Generative AI, Expertise, and Effective Labor Supply*

Seyed M. Hosseini† Guy Lichtinger‡

Preliminary Draft

January 10, 2026

Abstract

Measures of occupational exposure are widely used to assess the labor-market effects of generative AI (GenAI), but they treat tasks as homogeneous, missing how GenAI reshapes the expertise required to do work. 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 removed, 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 three facts: (i) PSS varies widely even among occupations with similar exposure; (ii) it increases with baseline expertise and wages across most of the distribution but declines sharply in the extreme upper tail; and (iii) it is positively associated with predicted augmentation and potential productivity gains. A task-based general equilibrium model maps the resulting supply and productivity shocks into wage and employment incidence and clarifies their distributional implications.

*This research draws extensively on the framework developed by Autor and Thompson (2025), and we are deeply indebted to their work for providing the foundation for our analysis. We are also extremely grateful to David Autor, Lawrence Katz, Jesse Shapiro, and Neil Thompson for their extremely valuable feedback and discussion.

†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 the content of work and the distribution of earnings across occupations? A common approach in recent work is to quantify the "exposure" of occupations by assessing which tasks or abilities are automatable with GenAI and then calculating the share of exposed tasks (e.g., ILO, 2025; Gmyrek et al., 2023; Eloundou et al., 2024; Felten et al., 2023). These occupation-level exposure indices play a central role in economic research and policy analyses that attempt to evaluate both the current and future impact of GenAI on labor markets (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).

While exposure measures provide valuable insights, simply calculating the share of exposed tasks has two important limitations. First, it treats tasks as homogeneous, abstracting from what is being automated. As emphasized by Autor and Thompson (2025), the consequences of automation depend on the expertise content of displaced tasks, not only on their count: automating peripheral, low-expertise work can raise the specialization of the remaining job, whereas automating core expert tasks can erode occupational identity, entry barriers, and wage premia. Second, standard exposure measures focus on the extensive margin, implicitly classifying tasks as either automated or unaffected. They therefore do not capture intensive-margin effects through which GenAI reduces the expertise required to perform tasks that remain human-performed.

This paper argues that understanding GenAI's labor market effects requires moving beyond exposure toward a task-based characterization of how GenAI reshapes occupational expertise, effective labor supply, and productivity. We proceed in several steps.

First, we use large language models (LLMs) to construct new task-level measures of GenAI exposure and task expertise for the O*NET database. Building on Eloundou et al. (2024), we update their task-level automation assessment to reflect current GenAI capabilities. Building on Autor and Thompson (2025), we construct a task-level expertise rating that captures the extent to which a task requires specialized training and functions as a barrier to entry. We validate the expertise ratings across multiple frontier LLMs and show that occupation-level aggregates correlate strongly with independent indicators of skill, including required education, required experience, and wages. We also construct a second expertise measure that rates each task under the counterfactual that the worker has access to a capable GenAI assistant, allowing us to quantify how GenAI can reduce the expertise required even when a task remains performed by labor.

Second, these measures allow us to distinguish two conceptually distinct channels through which GenAI affects occupational expertise. On the extensive margin, GenAI automates a subset of tasks, removing them from the bundle performed by labor. The extensive margin is a direct application of the "expertise exposure" concept of Autor and Thompson (2025), though our focus is on *potential* shifts induced by GenAI automation rather than on realized changes from past technologies. On the intensive margin, tasks remain human-performed but become easier because GenAI effectively expands workers' capabilities. This channel is motivated by Autor (2024) and closely related to the "task simplification" mechanism of Althoff and Reichardt (2025). Combining these channels, we construct a Potential Expertise Shift (PES) index that summarizes how the expertise content of an occupation's task bundle changes under GenAI.

Third, we translate these changes in expertise into labor market implications by introducing the Potential Supply Shift (PSS) index. PSS captures how GenAI changes the share of the workforce that is qualified to perform an occupation, taking into account both extensive- and intensive-margin effects and the distribution of expertise in the workforce. We show that PSS differs sharply from both exposure and PES. Occupations with similar PES can experience very different expansions in effective labor supply depending on where their expertise threshold lies in the overall expertise distribution. Consistent with this logic, PSS varies widely even among occupations with nearly identical exposure shares, underscoring that exposure alone is a poor predictor of how GenAI reshapes occupational entry barriers. On average, we estimate that GenAI expands the pool of qualified workers by roughly 10 percentage points, though the magnitude varies substantially across occupations.

Fourth, we study how GenAI-induced supply expansions vary across the baseline expertise and wage distributions. PSS rises with baseline expertise and wages across most of the distribution, implying that GenAI tends to relax entry barriers more for many initially higher-skill and higher-pay occupations. However, this pattern reverses in the extreme upper tail: above roughly the 90th percentile, PSS falls sharply. Intuitively, the highest-expertise occupations sit in a region where the expertise distribution has low density, so comparable reductions in required expertise translate into relatively small inflows of newly qualified workers. This non-monotonicity points to potentially important distributional consequences: GenAI may broaden access to many high-skill occupations while leaving the very top comparatively insulated from supply-side pressure.

We further connect expertise and supply shifts to productivity. Using task-level information on task frequency, importance, and augmentation potential, we construct an occupation-level measure of Potential Productivity Gains (PPG) from GenAI. We show that productivity gains are positively correlated with baseline expertise and with PSS, but that the relationship is highly non-linear. Occupations in the upper-middle of the expertise distribution tend to combine large reductions in effective expertise requirements with substantial productivity gains, while the highest-expertise occupations experience large productivity gains but relatively small supply expansions. These patterns suggest that GenAI is likely to compress wages across much of the distribution while simultaneously reinforcing outcomes at the very top.

To discipline and interpret these empirical patterns, we develop a task-based general equilibrium model of occupations and expertise, building on Autor and Thompson (2025). In the model, occupations differ in their expertise requirements, workers are heterogeneous in expertise, and sorting across occupations is governed by feasibility constraints and occupational choice. GenAI affects the economy through three channels: task removal (an extensive margin that alters occupational entry barriers), expertise expansion (an intensive margin that lowers the expertise required to perform tasks that remain human-performed), and productivity augmentation. The model maps empirically measured changes in feasibility and productivity into equilibrium wage and employment responses, clarifying why the effects of GenAI vary sharply across occupations and are not proportional to exposure. Small reductions in expertise requirements can generate large or small labor-supply responses depending on where an occupation lies in the expertise distribution and on the outside options of marginal workers. As a result, occupations with similar exposure can experience very different wage and employment outcomes.

We close by noting limitations. We abstract from the creation of new tasks and occupations in response to GenAI, and we treat the distribution of worker expertise as fixed, ruling out endogenous training and retraining. Some LLM-based assessments, particularly those that quantify how GenAI changes the expertise required to perform tasks, are difficult to validate directly and should be interpreted cautiously. Finally, the timing of GenAI's extensive-margin, intensive-margin, and productivity effects is uncertain, whereas our empirical and model exercises implicitly treat them as contemporaneous.

Despite these caveats, the analysis yields a clear message: exposure alone is insufficient to characterize GenAI's labor market effects. Incorporating task expertise and distinguishing between task removal and task transformation changes both the measurement and the predicted incidence. More broadly, the results highlight expertise as a central organizing concept for understanding how GenAI reshapes work, entry barriers, productivity, and inequality.

2 The Exposure and Expertise of Tasks and Occupations

Our analysis draws primarily on the O*NET database (O*NET, 2023), which provides detailed information on 19,265 tasks across 923 occupations. We complement this data with several task-level and occupation-level variables, as described below. The complete task-level and occupation-level datasets are publicly available.[1]

2.1 The Exposure of Tasks and Occupations

GenAI Exposure: We first construct a task-level measure of GenAI automation exposure by updating the methodology of Eloundou et al. (2024). Using ChatGPT 5.2, we recalibrate their original prompt to reflect current GenAI capabilities. The full prompt is provided in Appendix A.1.[2]

Following Eloundou et al. (2024), the model evaluates the share of each task's components that can be performed by current GenAI systems and assigns each task to one of five categories: 1 (0 percent), 2 (0–50 percent), 3 (50–80 percent), 4 (80–100 percent), or 5 (100 percent automatable). We convert this scale into a binary exposure indicator, classifying tasks in categories 4 or 5, that is, tasks with more than 80 percent automatable

[1] The datasets are available at https://github.com/s-mahdihosseini/GenAI_Expertise.
[2] See Supplementary Material 3.2 in Eloundou et al. (2024) for the original prompt.

components, as exposed to GenAI automation. Under this definition, 4,107 tasks, or 21.3 percent of all O*NET tasks, are classified as exposed.

We then aggregate task-level exposure to the occupation level by computing the share of exposed tasks within each occupation. Tasks are weighted according to the O*NET structure, with core tasks receiving a weight of 1 and supplemental tasks a weight of 0.5, consistent with Eloundou et al. (2024). Figure 1 reports the distribution of exposure shares across occupations. Appendix A.2 shows that our updated exposure measure is strongly correlated with the original measure of Eloundou et al. (2024).

