058
	(-1.92)	(-1.93)	(-1.64)	(-3.95)	(-1.61)
Individual Characteristics	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
year-month FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes
Observations	8,335	3,588	4,742	1,835	6,426
R^2	0.317	0.384	0.318	0.389	0.335
Adjusted R^2	0.275	0.328	0.255	0.271	0.285

Table 3: AI Exposure and Workday

The table reports weighted linear regression results based on individual responses to the ATUS survey from 2004–2023 using ATUS sample weights (Aguiar et al., 2021). The dependent variable is weekly hours spent on market work in columns (1)–(3) and leisure in columns (4)–(6). The main explanatory variable, AI^{EXP}, is AI exposure measure in percentile ranks at the occupation ("occ1990dd")-year level, and is based on AI-related patents granted in a five-year window ending in the current year (detailed description in Section 3.6). All specifications incorporate individual-level controls, including age, the number of children, and a series of indicator variables for gender, educational attainment, marital status, and race, and fixed effects at the following levels: state × year, industry × year, year-month and day-of-week. Columns (2) and (5) include additional occupational exposure measures, including robot exposure (Webb, 2019), routine task index (RTI) (Autor and Dorn, 2013), and offshorability exposure (Firpo et al., 2011; Autor and Dorn, 2013), all in percentile ranks. Columns (3) and (6) include occupation fixed effects, which subsume occupation-level controls. Standard errors are double clustered by occupation and state. Asterisks denote significance levels (***=1%, **=5%, *=10%).

DV	Weekly Hours$_{i,o,t}$					
	Work			Leisure		
	(1)	(2)	(3)	(4)	(5)	(6)
$AI^{EXP}_{o,t-1}$	0.044***	0.034***	0.018*	-0.033***	-0.025***	-0.016**
	(3.26)	(2.86)	(1.79)	(-3.18)	(-2.96)	(-2.04)
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Other Occupation Exposure	No	Yes	No	No	Yes	No
Occupation FE	No	No	Yes	No	No	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	121,841	121,841	121,841	121,841	121,841	121,841
R^2	0.270	0.272	0.281	0.235	0.237	0.244
Adjusted R^2	0.257	0.259	0.266	0.222	0.223	0.228

Table 4: AI Technology Complementarity and Workday

The table reports weighted linear regression results based on individual responses to the ATUS survey from 2004 – 2023 using the ATUS sample weights (Aguiar et al., 2021). The dependent variable is weekly hours spent on market work in columns (1)–(3) and leisure in columns (4)–(6). The main explanatory variable, AI^{COMP}, is AI net complementarity measure in percentile ranks at the occupation ("occ1990dd")-year level, and is based on AI-related patents granted in a five-year window ending in the current year (detailed description in Section 3.6). All specifications incorporate individual-level controls, including age, the number of children, and a series of indicator variables for gender, educational attainment, marital status, and race, and fixed effects at the following levels: state × year, industry × year, year-month and day-of-week. Columns (2) and (5) include additional occupational exposure measures, including robot exposure (Webb, 2019), routine task index (RTI) (Autor and Dorn, 2013), and offshorability exposure (Firpo et al., 2011; Autor and Dorn, 2013), all in percentile ranks. Columns (3) and (6) include occupation fixed effects, which subsume occupation-level controls. Columns (4) and (8) include both occupation fixed effects and orthogonalized general AI exposure, $\widetilde{AI^{EXP}_{o,t-1}}$, the residual obtained from regressing general AI exposure on $AI^{COMP}_{o,t}$. Standard errors are double clustered by occupation and state. Asterisks denote significance levels (***=1%, **=5%, *=10%).

DV	Weekly Hours$_{i,o,t}$							
	Work				Leisure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$AI^{COMP}_{o,t-1}$	0.055***	0.041***	0.027**	0.024*	-0.043***	-0.034***	-0.021**	-0.016**
	(3.75)	(3.22)	(2.08)	(1.86)	(-3.97)	(-3.72)	(-2.62)	(-2.34)
$\widetilde{AI^{EXP}_{o,t-1}}$				-0.015				0.020
				(-0.60)				(0.94)
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Occupation Exposure	No	Yes	No	No	No	Yes	No	No
Occupation FE	No	No	Yes	Yes	No	No	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	121,841	121,841	121,841	121,841	121,841	121,841	121,841	121,841
R^2	0.270	0.272	0.281	0.281	0.236	0.237	0.244	0.244
Adjusted R^2	0.257	0.259	0.266	0.266	0.222	0.223	0.228	0.228

Table 5: AI Exposure and Wage

The table reports weighted linear regression results based on individual responses to the ATUS survey from 2004 – 2023 using the ATUS sample weights (Aguiar et al., 2021). The dependent variable is the natural logarithm of hourly wages in 2023 dollars. The main explanatory variable represents AI exposure measures at the occupation("occ1990dd")-year level, expressed in percentile ranks, and is based on AI-related patents granted in a five-year window ending in the current year (detailed description in Section 3.6). Specifically, it refers to general AI exposure (AI^{EXP}) in columns (1)–(2) and AI net complementarity exposure (AI^{COMP}) in columns (3)–(4). All specifications incorporate individual-level controls, including age, the number of children, and a series of indicator variables for gender, educational attainment, marital status, and race, and fixed effects at the following levels: state × year, industry × year, year-month and day-of-week. Columns (2) and (5) include additional occupational exposure measures, including robot exposure (Webb, 2019), routine task index (RTI) (Autor and Dorn, 2013), and offshorability exposure (Firpo et al., 2011; Autor and Dorn, 2013), all in percentile ranks. Columns (3) and (6) include occupation fixed effects, which subsume occupation-level controls. Standard errors are double clustered by occupation and state. Asterisks denote significance levels (***=1%, **=5%, *=10%).

DV	Log (Hourly Wage \$)$_{i,o,t}$× 100					
	(1)	(2)	(3)	(4)	(5)	(6)
$AI^{EXP}_{o,t-1}$)	0.250***	0.149***	0.023*			
	(5.28)	(3.28)	(1.78)			
$AI^{COMP}_{o,t-1}$				0.352***	0.254***	0.046**
				(7.95)	(4.96)	(2.41)
Individual Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Occupational FE	No	No	Yes	No	No	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102,804	102,804	102,803	102,804	102,804	102,803
R^2	0.491	0.504	0.566	0.499	0.508	0.566
Adjusted R^2	0.480	0.494	0.555	0.489	0.497	0.556

Table 6: Exposure to AI Surveillance Technology and Workday

The table reports the weighted linear regression results using the ATUS sample weights (Aguiar et al., 2021) that examine the heterogeneity effect of AI surveillance exposure on work-life balance based on individual responses of remote workers in the ATUS survey from 2015 to 2023. The occupations are uniquely identified by "occ1990dd" codes from Dorn (2009). Remote workers are defined as those in occupations with a work-from-home (WFH) feasibility index from Dingel and Neiman (2020) equals one. The dependent variable is weekly hours spent on market work in column (1)–(2) and leisure in column (3)–(4) . In each pair, the first column presents the results for employees while the second column reports the results for a subsample of self-employed workers. The main explanatory variable, AI_o^{SUR}, is AI surveillance exposure at the occupation level (detailed description in Section B.4 of Online Appendix) and transformed to percentile ranks (e.g., Autor and Dorn, 2013; Webb, 2019). *POST* dummy equals one for the years since 2020. All specifications include individual-level controls including age, the number of children, and a series of indicator variables for gender, educational attainment, marital status, and race, and fixed effects at the following levels: occupation, state × year, industry × year, year-month, and day-of-week. Standard errors are double clustered by occupation and state. Asterisks denote significance levels (***=1%, **=5%, *=10%).

DV	Weekly $\text{Hours}_{i,o,t}$			
	Work		Leisure	
Sample	Employees	Self-Employed	Employees	Self-Employed
	(1)	(2)	(3)	(4)
$AI_o^{SUR} \times POST_t$	0.043**	-0.021	0.013	0.179
	(2.07)	(-0.11)	(0.72)	(1.44)
Individual Characteristics	Yes	Yes	Yes	Yes
Occupational FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
year-month FE	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes
Observations	9,838	515	9,838	515
R^2	0.510	0.893	0.404	0.867
Adjusted R^2	0.457	0.522	0.339	0.405

Table 7: AI Exposure and Employee Satisfaction: Evidence from Glassdoor and LinkedIn

The table presents estimations from linear regressions examining the effects of occupational AI exposure on employee ratings at the job type (k) $\times$ firm (i) $\times$ year (t) level. The sample includes private and public firms from the Glassdoor database between 2008 and 2023. The dependent variables are 100 times the overall satisfaction rating in columns (1)–(2) and the Work-Life Balance (WLB) ratings in columns (4)–(5). The dependent variables in columns (3) and (6) are 100 times the average annual compensation (natural logarithm) from Linkedin. The main explanatory variable, lagged AI exposure at the job type $\times$ firm level, is constructed in two steps. First, occupational AI exposure is aggregated to the job type $\times$ firm level, using employment weights from Linkedin. Second, a three-year moving average is applied to the job type AI exposure to smooth variations over time. Occupational AI exposure is constructed using AI-related patents within the past five years (detailed description in Section 3.6). Specifically, it refers to general AI exposure ($AI^{EXP}_{k,i,t-3:t-1}$) in columns (1)–(3) and AI net complementarity exposure ($AI^{COMP}_{k,i,t-3:t-1}$) in columns (4)–(6). All specifications control for employment in the natural logarithm at the job type $\times$ firm level, firm $\times$ job type fixed effects, and job type $\times$ year fixed effects. Standard errors are double clustered by firm and year. Asterisks denote significance levels (***=1%, **=5%, *=10%).

