Generative AI, Expertise, and Inequality: A Race Between Productivity and Scarcity*

Seyed M. Hosseini† Guy Lichtinger‡

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Abstract

How will generative AI (GenAI) affect wage inequality across occupations? This paper argues that, beyond productivity effects, GenAI reshapes wage premia by altering occupational entry barriers through changes in expertise requirements. Using O*NET task data and large language model evaluations, we distinguish two channels through which GenAI affects occupational expertise: an extensive margin in which some tasks are automated, and an intensive margin in which tasks remain human-performed but become easier. We introduce, and make publicly available, a Potential Supply Shift (PSS) index that translates these expertise changes into labor-market flows by measuring how GenAI changes the share of the workforce qualified to perform an occupation. We document that PSS (i) rises with baseline expertise and wages across most of the distribution, but falls sharply in the upper tail; (ii) is positively associated with predicted productivity gains; and (iii) varies widely even among occupations with similar exposure. A task-based general equilibrium model suggests that expertise-driven supply expansions and productivity gains exert offsetting effects on cross-occupation wage inequality.

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†Harvard University. Email: shosseinimaasoum@fas.harvard.edu.

‡Harvard University. Email: guylichtinger@g.harvard.edu.

1 Introduction

The rapid diffusion of generative AI (GenAI) tools since 2023 and the accelerating pace of model improvement have raised a central question for labor economics: how will GenAI reshape wage inequality across occupations? Much of the debate focuses on productivity, asking which jobs will experience the largest time savings or output gains. This paper emphasizes a second, distinct channel: GenAI can shift the *potential supply* of labor to occupations by changing the expertise required to perform their task bundles. When entry barriers fall, occupations become more contestable, scarcity premia diminish, and wages adjust even if demand is unchanged. The distributional consequences of GenAI therefore reflect a productivity–scarcity race: productivity gains that tend to raise wages where GenAI is most useful, and expertise-driven supply expansions that compress wage premia by expanding access to high-expertise work.

We study these mechanisms theoretically and empirically. We begin by developing a task-based general equilibrium model of occupations and expertise, building on Autor and Thompson (2025). In the model, occupations consist of discrete tasks with heterogeneous expertise requirements; workers differ in innate expertise and face hierarchical feasibility constraints; and wages are determined competitively under CES demand. Inequality arises because high-expertise occupations draw from a thin upper tail of the expertise distribution, generating scarcity premia. To map feasibility into realized employment, we embed occupational choice in a discrete-choice framework: more expert workers are more likely to sort into higher-barrier occupations, but may choose lower-barrier jobs due to idiosyncratic fit and outside options. Within this framework, GenAI affects wages through two channels: it raises labor productivity, and it alters the expertise requirements that govern occupational entry.

We then bring the model to the data using the O*NET database, which provides task statements for 19,265 tasks across 923 occupations. We construct occupation-level measures of the two forces in the productivity–scarcity race. The first is an expertise-driven *Potential Supply Shift* (PSS), which captures how GenAI changes occupational entry barriers and the size of the workforce that is qualified to perform each occupation. The second is a *Potential Productivity Gain* (PPG), which summarizes predicted time savings from GenAI augmentation. We make the complete task-level and occupation-level datasets publicly available.[1]

Constructing PSS proceeds in three steps. First, we use large language models (LLMs) to generate task-level measures of expertise requirements. Following Autor and Thompson (2025), expertise is defined as a barrier to entry: tasks that require specialized training, credentials, or substantial occupation-specific knowledge receive higher scores, while tasks that most workers can perform with minimal instruction receive lower scores. We validate the resulting occupation-level expertise measures across multiple frontier LLMs and show that they are strongly correlated with independent indicators of skill, including required education, required experience, and wages.

Second, we measure how GenAI affects occupational expertise through two distinct channels. On the *extensive margin*, some tasks are automated and removed from the bundle performed by labor. To capture this channel, we update the task-level automation exposure measure of Eloundou et al. (2024) to reflect current GenAI capabilities and use it to assess how occupational expertise changes when exposed tasks are automated. This margin corresponds to the "expertise exposure" concept of Autor and Thompson (2025), though our focus is on potential shifts induced by GenAI rather than realized changes from past technologies. On the *intensive margin*, tasks remain human-performed but become easier because GenAI expands workers' effective capabilities. We measure this channel by re-rating task expertise under the counterfactual that workers have access to a capable GenAI assistant, allowing us to quantify reductions in required expertise even without task removal. This mechanism is motivated by Autor (2024) and closely related to the task-simplification framework of Althoff and Reichardt (2025). Combining these two margins yields a post-GenAI occupational expertise requirement.

Third, we construct PSS by mapping changes in occupational expertise requirements into changes in the share of the workforce that is qualified to perform each occupation, using the employment-weighted distribution of baseline expertise. PSS therefore incorporates both extensive- and intensive-margin effects as well as the shape of the expertise distribution itself. A positive PSS indicates that GenAI lowers effective entry barriers and expands the pool of qualified workers. On average, we estimate that GenAI increases the qualified labor pool by roughly 10 percentage points, though the magnitude varies widely across occupations.

[1] The datasets are available at `https://github.com/s-mahdihosseini/GenAI_Expertise`.

In parallel, we construct the Potential Productivity Gain (PPG) using the task-level augmentation index of Eloundou et al. (2024), which identifies tasks for which GenAI can reduce completion time by at least 50 percent while maintaining quality. We weight these task-level predictions by O*NET measures of task frequency and importance to obtain an occupation-level measure of predicted productivity gains.

Using these measures, we document three empirical facts. First, PSS rises with baseline expertise and wages across most of the distribution, implying that GenAI tends to relax entry barriers more for many initially high-skill and high-pay occupations. However, this relationship is non-monotonic: above roughly the 90th percentile, PSS declines sharply. The highest-expertise occupations sit in regions of the expertise distribution where worker density is low, so comparable reductions in expertise requirements translate into relatively small supply expansions. As a result, GenAI may broaden access to many high-skill occupations while leaving the very top comparatively insulated from supply-side pressure.

Second, predicted productivity gains are positively correlated with both baseline expertise and PSS. Therefore, occupations in the upper-middle of the expertise distribution tend to combine large reductions in effective expertise requirements with substantial productivity gains, whereas the highest-expertise occupations experience large productivity gains but relatively modest supply expansions. This joint structure highlights the central tension in the distributional effects of GenAI.

Third, we compare PSS to the widely used occupational exposure measures that classify tasks as automatable and compute the share of exposed tasks. These exposure measures have two key limitations: (i) they generally treat tasks as homogeneous and therefore abstract from what is being automated, and (ii) they usually focus on the extensive margin, implicitly classifying tasks as either automated or unaffected, and therefore miss intensive-margin effects through which GenAI reduces the expertise required to perform tasks that remain human-performed. PSS addresses both limitations by incorporating task expertise and combining extensive-margin automation with intensive-margin task simplification. We show that PSS varies widely even among occupations with nearly identical exposure shares, suggesting that exposure alone is a poor predictor of how GenAI reshapes occupational entry barriers.[2]

[2]Relatedly,Freund and Mann (2025) develop a quantitative model in which AI changes the task con-

Finally, we use the task-based general equilibrium model to map empirically measured expertise-driven supply expansions and productivity gains into equilibrium wage and employment responses. We show that supply expansions compress the wage distribution, while productivity gains tend to widen it. In our quantitative exercises, these two forces partially offset, yielding modest net changes in overall cross-occupation wage inequality induced by GenAI. We then return to our simple Potential Supply Shift (PSS) measure and show that it captures the core general-equilibrium implications of GenAI-driven expertise reductions: in the expertise-reduction counterfactual, occupations with larger PSS experience lower wages and higher employment. Despite abstracting from the model's full structure of endogenous choice and reallocation, PSS explains a substantial share of the cross-occupation variation generated by the full general-equilibrium model, indicating that much of the supply-side impact of GenAI is already visible in how it relaxes occupational entry barriers.

We conclude by noting several limitations. We abstract from endogenous task creation and occupational change and treat the distribution of worker expertise as fixed, ruling out retraining responses. Some LLM-based counterfactual assessments, particularly those concerning changes in task expertise, are difficult to validate directly and should be interpreted cautiously. With these caveats, the central message is clear: beyond productivity, GenAI reshapes wage inequality by altering occupational entry barriers. The balance between productivity gains and expertise-driven supply expansions will play a decisive role in determining the distributional impact of GenAI.

2 Model

In this section, we develop a task-based general equilibrium model, building on Autor and Thompson (2025), in which occupational wage inequality reflects both heterogeneity in labor productivity across occupations and differences in the scarcity of workers able to perform them. Occupations command higher wages because they are more productive (the productivity channel) and/or because only a limited share of the workforce can meet their entry requirements (the expertise channel).

tent of jobs and hence skill requirements, implying that exposure shares can miss important heterogeneity because outcomes depend on *which* tasks are automated. Their framework also features an entry-barrier channel in which automating skill-intensive tasks expands effective occupational labor supply.

We use the model to study how a new technology such as generative AI reshapes wage inequality by simultaneously affecting these two margins. On the productivity side, GenAI can raise the efficiency with which labor performs tasks, increasing marginal revenue products in exposed occupations and the labor demand. On the scarcity side, GenAI can relax expertise-based entry barriers and expand effective labor supply.

We formalize this by distinguishing two broad ways in which GenAI affects occupational outcomes. First, GenAI can alter *labor scarcity* by changing the expertise required to perform an occupation and thereby expanding effective labor supply. We capture this scarcity channel through two task-level mechanisms. On the *extensive margin*, GenAI fully automates some tasks, eliminating them from the set of tasks that must be performed by labor and potentially relaxing the occupation's binding expertise requirement. On the *intensive margin*, tasks remain performed by workers, but access to GenAI lowers the expertise required to perform them, allowing workers to complete tasks that previously lay beyond their unaided capabilities. Second, GenAI can raise *labor productivity* by augmenting workers' efficiency in performing tasks.[3] The model provides a unified framework for analyzing how productivity gains and expertise-driven changes in labor scarcity interact in general equilibrium to shape wages and inequality.

2.1 Environment

Workers, Expertise, and Tasks. The economy consists of workers and occupations. Workers differ in an innate level of expertise that limits which tasks they can perform. Formally, the economy is partitioned into occupational groups $g \in \mathcal{G}$, each containing a mass M_g of workers. Each worker i in group g has expertise $e_i \in \mathbb{R}_+$, drawn from a continuous distribution F_g with density f_g. Expertise is fixed. A worker in group g can supply labor only to occupations in $\mathcal{O}_g$, with $\mathcal{O} := \cup_g \mathcal{O}_g$.[4]

Each occupation $o \in \mathcal{O}$ consists of a finite set of tasks $T_o = \{1, \ldots, J_o\}$. Task t has a baseline expertise requirement $r_{ot} \in \mathbb{R}_+$ and weight $w_{ot} > 0$. As discussed above, access

[3]We abstract from an explicit capital factor. When GenAI automates a task (extensive margin), we interpret the task as being produced by an external AI service, so it no longer requires labor time and no longer enters the worker's feasibility constraint. Our focus is wage inequality across occupations rather than the labor share or capital income.

[4]In the main analysis we abstract from occupational groups; future extensions restrict mobility across groups.

to technology can reduce the expertise required to perform a task without eliminating it (the intensive margin). We denote the expertise required to perform task t when workers have access to the technology by $\widetilde{r}_{ot}$. We assume hierarchical feasibility: a worker with expertise e can perform task (o, t) if and only if $e \geq \widetilde{r}_{ot}$. Production requires completing all tasks assigned to labor, so an occupation's binding expertise requirement is

$$\widetilde{R}_o := \max_{t \in T_o} \widetilde{r}_{ot}. \tag{1}$$

In the baseline without GenAI, $\widetilde{r}_{ot} = r_{ot}$ and $R_o := \max_{t \in T_o} r_{ot}$.

2.2 Production

Occupational Output. Each occupation produces a differentiated intermediate input Y_o using effective labor:

$$Y_o \;=\; A_o \, L_o, \tag{2}$$

where $A_o > 0$ is occupation-specific labor productivity and L_o is employment in occupation o. Differences in A_o generate heterogeneity in marginal revenue products across occupations and constitute the productivity channel through which technology and demand affect wages.

Final Demand. The final good aggregates occupational inputs with a CES technology:

$$Y \;=\; \left(\sum_{o \in \mathcal{O}} \vartheta_o^{\frac{1}{\sigma}} \, Y_o^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \qquad \sigma > 1, \tag{3}$$

where $\vartheta_o > 0$ captures demand/importance weights. The final good is the numeraire.

Under perfect competition, occupational prices satisfy CES demand, and wages equal marginal revenue product. Combining CES demand with (2) yields

$$w_o \;=\; \underbrace{P \, Y^{\frac{1}{\sigma}}}_{\kappa} \, \vartheta_o^{\frac{1}{\sigma}} \, A_o^{1-\frac{1}{\sigma}} \, L_o^{-\frac{1}{\sigma}}, \tag{4}$$

where P is the CES price index and $\kappa := P \, Y^{1/\sigma}$ is common across occupations. Define the demand–productivity shifter

$$B_o \ := \ \kappa \, \vartheta_o^{\frac{1}{\sigma}} \, A_o^{1-\frac{1}{\sigma}}, \tag{5}$$

so (4) is the inverse labor demand curve $w_o = B_o L_o^{-1/\sigma}$. Equation (4) highlights the productivity-side source of wage dispersion: occupations with higher productivity or demand weights command higher wages through marginal revenue products.

