Task-Specific Technical Change and Comparative Advantage*

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Abstract

Artificial intelligence is transforming the task content of work. Predicting the labor market consequences requires understanding how workers' skills determine productivity across tasks, how workers adapt by changing occupations and acquiring new skills, and how wages adjust in general equilibrium. We introduce a dynamic task-based model in which workers accumulate multidimensional skills that shape their comparative advantage across tasks and, in turn, their occupational choices. We then develop an estimation strategy that recovers (i) the mapping from skills to task-level productivity, (ii) the law of motion for skill accumulation, and (iii) the determinants of occupational choice. We use the quantified model to study generative AI's impact through task augmentation, automation, and simplification. We predict long-run average wage gains of 24 percent and a substantial reduction in wage inequality. The distributional effects arise almost entirely due to task simplification—the degree to which AI reduces the skill level required to perform tasks. We show that AI's labor market effects critically hinge on its technological scope by contrasting generative AI with physically-capable AI robots.

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1 Introduction

Technological change alters the tasks performed in production and the returns to the skills that determine workers' productivity in those tasks. Turning information on how workers' tasks change into quantitative predictions about the labor market requires an understanding of (i) how skills map into productivity across tasks (and thus govern workers' comparative advantage), (ii) how workers build those skills over their careers, and (iii) how prices, wages, and workers' occupational choices adjust in general equilibrium. This paper develops and estimates a dynamic task-based labor market model that allows researchers to estimate the effects of any task-specific technical change—observed or counterfactual—on individual workers and the overall labor market. We apply this methodology to study the labor market effects of artificial intelligence.

To illustrate the need for this framework, consider radiologists, an occupation where AI is reshaping tasks in multiple ways: AI can assist with detection of abnormalities, automate screening procedures, and simplify report generation (e.g., Hosny et al., 2018; Eloundou et al., 2024; Mousa, 2025). How do these shifts in task composition affect radiologists? Do their skills become more or less valuable in the era of AI? If necessary, could they transition to related medical specialties? If retraining is required, at what pace can workers accumulate new skills? Without answering such questions—jointly and in general equilibrium—one cannot predict how workers will be impacted by AI.

Our model captures key features necessary to understand the labor market effects of task-specific technical change. Workers have multidimensional skills. Their productivity in a given task follows from the match between these skills and the task's skill requirements. Workers learn on the job depending on their occupation, and their ability to learn. Each period, they choose from a menu of occupations, each consisting of a set of tasks. These occupational choices are forward-looking as workers internalize that their skill accumulation depends on those choices. In equilibrium, demand for each occupation's output equals the amount produced by workers choosing that occupation.

We model technical change as the augmentation, automation, and simplification of tasks. Augmentation increases human productivity in tasks. Automation expands the set of tasks that can be performed without human input. Both are standard features of task-based models (e.g., Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018). Beyond those standard forces, we also consider that technology can reduce the level of skill required to complete a task. We refer to this as *simplification*. Together, the three channels determine how each worker's productivity is affected by technical change.

Identifying the parameters that govern workers' comparative advantage and skill accumulation requires overcoming two main challenges. First, wages provide information on workers' productivity in an occupation as a whole, but not in the separate tasks. Second, we lack data on how workers' multidimensional skills evolve over their careers; instead, we only observe skills at labor market entry.

Our strategy to identify workers' task-level productivity exploits how task-specific productivity aggregates into occupational output and earnings in the model. We first show that the optimal allocation of time across tasks yields a closed-form occupational production function: a mapping from workers' skills and the set of occupational tasks and their skill requirements to occupational productivity. We use this occupational production function to recover the underlying task-level productivity from data on wages, worker skills, occupational tasks, and task-specific skill requirements. The recovered task-level production function fully characterizes each worker's absolute and comparative advantage across tasks given their skills.

We show that the skill-accumulation process can be recovered from micro data on initial skills, occupational histories, and wages. Conditional on initial skills, workers' learning depends only on their occupational choices. Any given set of learning parameters therefore implies a path for each worker's skills over the career, given that history. Because skills determine wages, these learning parameters are identified from data on initial skills, occupational choices, and subsequent wage progression.

We estimate the model parameters by maximum likelihood using data from the National Longitudinal Survey of Youth 1979 (NLSY79). Our procedure is computationally efficient because it exploits that many parameters either admit closed-form expressions or can be obtained with a fast iterative routine conditional on the remaining parameters, substantially reducing the dimension of the parameter space that must be searched non-linearly. In our quantitative application, workers' skills are five-dimensional: manual, social, math, technical, and verbal.[1] In addition, workers differ in their "ability to learn", that is, the

[1]We define and measure these skills in the NLSY79 similar to (Addison et al., 2020; Baley et al., 2022). Relative to these papers, we add manual skills as we believe that to be an important

rate at which they accumulate skills. Following Heckman et al. (1998), we estimate learning ability separately by quartiles of the AFQT score distribution.[2]

Having estimated its parameters, we provide a method to solve for the model's equilibrium prices. We do so by iteratively updating prices to equate demand and supply. In each iteration, we solve the worker's occupational choice problem and simulate their implied choices given the set of prices. These choices then imply a new vector of prices. We provide algorithms to solve for the steady state and the transition path based on this logic. Since the worker's state space is large, these procedures are computationally costly. The fact that our strategy to estimate the model's parameters does not require solving for the equilibrium is therefore a large computational advantage.

The quantified model offers a laboratory to study the labor market effects of any counterfactual task-specific technical change.[3] The model predicts how workers' comparative advantage changes in response, how workers reallocate and retrain, and how prices adjust in general equilibrium.

The case of artificial intelligence. We apply the quantified model to predict how AI will affect individual workers and the labor market as a whole. We follow Eloundou et al. (2024); Eisfeldt et al. (2023) in using large language models (LLMs) to obtain estimates of AI's capability to augment, automate, and simplify tasks. Our prompts closely follow the survey design used to collect assessments from human experts, while enabling hundreds-of-thousands of evaluations. We provide evidence that these LLM-generated estimates are reasonable, including validation against human expert assessments and experimental evidence.

Our first key finding is that generative AI yields large wage gains, especially to the bottom of the distribution. The model predicts an average wage gain of 24%. However, the average masks large differences across the distribution. The bottom 50% increases by over 40% while the wage gains of the top percentiles are close to zero. Simplification drives this distributional effect. Automation and augmentation, on the other hand, yield positive effects that are quite broadly shared across the population.

dimension for our AI counterfactual.

[2]AFQT stands for the Armed Forces Qualification Test: a measure of ability used by the US military to determine enlistment eligibility.

[3]The estimated model can also be applied to study changes in occupational demand (since the estimation of none of the supply-side parameters depend on assumptions on demand).

Second, we find that the introduction of AI generates sizable ex-ante welfare gains for almost all workers at labor market entry. We estimate welfare improvements equivalent to permanent wage gains of 29–35% for most workers. Consistent with the decline in wage inequality, we find that the welfare gains are largest for less skilled workers. Workers with less verbal skills see particularly large welfare increases. Math is the only dimension of skill for which the return increases.

The third finding is that AI has highly heterogeneous effects across occupations, generating large reallocations of employment and wage bills. While average wages rise modestly, some occupations experience absolute wage declines and employment losses exceeding half their initial employment, whereas others—particularly *Architecture and Engineering*, *Management*, and *Computer and Mathematical* occupations—see sizable employment and wage bill gains. Decomposing these changes, we show that augmentation raises wages quite uniformly across occupations and does not lead to large reallocation, automation shifts employment away from highly exposed occupations. Simplification increases employment, while decreasing the average wages.

Early labor market evidence provides suggestive support for our model's predictions. Using an event study design around ChatGPT's November 2022 release, we find that occupations predicted to benefit from AI show differential positive trends in wage bill shares, with approximately 10 percent of our predicted long-run effects materializing by early 2025.

Related literature. To predict how technologies affect workers through their task-specific comparative advantage, we integrate three previously separate literatures—on task-based production, multidimensional skills, and dynamic occupational choice—in a single empirically tractable framework.

Our contribution to the literature on task-based production and technological change is threefold (e.g., Zeira, 1998; Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018, 2022; Autor and Thompson, 2025). First, we provide methods to estimate workers' comparative advantage across tasks, a key object in shaping how technical change affects workers. The absence of such methods has inhibited quantifying the general equilibrium effects of future technical change (Woessmann, 2024).[4] Second, while the literature on task-

[4] Acemoglu and Restrepo (2022) show that the role of comparative advantage across groups can, to a first order, be captured by a low-dimensional propagation matrix. However, estimat-

based production treats workers' skills as fixed, we allow for and estimate skill accumulation—a force shaping workers' adaptation to technical change. Third, we integrate task-based production into a general equilibrium dynamic occupational choice model (in the spirit of Keane and Wolpin, 1997; Heckman et al., 1998; Lee and Wolpin, 2006; Dix-Carneiro, 2014; Traiberman, 2019), capturing workers' choices over a discrete set of task-bundled occupations (Autor and Handel, 2013; Hurst et al., 2024).

We also build on the literature emphasizing the multi-dimensionality of skills (Lindenlaub, 2017; Guvenen et al., 2020; Lise and Postel-Vinay, 2020; Baley et al., 2022). First, we integrate the micro-foundations of multi-dimensional comparative advantage and skill accumulation into a model of task-based production. Second, we overcome the empirical challenges that result from this task-based approach with a new estimation strategy. The estimation routine avoids having to solve for the full equilibrium, ensuring computational feasibility and carrying the conceptual advantage that the sources of identification of the model's parameters can be clearly distinguished. Third, to enable task-level estimation and counterfactual analysis, we construct a database of task-level skill requirements. Prior work relies on O*NET's occupational aggregates (e.g., Lise and Postel-Vinay, 2020; Baley et al., 2022). We extend these to the task-level using large language models and validate the database's accuracy.

Finally, our work relates to a growing literature that quantifies the effects of task-specific technical change. Freund and Mann (2025) introduce a partial equilibrium framework to understand how automation affects wages through changes in the importance of tasks within an occupation, together with a strategy to estimate the distribution of workers' task-level productivity. In comparison, our approach allows to understand how prices, wages, and workers' skills adjust dynamically to AI in general equilibrium. Hampole et al. (2025) provide a structural framework to quantify AI's effect on occupational demand through actual adoption patterns across firms. In contrast, our paper predicts how AI affects individual workers and the overall labor market by modeling and estimating workers' comparative advantage and skill accumulation.

ing this matrix relies on the identification of the technology's labor market effects, so that it cannot be used to study effects of *counterfactual* technical change.

2 Model

In the model below, we describe how workers choose occupations, perform tasks, and accumulate skills over their careers. Productivity and wages depend on the match between a worker's skills and the skill requirements of the tasks relevant to the occupation of choice. Workers accumulate skills on the job, so that their occupational choice depends on the current wage as well as the learning benefits that the job offers. Overlapping generations of workers live for A periods. Technical change can take the form of augmentation, automation, and simplification of tasks.

2.1 The Firm's and Worker's Problem

Occupations and tasks. Each occupation produces a distinct good by combining a unique combination of tasks. These tasks are combined with a constant elasticity of substitution ρ, so that the production function of occupation j is

$$Y_j = \left(\sum_{\tau \in \mathcal{T}_j} \theta_{j,\tau}^{\frac{1}{\rho}} y_\tau^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} \tag{1}$$

where $\mathcal{T}_j$ is the discrete set of relevant tasks, y_τ is the output of task τ, and $\theta_{j,\tau}$ is task τ's importance weight that satisfies $\sum_{\tau \in \mathcal{T}_j} \theta_{j,\tau} = 1$.

Task-level productivity and skills. The production function for task τ in occupation j depends on whether the task is automatable, i.e., $\tau \in \mathcal{A}_j$, or not, i.e., $\tau \in \mathcal{N}_j$:

$$y_\tau(\boldsymbol{h}, \ell_\tau, k_\tau) = \begin{cases} \ell_\tau \gamma_\tau f(\boldsymbol{h}, \boldsymbol{r}_\tau) & \text{if } \tau \in \mathcal{N}_j \\ \ell_\tau \gamma_\tau f(\boldsymbol{h}, \boldsymbol{r}_\tau) + k_\tau & \text{if } \tau \in \mathcal{A}_j \end{cases} \tag{2}$$

where ℓ_τ represents the share of time allocated to task τ, γ_τ is a task-specific productivity parameter, $\boldsymbol{h} = (h_s)'_{s \in S}$ denotes the worker's specialized skills, and $\boldsymbol{r}_\tau \equiv (r_{\tau,s})'_{s \in S}$ is the skill requirement of task τ, and k_τ is capital devoted to task τ. If the task is automatable, capital and labor are perfect substitutes.

The function $f(\cdot)$ determines how workers with different skills $\boldsymbol{h}$ are differentially productive in tasks depending on its skill requirements, $\boldsymbol{r}_\tau$. Intuitively, this function captures how workers productivity depends on the "match" between their skills and the skills required (Lise and Postel-Vinay, 2020; Baley et al., 2022). For our quantification, we will assume a functional form for $f(\cdot)$ (in section 2.4, equation (14)) and show how its parameters can be identified and estimated. However, for the purpose of presenting the model, the functional form is not needed, so we keep $f(\cdot)$ in this general form.

Technical change. We consider three different ways in which technical change affects the task-level production function:

Augmentation	Enhancing human productivity, increasing γ_τ;
Automation	Performing tasks autonomously at a cost c_τ;
Simplification	Simplifying tasks for humans, reducing $\boldsymbol{r}_\tau$.

The first two are standard in the literature (e.g., Acemoglu and Autor, 2011). We introduce simplification because we think it is a natural extension in the context of our model. Furthermore, experimental evidence has shown that AI's productivity effects tend to be stronger for less skilled workers, suggesting that simplification can be an important force in practice (e.g., Brynjolfsson et al., 2025b).

The firm's problem. Each good j is produced by a representative firm that takes the equilibrium wage $\{w_j(\boldsymbol{h})\}_{\boldsymbol{h}}$ and the costs of automation capital $\{c_\tau\}_{\tau\in\mathcal{A}_j}$ as given. The firm chooses how many workers of each skill level to hire, how to allocate their time across tasks, and how to allocate capital to automatable tasks. Formally, the firm solves the following profit maximization problem:

$$
\begin{aligned}
\max_{\{n_j(\boldsymbol{h}),\ell_{j,\tau}(\boldsymbol{h}),k_{j,\tau}(\boldsymbol{h})\}} \int_{\boldsymbol{h}} n_j(\boldsymbol{h}) &\left(p_j Y_j(\boldsymbol{h}) - w_j(\boldsymbol{h}) - \sum_{\tau\in\mathcal{A}_j} c_\tau k_{j,\tau}(\boldsymbol{h}) \right) \\
\text{s.t. } Y_j(\boldsymbol{h}) &= \left(\sum_{\tau\in\mathcal{T}_j} \theta_{j,\tau}^{\frac{1}{\rho}} \tilde{y}_\tau(\boldsymbol{h}))^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} \\
\sum_{\tau\in\mathcal{T}_j} \ell_{j,\tau}(\boldsymbol{h}) &= 1 \; \forall \boldsymbol{h} \\
\tilde{y}_\tau(\boldsymbol{h}) &\equiv y_\tau(\boldsymbol{h}, \ell_{j,\tau}(\boldsymbol{h}), k_{j,\tau}(\boldsymbol{h})) \text{ given by (2)},
\end{aligned}
\tag{3}
$$

where $n_j(\boldsymbol{h})$ is the amount of labor employed with skill $\boldsymbol{h}$, $l_{j,\tau}(\boldsymbol{h})$ is the share of time allocated to task τ, and $k_{j,\tau}(\boldsymbol{h})$ denotes capital dedicated to task τ.

Since the firm takes wages as given the equilibrium wage must be equal to the worker's marginal product. That is,

$$w_j(\boldsymbol{h}) = p_j Y_j(\boldsymbol{h}) - \sum_{\tau \in \mathcal{A}_j} c_\tau k_{j,\tau}(\boldsymbol{h}), \tag{4}$$

so that the wage is equal to the value of output minus the cost of capital.

The task allocation problem reduces to maximizing the value added of each individual worker. To simplify this problem, we assume that capital is productive enough so that no firm finds it optimal to allocate any worker's time to automatable tasks.

Assumption 1 (Full automation of automatable tasks)**.** The unit cost of producing a task with capital is lower than the cost of producing it with labor for all occupations, tasks, and skills. That is, for all occupations j, skills $\boldsymbol{h}$, and tasks $\tau \in \mathcal{A}_j$,

$$\frac{w_j(\boldsymbol{h})}{\gamma_\tau f(\boldsymbol{h}, \boldsymbol{r}_\tau)} > c_\tau.$$

Optimal time allocation. Under Assumption 1, the worker's time is allocated only to non-automatable tasks $\tau \in \mathcal{N}_j$. Hence, the firm maximizes

$$\{\ell_{j,\tau}(\boldsymbol{h})\}_{\tau \in \mathcal{N}_j} = \underset{\{\ell_\tau\}_{\tau \in \mathcal{N}_j}}{\arg\max} \left(\sum_{\tau \in \mathcal{N}_j} \theta_{j,\tau}^{\frac{1}{\rho}} \left(\ell_\tau \gamma_\tau f(\boldsymbol{h}, \boldsymbol{r}_\tau)\right)^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} \quad \text{s.t.} \sum_{\tau \in \mathcal{N}_j} \ell_\tau = 1.$$

The solution to this problem for a given task $\tau \in \mathcal{N}_j$ is

$$\ell_{j,\tau}(\boldsymbol{h}) = \frac{\theta_{j,\tau} \gamma_\tau^{\rho-1} f(\boldsymbol{h}, \boldsymbol{r}_\tau)^{\rho-1}}{\sum_{\kappa \in \mathcal{N}_j} \theta_{j,\kappa} \gamma_\kappa^{\rho-1} f(\boldsymbol{h}, \boldsymbol{r}_\kappa)^{\rho-1}}, \tag{5}$$

which shows that more time is spent on tasks with greater effective weight $\theta_{j,\tau}$. If tasks are substitutes ($\rho > 1$) a worker's time is allocated to the most productive tasks, i.e., tasks for which $\gamma_\tau f(\boldsymbol{h}, \boldsymbol{r}_\tau)$ is greater. If instead tasks are complements ($\rho < 1$), workers spend more time on the less productive tasks.

Optimal automation. In choosing how much capital to allocate to each worker-task pair, the firm balances the marginal benefit of increased output against the cost of capital. The first order condition implies that for all tasks $\tau \in \mathcal{A}_j$

$$k_{j,\tau}\left(\boldsymbol{h}\right) = \theta_{j,\tau} Y_j\left(\boldsymbol{h}\right)\left(\frac{p_j}{c_\tau}\right)^{\rho}, \tag{6}$$

where $Y_j\left(\boldsymbol{h}\right)$ is the profit-maximizing level of output when a worker with skill vector $\boldsymbol{h}$ works in occupation j. Clearly, the lower the cost of capital relative to the price of the output, the more the firm uses capital.

Occupational productivity. Given the optimal allocation of time and automation technology to the production of tasks, the output per worker of type $\boldsymbol{h}$ is

$$\begin{aligned} Y_j\left(\boldsymbol{h}\right) &\equiv \left(\sum_{\tau\in\mathcal{A}_j} \theta_{j,\tau}^{\frac{1}{\rho}} k_{j,\tau}(\boldsymbol{h})^{\frac{\rho-1}{\rho}} + \sum_{\tau\in\mathcal{N}_j} \theta_{j,\tau}^{\frac{1}{\rho}}\left(\ell_{j,\tau}(\boldsymbol{h})\gamma_\tau f(\boldsymbol{h},\boldsymbol{r}_\tau)\right)^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}} \\ &= \Gamma_j^{\frac{\rho}{1-\rho}}\left(\sum_{\tau\in\mathcal{N}_j} \theta_{j,\tau}\gamma_\tau^{\rho-1} f(\boldsymbol{h},\boldsymbol{r}_\tau)^{\rho-1}\right)^{\frac{1}{\rho-1}} \end{aligned} \tag{7}$$

where

$$\Gamma_j = 1 - \sum_{\tau\in\mathcal{A}_j} \theta_{j,\tau}\left(\frac{c_\tau}{p_j}\right)^{1-\rho}$$

is the equilibrium income share accruing to the worker in occupation j. Equation (7) thus shows that a worker's comparative advantage in occupation j is a function of their productivity in the non-automated tasks $\tau \in \mathcal{N}_j$.

Wages. Combining equation (4) and (7), yields the wage when a worker of skill $\boldsymbol{h}$ chooses occupation j:

$$w_j(\boldsymbol{h}) = p_j Y_j(\boldsymbol{h})\Gamma_j. \tag{8}$$

Equation (4) shows that if none of the tasks are automatable, i.e. $\mathcal{A}_j = \varnothing$ and $\Gamma_j = 1$, a worker's income equals total revenue $w_j(\boldsymbol{h}) = p_j Y_j(\boldsymbol{h})$.

Skill accumulation. Before entering the labor market at age $a = 1$, each worker draws an initial skill vector $\boldsymbol{h}_1$ after which they accumulate further skills on the job. We assume that a worker's human capital accumulation depends on their current skills, their "ability to learn" ψ, and the skill requirements of the tasks in job j: $\boldsymbol{h}' = g_j(\boldsymbol{h}, \psi)$.