DV	Rating $\times$ 100		Log(Compen-sation)$\times$ 100	Rating $\times$ 100		Log(Compen-sation)$\times$ 100
	Overall	WLB		Overall	WLB	
	(1)	(2)	(3)	(4)	(5)	(6)
$AI^{EXP}_{k,i,t-3:t-1}$	-0.085	-0.111**	0.044*			
	(-1.74)	(-2.40)	(2.04)			
$AI^{COMP}_{k,i,t-3:t-1}$				-0.075	-0.138**	0.109***
				(-1.22)	(-2.39)	(3.57)
Employment Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm $\times$ Job Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Job Type $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102,483	98,844	102,483	102,483	98,844	102,483
R^2	0.341	0.337	0.947	0.341	0.337	0.947
Adjust R^2	0.227	0.223	0.938	0.227	0.223	0.938

Table 8: AI Exposure and Workday: In Relation to Labor Market Competition

The table reports the weighted linear regression results that estimate the heterogeneity effect of AI on work-life balance sorted by labor market competition. The regression is weighted by ATUS sample weights (Aguiar et al., 2021). The dependent variable is weekly hours spent on market work in columns (1)-(2) and leisure in columns (3)-(4). The main explanatory variable, AI^{COMP}, represents AI net complementarity exposure at the occupation ("occ1990dd")-year level, expressed in percentile ranks, and is based on AI-related patents granted in a five-year window ending in the current year (detailed description in Section 3.6). Two proxies for the labor market power of firms are specified: the lagged state-level labor market concentration measured by the Herfindahl-Hirschman Index (HHI) in columns (1) and (3) and the 2023 Best States to Work Index (BSWI) provided by Oxfam in columns (2) and (4). The state-level labor market HHI is calculated using the employment and headquarters state data of public firms from Compustat. *I(Worker Power vs. Firm)* is the indicator of firms' labor market power that equals one if the labor market concentration is in the bottom quartile or BSWI is in the top quartile and zero otherwise. All specifications incorporate individual-level controls, including age, the number of children, and a series of indicator variables for gender, educational attainment, marital status, and race, and fixed effects at the following levels: occupation, state × year, industry × year, year-month and day-of-week. Standard errors are double clustered by occupation and state. Asterisks denote significance levels (***=1%, **=5%, *=10%).

DV	Weekly Hours$_{i,o,t}$			
	Work		Leisure	
Factor	HHI	BSWI	HHI	BSWI
	(1)	(2)	(3)	(4)
$AI^{COMP}_{o,t-1}$	0.034**	0.030**	-0.024***	-0.023***
	(2.58)	(2.49)	(-2.98)	(-3.27)
× *I(Worker Power vs. Firm)*$_{s,t-1}$	-0.024***	-0.014**	0.011**	0.009**
	(-9.47)	(-2.15)	(2.63)	(2.10)
Individual Characteristics	Yes	Yes	Yes	Yes
Occupational FE	Yes	Yes	Yes	Yes
State× Year FE	Yes	Yes	Yes	Yes
Industry× Year FE	Yes	Yes	Yes	Yes
Year× Month FE	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes
Observations	121,799	121,841	121,799	121,841
R^2	0.281	0.281	0.244	0.244
Adjusted R^2	0.266	0.266	0.228	0.228

Table 9: AI Exposure and Workday: In Relation to Product Market Competition

The table reports the weighted linear regression results that examine the heterogeneity effect of AI on work-life balance sorted by product market competition. The regression is weighted by ATUS sample weights (Aguiar et al., 2021). The occupations are uniquely identified by "occ1990dd" codes from Dorn (2009). The dependent variable is weekly hours spent on market work in columns (1)-(2) and leisure in columns (3)-(4). The main explanatory variable, AI^{COMP}, represents AI net complementarity exposure at the occupation-year level, expressed in percentile ranks, and is based on AI-related patents granted in a five-year window ending in the current year (detailed description in Section 3.6). Two proxies for the product market power of firms are specified: the industry-level product similarity in column (1) and (3) and product market concentration (HHI) in column (2) and (4). Firm-level product similarity and HHI scores provided by Hoberg and Phillips (2016) were weighted by Compustat sales to calculate each of the proxies. *I(Firm Power vs. Consumer)* is an indicator of firms' product market power relative to consumers, which equals one if the lagged product similarity is in the bottom quartile or the product similarity in the top quartile and zero otherwise. All specifications incorporate individual-level controls, including age, the number of children, and a series of indicator variables for gender, educational attainment, marital status, and race, and fixed effects at the following levels: occupation, state × year, industry × year, year-month and day-of-week. Standard errors are double clustered by occupation and state. Asterisks denote significance levels (***=1%, **=5%, *=10%).

DV	Weekly Hours$_{i,o,t}$			
	Work		Leisure	
Factor	Product Similarity	Product HHI	Product Similarity	Product HHI
	(1)	(2)	(3)	(4)
$AI^{COMP}_{o,t-1}$	0.027**	0.027**	-0.024***	-0.024***
	(2.08)	(2.19)	(-2.76)	(-2.82)
× $I(Firm\ Power\ vs.\ Consumer)_{j,t-1}$	-0.016*	-0.021*	0.024***	0.031***
	(-1.74)	(-1.93)	(2.87)	(2.73)
Individual Characteristics	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
year-month FE	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes
Observations	112,477	112,272	112,477	112,272
R^2	0.279	0.279	0.245	0.245
Adjusted R^2	0.263	0.263	0.228	0.228

Online Appendix

A. Optimal worker effort in a Principal-Agent Model

This model is a simple adaptation of Holmstrom and Milgrom (1987), aiming at illustrate the relation between agent "effort" (which maps to length of work day) and a set of factors including marginal productivity, effort observability, and bargaining power.

The output X_t follows a continuous-time stochastic process, affected by the agent's effort a and a noise term that is outside the control of the agent:

$$dX_t = \gamma a_t dt + \sigma dW_t, \tag{6}$$

where:

a_t is the agent's effort level ("working time" in our empirical setting) at time t, which is not directly observed by the principal. γ is the productivity parameter. σ represents the level of uncertainty in the noise term, and W_t is the standard Wiener process.

The principal is risk neutral with the following utility function V, which is the difference between the expected output γa_t and the compensation to the agent, $C_t = f(X_t)$:

$$V = \int_0^1 (\gamma a_t - f(X_t))dt \tag{7}$$

Effort, a_t, is not contractible and hence the compensation function relies on output which is a noisy representation of agent effort.

The Agent is risk-averse with CARA utility with a risk-aversion coefficient of r, with a utility function depending on income C and leisure, and with a researvation utility of U_0. Assume the agent has one unit of time to allocate between work and leisure, his expected utility is $E[U(C, 1-a)]$. If we rule out the income effect of leisure for now, we assume that the U take the simple form of

$$U = \int_0^1 (C_t - \frac{1}{2} r Var(C_t) - \frac{1}{2} k a^2)dt \tag{8}$$

The principal solves the following optimization problem:

$$\begin{aligned} \text{Max}_{f(X_t)} \ V = \int_0^1 (\gamma a_t - f(X_t))dt \\ s.t. E(U[f(X_t), a_t^*]) \geq \underline{U} \ (Participation\ constraint) \\ a^* = \text{Argmax}_{a_t} \ E(U[f(X_t), a_t]) \ (Incentive\ compatibility) \end{aligned} \tag{9}$$

Holmstrom and Milgrom (1987) shows that the optimal dynamic contract converges in the aggregate to a linear contract in the form of

$$C_t = \alpha + \beta X_t, \tag{10}$$

where β could be characterized as

$$\beta = \frac{1}{1 + kr\sigma^2} \tag{11}$$

Finally, the agent's effort level in response to the incentive is

$$a_t = \frac{\gamma}{k(1 + kr\sigma^2)} \tag{12}$$

In summary, equilibrium effort input is positively related to γ, the marginal productivity of effort; and negatively associated with k, the marginal cost of effort; r, the agent's risk aversion; and σ, the volatility of the noise in performance attribution to agent effort. Such comparative statics are robust with more general functional forms, though there is no closed-form solution.