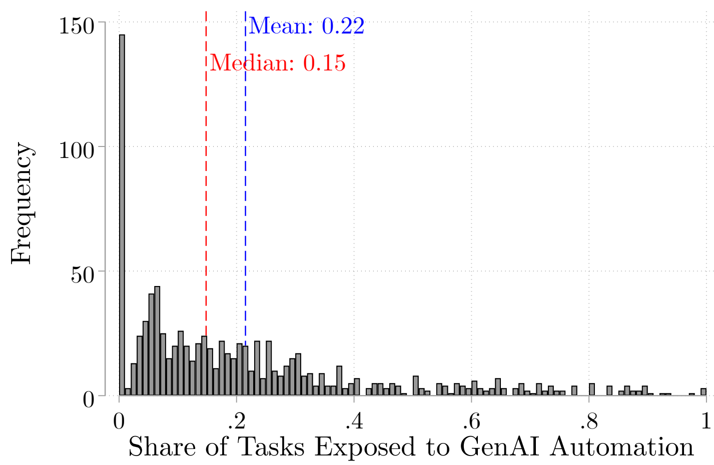


Figure 1: Share of Exposed Tasks

Notes: The figure shows the distribution of the occupation-level share of tasks exposed to GenAI automation. Task exposure is measured using ChatGPT 5.2 to update the automation rubric of Eloundou et al. (2024). Tasks in categories 4 or 5 (more than 80 percent automatable) are classified as exposed. Occupation-level exposure shares weight core tasks by 1 and supplemental tasks by 0.5.

2.2 The Expertise of Tasks and Occupations

2.2.1 Expertise of Tasks

Building on the framework of Autor and Thompson (2025), we construct a task-level measure of expertise using ChatGPT 5.2. 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. Each task is assigned an expertise score on a five-point scale ranging from 1 (minimal expertise) to 5 (very high expertise). The full prompt is provided in Appendix A.3.

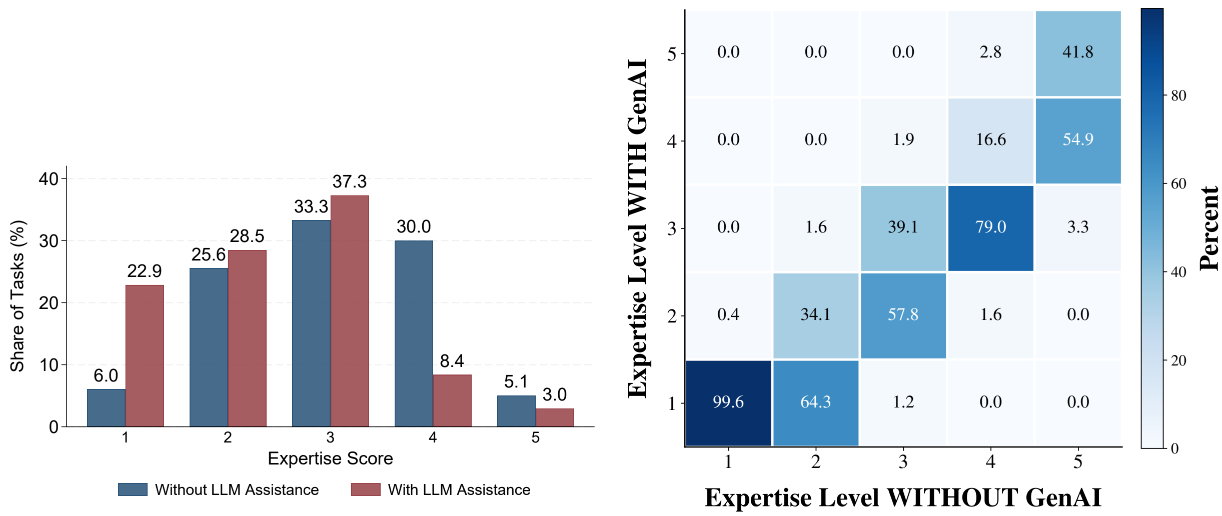
Additionally, we assess how access to a GenAI assistant alters the expertise required to perform each task. Using a *separate* LLM prompt that combines the assumptions of the automation and expertise measures, we re-rate task expertise under the assumption that workers have access to a capable GenAI assistant. The definition of expertise and the assumed GenAI capabilities remain unchanged. The full prompt is reported in Appendix A.6.

Figure 2a compares the distribution of tasks across expertise categories with and without GenAI assistance. The share of tasks classified as high expertise (category 4) declines from 30.0 percent without GenAI assistance to 8.4 percent with assistance, while the share of tasks in the lowest expertise category increases from 6.0 percent to 22.9 percent. Figure 2b details the specific transitions underlying these shifts. Except category 1, more than half of tasks in each expertise category are predicted to experience a one-category decline in expertise. This pattern is most pronounced for category 4 tasks, of which 79.0 percent are expected to require only category 3 expertise with GenAI assistance.

2.2.2 Expertise of Occupations

Following Autor and Thompson (2025), we aggregate task-level expertise to the occupation level by averaging expertise across an occupation's tasks. Since our expertise measure is categorical, we first map expertise categories into a continuous measure based on the training time required for a typical adult to learn to perform each task at a professional level. To construct this mapping, we use an additional LLM to estimate the required task-specific training time in months for each O*NET task without GenAI assistance. The prompt is provided in Appendix A.4. Each expertise category is then mapped to the median training time implied by these estimates. Table 1 reports the resulting category-to-training-time mapping.

Using this mapping, occupation-level expertise is calculated as the weighted average expertise across an occupation's tasks, using weights of 1 for core tasks and 0.5 for supplemental tasks. Formally, the occupation-level of expertise is calculated as



(a) Expertise Categories

(b) Expertise Transition Matrix

Figure 2: 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.

$$X_o^{noAI} = \underbrace{\frac{\sum_{t \in T_o} w_{ot} x_{ot}^{noAI}}{\sum_{t \in T_o} w_{ot}}}_{\mathbb{E}[x_{ot}^{noAI}]}, \tag{1}$$

where x_{ot}^{noAI} denotes the expertise (after mapping to training months) of task t without access to GenAI assistance and w_{ot} denotes task weights (1 for core tasks, 0.5 for supplemental). We denote it by X_o^{noAI} because this is the level of expertise required to do this occupation without any effect of GenAI. Appendix A.5 validates this measure, showing it is highly correlated ($R^2 \geq 0.90$) across different LLMs (Llama, Claude) and strongly correlated with O*NET-based data on occupational required education and experience, as well as wages. Figure 3 presents the distribution each of the expertise scores across occupations. It shows that the average expertise is 8.15 months with standard deviation of 8.33. The median is 5.53 months.

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.

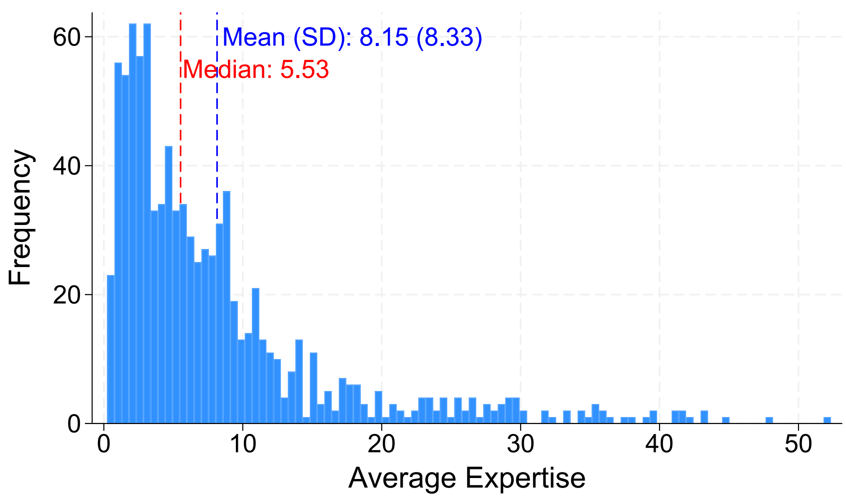


Figure 3: Average Expertise Across Occupations

Notes: The figure displays the distribution of occupation-level expertise level.

3 The Effects of GenAI on the Expertise of Occupations

3.1 GenAI and Occupational Average Expertise

3.1.1 Occupational Expertise With GenAI

Next, we calculate, for each occupation, three types of expertise score, reflecting different effects of GenAI. First, the "extensive" expertise of an occupation reflects the average expertise of the occupation after all its exposed tasks are removed (in other words, the average expertise of non-exposed tasks). Formally, it is calculated:

$$X_o^{ext} = \underbrace{\frac{\sum_{t \in T_o} w_{ot}(1 - a_{ot}) x_{ot}^{withoutAI}}{\sum_{t \in T_o} w_{ot}(1 - a_{ot})}}_{\mathbb{E}[x_{ot}^{withoutAI} | a_{ot} = 0]}, \tag{2}$$

with $a_{ot} \in \{0, 1\}$ indicates that task t is exposed to GenAI automation.

Next, the "intensive" expertise of an occupation reflects the average expertise across all the tasks of the occupation when the worker as an access to GenAI assistance

$$X_o^{int} = \underbrace{\frac{\sum_{t \in T_o} w_{ot} x_{ot}^{withAI}}{\sum_{t \in T_o} w_{ot}}}_{\mathbb{E}[x_{ot}^{withAI}]}, \tag{3}$$

where x_{ot}^{withAI} denotes the expertise (after mapping to training months) of task t without access to GenAI assistance.

Finally, the combined (final) expertise of an occupation is calculated as

$$X_o^{combined} = \underbrace{\frac{\sum_{t \in T_o} w_{ot}(1 - a_{ot}) x_{ot}^{withAI}}{\sum_{t \in T_o} w_{ot}(1 - a_{ot})}}_{\mathbb{E}[x_{ot}^{withAI} | a_{ot} = 0]}, \tag{4}$$

which combines both the intensive and extensive margins of the GenAI effects.