Occupational choice. Every period, each worker chooses from a discrete set of occupations to maximize utility. Workers are hand-to-mouth. A worker lives for A periods and their expected lifetime utility (before observing productivity shocks ε_j) at age a when their previous occupation is k, is represented by the value function

$$V_a(\boldsymbol{h}, \psi, k) = \mathbb{E}\left[\max_j \log w_j(\boldsymbol{h}) + \log \varepsilon_j + \mu_j - \kappa(k,j) + \beta V_{a+1}\left(g_j\left(\boldsymbol{h}, \psi\right), \psi, j\right)\right] \tag{9}$$

and the value after the terminal age A is zero, $V_{A+1}(\cdot, \cdot) = 0$. $\mathbb{E}[\cdot]$ represents the expectation over occupation-specific productivity shocks ε_j, μ_j the amenity-value of occupation j, and $g_j\left(\boldsymbol{h}, \cdot\right)$ is next period's human capital when choosing occupation j. $\kappa(k,j)$ is a cost of switching from occupation k to j. In our quantitative application, we set this to $\kappa(k,j) = \kappa \mathbb{1}[j \neq k]$ for some constant κ.[5]

We assume that the log productivity shocks $\log \varepsilon_j$ follow a type I generalized extreme value (Gumbel) distribution with mean 0 and scale parameter ζ.[6] This assumption implies that the conditional probability of choosing occupation j has the closed-form solution

$$\mathbb{P}_a(j \mid \boldsymbol{h}, \psi, k) = \frac{\exp\left(\frac{1}{\zeta}\left(\log w_j(\boldsymbol{h}) + \mu_j - \kappa(k,j) + \beta V_{a+1}\left(g_j\left(\boldsymbol{h}, \psi\right), \psi, j\right)\right)\right)}{\sum_{l=1}^{J} \exp\left(\frac{1}{\zeta}\left(\log w_l(\boldsymbol{h}) + \mu_l - \kappa(k,l) + \beta V_{a+1}\left(g_l\left(\boldsymbol{h}, \psi\right), \psi, l\right)\right)\right)} \tag{10}$$

so that the value function in (9) can be simplified to

$$V_a(\boldsymbol{h}, \psi, k) = \zeta \log \sum_{j=1}^{J} \exp\left(\frac{1}{\zeta}\left(\log w_j(\boldsymbol{h}) + \mu_j - \kappa(k,j) + \beta V_{a+1}\left(g_j\left(\boldsymbol{h}, \psi\right), \psi, j\right)\right)\right) \tag{11}$$

Since $V_{A+1}(\cdot, \cdot) = 0$, equations (4), and (11) solve the value function, and thus the occupational choice problem, by backward iteration from age A to 1 for a

[5] We assume that occupational switching costs do not apply in the first period.

[6] The CDF is $\Pr(\log \varepsilon < x) = \exp\left(-\exp\left(-\frac{x+\zeta\overline{\gamma}}{\zeta}\right)\right)$ where $\overline{\gamma} \approx 0.577$ is Euler's constant. This is equivalent to assuming that ε_j follows a Weibull distribution.

given sequence of prices. Note that we have suppressed any dependence on time in the model above. In principle, prices vary over time, so that the wage schedule $w_{j,t}(\boldsymbol{h})$, and thus the value functions, are time-dependent.

2.2 Equilibrium

The price of each occupational good p_j is determined in equilibrium through demand and supply. The supply is characterized by the solution to the worker's problem. The workers, in turn, consume and generate demand for the occupational goods. We assume that demand is characterized by a homothetic and invertible demand function $D\left(\{p_j\}_{j=1}^{J}\right)$ that maps prices p_j into relative demand for each occupational good. In our application, we use CES demand. Having specified demand, we can now define the competitive equilibrium.

Definition (Competitive equilibrium)**.** Given an initial joint distribution of age, human capital, ability, and occupations, $G_{a,t}(\boldsymbol{h}, \psi, k)$, a distribution of human capital at birth $G_{1,t}(\boldsymbol{h}, \psi)$, and the supply of automation technology $\{\mathcal{K}_{\tau,t}\}_{t=1}^{\infty}$, a *competitive equilibrium* is defined as a sequence of prices $\{p_{1,t}, \cdots, p_{J,t}, \{r_{\tau,t}\}\}_{t=1}^{\infty}$ such that

- Workers' occupational choices maximize the present value of lifetime utility given the sequence of prices. That is, their occupational choice probabilities are as in (10);
- The distribution over states follows from occupational choices. That is,

$$G_{a+1,t+1}\left(\boldsymbol{h}', \psi, j\right) = \sum_{k=1}^{J} \int_{g_k(\boldsymbol{h}',\psi)\leq \boldsymbol{h}} \mathbb{P}_{a,t}\left(j \mid \boldsymbol{h}, \psi, k\right) dG_{a,t}\left(\boldsymbol{h}, \psi, k\right); \quad (12)$$

- Demand for goods equals supply. That is, $D(\{p_{j,t}\}_{j=1}^{J}) \propto \mathcal{Y}_{j,t}$ where

$$\mathcal{Y}_{j,t} \equiv \sum_{a=1}^{A} \sum_{k=1}^{J} \int Y_j(\boldsymbol{h})\, \mathbb{P}_{a,t}(j \mid \boldsymbol{h}, \psi, k)\, \mathbb{E}[\varepsilon_j \mid j, \boldsymbol{h}, \psi, k]\, dG_{a,t}(\boldsymbol{h}, \psi, k);^{7} \quad (13)$$

[7] $\mathbb{E}[\varepsilon_j \mid j, \boldsymbol{h}, \psi, k]$ is the expectation of the productivity shock conditional on choosing occupation j when your states were $\boldsymbol{h}, \psi, k$. The Gumbel distribution of $\log \varepsilon_j$ implies that this expectation has a closed-form solution: $\mathbb{E}[\varepsilon_j \mid j, \boldsymbol{h}, \psi, k] = \exp(-\zeta\gamma)\Gamma(1-\zeta)\mathbb{P}_{a,t}(j \mid \boldsymbol{h}, \psi, k)^{-\zeta}$.

– Demand for automation equals supply. That is, for all τ

$$\mathcal{K}_{\tau,t} = \sum_{j=1}^{J} \mathbb{1}[\tau \in \mathcal{A}_j] \left(\frac{p_{j,t}}{c_{\tau,t}}\right)^{\rho} \theta_{j,\tau} \mathcal{Y}_{j,t}.$$

2.3 Solution Methods

We provide algorithms to solve for a stationary competitive equilibrium as well as the transition path after an unexpected one-off change to the parameters of the model.

Stationary equilibrium. To solve for a stationary equilibrium, we use the following algorithm:

1. Guess an initial vector of relative prices $\left(p_1^{(1)}, \cdots, p_J^{(1)}\right)$.
2. For iteration r, given the prices $\left(p_1^{(r)}, \cdots, p_J^{(r)}\right)$, solve the worker's problem and compute the implied output of each good $\left(\mathcal{Y}_1^{(r)}, \cdots, \mathcal{Y}_J^{(r)}\right)$. Then, update prices to clear the market given supply: $\boldsymbol{p}^{(r+1)} = D^{-1}\left(\{\mathcal{Y}_j^{(r)}\}_{j=1}^{J}\right)$.
3. Repeat step 2 until $\left\|\boldsymbol{p}^{(r+1)} - \boldsymbol{p}^{(r)}\right\| < \epsilon$ for a threshold $\epsilon > 0$.

Transition path. We also solve for the transition path after a one-off unexpected parameter change. Starting from the initial stationary equilibrium, we solve for the transition path of prices $\{p_{1,t}, \cdots, p_{J,t}\}_{t=1}^{\infty}$ from the moment the shock is realized. We numerically approximate this infinite sequence by solving for $\{p_{1,t}, \cdots, p_{J,t}\}_{t=1}^{T}$ for a large enough T such that prices are constant after period T. The solution algorithm is based on (Boppart et al., 2018):

1. Compute the stationary equilibrium before ($t = 0$) and after the change ($t = T$).
2. Guess a path for the sequence of prices.[8]
3. For iteration r, given the sequence of prices $\left\{p_{1,t}^{(r)}, \cdots, p_{J,t}^{(r)}\right\}_{t=1}^{T}$, solve for the value function at $t = T, T-1, \ldots, 1$. Then, compute the implied

[8] A reasonable guess is the path where prices adjust immediately to the new stationary equilibrium.

output of each good at each time and the corresponding prices $\boldsymbol{p}_t^{(r+1)} = D^{-1}\left(\{\mathcal{Y}_{j,t}^{(r)}\}_{j=1}^{J}\right)$ for $t = 1, \dots, T$.

4. Repeat step 3 until $\left\|\boldsymbol{p}_t^{(r+1)} - \boldsymbol{p}_t^{(r)}\right\| < \epsilon \; \forall t = 1, \dots, T$ for a threshold $\epsilon > 0$.

Computing implied output given the sequence of prices is the main computational challenge in these algorithms. It consists of three main steps on which we provide more detail below.

First, we solve for the value function. This step is conceptually straightforward. However, when skills are multi-dimensional and there are many occupations j, the state space $(\boldsymbol{h}, \psi, j)$ is large and value function iteration costly. We exploit a convenient feature of the logit to provide relief. Since the occupational switching cost is $\kappa(j,k) = \kappa 1[j \neq k]$, the value function in equation (11) can be written as

$$V_a(\boldsymbol{h}, \psi, k) = \zeta \log\left[e^{-\frac{\kappa}{\zeta}} \sum_{j=1}^{J} \tilde{V}_a^j(\boldsymbol{h}, \psi) + \left(1 - e^{-\frac{\kappa}{\zeta}}\right) \tilde{V}_a^k(\boldsymbol{h}, \psi)\right]$$

where $\tilde{V}_a^j(\boldsymbol{h}, \psi) \equiv \exp\left(\frac{1}{\zeta}\left(\log w_j(\boldsymbol{h}) + \mu_j + \beta V_{a+1}\left(g_j(\boldsymbol{h}, \psi), \psi, j\right)\right)\right)$. This solution implies that it is sufficient to solve for $\tilde{V}_a^j(\boldsymbol{h}, \psi)$. Using this property, we effectively shrink the state space in the value function iteration step by a factor J (in our exercise, $J = 93$). Conditional choice probabilities can then be recovered as

$$\mathbb{P}_a(j \mid \boldsymbol{h}, \psi, k) = \frac{\tilde{V}_a^j(\boldsymbol{h}, \psi)\, e^{-\frac{\kappa}{\zeta}1[j \neq k]}}{e^{-\frac{\kappa}{\zeta}} \sum_{j=1}^{J} \tilde{V}_a^j(\boldsymbol{h}, \psi) + \left(1 - e^{-\frac{\kappa}{\zeta}}\right) \tilde{V}_a^k(\boldsymbol{h}, \psi)}.$$

Second, after computing the value function and conditional choice probabilities, we compute the joint distribution of age a, human capital $\boldsymbol{h}$, learning ability ψ, and occupations k using the law of motion in equation (12). We do so by simulation. That is, we first draw from the distribution of skills and learning ability at age $a = 1$ from the NLSY79. Their states imply a conditional probability to choose each occupation. We draw occupational choices randomly to obtain the distribution at age $a = 2$. We iterate this process forward until $a = A$.[9]

Third, to obtain an update for the relative prices, we compute total implied production of each good given the previous price iteration. The previous steps

[9] To save computational costs at early price iterations, we begin with a small number of simulations, and increase sample sizes as the difference between subsequent price iterations decrease.

yield a sample of workers with skills and occupational choice. From there, we approximate the integral in equation (13) for each occupation j. That is, we evaluate the term $Y_j(\boldsymbol{h})\,\mathbb{P}_{a,t}(j \mid \boldsymbol{h}, \psi, k)\,\mathbb{E}[\varepsilon_j \mid j, \boldsymbol{h}, \psi, k]$ for each worker-age and for each $j = 1, \ldots, J$. In other words, we do not condition on the occupational draw in the computation of production so that sampling noise only affects workers' states, not production conditional on those states.

2.4 Parametrization

In our quantitative application, we make assumptions on the functions that govern task-level productivity and human capital accumulation.

Production. We specify the task-level production function as

$$f(\boldsymbol{h}, \boldsymbol{r}_\tau) = \prod_{s \in S} h_s^{\omega_s} \exp\left(-\eta \min\left\{h_s - r_{\tau,s}, 0\right\}^2\right). \tag{14}$$

This production function is similar to that proposed by (Lise and Postel-Vinay, 2020). The first term in equation (14) reflects a force that makes workers with higher skills more productive in any task, independent of its skill requirements. The second term captures the degree to which the worker's productivity is diminished when performing tasks for which they are "underqualified". Figure A.1a shows the functional form graphically.

This functional form assumption implies that the wage function in (4) equals

$$w_j(\boldsymbol{h}) = p_j \Gamma_j^{\frac{1}{1-\rho}} \prod_{s \in S} h_s^{\omega_s} \left(\sum_{\tau \in \mathcal{N}_j} \theta_{j,\tau} \gamma_\tau^{\rho-1} \exp\left(-\eta \sum_{s \in S} \min\left\{h_s - r_{\tau,s}, 0\right\}^2\right)^{\rho-1} \right)^{\frac{1}{\rho-1}}. \tag{15}$$

Skill accumulation. We assume that the human capital accumulation function has the following functional form:

$$g_{j,s}(\boldsymbol{h}, \psi) = (1-\delta) h_s + \sum_{\tau \in \mathcal{N}_j} \ell_{j,\tau}(\boldsymbol{h}) \max\left\{r_{\tau,s} - h_s, 0\right\} e^{-\lambda(\psi) \max\{r_{\tau,s} - h_s, 0\}}. \tag{16}$$

where $\ell_{j,\tau}(\boldsymbol{h})$ is defined in equation (5). Equation (16) has several intuitive implications for skill accumulation. First, workers' learning is most affected by the tasks they spent most time on, i.e., for which $\ell_{j,\tau}(\boldsymbol{h})$ is greatest. Second, workers learn by performing tasks that are "hard" for them, i.e., tasks that have skill requirements above their current skill levels. However, workers learn most from tasks that are not "too hard". As tasks become harder relative to the workers' skill, the rate at which skills catch up decreases; $\lambda(\psi) \geq 0$ governs the rate of this slowdown. Figure A.1b illustrates how learning varies with the distance between the worker's skills and the task's requirements.[10] Similar to Heckman et al. (1998), we allow for workers to differ in their ability to learn ψ. Lastly, some skill depreciation occurs independently of which tasks are performed, governed by δ.

Note that we have assumed that the worker does not consider the allocation's effects on human capital accumulation when allocating their time across tasks. The assumption allows for a closed-form mapping from the task-level to the occupation-level, greatly reducing the computational burden. This assumption can be interpreted as resulting from a constraint on time allocation imposed by employers that do not internalize workers' human capital accumulation.

3 Data

We use three main data sources to estimate the model's parameters. First, we rely on O*NET to measure each occupations' tasks and skill requirements. Second, we provide and validate a new database of task-level skill requirements by extending O*NET's occupation-level survey on skill requirements to the task-level using large language models. Third, we use panel data on wages, occupational choices, and multidimensional skills from the NLSY79.

For the application of our methodology to artificial intelligence, we also require data on AI's task capabilities. We follow the literature in using large language models to estimate these capabilities (e.g., Eloundou et al., 2024; Acemoglu, 2025).

[10]Since $f(x) = x\exp(-\lambda x)$ is strictly increasing for $x < \frac{1}{\lambda}$ and strictly decreasing after, learning from task τ is maximized when $r_{\tau,s} - h_s = 1/\lambda$, yielding a learning gain of $1/(e\lambda)$.

3.1 Estimation Data

3.1.1 Occupations and Tasks (O*NET)

O*NET is the leading database on occupations, tasks, and skills in the US economy (e.g., Autor et al., 2003; Acemoglu and Autor, 2011; Lise and Postel-Vinay, 2020). O*NET contains detailed descriptions of 19,530 tasks linked to 974 occupations. We rely on these data to define both the occupations and tasks in our model. That is, we set the tasks employed across occupations in our model, $\mathcal{T}_j$, to mirror those in the O*NET data. We set the weights of each task τ in an occupation, $\theta_{j,\tau}$, to the importance measure of that task as reported in O*NET.[11]

We also use O*NET's definition of worker skills across 35 dimensions (e.g., "reading comprehension" or "social perceptiveness"). O*NET rates skills on a scale from 1 to 7 and provides anchors for each level (e.g., level 2 in reading comprehension means being able to "read step-by-step instructions for completing a form" and 4 to "understand an email from management describing new personnel policies").[12]

We reduce O*NET's dimensions into five skill categories: manual, mathematics, social, technical, and verbal.[13] Table B.1 shows this mapping. Each skill's requirements equal the average of its related O*NET skills.

In our quantitative analysis, we normalize the original skill requirements (ranging from 1 to 7) to the [0,1] scale by subtracting one and dividing by six.

3.1.2 Task-level Skill Requirements

Workers' comparative advantage in a task is governed by the match between their skills and the task's skill requirements, $\boldsymbol{r}_\tau$. While O*NET provides data on occupation-level skill requirements, it lacks task-specific data. To address this gap, we use OpenAI's GPT-4o to estimate the task-level skill requirements. To ensure consistency with O*NET and a valid survey design, we replicate O*NET's occupation-level questionnaire on the level of the task, by using their questionnaire format, skill dimensions, and skill anchors. This process covered 19,530 task descriptions across 35 skills using 683,550 queries. See Appendix

[11] The importance weights are normalized to sum to 1 within occupations.

[12] The original O*NET questionnaire and skill level descriptions are available here.

[13] Relative to Addison et al. (2020); Baley et al. (2022); DeLoach et al. (2022), we include manual as a separate skills because we believe its interaction with AI is of particular interest.

D.1 for further prompt design details.

We validate our data by comparing aggregations of our newly generated task-level data with O*NET's occupation-level measures. For each occupation, we calculate importance-weighted average task-level skill requirements ($\sum_{\tau \in \mathcal{T}_j} \theta_{j,\tau} r_{\tau,s}$) and compare these with corresponding O*NET values. The five aggregated skills have high agreement rates, with correlations ranging from 0.83 to 0.95 (see Figure A.2).[14]

3.1.3 Skills, Occupational Choice, and Wages (NLSY79)

We use data from the NLSY79 to estimate the task-level production function and the skill accumulation function. The data contain information on wages, occupations, and multi-dimensional skill assessment scores.

We follow the literature in measuring skills in the NLSY79. As Addison et al. (2020); Baley et al. (2022), we measure skills with the Armed Services Vocational Aptitude Battery (ASVAB): manual skills are measured as the average of scores on *auto and shop information* and *mechanical comprehension*, math skills are based on *mathematics knowledge* and *arithmetic reasoning* scores; technical skills on *general science* and *electronics information*; verbal skills on *paragraph comprehension* and *word knowledge*.[15] We standardize each of the subscores before aggregating. For social skills, we use a composite measure of self-reported sociability as a young adult, sociability at age 6, the *Rotter Locus of Control Scale*, and the *Rosenberg Self-Esteem Scale* (see also Deming, 2017; Addison et al., 2020; Guvenen et al., 2020).

These data only provide an ordinal measure of skills. That is, we only observe $\tilde{\boldsymbol{h}} = F(\boldsymbol{h})$ where $F(\cdot)$ is the distribution function of the initial skill distribution. We do not directly observe the cardinal measure $\boldsymbol{h}$ that is on the same scale as the skill requirements. We therefore estimate the marginal distribution of skills together with all other parameters (see section 4).

We follow the NLSY79 cohort's labor market history from age 25 to the survey in 2022. We retain information on all jobs held, including their start and end dates, the occupational code, the hourly wage, and the number of hours worked per week. Similar to Lise and Postel-Vinay (2020), we only consider

[14] Agreement rates are also high across most of the 35 original O*NET skill dimensions (see Figure A.3).

[15] Relative to the set of skills in (Baley et al., 2022), we add manual skills as we believe this skill is of particular interest in the context of AI.

workers for which the maximum gap between observed jobs is no larger than 18 months. We collapse this data to a worker panel of yearly frequency.

3.2 Data on AI's Capabilities

In the model presented in section 2, AI's capabilities can take three forms: augmentation, automation, and simplification. Below we describe how we estimate these capabilities by task. We acknowledge that there is substantial uncertainty surrounding these capabilities. However, we view these estimates as reasonable and provide evidence to that effect. As our baseline, we only consider the effects of generative AI (data summarized in Table B.3).[16] However, we also consider smart robots and autonomous vehicles in an alternative scenario.[17]

Augmentation. In measuring AI's potential to augment human productivity, we follow Eloundou et al. (2024) who asked human raters and OpenAI's GPT-4 whether they believed that LLMs can reduce the time required to complete a task by at least half. From the perspective of the model, we interpret this as asking about the increase in human's productivity, governed by γ_τ. We replicate their exercise with GPT-4o, except that we asked for a continuous estimate of the percentage of time saved rather than a binary measure and consider generative AI more broadly. On average, we estimate that generative AI saves 20.2% of worker time (see Table B.3). Appendix D.2.1 describes our prompt design. The prompt also describes how we extend it to smart robots and autonomous vehicles.