In this simple model when agent's utility function is separable in consumption and leisure (see equation 8), a change in the agent's reservation utility (which is determined by her next best alternatives) does not affect the incentives and effort input. This will change with the relaxation of agent's utility function to a more general form, such as the constant elasticity of substitution (CES) utility function:

$$U(C, 1-a) = [\eta C^\rho + (1-\eta)(1-a)^\rho]^{\frac{1}{\rho}} - \frac{1}{2} rVar(C_t), \tag{13}$$

where $\eta \in (0, 1)$ is the relative preference for consumption and leisure, and $\rho < 1$ is the substitution parameter, or $\frac{1}{1-\rho}$, the elasticity of substitution between C and $1 - a$, is strictly positive.

Under this setup, the relation between a^* and $\underline{U}$ is not monotone. However, under reasonable parameters (e.g., agents are reasonably risk averse, and measuring performance is reasonably noisy), increasing $\underline{U}$ (because the agent has better outside opportunities due to bargaining power over their employer and the job market) tends to decrease work time. In addition, the following two conditions would each on its own serve as a sufficient condition for effort (work time) to shrink when $\underline{U}$ rises:

1. $\rho < 0$, i.e., consumption and leisure are strict complements.

2. $\underline{U}$ is sufficiently large, such that there is a limit on increasing β to agent the required utility due to agent's risk aversion.

Overall, because leisure is a normal good, the agent values leisure more when the agent's welfare improves. This force induces the agent to allocate more time into leisure from work, other things equal. The effect is stronger when agent risk aversion is high; performance measurement is noisy, complimentarity between consumption and leisure is high, and the agent has good alternatives (hence demands high reservation utility).

B. Documentation

B.1. Historical panel of O*NET data

The O*NET Data Collection Program currently makes updates to the O*NET Database quarterly, with a primary update occurring in the 3rd quarter (August) of each year. Prior to year 2015, the data was primarily updated once per year. To create a consistent annual panel of job tasks, we use the O*NET databases released each August from 2015 onward. For years prior to 2015, we select the data release closest to August, prioritizing those published between June and August when multiple versions are available in the same year. Table OA.1 of Online Appendix lists the O*NET data release we use to construct the annual panel of occupations' job tasks from 2000–2023.

B.2. Measure AI exposure at the occupation level using ChatGPT

This section provides details on how we use ChatGPT to quantify AI exposure measures for occupations. Our practice was conducted on November 22, 2024 using the "gpt-4o-mini-2024-07-18" model with the GPT "temperature" parameter set to 0.[28]

B.2.1. Prompt setup

ChatGPT, developed by OpenAI, is based on the GPT (Generative Pre-trained Transformer) architecture, which uses a transformer design with self-attention mechanisms for advanced contextual understanding. Pre-trained on vast datasets, it is highly proficient in processing and analyzing text.

We use ChatGPT to classify the impact of AI patents on occupations due to its ability to identify complex relationships and nuances in language. Specifically, we define a prompt, which serves as a clear instruction or context-setting input that shapes the model's output, as following and apply it to a given patent-occupation combination in our sample:

You are a labor economist. Evaluate the extent to which a new AI patent substitutes or complements job tasks of a given occupation, and its impact on task completion time. Respond strictly in JSON format:

"overlap": [similarity_score], # Similarity between patent and tasks (1-10)

"label": [effect_label], # indicator of the impact of patent on tasks (-1 = substitute, 1 = complement, 0 = unrelated)

Include no text other than the JSON object.

In this prompt, we ask ChatGPT to assume the role of a labor economist to classify the impact of a patent filing on a given occupation. The terms Patent Title and Patent Abstract are substituted by the title and abstract of a particular patent during the query. Similarly, Occupation Title and Tasks are substituted by the title and the combined text of all task statements of a particular occupation.

B.2.2. Example

We provide two examples of how ChatGPT scores the overlap between an occupation and AI patent and labels the impact of the patent on the occupation.

Example 1)

Occupation: Urban and Regional Planners (SOC Code: 19-3051.00)

Task Statements: "Hold public meetings with government officials, social scientists, lawyers, developers, the public, or special interest groups to formulate, develop, or address issues regarding land use or community plans.— Design, promote, or administer government plans or policies affecting land use, zoning, public utilities, community facilities, housing, or transportation.— Advise planning officials on project feasibility, cost-effectiveness, regulatory conformance, or possible alternatives.— Recommend approval, denial, or conditional approval of

[28]Temperature is a parameter in ChatGPT that controls the randomness and creativity of its responses. Setting the temperature to 0 makes the model consistently choose the most probable word.

proposals.— Discuss with planning officials the purpose of land use projects, such as transportation, conservation, residential, commercial, industrial, or community use.— Conduct field investigations, surveys, impact studies, or other research to compile and analyze data on economic, social, regulatory, or physical factors affecting land use.— Determine the effects of regulatory limitations on land use projects.— Advocate sustainability to community groups, government agencies, the general public, or special interest groups.— Mediate community disputes or assist in developing alternative plans or recommendations for programs or projects.— Keep informed about economic or legal issues involved in zoning codes, building codes, or environmental regulations.— Assess the feasibility of land use proposals and identify necessary changes.— Supervise or coordinate the work of urban planning technicians or technologists.— Identify opportunities or develop plans for sustainability projects or programs to improve energy efficiency, minimize pollution or waste, or restore natural systems.— Create, prepare, or requisition graphic or narrative reports on land use data, including land area maps overlaid with geographic variables, such as population density.— Evaluate proposals for infrastructure projects or other development for environmental impact or sustainability.— Coordinate work with economic consultants or architects during the formulation of plans or the design of large pieces of infrastructure.— Review and evaluate environmental impact reports pertaining to private or public planning projects or programs.— Develop plans for public or alternative transportation systems for urban or regional locations to reduce carbon output associated with transportation.— Investigate property availability for purposes of development."

Patent #1 Title: Data processing systems for fulfilling data subject access requests and related methods (Patent ID: 10452866)

Patent Abstract: "In particular embodiments, in response a data subject submitting a request to delete their personal data from an organization's systems, the system may: (1) automatically determine where the data subject's personal data is stored; and (2) in response to determining the location of the data (which may be on multiple computing systems), automatically facilitate the deletion of the data subject's personal data from the various systems (e.g., by automatically assigning a plurality of tasks to delete data across multiple business systems to effectively delete the data subject's personal data from the systems)."

ChatGPT Overlap Score: 4. Reasoning: While urban and regional planners work with data in the context of zoning, land use, and sustainability projects, the patent's focus is on automating the deletion of personal data from organizational systems. This functionality has limited direct relevance to the core tasks of urban planning, which involve regulatory, environmental, and community-based considerations. **ChatGPT Label: Substitute.** Reasoning: The patent describes an automated process that could replace certain aspects of planners' data management responsibilities, such as managing personal data in environmental or impact studies. By automating these tasks, the need for manual intervention by planners in related data handling activities may decrease.

Patent #2 Title: Device location based on machine learning classifications (Patent ID: 9980100)

Patent Abstract: "A venue system of a client device can submit a location request to a server, which returns multiple venues that are near the client device. The client device can use one or more machine learning schemes (e.g., convolutional neural networks) to determine that the client device is located in one of specific venues of the possible venues. The venue system can further select imagery for presentation based on the venue selection. The presentation may be published as ephemeral message on a network platform."

ChatGPT Overlap Score: 7. Reasoning: Urban and regional planners often work with location-based data and mapping to analyze land use and zoning, making the machine learning-based venue location system relevant. This patent can enhance planners' ability to determine precise location contexts, aiding in tasks such as field investigations, land area mapping, and transportation system planning. **ChatGPT Label: Complement.** Reasoning: The impact is labeled as complementary because the patent provides tools that augment planners' capabilities by improving accuracy and efficiency in location-based decision-making. It supports planners' tasks without replacing their expertise, enabling more informed analyses and better integration of spatial data into urban planning processes.

Example 2)

Occupation: Financial Quantitative Analysts (SOC Code: 13-2099.01)

Task Statements: "Develop core analytical capabilities or model libraries, using advanced statistical, quantitative, or econometric techniques.— Provide application or analytical support to researchers or traders on issues such as valuations or data.— Research or develop analytical tools to address issues such as portfolio construction or optimization, performance measurement, attribution, profit and loss measurement, or pricing models.— Maintain or modify all financial analytic models in use.— Apply mathematical or statistical techniques to address practical issues in finance, such as derivative valuation, securities trading, risk management, or financial market regulation.— Research new financial products or analytics to determine their usefulness.— Devise or apply independent models or tools to help verify results of analytical systems.— Define or recommend model specifications or data collection methods.— Confer with other financial engineers or analysts on trading strategies, market dynamics, or trading system performance to inform development of quantitative techniques.— Interpret results of financial analysis procedures.— Collaborate with product development teams to research, model, validate, or implement quantitative structured solutions for new or expanded markets.— Produce written summary reports of financial research results.— Consult traders or other financial industry personnel to determine the need for new or improved analytical applications.— Identify, track, or maintain metrics for trading system operations.— Prepare requirements documentation for use by software developers.— Collaborate in the development or testing of new analytical software to ensure compliance with user requirements, specifications, or scope.— Develop solutions to help clients hedge carbon exposure or risk.— Analyze pricing or risks of carbon trading products.— Develop methods of assessing or measuring corporate performance in terms of environmental, social, and governance (ESG) issues.— Develop tools to assess green technologies or green financial products, such as green hedge funds or social responsibility investment funds.— Assess the potential impact of climate change on business financial issues, such as damage repairs, insurance costs, or potential disruptions of daily activities."

