Job Transformation, Specialization, and the Labor Market Effects of AI*

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Abstract

Who will gain and who will lose as AI automates tasks? While much attention has been devoted to job *displacement*, we show that automation creates large, heterogeneous earnings effects through job *transformation*: changes in what tasks workers perform within jobs. We develop a quantitative, task-based framework where workers possess heterogeneous portfolios of task-specific skills; occupations bundle multiple tasks; and automation shifts the relative importance of these tasks within each occupation. We analytically characterize the wage effects of job transformation. To quantify the model, we rely on its structure along with natural language processing (NLP) tools to measure the task content of jobs, estimate the distribution of task-specific skills, and exploit mappings to prominent automation exposure measures to identify task-specific automation shocks. We use the model to study automation by large language models (LLMs). Workers whose skills are concentrated in information-processing tasks lose, exiting their incumbent jobs that no longer reward their comparative advantage. However, other workers in highly exposed office and administrative roles stay and gain as work re-balances toward customer-facing and coordination tasks. Our findings challenge the common practice of equating automation exposure with wage losses.

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1 Introduction

Rapid advances in artificial intelligence (AI) raise the prospect of machines taking over an expanding set of tasks. Who will gain and who will lose from this wave of automation? While public discourse often centers on entire jobs being eliminated (Frey and Osborne, 2017; Susskind, 2020), the historical record suggests that automation transforms what tasks workers perform within jobs long before it erases them (Autor *et al.*, 2003) – a process we refer to as *job transformation*. During the industrial revolution, weavers continued working in large numbers after power-looms were introduced, but their responsibilities shifted toward monitoring multiple looms, fixing mechanical issues, and coordinating workflow across devices (Bessen, 2012). Similarly, in the late 20th century, CNC tools shifted machinists' roles from routine tasks like moving and positioning tools to specialized problem-solving like monitoring and correcting digital processes (Bartel *et al.*, 2007).[1] Early surveys suggest that such task shifts are likely to play a major role in the case of AI (Bonney *et al.*, 2024).

While job transformation appears of first-order importance for understanding the earnings effects of AI, quantifying them presents significant measurement challenges. First, the sign and magnitude of these effects depend on workers' entire portfolios of task-specific skills, which are typically unobserved. Second, the analysis of such effects requires information on the specific tasks being automated and the resulting shifts in workers' time allocation. State-of-the-art models quantifying automation effects therefore typically abstract from job transformation: assuming the tasks in any occupation remain unchanged allows characterizing wage effects through the competing forces of overall labor share declines and productivity gains (Acemoglu and Restrepo, 2018a,b).

We develop a task-based framework of job transformation and use it to quantify how automation through large language models (LLMs) affects wages for heterogeneously skilled workers. To overcome the two measurement challenges, we develop a method to estimate the distribution of task-specific skills and exploit a flexible mapping between our model and influential task-level automation exposure measures (Webb, 2019; Eloundou *et al.*, 2023) to identify task-specific automation shocks. Our analysis yields three main findings. First, LLM-driven automation of information-processing tasks generates more occupational reallocation than past automation by industrial robots. Occupation-level averages therefore provide a limited guide to worker-level outcomes. Second, workers specialized in LLM-exposed tasks leave their transformed jobs and experience wage losses. Third, the same shock creates two groups of winners: incumbent workers remaining in highly exposed office and administrative jobs, freed to spend more time

[1] Systematic studies corroborate these vignettes, demonstrating that the shift from routine tasks toward non-routine analytic and social tasks over the past decades arose predominantly from changes in task content within occupations rather than shifts in occupations' employment shares (Spitz-Oener, 2006; Atalay *et al.*, 2020).

on customer-facing and coordination tasks in which they excel; and workers previously deterred from highly exposed occupations by skill barriers in now-automated tasks, who following automation switch into these transformed roles.

Framework. Our analysis builds on the canonical task-based theoretical framework.[2] In our model, task aggregation occurs at occupational level, with occupations attaching heterogeneous weights to tasks. Each worker has portfolio of (time-invariant) task-specific skills drawn from a log-normal distribution. Each job is filled with one worker. Firms optimally assign tasks to either labor or machines depending on their relative productivity and choose the quantity of machine capital to rent. We integrate this production framework with Roy (1951)-style occupational choice, where workers select occupations based on comparative advantage and time-varying occupational preference shocks.

The model features *task bundling*: to produce positive output, a worker must perform all tasks in an occupation, including tasks where they are relatively less skilled. We do not explicitly model the sources of bundling, which may reflect transaction costs, but view it as plausible — most economists may be more productive at data analysis or math than at emailing, yet emailing remains part of their job — and discipline the degree of bundling in our empirical analysis. Task bundling significantly affects how automation works. Automation reassigns tasks from labor to machines, and in the presence of bundling, this creates job transformation: when an occupation involves an automated task, workers spend less time on that task—zero if fully automated—while time on all other bundled tasks increases proportionately.

The model provides an intuitive characterization of wages and their response to automation based on individual specialization. Wages reflect both absolute advantage (captured by average skill) and comparative advantage (alignment between skill specialization and occupational task requirements). Under automation, the standard displacement and productivity effects appear as an occupation-level shifter that rises or falls depending on which force dominates. Job transformation generates additional effects: workers relatively more skilled at automated tasks than at non-automated bundled tasks tend to lose earnings, whereas wage gains accrue to those relatively unskilled at automated tasks.

To help interpret these wage effects, we offer an analytical decomposition of automation-induced changes in average occupational wages. Beyond the occupation-level shifter, job transformation effects comprise three components. The *task shift* effect captures wage changes from shifting task weights for a representative worker with the population-average bundle of skills. It varies across occupations and can be positive (*task upgrading*) or negative (*task downgrading*) depending on a worker's relative skill in automated versus other bundled tasks. The *selection*

[2] See, in particular, Autor *et al.* (2003); Acemoglu and Autor (2011); Acemoglu and Restrepo (2018b).

effect captures that incumbents in heavily exposed occupations tend to lose from automation, because sorting into exposed occupations signals relatively higher skill in automated tasks compared to the population average. Lastly, the *re-sorting* effect quantifies how occupation-level wages change due to mobility-induced shifts in occupational skill composition. The absolute and relative magnitude of these effects depends on the underlying means and covariance matrix of multi-dimensional skills, which are generally unobserved, reflecting the methodological challenge highlighted above.

Measurement. We estimate the distribution of multi-dimensional skills by leveraging our model's structure and relying only on publicly available data. Consider the conceptual problem first. Suppose we have panel data tracking workers' job histories and know the weights different occupations attach to tasks. To illustrate the identification strategy, consider two occupations, economists and software engineers, where both code, but economists also write. Identification comes from two sources: wage comparisons and occupational choice patterns. If you observe a worker in both occupations, their wage as a software engineer reveals their coding skill, allowing us to infer their writing skill from their economist wage. If we only ever observe the worker as an economist, this reveals their coding skills lie below the threshold at which they would have chosen software engineering. We formalize these intuitions in a maximum-likelihood estimation technique that recovers the means and variance-covariance structure of skills, alongside other structural parameters.[3]

In our empirical implementation, we use the National Longitudinal Survey of Youth (NLSY) 1979, which tracks a large panel of workers' occupations and wages, and measure occupational task weights using natural language processing (NLP) techniques and LLMs. For the latter, our starting point are the approximately 19,000 detailed occupation-specific tasks from the Occupational Information Network (O*NET). To obtain tractable and interpretable tasks, we cluster these detailed O*NET tasks based on the similarity of required skills, yielding 38 task categories that serve as our model tasks. Crucially, because detailed O*NET tasks are widely used to construct empirical task-level exposure measures, our approach yields a direct mapping between model tasks and these exposure measures. Our theory implies that occupational task weights reflect optimal time allocation, so we measure these weights as time shares using an LLM (OpenAI's o3 model), which quantitatively summarizes unstructured information on time allocation across tasks for each occupation.[4] The resulting task-weight matrix indicates task bundling: only 2% of occupations have a single task comprising more than half their time.

Despite its simplicity, the estimated model fits several salient empirical moments well. Be-

[3]Monte Carlo exercises, using simulated data, verify that our method successfully recovers the skill distribution.

[4]To validate this LLM-based approach we conduct extensive exercises, including comparisons to worker-level survey time diary data.

yond generating realistic wage distributions within and between occupations, the model predicts that, conditional on switching occupations, workers tend to move to jobs with task requirements similar to their origin occupation—a pattern consistent with empirical evidence for task-specific human capital (Gathmann and Schönberg, 2010), but hard to explain if skills were fully general or occupation-specific.

Results: the labor market consequences of LLM automation. We use the estimated model to quantify how automation through generative AI differentially affects workers' earnings based on their skill profiles. We focus on automation due to large language models (LLMs), given their rapid rollout (Bick *et al.*, 2024) and policymakers' interest in their labor market consequences (e.g. Cazzaniga, 2024).[5] To identify the tasks most likely to be automated by LLMs, we leverage the direct mapping between our model and the task-level measure of LLM automaton exposure by Eloundou *et al.* (2023). This identifies "Processing and Analyzing Records" as the most exposed task, prevalent in office and administrative support roles such as financial clerks and information and record clerks. To highlight similarities and differences in effects across different technologies, respectively tasks, we also evaluate the consequences of industrial robots, which we identify as automating "Performing Detailed Manual Tasks" by drawing on Webb's (2019) exposure measures.

Our first result is that LLM-induced job transformation prompts occupational reallocation that makes average occupational wages a poor guide to individual worker experiences. While average wages in the most exposed occupations increase following automation, re-sorting effects explain much of this increase. The task requirements of these occupations change significantly – customer-facing and coordination tasks rise in significance as information-processing tasks are automated – so the worker composition before and after automation differs substantially. This reflects a general pattern: re-sorting wage effects are larger for shocks affecting more dispersed skills. Our estimation shows that this holds for tasks exposed to gen-AI, whereas tasks exposed to industrial robots feature lower skill dispersion. Consequently, occupation-level comparisons, while informative about the historical case of automation through industrial robots, provide worse guidance for the labor market consequences of gen-AI. We therefore use the model to characterize the individual-level automation effects.

Our second result highlights which workers lose most from LLM automation: those who selected office and administrative support roles because they excelled at processing and analyzing records. Automation of this task erases these workers' comparative advantage in their current jobs, leading them to exit for the next-best occupation, at the cost of large wage losses. The

[5] See, for instance, recent speeches by IMF and ECB heads Georgieva and Lagarde: `https://www.imf.org/en/Blogs/Articles/2024/01/14/ai-will-transform-the-global-economy-lets-make-sure-it-benefits-humanity` and `https://www.ecb.europa.eu/press/key/date/2025/html/ecb.sp250401_1~d6c9d8df11.en.html`.

experience of these incumbent-leavers reflects the selection effect and underpins a negative relationship between incumbents' wages and exposure that contrasts sharply with occupation-level outcomes.

But not all incumbents lose. Our third result shows that workers who sorted into highly exposed occupations because they excelled at tasks bundled with the automated tasks — such as customer service or administrative coordination—experience wage gains from task upgrading. Automation frees them to allocate more time on non-automated tasks in which they are relatively more productive. Finally, the largest wage gains accrue to workers who switch into highly exposed occupations. These in-switchers would have been productive in exposed occupations except for the large weight on processing and analyzing records. Automating this activity removes a skill-based entry barrier and generates significant wage gains.