We validate our new data on task-level AI augmentation in two ways. First, we find that our estimates are strongly correlated with both the human rated and GPT-4 rated data from Eloundou et al. (2024), especially considering that their measures are binary (see Figure A.4a). Second, we compiled experimental estimates of the productivity effects of generative AI in various tasks and occupations and and compared them with our estimates (see Table B.4). Reassuringly, our estimates closely approximate those experimental estimates.

Automation. We also follow Eloundou et al. (2024) by eliciting automatability by task from large language models. That is, we ask for each task in the O*NET

[16] We use Gartner's definition which can be found here.

[17] For definitions of these technologies, we again follow Gartner: see here and here.

database whether AI can complete the task autonomously. From the perspective of the model, we view this as asking whether a task τ is in the automatable set $\mathcal{A}_j$. Eloundou et al. (2024) classify tasks as having either "no", "low", "moderate", "high" or "full" exposure to automation.[18] We classify a task as "automated" if it has high or full automation exposure, which is restricted to cases where the LLM indicates that generative AI can complete at least 90% of the components of the tasks. We estimate that 22.2% of all tasks can be fully automated by generative AI (see Table B.3). The prompt is documented in Appendix D.2.2.

We find high agreement rates between our measures and those obtained by Eloundou et al. (2024). The share of tasks that are automatable is almost identical across the measures (21 vs. 22%). Importantly for our exercise, we find strong agreement on the share of automated tasks by occupation ($\rho = 0.82$, see Figure A.4b). Table B.2 shows that agreement is also strong on the task-level.

Simplification. Lastly, we elicit the degree to which AI makes tasks easier. In addition to our new data on pre-AI task-level skill requirements, we prompt GPT-4o to evaluate the task's skill requirements before and after workers gain access to generative AI. The prompt can be found in Appendix D.2.3. We estimate that across all tasks and skill dimensions, the average required level falls by 18.3% once workers get access to generative AI (see Table B.3). A one-step reduction (on O*NET's 7-step scale) is the most common change. We cannot directly validate the accuracy of these predicted changes. However, we do find that the predicted pre-AI skill requirements strongly correlate ($\rho = 0.86$) with those resulting from the prompt to elicit task-level skill requirements in section 3.1.2, which contained no reference to AI (internal consistency).

AI capabilities across occupations and skills. The degree to which an occupation is affected by these three channels is positively correlated. Automatability is highly correlated with augmentation ($\rho = 0.89$). Occupational tasks experiencing strong augmentation also see the greatest skill requirement reductions ($\rho = 0.90$).

There is large heterogeneity in what AI can simplify across skills: the strongest simplification occurs in time management, writing, judgment and decision making, and critical thinking, versus the least simplification in the manual skills of

[18] The specific prompt is documented in (Eloundou et al., 2024, Supplementary Materials).

equipment maintenance, repairing, and installation.

Lastly, we find that augmentation and simplification is most common for tasks with initially high skill requirements. Automation is less correlated with skill requirements: if anything, the middle-skilled tasks are most prone to automation A.5.

4 Estimation and Model Fit

We jointly estimate the parameters governing productivity, skill accumulation, occupational choices, and the initial skill distribution. We provide a computationally efficient methodology to do so using direct inference on the NLSY79 estimation sample. Importantly, it recovers the equilibrium prices directly, avoiding the need to solve for the equilibrium within the estimation loop. Table B.5 shows an overview of all model parameters and their estimated values. In this section, we discuss the procedure in detail.

4.1 Estimation strategy

The goal of the estimation strategy is to find the parameters that maximize the likelihood of the observed wages and occupational choices. Relative to a full maximum likelihood approach, we reduce the computational burden in two main ways. First, we use a sequential approach. That is, we maximize the likelihood

$$L\left(\boldsymbol{\theta}_1, \boldsymbol{\theta}_y(\boldsymbol{\theta}_1), \boldsymbol{p}(\boldsymbol{\theta}_1), \boldsymbol{\mu}(\boldsymbol{\theta}_1)\right)$$

with respect to $\boldsymbol{\theta}_1$, where $\boldsymbol{\theta}_y = \{\eta, \{\omega_s\}_{s\in S}, \{\mu_j\}_{j=1}^{J}\}$ are task-level productivity parameters, $\boldsymbol{\mu} = \{\mu_j\}_{j=1}^{J}$ are occupational amenities, and $\boldsymbol{p} = \{p_j\}_{j=1}^{J}$ are equilibrium prices. We show how to obtain consistent estimates of $\boldsymbol{\theta}_y(\boldsymbol{\theta}_1)$, $\boldsymbol{\mu}(\boldsymbol{\theta}_1)$, and $\boldsymbol{p}(\boldsymbol{\theta}_1)$ using a computationally efficient algorithm. Second, we only maximize the likelihood of the old population's occupational choices (for whom the problem is static), avoiding repeated solution of the dynamic value function.

Inner algorithm. The first step in the inner algorithm is to compute the workers' skills given $\boldsymbol{\theta}_1$. The NLSY79 provides multi-dimensional skill scores. However, we observe those skills i) only as percentile scores, not as cardinal measures, and ii) only at labor market entry, not later. We first map percentile scores into cardinal skills $\boldsymbol{h}$ using the marginal distribution, approximated with a Beta distribution with parameters in $\boldsymbol{\theta}_1$.[19] We then use successively applying the skill accumulation function $g_j(\cdot, \psi)$ in equation (16) to infer workers' skills at later ages. That is, given worker i's occupational history $\boldsymbol{j}_i^{a-1} \equiv \{j_{i,1}, \ldots, j_{i,a-1}\}$, worker i's skill level at age a is

$$\boldsymbol{h}_{i,a}(\lambda(\psi_i), \delta) \equiv \left(g_{j_{i,a-1}}(\cdot, \psi_i) \circ g_{j_{i,a-2}}(\cdot, \psi_i) \circ \ldots \circ g_{j_{i,1}}(\cdot, \psi_i)\right)(\boldsymbol{h}_{i,1}).$$

where $(f \circ g)(x) \equiv f(g(x))$.[20] Following Heckman et al. (1998), we proxy ψ_i by the Armed Forces Qualification Test (AFQT) score. The parameters $\{\lambda(\psi)\}_{\psi=1}^{4}$ and δ are in $\boldsymbol{\theta}_1$.

We estimate the occupational wage functions using a simple linear regression given workers' skills. The derived occupational wage function in equation (15) governs how skills translate into earnings in each occupation depending on the prices, the occupation's tasks, and the parameters of the production function $\{\omega_s\}_{s\in S}$ and η. A log-linearization of this function (around no mismatch) implies that

$$\log w_j(\boldsymbol{h}_{ia}) \approx \log p_j + \sum_{s\in S} w_s \log(h_{is}) - \eta \sum_{s\in S} \sum_{\tau\in\mathcal{T}_j} \tilde{\theta}_{j,\tau} \min\{h_{is} - r_{\tau,s}, 0\}^2 \tag{17}$$

where $\tilde{\theta}_{j,\tau} \equiv \theta_{j,\tau}\gamma_\tau^{\rho-1}$ (see Appendix C.2 for the proof).[21] Equation (17) shows that we can estimate the equilibrium prices p_j and the parameters of the production function using a simple OLS regression of wages on occupational fixed effects, skills, and skill mismatch. We use a control function approach to correct for selection on the productivity shocks ε_j (Dubin and McFadden, 1984).[22]

Given the wage function, we estimate the occupational amenities $\boldsymbol{\mu}$ using a fast iterative procedure. The worker's occupational choice problem is static at the terminal age since their choice probabilities no longer reflect occupations'

[19]The Beta distribution is a flexible distribution characterized by two parameters B_a and B_b with support on [0,1]. We assume that this distribution is common across skill dimensions.

[20]To save notation, it is left implicit above that $\boldsymbol{h}_{i,a}$ depends on $\lambda(\psi_i)$ and δ through $g_j(\cdot, \psi_i)$.

[21]For estimation, we assume that $\sum_{\tau\in\mathcal{T}_j} \tilde{\theta}_{j,\tau} = 1$ for all $j = 1, \ldots, J$ and that O*NET's task-importance weights capture $\tilde{\theta}_{j,\tau}$. Also, since we estimate the model on data before the change of interest, the equation above reflects wages when no task is automated, i.e., $\mathcal{A}_j = \varnothing$.

[22]Due to non-random occupational choice, the expected value of $\log \varepsilon_j$ conditional on choosing j is $-\zeta \log \mathbb{P}_a(\boldsymbol{h}, \psi, k)$. We control for this term in the regression. We estimate the probabilities using occupation-specific logit regressions that condition on workers' previous occupation, 10-year age bins, and each dimension of their initial skill.

differential learning value. That is, for $a = A$, equation (10) simplifies to

$$\mathbb{P}_A(j \mid \boldsymbol{h}, \psi, k) = \frac{\exp\left(\frac{1}{\zeta}\left(\log w_j(\boldsymbol{h}) + \mu_j - \kappa(k,j)\right)\right)}{\sum_{l=1}^{J} \exp\left(\frac{1}{\zeta}\left(\log w_l(\boldsymbol{h}) + \mu_l - \kappa(k,l)\right)\right)}. \tag{18}$$

where ζ (scale of productivity shocks), κ (switching costs) are in $\boldsymbol{\theta}_1$ and thus taken as given in this step. The likelihood is maximized with respect to $\boldsymbol{\mu}$ when the observed share of workers in each occupation j, s_j, equal the model-implied share, $\tilde{s}_j(\boldsymbol{\mu})$. We solve for this $\boldsymbol{\mu}$ using the contraction mapping proposed by Berry et al. (1995):

$$\mu_j^{(r+1)} = \mu_j^{(r)} + \phi\left(\ln(s_j) - \ln\left(\tilde{s}_j(\boldsymbol{\mu})\right)\right) \qquad \text{for some } \phi \in (0,1] \tag{19}$$

where ϕ is a damping parameter. In practice, we use the SQUAREM algorithm to speed up convergence (Varadhan and Roland, 2008; Reynaerts et al., 2012; Conlon and Gortmaker, 2020).

Outer algorithm. In the outer algorithm, we optimize over the remaining parameters governing skill accumulation function, occupational choices, and initial skills. We choose these parameters to maximize the joint likelihood of the wage function and the occupational choices (of the old population). That is,

$$\begin{aligned}\hat{\boldsymbol{\theta}}_1 = \arg\max_{\boldsymbol{\theta}_1} \sum_{i=1}^{N}\sum_{a=1}^{A}\sum_{j=1}^{J} 1[j_{i,a} = j]\ \log \pi\left(\log w_{i,a,j} - \log \tilde{w}_{i,a,j}(\boldsymbol{\theta}_1)\right)\ + \\ \sum_{i=1}^{N}\sum_{j=1}^{J} 1[j_{i,A} = j]\ \log \mathbb{P}_A(j \mid \boldsymbol{h}_{i,A}, \psi_i, k_i; \boldsymbol{\theta}_1)\end{aligned} \tag{20}$$

where $\tilde{w}_{i,a,j}(\boldsymbol{\theta}_1)$ is the expected wage based on the inner-step given $\boldsymbol{\theta}_1$.

In the model, the choice-relevant shocks $\log \varepsilon_j$ are Gumbel. To allow for additional *choice-irrelevant* wage noise (measurement error, idiosyncratic pay), we add an independent term ν_j so that the total wage shock is $\log \epsilon_j \equiv \log \varepsilon_j + \log \nu_j$. We take $\log \nu_j$ to be Gaussian and approximate $\log \epsilon_j$, and thus the density function $\pi(\cdot)$, by a normal distribution.[23]

[23]Strictly speaking, the sum is not Gaussian and the distribution becomes a convolution. However, given that we find that the variance of the choice-irrelevant shocks is considerably larger than that of $\log \varepsilon_j$, the impact of this simplification is minimal.

Estimation results. Table 1 shows the results of the estimation of the production function in equation (17). The first five columns show the degree which various skills increase productivity across all skills. We find that the returns to math and social skills are highest, consistent with Deming (2017). Importantly, we also find that the cost of underqualification is substantial, yielding strong comparative advantage across tasks with different skill requirements. The coefficient on η implies that if a worker's skill is one level below the task's skill requirement (on O*NET's 1 to 7 scale) in each dimension, their productivity in that task is about 79% of their productivity in tasks for which they are not unqualified in any dimension.[24]

TABLE 1: PRODUCTION FUNCTION: PARAMETER ESTIMATES

General skill					Mismatch
ω_{Mn}	ω_{Mt}	ω_S	ω_T	ω_V	η
0.228	0.571	0.401	0.171	0.250	1.657
(0.018)	(0.021)	(0.016)	(0.027)	(0.023)	(0.083)

Notes: This table shows estimates of the task-level productivity parameters. Subscripts Mn, Mt, S, T, V refer to manual, math, social, technical, and verbal, respectively. Estimates are obtained through OLS based on equation (17). Standard errors in parentheses (not corrected for uncertainty in other parameters).

The occupational prices are recovered from the occupational fixed effects in the production function regression. Consistent with the model, the estimated occupational prices $\hat{p}_j$ are strongly correlated with the skill requirements in the respective occupations: skill requirements explain around 73% of the variance in prices across occupations (see Table B.6).

We show estimates of the parameters that determine initial skills and skill accumulation in Table 2. The depreciation rate of human capital when doing work for which one is overqualified is 0.0004. $\lambda(\psi)$ is inversely related to someone's ability to learn. The results in Table 2 thus suggest that the learning cost decreases with the AFQT score. Lastly, B_a and B_b are the shape parameters of the initial Beta distribution of skills. The implied average is $\frac{B_a}{B_a+B_b} = 0.35$. This translates to an average of 3.11 on the original O*NET scale from 1 to 7, in between the "low" and "medium" skill requirement levels. Figure A.6 plots the

[24] A 1-point skill gap on the O*NET scale correspond to a 1/6 gap on our [0,1] scale. Hence, using equation (14) implies that the mismatch term is $\exp\left(-\eta \cdot 5 \cdot (\frac{1}{6})^2\right) \approx 0.79$.

density function.

TABLE 2: SKILLS AND SKILL ACCUMULATION: PARAMETER ESTIMATES

Learning costs				Depr.	Initial dist.	
$\lambda(1)$	$\lambda(2)$	$\lambda(3)$	$\lambda(4)$	δ	B_a	B_b
21.20	18.01	17.07	16.06	0.0004	67.95	125.05

Notes: This table shows parameters estimates for the law of motion for skill accumulation in (16) and the intial skill distribution. $\lambda(\psi)$ refers to the learning cost at quartile ψ of the AFQT distribution.

Lastly, our estimate of the scale parameter $\hat{\zeta} = 0.053$ and of the switching cost parameter $\hat{\kappa} = 0.340$. The estimate for κ implies that the utility cost of switching occupations is equivalent to a 29% wage loss.

Calibrated parameters. Some parameters are set externally. In sections 3.1.1 and 3.1.2 we explain how we measure the task set $\mathcal{T}_j$, the task weights $\theta_{j,\tau}$, and the skill requirements $\boldsymbol{r}_\tau$ for each occupation j and for each task $\tau \in \mathcal{T}_j$. We set the number of periods A to 40 so that each period in the model represents a year between ages 25 and 64. Following Keane and Wolpin (1997), we set the discount factor β is set to 0.78 (see also Postel-Vinay and Robin (2002) for similar estimates).

We set the elasticity of substitution between occupations σ to 1.57—the midpoint between Burstein et al. (2019) (1.81) and Caunedo et al. (2023) (1.34)—and the substitutability between tasks ρ to 0.49, as estimated by Humlum (2019).

Lastly, we need to calibrate the share of income that will accrue to AI in each occupation. Equation (4) shows that this share is equal to $\sum_{\tau \in \mathcal{A}_j} \theta_{j,\tau} \left(c_\tau / p_j\right)^{1-\rho}$. In Appendix C.1, we derive how this share is identified from the share of tasks that are automated and the average cost savings by automated task:

$$1 - \Gamma_j = \sum_{\tau \in \mathcal{A}_j} \theta_{j,\tau} \left(\frac{c_\tau}{p_j}\right)^{1-\rho} = \frac{\sum_{\tau \in \mathcal{A}_j} \theta_{j,\tau}}{\sum_{\tau \in \mathcal{A}_j} \theta_{j,\tau} + \left(1 - \sum_{\tau \in \mathcal{A}_j} \theta_{j,\tau}\right) \chi^{\rho-1}}. \tag{21}$$

where χ is the cost of producing automatable tasks with AI relative to with human time. Following Acemoglu (2025), who based the estimated cost savings on experimental evidence, we set $\chi = 0.73$.

Demand for occupations. Lastly, we estimate the demand for occupations.[25] We assume that occupational goods are substituted with a constant elasticity of substitution (CES) σ. Formally, demand for occupation j, $D_j(\{p_j\}_{j=1}) \propto \alpha_j p_j^{-\sigma}$ where α_j is the CES weight of occupation j. This demand system implies that, for two occupations i and j,

$$\frac{\alpha_i}{\alpha_j} = \left(\frac{p_i}{p_j}\right)^{\sigma-1} \times \frac{\text{Wage share of occupation } i}{\text{Wage share of occupation } j}.$$

We compute occupational wage shares from the 2018 BLS Occupational Employment and Wage Statistics (OEWS). The occupational fixed effects in equation (17) are consistent estimates of the (log) occupational prices.[26] From those estimates, we can compute the implied weights $\{\alpha_j\}_{j=1}^{J}$ for a given σ.

4.2 Model Fit

The model's steady state moments fit labor market data well. The model's moments are computed from a simulated sample of 100,000 workers living in the steady state before any technical change occurs. Figure 1 reports how well the moments from this simulated panel matches the data.

First, Figure 1a shows that the model acaptures the unconditional distribution of wages reasonably well. Given that some drivers of wage inequality, such as regional, racial, and gender differences, are omitted from the model it is not surprising that inequality is somewhat underestimated. However, this underestimation is quite limited. For instance, the ratio between the 75$^{\text{th}}$ and the 25$^{\text{th}}$ percentile 2.04 in the data, compared to 1.84 in the model and the top 10% wage share is 20% in the model, compared to 26% in the data. Table B.7 reports how various other measures of inequality compare between the model and the data.

The model also accurately replicates patterns of occupational sorting. Figure 1b shows the correlation between the average skill by occupation in the model and the NLSY79 data. To compute this correlation, we only use the occupational choices of the young population for which we observe the skills di-

[25]Note that we estimate all supply-side parameters independently of demand. This is an advantage as it allows to change the demand structure without having to re-estimate any other parameters.

[26]To reduce noise in the price estimates, we apply empirical Bayes regression to the price predicted by the skill requirements (see e.g., Walters, 2024).

rectly from the skill assessment scores.[27] The correlations range between 0.6 and 0.8 across skill dimensions, implying that 1) the skill assessment scores in the NLSY79 are predictive of occupational choices (see also Lise and Postel-Vinay, 2020) and 2) workers in the model select into occupations based on their skills in ways similar to that observed in the NLSY79.

Figure A.7a shows that the average wage by occupation matches the data almost perfectly. This is the most directly targeted moment, as we estimated demand based on occupational wage shares and job-specific amenities based on occupational employment shares.

The median wage by age also matches the pattern observed in the data. Figure A.7b shows that the model matches the growth rate of wages from labor market entry to around age 55. However, the wage pattern in the model is not as concave as in the data, so that growth in the first years is underestimated and growth in the last 10 years overestimated. Furthermore, the model predicts markedly higher wages in the first period than those directly after. This feature is caused by the fact that occupational switching costs are only incurred after the first period. Workers are therefore more likely to choose occupations in which they are highly productive (i.e., with a high ε_j) in the first period than in any later periods.

The model also accurately reflects the probability that a worker changes occupation from one year to another. The probability of staying within the same 3-digit occupation is 0.86 in the model and 0.90 in the CPS data. This moment is directly targeted by the switching cost parameter κ. However, we also find that the model fits the (untargeted) probability that a worker stays within a broader 2-digit occupational group well: 0.92 (model) and 0.94 (CPS data). In other words, even though the occupational switching cost applies equally across all but one occupation, the model captures that workers are more likely to stay within a similar set of occupations.

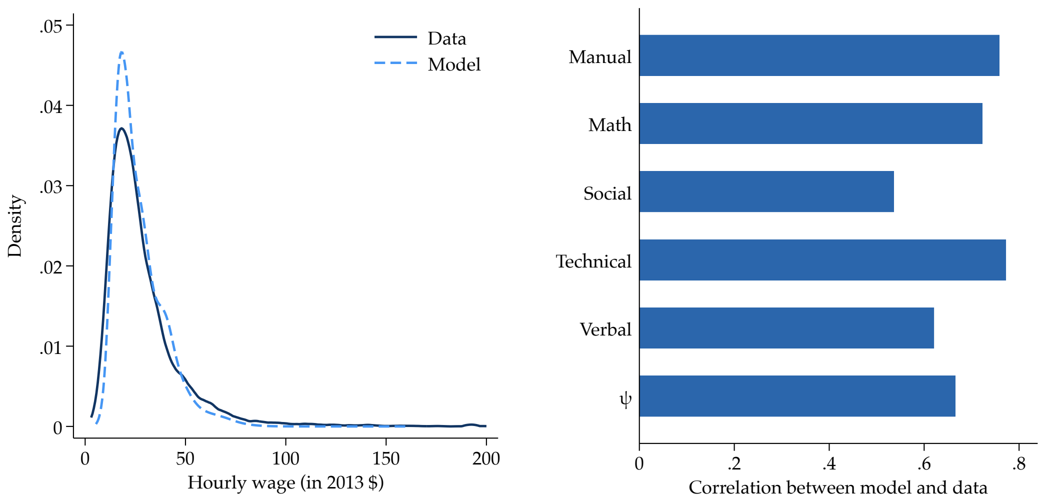
We further compare the transition probabilities between occupations conditional on switching. The correlation between the (log of) the transition probabilities in the model and data is 0.56 on the 2-digit occupation level. On the 3-digit level, it is substantially lower: 0.20. In other words, the model accurately predicts occupational transitions across 23 broader occupational groups. Within those groups, occupational transitions are harder to predict, because oc-

[27] This makes the test as stringent as possible because it prevents the skills in each occupation to "mechanically" reflect the skills required in the occupation through the estimated learning.

cupations are more similar in skill requirements within those groups.