2.3 Labor Supply and Occupational Choice

A central mechanism in the model is that expertise requirements limit who can work in each occupation. Low-expertise occupations can be performed by many workers, while high-expertise occupations are accessible to only a small fraction of the workforce. This difference in effective labor supply generates scarcity premia, which constitute one of the two channels of wage inequality in our framework.

In order to translate potential eligibility—who *could* do a job—into realized employment and wages, we microfound occupational labor supply using a discrete-choice model. In this framework, higher-expertise workers systematically sort into higher-expertise occupations, but there remains a non-zero probability that they choose lower-expertise jobs due to idiosyncratic fit or mobility costs.[5]

Feasibility. A worker with expertise e_i in group g can choose occupation $o \in \mathcal{O}_g$ if and only if $e_i \geq \widetilde{R}_o$. Equivalently, her feasible set of occupations is $\mathcal{O}_g(e_i) := \{o \in \mathcal{O}_g : \ e_i \geq \widetilde{R}_o\}$, which expands with expertise.

Occupational Choice. Workers value wages but also experience idiosyncratic occupation-specific fit, mobility costs, or preferences. Among feasible occupations, workers choose where to work based on wages and an idiosyncratic fit term. Utility is

$$u_{io} = \log w_o + \varepsilon_{io},$$

with ε_{io} i.i.d. Type-I extreme value with scale $\tau > 0$, and $u_{io} = -\infty$ if $e_i < \widetilde{R}_o$ (i.e. the worker is not qualified for that occupation). This implies multinomial logit choice proba-

[5]Here we deviate from Autor and Thompson (2025) in that workers do not always choose the highest-expertise occupation available to them.

bilities:

$$s_{go}(e; w, \widetilde{R}) = \frac{w_o^{1/\tau}}{\sum_{k \in \mathcal{O}_g(e)} w_k^{1/\tau}} \mathbf{1}\{e \geq \widetilde{R}_o\}. \tag{6}$$

As $\tau \to 0$, choices concentrate on the highest-wage feasible occupation.

Aggregate labor supply (employment) in occupation $o \in \mathcal{O}_g$ is the mass of group-g workers choosing o:

$$L_o^S(w, \widetilde{R}) \;=\; M_g \int_0^\infty s_{go}(e; w, \widetilde{R})\, f_g(e)\, de, \qquad o \in \mathcal{O}_g. \tag{7}$$

Because feasibility is a threshold rule, (7) can equivalently be written as an integral over the upper tail $e \geq \widetilde{R}_o$. It is often useful to define the *potential* (eligible) pool

$$S_o(\widetilde{R}) \;:=\; M_g\big(1 - F_g(\widetilde{R}_o)\big), \tag{8}$$

and the *average take-up rate* among eligible workers

$$\bar{s}_o(w, \widetilde{R}) := \frac{1}{1 - F_g(\widetilde{R}_o)} \int_{\widetilde{R}_o}^\infty \frac{w_o^{1/\tau}}{\sum_{k \in \mathcal{O}_g(e)} w_k^{1/\tau}}\, f_g(e)\, de,$$

so that $L_o^S = S_o \cdot \bar{s}_o$. This decomposition separates two distinct forces shaping labor supply. The eligible pool S_o captures the *scarcity margin*: it reflects how many workers are able to perform the occupation at all, given expertise requirements. Changes in S_o shift labor supply by altering contestability. Actual employment, however, depends on how these eligible workers allocate across all feasible occupations; the average take-up rate $\bar{s}_o$ captures this allocation margin.

Equilibrium. An equilibrium is a vector of wages $\{w_o\}_{o \in \mathcal{O}}$ and employments $\{L_o\}_{o \in \mathcal{O}}$ such that, for each occupation o,

$$w_o = B_o\, L_o^{-1/\sigma} \qquad \text{and} \qquad L_o = L_o^S(w, \widetilde{R}). \tag{9}$$

Equivalently, substituting (4) into (7) yields a fixed point in wages (or employment). In the quantitative exercise we solve (9) group-by-group, noting that κ scales all wages proportionally.

2.4 How GenAI Affects the Race Between Productivity and Scarcity

We now introduce how GenAI affects the productivity–scarcity race that governs occupational wages. GenAI operates through two broad channels: a *productivity* channel, which raises marginal revenue products and shifts labor demand, and a *scarcity (expertise)* channel, which changes the expertise required to perform tasks and thereby expands the set of workers who can do the job. Within the scarcity channel, we distinguish an *extensive margin* in which some tasks are fully automated and removed from labor's bundle, and an *intensive margin* in which tasks remain performed by workers but require less expertise when workers have access to GenAI.

2.5 How GenAI Shifts the Productivity–Scarcity Race

We now introduce how GenAI shifts the productivity–scarcity race that governs occupational wages. GenAI operates through two broad channels. First, it can change *labor scarcity* by altering the expertise required to perform the tasks that make up an occupation, thereby expanding (or contracting) the set of workers who can do the job. Second, it can change *labor productivity* by raising workers' efficiency in performing tasks, shifting labor demand. We present each channel in turn.

2.5.1 The Scarcity (Expertise) Channel

GenAI can reduce scarcity premia by expanding effective labor supply—either by eliminating tasks from labor's bundle or by lowering the expertise required to perform tasks that remain performed by workers.

Extensive Margin: Task Automation. On the extensive margin, GenAI fully automates a subset of tasks, removing them from the set that must be performed by labor. Let $a_{ot} \in \{0, 1\}$ indicate whether task t in occupation o is automated, and define the tasks that remain assigned to labor as

$$T_o^L := \{t \in T_o : \ a_{ot} = 0\}.$$

Because production requires completing all tasks assigned to labor, automating tasks can relax the occupation's binding expertise requirement. The post-automation barrier is

$$R_o^{\text{ext}} := \max_{t \in T_o^L} r_{ot}, \tag{10}$$

with the convention $\max \emptyset = 0$ if all tasks are automated. In the race interpretation, this margin expands the eligible pool by shrinking the set of tasks that gate entry.

Intensive Margin: Lowering Task Requirements. On the intensive margin, tasks remain performed by labor, but access to GenAI lowers the expertise required to perform them. We capture this by mapping baseline task requirements into technology-adjusted requirements:

$$\widetilde{r}_{ot} \;=\; \rho(r_{ot}), \tag{11}$$

where $\rho : \mathbb{R}_+ \to \mathbb{R}_+$ is increasing and satisfies $\rho(x) \leq x$ for all $x \geq 0$, with strict inequality on a set of positive measure. The associated occupation-level barrier becomes

$$R_o^{\text{int}} := \rho(R_o). \tag{12}$$

In the race interpretation, this margin expands effective labor supply by making previously infeasible tasks feasible for a larger share of workers.

Combining extensive and Intensive Margins. When both margins operate, tasks may be removed from labor and the remaining tasks may become easier to perform. The resulting barrier is

$$R_o^{\text{comb}} := \rho(R_o^{\text{ext}}). \tag{13}$$

2.5.2 The Productivity Channel

Finally, GenAI may raise workers' efficiency in producing occupational output, shifting labor demand. We model this as a labor-augmenting productivity gain:

$$A_o^{\text{AI}} \;=\; A_o \cdot \exp(\pi_o), \tag{14}$$

where π_o is the (log) productivity gain induced by GenAI in occupation o. In the race interpretation, this channel pushes wages up by raising marginal revenue products, holding scarcity fixed.

2.6 From Expertise Barriers to Wages: Incidence

We now connect these channels to wages and employment. The effect of expertise reductions depends not only on the size of the barrier change, but also on how many workers sit near the threshold and what jobs they can choose instead. If the expertise distribution is thick around the occupation's cutoff, a small reduction in requirements can make many workers newly eligible, raising effective competition and putting downward pressure on wages. But those newly eligible workers only enter in force if the occupation is attractive relative to their feasible alternatives—so outside options determine how much the potential expansion in eligibility turns into actual employment shifts.

Potential Eligibility and Expertise Density. Fix an occupation $o \in \mathcal{O}_g$. Given an entry requirement R, the mass of workers in group g who are eligible to perform the occupation is $M_g(1 - F_g(R))$. When the entry barrier falls from R_o to $\widetilde{R}_o$, the increase in the eligible pool is

$$\mathrm{PSS}_o := M_g\big[F_g(R_o) - F_g(\widetilde{R}_o)\big], \tag{15}$$

which we call the *potential supply shift* (PSS). For a small reduction $\widetilde{R}_o = R_o - \Delta R_o$,

$$\mathrm{PSS}_o \;\approx\; M_g\, f_g(R_o)\, \Delta R_o, \tag{16}$$

so potential inflows are larger when expertise density is high at the pre-AI threshold.

Outside Options and Actual Labor Supply. Newly eligible workers also have feasible alternatives. Holding wages fixed, the fraction of marginal entrants who choose occupation o depends on its wage relative to outside options. Define the outside-option index just below the threshold:

$$\Omega_g(R_o^-) := \sum_{k:\, R_k < R_o} w_k^{1/\tau}.$$

The take-up rate of marginally newly eligible workers is

$$s_o^m := \frac{w_o^{1/\tau}}{w_o^{1/\tau} + \Omega_g(R_o^-)}. \tag{17}$$

At fixed wages, the induced increase in labor supply is approximately

$$\Delta L_o^S\big|_w \;\approx\; s_o^m \cdot \mathrm{PSS}_o. \tag{18}$$

Local Wage and Employment Incidence. Consider a productivity gain $A_o \mapsto A_o e^{\pi_o}$ and an expertise expansion $R_o \mapsto R_o - \Delta R_o$. Let ε_o denote the own-wage elasticity of labor supply. To first order, equilibrium wage and employment changes satisfy

$$\Delta \log w_o \approx \underbrace{\frac{\sigma - 1}{\sigma + \varepsilon_o}\,\pi_o}_{\text{productivity}} \;-\; \underbrace{\frac{1}{\sigma + \varepsilon_o}\, s_o^m\, \frac{\mathrm{PSS}_o}{L_o}}_{\text{expertise expansion}}, \tag{19}$$

$$\Delta \log L_o \approx \underbrace{\frac{(\sigma - 1)\varepsilon_o}{\sigma + \varepsilon_o}\,\pi_o}_{\text{productivity}} \;+\; \underbrace{\frac{\sigma}{\sigma + \varepsilon_o}\, s_o^m\, \frac{\mathrm{PSS}_o}{L_o}}_{\text{expertise expansion}}. \tag{20}$$

Together, these expressions summarize the race: productivity gains raise wages through demand, while expertise-driven expansions reduce scarcity premia through supply, with the strength of the supply effect governed by (i) how many workers become newly eligible (PSS) and (ii) how attractive the occupation is relative to marginal outside options (s_o^m).

3 Data and Key Variables

This section describes the data and defines the two occupation-level objects we use to study how GenAI may affect wages: the Potential Supply Shift (PSS), which captures GenAI-induced changes in occupational entry barriers and effective labor supply, and the Potential Productivity Gain (PPG), which summarizes predicted time savings from GenAI augmentation. Our primary data source is O*NET (O*NET, 2023), which provides task statements for 19,265 tasks across 923 occupations. We complement O*NET with two key measures. First, we use LLM-based evaluations to quantify how GenAI changes occupational expertise requirements through both extensive and intensive margins, and then map these expertise changes into shifts in the share of workers qualified to perform each occupation. Second, we construct an occupation-level measure of predicted productivity gains using the task-level augmentation index of Eloundou et al. (2024) together with O*NET task frequency and importance. The complete task-level and occupation-level datasets are publicly available.[6]

3.1 Potential Supply Shift (PSS)

The central supply-side object in the paper is the change in the fraction of workers who can plausibly perform an occupation once GenAI affects the occupation's task bundle. We construct PSS in two steps. First, we measure how GenAI changes an occupation's effective expertise requirement through an extensive margin (task removal via automation) and an intensive margin (task simplification through GenAI assistance). Second, we map changes in these occupational expertise requirements into changes in the size of the qualified workforce using an empirical distribution of worker expertise.

3.1.1 Baseline Expertise of Tasks and Occupations

We begin by constructing a task-level measure of expertise following the framework of Autor and Thompson (2025). Expertise is defined as a barrier to entry: tasks that require specialized training, credentials, or substantial occupation-specific knowledge receive higher scores, while tasks that most workers can perform with minimal instruction receive lower scores. Using ChatGPT 5.2, we assign each O*NET task an expertise score on a five-point scale from 1 (minimal expertise) to 5 (very high expertise). The full prompt is provided in Appendix A.3.

We then aggregate task-level expertise to the occupation level. Because expertise is measured on an ordinal scale, we map expertise categories into a continuous measure based on the task-specific training time, measured in months, required for a typical adult to perform the task at a professional level. To construct this mapping, we use an additional LLM prompt to estimate training months for each task without GenAI assistance (Appendix A.4). Rather than imposing a single global mapping, we construct an occupation-specific mapping by assigning, for each occupation and expertise category, the median training time among tasks in that category. This approach captures system-

[6] The datasets are available at https://github.com/s-mahdihosseini/GenAI_Expertise.

atic cross-occupation differences in how expertise translates into training requirements. Table 1 reports the pooled category-to-training-time mapping for reference.