Literature. Our paper contributes to a burgeoning literature that evaluates the labor market consequences of AI. It is useful to distinguish between two strands of work. One influential set of papers empirically quantifies how exposed different tasks are to new technologies, AI foremost among them, drawing on information from patents (Webb, 2019; Kogan *et al.*, 2023), capability-specific AI benchmarks (Felten *et al.*, 2018, 2021) and judgment by experts or machines themselves (Brynjolfsson *et al.*, 2018; Eloundou *et al.*, 2023). By themselves, these exposure measures are not informative about downstream earnings consequences. Our paper is distinctly complementary, offering a structural approach to map task exposure measures — in our exercises we specifically draw on the work by Webb (2019) and Eloundou *et al.* (2023) — to individual-level labor market outcomes. Our findings underscore that similarly exposed individuals may experience very different earnings effects.

Methodologically, our work belongs to a second strand of research on AI that uses structural models to evaluate the labor market consequences. The most closely related paper is Hampole *et al.* (2025).[6] Hampole *et al.* (2025) provide a rich, empirical analysis that uses rich CV and job posting data to construct firm- and time-varying measures of exposure to machine learning/AI technologies. This allows them to study heterogeneity in both adoption and downstream effects across firms, whereas our analysis is largely silent on the role of firms. Similar to ours, the theoretical model in Hampole *et al.* (2025) features occupations that involve a collection of tasks, so automation may positively affect wages through reallocation of time to potentially complementary tasks. We make two distinct contributions. First, whereas workers in their model are ex-ante identical, our theory instead features rich, multi-dimensional skill heterogeneity. We contribute a methodology to empirically discipline this heterogeneity. Jointly, theory and

[6]Several concurrent works are developing quantitative task-based models of AI (Fan and Restrepo, 2025; Lashkari *et al.*, 2025; Althoff and Reichardt, 2025). A comparative discussion of these complementary approaches will follow once working papers become available.

measurement of worker skills allow us to show how automation, through job transformation, differentially affects workers' earnings based on their heterogeneous skillets. We are distinctively able to show, in particular, that workers in similarly exposed occupations may fare very differently depending on their specialization. Second, our model is designed to link to a variety of existing measures of task exposure, both backward- and forward-looking ones. This allows us to quantify the labor market consequences of the current wave of generative AI, which is of central interest to both policymakers and society at large.[7]

A second major strand of literature we contribute to is the task-based theory of production.[8] Our first, smaller contribution is to integrate this model of production with dynamic occupational choice (Dix-Carneiro, 2014; Hsieh *et al.*, 2019; Traiberman, 2019).[9] In addition to being instrumental for our measurement strategy, this approach enables us to capture worker reallocation across jobs as an individual-level adjustment mechanism that empirical studies highlight as important (Dauth *et al.*, 2021; Boustan *et al.*, 2022). Our second, major contribution, is to theoretically and quantitatively characterize the labor market effects of automation through job transformation. Theoretically, we relax the assumption that the task content of occupations remains unchanged following automation by modeling production at the level of occupations – instead of the entire economy or industries –and as being subject to task bundling. We stress that, technically, this is a straightforward extension of the canonical task-based model. We sharply characterize the wage effects that emerge on top of the typical displacement and productivity effects.[10] Our primary contribution lies in measurement: To quantify job transformation effects, knowledge of the distribution of task-specific skills is required, which we estimate; and as the labor share is no longer a sufficient statistic for displacement, we show how to leverage measures of technology-specific task exposure to construct automation shocks. In highlighting the importance of task bundling we are related to the contemporaneous work of Autor and Thompson (2025). The two papers are very different in method and focus otherwise. In Autor and Thomp-

[7]Three further strands of research on AI merit highlighting. The first comprises surveys that characterize patterns of adoption and early trends in work reorganization (Bick *et al.*, 2024; Humlum and Vestergaard, 2025b,a). The second line focuses on the possibility that the rate of economic growth will rise because AI can automate at least some of the tasks involved in the production of innovative ideas (Aghion *et al.*, 2017; Jones, 2022, 2024). Incorporating this possibility is beyond the scope of this paper but we note that it would roughly correspond to a level shift in incomes, leaving open the question about the distribution of gains that is at the core of this paper (cf. Autor, 2015, p.28). The third line involves RCTs that causally identify the productivity effects of generative AI adoption in very narrowly defined empirical contexts. Leading examples include Dell'Acqua *et al.* (2023), Noy and Zhang (2023) and Brynjolfsson *et al.* (2025).

[8]See, among others, Autor *et al.* (2003); Acemoglu and Autor (2011); Acemoglu and Restrepo (2018b, 2022); Freund (2023); Restrepo (2024).

[9]Several studies focus on the role of occupational reallocation in response to technological shocks, with an emphasis on GE interactions (Humlum, 2019; del Rio-Chanona *et al.*, 2021; Bocquet, 2022; Fan, 2025).

[10]An additional difference is that, in our approach, positive productivity effects accrue only to exposed occupations, because automated tasks are not bundled together with every other task as in existing models.

son's (2025) model, there is a strict expertise hierarchy, in which more expert workers compete with less expert workers but not vice-versa. In contrast, our model does not feature a notion of expertise as an occupation-level concept. Instead, workers differ in skills across tasks, which don't exhibit any ex-ante ordering. We estimate the distribution of skills directly, so some tasks turn out to be "expert" ex post (i.e., low mean and high dispersion). Autor and Thompson (2025) use their model, alongside a novel reduced-form empirical approach, to resolve the historical puzzle why routine task automation has often raised wages in routine task-intensive occupations while employment declined. In contrast, we provide a fully-structural quantitative analysis of the distributional earnings effects of ongoing or future automation through AI.

Third, our focus on the shifting task content of occupations is motivated by a rich empirical literature which highlights the importance of what we call job transformation. Starting with the seminal work of Autor *et al.* (2003), occupations were conceptualized as bundles of tasks, some of which were more susceptible to computerization. Across many studies, data on task inputs – including the Dictionary of Occupational Titles (DOT) and O*NET, worker surveys (Autor and Handel, 2013; Spitz-Oener, 2006; Freund, 2023), and job ads (Atalay *et al.*, 2020) – highlight that task requirements *within* jobs have shifted significantly over time. The vast majority of this work has not connected these tasks, which are characteristics of jobs, to multi-dimensional skills, which are worker characteristics and not observable in typical data. This paper provides a structural framework to measure the distribution of task-specific skills and to quantify the heterogeneous earnings effects of automation-induced job transformation.

Fourth, we contribute to a growing body of research that demonstrates the importance of accounting for the multi-dimensional nature of skills for labor markets.[11] Thus, in terms of theory, we build on the influential work by Lindenlaub (2017) and likewise study the multidimensional matching between workers and jobs, and how technological change shapes it. Whereas Lindenlaub (2017) studies shifts in the complementarity between skills and production requirements across skill dimensions, this paper adopts a task-based production approach to study automation.[12] Our primary contribution to the broader literature lies in measurement: We develop and implement a methodology to estimate the economy-wide distribution of task-specific skills. We build on work by Guvenen *et al.* (2020) and Lise and Postel–Vinay (2019), who used (military) test scores to approximate the skill distribution among young workers. Our estimation methodology is not anchored by observed test scores, but offers two distinct advantages. First, it is flexible: Because we are not limited by the availability of test score data, our methodology can be applied to any large-scale, representative worker dataset with information on occupations

[11]For recent surveys see Deming (2023) and Woessmann (2024).

[12]Our model also resembles **?**'s (**?**) skills-weights approach, treating skills not as inherently specific to a single production unit – firms in Lazear's work, occupations in ours — but recognizing that different units attach heterogeneous weights to different skills.

and wages. Second, and more importantly, we are not restricted to a low-dimensional list of skills (e.g., cognitive, manual, and interpersonal skills). Instead, we can estimate the distribution of skills in the potentially high-dimensional space of tasks. This allows us to connect our skills estimation to tasks examined in the automation exposure literature and use their measures to discipline our counterfactuals. In summary, this paper closes the gap between the literatures on multi-dimensional skills — which has thought carefully about worker-job sorting and skill measurement but relies on an abstract notion of technological change — and task-based production — which highlights how the demand for specific skills is shaped by automation through robots and AI.[13]

Lastly, by integrating an LLM into our empirical workflow we relate to a nascent literature showing how this tool can be leveraged in economics research. Beyond taking over or assisting in tasks like coding and writing (Korinek, 2023), Athey *et al.* (2024), for example, use a LLM to make predictions about the evolution of worker careers. Our use of LLMs to cluster tasks and measure occupational task allocation is closer to the data processing and classification use cases discussed by Dell (2024). We show that this approach produces results consistent with established measurement frameworks while offering greater flexibility.

Outline. Section 2 presents the theory, Section 3 takes it to the data, Section 4 evaluates the earnings effects of LLMs, and Section 5 offers a concluding discussion.

2 Theoretical Framework

In this section we set out the theoretical environment (Section 2.1), derive optimality conditions and define the equilibrium (Section 2.2). We then define automation in the context of the model and characterize its effects on wages (Section 2.3).

2.1 Environment

Time is discrete and runs forever. The economy is populated by workers and entrepreneurs who produce and consume a single, homogeneous numeraire good.

Workers. There is a unit mass of infinitely lived workers. Before the onset of time, each worker draws and observes their skill vector $s_i \in \mathbb{R}^{n_{\text{skill}}}$, where $s_i \sim \mathcal{N}(\bar{s}, \Sigma_s)$. This skill vector remains fixed forever. In each period t, a worker draws two shocks. First, a productivity shock

[13] Woessmann (2024, p.4) review aptly summarizes the gap in the literature this paper helps fill: "[Although] worker skills motivate the entire task-based approach to how labor markets adjust to technological change, the consideration of multidimensional tasks has not been matched by multidimensional measurement of skills on the empirical side. While the tasks required in different jobs are richly described, worker skills are still mostly proxied rudimentarily by educational degree."

$\varepsilon_{i,t} \sim \mathcal{N}(0, \varsigma^2)$. Second, a vector of occupation-specific preference shocks $u_{i,\cdot,t} \in \mathbb{R}^{n_{\text{occ}}}$, $u_{i,\cdot,t} \sim$ Gumbel$(0, \nu)$.