Patent #1 Title: Systems and methods for predicting security threat attacks (Patent ID: 9948663)

Patent Abstract: "A computer-implemented method for predicting security threat attacks may include (1) identifying candidate security threat targets with latent attributes that describe features of the candidate security threat targets, (2) identifying historical attack data that describes which of the candidate security threat targets experienced an actual security threat attack, (3) determining a similarity relationship between latent attributes of at least one specific candidate security threat target and latent attributes of the candidate security threat targets that experienced an actual security threat attack according to the historical attack data, (4) predicting, based on the determined similarity relationship, that the specific candidate security threat target will experience a future security threat attack, and (5) performing at least one remedial action to protect the specific candidate security threat target in response to predicting the future security threat attack. Various other methods, systems, and computer-readable media are also disclosed."

ChatGPT Overlap Score: 6. Reasoning: Financial quantitative analysts often use advanced statistical and predictive modeling techniques to assess risks and outcomes, which aligns with the patent's focus on using historical data and latent attributes for predictive analytics. However, the application domain of this patent—security threat prediction—diverges from the financial focus, leading to only a moderate overlap.. **ChatGPT Label: Substitute.** Reasoning: the patent's automated system for predicting security threats could potentially replace similar risk assessment models developed by financial quantitative analysts, especially in contexts where these analysts might also evaluate risks related to cybersecurity or operational disruptions. The automation reduces the need for manual model development in overlapping areas of risk prediction.

Patent #2 Title: Authenticated access and aggregation database platform (Patent ID: 10671749)

Patent Abstract: "A data processing system is disclosed for data processing, including database and file management, as well accessing one or more databases or other data structures, authenticating users, and categorizing data items for addition to the database system. In some embodiments, the system may be configured to coordinate access to user account information via user-provided authentication credentials; apply account identification rules to the accessed account information to identify a plurality of accounts of the user; and initiate updates to a database record associated with the user indicative of any accounts identified."

ChatGPT Overlap Score: 8. Reasoning: The patent describes a system for data processing, authentication, and database management, which directly supports tasks performed by financial quantitative analysts, such as managing large datasets, ensuring data integrity, and applying analytical models to categorized financial data. The functionalities align closely with analysts' reliance on structured and accessible data for developing and maintaining financial models. **ChatGPT Label: Complement.** Reasoning: The patent's system enhances analysts' ability to manage and process complex datasets efficiently. By automating aspects of data access, categorization, and updates, the technology supports analysts in focusing on higher-value tasks such as developing models and interpreting data, rather than replacing their expertise or core responsibilities.

B.2.3. Validating GPT-generated AI general exposure

Generative Large Language Models, such as ChatGPT, provide improved textual analysis approaches over non-generative methods, mainly because that they enable expressing a task through natural language and exhibit more sophisticated reasoning abilities (de Kok, 2025). However, the black-box nature of these models poses challenges to the validation of the measures created by them. Here, we apply a non-generative natural language processing method to calculate a comparative variable to our overlap variable generated by GPT. Specifically, following Kogan et al. (2023), we employ a combination of word embedding and term-frequency-inverse-document-frequency (TF-IDF) approach to calculate the similarity between the text description of an occupation and the abstract of a patent. Then, we aggregate the similarity score at the occupation-year level to represent the time-varying relevance of AI to each occupation's tasks. Finally, we compare the TF-IDF cosine similarity score to the GPT-generated AI exposure score.

The specific procedure is as follows. First, we pre-process each text portion of the task description of each SOC 8-digit occupation and patent abstracts by removing non-alphabetic characters, lowercasing all text, removing all stopwords listed in the sources in Kogan et al. (2023), and retaining lemmatized versions of nouns and verbs only. Next, we represent each word of a text as a 100-dimensional vector using the word vectors provided by Pennington et al. (2014). The word vectors are numerical representations of word meanings that can effectively capture pairwise distances between words based on co-occurrence probabilities (Kogan et al., 2023). Then, to measure the document similarity between an occupation task description and a patent abstract, we construct a document-level vector, which is a weighted average of the set of word vectors in each task description or patent abstract text. We use TF-IDF to weigh each word vector, which gives higher weights for terms that occur more frequently in a document and lower weights for terms that occur commonly across many documents (Kogan et al., 2023). Finally, we calculate the cosine similarity between the task description of each occupation and a patent abstract, each represented as a document vector, to measure the relevance of the AI patent to the tasks performed by the occupation.

We aggregate the TF-IDF similarity scores from the SOC 8-digit occupation by patent level to the occ1990dd occupation by year level following the procedures outlined in Section 3.6.2. The TF-IDF score and the GPT-based AI exposure score ($AI_{o,t}^{EXP}$) constructed using the same patents show a high correlation of 0.83, demonstrating a strong alignment between the two measures and confirming the robustness of the GPT-derived approach.

B.2.4. Validating GPT-generated AI net complementarity exposure

To study the wage effects of AI, Kogan et al. (2023) use ChatGPT4 released in March 2023 to identify whether AI is a substitute or complement to occupation tasks using a question-based approach. Specifically, they ask ChatGPT whether AI's is able to perform specific job tasks with or without human intervention. This approach yields time-invariant measures of the occupation's exposure to AI substitution and AI complementarity.

Kogan et al. (2023) do not report the AI exposures at the occupation level. However, Table A8–9 in their Online Appendix provide different components of AI exposure-related earnings changes for occupations with the highest AI substitution (or complementarity) exposure at the SOC 6-digit occupation level. We validate our AI Net complementarity exposure ($AI_{o,t}^{COMP}$) by comparing it to those wage growth components. To summarize, $AI_{o,t}^{COMP}$ in 2023 exhibits a strong negative correlation of -0.59 with the wage growth attributed to the substitution effect of AI (column (3) in Table A8–9) documented in Kogan et al. (2023)). In contrast, $AI_{o,t}^{COMP}$ shows a positive correlation of 0.47 with wage growth related to labor-complementing effects (column (4) of in Table A8–9) and a correlation of 0.60 with the overall wage growth of AI (column (6)). This underscores a strong consistency between the methods, validating the reliability of our AI net complementarity measure.

B.3. Measure generative AI exposure at the occupation level using ChatGPT

This section provides details on how we use ChatGPT to quantify the exposure to Generative AI of each task following Eisfeldt et al. (2023) and to distinguish the substitute and complementarity impact of Generative AI on each task following Kogan et al. (2023). We conducted this categorization on November 12, 2024 using the "gpt-4o" model with the GPT "temperature" parameter set to 0. The job task descriptions of occupations are obtained from the O*NET 27.0 database released on August 1, 2022. Using the task statement, we generated two output variables for each of the 19,267 tasks including (i) to which extent the task is exposed to Generative AI technologies or not (ii) whether it is substituted or complemented by Generative AI technologies.

B.3.1. Prompt setup

We define a prompt as following and apply it to each job task in our sample:

"Generate two outcomes in the exact format of '[val1, val2, val3], [label]' based on the following instructions."

"First Task: Pretend you are a labor economist evaluating the extent to which Generative AI (specifically ChatGPT) might substitute or complement a job task of an occupation. "

"The output must be exactly a list of numbers in this format: [val1, val2, val3], where: - val1 is ChatGPT's substitute score (1-10)," "- val2 is its complement score (1-10)," "- val3 is a label (-1 = substitute, 1 = complement, 0 = unrelated) indicating if ChatGPT primarily complements or substitutes the job task."

"Second Task: For the second task, use the following Context for Evaluation and Exposure Rubric to label a given occupation task with one of the labels (E0, E1, E2, or E3) based on its exposure to LLM capabilities."

"The output must be exactly in this format: [label] that best describes the task's exposure to the LLM."

"Context for Evaluation: Assume access to the most powerful OpenAI large language model (LLM). This model can complete tasks involving text input and output, as long as the context can be captured in 2000 words. However, it cannot retrieve up-to-date facts from the past year unless provided in the input. Assume you are a worker with average expertise, using the LLM along with other software or hardware tools specified in the task. You also have commonly available technical tools (e.g., microphone, speakers) but no other physical materials. Your goal is to label tasks according to the rubric below, ensuring equivalent quality (i.e., a reviewer cannot distinguish whether a human completed it independently or with LLM assistance). If you are unsure how to judge time savings, consider if the described tools cover the majority of the subtasks."