3.1.2 The Potential Expertise Shift (PES) of Occupations

The scores above allow us to calculate the potential expertise shift of occupations, namely, how GenAI will change the expertise level of occupations through each of the margins. Specifically, we calculate:

$$PES_o^j = X_o^j - X_o^{noAI}, \quad j \in \{extensive, intensive, combined\}. \tag{5}$$

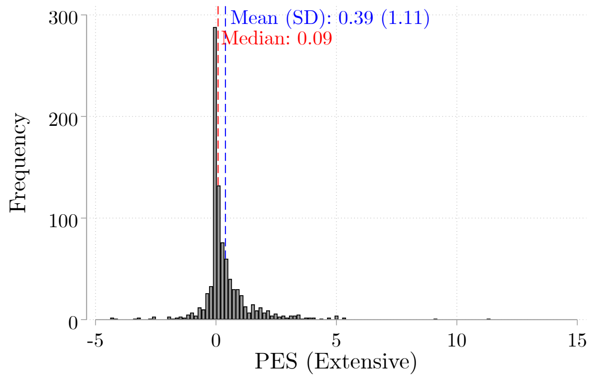
Figure 4 presents the distribution of the potential expertise shift (PES) index across the 923 O*NET occupations. Panel 4a presents the extensive PES, reflecting the potential change in occupation's expertise due to GenAI automation of exposed tasks. The extensive PES is a direct application of the "expertise exposure" concept of Autor and Thompson (2025), though our focus is on *potential* shifts induced by GenAI automation rather than on realized changes from past technologies. shows that the extensive PES is positive, suggesting that, on average, GenAI-exposed tasks tend to be lower expertise among occupations.

Panel 4b presents the distribution of the intensive PES, reflecting the change in an occupation's average expertise due to simplification of its tasks by GenAI. As expected, the PES is non-positive for almost all occupations. This channel is closely related to the "task simplification" of Althoff and Reichardt (2025).

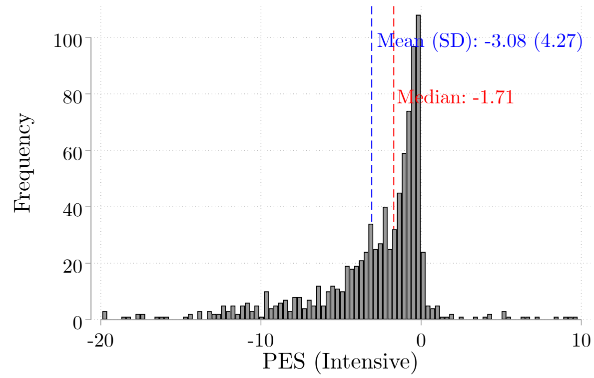
Finally, Panel 4c presents the distribution of the combined PES, accounting for both the intensive and extensive margins. The combined distribution is relatively similar to the intensive PES, suggesting that the intensive margin dominates the extensive one. This means that on average, according to this exercise, GenAI is predicted to decrease the expertise required to do occupations. An important caveat is that our exercise does not take into account the creation of new tasks within occupations, as well the creation of new occupations, which might required higher level of expertise.

3.2 The Potential Supply Shift (PSS) of Occupations

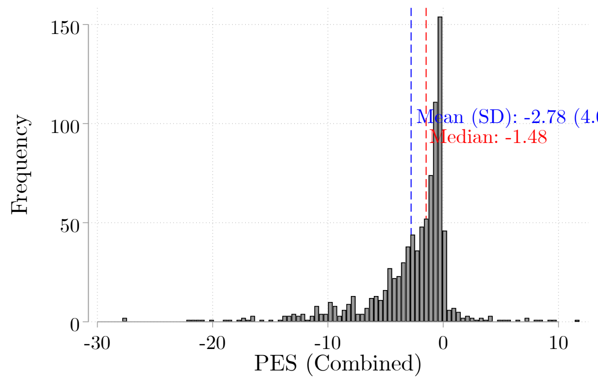
While the Potential Expertise Shift (PES) summarizes how GenAI changes the expertise requirements of an occupation, it does not directly translate these changes into labor market implications. The relevant economic object is not the level of required expertise per se, but the size of the pool of workers who can plausibly perform the occupation, that is,



(a) Extensive



(b) Intensive



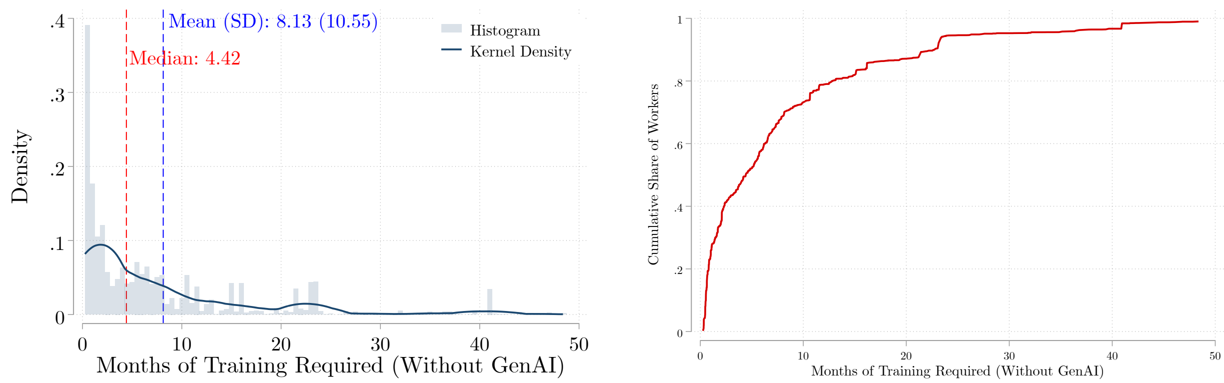
(c) Combined

Figure 4: The Distribution of PES Across Occupations

Notes: The figure displays histograms of occupation-level PES.

workers whose expertise is at least as high as the occupation's requirement. We therefore define the *Potential Supply Shift* (PSS) as the change in the share of the aggregate workforce qualified to perform an occupation after incorporating both the extensive and intensive GenAI effects on the occupation's task bundle.

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, under the equilibrium assumption that workers sort into the most complex occupation they are able to perform. Let $F(x)$ denote the cumulative distribution function (CDF) of baseline occupational expertise X_o^{noAI}, weighted by employment. Figure 5 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 5: 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.

Using $F(\cdot)$, we define the *Potential Supply* of an occupation as the share of workers with expertise weakly above the occupation's requirement. For an occupation requiring expertise level x, potential supply is

$$PS(X) = 1 - F(X). \tag{6}$$

The *Potential Supply Shift* for occupation o is the change in potential supply induced by the shift in expertise requirements from the baseline X_o^{noAI} to the post-GenAI combined requirement $X_o^{combined}$:

$$PSS_o = PS(X_o^{combined}) - PS(X_o^{noAI}) = F(X_o^{noAI}) - F(X_o^{combined}). \tag{7}$$

A positive PSS_o indicates that GenAI lowers barriers to entry, increasing the fraction of the workforce that is qualified to perform occupation o. Figure 6 shows 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.

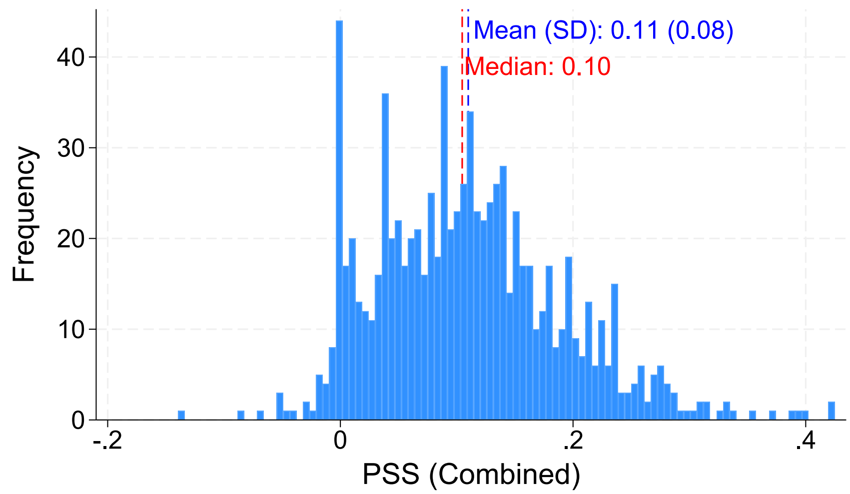


Figure 6: Potential Supply Shift (PSS) Across Occupations

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 $(F(X_o^{noAI}) - F(X_o^{combined}))$.

4 The Relationships Between PSS and Key Measures

4.1 PSS vs. Exposure

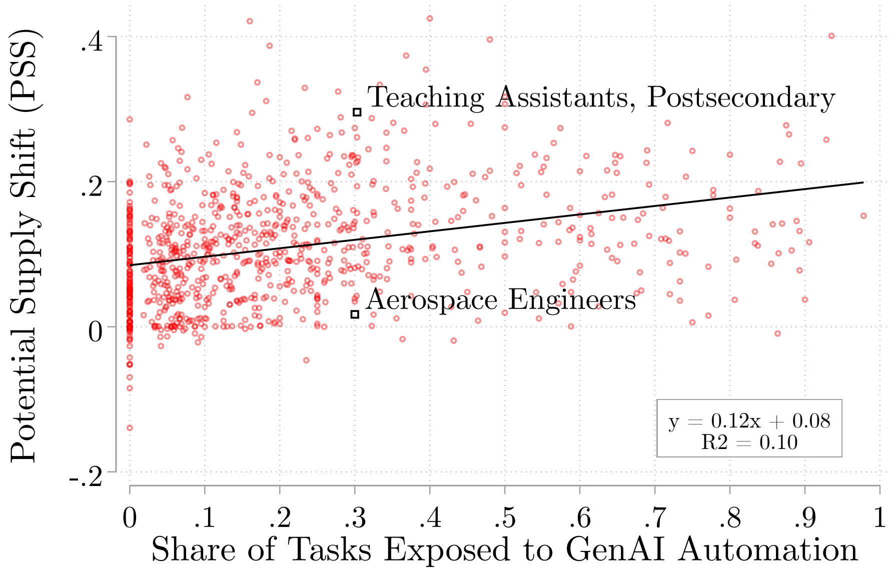
Most empirical studies assessing the current and future labor market effects of GenAI rely on a simple measure of occupational exposure, typically defined as the share of tasks within an occupation that are classified as automatable. While this measure provides valuable insights, it has two important limitations. First, it treats all tasks as homogeneous, abstracting from their content. As emphasized by Autor and Thompson (2025), the consequences of automation depend critically on the expertise of the tasks being displaced, not merely on their number. Second, standard exposure measures focus exclusively on the extensive margin, implicitly assuming that tasks are either fully automated or unaffected. They do not capture intensive-margin effects whereby GenAI reduces the expertise required to perform tasks that remain human-performed. The Potential Supply Shift (PSS) addresses both limitations by explicitly incorporating the expertise content of tasks and by accounting for both extensive-margin automation and intensive-margin task simplification.