Production. Production occurs across n_{occ} occupations indexed by $o \in \mathcal{O}$. A job and a single worker are required for production. Production in any occupation o requires that a series of tasks $\tau \in \mathcal{T}$ be carried out. What distinguishes occupations from each other are the weights $\{\alpha_{o,\tau}\}_{\tau\in\mathcal{T}}$ attached to these tasks, with $\sum_{\mathcal{T}} \alpha_{o,\tau} = 1\, \forall o \in \mathcal{O}$. Concretely, the amount of output in an occupation o job is determined by a Cobb-Douglas aggregator with occupation-specific weights $\alpha_{o,\tau}$. Hence, the output of a firm matched with worker i in occupation o is determined by

$$y_{i,o,t} = \prod_{\tau\in\mathcal{T}} x_{i,\tau,t}^{\alpha_{o,\tau}} \tag{1}$$

where $x_{i,\tau,t}$ is the amount of task τ used in production. We interpret these tasks as concrete work steps that need to be performed in a given occupation, such as analyzing business data, moving materials, delivering instruction, etc. A task can be produced using (i) the worker's time or (ii) machine capital. Machine capital has a productivity $\exp(z_\tau)$ at task τ and can be rented from an infinitely elastic capital market at exogenous rate r.[14]

Entrepreneurs. There is a large mass of entrepreneurs. In every period, every worker randomly matches with $N \geq 2$ entrepreneurs. Before the occupation and skill are revealed to the entrepreneur, the entrepreneur makes an automation decision. That is, they decide the set of tasks that are produced with human labor, $\mathcal{T}_l$, and the set of tasks done by machines, $\mathcal{T}_m$. For ease of notation, we suppress human skills for always-automated tasks from the vector of human skills. Thus, $|\mathcal{T}_l| = n_{\text{skills}}$. After automation decisions are taken, the occupation o and the worker's characteristics $(s_{i,\cdot}, \varepsilon_{i,t})$ are revealed. Wages are then set via Bertrand competition. Lastly, the winning entrepreneur forms a match with the worker and optimally allocates the worker's time to human tasks and machine capital to machine tasks. Given the partition of $\mathcal{T}$ into $\mathcal{T}_l$ and $\mathcal{T}_m$, the entrepreneur can freely allocate their worker's unit measure of labor across tasks in $\mathcal{T}_l$, employing effective labor $\exp\left(s_{i,\tau} + \varepsilon_{i,t}\right) \cdot \ell_{i,\tau,t}$ to produce task τ. For any task $\tau \in \mathcal{T}_m$, the firm chooses

[14]Capital supply being infinitely elastic will tend to make average wages rise following the adoption of a new automation technology (Caselli and Manning, 2019), relative to the case of a fixed capital stock (Acemoglu and Restrepo, 2018b, Section I). Our focus lies on the distributional effects.

what quantity of capital m_τ to rent. Thus, the firm optimizes output subject to the constraints

$$\sum_{\tau \in \mathcal{T}_l} \ell_{i,\tau,t} = 1$$
$$x_{i,\tau,t} = \exp\left(s_{i,\tau} + \varepsilon_{i,t}\right) \cdot \ell_{i,\tau,t} \quad \text{if } \tau \in \mathcal{T}_l$$
$$x_{i,\tau,t} = \exp\left(z_\tau\right) \cdot m_\tau \quad \text{if } \tau \in \mathcal{T}_m$$

Occupational choice. In every period t, each worker chooses an occupation to work in. Given their skill vector s_i and productivity shock $\varepsilon_{i,t}$, they fully anticipate their earnings conditional on entering occupation $o \in \mathcal{O}$. We assume that in any period t, the worker chooses the occupation yielding the highest utility given their individual vector of occupation-specific wages and preference shocks $u_{i,\cdot,t}$.[15] We further assume that each worker has log utility over their consumption of the numeraire, which is equal to their wage. Thus, the worker's occupational choice $\hat{o}_{i,t}$ is a function of log wages:

$$\hat{o}_{i,t} = \text{argmax}_o w_{i,o,t} + u_{i,o,t} \tag{2}$$

Automation choice. Entrepreneurs can choose which tasks to produce using machines and which tasks to produce with human labor, but this choice is made before the worker's characteristics and the occupation are revealed. Given some vector $\{z_\tau\}_{\tau \in \mathcal{T}}$, we thus define an optimal automation choice as task sets $(\mathcal{T}_l, \mathcal{T}_m)$ such that no entrepreneur finds it optimal to deviate from this task assignment. Note that the wage paid to a given worker is independent of the automation choice from the perspective of an individual firm considering a deviation. Thus, for any task τ, the condition that no firm finds it optimal to deviate from the assignment $(\mathcal{T}_l, \mathcal{T}_m)$ can be written as

$$\begin{aligned}
&\int \left(\max_{m'} y'(m') - \exp(w(s,o,\varepsilon)) - rm'\right) dF(s|o)dG(\varepsilon)d\Lambda(o) \\
\leq &\int \left(\max_{m} y(m) - \exp(w(s,o,\varepsilon)) - rm\right) dF(s|o)dG(\varepsilon)d\Lambda(o)
\end{aligned} \tag{3}$$

where y' denotes the production function under a given alternative choice of task sets $(\mathcal{T}_l', \mathcal{T}_m')$, and Λ, G, and F denote the distributions of occupational choices, idiosyncratic shocks ε (which are independent of occupational choices), and skills s conditional on occupational choices,

[15] We refrain from introducing exogenous occupational switching frictions. Any persistence in occupational choices therefore arises endogenously from the interaction of task-level skill specialization and heterogeneity in task bundles across occupations.

respectively. The task assignment $(\mathcal{T}_l, \mathcal{T}_m)$ is thus optimal if and only if, for any alternative task assignments $(\mathcal{T}_l', \mathcal{T}_m')$, equation (3) is satisfied.

2.1.1 Discussion

This is a good time to discuss three important assumptions. First, the Cobb-Douglas structure of the occupation-level production function (1) imposes a unit elasticity of substitution across bundled tasks. This represents a common baseline in the literature (e.g. Acemoglu and Restrepo, 2022, pp. 1986), provides a transparent way for measuring $\{\alpha_{o,\tau}\}_{o\in\mathcal{O}}$, as described in Section 3.2, and confers significant tractability when estimating the skill distribution by producing a log-linear wage equation. Substantively, though tasks are q-complements, the Cobb-Douglas structure implies task shares are invariant to shifts in task-specific productivity. This approach is "conservative" with respect to the wage effects of a productivity-enhancing automation shock, because such a shock does not increase the relative demand for human-performed tasks. The assumption thus transparently isolates earnings effects arising from automation-induced shifts in task weights.

Second, skills are time-invariant. This assumption is driven in part by computational constraints in the estimation — solving a forward-looking, high-dimensional decision problem for every worker and period would render the estimation infeasible. Consequently, the model's predictions for the dynamic earnings effects of automation are best interpreted as pertaining to a horizon of three to five years following the shock. Moreover, this modeling choice allows for closed-form analytical approximations that allow us to tractably characterize the aggregate effects of automation in a world with high-dimensional heterogeneous skills, selection, and occupational sorting.

Finally, and importantly, the model is avowedly partial equilibrium in nature: We do not model households' demand for heterogeneous consumption goods and, instead, treat occupational output prices as fixed — equivalently, demand for occupational output is perfectly elastic. This represents a notable departure from a majority of the literature, as we abstract from a central force – i.e. the interplay between non-neutral technological progress and consumer preferences — that can dampen or amplify the wage effects of automation (Autor and Dorn, 2013). While we could relax this assumption, we deliberately impose it to isolate what we argue are important and heterogeneous labor market effects of automation that arise from induced shifts in task requirements within occupations, i.e., job transformation.

In the following sections, we first derive optimal decisions and define the equilibrium under these assumptions, and then theoretically characterize describe automation and its earnings effects.

2.2 Optimality conditions and equilibrium

We next derive formulas for equilibrium wages and occupational choice. We begin by characterizing these variables conditional on the automation decision $(\mathcal{T}_l, \mathcal{T}_m)$. Then, we endogenize the automation decision. Lastly, we define an equilibrium.

Firm optimality and output. For a given partition of tasks $\mathcal{T}$ into tasks assigned to workers and machines ($\mathcal{T}_l$ and $\mathcal{T}_m$, respectively), the firm's problem is

$$\max_{\ell_{i,o,\tau,t}, m_{i,o,\tau,t}} \prod_{\tau \in \mathcal{T}_l} \left(\exp(s_{i,\tau} + \varepsilon_{i,t})\ell_{i,o,\tau}\right)^{\alpha_{o,\tau}} \prod_{\tau \in \mathcal{T}_m} \left(\exp(z_\tau) m_{i,o,\tau,t}\right)^{\alpha_{o,\tau}} - \exp(w_{i,o,t}) \cdot 1 - r \sum_{\tau \in \mathcal{T}_m} m_{i,o,\tau,t}$$
$$\text{s.t.} \sum_{\tau \in \mathcal{T}_l} \ell_{i,o,\tau,t} = 1.$$

Defining $m_{i,o,t} := \sum_{\tau \in \mathcal{T}_m} m_{i,o,\tau,t}$, taking first order conditions yields

$$\ell_{i,o,\tau,t} = \frac{\alpha_{o,\tau}}{\sum_{\tau' \in \mathcal{T}_l} \alpha_{o,\tau'}} \, \forall \tau \in \mathcal{T}_l, \tag{4}$$

$$m_{i,o,\tau,t} = \frac{\alpha_{o,\tau}}{\sum_{\tau' \in \mathcal{T}_m} \alpha_{o,\tau'}} m_{i,o,t} \, \forall \tau \in \mathcal{T}_m, \tag{5}$$

$$\left(\sum_{\tau \in \mathcal{T}_m} \alpha_{o,\tau} \right) \frac{y_{i,o}}{m_{i,o,t}} = r. \tag{6}$$

which implies that log output equals

$$\log y_{i,o,t} = \left[\sum_{\tau \in \mathcal{T}} \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} \log(\alpha_{o,\tau}) \right] - \log\left(\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau} \right) + \left[\sum_{\tau \in \mathcal{T}_m} \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} (z_\tau - \log r) \right]$$
$$+ \left[\sum_{\tau \in \mathcal{T}_l} \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} s_{i,\tau} \right] + \varepsilon_{i,t}.$$

Wages. Zero profits imply $w_{i,o,t} = \log\left(\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}\right) + \log y_{i,o,t}$, which means that the log wage of individual i in occupation o given their skill vector $s_{i,\cdot}$ and their productivity shock $\varepsilon_{i,t}$ can be written as the sum of an occupation-specific intercept, the weighted sum of log skills, and $\varepsilon_{i,t}$:

$$w_{i,o,t} = \mu_o + \sum_{\mathcal{T}_l} \frac{\alpha_{o,\tau}}{LS_o} \cdot s_{i,\tau} + \varepsilon_{i,t} \tag{7}$$

where $\mu_o = \sum_{\tau\in\mathcal{T}} \frac{\alpha_{o,\tau}}{\sum_{\tau\in\mathcal{T}_l}\alpha_{o,\tau}} \log\left(\alpha_{o,\tau}\right) + \left(\sum_{\tau\in\mathcal{T}_m} \frac{\alpha_{o,\tau}}{\sum_{\tau\in\mathcal{T}_l}\alpha_{o,\tau}}\left(z_\tau - \log r\right)\right)$ and $\text{LS}_o = \sum_{\tau\in\mathcal{T}_l}\alpha_{o,\tau}$ is the labor share in occupation o. For future reference, it is useful to define the following matrix of task weights.