"Exposure Rubric:"

"- E1 - Direct Exposure: Label tasks as E1 if direct access to the LLM (e.g., via ChatGPT or OpenAI playground) alone can reduce task time by at least half while maintaining quality. Examples include:" " - Writing and transforming text/code," " - Editing text/code as specified," " - Writing code for tasks previously done manually," " - Translating text," " - Summarizing medium-length documents," " - Providing document feedback," " - Answering questions about a document," " - Generating or answering questions," " - Writing or

responding to emails (including negotiation if via text)," " - Maintaining written records," " - Preparing general training materials, and" " - Informing others through written or spoken formats."

"- E2 - Exposure by LLM-powered Applications: Label tasks as E2 if the LLM alone may not halve the time required, but additional software built on the LLM could. Examples include:" " - Summarizing documents longer than 2000 words and answering questions on them," " - Retrieving recent/specialized information from the internet or organization data," " - Making recommendations based on data," " - Analyzing written information for decisions," " - Preparing specialized training materials, and" " - Maintaining complex databases."

"- E3 - Exposure with Image Capabilities: Label tasks as E3 if the combination of the LLM and an image-processing system (capable of viewing, captioning, and creating images, but not video) significantly reduces task time. Examples include:" " - Reading text from PDFs," " - Scanning images," " - Creating or editing digital images based on instructions (realistic but not highly detailed)."

"- E0 - No Exposure: Label tasks as E0 if none of the above criteria apply, and no clear reduction in task time by half is achieved. Examples include:" " - Tasks requiring significant human interaction (e.g., in-person demonstrations)," " - Tasks requiring precise physical measurements or detailed visual review," " - Decisions impacting human livelihood (e.g., hiring, grading)," " - Tasks legally requiring a human," " - Tasks already completed efficiently with existing (non-LLM) technology, and" " - When in doubt, default to E0."

B.3.2. Variable construction

Task scoring By applying the prompt, we categorize the Generative AI exposure, $GenAI_j$ of a given task j into one of the following three categories based on the ChatGPT output in the second task of the prompt:

- Direct Exposure ($GenAI_j = 1$): if ChatGPT enables a task to be completed in less than half the usual time, maintaining the same quality.
- Plus-Overlay Exposure ($GenAI_j = 0.5$): if ChatGPT alone cannot cut task time by half, but the addition of complementary software leveraging its functionality could achieve this efficiency without sacrificing quality.
- No Exposure ($GenAI_j = 0$): if ChatGPT neither reduces task time by half with comparable quality nor produces results of adequate quality.

Meanwhile, we classify a given task j as being substituted or complemented by Generative AI into one of the following three classifications based on the ChatGPT output "label" in the first task of the prompt:

- Substitute ($GenAI_j^{COMP} =$ -1): if ChatGPT primarily substitutes a job task.
- Complement ($GenAI_j^{COMP} = 1$) if ChatGPT primarily complements a job task.
- Unrelated ($GenAI_j^{COMP} = 0$) if ChatGPT is irrelevant to a job task.

Aggregation to the Occupation-Level We next aggregate tasks' exposures to Generative AI to the SOC 8-digit occupation level. Following Eisfeldt et al. (2023), we calculate the Generative AI exposure ($GenAI_o$) of a given occupation as the share of the total number of tasks for each occupation that have either a direct or "plus-overlay" exposure to Generative AI. We calculate Generative AI - Net complementarity ($GenAI_o^{COMP}$) for each SOC 8-digit occupation by taking the equal-weighted average of $GenAI_j^{COMP}$ across all tasks associated with that occupation. Next, we aggregate SOC 8-digit ocupation codes to occ1990dd codes following the procedures outlined in Section 3.6.2.

B.3.3. Validation

We validate our Generative AI exposure measures by comparing them to Table IA.1 of Eisfeldt et al. (2023) and Table A8–9 of Kogan et al. (2023).

Table IA.1 of Eisfeldt et al. (2023) lists the 20 SOC 6-digit occupations with the highest and lowest Generative AI exposure. Our replicated Generative AI exposure has a correlation of 0.95 with the numbers presented in that table.

Table A8–9 of Kogan et al. (2023) reports the predicted wage growth attributed to different components of AI exposure of occupations with the highest exposure to labor-complementing and labor-substituting potential of AI at the SOC 6-digit level. We find that $GenAI_o^{COMP}$ has a correlation of -0.42 with the wage growth attributed to the labor-substituting potential of AI (column (3) of Table A8–9 in Kogan et al. (2023)), and a correlation of 0.31 with that of labor-complementing (column (4)) and a correlation of 0.44 with the total wage growth of AI (column (6)), documented by Kogan et al. (2023)).

B.4. Measure AI surveillance exposure at the occupation level using ChatGPT

This section provides details on how we use ChatGPT to quantify the exposure to AI surveillance of each task. We conducted this categorization on Februray 9, 2025 using the “gpt-4o-2024-11-20” model with the GPT ”temperature” parameter set to 0. The job task descriptions of occupations are obtained from the O*NET 28.0 database released on August 1, 2023. Using the task statement, we generated two output variables for each of the 19,280 tasks including (i) to which extent the task is exposed to AI-powered surveillance technologies (ii) a concise, one-sentence rationale.

B.4.1. Prompt setup

We define a prompt as following and apply it to each job task in our sample:

“As a labor economist, assess AI’s ability to improve **monitoring efficiency** by better tracking and evaluating workers’ performance, effort, and compliance based on three perspectives of Algorithmic Control: Direction, Evaluation, and Discipline.”

“ **Context for Assessment:**”

“1. **Algorithmic Direction** – AI guides or restricts workers’ actions to align with goals.”

“ - **Recommending:** Prompts workers to align decisions with predefined goals.”
“ - *Example:* AI recommends optimal scheduling based on data analysis.”
“ - **Restricting:** Limits access to information or constrains behavior.”
“ - *Example:* AI restricts information or modifies behavior in online communities.”

“”2. **Algorithmic Evaluation** – AI monitors and assesses performance through data analysis.”

“ - **Recording:** Tracks behaviors and provides real-time feedback.”
“ - *Example:* AI logs work speed and accuracy for reviews.”
“ - **Rating:** Aggregates data (e.g., ratings, rankings) to evaluate productivity and predict performance.”
“ - *Example:* AI ranks employees based on task completion rates.”

“”3. **Algorithmic Discipline** – AI enforces compliance and incentivizes workers via automation and rewards.”

“ - **Replacing:** Automatically removes or reassigns underperforming workers.”
“ - *Example:* AI flags low-rated workers for reassignment.”
“ - **Rewarding:** Provides dynamic rewards or gamifies tasks to increase engagement.”
“ - *Example:* AI gives real-time rewards for task completion.”

“ **Output Format:**”

“Return one exact response per job task in the format: [val1, val2].”
“- **val1**: AI’s monitoring impact score (1–10), with 10 indicating the highest monitoring improvement.”
“- **val2**: A concise, one-sentence rationale.”

B.4.2. Variable construction

Task scoring By applying the prompt, we categorize the AI surveillance exposure, AI_j^{SUR} of a given task j and drop tasks ChatGPT could classify, leading to 19,273 tasks.