Table 1: Mapping Expertise Categories to Required Training Time

Expertise Category	Description	Training Months
1	No or minimal expertise; generic or basic tasks; learn quickly with little training	0.25
2	Low expertise; short training; limited occupation-specific knowledge	1
3	Moderate expertise; solid occupation-specific knowledge; often requires credentials, apprenticeship, or substantial on-the-job learning	4
4	High expertise; advanced specialized knowledge; significant training, degree, or certification	12
5	Very high expertise; deep specialized expertise; often advanced professional or graduate-level training	60

Notes: The table reports the mapping between the 1–5 ordinal expertise scale and the continuous measure of required training time (in months) used in our analysis. The mapping is derived by calculating the median training time for all tasks within each expertise category, based on estimates generated by ChatGPT 5.2.

Using this mapping, we follow the approach of Autor and Thompson (2025) and aggregate task-level expertise to the occupation level by averaging expertise across an occupation's tasks. Specifically, baseline occupation-level expertise is defined as the weighted average training-month requirement across tasks, where core tasks receive weight 1 and supplemental tasks weight 0.5, following the O*NET task structure and the approach of Eloundou et al. (2024). Formally,

$$X_o^{noAI} = \underbrace{\frac{\sum_{t \in T_o} w_{ot} x_{ot}^{noAI}}{\sum_{t \in T_o} w_{ot}}}_{\mathbb{E}[x_{ot}^{noAI}]}, \tag{21}$$

where T_o is the set of O*NET tasks associated with occupation o, x_{ot}^{noAI} is the training-month requirement assigned to task t in the baseline scenario without GenAI, and w_{ot} is the task weight.

Appendix A.5 validates this measure, showing it is highly stable across frontier LLMs

($R^2 \geq 0.90$) and strongly correlated with O*NET-based measures of required education and experience and with wages. Figure 2a plots the distribution of X_o^{noAI}. The mean baseline requirement is 8.15 months (SD 8.33), with a median of 5.53 months.

3.1.2 Extensive Margin

We next quantify the extensive-margin effect of GenAI, which captures the idea that some tasks are fully automated and removed from the set of tasks performed by labor. We identify automatable tasks by by updating the task-level automation exposure methodology of Eloundou et al. (2024) to reflect current GenAI capabilities. Using ChatGPT 5.2 and an updated prompt (Appendix A.1, the model assigns each task to one of five automation categories based on the share of task components that can be performed by current GenAI systems: 1 (0 percent), 2 (0–50 percent), 3 (50–80 percent), 4 (80–100 percent), and 5 (100 percent automatable). We define a binary automation exposure indicator $\alpha_{ot} \in \{0, 1\}$ that equals one for tasks in categories 4–5 (more than 80 percent automatable). Under this definition, 4,107 tasks (21.3 percent) are classified as exposed. Appendix A.2 shows that occupation-level exposure shares implied by this updated measure are strongly correlated with the original Eloundou et al. (2024) measure.

We define the extensive-margin occupational expertise requirement as the average expertise of the tasks that remain after removing exposed tasks:

$$X_o^{extensive} = \underbrace{\frac{\sum_{t \in T_o} w_{ot}(1 - a_{ot}) x_{ot}^{withoutAI}}{\sum_{t \in T_o} w_{ot}(1 - a_{ot})}}_{\mathbb{E}[x_{ot}^{withoutAI} | a_{ot}=0]}. \tag{22}$$

This object is closely related to the "expertise exposure" concept of Autor and Thompson (2025), though it focuses on potential shifts induced by GenAI automation rather than on realized changes from past technologies. Figure 2b presents the distribution $X_o^{extensive}$. Relative to Figure 2a, the extensive margin slightly raises both the mean and the dispersion of expertise requirements across occupations.

3.1.3 Intensive Margin

We next quantify intensive-margin effects, which capture the idea that tasks remain performed by humans but become easier because GenAI expands workers' capabilities. To measure this channel, we re-rate each task's expertise under a counterfactual in which the worker has access to a capable GenAI assistant, using a separate prompt that combines the expertise definition with explicit GenAI capability assumptions. The full prompt is reported in Appendix A.6.

Figure 1a compares the distribution of tasks across expertise categories with and without GenAI assistance, and Figure 1b summarizes the implied transitions. The share of tasks rated as high expertise (category 4) falls from 30.0 percent without GenAI to 8.4 percent with GenAI assistance, while the share in the lowest category rises from 6.0 percent to 22.9 percent. Except for category 1, more than half of tasks in each category are predicted to shift down by one expertise category; the pattern is most pronounced for category 4 tasks, of which 79.0 percent are predicted to require only category 3 expertise with GenAI assistance.

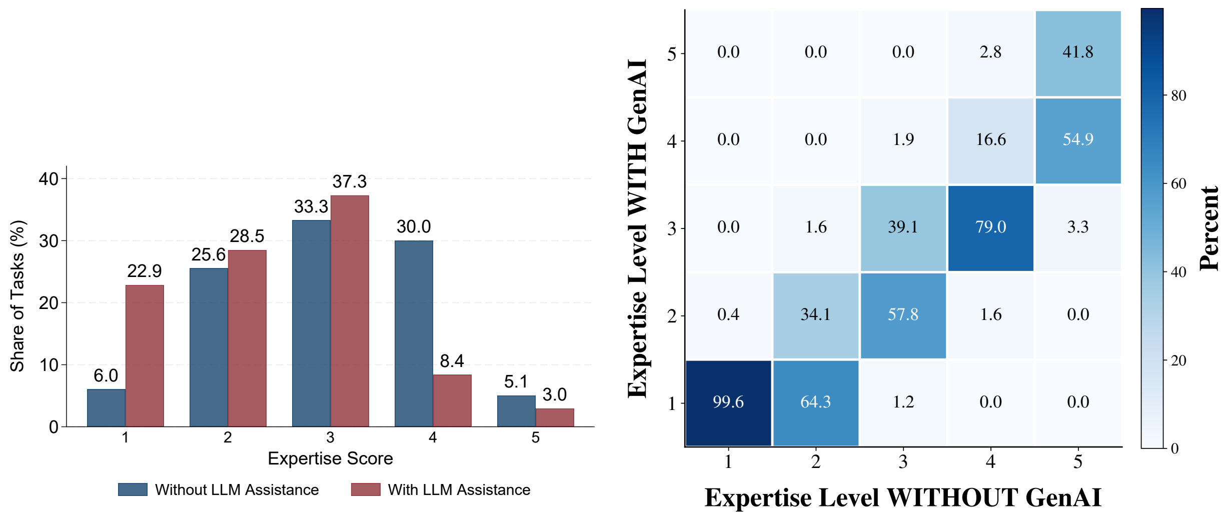
The intensive-margin expertise requirement for occupation o averages the GenAI-assisted expertise across all tasks:

$$X_o^{intensive} = \underbrace{\frac{\sum_{t \in T_o} w_{ot} x_{ot}^{withAI}}{\sum_{t \in T_o} w_{ot}}}_{\mathbb{E}[x_{ot}^{withAI}]}, \tag{23}$$

where x_{ot}^{withAI} denotes the mapped training-month requirement for task t when workers have access to GenAI assistance. This channel is closely related to "task simplification" in Althoff and Reichardt (2025). Figure 2c plots the distribution of $X_o^{intensive}$. Relative to the baseline distribution, the intensive margin substantially lowers both the average expertise requirement and its dispersion across occupations.

3.1.4 Combining the Extensive and Intensive Margins

The post-GenAI "combined" expertise requirement incorporates both margins by applying intensive-margin task simplification to the tasks that remain after extensive-margin automation:



(a) Expertise Categories

(b) Expertise Transition Matrix

Figure 1: The Expertise Distribution of Tasks With and Without GenAI Assistance

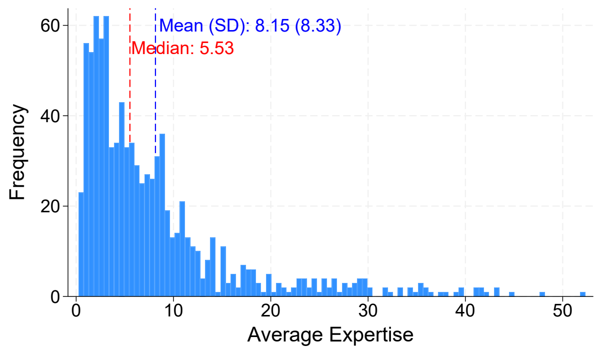
Notes: The figure displays the shift in task-level expertise requirements due to GenAI assistance. Panel (a) plots the distribution of tasks across the five expertise categories under two scenarios: "Without GenAI" (blue bars) and "With GenAI" (red bars). Panel (b) presents a transition matrix comparing the expertise level required without GenAI (x-axis) to the level required with GenAI (y-axis). The size of each bubble and the label above it correspond to the percentage of tasks starting in the x-axis category that transition to the y-axis category.

$$X_o^{combined} = \underbrace{\frac{\sum_{t\in T_o} w_{ot}(1-a_{ot})x_{ot}^{withAI}}{\sum_{t\in T_o} w_{ot}(1-a_{ot})}}_{\mathbb{E}[x_{ot}^{withAI}|a_{ot}=0]}. \tag{24}$$

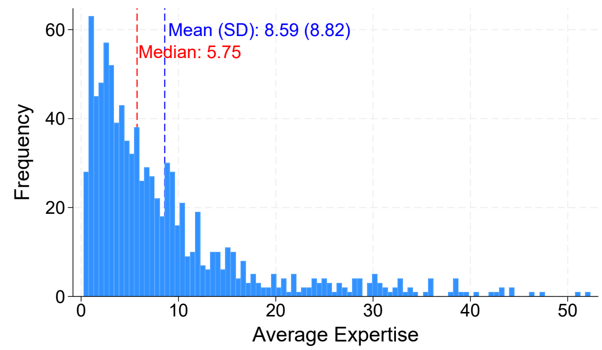
Figure 2d presents the distribution of $X_o^{combined}$. It is similar to the intensive-margin distribution, indicating that in our exercise the intensive margin is quantitatively dominant. This conclusion is methodological: alternative assumptions about automation thresholds, GenAI capability, or task re-optimization could shift the relative importance of the two margins. Another important caveat is that we abstract from the creation of new tasks and occupations in response to GenAI.

3.1.5 Mapping Expertise Changes to Potential Labor Supply Shifts

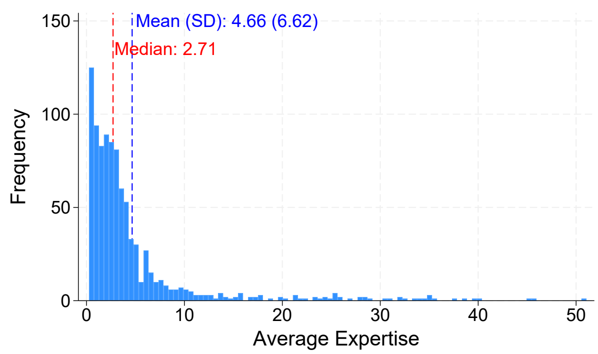
Changes in required expertise do not directly map into labor-market implications unless they are translated into changes in the set of workers who can plausibly perform the



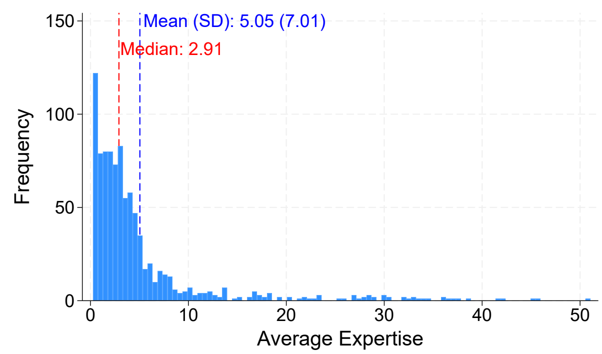
(a) Without GenAI Effects



(b) Extensive



(c) Intensive



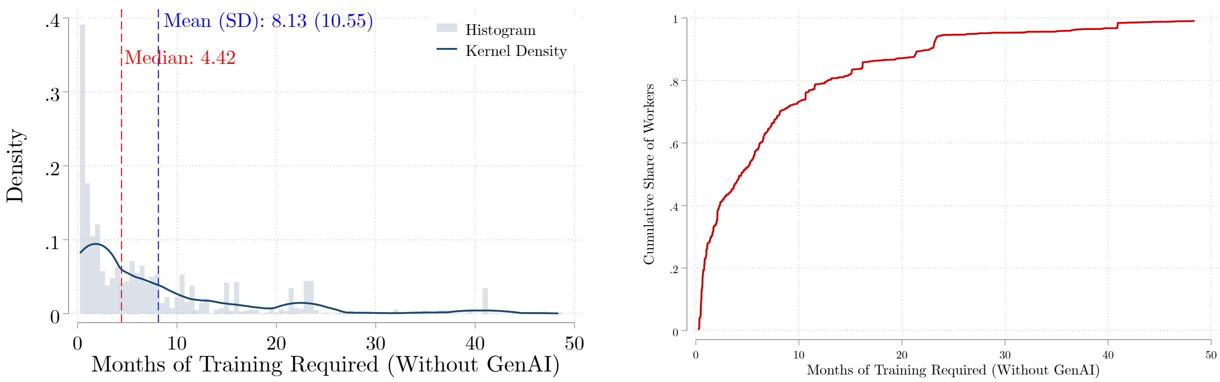
(d) Combined

Figure 2: Average Expertise Across Occupations

Notes: Each panel plots the distribution of occupation-level expertise requirements, measured in mapped training months. Panel (a) shows baseline expertise without GenAI, X_o^{noAI}. Panel (b) shows the extensive-margin expertise requirement after removing tasks classified as automatable, $X_o^{extensive}$. Panel (c) shows the intensive-margin requirement when all tasks are performed with GenAI assistance, $X_o^{intensive}$. Panel (d) shows the combined post-GenAI requirement, $X_o^{combined}$, which applies GenAI assistance to the tasks that remain after automation. Occupation-level measures are task-weighted averages, with weights of 1 for core tasks and 0.5 for supplemental tasks.

occupation. We therefore define the Potential Supply Shift (PSS) as the change in the share of the workforce qualified to perform an occupation after incorporating both extensive- and intensive-margin effects.