Remark 1 (Task-weight matrix.)**.** *The matrix A, defined as*

$$A = \begin{pmatrix} \frac{\alpha_{1,1}}{LS_1} & \frac{\alpha_{1,2}}{LS_1} & \cdots & \frac{\alpha_{1,n_{skill}}}{LS_1} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\alpha_{n_{occ},1}}{LS_{n_{occ}}} & \frac{\alpha_{n_{occ},2}}{LS_{n_{occ}}} & \cdots & \frac{\alpha_{n_{occ},n_{skill}}}{LS_{n_{occ}}} \end{pmatrix} \in \mathbb{R}^{n_{occ}\times n_{skill}} \tag{8}$$

summarizes the relative weights attached to each task $\tau \in \mathcal{T}_l$ across occupations $o \in \mathcal{O}$. The row vector $A_o := A_{o,\cdot}$ contains the task weights corresponding to occupation o.

Using this notation, we can alternatively write the vector of wages for a worker with skill vector s as

$$w = \mu + As + \varepsilon_{i,t} \in \mathbb{R}^{n_{\text{occ}}}$$

The wage equation allows for the following intuitive decomposition:

$$w_{i,o,t} = \mu_o + \underbrace{\frac{1}{n_{\text{skill}}}\sum_{\mathcal{T}_l} s_{i,\tau}}_{\text{scalar absolute advantage}} + \text{Cov}\left(n_{\text{skill}}\cdot\frac{\alpha_{o,\cdot}}{LS_o}, \underbrace{s_{i,\cdot} - \frac{1}{n_{\text{skill}}}\sum_{\mathcal{T}_l} s_{i,\tau}}_{\text{specialization vector}}\right) + \varepsilon_{i,t}$$

where the covariance operator is with respect to equal weights. The wage of a worker thus depends on their absolute advantage (captured by the average skill) and on how much the worker specializes in the skills that are important for that occupation (captured by the covariance term).

Occupational choice. Given the utility maximization problem in equation (2), the probability for individual i to choose occupation o conditional on their wage vector $w_{i,\cdot}$ is

$$P(\hat{o} = o|w_{i,\cdot}) = \frac{\exp(w_{i,o}/\nu)}{\sum_{o'}\exp(w_{i,o'}/\nu)} \tag{9}$$

Optimal automation choice. The optimal output and wage equations above were derived for a given assignment of tasks to labor or machines. We now discuss the *optimal* assignment. Using the expectations operator in place of integrals and substituting in optimality conditions, we can also write equation (3) as

$$
\begin{aligned}
&\mathbb{E}_{(s|o),\varepsilon,o}\left[\exp\left(\mu_o' + \sum_{\tau\in\mathcal{T}_l'} \frac{\alpha_{o,\tau}}{\sum_{\tau\in\mathcal{T}_l'}\alpha_{o,\tau}} s_{i,\tau} + \varepsilon_{i,t}\right)\right] \\
&\leq \mathbb{E}_{(s|o),\varepsilon,o}\left[\exp\left(\mu_o + \sum_{\tau\in\mathcal{T}_l} \frac{\alpha_{o,\tau}}{\sum_{\tau\in\mathcal{T}_l}\alpha_{o,\tau}} s_{i,\tau} + \varepsilon_{i,t}\right)\right].
\end{aligned}
\tag{10}
$$

A task assignment is optimal if it satisfies the above equation for any alternative task assignment $(\mathcal{T}_l', \mathcal{T}_m')$. It can be shown that it is always possible to find values of $\{z_\tau\}_{\tau\in\mathcal{T}}$ that justify a given initial task assignment $(\mathcal{T}_l, \mathcal{T}_m)$ as optimal.

We define the automation threshold $\bar{z}_\tau$ for a given task τ as the point at which Equation (10) holds with equality. That is, holding occupational choices constant, the average wage in the economy stays constant whether or not task τ is automated. It can be verified that, given an initially optimal assignment, there is such a threshold value $\bar{z}_\tau$ and it is finite for any task.

Equilibrium. An equilibrium is defined as a tuple of automation choices $(\mathcal{T}_l, \mathcal{T}_m)$ and a joint distribution Γ of occupation choices, log wages w, log skills s and idiosyncratic productivity shocks ε., such that: (i) equation (3) holds for any alternative choice of task sets $(\mathcal{T}_l', \mathcal{T}_m')$; (ii) equation (7) holds at any point in the distribution (that is, firms make zero profits); (iii) the marginal distribution of occupations conditional on wages follows equation (9) (that is, workers optimize); and (iv) the unconditional marginal distributions of skills s and occupational shocks ε follow $\mathcal{N}(\bar{s}, \Sigma_s)$ and $\mathcal{N}(0, \varsigma^2 I)$, respectively.

2.3 The wage effects of automation in theory

We next describe how automation of a particular task $\tau^\star$ is formalized and characterize the induced wage change as a function of skills. Throughout we allow for arbitrarily large shocks with potentially non-linear effects rather than relying on perturbation methods.

2.3.1 Automation in the model

We model an automation shock as a one-time, permanent change of $z_{\tau^\star}$ that leads to the reassignment of task $\tau^\star$ from labor to machines. Let the prime symbol denote variables after an automation shock in period $t^\star$ and let $(\mathcal{T}_l, \mathcal{T}_m)$ be the initial task allocation. We assume that the shock sets $z'_{\tau^\star} = \bar{z}_{\tau^\star}$; that is, the new value of $z_{\tau^\star}$ is just high enough to make automating this task optimal for firms. The new task sets are thus

$$\mathcal{T}_l' = \mathcal{T}_l \cup \tau^\star \qquad \text{and} \qquad \mathcal{T}_m' = \mathcal{T}_m \backslash \tau^\star.$$

Associated with this shock is a change in the occupational task weight matrix A, as defined in Remark 1, whereby automation reduces the weight on the automated task to zero and increases the weight on all other entries proportional to their weight:

$$\begin{aligned} A_o' - A_o &= \begin{pmatrix} \frac{\alpha_{o,1}}{LS_o'} \cdot \frac{\alpha_{o,\tau^\star}}{LS_o} & \frac{\alpha_{o,2}}{LS_o'} \cdot \frac{\alpha_{o,\tau^\star}}{LS_o} & \dots & -\frac{\alpha_{o,\tau^\star}}{LS_o} & \dots \end{pmatrix} \\ &= \begin{pmatrix} \frac{\alpha_{o,1}}{LS_o'} & \frac{\alpha_{o,2}}{LS_o'} & \dots & -1 & \dots \end{pmatrix} \cdot \frac{\alpha_{o,\tau^\star}}{LS_o} \\ &= (A_o' - \iota_{\tau^\star}) \cdot \frac{\alpha_{o,\tau^\star}}{LS_o} \end{aligned}$$

The change in the occupational wage vector of a worker i arises is a function of this change:

$$\begin{aligned} \Delta w_{i,o} = w_{i,o}' - w_{i,o} &= \Delta\mu_o + (A_o' - A_o)s + \Delta\varepsilon_i \\ = \Delta\mu_o + \frac{\alpha_{o,\tau^\star}}{LS_o} &\left(\sum_{\mathcal{T}_l \backslash \tau^\star} \frac{\alpha_{o,\tau}}{LS_o - \alpha_{o,\tau^\star}} s_{i,\tau} - s_{i,\tau^\star} \right) + \Delta\varepsilon_i \end{aligned} \tag{11}$$

where

$$\Delta\mu_o = \frac{\alpha_{o,\tau^\star}}{LS_o - \alpha_{o,\tau^\star}} \left(z_{\tau^\star} - \log r + \mu_o \right).$$

Equation (11) captures two important terms. First, workers are more likely to see increases in their origin-occupation wage when $\Delta\mu_o$ is large. This effect captures both the negative displacement and the positive productivity effects which together fully characterize the effects of automation in the canonical task-based model. In our model, a second important effect shapes earnings responses: the shift in task weights, which we refer to as *job transformation*. This second component depends on the worker's task-specific skills: Workers are more likely to benefit if they are relatively unskilled in automated task relative to other tasks, where the latter are weighted by the loadings of their current occupation.[16]

Partial automation. This way of conceptualizing automation nests the case where a skill becomes *partially* automated. A skill is said to be partially automated when A_o changes in a way

[16]This mechanism mirrors the analysis of team complementarities under skill specialization in Freund (2023): Your productivity is enhanced by a coworker – whether human or artificial – insofar as their presence enables you to focus on those task you are best at; and the magnitude of this complementarity effect is increasing in the degree of skill specialization.

that does not set the loading of the automated skill to zero:

$$A'_o - A_o = (A'_o - \iota_{\tau^\star}) \cdot \frac{\alpha_{o,\tau^\star}}{LS_o} \cdot \delta_{\tau^\star}, \quad \delta_{\tau^\star} \in (0,1)$$

To interpret this case, suppose $\tau^\star$ comprises two distinct tasks instead of one. We effectively suppose workers' skills for these two tasks are always identical – that is, perfectly correlated with identical skill means and standard deviations – but only one of the two tasks can be automated.

2.3.2 The role of task bundling

We just saw that in our model automation affects wages by altering the task content of occupations. We next explain that these effects distinctively arise when the economy exhibits *task bundling*; that is, multiple tasks are performed concurrently within the same occupation. We use the following nomenclature:

Remark 2 (Task bundling.)**.** *An occupation features* ***task-bundling*** *if*

$$|\{\tau \in \mathcal{T}_l : \alpha_{o,\tau} > 0| > 1.$$

Conversely, the economy features a ***no bundling property*** *if no occupation features task-bundling:*

$$|\{\tau \in \mathcal{T}_l : \alpha_{o,\tau} > 0| = 1 \quad \forall o \in \mathcal{O}.$$

In a no-bundling economy, there exists an assignment function $g : \mathcal{O} \to \mathcal{T}$ that pins down the unique task required in any given occupation.[17] In this case, the wage equation reduces to

$$w_{i,o,t} = \mu_o + s_{i,g(o)} + \epsilon_{i,o,t}. \tag{12}$$

In a no-bundling economy, workers in an occupation o subject to automation thus experience wage changes that are solely driven by changes in the occupation-specific shifter, i.e. $\Delta\mu_o$. The wage changes are, thus, driven by the well-understood balance (between negative displacement effect, associated with a declining labor share, and positive productivity effects, driven by $\bar{z}_{\tau^\star}$).[18] Crucially, workers do not experience any effects from a changing task mix of their occupation. Moreover, conditional on staying in the same occupation, all workers in an occupation experience the same wage change.[19]

[17] A special case of this is the case where $A = I$. With this case, our model nests the standard Roy model. Note that occupations having the same A_o is not sufficient for them to be perfect substitutes from a worker's perspective, as they may involve labor shares or different machine tasks with differing productivities.

[18] For a detailed review see **?**.

[19] A subtle difference in the operation of the positive productivity effects compared to the canonical model is

In contrast, under task bundling, individual wages change also because automation shifts the task content of their occupation. Equation (11) describes these effects for an individual worker. The next section offers a characterization of these wage effects due to job-transformation.