FIGURE 1: MODEL FIT: COMPARING MODEL MOMENTS WITH DATA

(A) WAGE DISTRIBUTION (B) SKILL SORTING BY OCCUPATION



Notes: Panel A shows a kernel density plot of the wage distributions of the NLSY79 data and the model's steady state. Panel B reports the correlation between the average skill by occupation in the model's first period and the NLSY79.

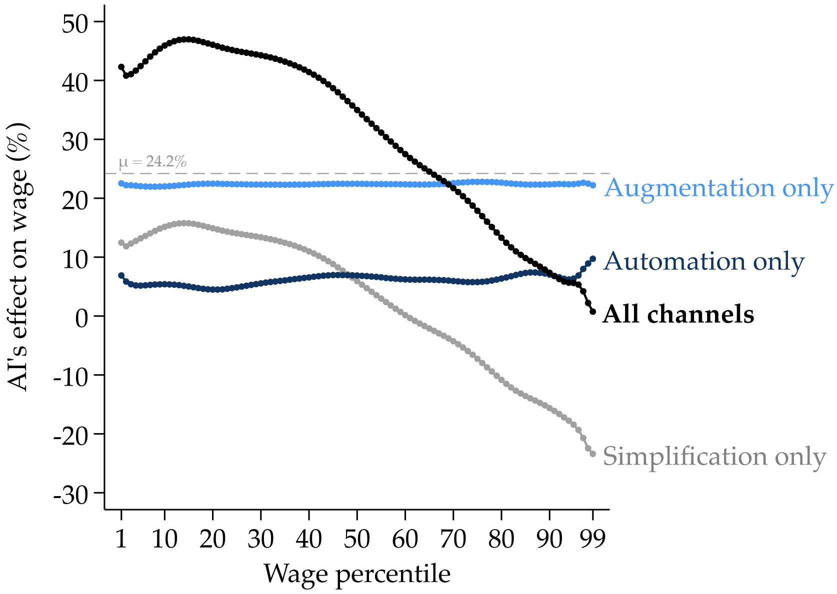
5 Artificial Intelligence and the Labor Market

This section applies our model to understand how AI affects labor markets. We consider AI-induced augmentation, automation, and simplification and study its general equilibrium effects on wages, wage inequality, welfare, skill returns, and occupations.

5.1 AI's Effect on Wages and Inequality

We start by studying AI's impact on the steady state wage distribution. Figure 2 shows sizable average wage gains (about 24%). These gains are concentrated at the bottom of the distribution and are nearly zero at the 99th percentile.

FIGURE 2: WAGE CHANGES ACROSS THE DISTRIBUTION



Notes: This figure shows the distribution of wage changes induced by generative AI across the wage percentile distribution. The horizontal axis represents wage percentiles weighted by pre-AI employment, and the vertical axis shows the percentage change in wages for each percentile. The black line shows the joint effect of AI's augmentation, automation, and simplification on each wage percentile. Other lines show the effects when each of the three channels are operating alone.

Simplification is the primary driver of the distributional effects. Figure 2 shows the impact when AI operates only through augmentation, automation, or simplification. Augmentation and automation yield broadly level impacts across the distribution. By contrast, simplification raises wages at the bottom while lowering them at the top in absolute terms.

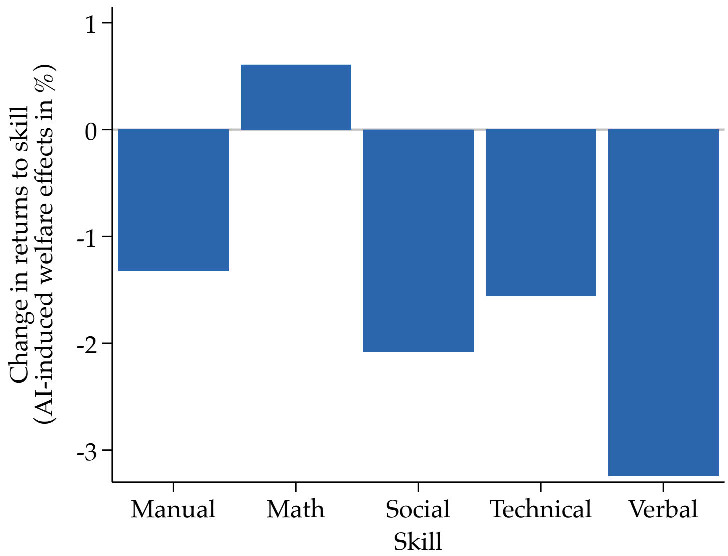
Simplification's effect on average wages is theoretically ambiguous because two forces work in opposite directions. On the one hand, simplification of a task increases productivity for any given skill (see equation 14). On the other, it limits opportunities for learning. We find that the net effect of these two forces is slightly negative (-2.6%).

Workers' ability to adjust their occupational choices and accumulate new skills dampens the long-run distributional impact of automation and augmentation. When augmentation and automation are not systematically biased toward tasks with particularly high or low skill requirements, they raise productivity proportionally for all workers in an occupation, and workers arbitrage away wage differentials by reallocating across occupations. In practice, AI's augmentation and automation capabilities are correlated with tasks' skill requirements (see Figure A.5), implying that they can also generate some distributional effects. We find that those effects are quantitatively small relative to the direct effects of task simplification, however.

5.2 Which Workers Gain or Lose the Most?

We next examine the implications of AI for workers' ex-ante welfare, given the sizable effects on the wage distribution. Specifically, we compare expected welfare at labor market entry, conditional on initial skills, in economies with and without AI. We measure welfare changes using equivalent variation, defined as the permanent wage increase across all occupations that delivers the same welfare gain as the introduction of AI. Figure A.8 reports the distribution of this measure, which lie between approximately 29% and 35% for most workers, implying sizable ex-ante welfare gains for almost everyone. The welfare gains exceed the average wage increase because utility is concave in income and AI disproportionately raises wages at the bottom of the distribution.

FIGURE 3: HOW WELFARE EFFECTS DIFFER BY SKILLS



Notes: This figure shows how welfare effects differ by skills. The welfare effects are measured in equivalent permanent percentage wage increases. This figure plots the coefficient of a regression of these welfare effects on skill levels across all dimensions. For interpretability, the skills are expressed on the O*NET scale from 1 to 7.

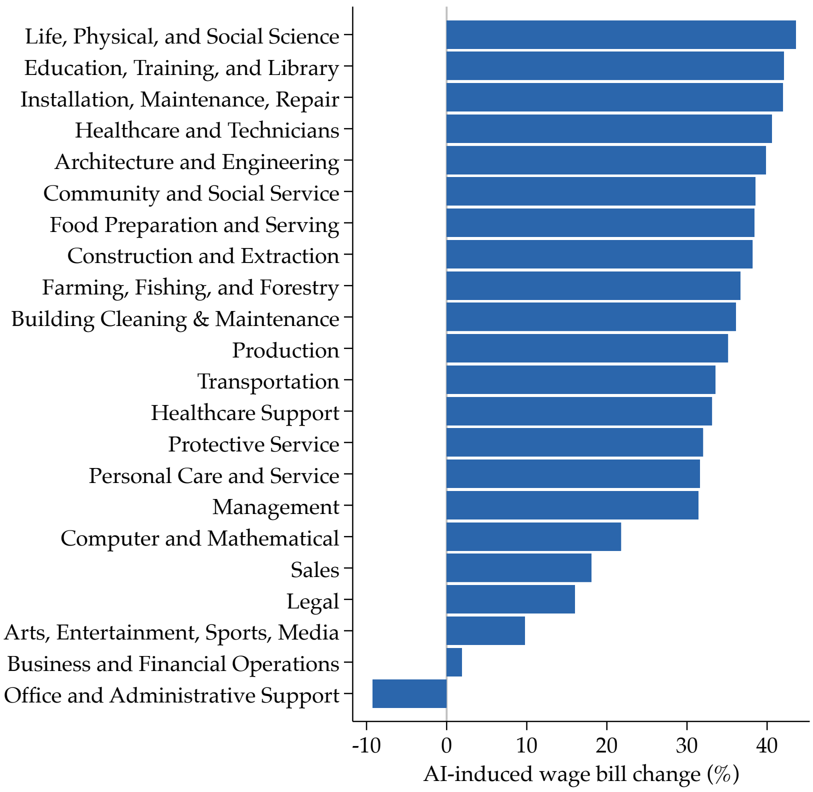
Consistent with the decrease in wage inequality, we find that the ex-ante welfare gains are largest for less skilled workers. Figure 3 shows the coefficients of a regression of the welfare gains on initial skill levels. Workers with high verbal skills see the smallest increases in welfare gain: a 1-point increase in verbal skills (on the 6-point O*NET scale) decreases the welfare gains by 3%. Higher math skills, in contrast, yield a slightly higher welfare gains.

5.3 How Do Occupations Change?

We next ask how occupations' employment and wages are affected by AI.

First, Figure A.9 shows that there are strongly heterogeneous effects on occupation's total wage bills, average wages, and employment shares. While wages increase by 24.2% on average, wages in some occupation decline in absolute terms (Figure A.9b). Because our framework allows for occupational re-sorting, part of these occupational effects reflects selection. The size of this occupational reallocation is evident in Figure A.9c, which shows that some occupations lose more than 50% of their employment.

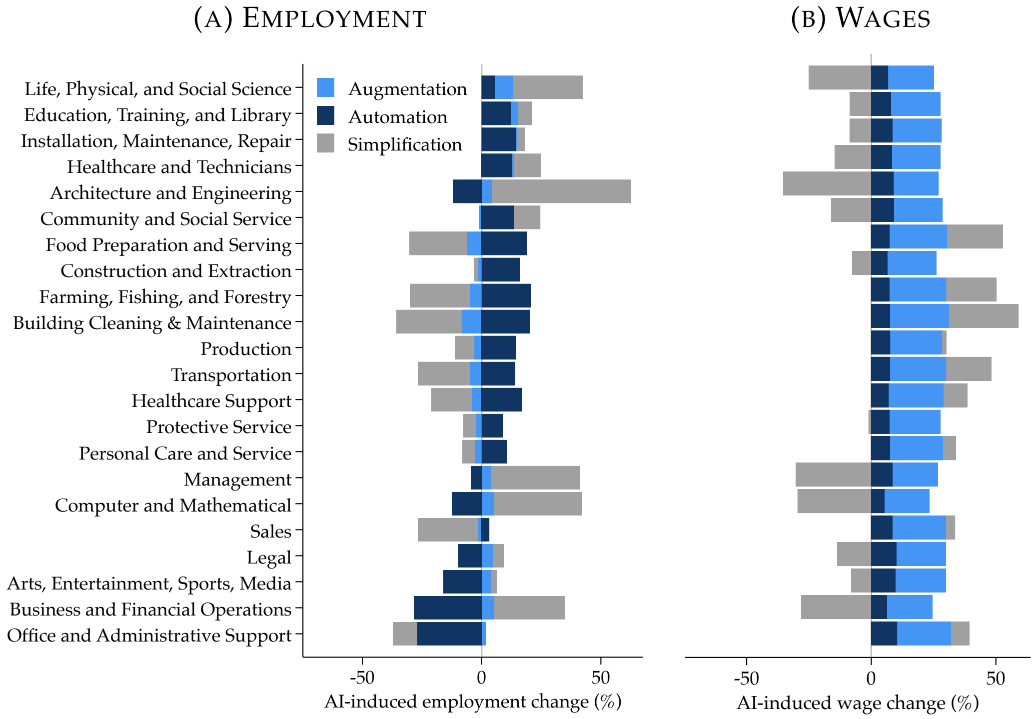
FIGURE 4: AI'S EFFECT ON OCCUPATIONS' WAGE BILLS



Notes: This figure shows the model predictions on AI's wage bill effects by occupational group. Appendix Figure A.11 disaggregates these effects across detailed occupations.

We then zoom in on individual occupations. Figure 4 displays AI's effects on the wage bills of 2-digit occupational groups. *Life, Physical and Social Science* experiences the largest wage bill increase, while *Office and Administrative Support* sees an absolute decline in its wage bill. The wage bill is the average wage times the employment. Figure A.10 shows that the effects on employment and wages often work in the opposite direction. For instance, *Architecture and Engineering* experiences the largest increase in employment share and the largest decrease in average wages. *Building Cleaning and Maintenance* experiences the largest increase in average wages and a decline in employment.

FIGURE 5: AI'S EFFECT ON OCCUPATIONAL EMPLOYMENT & WAGES



Notes: This figure shows the model's predictions on AI's employment and wage effects by occupational group. Occupations are sorted in descending order of AI's effect on the total wage bill, so that the first listed occupation experiences the largest wage bill increase. We conduct a Shapley-Owen decomposition to separate the overall change into the contribution of each channel: augmentation, automation, and simplification.

We assess how each AI channel—augmentation, automation, and simplification—contribute to these occupational outcomes. We recompute occupational outcomes under all possible combinations (e.g., only augmentation, only augmentation and simplification, etc.) and decompose the total effect into the contributions of the three channels. Figure 5 summarizes these results. First, augmentation generates little change in employment shares and raises average wages almost uniformly across occupations. Second, automation leads to large changes in employment, but not to substantially different wage growth across occupations. Finally, simplification generates sizable and opposing effects on employment and wages: by lowering skill requirements, it expands the pool of workers who can perform the occupation productively, which raises employment but compresses average wages.

The regression results in Table B.8 systematically relate occupational outcomes to augmentation, automation, and simplification exposure. It confirms that i) augmentation is not a major driver of relative employment or wage changes, ii) automation mostly reallocates employment to less exposed occupations while not having strong effects on wages, and iii) simplification leads to relative wage declines and employment growth. We further consider how augmentation and automation can indirectly induce simplification by shifting the effective weights of tasks with different skill requirements (Autor and Thompson, 2025; Freund and Mann, 2025). Such indirect simplification has effects on employment and wages that similar to those of direct simplification.

What characterizes occupations that gain the most from AI? Perhaps surprisingly, there is only a weak relationship between labor market gains and occupations' pre-AI skill or education levels (see Figure A.13a). Both the top and bottom deciles by wage bill increases have similar skill requirements and education levels. This weak overall relationship masks a U-shaped pattern: through the 80th percentile, occupations with larger gains tend to have progressively lower skill requirements (except manual skills), but this reverses sharply at the top, where the highest-gaining occupations skew toward higher skill intensity. Education follows the same pattern.

5.4 AI with Physical Capabilities

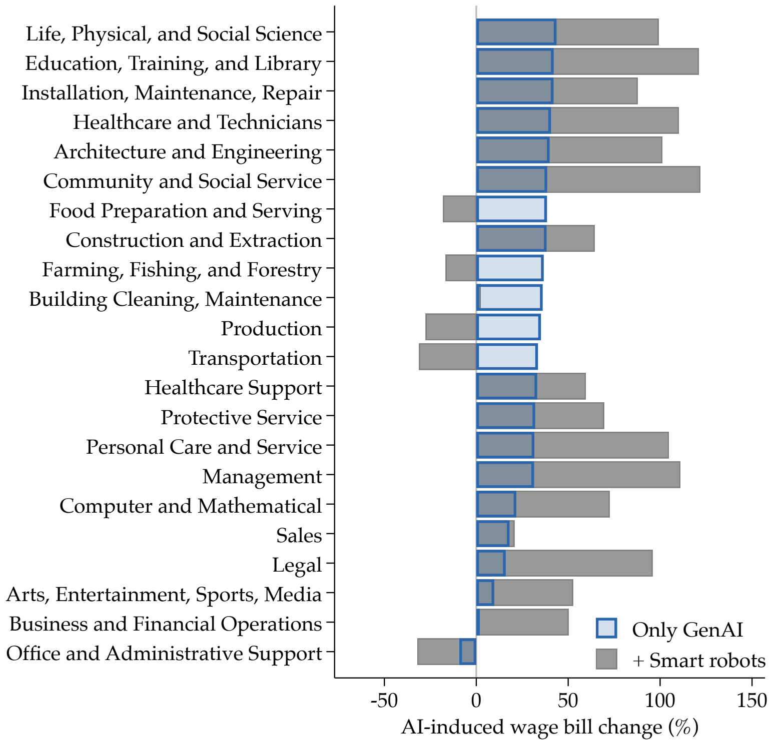
Lastly, we examine how these occupational effects change when considering AI technologies with physical manipulation capabilities, such as AI-powered robots and self-driving vehicles.These estimates are necessarily subject to more uncertainty, but highlight how technological capabilities determine which human skills retain value and thus which workers benefit or lose.

Aggregate effects. The addition of physical capabilities substantially amplifies AI's labor market impact. Average wages rise by 39 percent in this scenario—

an effect 60 percent larger than the gain from generative AI alone. Changes in inequality, previously shown to be driven mainly by simplification, follow a similar pattern in both AI scenarios.

Occupational reallocation. There are notable shifts in the patters of occupational reallocation as AI gains physical manipulation capabilities (see Figure 6). *Community and Social Service* and *Education, Training, and Library* occupations are the main winners, more than doubling in wage bill. In contrast, a larger number of occupational groups now lose over a quarter of their wage bill, including *Office and Administrative Support*, *Transportation*, and *Production* occupations.

FIGURE 6: AI'S IMPACT WITH VS. WITHOUT PHYSICAL CAPABILITIES



Notes: This figure shows the model's predictions on AI's wage bill effects by occupational group under two scenarios: one with only generative AI and one where AI systems also possess physical manipulation capabilities ("smart robots"). Occupations are sorted in descending order of generative AI's effect on the total wage bill, so that the first listed occupation experiences the largest wage bill increase.

Several occupations that were predicted to experience large gains from generative AI are predicted to experience large losses if AI gains physical capabilities. The most striking reversals occur for occupations in *food preparation and serving*, *farming, fishing, and forestry*, *production*, and *transportation* occupations.

Those are occupations requiring manual skills that AI with physical capabilities (but not generative AI) can provide but low levels non-manual skills that would otherwise shield those occupations from automation (see also Figure A.14a). Overall, the pattern of returns to skills also intensifies our findings for generative AI: math skills become even more valuable, while the returns to all other skill dimensions decline further.

Beyond skill requirements, what characterizes the occupations that gain the most? There is a strong positive correlation in the education level typical to an occupation and their wage bill increase (see Figure A.14b). This contrasts sharply with the generative AI scenario, in which education showed little correlation with changes in occupational outcomes. The winning occupations tend to employ slightly older or experienced workers and are far less likely to employ Black workers.

6 Early Signs of AI's Impact on the Labor Market

In this section, we turn from our model's theoretical predictions to empirical evidence. First, we use recent labor market data from the CPS to test whether the model's predictions are beginning to unfold. Specifically, we use an event study to assess whether predicted occupational outcomes correlate with observed changes following the first broad release of capable models in late 2022. Second, we zero in on two occupations frequently discussed in relation to AI's impact to explain and validate the model's predictions.

6.1 Event Study of Aggregate Labor Market Shifts

We implement an event study design using Current Population Survey (CPS) data from 2020 to 2025. Our continuous treatment variable is each occupation's model-predicted change in occupational outcome $\Delta\tilde{Y}_o$ (wage bill share, employment, or wages). The specification assesses whether the model predicts differential occupational trends after ChatGPT's release in late 2022, conditional on occupation fixed effects (α_o), time fixed effects (γ_t), and time fixed effects interacted with occupation-level controls ($\eta_t \cdot X_o$):

$$Y_{o,t} = \sum_{k \neq -1} \beta_k \cdot \mathbb{1}[t = k] \times \Delta\tilde{Y}_o + \alpha_o + \gamma_t + \eta_t \cdot X_o + \epsilon_{o,t}.$$

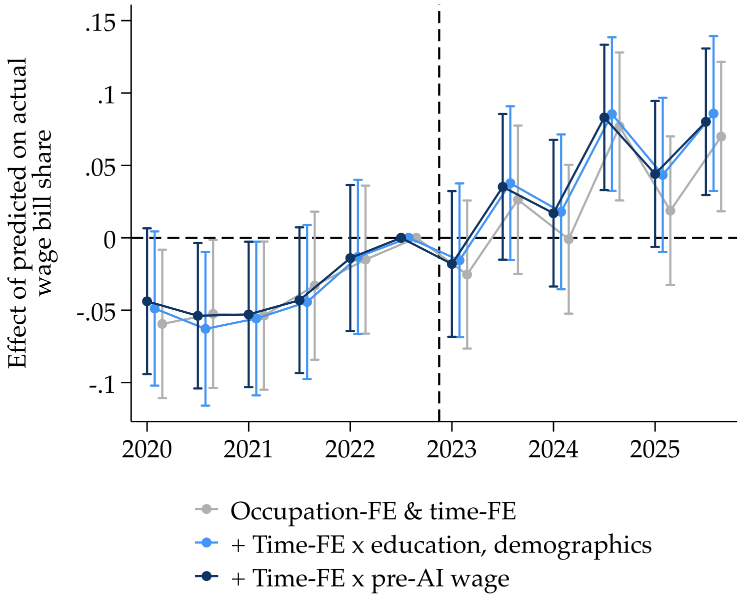
The coefficients β_k capture differential trends for occupations with higher predicted change, with $\beta_k = 1$ indicating that the full model-predicted effect has materialized by period k.[28]

Figure 7 presents our event study estimates. Occupations predicted to gain importance based on their wage bill's share of the overall economy indeed begin to see a relative increase starting around two years after OpenAI's first release of ChatGPT. This effect gradually increases over time. The magnitude of our estimates suggest that by late 2025, between 5 and 10 percent of the predicted wage bill share gains have materialized.