Computing PSS requires an estimate of the aggregate distribution of worker expertise. We approximate this distribution using the employment-weighted distribution of baseline occupational expertise requirements X_o^{noAI}, under the equilibrium assumption that workers sort into the most complex occupation they are able to perform. Let $F(x)$ denote the resulting employment-weighted CDF. Figure 3 plots the implied PDF and CDF. The distribution is right-skewed, with substantial mass at low-to-moderate expertise levels and a thin upper tail.



(a) PDF

(b) CDF

Figure 3: The Distribution of Workers Across Expertise Levels

Notes: Panel (a) displays the probability density function (PDF) and Panel (b) displays the cumulative distribution function (CDF) of baseline occupational expertise, weighted by 2024 employment. This distribution serves as our proxy for the aggregate distribution of workforce expertise.

We define an occupation's potential supply as the share of workers with expertise weakly above the occupation's requirement:

$$PS(X) = 1 - F(X). \tag{25}$$

The *Potential Supply Shift* for occupation o is then the change in potential supply induced by the GenAI-driven change in the occupation's expertise requirement:

$$PSS_o = PS(X_o^{combined}) - PS(X_o^{noAI}) = F(X_o^{noAI}) - F(X_o^{combined}). \tag{26}$$

A positive PSS_o indicates that GenAI lowers effective entry barriers, expanding the fraction of the workforce qualified to perform the occupation. Figure 4 plots the distribution of PSS_o across occupations. The mean PSS is about 0.10, implying that for the average occupation, GenAI expands the qualified labor pool by 10 percentage points of the workforce.

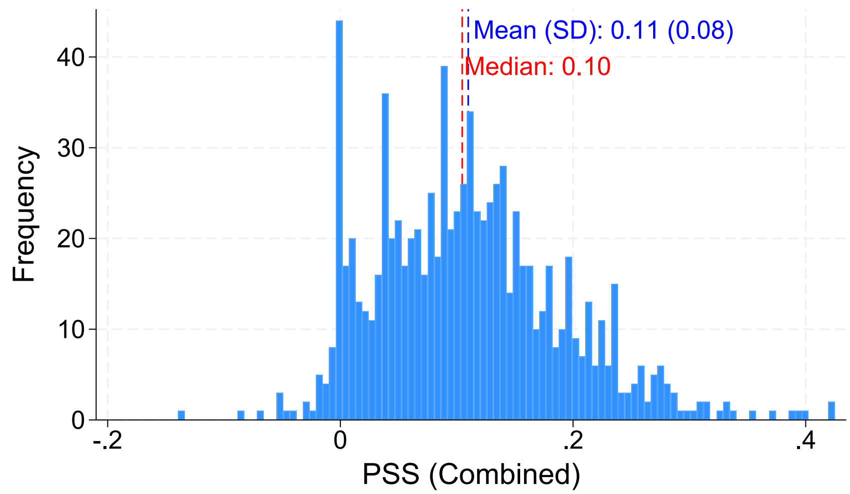


Figure 4: Potential Supply Shift (PSS) Across Occupations

Notes: The figure displays the distribution of the occupation-level Potential Supply Shift (PSS). PSS is defined as the increase in the share of the total workforce capable of performing the occupation after GenAI integration: $F(X_o^{noAI}) - F(X_o^{combined})$.

3.2 The Potential Productivity Gains (PPG) of Occupations

We next construct an occupation-level proxy for predicted productivity gains from GenAI augmentation. The goal is to measure, for each occupation, the share of total work activity that is plausibly subject to large time savings when workers use GenAI tools.

We define the "work volume" of task t in occupation o as the product of its frequency and importance. Specifically, $Freq_{ot}$ is the O*NET frequency rating converted from categorical bins into annualized occurrences, and Imp_{ot} is the O*NET importance rating on a 1–5 scale. We then use the task-level exposure index β_{ot} from Eloundou et al. (2024), which identifies tasks for which access to an LLM (alone or with complementary software) can reduce the time required for a human to complete the task by at least 50 percent while maintaining quality. Following their classification, we set $\beta_{ot} = 1$ for tasks exposed to an LLM alone, $\beta_{ot} = 0.5$ for tasks exposed only with additional software integration, and $\beta_{ot} = 0$ otherwise.

We summarize these task-level predictions in an occupation-level *Potential Productivity Gain* measure, PPG_o, defined as the work-volume-weighted average of β_{ot} and scaled by

0.5 to reflect a conservative lower bound on the implied time savings. Formally,

$$PPG_o = 0.5 \times \left(\frac{\sum_{t \in \mathcal{T}_o} Freq_{ot} \times Imp_{ot} \times \beta_{ot}}{\sum_{t \in \mathcal{T}_o} Freq_{ot} \times Imp_{ot}} \right). \tag{27}$$

Figure 5 plots the distribution of PPG_o across occupations. The mean is 0.17 (SD 0.11), implying that for the average occupation, GenAI could reduce total work time by roughly 17 percent under this conservative calibration.

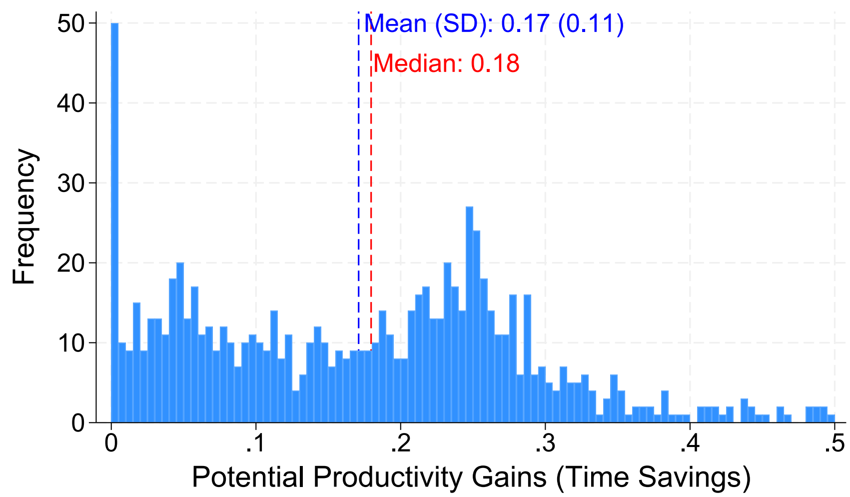


Figure 5: Potential Productivity Gains (PPG) Across Occupations

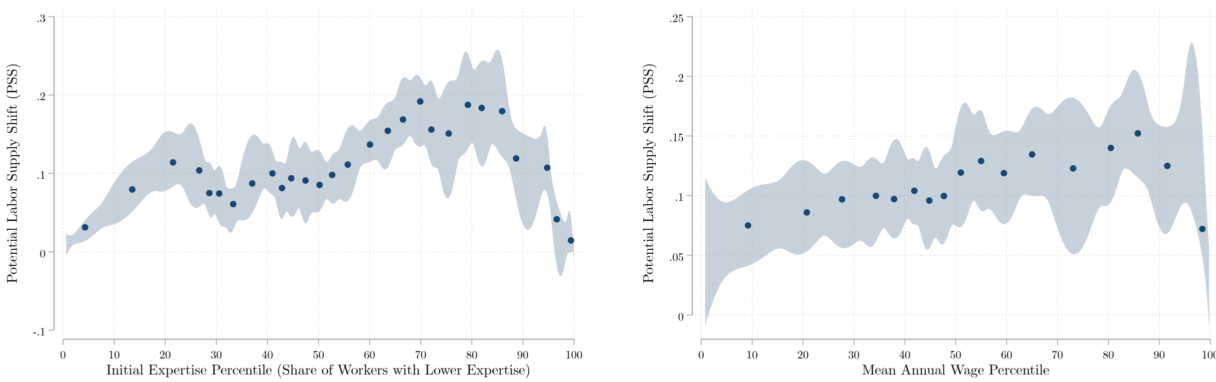
Notes: The figure shows the distribution of the occupation-level Potential Productivity Gain (PPG_o). PPG_o is defined in Equation 27 as 0.5 times the work-volume-weighted average of the task-level augmentation indicator β_{ot} from Eloundou et al. (2024), where task work volume is $Freq_{ot} \times Imp_{ot}$.

4 Three Facts on the Potential Supply Shift of Occupations

This section documents three empirical facts about the Potential Supply Shift (PSS). We begin by characterizing how PSS varies across the baseline expertise and wage distributions, which speaks directly to distributional implications. We then relate PSS to predicted productivity gains, motivating the model's productivity–scarcity tradeoff. We conclude by benchmarking PSS against the standard automation exposure measure used in much of the GenAI literature.

4.1 Fact 1: PSS vs. Initial Expertise and Wages

We first examine how GenAI-induced supply expansions vary across an occupation's baseline position in the expertise and wage distributions. Figure 6 reports bin-scatter plots of PSS against baseline expertise and wages. Panel 6a shows that PSS generally increases with baseline expertise, measured as $(1 - PS_o) \times 100$, across most of the distribution. This pattern implies that GenAI tends to relax entry barriers more for many initially higher-expertise occupations. However, importantly, the relationship is non-monotone: above roughly the 90th percentile, PSS declines sharply, indicating comparatively small supply expansions for the extreme upper tail. Panel 6b shows a broadly similar pattern with respect to the occupation's mean wage percentile. Together, these results suggest that GenAI may broaden access to many high-wage occupations while leaving the very top comparatively insulated from supply-side pressure.[7]



(a) PSS vs. Initial Expertise Percentile

(b) PSS vs. Mean Wage Percentile

Figure 6: Initial Expertise/Wage vs. PSS—Bin-scatter Plot

Notes: The figure reports bin-scatter plots at the occupation level. Occupations are sorted by the x-axis variable and grouped into equal-sized bins; each point plots the mean Potential Supply Shift (PSS) within a bin against the bin mean of the x-axis variable. Panel (a) uses the occupation's baseline expertise percentile, defined as $(1 - PS_o) \times 100$. Panel (b) uses the occupation's mean wage percentile. PSS is defined as the change in the share of the workforce qualified to perform the occupation after GenAI integration. Percentiles are computed across occupations.

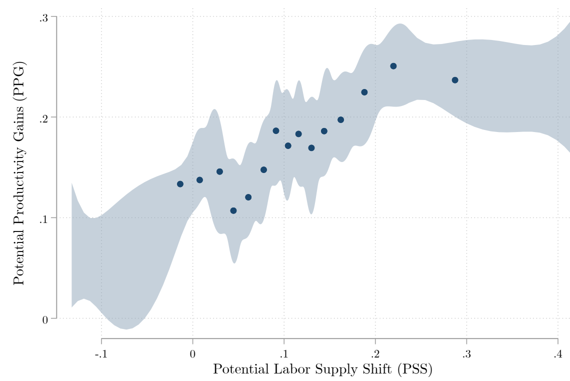
[7] Note that this exercise holds the task set fixed and abstracts from endogenous task creation and occupational change, which could materially affect these patterns.

4.2 Fact 2: PSS vs. Productivity Effects of GenAI

We next relate predicted productivity gains from GenAI to baseline expertise and to PSS. Figure 7 reports bin-scatter plots of the occupation-level Potential Productivity Gain, PPG_o, against the baseline expertise percentile and against PSS_o. Panel 7a shows that predicted productivity gains generally increase with baseline expertise. Panel 7b shows that PPG_o is positively associated with PSS_o: occupations predicted to experience larger expansions in effective labor supply also tend to be those with larger predicted time savings from GenAI augmentation.

These patterns highlight a key implications. Occupations in the upper-middle of the expertise distribution tend to combine both large supply expansions and sizable productivity gains. By contrast, the extreme upper tail is predicted to receive high productivity gains but relatively modest supply expansions, consistent with the thinness of the workforce expertise distribution at very high thresholds. This joint structure motivates the general equilibrium analysis below: GenAI can simultaneously raise wages through productivity while compressing wage premia by eroding occupational scarcity, and the net incidence depends on how these channels co-vary across occupations.

(a) PPG vs. PS



(b) PPG vs. PSS

Figure 7: PPG vs. Initial Expertise and PSS—Bin-scatter Plot

Notes: The figure reports bin-scatter plots. In each panel, occupations are sorted by the x-axis variable and grouped into equal-sized bins; each point plots the mean PPG_o within a bin against the bin mean of the x-axis variable. Panel (a) uses the baseline expertise percentile, defined as $(1 - PS_o) \times 100$, on the x-axis. Panel (b) uses the Potential Supply Shift (PSS_o) on the x-axis. PPG_o is defined in Section 3.2 and PSS_o is defined in Section 3.1.