2.3.3 The distributional effects of automation

We next characterize the economy-wide distributional effects of automation in the presence of task bundling by deriving a transparent decomposition of occupation-level wage changes due to automation.[20]

Remark 3 (Occupational wage change.)**.** *The occupation-level average wage change arising from automation is*

$$
\begin{aligned}
&\mathbb{E}[w'_o|\hat{o}'=o]-\mathbb{E}[w_o|\hat{o}=o]\\
&=\overbrace{\mathbb{E}[w'_o|\hat{o}=o]-\mathbb{E}[w_o|\hat{o}=o]}^{\Delta w_o \textit{ of incumbents}}+\overbrace{\mathbb{E}[w'_o|\hat{o}'=o]-\mathbb{E}[w'_o|\hat{o}=o]}^{\textit{re-sorting}}\\
&=\overbrace{\underbrace{\Delta\mu_o}_{\textit{productivity and displacement}}+\underbrace{(A'_o-A_o)\cdot\bar{s}}_{\textit{task shift}}+\underbrace{(A'_o-A_o)(\bar{s}_{|o}-\bar{s})}_{\textit{selection}}}^{\Delta w_o \textit{ of incumbents}}+\overbrace{\mathbb{E}[w'_o|\hat{o}'=o]-\mathbb{E}[w'_o|\hat{o}=o]}^{\textit{re-sorting}}\\
&=\overbrace{\underbrace{\Delta\mu_o}_{\textit{productivity and displacement}}+\underbrace{(A'_o-A_o)\cdot\bar{s}}_{\textit{task shift}}+\underbrace{\nu^{-1}(A'_o-A_o)\Sigma\left(A_o^\intercal-\sum_{o''}h_{o''}(\bar{s}_{|o})A_{o''}^\intercal\right)}_{\textit{selection}}}^{\Delta w_o \textit{ of incumbents}}\\
&\quad\underbrace{+\,\nu^{-1}A'_o\Sigma\left(\left((A'_o-A_o)^\intercal-\sum_{o''}\left(h'_{o''}(\bar{s}'_{|o})(A'_{o''})^\intercal-h_{o''}(\bar{s}_{|o})A_{o''}^\intercal\right)\right)\right)}_{\textit{re-sorting}}.
\end{aligned}
\tag{13}
$$

worth noting. In that model, considering for example Acemoglu and Restrepo (2022), specifically equations (6) and (13), the productivity effect raises the wages of *all* workers. What underlies this feature is the assumption that substitution across all tasks is governed by a uniform elasticity parameter. In contrast, our model generally features non-uniform task substitutability in production. While tasks are combined with a Cobb-Douglas aggregator within any occupation, many tasks may receive zero weight in the bundle defining a given occupation. (Indeed, our empirical analysis will show A_o is be relatively sparse for most occupations.) As a consequence, when task τ^* is automated, *both* displacement and productivity effects are zero for any occupation placing zero weight on τ^*. While not at the center of our analysis, we view this as a plausible feature of our model.

[20]We rely on Laplace approximations to derive our results in this section. This method approximates a posterior distribution with an appropriately chosen multivariate normal distribution. Details are in Appendix A.1.1.

where

$$\bar{s}_{|o} = \bar{s} + \nu^{-1}\Sigma \overbrace{\left(A_o^\intercal - \sum_{o''} h_{o''}(\bar{s}_{|o}) A_{o''}^\intercal\right)}^{\textit{relative task intensity of occupation } o} \tag{14}$$

is the posterior skill mean of workers choosing occupation o *and*

$$h_o(s) = \frac{\exp(\nu^{-1}\mu_{o'} + \nu^{-1}A_{o'} \cdot s)}{\sum_{o''} \exp(\nu^{-1}\mu_{o''} + \nu^{-1}A_{o''} \cdot s)} \tag{15}$$

is the employment share of occupation o *for workers with skill* s.

The first line of equation (13) captures occupational wage effects when worker composition is held constant. The second line captures wage changes from worker re-sorting into and out of occupation o. We discuss each term individually.

- The first term captures the net impact of the standard *displacement and productivity effects*. These effects operate even without task bundling, whereas the remaining terms are unique to economies with task bundling.
- The *task shift* effect captures how shifts in occupational task weights alter the productivity of an average worker and therefore wages. These effects can be positive when the task composition of the occupation shifts to more productive tasks ("task upgrading") or negative otherwise ("task downgrading").
- The *selection* term captures that incumbent workers in occupation o may have skills different from the population average and therefore respond differently to automation. Equation (14) characterizes the posterior mean skill of those choosing occupation o: it exceeds $\bar{s}$ for those tasks used more intensively in o, especially for tasks with high skill variance. The selection effect tends to be negative for more exposed occupations, since for these occupations A_o has larger positive entries exactly where $(A'_o - A_o)$ is negative. This effect strengthens when selection into automated skills is stronger, which occurs when ν is low and when skill dispersion is high for the automated task.
- The *re-sorting* effect captures that workers choosing occupation o after automation may have a different skill distribution than before. For exposed occupations, the sign is generally positive under full automation. The effect strengthens when skills, especially heavily utilized non-automated skills, are more dispersed. It can also be more pronounced for

more dispersed automated skills when they correlate negatively with other skills heavily utilized in affected occupations.

This decomposition illustrates that the effects of automation, especially as they relate to the implications of task bundling, depend in a critical way on the underlying distribution of worker skills s; that is, both the skill means $\bar{s}$ and the co-variance matrix Σ_s are informative about the properties of different types of automation shocks. A quantitative assessment of such shocks thus requires a careful estimation of these objects using real-world data. As we show in the following sections, our model provides a natural framework for this estimation.

3 Model Meets Data

We now take the theoretical model to data. We begin by describing the theoretical foundations for our approach to estimating the model's parameters (Section 3.1), then explain its empirical implementation (Section 3.2), validate it in Monte-Carlo exercises (Section 3.3), and finally present the estimation results alongside a comparison of the model along a few important empirical dimensions (Section 3.4).

3.1 Estimation methodology

To estimate the parameters of the model, the following data are required: (i) a panel of workers, indexed by i, for whom both wages $w_{i,t}$ and occupational choices $\hat{o}_{i,t}$ are observed over time; (ii) the occupational task weight matrix A, as defined in Remark 1; as well as (iii) a measure of occupation-level labor shares LS_o. While (i) and (iii) are relatively weak data requirements[21], (ii) is more involved. We argue that it is possible to obtain good measures of (iii) directly from the data and discuss the construction of our empirical measure of A in Section 3.2.

Conditional on observing (i)-(iii), we make two identifying assumptions. First, we assume that the model is in steady state throughout our estimation window. Second, in the initial steady state there is only one composite machine task with productivity normalized to $\log r$. This implies that the intercept term

$$\begin{aligned}\mu_o &= \sum_{\tau\in\mathcal{T}} \frac{\alpha_{o,\tau}}{\sum_{\tau\in\mathcal{T}_l}\alpha_{o,\tau}} \log\left(\alpha_{o,\tau}\right) + \left(\sum_{\tau\in\mathcal{T}_m} \frac{\alpha_{o,\tau}}{\sum_{\tau\in\mathcal{T}_l}\alpha_{o,\tau}} \left(z_\tau - \log r\right)\right) \\ &= \sum_{\tau\in\mathcal{T}_l} A_{o,\tau} \log\left(A_{o,\tau}\cdot LS_o\right) + \frac{1-LS_o}{LS_o}\left(\log LS_o\right)\end{aligned}$$

[21] We discuss the construction of occupation-level labor shares in Appendix B.3

depends only on occupational labor shares $LS_o = \sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}$ and elements of A and is therefore observable for all occupations.

Under these conditions, we can estimate the model with maximum likelihood techniques. In what follows, let $\hat{o}_{i,t}$ denote the recorded occupation choice of worker i in period t and $-\hat{o}_{i,t}$ be the set of occupations not chosen in period t. Let A be the matrix defined in (8). For a given worker observed in occupations $(\hat{o}_{o,1}, \ldots, \hat{o}_{i,T})$ and earning wages $(w_{i,\hat{o}_1,1}, \ldots, w_{i,\hat{o}_T,T})$,

$$\begin{pmatrix} s_1 \\ \vdots \\ s_{n_{\text{skill}}} \\ w_{i,\hat{o}_1,1} \\ \vdots \\ w_{i,\hat{o}_T,T} \end{pmatrix} = \begin{pmatrix} 0 \\ \vdots \\ 0 \\ \mu_{\hat{o}_1} \\ \vdots \\ \mu_{\hat{o}_T} \end{pmatrix} + \begin{pmatrix} I & 0 \\ A_{(\hat{o},\ldots,\hat{o}_T),\cdot} & I \end{pmatrix} \cdot \begin{pmatrix} s_1 \\ \vdots \\ s_{n_{\text{skill}}} \\ \varepsilon_{i,1} \\ \vdots \\ \varepsilon_{i,T} \end{pmatrix}, \quad \text{where} \begin{pmatrix} s_1 \\ \vdots \\ s_{n_{\text{skill}}} \\ \varepsilon_{i,1} \\ \vdots \\ \varepsilon_{i,T} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \bar{s}_1 \\ \vdots \\ \bar{s}_{n_{\text{skill}}} \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \begin{pmatrix} \Sigma_s & 0 \\ 0 & \varsigma^2 I \end{pmatrix} \right).$$

Thus, $w_{i,\hat{o}_{i,\cdot},\cdot}$ and s_i are jointly normal and thus yields easy to compute formulas for the distribution of $s_i|w_{i,\hat{o}_{i,\cdot},\cdot}$. The likelihood of observing $(w_{i,\hat{o}_{i,\cdot},\cdot}, \hat{o}_{i,\cdot})$ is then given by

$$\begin{aligned} \mathcal{L}(w_{i,\hat{o}_{i,\cdot},\cdot}, \hat{o}_{i,\cdot}|\nu, \varsigma, \bar{s}, \Sigma_s) = \prod_i \int_s \Bigg[\left(\int_{w_{i,-\hat{o}_{\cdot},\cdot}} \prod_t P(\hat{o}_{i,t}|w_{i,\cdot,t}, \nu) \cdot f(w_{i,-\hat{o}_{i,t},t}|s, w_{i,\hat{o}_{i,\cdot},\cdot}, \varsigma) \right) \\ \cdot f(s|w_{i,\hat{o}_{i,\cdot},\cdot}, \varsigma, \bar{s}, \Sigma_s) \Bigg] \cdot f(w_{i,\hat{o}_{i,\cdot},\cdot}|\varsigma, \bar{s}, \Sigma_s) \end{aligned}$$

This expression involves a high-dimensional integral which makes it intractable. To overcome this challenge, we use Monte Carlo integration to compute a numerical approximation of the likelihood instead of evaluating this expression analytically. That is, instead of maximizing the analytical likelihood, we instead maximize the mean of a simulated statistical object that converges to the likelihood value for large sample sizes, n_0. It can be shown that, as $n_0 \to \infty$, the argmax of this object converges to the true maximum likelihood estimate under mild regularity conditions. We find that, in practice, $n_0 = 40$ yields a sufficiently accurate approximation to deliver satisfactory results in a Monte Carlo exercise, which we report below.