Figure 7 illustrates the relationship between PSS and the standard aggregate exposure measure. The scatter plot in Panel A shows a positive association between exposure and PSS, but also substantial dispersion. For any given level of exposure, PSS varies widely across occupations. In other words, knowing the share of exposed tasks provides little information about the magnitude of the implied change in effective labor supply. The bin-scatter plot in Panel B further shows that PSS rises with exposure for occupations with low to moderate exposure levels, but the relationship flattens among highly exposed occupations. This pattern highlights that exposure alone is an incomplete statistic for characterizing the labor market consequences of GenAI.

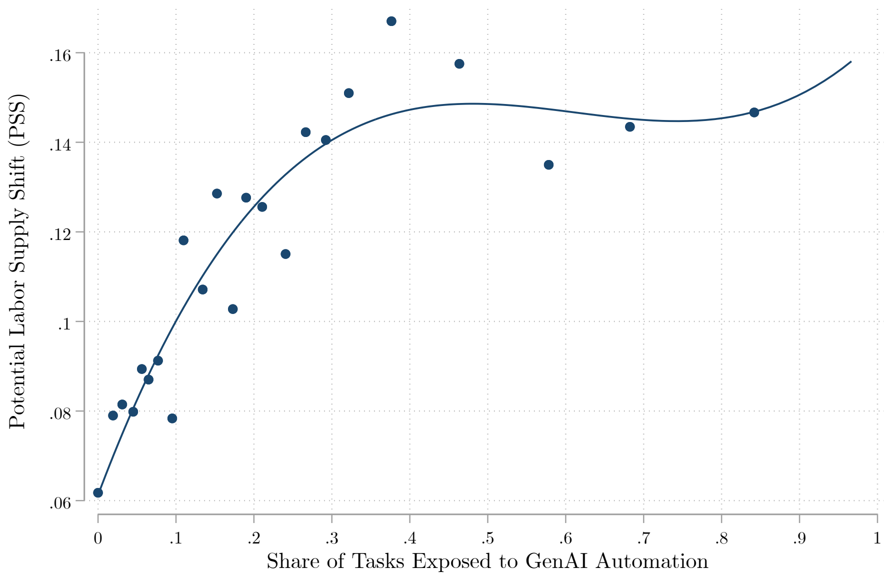
To make this point concrete, Figure 8 compares occupations with nearly identical aggregate exposure shares. The figure reports PSS for all occupations with exposure between 29 and 31 percent, corresponding to the 75th percentile of the exposure distribution. Despite their nearly identical exposure levels, these occupations exhibit large differences 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.

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, indicating that GenAI substantially expands the pool of workers who can plausibly perform the occupation's tasks. In contrast, the PSS for Aerospace Engineers is close to zero.

Several forces drive 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, GenAI exposure is concentrated in lower- and moderate-expertise tasks, such as documentation and record keeping, which increases the average expertise of the remaining task bundle and partially offsets intensive-margin effects. Crucially, initial expertise levels also matter. Aerospace Engineers sit far out in the upper tail of the expertise distribution, where the density of workers is low. As a result, a given reduction in required expertise translates into a much smaller increase in effective labor supply than for Teaching Assistants, who are closer to



(a) Scatter Plot



(b) Bin-Scatter Plot

Figure 7: 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.

the center of the expertise distribution where worker density is high. This interaction between task content and the underlying expertise distribution explains a large share of the observed heterogeneity in PSS across occupations with similar exposure.

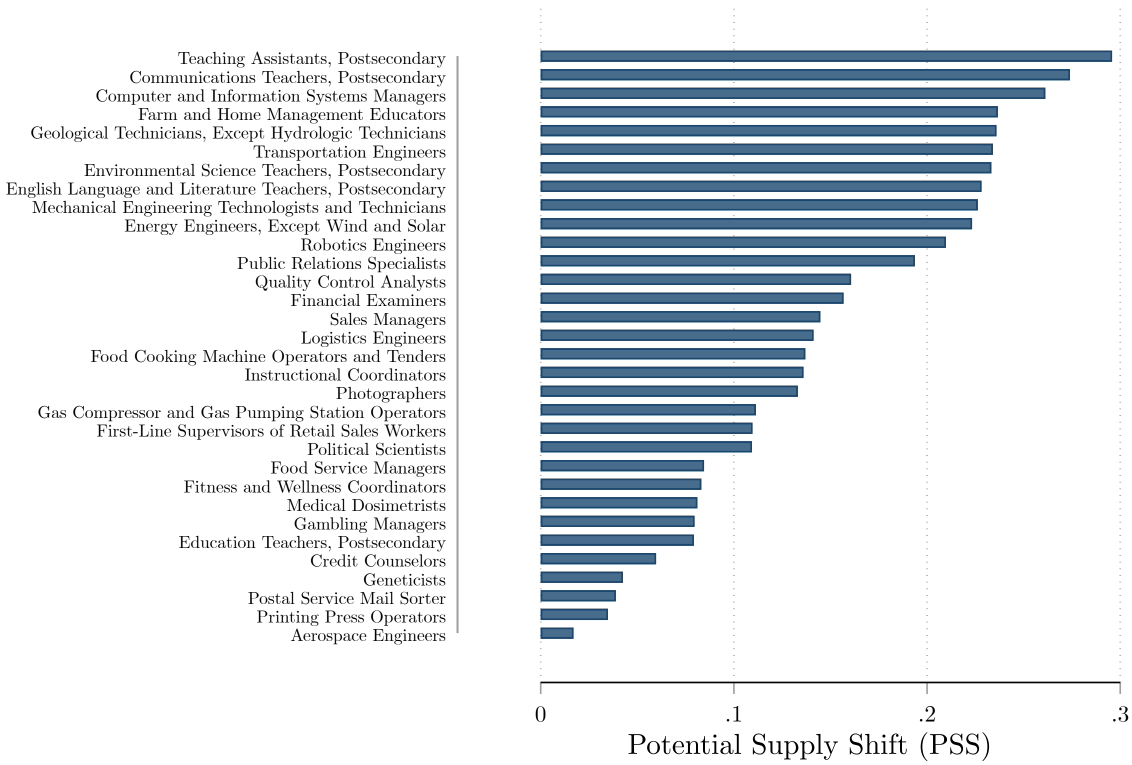
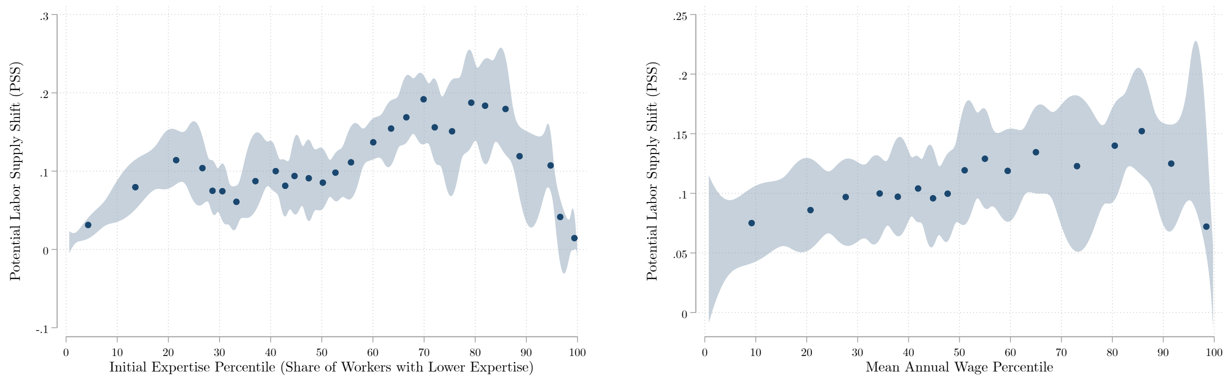


Figure 8: The PSS Index of Occupations With ∼30% Automatable Tasks

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

4.2 PSS vs. Initial Expertise and Wages

Next, in order to provide insights on the implication of the GenAI-induced PSS for inequality, we compare an occupation's PSS to the occupation's initial expertise and wage levels. Figure 9 examines how the Potential Supply Shift (PSS) varies with an occupation's baseline position in the expertise and wage distributions. Panel 9a shows that PSS increases with initial expertise, measured as $(1 - PS_0) \times 100$, across most of the distribution. This pattern indicates larger predicted expansions in effective labor supply, equivalently larger reductions in effective expertise requirements, for occupations that initially require higher expertise. However, above approximately the 90th percentile, PSS declines sharply, suggesting that the very highest-expertise occupations experience smaller supply expansions than most occupations.[3] Panel 9b relates PSS to the occupation's mean wage percentile (based on the O*NET database) and shows a broadly similar pattern.