Appendix Figure A.17 shows results for the wage bill's two components: employment and wages. Employment begins to rise significantly for occupations predicted to gain employment from AI starting around one year after ChatGPT's release. In contrast, we do not observe any meaningful effects on wages, suggesting that the initial adjustment of the labor market occurs mostly through quantities not prices (this finding is also consistent with evidence on young workers from Brynjolfsson et al., 2025a).

[28]To reduce sampling noise, we aggregate monthly CPS data into 6-month periods to compute the occupational outcomes $Y_{o,t}$. Our sample includes working-age individuals (18-65) in the labor force.

FIGURE 7: EARLY LABOR MARKET EFFECTS OF GENERATIVE AI



Notes: Event study estimates ($\widehat{\beta}_k$) show differential changes in occupational wage bill shares following ChatGPT's November 2022 release. Coefficients represent the effect of a one-unit model-predicted change in the outcome as predicted by the model on actual the outcome's empirical evolution. A coefficient of 1 would indicate complete realization of model predictions. Estimates use CPS data aggregated to 6-month periods with occupation fixed effects and time fixed effects. The specification with controls includes occupation-specific trends based on education, sectoral composition, demographics, and pre-AI wages. Error bars represent 95%-confidence intervals.

We interpret this evidence as suggestive, particularly given that some employment effects appear to predate 2022. While this timing could indicate that other factors correlated with AI adoption are driving these patterns, an alternative explanation is that occupations most exposed to AI (such as radiologists and telemarketers) had already begun adopting generative AI tools before ChatGPT's public release, experiencing labor market impacts correspondingly earlier (see, e.g., Acemoglu et al., 2022).

6.2 Case studies

Radiologists. In 2016, deep learning pioneer Geoffrey Hinton warned to "stop training radiologists," because AI would render them obsolete within five years. Since then, radiology has indeed accounted for more than 75 percent of all FDA-authorized clinical AI tools, and roughly two-thirds of US radiology departments report using AI (Mousa, 2025). However, the labor market for radiologists has only gotten stronger: their wage bill share increased by 6.6 percent between 2016 and 2024. This increase is driven by strong employment growth (23.2% versus average of 9.8%) and attenuated by below-average wage growth (30.1% versus average of 36.9%).

Our model's predictions line up with these observed labor market patterns. We predict a 42 percent wage bill increase, gains 1.75 times larger than the average occupation. In line with observed occupational changes, the model-predicted increase in the wage bill from AI is driven by above-average employment growth (28% versus average of 0% by construction) and a below-average wage growth (11% versus average of 24.2%; see Figure A.10).

The key to understanding these outcomes lies in how AI reshapes radiologists comparative advantage (see also Dranove and Garthwaite, 2022). While automation typically reduces employment, radiologists experience minimal automation exposure: only four of their 29 regular tasks are automatable (54th percentile). Moreover, these automatable tasks are their least skill-intensive (61st percentile versus 78th for non-automatable tasks; see Appendix Figure A.15). Augmentation provides modest productivity gains (22 percent, 53rd percentile) while direct simplification is below median (46th percentile).

Management Analysts. If radiologists exemplify how AI can complement human labor, management analysts (also known as management consultants) illustrate the opposite. They face one of the highest degrees of simplification of any occupation, ranking in the 97th percentile, as AI reduces the average skill level of their tasks by 25 percent. Consultants' productivity increase 28 percent through augmentation (85th percentile) and their tasks have moderate exposure to automation, with three of their eleven tasks being automatable (52nd percentile).

In addition to direct simplification, management analysts also experience substantial indirect simplification, as the tasks that are automated tend to be the most skill-intensive. Automated tasks have an average skill requirement at the 87th percentile of all tasks in the economy, compared to the 66th percentile for non-automated tasks. Automatable tasks typically involve structured problem-solving and documentation that follow predictable analytical procedures, whereas non-automatable tasks center on interpersonal interactions such as interviewing or coordinating with others.

This pattern of simplification aligns with experimental evidence. Dell'Acqua et al. (2023) find that when consultants use AI, lower-skilled workers experience larger productivity gains. Through the lens of our model, this can be directly explained through simplification: the reduction in the skill requirements increases the relative productivity of workers who have skills below the requirements.

As a result, the broader occupational group of *Business Operations Specialists* ranks among the more negatively affected. The model predicts a 4 percent decline in employment and no change in wages, well below the average worker's increase of 24 percent.

Telemarketers. Telemarketers also represent one of the clearest cases where AI substitutes for, rather than complements, human labor. Their work consists of 12 distinct tasks, all of which can be automated by generative AI. Indeed, our model predicts that telemarketers' occupational group, *Other Sales and Related Workers*, ranks among the 5 percent of most negatively affected groups in terms of both employment and total wage bill (see Appendix Figure A.11).

7 Conclusion

Technological change reorganizes production at the task level, so understanding its labor-market effects requires characterizing workers' comparative advantage across occupations and tasks. This paper develops and estimates a dynamic task-based framework that recovers this comparative advantage and embeds it in a general-equilibrium model of occupational choice and skill accumulation. We use this framework to study artificial intelligence as a technology that augments, automates, and simplifies tasks. The quantified model predicts that generative AI substantially raises wages, especially in the lower part of the wage distribution. A decomposition shows that simplification of tasks is the key driver behind AI's distributional effects.

This paper raises several important questions for future research. First, in our framework, we take the technical change brought about by AI as exogenous. One could, however, consider how simplifying technologies arise from directed innovation when particular skills are in short supply (Acemoglu, 2002; Acemoglu and Restrepo, 2018). Second, we treat workers' skills at labor market entry as exogenous. It is useful, however, to consider how technical change may affect people's educational choices (Heckman et al., 1998). Last, this paper only considers the effect of technical change on the labor market. However, technical change can also have strong distributional implications through capital income

(Moll et al., 2022) and business income (Reichardt, 2025). For the latter, it is particularly pressing to understand whether AI's simplifying capabilities allow specifically small firms to benefit from its use.

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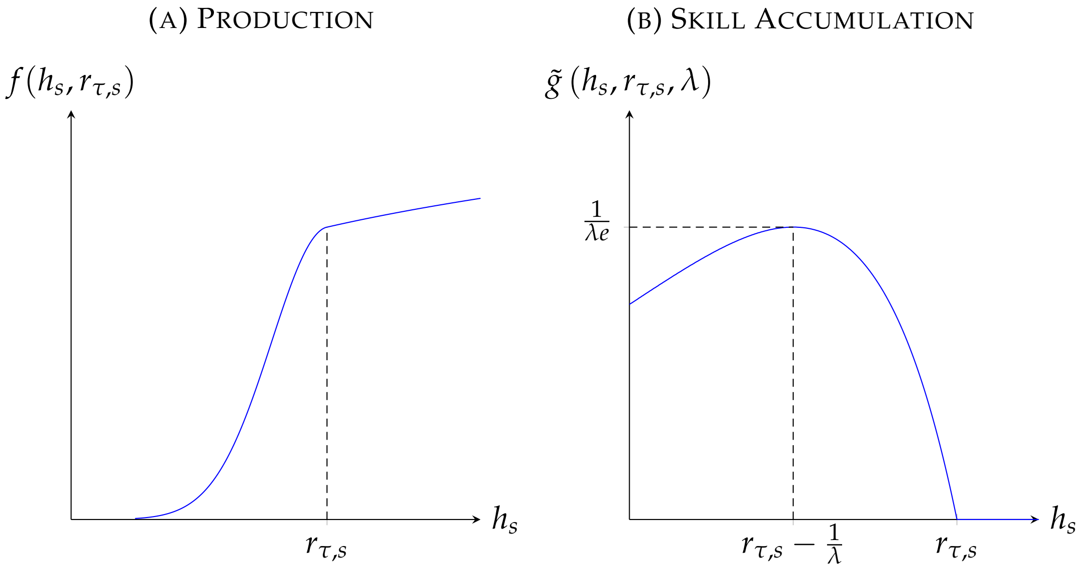
Appendix

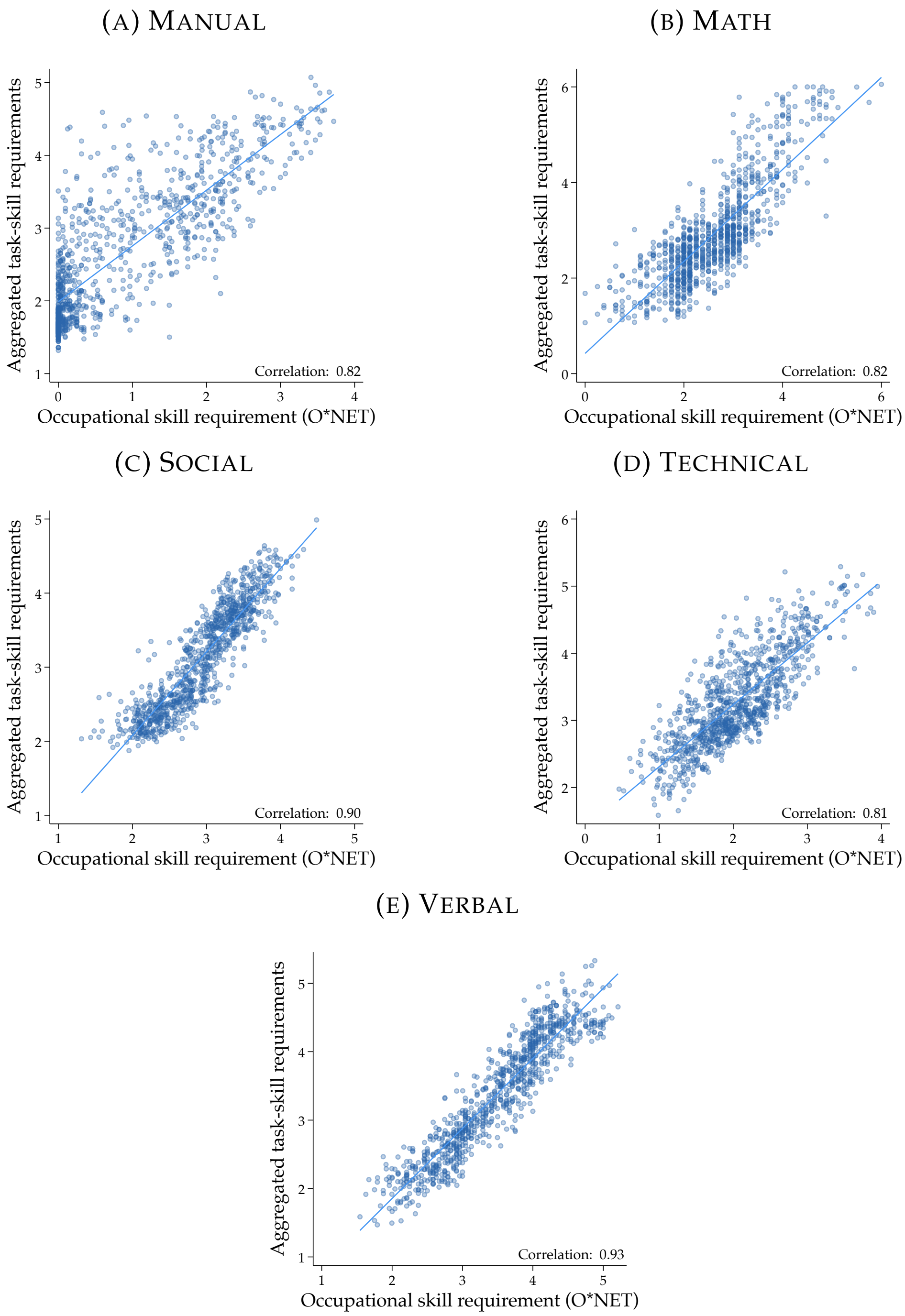
FIGURE A.1: PRODUCTION AND SKILL ACCUMULATION: FUNCTIONAL FORMS



Notes: This figure illustrates the functional forms of the production and skill accumulation functions in equations (14) and (16), respectively. Panel A shows the production function $f(h_s, r_{\tau,s}) = h_s^{\omega} \exp\left(-\eta \min\{h_s - r_{\tau,s}, 0\}^2\right)$. Panel B shows the learning part of the skill accumulation function: $\tilde{g}(h_s, r_{\tau,s}, \lambda) = \max\{r_{\tau,s} - h_s, 0\} \exp(-\lambda \max\{r_{\tau,s} - h_s, 0\})$. It illustrates that maximum learning is attained when the skills are $\frac{1}{\lambda}$ below the skill requirements.

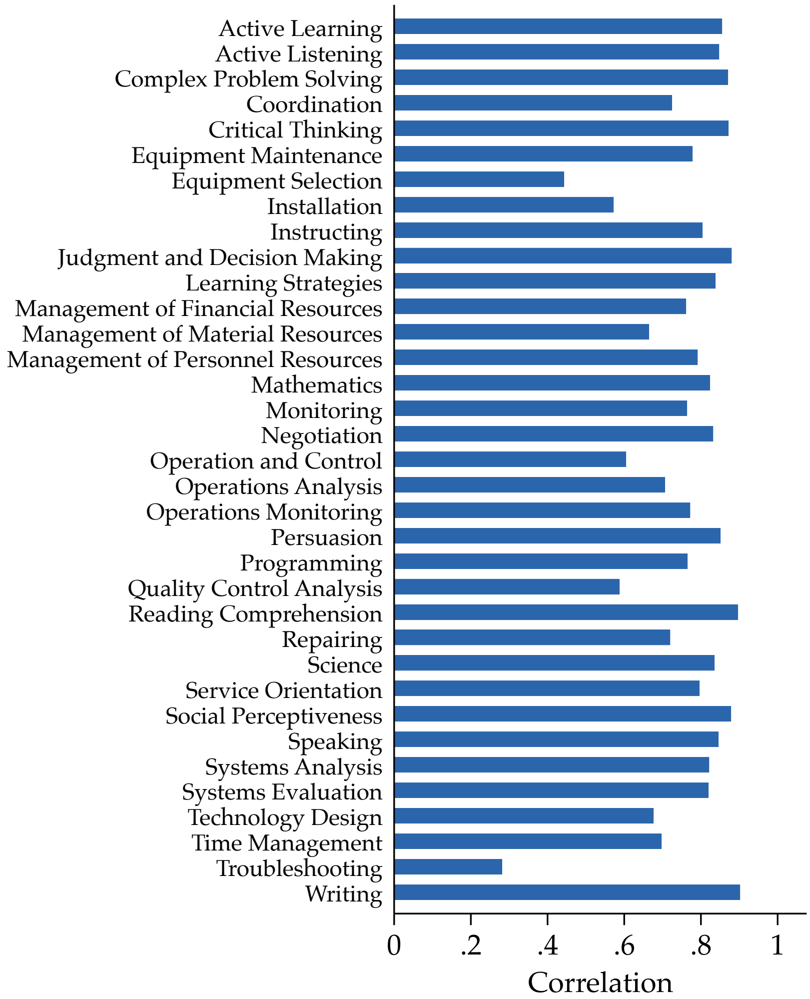
A Figures

FIGURE A.2: VALIDATION OF TASK SKILL REQUIREMENT DATA WITH O*NET



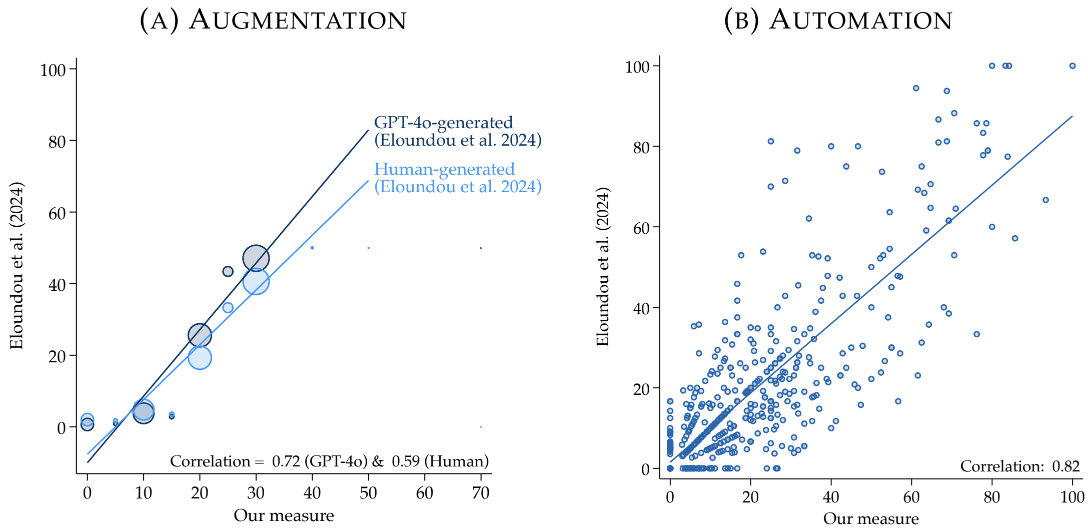
Notes: This figure shows the correlation between the occupation-level skill requirement in the O*NET database and the GPT-4o generated task-level skill requirements aggregated to the occupation-level for the skills used in the analysis. Each observation represents an occupation in the O*NET database.

FIGURE A.3: VALIDATION OF TASK SKILL REQUIREMENT DATA WITH O*NET (35 SKILL DIMENSIONS)



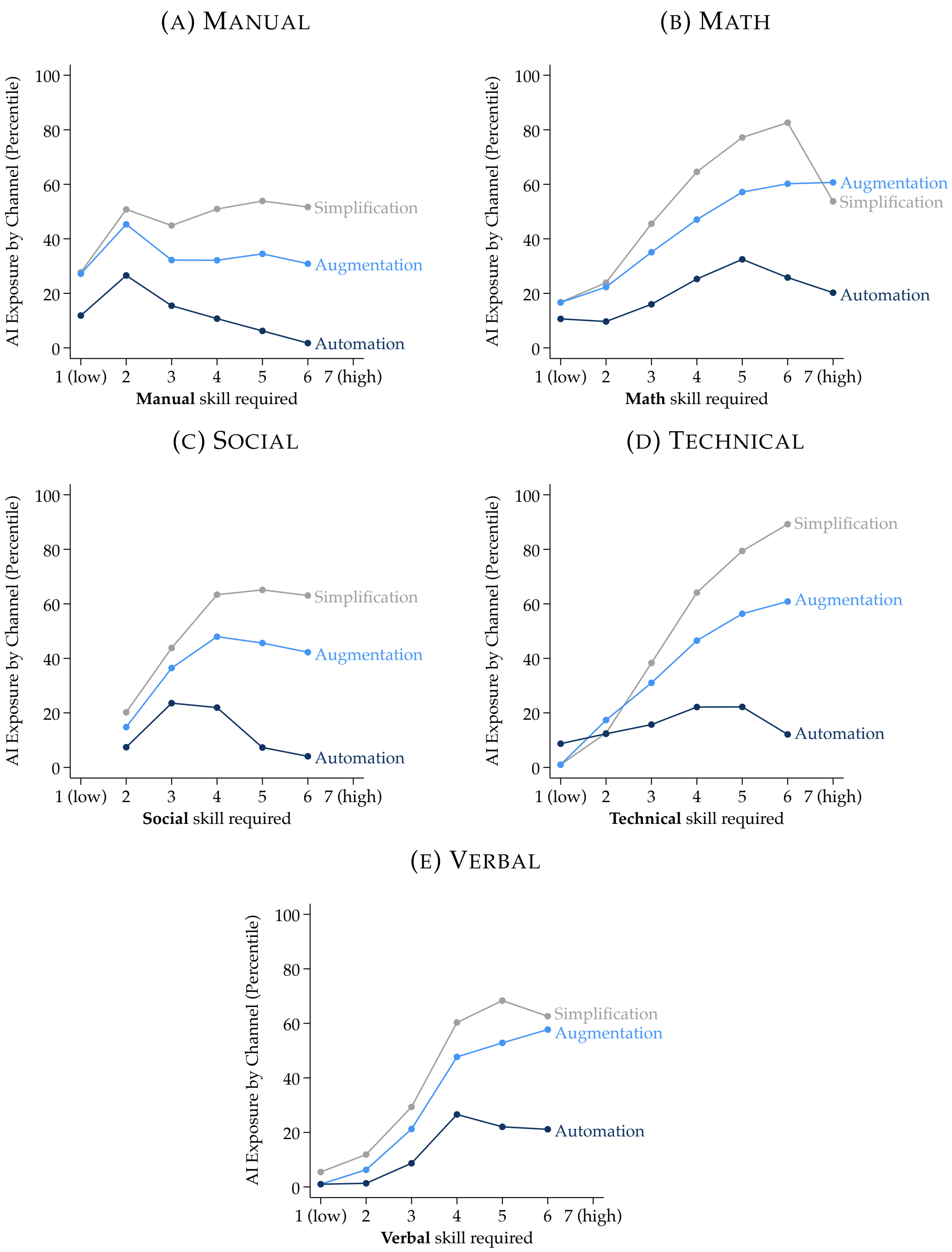
Notes: This figure shows the correlations between the occupation-level skill requirement in the O*NET database and the GPT-4o generated task-level skill requirements aggregated to the occupation-level for each of the 35 skills.