Concretely, our implementation of this idea is as follows: For all individual workers i, we generate n_0 draws from

$$f(w_{i,-\hat{o}_{i,\cdot},\cdot}|w_{i,\hat{o}_{i,\cdot},\cdot}, \varsigma, \bar{s}, \Sigma_s) = \int_s f(w_{i,-\hat{o}_{i,\cdot},\cdot}|s, w_{i,\cdot,\hat{o}_{i,\cdot}}, \varsigma) f(s|w_{i,\hat{o}_{i,\cdot},\cdot}, \varsigma, \bar{s}, \Sigma_s).$$

These draws can be generated by (i) drawing from the distribution $s_i|w_{i,\hat{o}_{i,\cdot},\cdot}$, (ii) computing $\varepsilon_{i,t}$

for every period (as a deterministic function of s_i and $w_{i,\hat{o}_{i,t},t}$), and (iii) computing the resulting vector of all occupational wages in every period. Using these wages, we then evaluate the mean of $P(\hat{o}_{i,t}|w_{i,\hat{o}_{i,\cdot},\cdot},\nu)$ to obtain an estimator for $\mathcal{L}_i(\theta)$:

$$\hat{\mathcal{L}}_i(w_{i,\hat{o}_{i,\cdot},\cdot},\hat{o}_{i,\cdot}|\nu,\varsigma,\bar{s},\Sigma_s)=\left(\frac{1}{n_0}\sum_j\prod_t P(\hat{o}_{i,t}|w_{j,\cdot,t},\nu)\right)\cdot f(w_{i,\hat{o}_{i,\cdot},\cdot}|\varsigma,\bar{s},\Sigma_s)$$

Holding constant all random variables in the estimator, we then proceed to maximize this objects over the parameter space $\theta=(\bar{s},\Sigma_s,\nu,\varrho)$. This parameter space is large and requires efficient numerical optimization methods. We utilize stochastic gradient descent paired with auto-differentiation techniques that allow us to efficiently compute gradients of $\hat{\mathcal{L}}_i$. Details are relegated to Appendix C.1.

3.2 Data & measurement

As noted, we require three data sources: a worker panel with information on wages and occupational choices, the occupational task weight matrix A, and occupational labor shares. For the worker panel we use the National Longitudinal Survey of Youth (NLSY) 1979. We construct the task weight matrix from a list of detailed occupational tasks from O*NET and by leveraging natural language processing (NLP) tools as well as large language models (LLMs). Lastly, we construct occupational labor shares using data from the Bureau of Economic Analysis (BEA). This section explains data sources and processing in detail.

NLSY. The NLSY 1979 tracks 6,033 workers' occupations and wages between 1979 and 2018, comprising 110,618 total observations. We construct an annual panel comprising each individual's primary job (if any), where in the case of multiple jobs the "primary job" is selected based on weekly hours worked. Wages are deflated using the CPI (1982-1984=100). We drop individuals in the military sample and the minority oversample. Following Lise and Postel-Vinay (2020), we create a harmonized occupational classification at the SOC-2000 level using crosswalks developed in Sanders (2012). We use the "minor groups" of occupations, of which there are 93 in our data.

Tasks & occupational task weights. We construct the occupational task weight matrix A defined in Remark 1 in two main steps. In step one, we cluster approximately 20,000 detailed tasks with similar skill requirements using NLP. In step two, we measure the occupational allocation of time across these task clusters using LLMs. Figure 1 summarizes this workflow, and Figure 2 illustrates the mapping from tasks to clusters with examples. Appendices B.1 and B.2 contain further details on the use of clustering algorithms and LLMs.

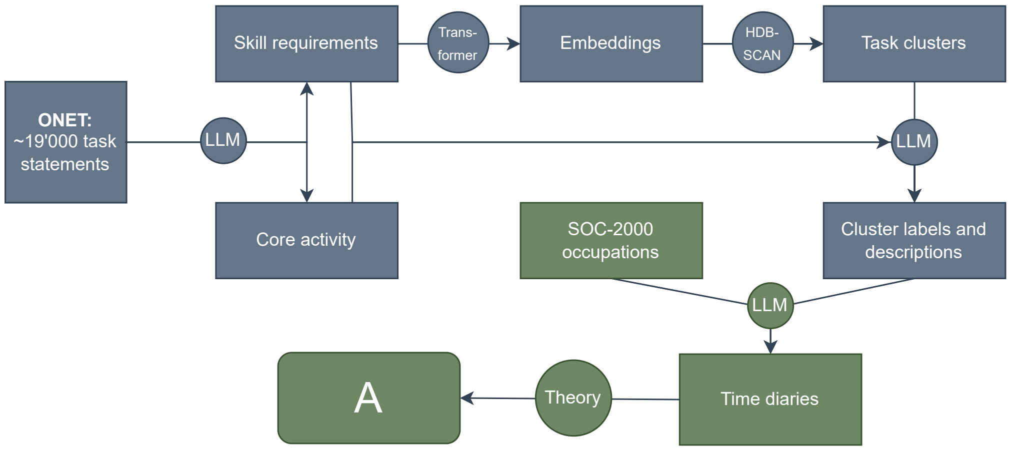


Figure 1: Schematic overview of the measurement of tasks and the A matrix

Notes. Step 1 (colored in blue) involves the clustering of tasks, step 2 (colored in green) the measurement of occupational task weights.

Our starting point is the list of 18,796 detailed, occupation-specific tasks in the O*NET database (version 29.2). Using this granular list of tasks is instrumental for our purposes, as many technology-specific task automation exposure measures use this list as a reference point, enabling us to use these exposure measures in Section 4.1 to identify technology- and task-specific automation shocks.

In step one, we group these detailed tasks into a set clusters that we use as the empirical analogue to the set of human-performed tasks $\mathcal{T}_l$. Our methodology aims to group together tasks with similar skill requirements — if a person is proficient in one detailed task from cluster τ, they should also be able to perform another task assigned to τ equally well. The constraint we confront is that O*NET provides limited meta-data, and specifically no skill requirements, for the detailed tasks.

We process these task statements using a multi-stage NLP pipeline. We start by feeding them through OpenAI's chatGPT-4o model to identify the core activity and the 1-5 essential skills required to be productive in the task. Next, we create word embeddings of these skill requirement descriptions —representations of their semantic content in a high-dimensional vector space — using Alibaba's GTE transformer model (gte-Qwen2-1.5B-instruct). This enables us to cluster detailed tasks by applying a hierarchical density-based clustering algorithm (HDBSCAN, McInnes *et al.* (2017)) to the embeddings. This yields a set of 38 clusters.[22]

[22]Two remarks about the HDBSCAN algorithm are in order. First, tasks that don't contribute to any stable cluster are automatically classified as noise; we drop these tasks from our analysis. Second, the algorithm automatically determines the number of clusters k through a hierarchical approach based on cluster stability, unlike the familiar

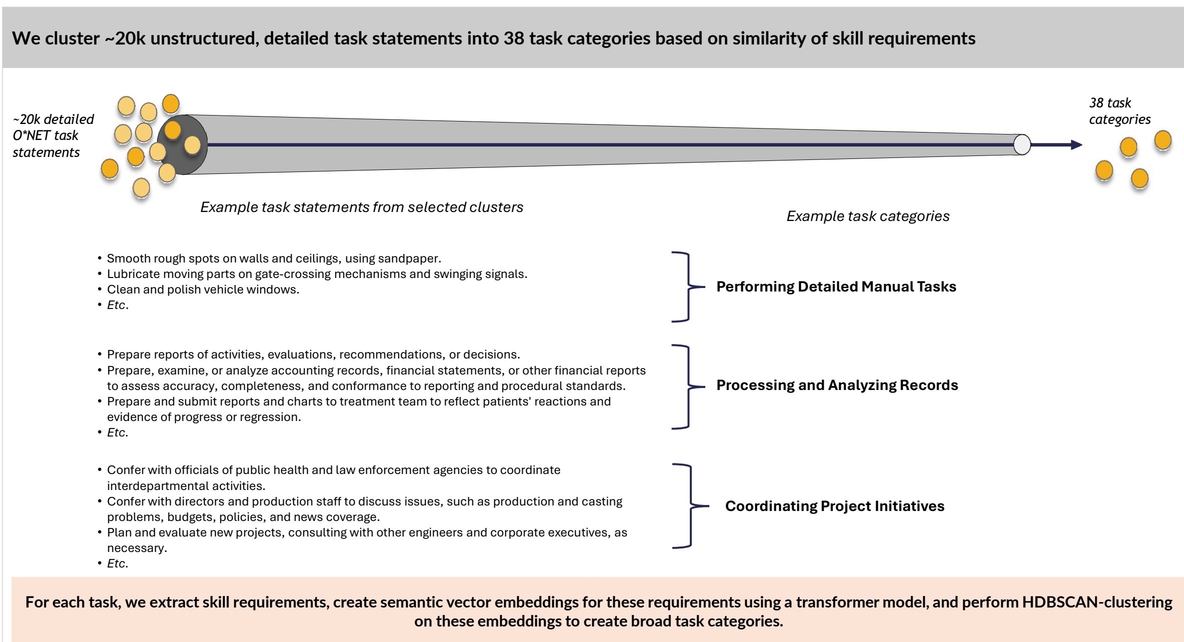


Figure 2: Examples of mapping from detailed tasks to clusters

To interpret the resulting clusters, we use OpenAI's o3-mini-high model, feeding it representative examples from each cluster and prompting it to generate descriptive labels and concise summaries that capture the underlying skill requirements.[23] Appendix Table B.1 gives examples of the core activity and skill requirements extracted for several detailed tasks as well as the resulting cluster. Appendix Table B.2 lists all 38 task clusters.

In step two, we then construct the occupational task weight matrix A. The theory guides measurement, as equation (4) indicates that each entry of the A matrix corresponds to the optimally chosen share of time allocated to task τ in any occupation o. We measure these shares across our 38 task categories – which we describe in terms of labels as well as the summary descriptions derived above – by prompting OpenAI's o3-mini-high model to construct time allocation diaries for each occupation. Appendix B.2 details our LLM prompts.

The A matrix thus obtained corroborates the importance of task bundling and has intuitive properties. Only 2 of occupations have a single task comprising more than half of incumbents' time, and in fewer than 30% of occupations does a single task account for more than a quarter of total time. Figure 3 visualizes A. For visualization purposes, we bi-cluster tasks and occupations, grouping similar categories together, as indicated by the white dividing lines. The A matrix exhibits sparsity with intuitively aligned entries. For instance, "Performing detailed manual tasks" appears as a prominent task across both service sector occupations, like "Food and Beverage Serving Workers" and manufacturing roles, like "Assemblers and fabricators." However, the former, service-sector occupations additionally emphasize tasks like "Providing customer service" while the latter, manufacturing-oriented jobs involve more technical tasks like "Operating, Calibrating, and Inspecting Equipment."

This LLM-powered approach is a useful and flexible tool, but of course invites some immediate questions: How could the LLM know this information? And are the resulting measurements reliable? Regarding the first question, LLM training data comprises virtually the entire internet, including vast amounts of unstructured data on what people across different occupations do at work, as well as summaries of time diary surveys reported in research papers. Since these data sources generally do not reference our exact tasks or occupations, and much input data is qualitative, the LLM's quantitative output results from interpolation.[24] Given the black-box nature of this data construction, we conduct a battery of exercises to evaluate LLM capability in

k-means algorithm where k is a user input.

[23]We explored several alternatives, including clustering on the raw embeddings for the detailed task statements. In practice, however, this approach leads to clusters of tasks that share a similar *context* (e.g., "hospital") but have very different *skill requirements*. For example:"Provide and manage long-term, comprehensive medical care, including diagnosis and nonsurgical treatment of diseases, for adult patients in an office or hospital." versus "Report facts concerning accidents or emergencies to hospital personnel or law enforcement officials."