(a) PSS vs. Initial Expertise Percentile

(b) PSS vs. Mean Wage Percentile

Figure 9: 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.

4.3 PSS vs. Productivity Effects of GenAI

Next, we examine the predicted productivity effects of GenAI and how they relate to expertise shifts. Our goal is to measure, for each occupation, the share of total work activity that is plausibly subject to large time savings from GenAI augmentation. 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

[3] An important caveat is that this exercise holds the task set fixed and does not incorporate the creation of new tasks or new occupations in response to GenAI.

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,

$$PPG_o = 0.5 \times \left(\frac{\sum_{t \in \mathcal{T}_o} Freq_{ot} \times Imp_{ot} \times \beta_{ot}}{\sum_{t \in \mathcal{T}_o} Freq_{ot} \times Imp_{ot}} \right). \quad (8)$$

Figure 10 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.

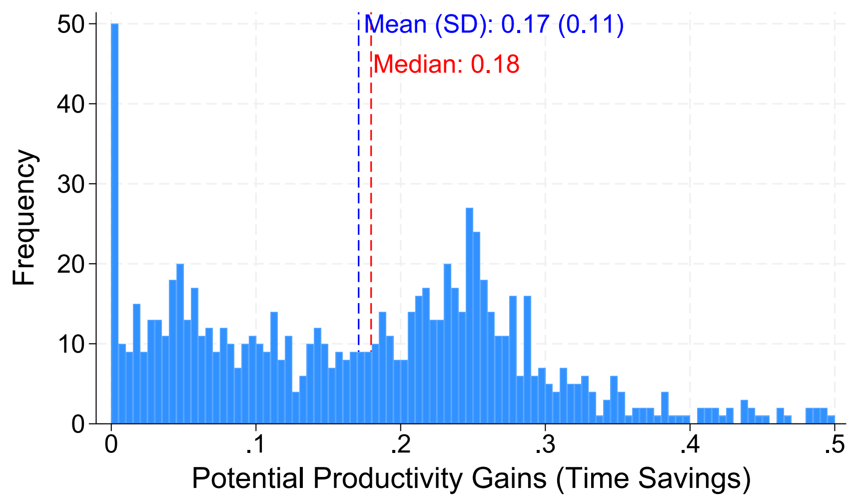
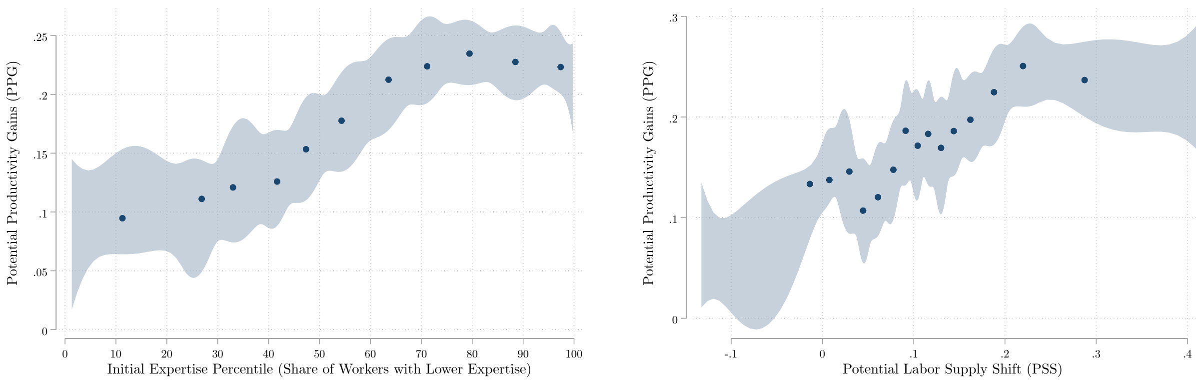


Figure 10: Potential Productivity Gains (PPG) Across Occupations

Notes: The figure shows the distribution of the occupation-level Potential Productivity Gain (PPG_o). PPG_o is defined in Equation 8 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 $Freq_{ot} \times Imp_{ot}$.

We then relate predicted productivity gains to baseline expertise and to the Potential Supply Shift. Figure 11 presents bin-scatter plots of these relationships. Panel 11a plots PPG_o against the occupation's baseline expertise percentile, $(1 - PS_o) \times 100$, and shows that predicted productivity gains generally rise with baseline expertise. Panel 11b shows a positive association between PPG_o and PSS_o, indicating that occupations predicted to experience larger expansions in effective labor supply also tend to be those with larger predicted productivity gains. Together with Figure 9a, these patterns suggest that occupations in roughly the 70th–90th percentiles of baseline expertise combine substantial reductions in effective expertise requirements with relatively large productivity gains. The top of the expertise distribution (roughly the 90th–100th percentiles) is predicted to receive high productivity gains with a relatively small decline in effective expertise, compared with other occupations.



(a) PPG vs. PS

(b) PPG vs. PSS

Figure 11: 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 Equation 8 and PSS_o is defined in Section 3.2.

5 Model: Expertise, Task Removal, Task Transformation, and Productivity

In this section, we build on Autor and Thompson (2025) and develop a task-based general equilibrium model of GenAI that distinguishes three conceptually distinct effects of GenAI on tasks and occupations: (i) an *extensive margin* in which GenAI removes (automates) a subset of tasks and thereby alters the expertise content and possibly the binding expertise barrier of an occupation; (ii) an *intensive margin* in which GenAI expands workers' effective expertise, enabling them to perform tasks previously beyond their unaided expertise (without eliminating the task from labor); and (iii) a *pure productivity* effect in which GenAI augments labor productivity in performing tasks. We use the model to study the implications of GenAI for inequality.

5.1 Environment

Workers and Expertise. The economy is partitioned into major occupational groups indexed by $g \in \mathcal{G}$, Group g contains a mass M_g of workers. Each worker i in group g is endowed with an innate level of expertise $e_i \in \mathbb{R}_+$ drawn from an continuous distribution F_g with density f_g. Expertise is fixed. Workers face potential mobility restrictions: a worker in group g can supply labor only to occupations in that same group [4]. Let $\mathcal{O}_g$ denote the set of occupations available to group g, and $\mathcal{O} := \cup_g \mathcal{O}_g$ the set of all occupations.

Occupations and Discrete Tasks. Each occupation $o \in \mathcal{O}$ consists of a finite set of tasks $T_o = \{1, \ldots, J_o\}$. Each task $t \in T_o$ has a baseline expertise requirement

$$r_{ot} \in \mathbb{R}_+, \tag{9}$$

interpreted as the minimum innate expertise required to perform task t without assistance. Tasks also carry weights $w_{ot} > 0$. Let $h_{ot} \in \{0, 1\}$ indicate whether task (o, t) is "high-expertise" in the sense of requiring specialized knowledge that acts as a barrier to entry. We adopt a hierarchical feasibility technology a la Autor and Thompson (2025) : a worker with expertise e can perform any task with requirement at most e. Occupations bundle tasks and successful production requires completing all tasks that remain assigned to labor.

Assumption 1 (Hierarchical feasibility)**.** A worker of expertise e can perform task (o, t) if and only if $e \geq \widetilde{r}_{ot}$, where $\widetilde{r}_{ot}$ is the (technology-adjusted) expertise threshold faced by labor.

[4] In the main analysis we abstract from occupational group and expertise is the only heterogeneity between workers. In order to take into account limited mobility, in the future iteration of this draft we conduct an exercise in which we only allow worker transitions between 1-digit SOC occupations.

Assumption 2 (Weakest-link task bundling)**.** A worker produces one unit of effective labor in occupation o if and only if she can perform all tasks that remain assigned to labor in that occupation.

Under Assumptions 1–2, the occupation's binding expertise barrier under a technology regime is

$$\widetilde{R}_o \;:=\; \max_{t\in T_o} \widetilde{r}_{ot}. \tag{10}$$

In the baseline without GenAI, $\widetilde{r}_{ot} = r_{ot}$ and thus

$$R_o \;:=\; \max_{t\in T_o} r_{ot}. \tag{11}$$

5.2 Production, Demand, and Wages

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

$$Y_o \;=\; A_o\, L_o, \tag{12}$$

where $A_o > 0$ is labor-augmenting productivity and L_o is employment in occupation o.

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

$$Y \;=\; \left(\sum_{o\in\mathcal{O}} \vartheta_o^{\frac{1}{\sigma}}\, Y_o^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \qquad \sigma > 1, \tag{13}$$

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 (12) yields

$$w_o \;=\; \underbrace{P\, Y^{\frac{1}{\sigma}}}_{\kappa}\, \vartheta_o^{\frac{1}{\sigma}}\, A_o^{1-\frac{1}{\sigma}}\, L_o^{-\frac{1}{\sigma}}, \tag{14}$$

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

$$B_o \;:=\; \kappa\, \vartheta_o^{\frac{1}{\sigma}}\, A_o^{1-\frac{1}{\sigma}}, \tag{15}$$

so (14) is the inverse labor demand curve $w_o = B_o L_o^{-1/\sigma}$.

5.3 Feasibility, Discrete Occupational Choice, and Equilibrium

A key part of the expertise mechanism is that wage inequality arises because low-expertise occupations can be performed by many workers, whereas high-expertise occupations draw from a much smaller pool. This relative scarcity generates wage premia at the top. Incorporating this logic into a competitive labor market is not straightforward, however, because wages are pinned down by realized labor supply—not by the number of workers who could potentially perform the job.

We therefore microfound how *potential eligibility* translates into *actual employment* using a standard discrete-choice model of occupational supply. 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 shocks.[5] This delivers a clean mapping from the upper tail of the expertise distribution to labor supply and wages, while maintaining competitive markets.