Figure A.4: Agreement on AI exposure with Eloundou et al. (2024)



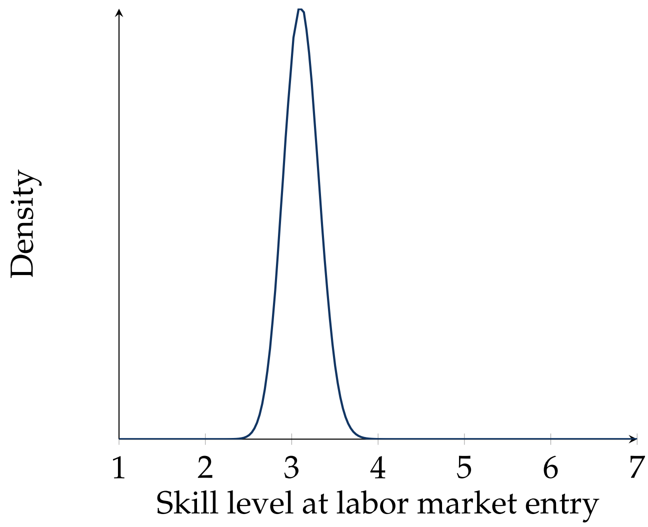
Notes: This figure compares our estimates tasks' exposure to augmentation and automation by generative AI. Panel A shows our task-level augmentation estimates (time saved to complete each task in an occupation) to those provided by Eloundou et al. (2024), measuring whether or not large language models can save at least 50 percent of time to complete a task (binary). Panel B shows the the share of tasks in each occupation that can be automated by generative AI with similar data provided by Eloundou et al. (2024).

FIGURE A.5: SKILLS & GENERATIVE AI EXPOSURE BY CHANNEL



Notes: This figure shows the correlation between a task's skill requirements and its potential to be augmented, automated, or simplified by Generative AI. Each dot represents the average percentile of exposure to each channel among tasks with the same requirement in a given skill.

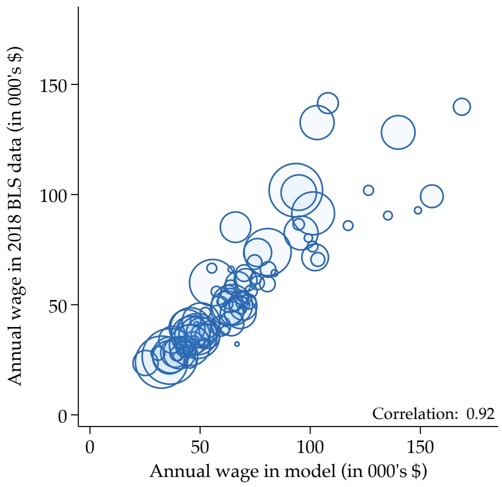
FIGURE A.6: INITIAL SKILL DISTRIBUTION



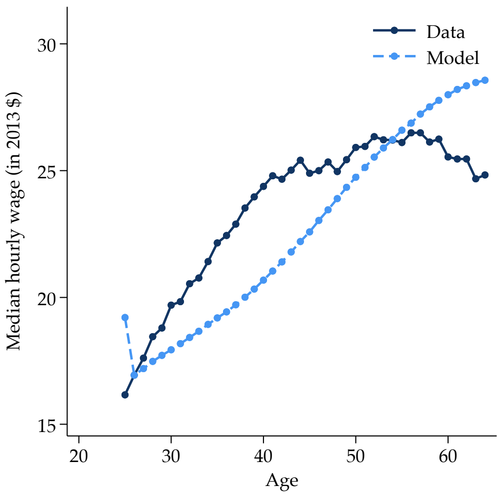
Notes: This figure shows the estimated density of the skill distribution of young workers (age $a = 1$ in the model) on O*NET's 1 to 7 scale. For comparison, for the skill "reading comprehension", a 2 means being able to "read step-by-step instructions for completing a form", 4 means being able to "understand an email from management describing new personnel policies", and 6 means being able to "read a scientific journal article describing surgical procedures".

FIGURE A.7: MODEL FIT: COMPARING MODEL MOMENTS WITH DATA

(A) OCCUPATIONAL WAGES

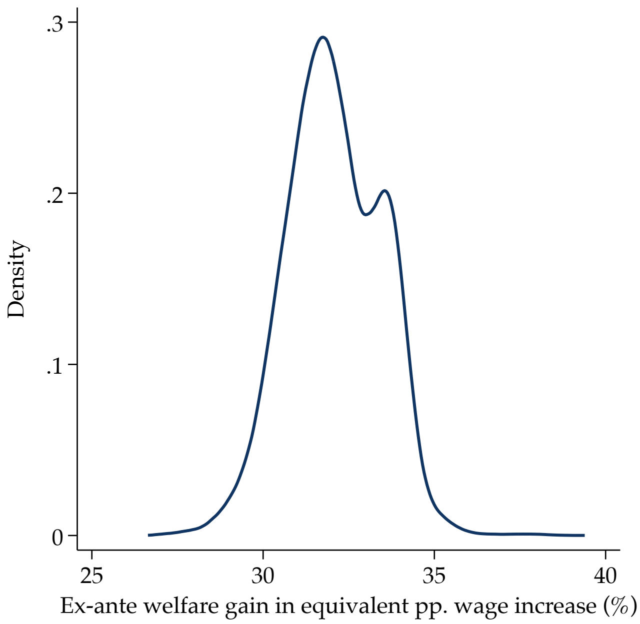


(B) LIFE-CYCLE OF WAGES



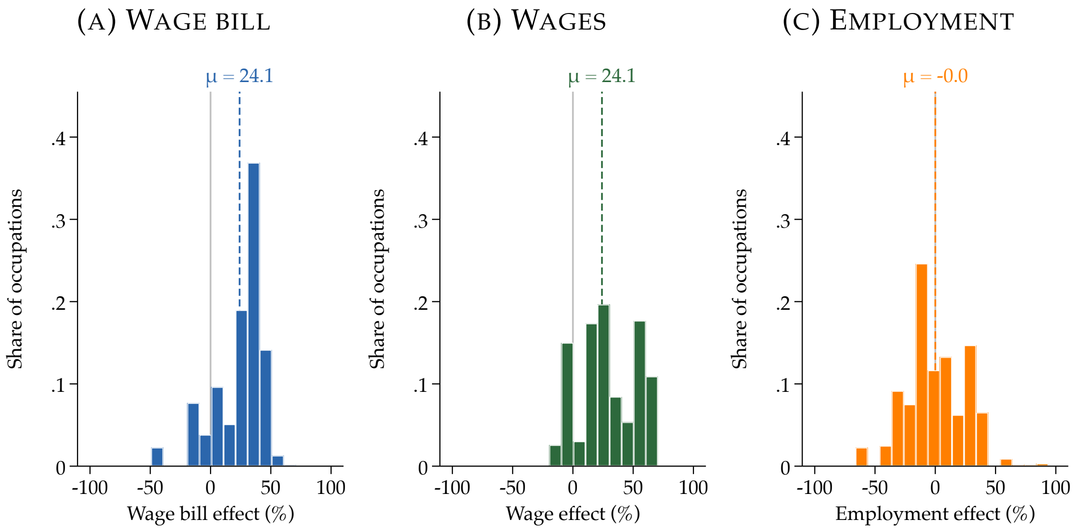
Notes: Panel A shows the correlation between the average wage in an occupation in the model's steady state and in the data as reported in the 2018 BLS OEWS data. Panel B reports the median wage by age in the NLSY79 and the model's steady state.

Figure A.8: Distribution of Welfare Effects



Notes: This figure shows the distribution of AI's welfare effect on individual workers. The welfare effect is measured in equivalent wage variation: it represents the permanent wage increase across all occupations that yields the same welfare gain as the introduction of AI.

Figure A.9: Generative AI's effect across occupations

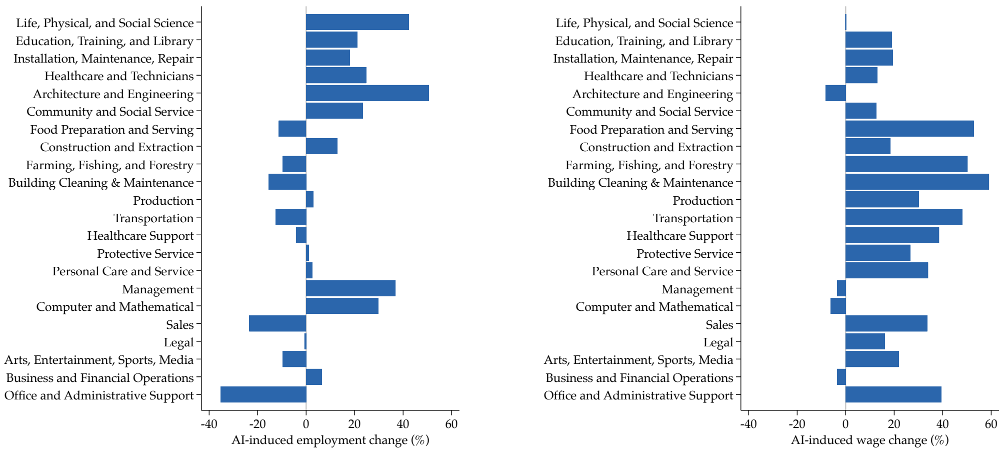


Notes: This figure shows the distribution of generative AI's predicted effects across occupations based on our structural model. Panel (A) shows wage bill changes (wages × employment). Panel (B) shows wage changes. Panel (C) shows employment effects, which are symmetric around zero by definition as our model does not feature unemployment.

FIGURE A.10: AI'S EFFECT ON OCCUPATIONAL EMPLOYMENT & WAGES

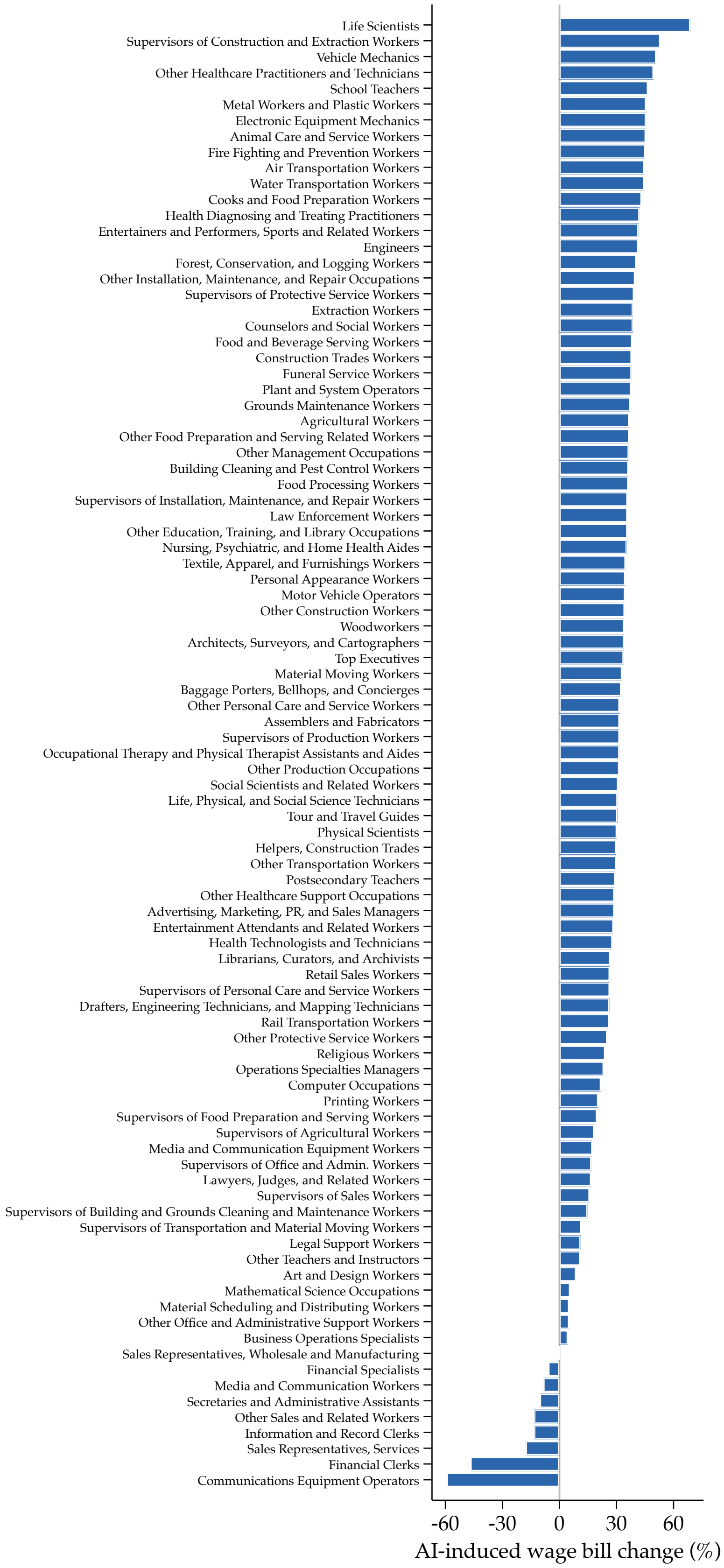
(A) EMPLOYMENT

(B) WAGES



Notes: This figure shows the model's predictions on AI's employment and wage effects by occupational group. Occupations are sorted in descending order of AI's effect on their wage bill, so that the first listed occupation experiences the largest wage bill increase.

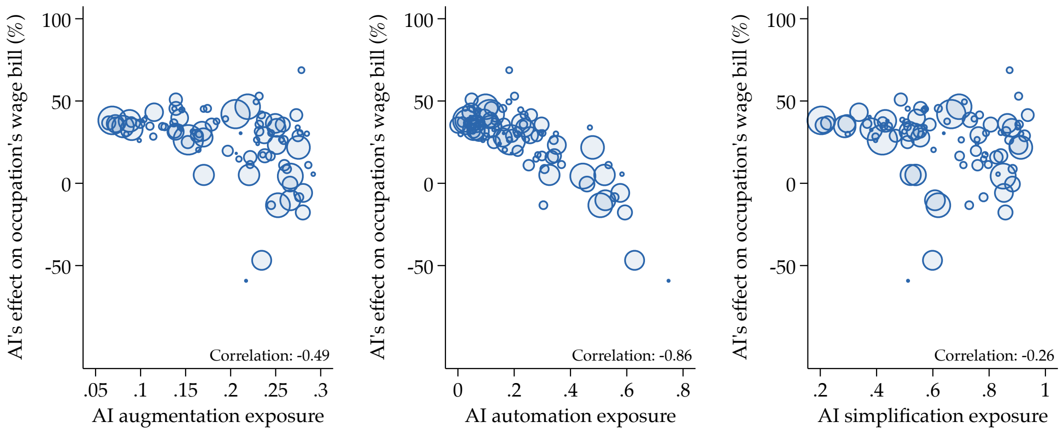
FIGURE A.11: AI'S EFFECT ON DETAILED OCCUPATIONS' WAGE BILLS



Notes: This figure shows the model predictions on AI's wage bill effects by occupation.

FIGURE A.12: AUTOMATION EXPOSURE MOST PREDICTIVE OF LABOR MARKET LOSSES

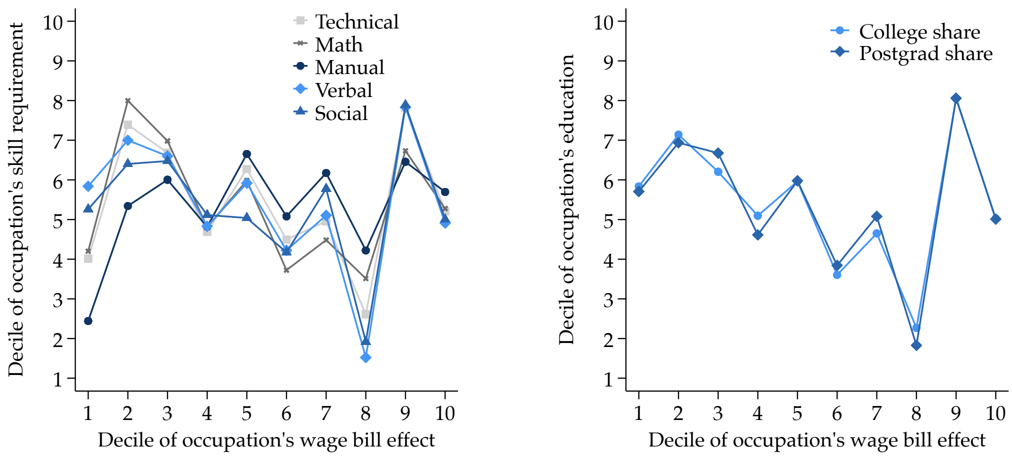
(A) AUGMENTATION (B) AUTOMATION (C) SIMPLIFICATION



Notes: This figure shows the relationship between three dimensions of AI exposure and model-predicted changes in occupational wage bills. Each bubble represents an occupation, with size proportional to pre-AI employment. Panel (A) shows augmentation exposure, measured as the share of time access to generative AI can save in completing an occupation's tasks. Panel (B) shows automation exposure, measured as the share of an occupation's tasks than generative AI can complete autonomously. Panel (C) shows simplification exposure, measured as the (negative) relative change of skill levels required to complete an occupation's tasks (averaged across all 35 O*NET skills).

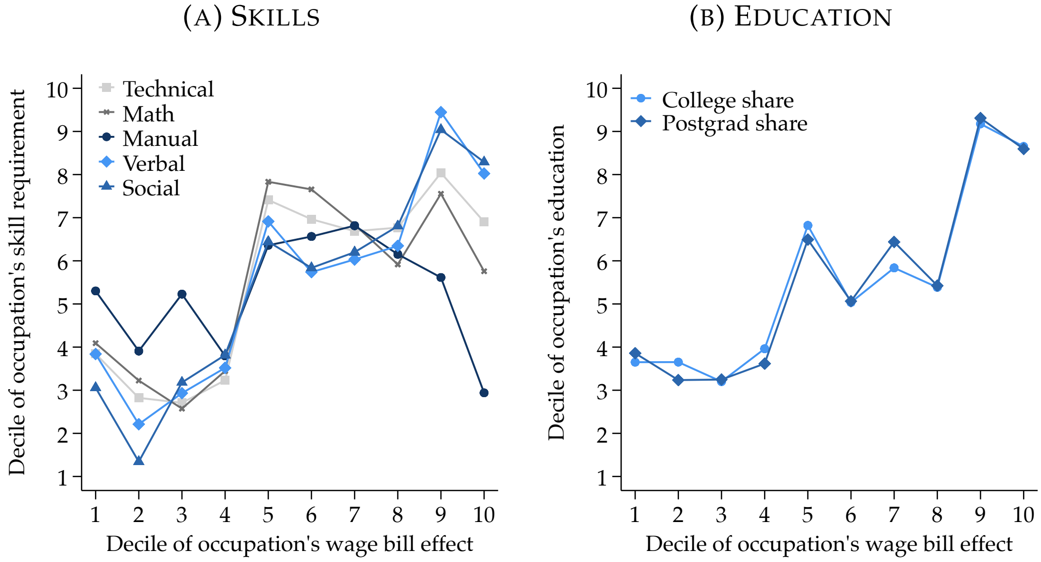
FIGURE A.13: SKILLS AND EDUCATION BY GENAI'S WAGE BILL EFFECT

(A) SKILLS (B) EDUCATION



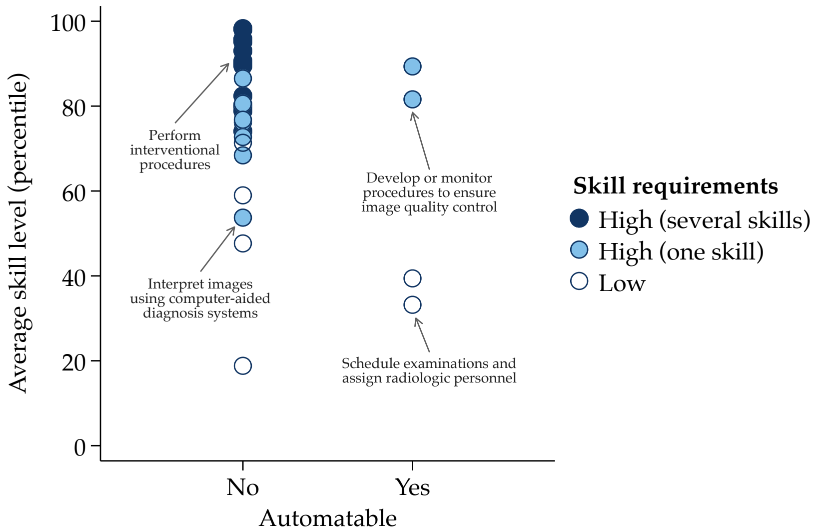
Notes: This figure shows the relationship between occupational characteristics and generative AI's wage bill effects. Panel A plots average skill requirement deciles against wage bill effect deciles. Panel B plots education levels against wage bill effect deciles. Each point represents a decile of occupations ranked by their predicted wage bill change, weighted by pre-AI employment.