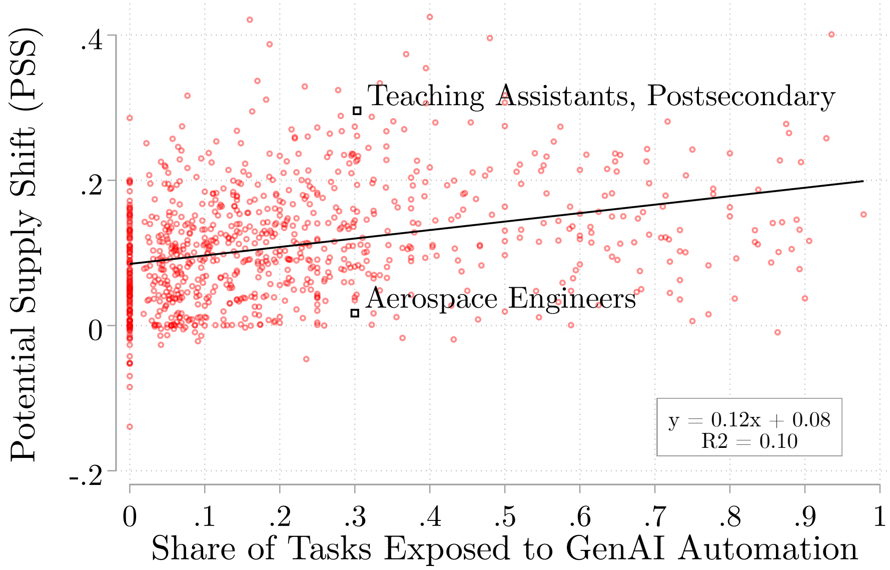
4.3 Fact 3: PSS vs. Exposure

A leading approach in the GenAI labor-market literature is to measure occupational "exposure" by classifying tasks as automatable and then computing the share of exposed tasks (e.g., ILO, 2025; Gmyrek et al., 2023; Eloundou et al., 2024; Felten et al., 2023). These exposure indices play a central role in both research and policy discussions of GenAI (e.g., Goldman Sachs, 2023; ILO, 2025; OECD, 2024; IMF, 2025; Brynjolfsson et al., 2025; Johnston and Makridis, 2025; The Budget Lab, 2025; Hosseini and Lichtinger, 2025). Because exposure remains the dominant benchmark, it is useful to benchmark it against PSS, even though this comparison is somewhat tangential to our main focus on distributional patterns in expertise and productivity.

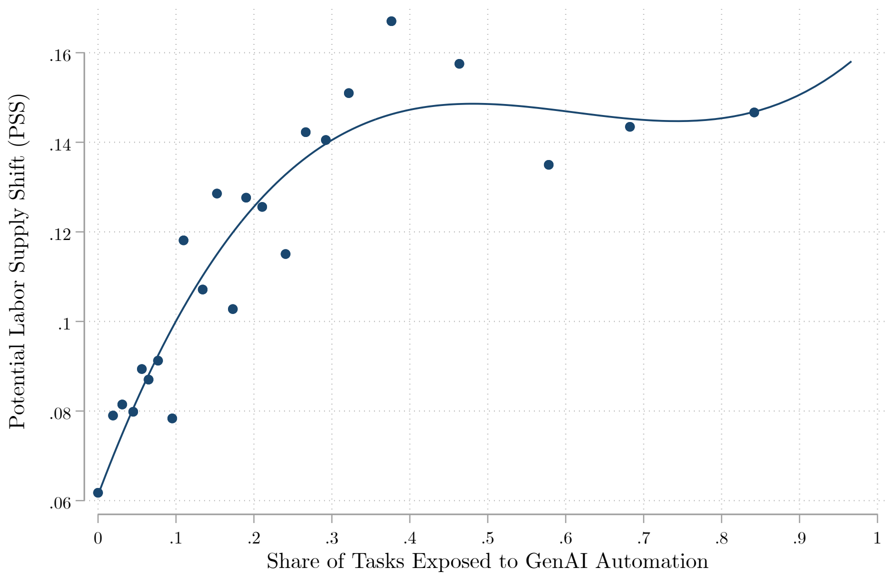
While exposure measures are informative, they have two key limitations. First, they generally treat tasks as homogeneous, abstracting from what is being automated. As emphasized by Autor and Thompson (2025), automation of low-expertise peripheral work can raise the specialization of the remaining job, whereas automation of core expert tasks can erode occupational identity, entry barriers, and wage premia. Second, standard exposure measures usually focus on the extensive margin, implicitly classifying tasks as either automated or unaffected, and therefore miss intensive-margin effects through which GenAI reduces the expertise required to perform tasks that remain human-performed. PSS addresses both limitations by incorporating task expertise and by combining extensive-margin automation with intensive-margin task simplification.

Figure 8 illustrates the relationship between PSS and the standard exposure measure. Panel (a) shows a positive association between exposure and PSS, but also substantial dispersion: for a given exposure level, PSS varies widely across occupations. Panel (b) shows that PSS rises with exposure at low to moderate exposure levels, but the relationship flattens among highly exposed occupations. Together, these patterns emphasize that exposure alone is an incomplete statistic for characterizing GenAI-induced changes in effective labor supply.

To make this point concrete, Figure 9 compares occupations with nearly identical aggregate exposure shares. The figure reports PSS for all occupations with exposure between 29 and 31 percent, corresponding to the 75th percentile of the exposure distribution. Despite their nearly identical exposure levels, these occupations exhibit large differ-



(a) Scatter Plot



(b) Bin-Scatter Plot

Figure 8: Automation Exposure vs. PSS

Notes: The figure plots the occupation-level relationship between the share of exposed tasks and the potential supply shift (PSS) index. Each dot in the scatter plots represents a single occupation. The bin-scatter plots group occupations into equal-sized bins based on aggregate exposure and plot the mean PSS within each bin.

ences in PSS. Treating them as equally exposed, as is common in the literature, obscures economically meaningful heterogeneity in how GenAI affects entry barriers and labor supply.

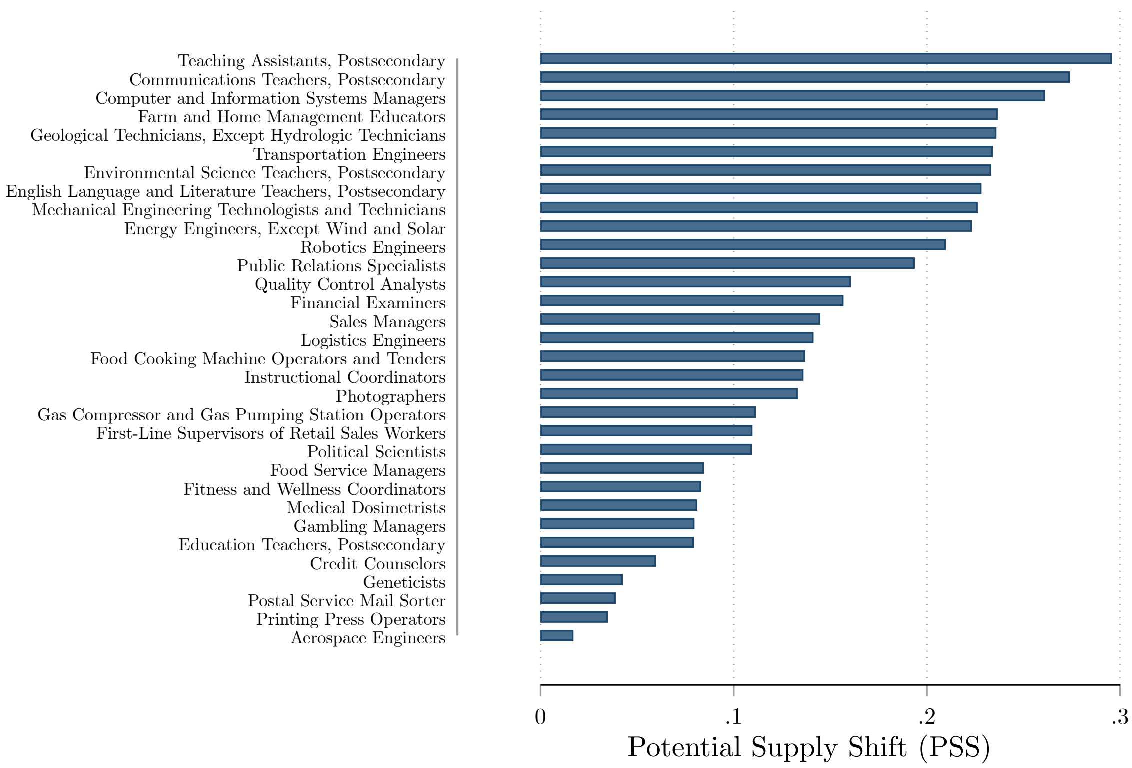


Figure 9: The PSS Index of Occupations With ∼30% Automatable Tasks

Notes: The figure displays the potential supply shift (PSS) index for all occupations with 29–31 percent exposed tasks (approximately the 75th exposure percentile).

Consider, for example, Postsecondary Teaching Assistants and Aerospace Engineers. Both occupations have similar shares of exposed tasks, yet their predicted PSS differs sharply: Teaching Assistants exhibit a large PSS, close to 30 percentage points, while the PSS for Aerospace Engineers is close to zero. Several forces contribute to this difference. On the intensive margin, GenAI simplifies tasks in both occupations, reducing required expertise. On the extensive margin, however, GenAI is predicted to automate relatively high-expertise tasks for Teaching Assistants, such as grading and course material preparation, which lowers the occupation's effective expertise requirement. For Aerospace Engineers, by contrast, exposure is concentrated in lower- and moderate-expertise tasks, such as documentation and record keeping, which raises the average expertise of the remaining task bundle and partially offsets intensive-margin effects. Initial expertise levels also matter: Aerospace Engineers sit far out in the upper tail of the expertise distribution, where worker density is low, so comparable reductions in required expertise translate into smaller increases in effective labor supply than for Teaching Assistants, who are closer to the center of the expertise distribution where density is higher. This interaction between task composition and the underlying expertise distribution explains why PSS can differ sharply even among occupations with similar exposure.

5 Inequality Implications: Counterfactual Exercise

5.1 Overview of the Counterfactual Exercise

This section quantifies how GenAI affects the distribution of occupational wages through the two forces emphasized in the model: (i) *productivity gains*, which raise marginal revenue products and shift labor demand, and (ii) *expertise reductions*, which relax feasibility constraints and expand the set of workers who can perform an occupation (the scarcity channel, operating through the intensive and extensive margins). We study three counterfactuals: expertise reductions only, productivity gains only, and both jointly. For each scenario, we report partial equilibrium (PE) outcomes—which hold the broader wage structure fixed—and general equilibrium (GE) outcomes—which allow workers to reallocate across occupations subject to hierarchical feasibility and idiosyncratic fit.

While the local comparative statics in Section 2.6 are useful for intuition, they are not designed for the potentially large and heterogeneous changes induced by GenAI. In particular, large shocks can generate non-linear responses, and expertise reductions can change the relevant scarcity margins by expanding feasible sets non-uniformly across the expertise distribution. For these reasons, we solve the full wage–employment system numerically and compute both PE and GE counterfactuals.

5.2 Calibration and Implementation

We take the baseline (pre-AI) occupational wage and employment vectors from the O*NET data. To construct the distribution of worker expertise, we assign each occupation an expertise level as described in Section 3.1.1 and map all workers employed in that occupation to that expertise level. This yields an employment-weighted distribution of occupational expertise, which we use as a proxy for the underlying distribution of worker expertise in the baseline economy. While this construction abstracts from within-occupation heterogeneity in expertise, it preserves the cross-occupation structure that governs feasibility and scarcity in the model.

We then solve for the model objects that rationalize these baseline wages and employment levels as an equilibrium under baseline feasibility. The two key parameters governing equilibrium sensitivity are the CES elasticity of substitution across occupational inputs, σ, and the dispersion parameter in occupational choice, τ. The vector of occupation-specific wedges $\{\psi_o\}$ is calibrated so that the observed baseline wage vector is an *exact* fixed point of the model given baseline employment and feasibility. This calibration ensures that counterfactual changes are interpreted as deviations from a correctly matched baseline equilibrium, rather than reflecting baseline misfit. Table 2 summarizes the parameters used in the quantitative exercise, their roles in the model, and the moments or conditions used for calibration.

Table 2: Calibration Targets and Parameter Values

Object	Role	Target (baseline)	Value / outcome
σ	Substitution across occupations	Standard value	4.0
τ	Choice dispersion (sorting / reallocation friction)	Baseline employment dispersion: $\mathrm{Var}(\log L_o)$	0.71
$\{\psi_o\}_{o\in\mathcal{O}}$	Occupation-specific wedges	GE fixed-point condition: $w_o = \psi_o L_o^{-1/\sigma}$	Calibrated occupation-by-occupation[1]

Notes: ψ_o is chosen so that the observed baseline wage vector is an exact fixed point of the model under baseline feasibility.