Feasibility. Under a technology regime, a worker in group g can work in occupation $o \in \mathcal{O}_g$ if and only if

$$e_i \geq \widetilde{R}_o. \tag{16}$$

Thus a worker with expertise e has feasible set

$$\mathcal{O}_g(e) := \{o \in \mathcal{O}_g : \ e \geq \widetilde{R}_o\}.$$

Because feasibility is hierarchical, $\mathcal{O}_g(e)$ expands (weakly) with e.

Occupational Choice with Idiosyncratic Fit. Workers value wages but also experience idiosyncratic occupation-specific fit, mobility costs, or preferences.

Assumption 3 (Discrete choice shocks)**.** For each worker i in group g and each occupation

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

$o \in \mathcal{O}_g$, utility from choosing occupation o is

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

where $\{\varepsilon_{io}\}_{o \in \mathcal{O}_g}$ are i.i.d. Type-I extreme value with scale parameter $\tau > 0$, independent of e_i. For infeasible occupations ($o \notin \mathcal{O}_g(e_i)$), utility is $-\infty$.

Assumption 3 implies a multinomial logit choice rule among feasible occupations. Conditional on group g, expertise e, and a wage vector w, the probability that a worker chooses occupation o is

$$s_{go}(e; w, \widetilde{R}) \;=\; \frac{\exp(\log w_o/\tau)}{\sum_{k \in \mathcal{O}_g(e)} \exp(\log w_k/\tau)} \, \mathbf{1}\{e \geq \widetilde{R}_o\} \;=\; \frac{w_o^{1/\tau}}{\sum_{k \in \mathcal{O}_g(e)} w_k^{1/\tau}} \, \mathbf{1}\{e \geq \widetilde{R}_o\}. \tag{17}$$

This specification has two attractive properties. First, it prevents double-counting: each worker selects a single occupation, so aggregate labor supplies across occupations sum to M_g. Second, as $\tau \to 0$, choices become sharply concentrated on the highest-wage feasible occupation, recovering the deterministic "highest-paying feasible job" logic as a limit case.

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

$$L_o^S(w, \widetilde{R}) \;=\; M_g \int_0^\infty s_{go}(e; w, \widetilde{R}) \, f_g(e) \, de, \qquad o \in \mathcal{O}_g. \tag{18}$$

Because feasibility is a threshold rule, (18) 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

$$S_o(\widetilde{R}) \;:=\; M_g\big(1 - F_g(\widetilde{R}_o)\big), \tag{19}$$

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 determines the scale of potential labor supply to occupation o: a larger S_o shifts the labor supply curve outward by increasing the number of workers who are able to consider the occupation (Expertise logic). 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—the fraction of eligible workers who choose occupation o once wages in alternative occupations are taken into account. As a result, an increase in S_o raises employment only insofar as occupation o remains attractive relative to workers' outside options.

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,

$$w_o = B_o\, L_o^{-1/\sigma} \qquad \text{and} \qquad L_o = L_o^S(w, \widetilde{R}). \tag{20}$$

Equivalently, substituting (14) into (18) yields a fixed point in wages (or employment). In the quantitative exercise we solve (20) group-by-group, noting that κ scales all wages proportionally.

5.4 Three GenAI effects

We now introduce the three effects of GenAI emphasized in the paper.

5.4.1 Effect 1: Extensive-Margin Task Automation and Expertise Content

On the extensive margin, GenAI can automate a subset of tasks, removing them from the set performed by labor. Let $a_{ot} \in \{0,1\}$ indicate whether task t in occupation o is automated. Define the set of tasks remaining performed by labor:

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

Under automation, labor no longer performs tasks in $T_o \setminus T_o^L$, while the requirements of remaining tasks are unchanged. Hence the post-automation entry barrier is

$$R_o^{\text{ext}} \;:=\; \max_{t \in T_o^L} r_{ot}, \tag{21}$$

5.4.2 Effect 2: Intensive-Margin Expertise Expansion (Task Transformation Without Removal)

On the intensive margin, tasks remain performed by labor, but GenAI can expand workers' effective expertise. We represent this as a mapping from baseline task requirements r_{ot} to technology-adjusted requirements faced by labor:

$$r_{ot}^{\text{int}} \;=\; \rho(r_{ot}), \tag{22}$$

where $\rho : \mathbb{R}_+ \to \mathbb{R}_+$ is increasing.

Assumption 4 (Expertise expansion)**.** ρ is increasing and satisfies $\rho(x) \leq x$ for all $x \geq 0$, with strict inequality on a set of positive measure.

Under Assumption 4, the intensive-margin entry barrier is

$$R_o^{\text{int}} \;:=\; \rho(R_o). \tag{23}$$

5.4.3 Effect 3: Pure Productivity (Labor-Augmenting) Effect

Finally, GenAI may raise the productivity of labor in performing occupational output. We model this as a labor-augmenting shift:

$$A_o^{\text{AI}} \;=\; A_o \cdot \exp(\pi_o), \tag{24}$$

where π_o is the (log) productivity gain induced by GenAI in occupation o.

5.4.4 Combining the Margins

When automation and expertise expansion operate jointly, the resulting entry barrier is obtained by applying $\rho(\cdot)$ to the remaining labor tasks:

$$R_o^{\text{comb}} \;:=\; \rho(R_o^{\text{ext}}). \tag{25}$$

5.5 Expertise Distribution, Outside Options, and Wage Incidence

A central implication of the model is that the wage and employment effects of AI-induced expertise expansions depend not only on how much entry barriers fall, but also on where those barriers lie in the initial distribution of worker expertise and on the set of outside options available to marginal workers. Barrier reductions matter because they expand the mass of workers who can potentially perform an occupation, but the extent to which this potential translates into actual employment depends on how newly eligible workers reallocate across all occupations they can perform.

Potential Eligibility and Expertise Density. Fix an occupation $o \in \mathcal{O}_g$. The mass of workers in group g who satisfy the entry requirement R 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

$$\text{PSS}_o \;:=\; M_g\big[F_g(R_o) - F_g(\widetilde{R}_o)\big], \tag{26}$$

which we refer to as the *potential supply shift*. This object captures how many workers become newly able to consider occupation o, abstracting from how they allocate across feasible alternatives. For small barrier reductions $\widetilde{R}_o = R_o - \Delta R_o$,

$$\text{PSS}_o \;\approx\; M_g\, f_g(R_o)\, \Delta R_o, \tag{27}$$

so the magnitude of the potential supply expansion depends directly on the density of expertise at the occupation's threshold. Barrier reductions that occur in dense regions of the expertise distribution generate large increases in potential competition, whereas reductions at extreme upper thresholds have smaller effects.

Outside Options and Actual Labor Supply. Potential eligibility does not translate one-for-one into employment because newly eligible workers face outside options among all occupations they can perform. Holding wages fixed, the fraction of marginal workers who select occupation o depends on its attractiveness relative to these alternatives. Let

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

denote the outside-option index just below the threshold. The take-up rate of marginally newly eligible workers is

$$s_o^m := \frac{w_o^{1/\tau}}{w_o^{1/\tau} + \Omega_g(R_o^-)}. \tag{28}$$

The induced increase in labor supply at fixed wages is therefore

$$\Delta L_o^S \big|_w \;\approx\; s_o^m \cdot \mathrm{PSS}_o. \tag{29}$$

This expression highlights that even large expansions in eligibility can generate muted employment responses when marginal workers have attractive outside options.

Local wage and employment incidence. To characterize equilibrium responses, 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. Then, to a first order, equilibrium wage and employment changes satisfy

$$\Delta \log w_o \approx \underbrace{\frac{\sigma - 1}{\sigma + \varepsilon_o}\,\pi_o}_{\text{productivity}} \;-\; \underbrace{\frac{1}{\sigma + \varepsilon_o}\, s_o^m\, \frac{\mathrm{PSS}_o}{L_o}}_{\text{expertise expansion}}, \tag{30}$$

$$\Delta \log L_o \approx \underbrace{\frac{(\sigma - 1)\varepsilon_o}{\sigma + \varepsilon_o}\,\pi_o}_{\text{productivity}} \;+\; \underbrace{\frac{\sigma}{\sigma + \varepsilon_o}\, s_o^m\, \frac{\mathrm{PSS}_o}{L_o}}_{\text{expertise expansion}}. \tag{31}$$

These expressions formalize a *productivity–scarcity race*. Productivity gains raise wages by increasing marginal revenue products, while expertise expansions erode scarcity by increasing contestability. The strength of the latter force depends on two empirically measurable objects: the density of workers at the expertise threshold and the quality of marginal outside options.

6 Results: GE Wage and Employment Responses to GenAI

6.1 Overview of the Counterfactual Exercise

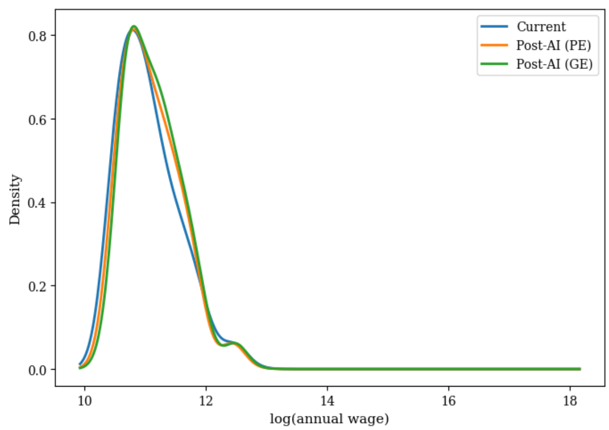
This section quantifies how GenAI affects the distribution of occupational wages through two channels: (i) *expertise expansion*, which lowers entry barriers and expands the set of workers who can perform an occupation, and (ii) *productivity gains*, which raise effective labor productivity. We study three counterfactuals: expertise expansion only, productivity only, and both channels jointly. For each scenario, we compare partial equilibrium (PE), which holds the broader wage structure fixed, to general equilibrium (GE), which allows workers to reallocate across occupations subject to hierarchical feasibility and outside options.