[24]Our LLM usage resembles employing a vast pool of research assistants with unlimited time to collect diverse data sources and make judgment calls in translating them into cardinal time shares.

constructing occupational time diaries. We summarize them here and refer to appendix B.2.2 for further information.

First, we compare LLM-generated task weights at the occupation-cluster level to the average importance rating that O*NET assigns to detailed tasks within each cluster. While O*NET weights do not directly map onto our A matrix entries — they represent importance rather than time shares—they are strongly correlated with our baseline measures. Second, we exploit a unique 2012 supplemental survey by the German Federal Institute for Vocational Training (Bundesinstitut fuer Berufsbildung, BIBB) in which workers across many occupations report their time allocation across 17 tasks. Though the occupations and tasks differ from our baseline analysis, our LLM-based method is flexible enough to generate time diaries for German BIBB classifications. This comparison reveals highly correlated time shares between the two approaches. Third, we use O*NET's Generalized Work Activities as a task classification, with importance ratings as weights. LLM-generated time shares for these activities again align strongly with importance ratings. Finally, we establish LLM internal consistency: occupational task weights constructed by averaging across constituent minor categories are highly correlated with those derived by directly querying the model for major groups. Together, these validation exercises confirm that our LLM-based approach aligns with established measurement frameworks while offering greater flexibility, notably in task and occupation classifications.

Occupation-level labor shares. Finally, we construct LS_o by combining industry-level data on value-added and wage payments from the BEA-BLS Integrated Industry-level Production Accounts with information on wage payments at the industry-occupation level from the BLS Occupational Employment and Wage Statistics (OEWS) Tables. Concretely, as value-added and hence labor shares are generally defined and measured at the establishment- or industry-level. We apportion industry-level value-added to occupations based on their share in an industry's total wage bill. Appendix B.3 provides more details.

3.3 Validation: Monte-Carlo exercises

We are now ready to estimate parameters according to the approach outlined in Section 3.1. To show that this approach indeed robustly identifies the parameters, we preface our estimation results by conducting a Monte-Carlo exercise. This exercise involves three steps: First, we generate parameter estimates by applying the methodology described above to the real world data described in Section 3.2. Second, we generate artificial data from our estimated model under the parameters estimated in step one. Third, we apply our methodology once more to the artificially generated data, then compare the resulting estimates with the estimates generated in step one. If our method correctly recovers the data generating parameters, then the parameters

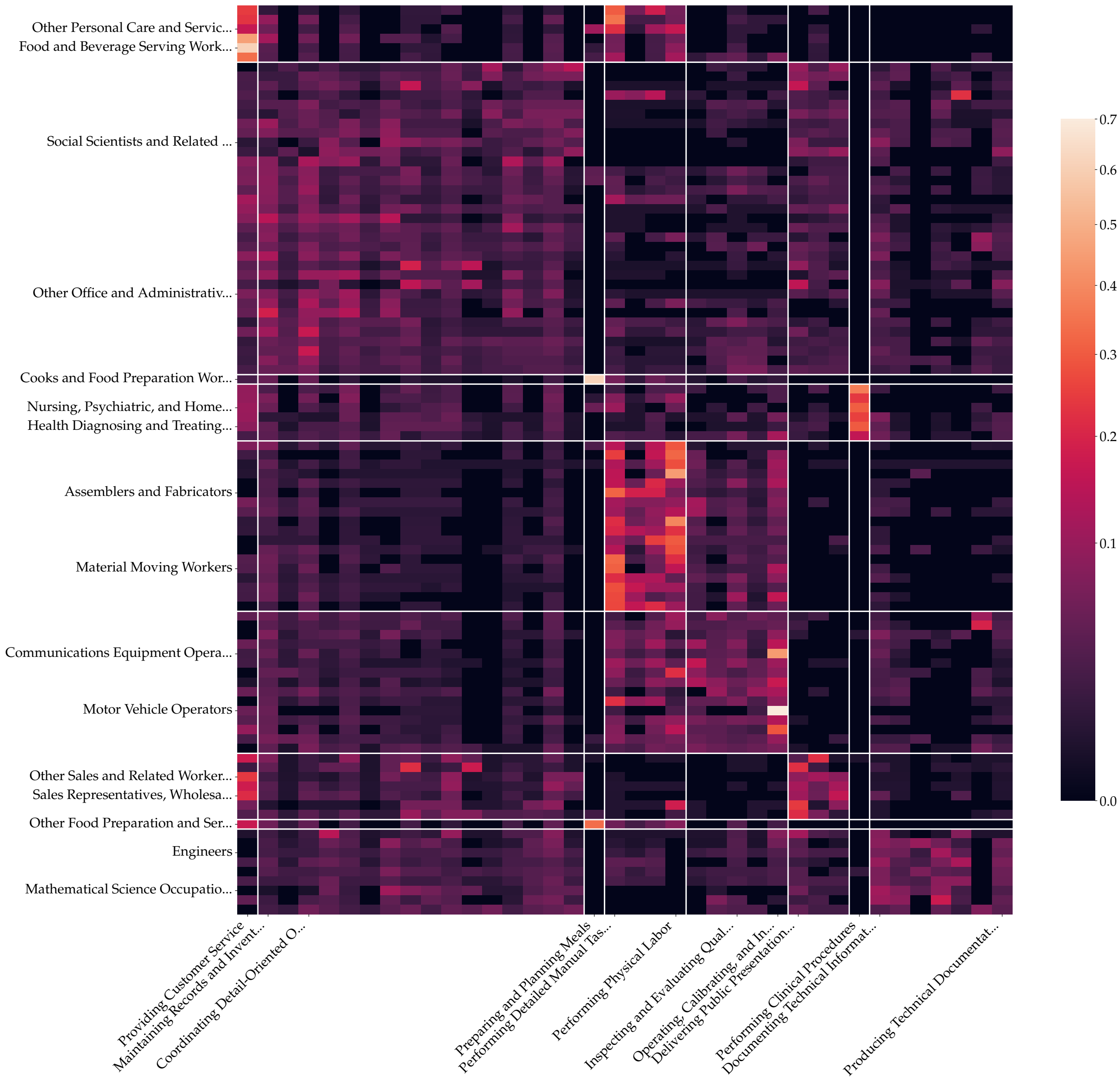


Figure 3: Task weight matrix

Notes. This figure shows the measured A matrix; each cell value corresponds to $\frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}}$. To aid visualization, the matrix is reordered using a spectral co-clustering algorithm, and example tasks and occupations are highlighted.

estimated in step 3 should align well with the parameters estimated in step 1, which are used as inputs when generating the artificial data.

This exercise corroborates our methodology, with the parameters estimated aligning well with the data generating process in the simulation ("dgp"). Figure 4 illustrates this comparison, with each panel showing one set of estimated parameters. We split the skill covariance matrix into its correlation component (C_s, omitting the diagonal of ones in the figure) and its vector of

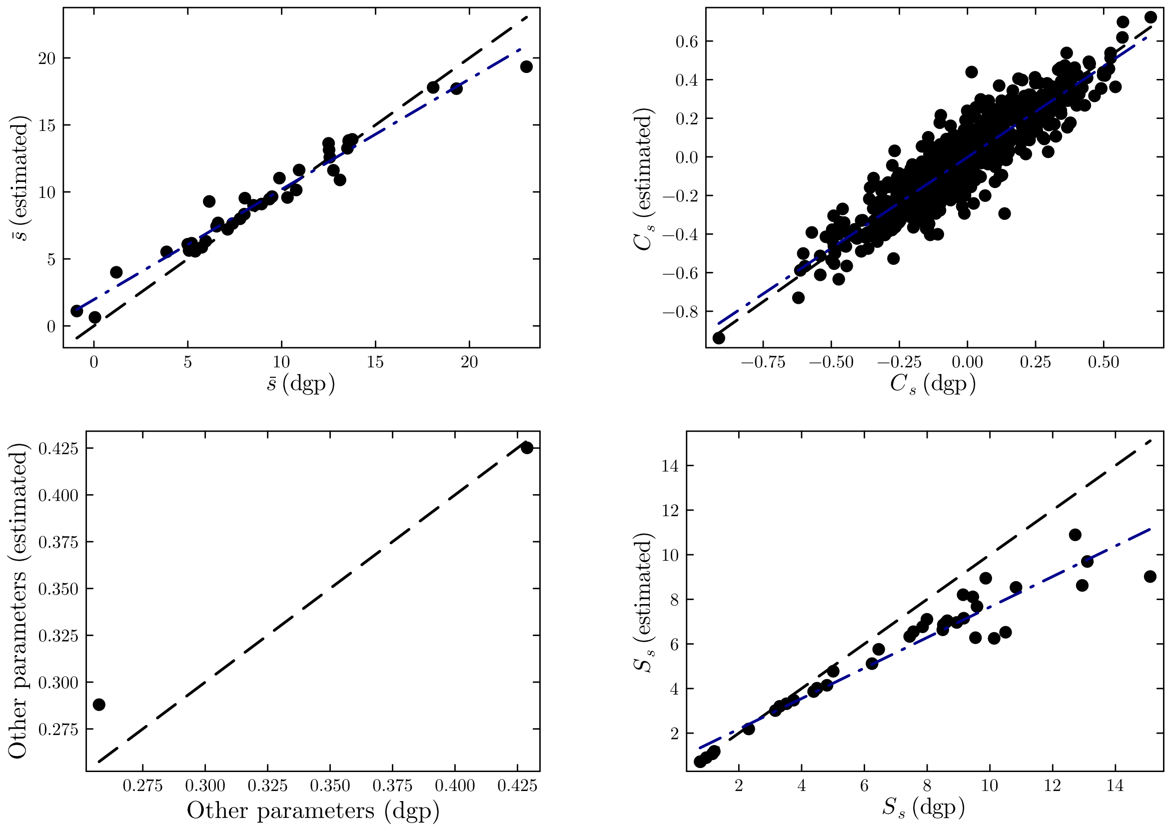


Figure 4: Data generating parameters and their estimates

Notes: The horizontal axis displays parameter values used to generate artificial data. The vertical axis displays corresponding estimated values. "Other parameters" refers to the tuple (ν, ς). The black dashed line is the 45 degree line. The blue dash-dotted line is the line of best fit.

standard deviations S_s; that is, we decompose it according to $\Sigma_s = \text{diagm}(S_s) \cdot C_s \cdot \text{diagm}(S_s)$. The remaining two panels show the estimated and data generating parameters for the vector of mean log skills, $\bar{s}$, and the remaining parameters (ν, ς), respectively. The fit is generally good; in particular, we are able to capture the rather large number of parameters governing bi-lateral skill-correlations quite well.

3.4 Estimation results & model validation

3.4.1 Parameter estimates

For the scalar parameters, we estimate $\nu = 0.26$ and $\varsigma = 0.43$. The estimate of ν implies that reducing prospective wages in a given occupation by 1% lowers the odds of choosing this occupation by about 3.8% since $\frac{1}{\nu} \approx 3.8$. $\varsigma = 0.43$ indicates that a one-standard-deviation occupation-specific random productivity shock can raise or lower wages by about 43% in a given year.