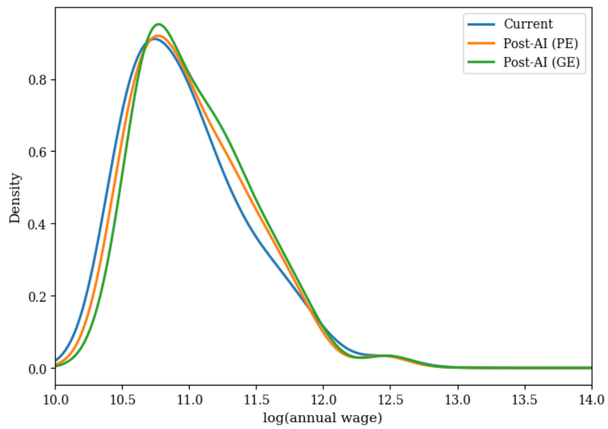
5.3 The Effect of GenAI on the Wage Distribution

In this section, we evaluate three counterfactual environments: (i) expertise reductions only, in which GenAI relaxes feasibility constraints through intensive and/or extensive margins without affecting productivity; (ii) productivity gains only, in which occupation-specific productivity shifts $A_o \mapsto A_o e^{\pi_o}$ occur with feasibility held fixed; and (iii) combined effects, in which expertise reductions and productivity gains operate simultaneously. For each environment, we compute PE outcomes that isolates the direct effect of the shock holding the broader wage structure fixed and GE outcomes that incorporate worker reallocation across feasible occupations. Distributional effects are summarized using employment-weighted densities of occupational log wages and standard inequality statistics.

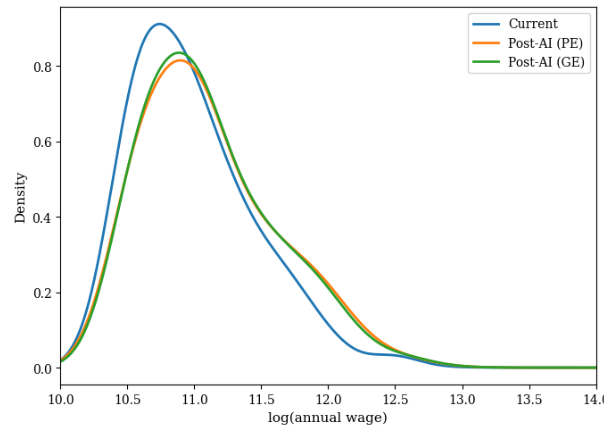
Expertise reductions only. Figure 10a and Table 3 show that relaxing expertise constraints is equalizing. In general equilibrium, the variance of log wages falls from 0.201 to 0.181, and upper-tail inequality declines substantially: the $p90 - p50$ gap falls from 0.732 to 0.673. These effects reflect reduced scarcity in high-expertise occupations as lower entry barriers expand the pool of eligible workers. General-equilibrium reallocation amplifies the compression relative to partial equilibrium, as newly eligible workers sort into previously scarce occupations.

Productivity gains only. When GenAI raises productivity without changing feasibility, wage dispersion increases. In general equilibrium, the variance of log wages rises to 0.237, and the $p90 - p50$ gap increases to 0.813. Although worker reallocation dampens these effects relative to partial equilibrium, productivity gains remain strongly disequalizing, with larger wage increases concentrated in higher-wage occupations.

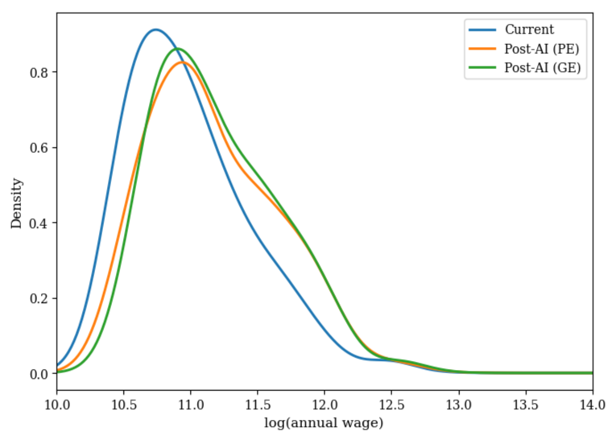
Joint counterfactual. When both expertise reductions and productivity gains operate simultaneously, the two forces partially offset. In general equilibrium, overall wage dispersion rises modestly relative to baseline: the variance of log wages increases from 0.201 to 0.211, while the $p90 - p50$ gap remains close to its baseline level (0.737 versus 0.732). Lower-tail inequality falls, with the $p50 - p10$ gap declining from 0.421 to 0.443 in GE, reflecting the continued equalizing effect of reduced scarcity. Overall, the joint outcome highlights the productivity–scarcity tradeoff: productivity gains push wages apart, while expertise reductions compress wage premia, yielding a net effect on inequality that is modest in aggregate but uneven across the distribution.



(a) Expertise Reductions Only



(b) Productivity Gains Only



(c) Expertise Reductions and Productivity Gains

Figure 10: Employment-Weighted Wage Distributions Across Counterfactuals

Notes: Employment-weighted densities of occupational log wages under three counterfactuals: (a) expertise reductions only, (b) productivity gains only, and (c) both. Each panel compares PE and GE; GE allows worker reallocation across feasible occupations. Densities are weighted by scenario employment and normalized to integrate to one.

Table 3: Wage Inequality Under Baseline and GenAI Counterfactuals

Scenario	Var(log w)	$p10$	$p50$	$p90$	$p50 - p10$	$p90 - p10$	$p90 - p50$
Baseline	0.201	10.495	10.916	11.647	0.421	1.153	0.732
Supply PE	0.187	10.536	10.959	11.625	0.423	1.089	0.665
Supply GE	0.181	10.605	10.988	11.661	0.383	1.056	0.673
Prod PE	0.245	10.535	11.016	11.865	0.481	1.330	0.849
Prod GE	0.237	10.546	11.026	11.839	0.480	1.293	0.813
Both PE	0.225	10.609	11.080	11.842	0.471	1.232	0.761
Both GE	0.211	10.674	11.118	11.855	0.443	1.181	0.737

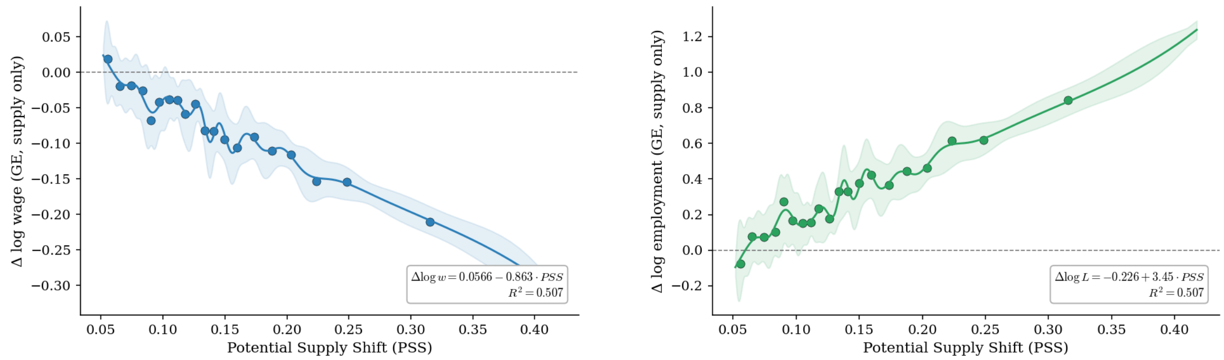
Notes: Employment-weighted wage moments. "Supply" corresponds to expertise reductions (scarcity channel); "Prod" corresponds to productivity gains (demand channel); "Both" combines both forces. PE holds the broader wage structure fixed; GE allows reallocation across feasible occupations.

5.4 GE Responses and the Role of PSS

This subsection examines how much of the general-equilibrium adjustment driven by expertise reductions can be explained by the Potential Supply Shift (PSS). Recall that PSS is a deliberately simple, reduced-form measure: it captures how GenAI changes occupational entry barriers and the size of the eligible workforce, but it abstracts from the full structure of endogenous occupational choice, outside options, and general-equilibrium feedbacks embedded in the model. In this sense, PSS is a coarse summary statistic of the supply-side shock rather than a structural object.

Despite this simplicity, PSS is highly informative about equilibrium outcomes. Focusing on the *supply-only* counterfactual, Figures 11a and 11b plot general-equilibrium changes in occupational wages and employment against PSS. Occupations with larger expertise-driven expansions of effective labor supply experience systematically larger declines in wages and larger increases in employment. The relationship is strong and monotone, with PSS explaining a substantial share of cross-occupation variation in general-equilibrium responses.

Importantly, these patterns emerge even though the underlying equilibrium incorporates endogenous worker reallocation across all feasible occupations, mediated by wages and outside options. That a single, reduced-form measure like PSS accounts for much of the equilibrium adjustment highlights the central role of expertise-based scarcity in shaping the distributional effects of GenAI. Put differently, while the model's full struc-



(a) GE Wage Changes vs. PSS (Supply Only) **(b)** GE Employ, Changes vs. PSS (Supply Only)

Figure 11: General-Equilibrium Supply Responses and Potential Supply Shift

Notes: Each panel plots binned scatterplots of general-equilibrium changes in occupational wages and employment against the Potential Supply Shift (PSS), focusing on the supply-only counterfactual. Changes are measured relative to the baseline equilibrium. Bins are employment-weighted. Occupations with zero PSS are excluded.

ture is necessary to translate feasibility changes into wages and employment, much of the cross-occupation heterogeneity in those outcomes is already visible in how GenAI shifts occupational entry barriers.

6 Conclusion

How will generative AI reshape wage inequality across occupations? This paper argues that an important part of the answer operates through a productivity–scarcity race. GenAI can raise wages by augmenting labor productivity, but it can also compress wage premia by lowering expertise-based entry barriers and expanding the set of workers who can perform high-expertise work. The distributional effects of GenAI depend on the relative strength of these channels and on where entry barriers are relaxed in the workforce expertise distribution.

To capture the supply-side channel, we introduce and make publicly available a Potential Supply Shift (PSS) index, which maps task-level GenAI effects into changes in the share of the workforce qualified to perform each occupation. Using O*NET task data for 923 occupations, we combine LLM-based evaluations with a task-based framework that distinguishes two mechanisms through which GenAI alters expertise requirements. On the extensive margin, some tasks are automated and removed from labor's task bundle. On the intensive margin, tasks remain human-performed but become easier, reducing the expertise required to perform them. Aggregating these effects yields a post-GenAI expertise threshold for each occupation. PSS then maps the implied change in expertise thresholds into the employment-weighted distribution of baseline expertise, capturing how many workers become newly eligible to work in each occupation.

We document three key facts. First, PSS increases with baseline expertise and wages across most of the distribution, but falls sharply in the extreme upper tail. This pattern is consistent with the thinness of the expertise distribution at very high thresholds, so comparable reductions in required expertise translate into only limited inflows of newly qualified workers. Second, PSS is positively associated with predicted productivity gains, implying that many upper-middle occupations combine sizable time savings with sizable reductions in entry barriers. Third, PSS varies widely even among occupations with nearly identical automation-exposure shares. This suggests that exposure measures, while informative about automatable task shares, are weak predictors of how GenAI reshapes occupational entry barriers and effective labor supply.

To interpret these patterns, we develop a task-based general equilibrium model with discrete tasks, hierarchical feasibility, CES demand, and occupational choice with outside options. The model clarifies how GenAI affects wages through two opposing forces: productivity gains raise marginal revenue products and tend to widen the wage distribution, while expertise-driven supply expansions increase contestability and compress scarcity premia. Quantitative counterfactuals show that expertise expansion alone is equalizing, while productivity gains alone increase dispersion. When both channels operate together, these forces partially offset. Under our baseline calibration, the net effect on cross-occupation wage inequality is modest, though the magnitude of each channel depends on assumptions about the strength and timing of GenAI's effects.

Several limitations apply. We abstract from endogenous task creation and occupational change and treat the distribution of worker expertise as fixed, ruling out training and retraining responses. Some LLM-based counterfactual assessments, particularly those concerning how GenAI changes task expertise, are difficult to validate directly and should be interpreted cautiously. More generally, realized impacts will depend on complementary investments, adoption, and the extent to which GenAI is integrated into production processes.

Overall, the results highlight that GenAI's distributional effects cannot be understood through productivity alone. If productivity gains and extensive-margin automation dominate, GenAI is more likely to increase wage inequality by reinforcing returns in high-wage occupations. If intensive-margin task simplification substantially lowers entry barriers and expands access to high-expertise work, GenAI is more likely to reduce inequality by eroding occupational scarcity premia. The balance between these forces will ultimately determine how GenAI reshapes the wage structure across occupations.

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A Supplemental Appendix

A.1 LLM Prompt—Automation Exposure Measure

"""

You are a "Dual-Expert" evaluator with two distinct, high-level competencies:

1. **Domain Expert:** You deeply understand the occupation listed below, including tacit knowledge, informal practices, interpersonal nuance, real-world context, and the hidden complexity that non-experts overlook.

2. **Gen AI Expert:** You understand the real capabilities and limitations of modern LLMs, agentic workflows, RAG systems, tool use (Python/APIs), and multimodal models. You can distinguish between "demo-level" and "production-reliable" AI behavior.

Your job is to integrate BOTH perspectives.