FIGURE A.14: SKILLS AND EDUCATION BY WAGE BILL EFFECT: PHYSICAL AI SCENARIO



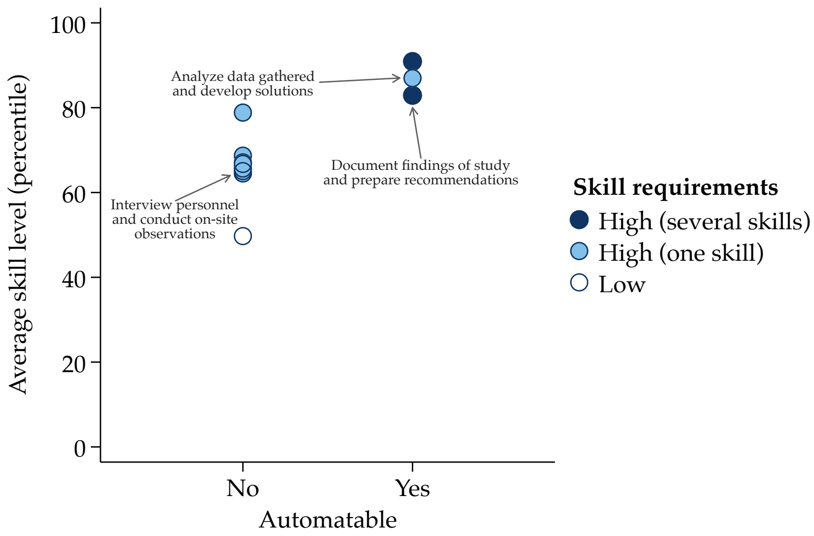
Notes: This figure shows the relationship between occupational characteristics and AI's wage bill effects when physical manipulation capabilities are available. Panel A plots average skill requirement deciles against wage bill effect deciles. Panel B plots education levels against wage bill effect deciles. Each point represents a decile of occupations ranked by their predicted wage bill change, weighted by pre-AI employment.

FIGURE A.15: RADIOLOGISTS' TASK-BASED AUTOMATION EXPOSURE



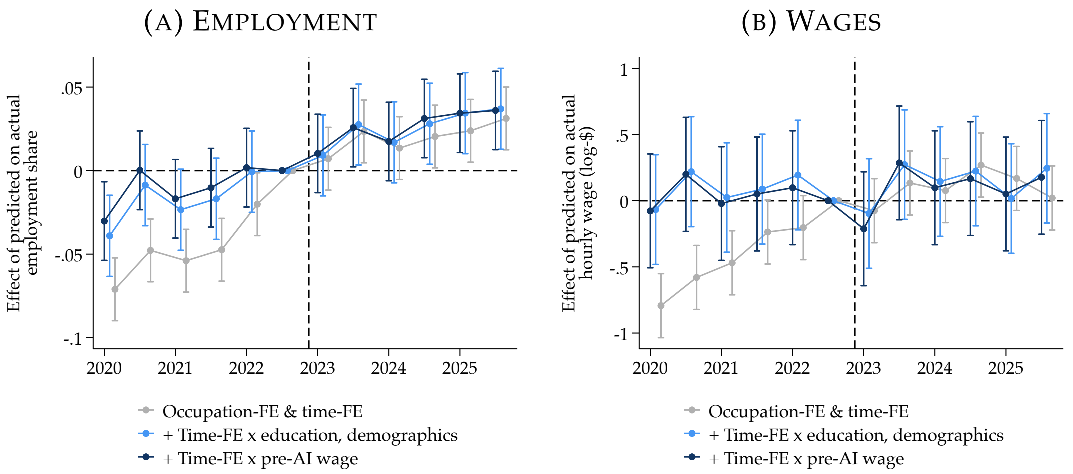
Notes: This figure shows radiologists' automation exposure across all tasks they engage in according to O*NET. We classify a task as 'automatable' if it has high or full automation exposure, which is restricted to cases where the LLM indicates that generative AI can complete at least 90% of the components of the tasks. We classify skill requirements as "high" if they exceed level 3.5 in O*NET's scale from 1 to 7.

FIGURE A.16: MANAGEMENT ANALYSTS' TASK-BASED AUTOMATION EXPOSURE



Notes: This figure shows management analysts' automation exposure across all tasks they engage in according to O*NET. We classify a task as 'automatable' if it has high or full automation exposure, which is restricted to cases where the LLM indicates that generative AI can complete at least 90% of the components of the tasks. We classify skill requirements as "high" if they exceed level 3.5 in O*NET's scale from 1 to 7.

FIGURE A.17: EARLY LABOR MARKET EFFECTS OF GENERATIVE AI



Notes: Event study estimates ($\widehat{\beta}_k$) show differential changes in occupational employment and wages following ChatGPT's November 2022 release. Coefficients represent the effect of a one-unit model-predicted change in the respective outcome as predicted by the model on actual the outcome's empirical evolution. A coefficient of 1.0 would indicate complete realization of model predictions. Estimates use CPS data aggregated to 6-month periods with occupation fixed effects and time fixed effects. The specification with controls includes occupation-specific trends based on education, sectoral composition, demographics, and pre-AI wages. Error bars represent 95%-confidence intervals.

B Tables

TABLE B.1: AGGREGATION OF O*NET'S SKILL REQUIREMENTS TO 5 DIMENSIONS

Skill	O*NET skill	O*NET skill category
Manual	Equipment Maintenance	Technical
	Equipment Selection	Technical
	Installation	Technical
	Repairing	Technical
Math	Mathematics	Basic Content
Social	Active Listening	Basic Content
	Coordination	Social
	Instructing	Social
	Management of Personnel Resources	Resource Management
	Negotiation	Social
	Persuasion	Social
	Service Orientation	Social
	Social Perceptiveness	Social
Technical	Complex Problem Solving	Complex Problem Solving
	Judgment and Decision Making	Systems
	Operation and Control	Technical
	Operations Analysis	Technical
	Operations Monitoring	Technical
	Programming	Technical
	Quality Control Analysis	Technical
	Science	Content
	Systems Analysis	Systems
	Systems Evaluation	Systems
	Technology Design	Technical
	Troubleshooting	Technical
Verbal	Reading Comprehension	Basic Content
	Speaking	Basic Content
	Writing	Basic Content

Notes: This table shows the mapping of the five skill clusters—Manual, Math, Social, Verbal, and Technical—to the relevant O*NET skills and their respective O*NET's skill category. For each of the skills, we set the requirement to the average across the relevant O*NET skills. We dropped 7 out of 35 O*NET skill dimensions that could not be clearly mapped into the skills used in the analysis.

TABLE B.2: AGREEMENT ON AUTOMATION EXPOSURE WITH ELOUNDOU ET AL. (2024)

	Eloundou et al. (2024)				
Our measure	None	Low	Medium	High	Full
None	26.86	1.65	0.01	0.34	0.14
Low	6.12	21.34	1.98	2.18	0.12
Medium	0.17	7.27	7.61	3.65	0.06
High	0.04	1.77	5.61	11.53	0.18
Full	0.02	0.07	0.02	1.02	0.24

Notes: This table shows the agreement rates between our measure of automation and that of Eloundou et al. (2024) on the task-level. The table is computed based on 14,209 tasks (out of 19,530) that are in both databases. We classify a task as automated if the exposure is "high" or "full". The share of automated tasks is 21% and 22% in Eloundou et al. (2024)'s and our measure, respectively.

TABLE B.3: SUMMARY OF TASK-LEVEL DATA ON AI CAPABILITIES

	Augmentation		Automation	Simplification
	Excluding automatable tasks	Including automatable tasks		
Mean	17.9%	20.2%	22.2%	18.3%
Std. Dev.	9.4%	9.6%	41.6%	6.6%
Median	20.0%	20.0%	0.0%	20.4%
Range	0.0% - 70.0%	0.0% - 70.0%	0.0% - 100.0%	0.0% - 32.0%
Tasks	15,192	19,530	19,530	19,530

Notes: This table summarizes our new estimates of generative AI's potential impact on tasks across three channels: augmentation (share of worker's time saved by technology to complete task), automation (share of tasks that can be fully automated by technology), and simplification (relative decrease in average skill requirements across all 35 O*NET skill dimensions). For augmentation, we present estimates both excluding and including tasks that can be automated. Augmentation and simplification estimates are generated by GPT-4o; automation estimates are generated by GPT-5 with low to medium reasoning effort.

TABLE B.4: EXPERIMENTAL ESTIMATES COMPARED TO OUR TASK AUGMENTATION DATA

Occupation	**Task**	**Tool**	**Estimate**		**N**	**Notes**	**Source**
			Theirs	**Ours**			
Software developer	Coding	GitHub Copilot	26%	30%	4,867	+26.1% number of completed tasks in lab; new developers higher adoption rates & higher productivity gains	[1]
Software developer	Coding	GitHub Copilot	56%	27%	95	55.8% time saved, quality ↑	[2]
Software developer	Coding	GitHub Copilot	36%	30%	23	36% time saved for familiar tasks; no change for unfamiliar tasks; 48% fewer issues	[3]
Programmer	Coding	GPT-3	27%	30%	100	27% time saved among 100 expert programmers; 50 non-programmers perform tasks similarly well with LLM	[4]
Programmer	Coding	GitHub Copilot	0%	28%	24	No time saved; however, most participants still preferred using LLM	[5]
Management consultant	Consulting	GPT-4	25%	30%	758	25.1% time saved, +12.2% tasks completed, +40% quality (decreased for tasks beyond AI frontier); lower-skilled consultants benefited more	[6]
Customer support	Resolution	GPT-4	14%	30%	5,179	+14% productivity (issues resolved per hour), +34% for new & low-skill workers; minimal impact on experienced & high-skill workers	[7]
–	Writing	GPT-3.5	40%	30%	453	40% time saved, +18% output quality; inequality between workers ↓; low-skill workers benefited most; likelihood of using AI after experiment ↑	[8]
Taxi driver	Selecting routes	AI Navi	14%	9%	520	Shorter cruising time; gains only among low-skill drivers	[9]
Lawyer	Legal writing	Vincent & o1-preview	20%	30%	127	19.9% time saved across different legal writing tasks, quality ↑, LLM "Vincent" slightly higher gains	[10]
Product designer	Product marketing & development	GPT-4o	13-16%	30%	776	+0.37 SD quality and 16.4% time saved for individuals; +0.39 SD quality and 12.7% time saved for teams	[11]
Software developer	Coding	GitHub Copilot	65%	27%	24	Developers implemented ∼65% more requirements with AI assistance	[12]
Software developer	Coding	Google AI Tools	21%	30%	96	AI users finished an enterprise-grade task 21% faster. Results stronger for senior developers.	[13]
Programmer	Coding	CodeFuse	55%	30%	1,219	Lines of code produced ↑ 55%, gains concentrated among junior staff	[14]
Knowledge workers	E-mail	MS 365 Copilot	11%	26%	7,137	Treated spent 12% less time on email each week; did not significantly change time spent in meetings.	[15]
Train commissioning technician	Trouble-shooting	GPT-3.5 + RAG	20%	20%	173	+1.14 SD quality score; 20% increase in tasks completed not significant; less-experienced benefit more.	[16]

Notes: Sources correspond to [1] Cui et al. (2024), [1] Cui et al. (2024), [2] Peng et al. (2024), [3] Clarke and Hanrahan (2024), [4] Campero et al. (2022), [5] Vaithilingam et al. (2022), [6] Dell'Acqua et al. (2023), [7] Brynjolfsson et al. (2025), [8] Noy and Zhang (2023), [9] Kanazawa et al. (2022), [10] Schwarcz et al. (2024), [11] Dell'Acqua et al. (2025), [12] Weber et al. (2024), [13] Paradis et al. (2024), [14] Gambacorta et al. (2024), [15] Dillon et al. (2025). [16] Lowhagen et al. (2025). To construct our own estimates of task augmentation (share of time saved to complete task) by generative AI at the level of work activities, we aggregate our task-level estimates within the relevant occupation as equally weighted averages for tasks we judge to be relevant to the work activity covered in each experiment.

TABLE B.5: OVERVIEW OF MODEL PARAMETERS

Model object	**Symbol**	**Value**	**How it is set**
Elast. of substitution: Occupations	σ	1.57	Burstein et al. (2019); Caunedo et al. (2023).
Elast. of substitution: Tasks	ρ	0.49	Humlum (2019).
Number of occupations	J	93	3-digit BLS SOC occupations.
Number of periods	A	40	Years between 25 and 65.
Discount factor	β	0.78	Following Keane and Wolpin (1997).
Skill dimensions	S		Addison et al. (2020); Baley et al. (2022), plus manual.
Occupational task sets	$\mathcal{T}_j$		O*NET tasks.
Occupational task weights	$\theta_{j,\tau}$		O*NET task importance.
Task-level skill requirements	$\boldsymbol{r}_\tau$		Large language model.
Task-level AI augmentation	γ_τ		"
Task-level AI automation	$\mathcal{A}_j$		"
Learning cost: 1st AFQT quartile	$\lambda(1)$	21.20	Maximum likelihood.
Learning cost: 2nd AFQT quartile	$\lambda(2)$	18.01	"
Learning cost: 3rd AFQT quartile	$\lambda(3)$	17.07	"
Learning cost: 4th AFQT quartile	$\lambda(4)$	16.06	"
Human capital depreciation	δ	0.0004	"
Scale of productivity shocks	ζ	0.053	"
Occupational switching cost	κ	0.340	"
Skill distribution (Beta)	(B_a, B_b)	(68,125)	"
Cost of underqualification	η	1.66	OLS within MLE routine.
Skill productivity: Manual	ω_{Mn}	0.23	"
Math	ω_{Mt}	0.57	"
Social	ω_S	0.40	"
Technical	ω_T	0.17	"
Verbal	ω_V	0.25	"
Occupational amenities	$\{\mu_j\}_{j=1}^J$		Match employment shares à la (Berry et al., 1995).
Occupational demand	$\{\alpha_j\}_{j=1}^J$		Using estimated prices and wage bills.

Notes: This table provides an overview of the parameters of the model, their mathematical symbols, the value at which they are set, and the procedure with which we arrived at the value.

TABLE B.6: OCCUPATIONAL SKILL REQUIREMENTS PREDICT OCCUPATIONAL PRICES

Skill requirements	Dependent variable: Log occupational price $\hat{p}_j$			
Manual	0.228	0.230	0.226	0.227
	(0.207)	(0.214)	(0.201)	(0.208)
Math	-0.070	-0.073	-0.077	-0.080
	(0.277)	(0.286)	(0.269)	(0.278)
Social	-0.083	-0.078	-0.077	-0.073
	(0.352)	(0.363)	(0.341)	(0.353)
Technical	1.342**	1.341**	1.353**	1.352**
	(0.599)	(0.619)	(0.581)	(0.601)
Verbal	0.554	0.554	0.550	0.550
	(0.376)	(0.388)	(0.364)	(0.377)
Sample occupations	All	50+	All	50+
Empirical Bayes applied	No	No	Yes	Yes
Observations	93	87	93	87
R^2	0.73	0.73	0.74	0.74

Notes: This table shows the coefficients and R^2 of a regression of the estimated occupational prices (in logs) on occupational skill requirements. Each observation represents one occupation and is weighted by the number of worker-year observations in that occupation. Columns where sample occupations indicates "50+" only include occupations with at least 50 observations. The third and fourth column show the results with fixed effects on which empirical Bayes regression has been applied. Occupational prices are estimated as the occupational fixed effects in regression equation (17). Occupational skill requirements refer to $\sum_{\tau \in \mathcal{T}_j} \theta_{j,\tau} r_{\tau,s}$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B.7: MODEL FIT: WAGE INEQUALITY IN DATA AND MODEL

	Gini	Ratios $\frac{p90}{p10}$	$\frac{p90}{p50}$	$\frac{p75}{p25}$	Top shares 10%	5%	1%
Data	0.32	4.01	2.13	2.04	0.26	0.16	0.05
Model	0.24	2.96	1.83	1.84	0.20	0.11	0.02

Notes: This table reports measure of inequality in the unconditional wage distribution in the data (NLSY79) and in the model's steady state. The unit of observation is a worker-age pair in the data and in the model. We only included workers who remain in the NLSY79 and work until 2020 without interruptions over 18 months. Sample weights are applied in the NLSY79 data.

TABLE B.8: SKILL CHANNELS AND LABOR MARKET OUTCOMES

	Wage growth (%)		Employment growth (%)	
	(1)	(2)	(3)	(4)
Augmentation	1.48	-2.89	2.11	6.79**
	(4.79)	(4.18)	(3.18)	(2.91)
Automation	4.74**	19.04***	-23.86***	-39.03***
	(1.80)	(3.94)	(1.39)	(3.67)
Simplification	-24.68***	-15.19***	24.81***	15.25***
	(4.25)	(3.38)	(2.93)	(2.94)
Indirect simplification				
Augmentation-led		3.52*		-2.50**
		(1.78)		(1.24)
Automation-led		-15.88***		17.05***
		(4.34)		(4.22)
Observations	93	93	93	93

Notes: This table presents weighted OLS regressions of occupation-level wage and employment growth on AI exposure measures and skill requirement changes. The dependent variable is wage growth in columns (1)–(2) and employment growth in columns (3)–(4). All independent variables are standardized to have standard deviation 1. Columns (1) and (3) include only direct AI exposure measures (augmentation, automation, simplification). Columns (2) and (4) add indirect skill requirement changes induced by AI. All regressions are weighted by pre-AI occupation employment shares. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Estimation

C.1 Cost savings and AI's income share

The cost of performing a task τ with the worker's unit of time equals

$$c_\tau^l(\boldsymbol{h}) \equiv \frac{\Lambda_j(\boldsymbol{h})}{\gamma_\tau f(\boldsymbol{h}, \boldsymbol{r}_\tau)}$$

where $\Lambda_j(h)$ is the shadow value of a unit of time in occupation j given skills $\boldsymbol{h}$. Thus, for any automated task $\tau \in \mathcal{A}_j$, the cost of producing the task with capital relative to performing the task by labor equals

$$\chi_\tau \equiv \frac{c_\tau}{c_\tau^l(\boldsymbol{h})} = c_\tau \frac{\gamma_\tau f(\boldsymbol{h}, \boldsymbol{r}_\tau)}{\Lambda_j(\boldsymbol{h})}.$$

Since the shadow value of a unit of time is the wage $w_j(\boldsymbol{h})$, equation (4) implies that cost savings are equal to

$$\chi_\tau = \frac{c_\tau}{p_j}\left(1 - \sum_{\tau \in \mathcal{A}_j} \theta_{j,\tau}\left(\frac{c_\tau}{p_j}\right)^{1-\rho}\right)^{\frac{1}{\rho-1}} \frac{\gamma_\tau f\left(\boldsymbol{h}, \boldsymbol{r}_\tau\right)}{\left(\sum_{\tau \in \mathcal{N}_j} \theta_{j,\tau} \gamma_\tau^{\rho-1} f(\boldsymbol{h}, \boldsymbol{r}_\tau)^{\rho-1}\right)^{\frac{1}{\rho-1}}}.$$

For our quantification, we need an estimate of $\sum_{\tau \in \mathcal{A}_j} \theta_{j,\tau}\left(\frac{c_\tau}{p_j}\right)^{1-\rho}$ for each occupation. To obtain this, we make two simplifying assumptions. First, we assume that the cost savings do not vary across automatable tasks, i.e., $\chi_\tau = \chi$ for all $\tau \in \mathcal{A}_j$ and $\forall j = 1, \ldots, J$. Second, we assume that the automated tasks are not different in skill requirements from the average remaining non-automatable tasks, i.e., $\gamma_\tau^{\rho-1} f\left(\boldsymbol{h}, \boldsymbol{r}_\tau\right)^{\rho-1} \approx \sum_{\tau \in \mathcal{N}_j} \theta_{j,\tau} \gamma_\tau^{\rho-1} f(\boldsymbol{h}, \boldsymbol{r}_\tau)^{\rho-1}$ for all $\tau \in \mathcal{A}_j$ and $\forall j = 1, \ldots, J$. Under those two assumptions, the cost savings simplify

$$\chi = \frac{c_\tau}{p_j}\left(1 - \sum_{\tau \in \mathcal{A}_j} \theta_{j,\tau}\left(\frac{c_\tau}{p_j}\right)^{1-\rho}\right)^{\frac{1}{\rho-1}}$$

Clearly, the solution is that c_τ/ρ is equal across tasks. From there, equation (21) follows. This equation is useful because it shows that the income share that accrues to automation capital in each occupation j is a function of the (weighted) share of tasks that are automatable and the cost savings by automated task.