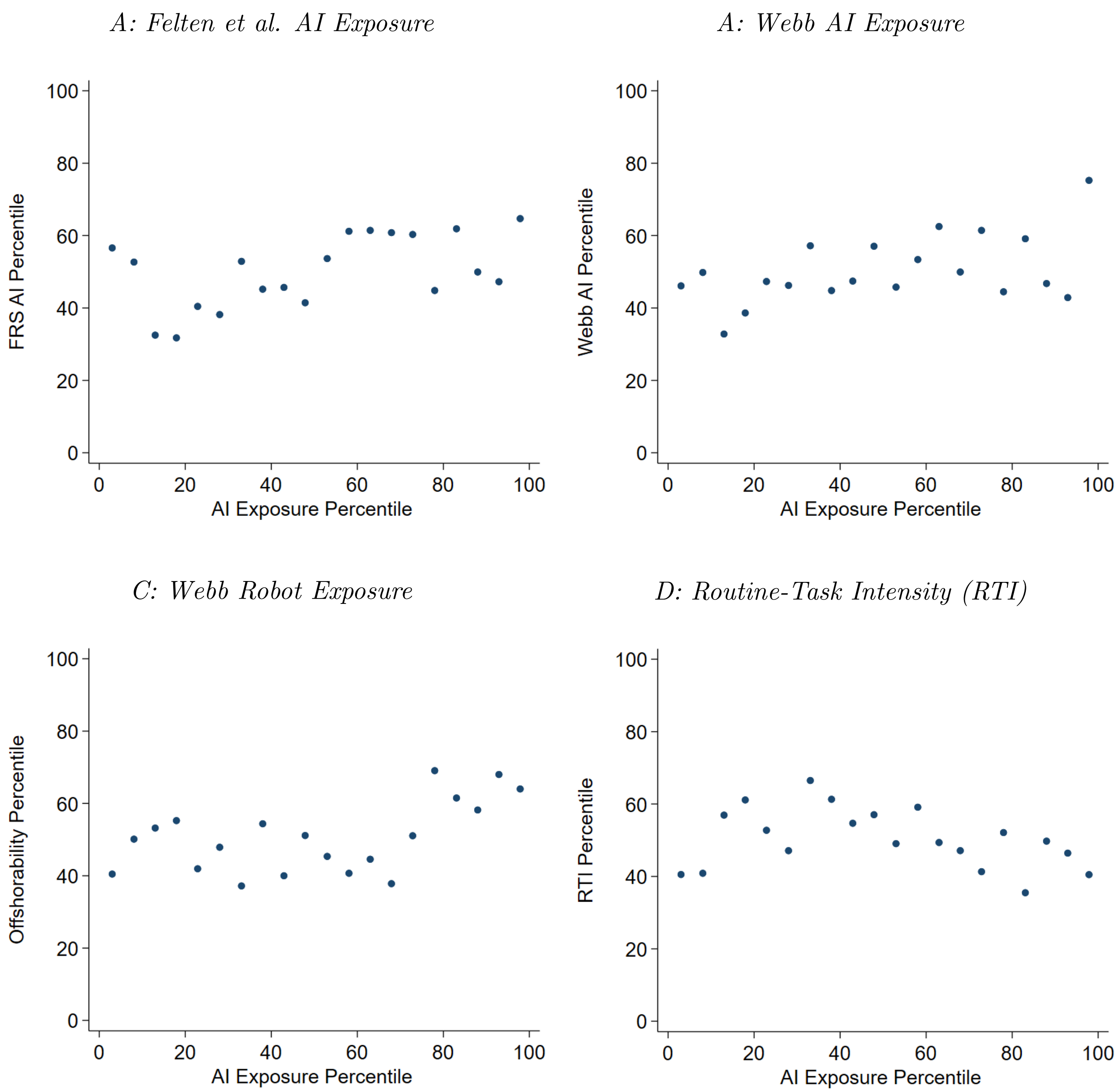
Aggregation to the Occupation-Level We next aggregate tasks' exposures to AI surveillance to the SOC 8-digit occupation level. Following Eisfeldt et al. (2023), we calculate AI surveillance (AI_o^{SUR}) for each SOC 8-digit occupation by taking the equal-weighted average of AI_j^{SUR} across all tasks associated with that occupation. Next, we aggregate SOC 8-digit ocupation codes to occ1990dd codes following the procedures outlined in Section 3.6.2.

B.4.3. Example

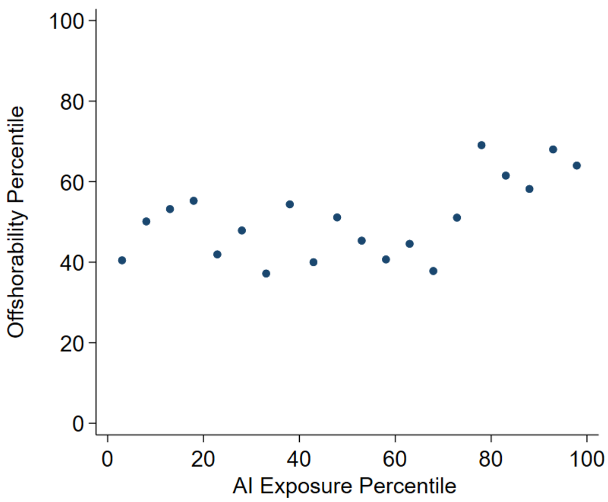
Table OA.7 of the Online Appendix lists top occupations grouped by AI surveillance exposure. On the top of the list are dispatchers, stockers and order fillers, data entry keyers, etc., while occupations with the lowest AI surveillance exposure include clergy, dentists, actors, and judges.

C. Figures

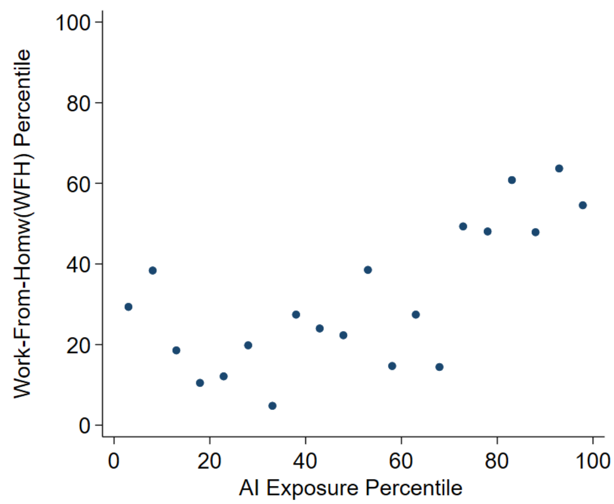
Figure OA.1. AI Exposure vs. General Technology Exposure



E: Offshorability Exposure

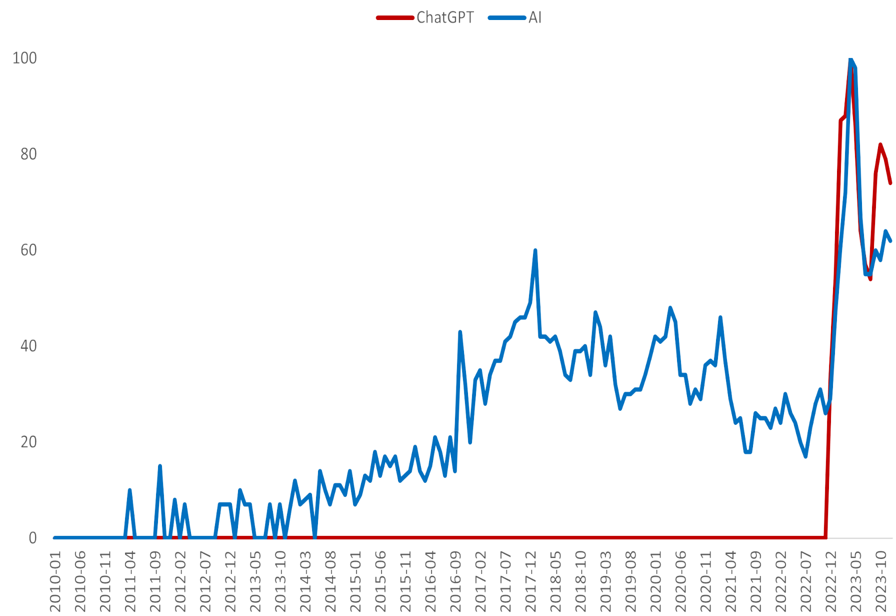


F: Work-From-Home (WFH) Exposure



The figure presents the correlation between occupational AI exposure and five occupational exposure measures including the AI exposure constructed by Felten et al. (2018), AI exposure and robot exposure constructed by Webb (2019), routine task intensity (RTI) from Autor and Dorn (2013), offshorability potentials from Firpo et al. (2011), and work-from-home (WFH) potentials from Dingel and Neiman (2020). All data series are at the *occ*1990*dd* occupation level. The AI exposure measure is constructed by the authors based on AI patent filings from 2000 to 2023. Following the literature (e.g., Autor and Dorn, 2013; Webb, 2019), the authors transform all occupation-level exposure scores to percentile ranks and plot the average AI exposure percentile over the other six exposure measures.

Figure OA.2. Google Search Trend of ChatGPT and AI



The figure presents the Google search trends of ChatGPT (launched on November 30, 2022) and artificial intelligence (AI) from 2010–2023. The Google Search Trend provides a monthly index scaled from 0 to 100 to indicate the popularity and frequency of particular search terms or topics, where "0" indicates low search volume terms.

D. Tables

Table OA.1: O*NET Database Annula Panel

This table lists the O*NET data release the authors use to construct the annual panel of occupations' job tasks from 2000–2023.