Note that while equations (30) and (31) are useful for intuition and local comparative statics, they have two important limitations. First, they are first-order approximations and are therefore not well suited to analyze the large shocks induced by GenAI. Second, these expressions are valid only locally around a fixed expertise hierarchy. If GenAI reorders occupations in the expertise ranking—so that some occupations move up or down in the hierarchy—the local formulas no longer apply. For these reasons, we solve the model numerically when conducting our counterfactual analysis.

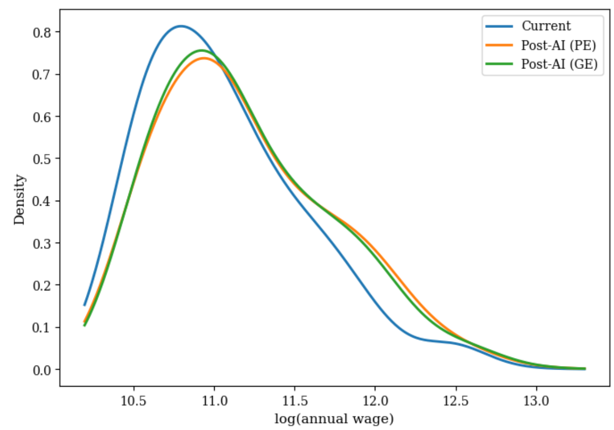
We summarize distributional effects using employment-weighted wage densities and a single table of standard inequality statistics. GE outcomes are our main object of interest; PE results are reported to clarify the role of reallocation.

6.2 The Effect of GenAI on the Wage Distribution

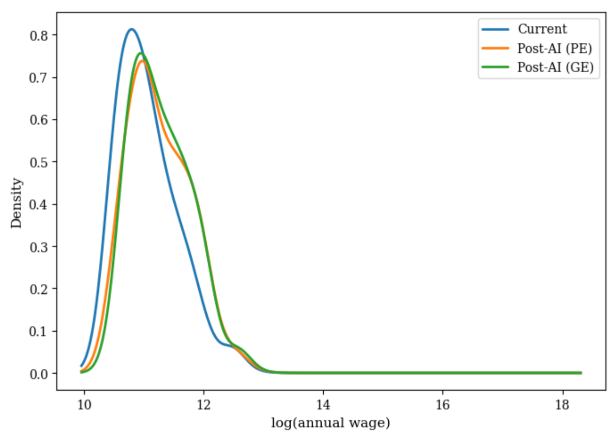
Expertise Expansion Only We begin with the counterfactual in which GenAI lowers expertise barriers but does not affect productivity. Figure 12a plots the employment-weighted wage density under this scenario. Expertise expansion is equalizing. In GE, the variance of log wages falls relative to baseline, and upper-tail dispersion declines substantially. The $p90-p50$ gap falls from 0.79 to 0.68, reflecting reduced scarcity in higher-expertise occupations as entry barriers fall. GE compression is stronger than in PE, indicating that worker reallocation amplifies the wage effects of increased contestability.



(a) Expertise Expansion Only



(b) Productivity Only



(c) Expertise Expansion and Productivity

Figure 12: Employment-Weighted Wage Distribution

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

Productivity Only: We next consider a counterfactual in which AI raises productivity without changing feasibility. Figure 12b shows the resulting wage distributions. Productivity gains increase wage dispersion. Both PE and GE exhibit higher variance of log wages and wider upper-tail gaps relative to baseline. In GE, reallocation dampens but does not eliminate these effects: the $p90-p50$ gap remains substantially above baseline, indicating that productivity gains accrue disproportionately to higher-wage occupations.

Joint Counterfactual: Expertise Expansion and Productivity: Finally, we combine both channels. Figure 12c plots the resulting wage distribution. The joint GE effect reflects a combination of compression and dispersion. Relative to baseline, lower- and middle-wage gaps shrink, while upper-tail inequality remains elevated compared to the supply-only case. The $p50-p10$ gap rises very slightly from 0.47 to 0.48 in GE, while the $p90-p50$ gap remains close to baseline. Overall variance of log wages declines modestly. These patterns reflect an interaction between the two channels: expertise expansion reduces scarcity where expertise is relatively abundant, while productivity gains sustain higher wages at the top.

6.3 Inequality Effects

Table 2 reports inequality statistics under the baseline and each counterfactual. All statistics are employment-weighted and reported in logs.

Table 2: Wage Inequality Under Baseline and GenAI Counterfactuals

Scenario	$\text{Var}(\log w)$	$p10$	$p50$	$p90$	$p50-p10$	$p90-p10$	$p90-p50$
Baseline	0.246	10.505	10.975	11.768	0.469	1.263	0.794
Supply PE	0.224	10.567	11.012	11.732	0.445	1.164	0.720
Supply GE	0.218	10.616	11.082	11.760	0.466	1.143	0.677
Prod PE	0.287	10.548	11.092	11.974	0.545	1.426	0.881
Prod GE	0.279	10.560	11.088	11.945	0.528	1.386	0.858
Both PE	0.256	10.648	11.154	11.969	0.506	1.321	0.814
Both GE	0.244	10.717	11.201	11.965	0.484	1.248	0.764

Notes: Employment-weighted wage moments. "Supply" corresponds to expertise expansion only; "Prod" corresponds to productivity gains only; "Both" combines both channels. PE holds wages fixed outside the shocked occupation; GE allows reallocation across occupations.

7 Conclusion

In this paper, we construct the Potential Supply Shift (PSS) to translate GenAI's task-level effects into an occupation-level change in effective labor supply. We first measure how GenAI changes the expertise required to perform each occupation's task bundle through two channels. On the extensive margin, tasks deemed automatable are removed from labor's bundle. On the intensive margin, we re-rate task expertise under the counterfactual that workers have access to a capable GenAI assistant, capturing task simplification without task removal. Aggregating these task-level objects yields a post-GenAI "combined" occupational expertise requirement. PSS is then the implied change in the share of the workforce qualified to perform the occupation, computed by mapping pre and post expertise thresholds into the employment-weighted distribution of baseline expertise.

PSS exhibits systematic patterns that standard exposure indices do not capture. We document three facts. First, PSS varies widely even among occupations with similar exposure shares, reflecting differences in task composition and where an occupation sits in the baseline expertise distribution. Second, PSS increases with baseline expertise and wages across most of the distribution but declines sharply in the extreme upper tail, where the workforce expertise distribution is thin. Third, PSS is positively associated with predicted augmentation and potential productivity gains, with pronounced non-linearities across the expertise distribution. To interpret the implications of these facts, we develop a task-based general equilibrium model with discrete tasks, hierarchical feasibility, and occupational choice. The model separates task removal, expertise expansion, and productivity augmentation, and maps the implied supply and productivity shocks into wage and employment incidence.

Several limitations qualify the interpretation. We abstract from endogenous task creation and occupational change, and we treat the distribution of worker expertise as fixed, ruling out retraining responses. Some LLM-based counterfactual assessments, especially those about how GenAI changes task expertise, are difficult to validate directly and should be interpreted cautiously. With these caveats, the main conclusion is clear: exposure alone is an insufficient statistic, and incorporating task expertise and both margins of GenAI impact changes the measurement of risk and the predicted distributional incidence.

References

Althoff, L. and Reichardt, H. (2025). Task-specific technical change and comparative advantage.

Autor, D. (2024). Applying AI to Rebuild Middle Class Jobs. Technical report, National Bureau of Economic Research.

Autor, D. and Thompson, N. (2025). Expertise. NBER Working Paper 33941, National Bureau of Economic Research.

Brynjolfsson, E., Chandar, B., and Chen, R. (2025). Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence. Working paper. Latest version available at https://digitaleconomy.stanford.edu/publications/canaries-in-the-coal-mine/.

Eloundou, T., Manning, S., Mishkin, P., and Rock, D. (2024). GPTs Are GPTs: Labor Market Impact Potential of LLMs. *Science*, 384(6702):1306–1308.

Felten, E. W., Raj, M., and Seamans, R. (2023). Occupational Heterogeneity in Exposure to Generative AI. *Available at SSRN 4414065*.

Gmyrek, P., Berg, J., and Bescond, D. (2023). Generative AI and Jobs: A Global Analysis of Potential Effects on Job Quantity and Quality. *ILO Working paper*, 96.

Goldman Sachs (2023). The Potentially Large Effects of Artificial Intelligence on Economic Growth. *Goldman Sachs*, 1(5):268–296.

Hosseini, S. M. and Lichtinger, G. (2025). Generative AI as Seniority-Biased Technological Change: Evidence From U.S. Resume and Job Posting Data. *Available at SSRN*.

ILO (2025). *Generative AI and Jobs: A Refined Global Index of Occupational Exposure*. Number 140. ILO Working Paper.

IMF (2025). Global Impact of AI: Mind the Gap. Technical report, International Monetary Fund.

Johnston, A. and Makridis, C. (2025). The Labor Market Effects of Generative AI: A Difference-in-Differences Analysis of AI Exposure. *Available at SSRN 5375017*.

OECD (2024). Miracle or myth? assessing the macroeconomic productivity gains from artificial intelligence. Technical report, OECD Publishing.

O*NET (2023). O*NET database version 27.2. https://www.onetcenter.org/database.html. Accessed: 2024-2025.

The Budget Lab (2025). Evaluating the Impact of AI on the Labor Market: The Current State of Affairs. Accessed: 11-27-2025.

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.