C.2 Log-linearization of the production function

In this paragraph, we derive the log-linear wage regression equation in (17). Starting from the wage equation (15), and imposing $\mathcal{A}_j = \varnothing$ (so that $\Gamma_j = 1$ and $\mathcal{N}_j = \mathcal{T}_j$) for all $j = 1, \ldots, J$, we obtain

$$\begin{aligned}\log w_j(\boldsymbol{h}) = \log p_j + \sum_{s \in S} \omega_s \log(h_s) \\ + \frac{1}{\rho - 1} \log \left(\sum_{\tau \in \mathcal{T}_j} \theta_{j,\tau} \gamma_\tau^{\rho-1} \exp \left(-\eta \min \{ h_s - r_{\tau,s}, 0 \}^2 \right)^{\rho - 1} \right).\end{aligned}$$

Now define the variable $m_\tau \equiv \sum_{s \in S} \min\{h_s - r_{\tau,s}, 0\}^2$ and log-linearize the wage function around $m_\tau = 0$ for all $\tau \in \mathcal{T}_j$. That is, we linearize the wage function around the perfectly matched worker.

A first-order Taylor expansion around this point yields

$$\begin{aligned}&\log \left(\sum_{\tau \in \mathcal{T}_j} \theta_{j,\tau} \gamma_\tau^{\rho-1} \exp \left((1 - \rho)\, \eta \, m_\tau \right) \right) \\ &\approx \log \left(\sum_{\tau \in \mathcal{T}_j} \theta_{j,\tau} \gamma_\tau^{\rho-1} \right) + \eta (1 - \rho) \frac{\sum\limits_{\tau \in \mathcal{T}_j} \theta_{j,\tau} \gamma_\tau^{\rho-1} m_\tau}{\sum\limits_{\tau \in \mathcal{T}_j} \theta_{j,\tau} \gamma_\tau^{\rho-1}} \\ &= (1 - \rho) \left(\eta^{-} \sum_{\tau \in \mathcal{T}_j} \theta_{j,\tau} \gamma_\tau^{\rho-1} m_\tau \right)\end{aligned}$$

where the second equality follows from $\sum_{\tau \in \mathcal{T}_j} \theta_{j,\tau} \gamma_\tau^{\rho-1} = 1$. Combining the equations above with the definition of m_τ yields equation (17).

D Data

D.1 Task-level Skill Requirements

We elicit a task's skill requirements by replicating O*NET's occupation-level questionnaire on the task-level using OpenAI's GPT-4o. We requested the skill requirement for each of the 19,530 tasks for each of the 35 skill dimensions, resulting in 683,550 independent prompts. As in O*NET, the skill requirements are rated from 1 to 7 and each of the 35 skills have different “level anchors” to indicate the meaning of levels 2, 4, and 6. These anchors, as well as the set of tasks in each occupation, and their descriptions, are taken from the O*NET database. Below, we present the full text of the prompt for the skill *Reading comprehension*, the occupation *Chief Executives*, and the task *“Prepare budgets for approval, including those for funding or implementation of programs.”*

> *The occupation [Chief Executives] contains the task: [Prepare budgets for approval, including those for funding or implementation of programs].*
>
> *What level of skill in [reading comprehension] is needed to perform the task in this occupation well?*
>
> *Provide the answers on a scale from 1 to 7, where 2 means [Read step-by-step instructions for completing a form], 4 means [Understand an email from management describing new personnel policies], and 6 means [Read a scientific journal article describing surgical procedures].*
>
> *Output only a single integer, valued between 1 and 7. Do not output anything else.*

D.2 AI and Task Augmentation, Automation, Simplification

We model technologies’ impact on workers through three distinct channels: augmentation, automation, and simplification. We leverage O*NET’s assessment framework and descriptions of occupations, tasks, and skills to generate new data using OpenAI’s large language models. In our baseline scenario, we only consider Generative AI. However, we also consider automation by Autonomous Vehicles, and Smart Robots. For automation assessments, we use GPT-5; for augmentation and simplification channels, we use GPT-4o (completed before GPT-5’s release).

D.2.1 Augmentation of Tasks

For augmentation assessment, we ask GPT-4o to estimate time savings when workers get access to these technologies. We assess all 19,530 O*NET tasks and the technologies “generative AI,” “smart robots,” and “autonomous vehicles,” resulting in 58,590 prompts that are evaluated independently. We use OpenAI’s GPT-4o with temperature between 0.05 and 0.1.

The prompt structure is consistent across technologies, varying only in the technology description. Here we show the full prompt for **Generative AI**:

> *We are conducting a rigorous assessment of the time a worker can save on specific tasks by using Generative AI.*
>
> *1. Description of technology: Generative AI*
>
> *Generative AI refers to AI techniques that learn a representation of artifacts from data, and use it to generate brand-new, unique artifacts that resemble but don't repeat the original data. These artifacts can serve benign or nefarious purposes. Generative AI can produce totally novel content (including text, images, video, audio, structures), computer code, synthetic data, workflows and models of physical objects. Generative AI also can be used in art, drug discovery or material design.*
>
> *2. Description of the worker and the task:*
>
> *Worker's role: [Occupation] with an average level of expertise.*
>
> *Worker's access to tools: Has all the standard tools available to someone in this position. In addition, this worker now gains access to a Generative AI.*
>
> *Worker's task: [Occupational task]*
>
> *3. Question:*
>
> *Estimate the percentage of time that the worker can save by using the described Generative AI to assist with the task.*
>
> *4. Output Format:*
>
> *Provide your answer as a percentage (numeric value between 0 and 100). Do not output an explanation or any additional information. The answer should be a single number representing the estimate.*

For **Smart Robots**, the technology description changes to:

> *A smart robot is an AI-powered, often-mobile machine designed to autonomously execute one or more physical tasks. These tasks may rely on, or generate, machine learning, which can be incorporated into future activities or support unprecedented conditions. Smart robots can be split into different types based on the tasks/use cases, such as personal, logistics and industrial.*

For **Autonomous Vehicles**, the description is:

> *An autonomous vehicle is one that can drive itself from a starting point to a predetermined destination in "autopilot" mode using various in-vehicle technologies and sensors, including adaptive cruise control, active steering (steer by wire), anti-lock braking systems (brake by wire), GPS navigation technology, lasers and radar.*

D.2.2 Automation of Tasks

To measure technologies' potential to automate occupational tasks, we follow Eloundou et al. (2024) in using a five-tier rubric ranging from no automation (T0) to full automation (T4) exposure. We assess all 19,530 O*NET tasks and the technologies "generative AI", "smart robots", and "autonomous vehicles", resulting in 58,590 prompts that are evaluated independently. We use OpenAI's GPT-5 with low to medium reasoning effort and temperature between 0.05 and 0.1.

The automation prompt follows Eloundou et al. (2024)'s format, with technology-specific definitions and examples. The prompt for **Generative AI** is:

> *T Automation Rubric*
>
> *1. Determine if the occupation/task pair meets the definition of T0 No-Automation Exposure. If it does, label it as T0 and stop.*
>
> *2. If the occupation/task pair does not meet the definition of T0 No-Automation Exposure, determine if the occupation/task pair meets one of the other definitions and select the label that applies:*
>
> - *T4: Full automation exposure*
> - *T3: High automation exposure*
> - *T2: Moderate automation exposure*
> - *T1: Low automation exposure*
>
> *Rubric*
>
> *Generative AI refers to AI techniques that learn a representation of artifacts from data, and use it to generate brand-new, unique artifacts that resemble but don't repeat the original data. These artifacts can serve benign or*

nefarious purposes. Generative AI can produce totally novel content (including text, images, video, audio, structures), computer code, synthetic data, workflows and models of physical objects. Generative AI also can be used in art, drug discovery or material design.

Assume you are a worker with an average level of expertise in your role trying to complete the given task. You have access to Generative AI as well as any other existing software or computer hardware tools mentioned in the task. You also have access to any commonly available technical tools accessible via a laptop (e.g. a microphone, speakers, etc.). You do not have access to any other physical tools or materials.

Please label the given task according to the rubric below.

T0 No-Automation Exposure *A class of tasks for which Generative AI cannot conceivably perform any aspect of the task in any manner.*

T4 Full Automation Exposure *A class of tasks where, in most contexts in which this task is currently performed by a human, Generative AI can complete all aspects of this task with high quality when prompted by a human. The output does not normally require oversight by a human. Oversight is not normally required for tasks labeled T4 because the consequences for failure or inaccuracy are small for this task, human judgment is not necessary to complete this task, and generative models can consistently perform this task with very high quality.*

T3 High Automation Exposure *A class of tasks where, in most contexts in which this task is currently performed by a human, Generative AI could complete 90-100% of the components of the task when prompted, but the output requires oversight from a human. Oversight is normally required because the consequences for failure or inaccuracy are significant for this task, human judgment is necessary to complete this task, and/or generative models cannot perform all aspects of this task with high quality consistently. These tasks rely almost exclusively on the processing of digital information, but human judgment is needed to ensure that any digital outputs from Generative AI are high enough quality to be acceptable for the particular context.*

T2 Moderate Automation Exposure *A class of tasks where, in most contexts in which this task is performed by a human, Generative AI could complete between 50%-90% of the components of the task at high quality.*

These tasks normally rely heavily on the processing of digital information, but a significant portion of the task also involves actions that Generative AI cannot perform with high quality. These tasks require at least some human action beyond just double-checking generative model outputs (such as interpretation, judgment, human-to-human communication, or physical actions).

T1 Low Automation Exposure *A class of tasks where, in most contexts in which this task is performed by a human, Generative AI could complete between 0%-50% of the components of the task at high quality. These tasks normally rely only partially on the processing of digital information, while the majority of the task involves actions that Generative AI cannot perform with high quality. A majority of the actions that need to be taken to complete this task require a human to perform the action.*

Definitions

High quality *means someone receiving or reviewing the output would not be able to tell the difference between whether it came from Generative AI or a human. For tasks that require a lot of interaction during the completion of the task (e.g. meetings, negotiations), high quality means the people you were interacting with either would not know or would not care that they were interacting with Generative AI.*

Digital information *or* ***information that can easily be expressed digitally*** *includes but is not limited to text, audio, images, video, PDFs, books, code, and data.*

Annotation Examples

Occupation: Special Education Teachers, Preschool

Task: Develop individual educational plans (IEPs) designed to promote students' educational, physical, or social development.

Automation score (T0/T1/T2/T3/T4): T1

Explanation: GenAI drafts SMART goals, accommodations, progress-monitoring templates, and meeting summaries well. But "develop" in practice includes assessments, legal compliance under IDEA, multi-party negotiation, and parent/team consensus—high-stakes, non-digital work that goes far beyond checking model output. The human does a majority of the task through judgment and human-to-human interaction → <50% automatable at high quality.

Occupation: Construction and Building Inspectors

Task: Inspect and monitor construction sites to ensure adherence to safety standards, building codes, or specifications.

Automation score (T0/T1/T2/T3/T4): T1

Explanation: T1 is right because authority, on-site judgment, and safety liability are inherently human/embodied. Modern AI (CV on photos/video, drone logs, code lookups) can pre-screen and draft reports, but the core task is physical inspection plus enforcement. The given explanation is dated—codes are digital; the real blockers are embodiment, accountability, and legal sign-off.

Occupation: Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders

Task: Dump sugar dust from collectors into melting tanks and add water to reclaim sugar lost during processing.

Automation score (T0/T1/T2/T3/T4): T0

Explanation: The task as phrased is purely physical and you've restricted tools to what's on a laptop. GenAI can't perform any part of this task (not "write SOPs" but do the dumping). If the task were broadened to "optimize reclaim procedure / generate checklists," exposure would rise, but for the literal action it's T0.

Occupation: Interpreters and Translators

Task: Refer to reference materials (dictionaries, lexicons, encyclopedias, computerized terminology banks) as needed to ensure translation accuracy.

Automation score (T0/T1/T2/T3/T4): T4

Explanation: GenAI can autonomously retrieve, disambiguate, and compile authoritative references and recommended terms with citations and confidence scores across most high-resource language pairs. The subtask is fully digital, consistent, and does not normally require human oversight.

Occupation: Electronics Engineer

Task: Prepare documentation containing information such as confidential descriptions or specifications of proprietary hardware or software, product development or introduction schedules, product costs, or information about product performance weaknesses.

Automation score (T0/T1/T2/T3/T4): T3

Explanation: Given structured inputs (requirements, BOMs, test data), GenAI can generate nearly all documentation variants (design specs, DFMEA summaries, release notes, red-team risk write-ups), maintain traceability tables, and enforce style guides. Consequences and confidentiality mean human review is required, but the model can complete 90–100% of components in digital form.

Occupation: Advanced Practice Psychiatric Nurse

Task: Write prescriptions for psychotropic medications as allowed by state regulations and collaborative practice agreements.

Automation score (T0/T1/T2/T3/T4): T3

Explanation: If the medication choice is already clinically decided, GenAI can populate eRx fields, check interactions/contraindications, map to formularies, and draft prior-auth notes—essentially all digital components. High-stakes legality and safety mandate human sign-off, but execution is 90–100% automatable with oversight. (If the task were "evaluate and decide what to prescribe," exposure would drop; the annotation's verb is "write.")

Now, apply the above rubric to the example below:

Occupation: [Occupation]

Task: [Occupational task]

Automation score (T0/T1/T2/T3/T4):

Explanation:

Below, we highlight the substantive changes for prompts related to **Smart Robots** (other than pure wording changes that replace "generative AI" with "smart robots"):

T Automation Rubric

[...]

Rubric

A smart robot is an AI-powered, often-mobile machine designed to autonomously execute one or more physical tasks. These tasks may rely on, *or generate, machine learning, which can be incorporated into future activities or support unprecedented conditions. Smart robots can be split into different types based on the tasks/use cases, such as personal, logistics and industrial.*

[...]

Definitions

[...]

Annotation Examples

Occupation: Special Education Teachers, Preschool

Task: Develop individual educational plans (IEPs) designed to promote students' educational, physical, or social development.

Automation score (T0/T1/T2/T3/T4): T1

Explanation: A robot can assist with data capture (sensor-based observations), simple assessments, and pre-filling forms, but developing IEPs requires pedagogical judgment, legal compliance, and multi-party collaboration—most of which remains human.

Occupation: Construction and Building Inspectors

Task: Inspect and monitor construction sites to ensure adherence to safety standards, building codes, or specifications.

Automation score (T0/T1/T2/T3/T4): T3

Explanation: Robots (drones/UGVs) with CV/LiDAR can navigate, capture, measure, compare against BIM/specs, and draft reports (90–100% of components). Human oversight is needed for code interpretation, contractor communication, and legal sign-off.

Occupation: Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders

Task: Dump sugar dust from collectors into melting tanks and add water to reclaim sugar lost during processing.

Automation score (T0/T1/T2/T3/T4): T4

Explanation: Repetitive material handling and dosing in a controlled plant are fully automatable with robotic manipulation, sensing, and safety interlocks.

Occupation: Interpreters and Translators

Task: Refer to reference materials (dictionaries, lexicons, encyclopedias, computerized terminology banks) as needed to ensure translation accuracy.

Automation score (T0/T1/T2/T3/T4): T4

Explanation: Purely digital retrieval/matching. A robot running GenAI can autonomously consult termbases, disambiguate senses, enforce glossaries, and return citations without routine human oversight.

Occupation: Electronics Engineer

Task: Prepare documentation containing information such as confidential descriptions or specifications of proprietary hardware or software, product development or introduction schedules, product costs, or information about product performance weaknesses.

Automation score (T0/T1/T2/T3/T4): T3

Explanation: With structured inputs (requirements, BOMs, test data), a robot+GenAI stack can draft nearly all documents and maintain traceability. Human review remains for accuracy, confidentiality, and compliance.

Occupation: Advanced Practice Psychiatric Nurse

Task: Write prescriptions for psychotropic medications as allowed by state regulations and collaborative practice agreements.

Automation score (T0/T1/T2/T3/T4): T3

Explanation: A robot can complete the eRx workflow (populate fields, check interactions, format to payer formularies, draft prior auth), but human authorization/clinical judgment is required; oversight is routine.

Occupation: Warehouse Workers

Task: Move inventory from receiving dock to storage locations using hand trucks or pallet jacks.

Automation score (T0/T1/T2/T3/T4): T4

Explanation: AMRs/AGVs integrated with WMS can autonomously transport pallets/totes end-to-end in structured warehouses.

Occupation: Assembly Line Workers

Task: Attach components to products moving along assembly line according to specifications.

Automation score (T0/T1/T2/T3/T4): *T4*

Explanation: *In the typical modern assembly context, robots can complete all attachment steps with consistently high quality. Errors are caught by automated fail-safes/poka-yoke and do not require routine human oversight; technicians intervene only on rare exceptions or maintenance, which is outside the task scope.*

Now, apply the above rubric to the example below:

[...]

Below, we highlight the substantive changes for prompts related to **Autonomous Vehicles** (other than pure wording changes that replace "generative AI" with "autonomous vehicles"):

T Automation Rubric

[...]

Rubric

An autonomous vehicle is one that can drive itself from a starting point to a predetermined destination in "autopilot" mode using various in-vehicle technologies and sensors, including adaptive cruise control, active steering (steer by wire), anti-lock braking systems (brake by wire), GPS navigation technology, lasers and radar.

[...]

Definitions

[...]

Annotation Examples

Occupation: Special Education Teachers, Preschool

Task: Develop individual educational plans (IEPs) designed to promote students' educational, physical, or social development.

Automation score (T0/T1/T2/T3/T4): *T0*

Explanation: *Purely cognitive/interpersonal; no driving component for an AV to perform.*

Occupation: Construction and Building Inspectors

Task: Inspect and monitor construction sites to ensure adherence to safety standards, building codes, or specifications.

Automation score (T0/T1/T2/T3/T4): T1

Explanation: An AV can transport the inspector to/around sites, but the inspection, judgments, and sign-off remain human; AV contributes a minority transport component.

Occupation: Veterinarians

Task: Drive mobile clinic vans to farms so that health problems can be treated or prevented.

Automation score (T0/T1/T2/T3/T4): T2

Explanation: AVs can perform most road driving to rural sites, but last-meters access (gates, unmarked farm roads, ad-hoc parking/turnarounds) and dynamic on-site constraints often require human intervention. Overall, the AV covers a large portion of the task, but not reliably $\geq$*90% across most contexts.*

Occupation: Correctional Officers and Jailers

Task: Drive passenger vehicles and trucks used to transport inmates to other institutions, courtrooms, hospitals, and work sites.

Automation score (T0/T1/T2/T3/T4): T3

Explanation: On-road transport between facilities is highly automatable; AVs can execute routing and vehicle control end-to-end. However, the context is high-stakes (security protocols, perimeter handoffs, incident response), so human oversight remains standard even if the driving component is largely automated.

Occupation: Taxi Drivers and Chauffeurs

Task: Test vehicle equipment, such as lights, brakes, horns, or windshield wipers, to ensure proper operation.

Automation score (T0/T1/T2/T3/T4): T4

Explanation: AV platforms can autonomously run pre-trip self-checks and diagnostics (actuate systems, read sensors/OBD, verify via cameras), producing pass/fail results without routine human oversight in most contexts.

Now, apply the above rubric to the example below:

[...]

D.2.3 Simplification of Tasks

The simplification channel assesses how technologies change the skill requirements for performing tasks. We ask GPT-4o to evaluate skill levels both without and with technology access, allowing us to measure the change in required skills. The prompt asks for both values simultaneously. For example, with **Generative AI**:

> *The occupation [Occupation] contains the task: [Occupational task].*
>
> *Technology name: Generative AI*
>
> *Technology description: Generative AI refers to AI techniques that learn a representation of artifacts from data, and use it to generate brand-new, unique artifacts that resemble but don't repeat the original data. These artifacts can serve benign or nefarious purposes. Generative AI can produce totally novel content (including text, images, video, audio, structures), computer code, synthetic data, workflows and models of physical objects. Generative AI also can be used in art, drug discovery or material design.*
>
> *What level of skill in [Skill] is needed to perform the task in this occupation well WITHOUT access to Generative AI? What level of skill in [Skill] is needed to perform the task in this occupation well WITH access to Generative AI?*
>
> *Provide the answers on a scale from 1 to 7, where 2 means [Skill Level 2 Anchor], 4 means [Skill Level 4 Anchor], and 6 means [Skill Level 6 Anchor].*
>
> *Output only two integers separated by a comma, valued between 1 and 7. The first integer is the skill level WITHOUT access to Generative AI, the second integer is the skill level WITH access to Generative AI. Do not output anything else.*

All 35 O*NET skills and 19,530 O*NET tasks are evaluated independently. Skill level anchors and task descriptions are drawn from O*NET as discussed in Appendix D.1.

This approach allows us to measure both the baseline skill requirements $\boldsymbol{r}_\tau$ and the technology-adjusted requirements $\boldsymbol{r}'_\tau$ in a single API call for each skill and task, improving consistency and reducing potential discrepancies from separate queries. The difference between these two values captures the simplification effect of the technology on task skill requirements.

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