Database	Date Published
O*NET 3.0	8/1/2000
O*NET 3.1	6/1/2001
O*NET 4.0	6/1/2002
O*NET 5.0	4/1/2003
O*NET 6.0	7/1/2004
O*NET 8.0	6/1/2005
O*NET 10.0	6/1/2006
O*NET 12.0	6/1/2007
O*NET 13.0	6/1/2008
O*NET 14.0	6/1/2009
O*NET 15.0	7/1/2010
O*NET 16.0	7/1/2011
O*NET 17.0	7/1/2012
O*NET 18.0	7/1/2013
O*NET 19.0	7/1/2014
O*NET 20.0	8/1/2015
O*NET 21.0	8/1/2016
O*NET 22.0	8/1/2017
O*NET 23.0	8/1/2018
O*NET 24.0	8/1/2019
O*NET 25.0	8/1/2020
O*NET 26.0	8/1/2021
O*NET 27.0	8/1/2022
O*NET 28.0	8/1/2023

Table OA.2: Top Occupations by AI Exposure Scores and and AI Net Complementarity

This table presents the top occupations grouped by AI exposure (AI^{EXP}) and AI net complementarity (AI^{COMP}) at the SOC 6-digit level in 2023. Occupations are categorized into three groups: high AI^{EXP} & high AI^{COMP}, high AI^{EXP} & low AI^{COMP}, and low AI^{EXP} & low AI^{COMP}. AI^{EXP} and AI^{COMP} is measured by the annual AI-related patent filings from 2018 to 2023, representing the level of AI integration in each occupation.

Occupation Title	O*NET Code	occ1990dd Title	occ1990dd Code	AI^{EXP} Score	AI^{EXP} Pct.	AI^{COMP} Score	AI^{COMP} Pct.
High AI^{EXP} & High AI^{COMP}							
Computer and Information Systems Managers	11-3021	Managers and administrators, n.e.c.	22	2.32	100	2.32	100
Electrical Engineers	17-2071	Electrical engineers	55	2.23	100	2.20	100
Computer Hardware Engineers	17-2061	Electrical engineers	55	2.21	100	2.19	100
Inspectors, Testers, Sorters, ...	51-9061	Production checkers, ...	799	2.21	100	1.97	99
Remote Sensing Scientists and Technologists	19-2099	Physical scientists, n.e.c.	76	2.18	100	2.16	100
Operations Research Analysts	15-2031	Operations and systems researchers ...	65	2.14	100	2.12	100
Management Analysts	13-1111	Management analysts	26	2.10	100	2.07	100
Radio Frequency Identification ...	17-2072	Electrical engineers	55	2.10	99	2.06	100
Cartographers and Photogrammetrists	17-1021	Surveryors, cartographers,...	218	2.02	99	1.90	99
Bioinformatics Technicians	43-9111	Statistical clerks	386	2.02	99	1.94	99
High AI^{EXP} & Low AI^{COMP}							
Data Entry Keyers	43-9021	Data entry keyers	385	1.82	96	0.33	23
Log Graders and Scalers	45-4023	Timber, logging, ...	496	1.32	65	-0.34	2
Extruding, Forming, Pressing...	51-9041	Extruding and forming machine ...	755	1.48	80	0.31	21
Office Machine Operators,...	43-9071	Office machine operators, n.e.c.	347	1.48	79	0.33	23
Tellers	43-3071	Bank tellers	383	1.52	83	0.44	29
Transportation Security Screeners	33-9093	Production checkers, ...	36	1.44	77	0.33	23
Parts Salespersons	41-2022	Parts salesperson	275	1.48	80	0.49	31
Rolling Machine Setters, ...	51-4023	Rollers, roll hands, ...	707	1.34	66	0.28	19
Bill and Account Collectors	43-3011	Bill and account collectors	378	1.58	86	0.68	43
Meter Readers, Utilities	43-5041	Meter readers	366	1.40	73	0.50	32
Low AI^{EXP} & Low AI^{COMP}							
Naturopathic Physicians	29-1199	Other health and therapy...	89	0.53	1	0.10	10
Retail Loss Prevention Specialists	33-9099	Protective service, n.e.c.	427	0.53	1	0.06	8
Barbers	39-5011	Barbers	457	0.57	2	-0.03	5
Excavating and Loading Machine ...	53-7032	Excavating and loading machine ...	853	0.59	2	-0.02	6
Welders, Cutters, and ...	51-4121	Welders, solderers, and ...	783	0.59	3	-0.09	3
Shampooers	39-5093	Hairdressers and cosmetologists	458	0.67	5	-0.40	1
Janitors and Cleaners,...	37-2011	Janitors	453	0.70	6	-0.11	3
Sewers, Hand	51-6051	Tailors, dressmakers, and sewers	666	0.71	7	-0.03	5
Dancers	27-2031	Dancers	193	0.71	7	-0.06	5
Slaughterers and Meat Packers	51-3023	Butchers and meat cutters	686	0.74	9	-0.64	1

Table OA.3: Top Occupations by Generative AI Exposure

This table presents the top occupations grouped by Generative AI exposure ($GenAI^{EXP}$) and Generative AI net complementarity ($GenAI^{COMP}$) at the SOC 6-digit level in 2023. Occupations are categorized into three groups: high $GenAI^{EXP}$ & high $GenAI^{COMP}$, high $GenAI^{EXP}$ & low $GenAI^{COMP}$, and low $GenAI^{EXP}$ & low $GenAI^{COMP}$. $GenAI^{EXP}$ and $GenAI^{COMP}$ are constructed following Eisfeldt et al. (2023) and Kogan et al. (2023), respectively, as outlined in Section B.3 of the Online Appendix.

Occupation Title	O*NET Code	occ1990dd Title	occ1990dd Code	$GenAI^{EXP}$ Score	$GenAI^{EXP}$ Pct.	$GenAI^{COMP}$ Score	$GenAI^{COMP}$ Pct.
High $GenAI^{EXP}$ & High $GenAI^{COMP}$							
Training and Development Managers	11-3131	Human resources and labor ...	8	0.92	99	1.00	100
Market Research Analysts ...	13-1161	Computer systems analysts ...	64	0.92	99	0.84	99
Archivists	25-4011	Archivists and curators	165	0.92	99	0.77	98
Computer Systems Analysts	15-1211	Computer systems analysts ...	64	0.90	99	0.67	96
Software Quality Assurance Analysts ...	15-1253	Computer systems analysts ...	64	0.90	99	0.40	81
Credit Counselors	13-2071	Other financial specialists	25	0.87	98	0.74	98
Logisticians	13-1081	Operations and systems researchers ...	65	0.87	98	0.67	96
Environmental Scientists and Specialists,...	19-2041	Geologists	75	0.89	98	0.65	95
Web and Digital Interface Designers	15-1255	Computer systems analysts ...	64	0.84	97	0.87	99
Management Analysts	13-1111	Management analysts	26	0.82	96	0.91	100
High $GenAI^{EXP}$ & Low $GenAI^{COMP}$							
Tax Preparers	13-2082	Other financial specialists	25	0.92	99	-0.08	52
Credit Analysts	13-2041	Other financial specialists	25	0.82	96	-0.09	52
Financial Specialists, All Other	13-2099	Other financial specialists	25	0.77	94	0.09	60
Customer Service Representatives	43-4051	Customer service reps, invest., ...	376	0.73	92	0.07	58
Insurance Underwriters	13-2053	Insurance underwriters	24	0.71	91	-0.29	42
Securities, Commodities, and Financial ...	41-3031	Financial service sales occupations	255	0.70	90	-0.27	44
Actuaries	15-2011	Actuaries	66	0.67	88	-0.13	50
Data Entry Keyers	43-9021	Data entry keyers	385	0.67	88	0.00	55
Appraisers of Personal and Business Property	13-2022	Real estate sales occupations	254	0.64	87	-0.43	34
Mathematicians	15-2021	Mathematicians and statisticians	68	0.64	86	-0.09	52
Low $GenAI^{EXP}$ & Low $GenAI^{COMP}$							
Terrazzo Workers and Finishers	47-2053	Concrete and cement workers	588	0	1	-1.00	1
Tire Builders	51-9197	Machine operators, n.e.c.	779	0	1	-1.00	1
Stonemasons	47-2022	Masons, tilers, and carpet installers	563	0	1	-0.94	3
Slaughterers and Meat Packers	51-3023	Butchers and meat cutters	686	0	1	-0.93	4
Structural Metal Fabricators and Fitters	51-2041	Structural metal workers	597	0	1	-0.91	5
Structural Iron and Steel Workers	47-2221	Structural metal workers	597	0	1	-0.90	5
Surgical Assistants	29-9093	Health technologists ...	208	0	1	-0.89	6
Tire Repairers and Changers	49-3093	Heavy equipment and farm ...	516	0	1	-0.85	9
Tool Grinders, Filers, and Sharpeners	51-4194	Precision grinders and fitters	644	0	1	-0.83	10
Wellhead Pumpers	53-7073	Misc. material moving equipment...	859	0	1	-0.63	24

Table OA.4: AI Exposure and Alternative Specifications

The table reports the regression results of alternative specifications that estimate the effect of occupational AI exposure on work-life balance at the individual level based on the ATUS survey from 2004–2023. For detailed information, please see the next page.