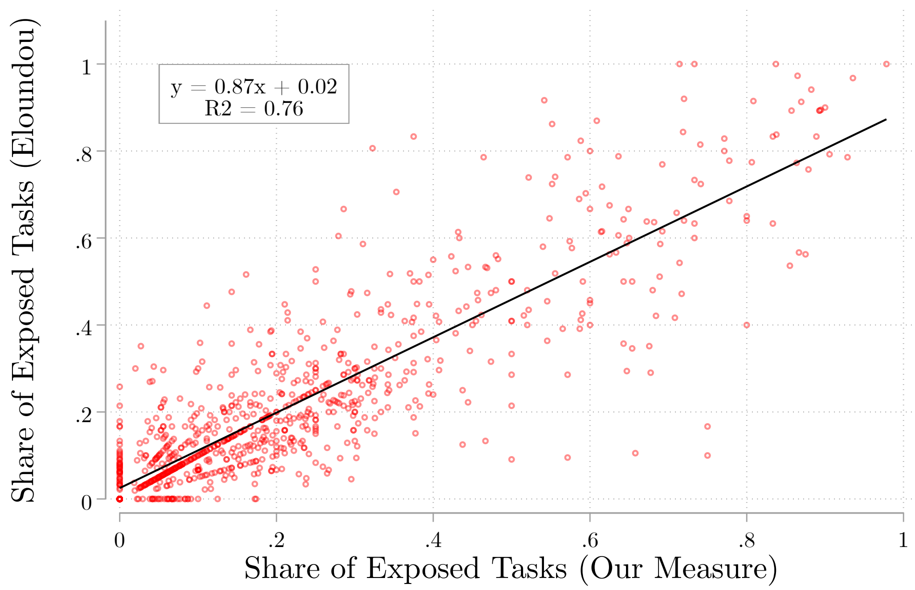


Figure A.1: Comparing Our Automation Exposure Measure to Eloundou et al. (2024)

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:

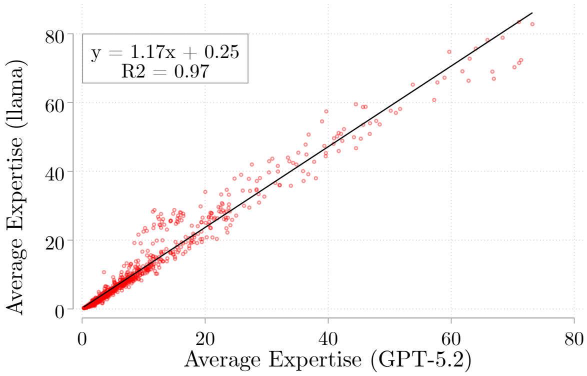
"training$_{m}onths" : number, "confidence" : 0.0 - 1.0$

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. """

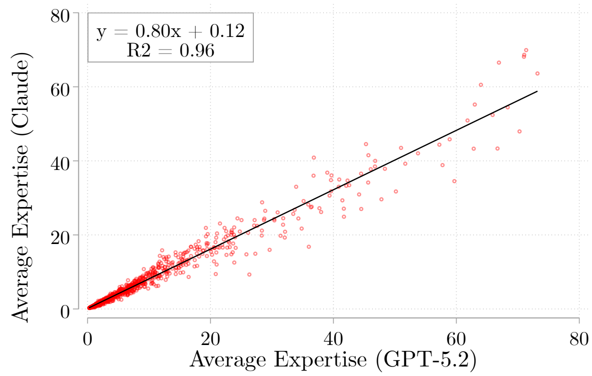
A.5 Validation of the LLM-Based Expertise Measure

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.

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



(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.

experience expected of a new hire.[6] We additionally merge average and median wage levels from the May 2024 Occupational Employment and Wage Statistics (OEWS) provided by the BLS.[7] 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.

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.

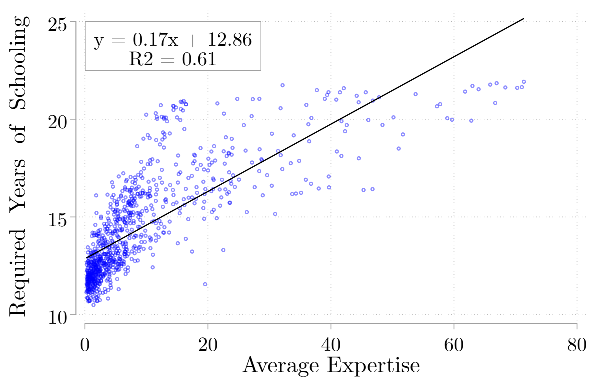
GOAL For the task below, provide TWO expertise ratings AND TWO training-time estimates: 1) WITHOUT access to an LLM assistant 2) WITH access to a capable LLM assistant (current December 2025 abilities)

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.

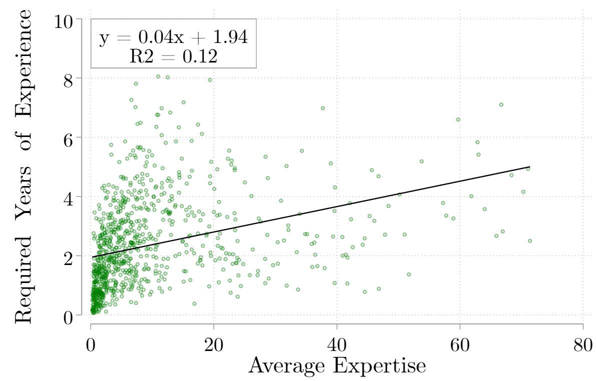
Use the SAME 1–5 scale for both expertise ratings:

[6] 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.

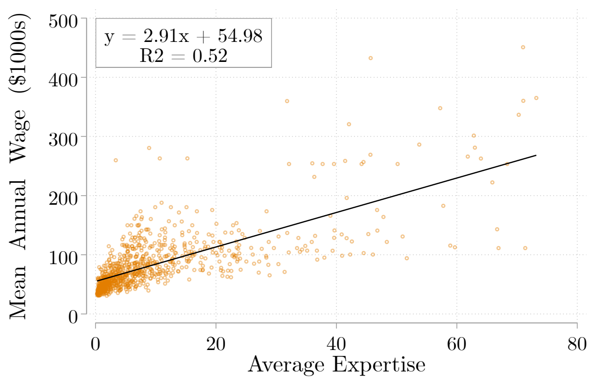
[7] For the OEWS data, see https://www.bls.gov/oes.



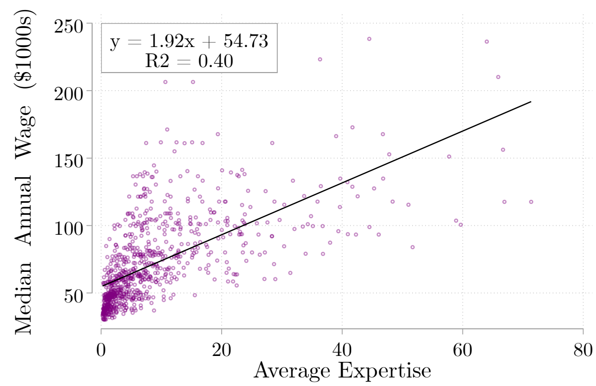
(a) Required Level of Education



(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).

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

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 5.5

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 $\Delta L_o^S|_w \approx s_o^m \text{PSS}_o$, 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 (30). 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 (31). $\square$

A.10 Local matrix comparative statics

This appendix derives the local general-equilibrium wage response in equation (36).

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

Now consider all occupations in a mobility group g jointly. Let $\mathcal{O}_g = \{1, \ldots, J\}$ 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

$$s_j(e; w, R) = \frac{w_j^{1/\tau}}{\sum_{k \in \mathcal{O}_g(e)} w_k^{1/\tau}} \mathbf{1}\{e \geq R_j\}. \tag{32}$$

Employment in occupation j is

$$L_j(w, R) = M_g \int_0^\infty s_j(e; w, R)\, f_g(e)\, de = M_g \int_{R_j}^\infty \frac{w_j^{1/\tau}}{\sum_{k:\, R_k \leq e} w_k^{1/\tau}} f_g(e)\, de. \tag{33}$$

For each occupation j,

$$w_j = B_j L_j^{-1/\sigma}. \tag{34}$$

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

Eliminating L gives J equations in w:

$$\left(\frac{B_j}{w_j}\right)^\sigma = M_g \int_{R_j}^\infty \frac{w_j^{1/\tau}}{\sum_{k:\, R_k \leq e} w_k^{1/\tau}} f_g(e)\, de, \qquad j = 1, \ldots, J. \tag{35}$$

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

$$d \log w = \left(I + \frac{1}{\sigma} E \right)^{-1} \left(d \log B - \frac{1}{\sigma} H \, dR \right), \tag{36}$$

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,

$$d \log B = \left(1 - \frac{1}{\sigma} \right) \pi + \frac{1}{\sigma} d \log \vartheta + d \log \kappa, \tag{37}$$

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 (36) 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 $\mathcal{O}_g = \{1, \ldots, J\}$ denote occupations in mobility group g. Define the elasticity matrix $E \in \mathbb{R}^{J \times J}$ with elements

$$E_{jk} := \frac{\partial \log L_j}{\partial \log w_k} = \frac{M_g}{\tau L_j} \int_0^\infty s_j(e) \left(\mathbf{1}\{j = k\} - s_k(e) \right) f_g(e) \, de. \tag{38}$$

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,

$$\frac{\partial L_j}{\partial R_m} = -M_g f_g(R_m)\big(s_{j,m}^+ - s_{j,m}^-\big), \qquad H_{jm} = \frac{1}{L_j}\frac{\partial L_j}{\partial R_m}. \tag{39}$$

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 (36). 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 (18),

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

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

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

. □