Evaluate the automation exposure of a specific occupational task: **Cuurent December 2025 LLM abilities

—

AUTOMATION RUBRIC (T0–T4 — USE EXACT DEFINITIONS)

T0 — No Automation System cannot perform any meaningful component of the task. Typically highly physical, deeply emotional, or restricted by legal requirements.

T1 — Low Automation System can perform 0–50% of the task. Core work relies on physical action, real-world perception, in-person nuance, or tacit knowledge AI cannot substitute.

T2 — Moderate Automation (Hybrid) System can perform 50–80% of the task at high quality. Human involvement remains essential for: - physical actions, - in-person communication, - or tacit, context-dependent judgment.

T3 — High Automation (Human-in-the-Loop) System can perform 80–100% at high quality, BUT human oversight is required because of: - liability/safety, - stakeholder trust expectations, - rare catastrophic failure modes.

T4 — Full Automation (Autonomous) System performs 100% of the task with high quality. Human oversight is *not routinely needed* and humans are *not liable* for errors. The entire workflow is digitally executable end-to-end.

—

CAPABILITY ASSUMPTIONS
LLM(Current, Year 2025)**
CAN:
- Multi-step planning and reasoning
- Advanced multimodal analysis (vision/audio/docs/charts)
- Retrieval-augmented generation with large knowledge bases
- API/Python/Excel/SQL tool use
- Code generation, debugging, and software automation
- Structured workflow execution and agentic autonomy
- Up-to-date factual retrieval via internet tools
- Data analysis, visualization, and cleaning
- Idea generation, brainstorming, and research assistance
- High-quality writing, summarization, and translation
- Professional communication and long-context coherence
- Document extraction, comparison, and synthesis
- Business analytics, forecasting, and competitive intelligence
- UX/UI design, creative writing, images, audio, and video generation
- App/website creation and end-to-end automation

- Long-term memory and personalization (where enabled)
- Self-correction, critique, and verification loops
- Persistent agentic behaviors across sessions
- Scientific reasoning: literature synthesis, experimental design

CANNOT: - Perform any physical actions
- Conduct tactile or in-person inspection
- Guarantee correctness in high-stakes situations
- Substitute for human judgment where regulation requires a human
- Provide genuine emotional presence or tacit human understanding

OUTPUT FORMAT (MANDATORY JSON)
Return exactly:

{ "T": "T0 — T1 — T2 — T3 — T4" }
"""

A.2 Comparing Automation Exposure Measures

This appendix compares our updated occupation-level automation exposure measure to the original measure developed by Eloundou et al. (2024). Figure A.1 plots, for each occupation, the share of tasks classified as automatable under our GPT-5.2-based measure against the corresponding share implied by the original GPT-4-based measure. Each point represents a single O*NET occupation. The figure shows a strong positive relationship between the two measures.

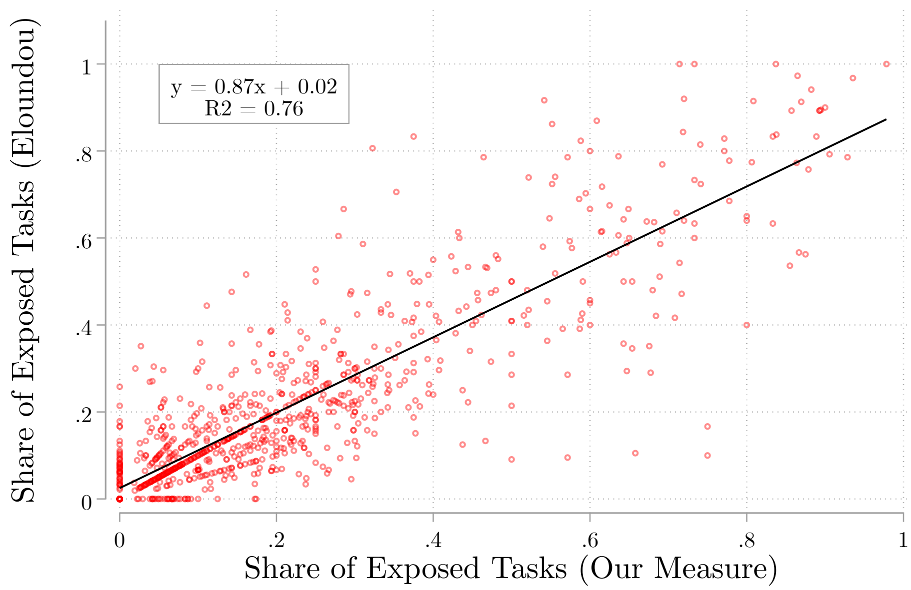


Figure A.1: Comparing Our Automation Exposure Measure to Eloundou et al. (2024)

Notes: Each point represents an O*NET occupation. The vertical axis reports the share of tasks classified as automatable using the exposure measure of Eloundou et al. (2024), while the horizontal axis reports the corresponding share under our updated GPT-5.2-based measure.

A.3 LLM Prompt—Task-Level Expertise Measure

"""

You are rating the expertise required to perform individual job tasks from O*NET.
By "expertise" we mean specialized knowledge, training, or skill that: - acts as a barrier to entry (not everyone can do it), and - typically commands a wage premium.
Generic physical or social tasks that almost any adult could do with minimal training are "no or low expertise".

Give each task a 1–5 expertise score:
1 = No or minimal expertise - Generic or very basic tasks - Can be learned quickly with little training.
2 = Low expertise - Some short training required - Limited occupation-specific knowledge.
3 = Moderate expertise - Solid occupation-specific knowledge - Often some credential, apprenticeship, or substantial on-the-job learning.
4 = High expertise - Advanced specialized knowledge - Significant training, degree, or certification.
5 = Very high expertise - Deep specialized expertise - Often advanced professional or graduate-level training.

Output STRICT JSON ONLY:
"expertise_score": 1-5 integer,
"expertise_label": "no_or_minimal" — "low" — "moderate" — "high" — "very_high",
"confidence": 0.0-1.0

Do NOT include explanations. Do NOT include text before or after the JSON. Output ONLY valid JSON. No markdown. No comments. No words before or after.

"""

A.4 LLM Prompt—Required Training Time

””” You are rating the expertise required to perform individual job tasks from O*NET.

For each task, estimate the minimum amount of specific education and training time (in months) required for a typical adult to learn to perform this task at a professional level.

Guidelines: - Consider specialized knowledge, training, or skill needed. - Focus on training/education time required to reach professional competence, not years of generic work experience. - Respond with a single number in months (e.g., 0.5, 6, 18, 36, 60).

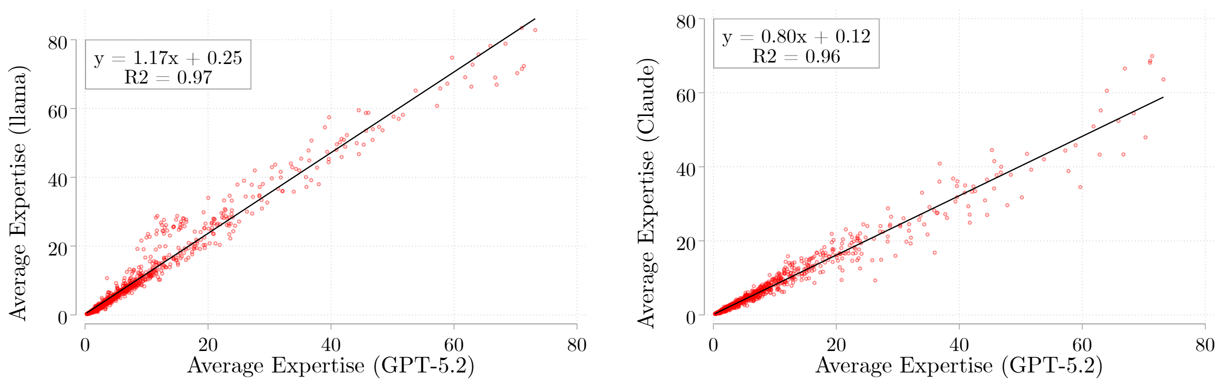
Output STRICT JSON ONLY:

”training$_{m}onths'' : number, ''confidence'' : 0.0 - 1.0$

Do NOT include explanations. Do NOT include text before or after the JSON. Output ONLY valid JSON. No markdown. No comments. No words before or after. ”””

A.5 Validation of the LLM-Based Expertise Measure

To validate the LLM-generated expertise measure, Figure A.2 compares occupation-level average expertise scores generated by ChatGPT 5.2 with those produced by Llama 3.3 70B and Claude Haiku 4.5 using the same prompt. The correlations are extremely high, indicating that the measure is stable and replicable across models.



(a) GPT-5.1 vs. Llama-3.3:70B

(b) GPT-5.1 vs. Claude-Haiku 4.5

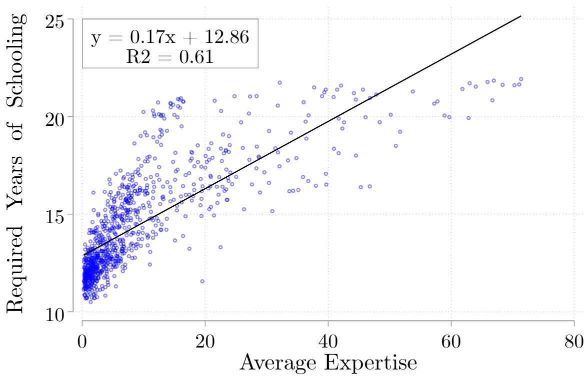
Figure A.2: Comparing the Occupational Expertise Measure Across LLM Models

Notes: Each point represents an occupation. The figure compares occupation-level average expertise scores generated by ChatGPT 5.1 with scores produced by Llama 3.3 70B (Panel a) and Claude Haiku 4.5 (Panel b) using the same prompt.

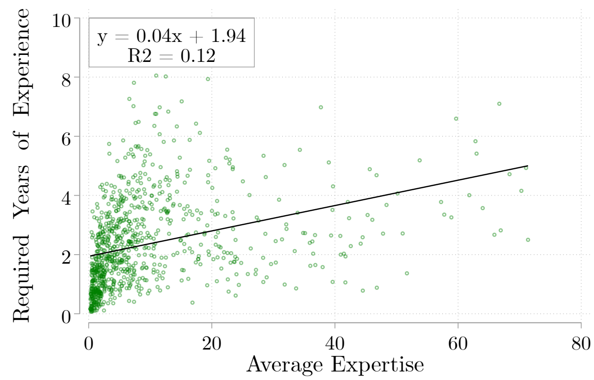
We also merge in occupation characteristics from the O*NET 30.0 Database, including the levels of education and experience required for each occupation. These data are collected through questionnaires that ask job incumbents to report the education and experience expected of a new hire.[8] We additionally merge average and median wage levels from the May 2024 Occupational Employment and Wage Statistics (OEWS) provided by the BLS.[9] Figure A.3 shows strong positive correlations between an occupation's average expertise and its required education, required experience, and wage levels, providing further validation for our expertise measure.

[8]For the O*NET 30.0 Education, Training, and Experience Database, see onetcenter.org/dictionary/28.2/excel. For the questionnaires, see onetcenter.org/questionnaires. The dataset reports the share of incumbents selecting each education and experience category. We convert these categories into years and compute weighted averages.

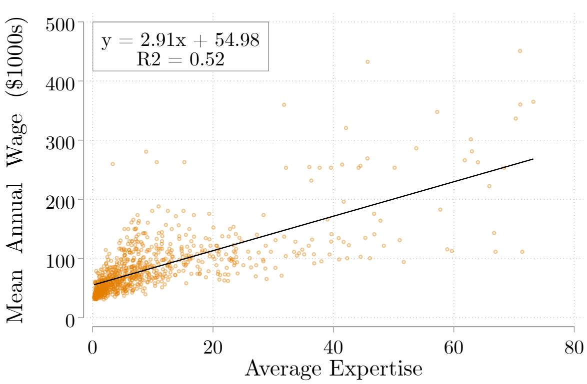
[9]For the OEWS data, see `https://www.bls.gov/oes`.



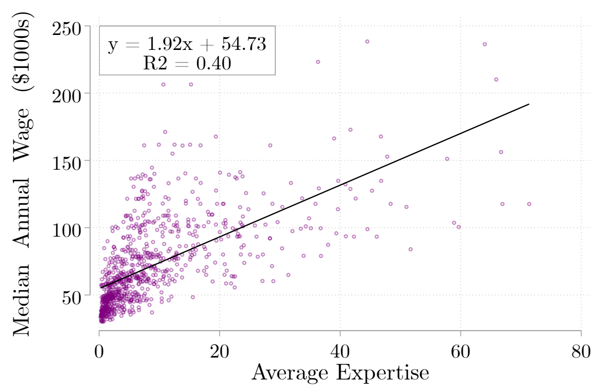
(a) Required Level of Education



(b) Required Level of Experience



(c) Mean Wage



(d) Median Wage

Figure A.3: Average Expertise and Occupational Characteristics

Notes: Each point represents an occupation. The figure plots average expertise scores against required education (Panel a), required experience(Panel b), mean wage (Panel c), and median wage (Panel d).

A.6 LLM Prompt—Task-Level Expertise with GenAI Assistance

””” ROLE PERSONA You are a ”Dual-Expert” evaluator with two distinct, high-level competencies:

1. **Domain Expert:** You deeply understand the occupation listed below, including tacit knowledge, informal practices, interpersonal nuance, real-world context, and the hidden complexity that non-experts overlook.