DV	Weekly Hours$_{i,o,t}$						
Sample						Exclude Unemployment	
	Work w. Commute	Work	Leisure	Work	Leisure	Work	Leisure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$AI^{EXP}_{o,t-1}$	0.018*	0.020**	-0.017**	0.021*	-0.014**	0.018*	-0.017**
	(1.71)	(2.01)	(-2.15)	(1.84)	(-2.28)	(1.91)	(-2.22)
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race indicators	Yes	Yes	Yes	No	No	Yes	Yes
Occupational FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Part-Time Work FE	No	Yes	Yes	No	No	No	No
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	121,841	121,841	121,841	121,844	121,844	116,504	116,504
R^2	0.284	0.310	0.252	0.281	0.243	0.303	0.252
Adjusted R^2	0.269	0.296	0.236	0.266	0.228	0.288	0.235

DV	Weekly Hours$_{i,o,t}$					
Sample	Exclude Weekends		Exclude Absences		Hourly Workers	
	Work	Leisure	Work	Leisure	Work	Leisure
	(6)	(7)	(8)	(9)	(10)	(11)
$AI^{EXP}_{o,t-1}$	0.024*	-0.021**	0.017*	-0.015*	0.032**	-0.028**
	(1.99)	(-2.35)	(1.69)	(-1.96)	(2.04)	(-2.44)
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Race indicators	Yes	Yes	Yes	Yes	Yes	Yes
Occupational FE	Yes	Yes	Yes	Yes	Yes	Yes
Part-Time Work FE	No	No	No	No	No	No
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,940	60,940	116,737	116,737	58,590	58,590
R^2	0.153	0.145	0.296	0.256	0.278	0.253
Adjusted R^2	0.118	0.108	0.281	0.240	0.246	0.220

The table reports the regression results of alternative specifications that estimate the effect of occupational AI exposure on work-life balance at the individual level based on the ATUS survey from 2004–2023. Following Aguiar et al. (2021), the regression is weighted by ATUS sample weights. The occupations are uniquely identified by "occ1990dd" codes from Dorn (2009). The dependent variables are weekly hours spent on market work and leisure. The main explanatory variable is occupational AI exposure in percentile rank ($AI_{o,t}^{EXP}$), constructed by the authors using AI patents in a five-year rolling window as described in Section 3.6. We additionally include individual-level controls which include age, the number of children, and a series of indicator variables for gender, educational attainment, marital status, and race, A battery of fixed effects at the following levels are included: occupation, state × year, industry × year, year-month and day-of-week. Standard errors are double clustered by occupation and state. Asterisks denote the significance levels (***=1%, **=5%, *=10%). The unique specification for each column is described as follows.

(a.) Column (1): The alternative dependent variable is market work hours, including hours for commute, work-related travels and social&leisure activities at work.

(b.) Columns (2)-(3): The regression additionally controls for an indicator variable for part-time workers.

(c.) Columns (4)-(5): The regression does not control for race indicators.

(d.) Columns (6)-(7): Currently unemployed individuals are excluded from the sample.

(e.) Columns (8)-(9): Individuals surveyed on weekends are excluded from the sample.

(f.) Columns (10)-(11): Individuals who are currently employed but are absent from work on the ATUS interview date are excluded from the sample.

(g.) Columns (12)-(13): Only individuals compensated on the hourly bases are included from the sample.

Table OA.5: Decomposed Leisure Activities

The table reports the weighted linear regressions that estimate the effect of occupational AI exposure on leisure activities at the individual level based on the ATUS survey from 2004–2023. Following Aguiar et al. (2021), the regression is weighted by ATUS sample weights. The occupations are uniquely identified by "occ1990dd" codes from Dorn (2009). The dependent variable, weekly hours spent on leisure activities, is categorized into screen-based leisure activities (recreational computer use, gaming, and watching TV) in columns (1) and (7), and non-screen leisure activities in columns (2) and (8). Column (3)–(6) and column (9)–(12) further decompose the non-screen leisure activities subdivided into four categories: recreation (relaxing, listening to music, traveling, etc.), socializing, leisure aspects of eating, sleeping, and personal care (ESP), and others (hobbies, reading, and sports). The main explanatory variable represents AI exposure measures at the occupation-year level, expressed in percentile ranks, and is based on AI-related patents granted in a five-year window ending in the current year (detailed description in Section 3.6). We additionally include individual-level controls, including age, the number of children, and a series of indicator variables for gender, educational attainment, marital status, and race, and fixed effects at the following levels: occupation, state × year, industry × year, year-month, and day-of-week. Standard errors are double clustered by occupation and state. Asterisks denote the significance levels (***=1%, **=5%, *=10%).

DV	Weekly Leisure Hours$_{i,o,t}$					
	Screen-Based	Non-Screen	Non-Screen			
			Recreation	Socializing	ESP	Other
	(1)	(2)	(3)	(4)	(5)	(6)
$AI^{EXP}_{o,t-1}$	-0.001	-0.014**	-0.005*	-0.003	-0.008	0.001
	(-0.23)	(-2.52)	(-1.93)	(-0.65)	(-1.52)	(0.40)
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Occupational FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	121,841	121,841	121,841	121,841	121,841	121,841
R^2	0.132	0.154	0.051	0.078	0.137	0.075
Adjusted R^2	0.114	0.136	0.0317	0.0587	0.119	0.0557

Table OA.6: AI Exposure and Alternative Activities

The table reports the weighted linear regressions that examine the effect of occupational AI exposure on time allocated to activities other than market work and leisure at the individual level based on ATUS survey from 2004–2023. Following Aguiar et al. (2021), the regression is weighted by ATUS survey weights. The occupations are uniquely identified by "occ1990dd" codes from Dorn (2009). The dependent variable is weekly hours spent on home production in column (1), child care in column (2), personal education in column (3), job search in column (4), own medical care in column (5), and civic activities in column (6). The main explanatory variable, AI^{EXP}, represents AI exposure at the occupation-year level, expressed in percentile ranks, and is based on AI-related patents granted in a five-year window ending in the current year (detailed description in Section 3.6). We additionally include individual-level controls, including age, the number of children, and a series of indicator variables for gender, educational attainment, marital status, and race, and fixed effects at the following levels: occupation, state × year, industry × year, year-month, and day-of-week. Standard errors are double clustered by occupation and state. Asterisks denote the significance levels (***=1%, **=5%, *=10%).

DV	Weekly Hours$_{i,o,t}$					
	Home Production	Child Care	Education	Job Search	Own Medical Care	Civic Activities
	(1)	(2)	(3)	(4)	(5)	(6)
$AI^{EXP}_{o,t-1}$	-0.000	0.002	-0.005	-0.000	-0.001	0.004**
	(-0.04)	(0.56)	(-1.63)	(-0.54)	(-1.23)	(2.07)
Individual Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Occupational FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	121,841	121,841	121,841	121,841	121,841	121,841
R^2	0.143	0.174	0.163	0.047	0.043	0.080
Adjusted R^2	0.125	0.156	0.146	0.027	0.023	0.061

Table OA.7: Top Occupations by AI Surveillance

This table presents the top occupations grouped by AI Surveillance exposure (AI^{SUR}) at the SOC 6-digit level. The procedures measuring AI^{SUR} are described in Section B.4 of Online Appendix.

Occupation Title	O*NET Code	occ1990dd Title	occ1990dd Code	AI^{SUR} Score	AI^{SUR} Pct.
		Highest			
Gambling Surveillance Officers ...	33-9031	Guards and police, except public service	426	8.63	100
Air Traffic Controllers	53-2021	Air traffic controllers	227	8.26	100
Dispatchers, Except Police, Fire, ...	43-5032	Dispatchers	359	8.23	100
Packaging and Filling Machine Operators...	51-9111	Packers, fillers, and wrappers	754	8.20	100
Customer Service Representatives	43-4051	Customer service reps, invest., adjusters,...	376	8.07	99
First-Line Supervisors of Retail Sales Workers	41-1011	Sales supervisors and proprietors	243	8.05	99
Stockers and Order Fillers	53-7065	Stock and inventory clerks	365	8.03	98
Data Entry Keyers	43-9021	Data entry keyers	385	8.00	97
Heavy and Tractor-Trailer Truck Drivers	53-3032	Driver/sales workers and truck Drivers	804	8.00	97
First-Line Supervisors of Gambling Services Workers	39-1013	Managers and administrators, n.e.c.	459	7.90	96
		Lowest			
Oral and Maxillofacial Surgeons	29-1022	Dentists	85	4.36	1
Funeral Attendants	39-4021	Personal service occupations, n.e.c	469	4.65	1
Clergy	21-2011	Clergy	176	4.71	1
Judges, Magistrate Judges, and Magistrates	23-1023	Lawyers and judges	178	4.95	1
Musicians and Singers	27-2042	Musicians and composers	186	5.37	2
Labor Relations Specialists	13-1075	Personnel, HR, training, and labor...	27	5.43	2
Historians	19-3093	Social scientists and sociologists, n.e.c.	169	5.52	2
Actors	27-2011	Actors, directors, and producers	187	5.53	2
Barbers	39-5011	Barbers	457	5.75	3
Psychologists, All Other	19-3039	Psychologists	167	5.78	3