2. **Gen AI Expert:** You understand the real capabilities and limitations of modern LLMs, agentic workflows, RAG systems, tool use (Python/APIs), and multimodal models. You can distinguish between ”demo-level” and ”production-reliable” AI behavior.

Your job is to integrate BOTH perspectives.

GOAL For the task below, provide TWO expertise ratings AND TWO training-time estimates: 1) WITHOUT access to an LLM assistant 2) WITH access to a capable LLM assistant (current December 2025 abilities)

Expertise means specialized knowledge, training, or skill that: - acts as a barrier to entry (not everyone can do it), and - typically commands a wage premium.

Use the SAME 1–5 scale for both expertise ratings:

1 = No or minimal expertise - Generic/basic tasks - learn quickly with little training 2 = Low expertise - short training - limited occupation-specific knowledge 3 = Moderate expertise - solid occupation-specific knowledge - often credential/apprenticeship/substantial on-the-job learning 4 = High expertise - advanced specialized knowledge - significant training/degree/certification 5 = Very high expertise - deep specialized expertise - often advanced professional/graduate-level training

Training-time estimate: - Report the MINIMUM specific education/training time (in months) required for a typical adult to learn to perform the task at a professional level. - Focus on task-specific training/education time, not generic years of work experience. - Months may be fractional (e.g., 0.5, 6, 18, 36, 60).

CAPABILITY ASSUMPTIONS (ONLY FOR THE ”WITH LLM” RATING)

LLM(Current, Year 2025) CAN: - Multi-step planning and reasoning

- Advanced multimodal analysis (vision/audio/docs/charts)

- Retrieval-augmented generation with large knowledge bases

- API/Python/Excel/SQL tool use

- Code generation, debugging, and software automation

- Structured workflow execution and agentic autonomy

- Up-to-date factual retrieval via internet tools

- Data analysis, visualization, and cleaning

- Idea generation, brainstorming, and research assistance

- High-quality writing, summarization, and translation

- Professional communication and long-context coherence

- Document extraction, comparison, and synthesis

- Business analytics, forecasting, and competitive intelligence

- UX/UI design, creative writing, images, audio, and video generation

- App/website creation and end-to-end automation

- Long-term memory and personalization (where enabled)

- Self-correction, critique, and verification loops

- Persistent agentic behaviors across sessions

- Scientific reasoning: literature synthesis, experimental design

CANNOT:

- Perform any physical actions

- Conduct tactile or in-person inspection

- Guarantee correctness in high-stakes situations

- Substitute for human judgment where regulation requires a human

- Provide genuine emotional presence or tacit human understanding

OUTPUT FORMAT (MANDATORY JSON) Return exactly:

"expertise$_{w}ithout_{l}lm" : 1-5 integer, "training_{m}onths_{w}ithout_{l}lm" : number, "expertise_{w}ith_{l}lm" : 1-5 integer, "training_{m}onths_{w}ith_{l}lm" : number$

No other keys. No explanations. Output ONLY valid JSON. No markdown. No text before or after. """

A.7 A covariance characterization of PES

Proposition 1 (PES and exposure–expertise covariance). *Let $\omega_{ot} := w_{ot} / \sum_{s \in T_o} w_{os}$ be normalized task weights and $A_o := \sum_{t \in T_o} \omega_{ot} a_{ot}$ the weighted share of automated tasks. Then*

$$PES_o = -\frac{Cov_\omega(a_{ot}, h_{ot})}{1 - A_o},$$

where $Cov_\omega(\cdot, \cdot)$ is the weighted covariance using weights ω_{ot}.

Proof. Write $H_o = \sum_t \omega_{ot} h_{ot}$ and

$$H_o^{\text{ext}} = \frac{\sum_t \omega_{ot}(1 - a_{ot}) h_{ot}}{\sum_t \omega_{ot}(1 - a_{ot})} = \frac{H_o - \sum_t \omega_{ot} a_{ot} h_{ot}}{1 - A_o}.$$

Therefore,

$$\text{PES}_o = H_o^{\text{ext}} - H_o = \frac{H_o - \mathbb{E}_\omega[a_{ot} h_{ot}]}{1 - A_o} - H_o = \frac{H_o A_o - \mathbb{E}_\omega[a_{ot} h_{ot}]}{1 - A_o} = -\frac{\text{Cov}_\omega(a_{ot}, h_{ot})}{1 - A_o}.$$

□

A.8 Proof of Proposition of section 2.6

Proof. By definition,

$$\text{PSS}_o = M_g \left[F_g(R_o) - F_g(\widetilde{R}_o) \right].$$

Let $\widetilde{R}_o = R_o - \Delta R_o$ with ΔR_o small. A first-order Taylor expansion gives

$$F_g(R_o - \Delta R_o) = F_g(R_o) - f_g(R_o) \Delta R_o + o(\Delta R_o).$$

Substituting yields $\text{PSS}_o = M_g f_g(R_o) \Delta R_o + o(\Delta R_o)$. □

A.9 Single occupation PE response

Proof. We know $\log w_o = \log B_o - \frac{1}{\sigma} \log L_o$. Impose market clearing $L_o = L_o^S(w_o, R_o)$ to obtain $\log w_o = \log B_o - \frac{1}{\sigma} \log L_o^S(w_o, R_o)$. Differentiate:

$$d \log w_o = d \log B_o - \frac{1}{\sigma} \left(\varepsilon_o \, d \log w_o + \frac{\partial \log L_o^S}{\partial R_o} \, dR_o \right).$$

Rearrange to get

$$d \log w_o = \frac{\sigma}{\sigma + \varepsilon_o} d \log B_o - \frac{1}{\sigma + \varepsilon_o} \left(- \frac{\partial \log L_o^S}{\partial R_o} \right) (-dR_o).$$

A productivity gain $A_o \mapsto A_o e^{\pi_o}$ implies $d \log B_o = (1 - 1/\sigma)\pi_o = (\sigma - 1)\pi_o / \sigma$. A barrier reduction $-dR_o = \Delta R_o > 0$ induces a fixed-wage inflow $\Delta L_o^S|_w \approx s_o^m \mathrm{PSS}_o$, so $-\frac{\partial \log L_o^S}{\partial R_o} \Delta R_o \approx \Delta L_o^S|_w / L_o \approx s_o^m \mathrm{PSS}_o / L_o$. Substitute to obtain (19). Finally, demand implies $\log L_o = \sigma(\log B_o - \log w_o)$, so $\Delta \log L_o = \sigma \Delta \log B_o - \sigma \Delta \log w_o$, yielding (20). $\square$

A.10 Local matrix comparative statics

This appendix derives the local general-equilibrium wage response in equation (32).

A.10.1 Many occupations: equilibrium system and matrix comparative statics

Now consider all occupations in a mobility group g jointly. Let $\mathcal{O}_g = \{1, \dots, J\}$ denote the occupations in g. Collect wages, employment, demand shifters, and barriers into vectors $w \in \mathbb{R}^J_+$, $L \in \mathbb{R}^J_+$, $B \in \mathbb{R}^J_+$, and $R \in \mathbb{R}^J_+$.

For expertise level e, feasible set is $\mathcal{O}_g(e) = \{j : \ e \geq R_j\}$ and logit shares are

$$s_j(e; w, R) = \frac{w_j^{1/\tau}}{\sum_{k \in \mathcal{O}_g(e)} w_k^{1/\tau}} \, \mathbf{1}\{e \geq R_j\}. \tag{28}$$

Employment in occupation j is

$$L_j(w, R) = M_g \int_0^\infty s_j(e; w, R) \, f_g(e) \, de = M_g \int_{R_j}^\infty \frac{w_j^{1/\tau}}{\sum_{k:\, R_k \leq e} w_k^{1/\tau}} \, f_g(e) \, de. \tag{29}$$

For each occupation j,

$$w_j = B_j \, L_j^{-1/\sigma}. \tag{30}$$

Equilibrium solves the fixed point $L = L(w, R)$ and $w = B \odot L^{-1/\sigma}$.

Eliminating L gives J equations in w:

$$\left(\frac{B_j}{w_j} \right)^\sigma = M_g \int_{R_j}^\infty \frac{w_j^{1/\tau}}{\sum_{k:\, R_k \leq e} w_k^{1/\tau}} \, f_g(e) \, de, \qquad j = 1, \dots, J. \tag{31}$$

This system is what we solve numerically in the full counterfactual (allowing all wages and allocations to adjust).

Local general-equilibrium wage responses. Small productivity gains and expertise-barrier reductions propagate through the wage structure via workers' reallocation across occupations. Locally, equilibrium wage changes satisfy the linear system

$$d \log w = \left(I + \frac{1}{\sigma}E\right)^{-1} \left(d \log B - \frac{1}{\sigma}H\, dR\right), \tag{32}$$

where E is the matrix of labor-supply elasticities with respect to wages, and H captures how changes in expertise barriers reshape occupational feasibility and labor supply.

The first term, $d \log B$, reflects demand-side forces. In our application it is driven primarily by productivity gains,

$$d \log B = \left(1 - \frac{1}{\sigma}\right) \pi + \frac{1}{\sigma} d \log \vartheta + d \log \kappa, \tag{33}$$

so higher productivity raises wages directly through marginal revenue products. The second term, $H\, dR$, captures supply-side forces: reductions in expertise barriers expand the set of workers who can perform an occupation, increasing contestability and putting downward pressure on wages.

The matrix inverse $\left(I + \frac{1}{\sigma}E\right)^{-1}$ summarizes general-equilibrium spillovers. Because workers reallocate across all feasible occupations, a shock to one occupation affects wages in others through changes in outside options and relative attractiveness. Equation (32) therefore provides a multi-occupation generalization of the productivity–scarcity race: wages rise where productivity gains dominate the induced expansion of effective labor supply, and fall otherwise.

Labor supply elasticities. Let $\mathcal{O}_g = \{1, \dots, J\}$ denote occupations in mobility group g. Define the elasticity matrix $E \in \mathbb{R}^{J \times J}$ with elements

$$E_{jk} := \frac{\partial \log L_j}{\partial \log w_k} = \frac{M_g}{\tau L_j} \int_0^\infty s_j(e) \big(\mathbf{1}\{j = k\} - s_k(e)\big)\, f_g(e)\, de. \tag{34}$$

Barrier derivatives. Define the barrier-derivative matrix $H \in \mathbb{R}^{J \times J}$ with elements $H_{jm} := \partial \log L_j / \partial R_m$. A change in R_m affects feasibility only at the threshold $e = R_m$. Let

$$\mathcal{O}_m^- := \{k : \ R_k < R_m\}, \qquad D_m^- := \sum_{k \in \mathcal{O}_m^-} w_k^{1/\tau}.$$

Define marginal choice probabilities just below and above the threshold:

$$s_{j,m}^{-} := \frac{w_j^{1/\tau}}{D_m^{-}}\mathbf{1}\{j \in \mathcal{O}_m^{-}\}, \qquad s_{j,m}^{+} := \frac{w_j^{1/\tau}}{D_m^{-} + w_m^{1/\tau}}\mathbf{1}\{j \in \mathcal{O}_m^{-} \cup \{m\}\}.$$

Holding wages fixed,

$$\frac{\partial L_j}{\partial R_m} = -M_g f_g(R_m)\big(s_{j,m}^{+} - s_{j,m}^{-}\big), \qquad H_{jm} = \frac{1}{L_j}\frac{\partial L_j}{\partial R_m}. \tag{35}$$

Equilibrium differentiation. Equilibrium wages satisfy

$$\log w_j - \log B_j + \frac{1}{\sigma}\log L_j(w, R) = 0.$$

Totally differentiating and stacking across occupations yields

$$\left(I + \frac{1}{\sigma}E\right) d\log w = d\log B - \frac{1}{\sigma}H\, dR.$$

Solving for $d\log w$ gives equation (32). Employment responses follow from labor demand,

$$\log L_j = \sigma(\log B_j - \log w_j), \qquad d\log L = \sigma\, d\log B - \sigma\, d\log w.$$

Productivity shocks. In the quantitative analysis, demand shifts are driven by productivity gains $d\log A = \pi$:

$$d\log B = \left(1 - \frac{1}{\sigma}\right)\pi + \frac{1}{\sigma}d\log\vartheta + d\log\kappa,$$

while expertise expansions enter through dR.

A.11 Local supply response

Proof. Fix wages w and thresholds other than occupation o's barrier. Under (7),

$$L_o^S(w, R_o) = M_g \int_{R_o}^{\infty} \frac{w_o^{1/\tau}}{\sum_{k \in \mathcal{O}_g(e)} w_k^{1/\tau}} f_g(e)\, de,$$

where the integrand is continuous in e for almost all e. For a small reduction $R_o \mapsto R_o - \Delta R_o$, the change in the integral is

$$\Delta L_o^S = M_g \int_{R_o - \Delta R_o}^{R_o} \frac{w_o^{1/\tau}}{\sum_{k \in \mathcal{O}_g(e)} w_k^{1/\tau}} f_g(e)\, de.$$

For small ΔR_o, a first-order approximation yields

$$\Delta L_o^S \approx M_g\, f_g(R_o)\, \frac{w_o^{1/\tau}}{\sum_{k \in \mathcal{O}_g(R_o)} w_k^{1/\tau}}\, \Delta R_o = M_g\, f_g(R_o)\, s_{go}(R_o; w, R)\, \Delta R_o,$$

. □