Next, we investigate the mean and dispersion of skills. Figure 5 documents the estimate of mean skills $\bar{s}$ and illustrates their dispersion as error bands, which is given by their standard deviation (S_s where $\Sigma_s = \text{diagm}(S_s) \cdot C_s \cdot \text{diagm}(S_s)$). The values of $\bar{s}$ indicate tasks that are more or less productive on average in the population. For example, "coordinating project initiatives" and "monitoring and inspecting systems" are tasks that are more productive on average, whereas for example, "mediating and consulting clients" is associated with lower skill productivity. However, skills also differ in their dispersion across the worker population. For example, workers differ most in their capability to "coordinate multifunctional processes" and in their ability to "produce technical documentation", but relatively little in their skill for "preparing and planning meals", "performing detailed manual tasks", or "performing physical labor".

This contrast is interesting from the perspective of the formulas derived in Section 2.3.3. One one hand, the decomposition of equation (13) indicates that the magnitude of some automation effects, such as selection and re-sorting effects, depend crucially on skill dispersion. Figure 5, on the other hand, indicates that the dispersion of skills varies widely with the type of task being automated. Specifically, traditional, pre-AI types of automation, which primarily affected manual tasks (e.g., "performing detailed manual tasks" or "performing physical labor") automate skills for which we estimate a low skill dispersion. The advent of AI technologies, meanwhile, has brought about prospects of skill automation for those skills which are much more dispersed. We will come back to this discussion in Section 4, when we talk about the implications of various types of automation shocks.

Lastly, we estimate the full correlation matrix C_s of all pairwise skills. This matrix is displayed in Appendix C.2.[25]

3.4.2 Model properties

We now describe the properties of the estimated model, starting with properties of the wage distribution.[26] In the data, the standard deviation of log wages is 0.60. Decomposing the total variance of log wages into within-occupation and between-occupation components, the within-term accounts for 71.5% of variation and the between term for 28.5%. The model does a solid job in matching these moments: The overall standard deviation is 0.70, with the within and between terms accounting for 18.6% and 81.4% of the total variance, respectively.

Turning to occupational choice, workers sort into occupations on the basis of task-level

[25]It is difficult to directly validate the plausibility of any given correlational estimate. However, the Monte Carlo exercises conducted in Section 3.3 indicate that we are able to obtain a robust estimate of the correlation structure for any pair of tasks.

[26]All results are based on a simulation of 50,000 workers.

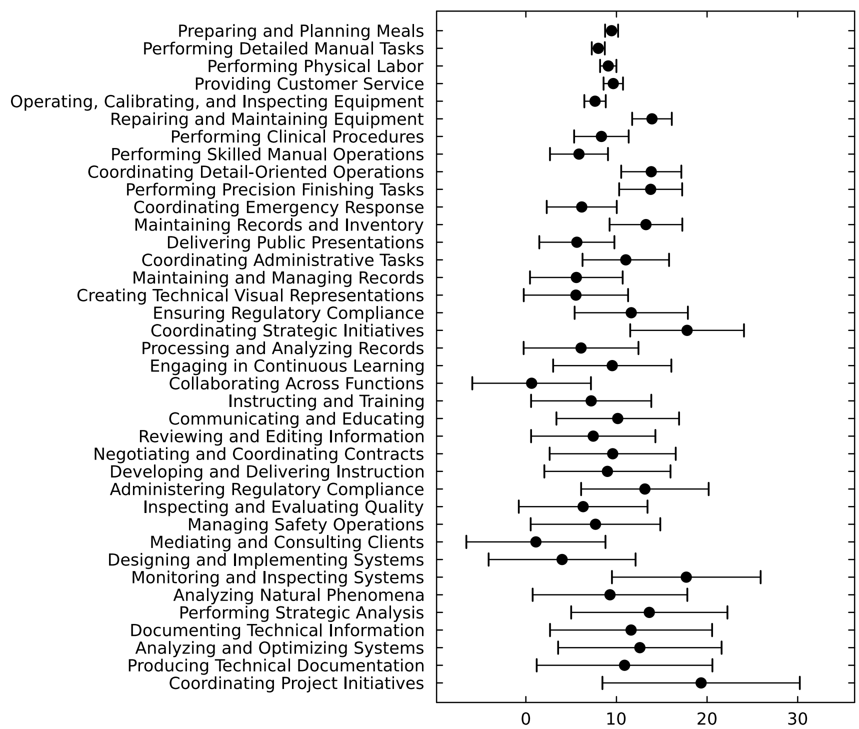


Figure 5: Estimated mean skills and dispersion

Notes: Dots show point estimates for mean log skills $\bar{s}_\tau$ by category τ. Plotted intervals cover one standard deviation of the corresponding marginal distribution in each direction. Tasks are ordered by increasing skill dispersion.

comparative advantage: In the model, workers sort into jobs that emphasize tasks where they possess relative skill advantages. For example, workers choosing to become Top Executives exhibit notably higher specialization in "'Coordinating Strategic Initiatives" – a task with a disproportionately high weight in this occupation – compared to the unconditional distribution of workers. This reflects the type of sorting captured in equation (14). Figure C.2 in the appendix provides an illustration.

What are the patterns of occupational switches in the estimated model, and how do they compare to the data? Figure 6 compares the model-implied occupational transition matrix entries to those observed in the NLSY. The model generates positive correlations with data in terms of both staying probabilities (diagonal elements, 0.36) and switching probabilities (off-diagonal elements, 0.41). While the model captures the directional pattern of occupational transitions, it notably under-predicts persistence in the same occupation: The average annual staying probability is 18%, well below the 63% measured in the NLSY. This gap likely reflects the absence of switching frictions or costs in our current specification, where transitions are driven purely by relative skill advantages and preference shocks.

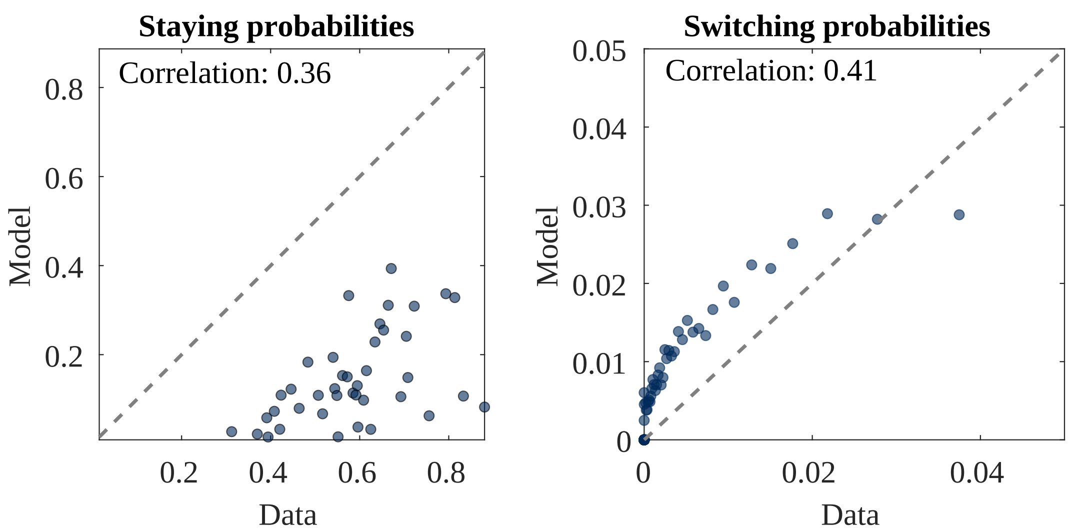
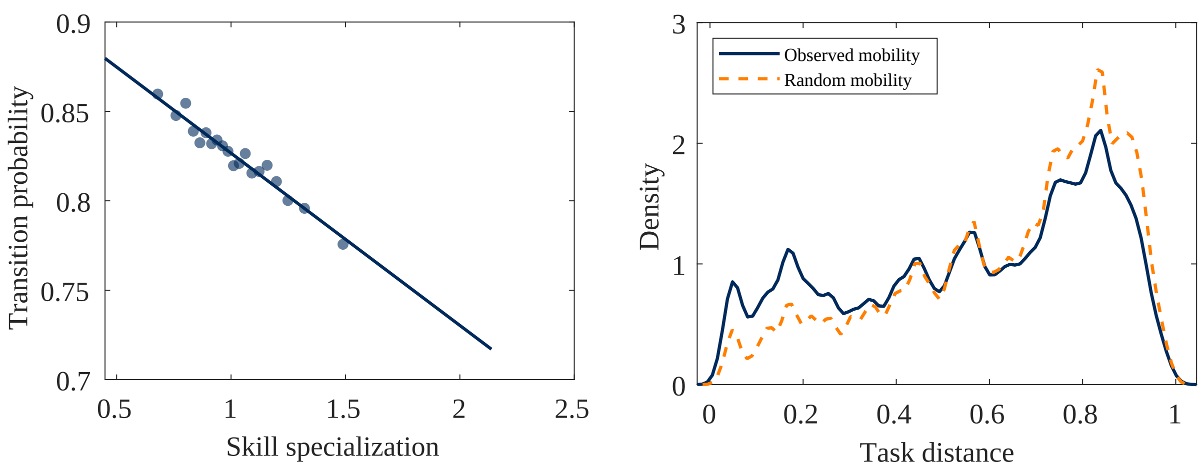


Figure 6: Occupational transition matrix: model vs. data

Notes. This figure compares the model-generated entries of the transition matrix to those derived from the NLSY. The left panel is a binned scatter plot of diagonal entries, the right panel a binned scatter of off-diagonal entries.

An important piece of validation for our task-based model are its distinctive predictions for the effect of skill specialization on the *frequency* and the *direction* of occupational switches, which we show are at least qualitatively consistent with the data. First, the empirical evidence suggests that skill specialization tends to generate persistence in occupational choice (Kambourov and Manovskii, 2008; Geel *et al.*, 2011). Consistent with this idea, our theory implies that individuals with more specialized skills tend to move less. Our measure of individual skill specialization is the within-worker coefficient of variation of skills. Figure 7a shows that greater specialization is associated with a decreasing probability of switching occupation in any given period.

Next, consider the direction of moves conditional on occupational switching. Gathmann and Schönberg (2010) show, using German worker panel level data, that workers are more likely to move to occupations with similar task requirements. Whereas this relationship cannot be rationalized by models featuring skills that are either one-dimensional or fully occupation-specific, it is successfully reproduced by our model. To illustrate this property, we replicate the analysis conducted by Gathmann and Schönberg (2010) using data generated from our model. Concretely, we compare the realized distribution of between-occupation distances traveled in the space of tasks to that we would observe if mobility was random. The distance between any two occupations o and o' is one minus the angular separation of the task-weight vectors. Further, under the random mobility benchmark, only the relative size of occupations influences the direction of moves. Figure 7b demonstrates that under the observed distribution of distances more density is concentrated at shorter distances than under the random-mobility benchmark.



(a) More specialized workers move less

(b) Observed moves reflect task similarity

Figure 7: Specialization shapes the frequency and direction of moves

Notes. The left panel is a binscatter of individual-level observations, relating the normalized frequency of occupation switches to the coefficient of variation of skills. The right panel plots the observed density of distances conditional on switching occupation (solid line) and that under the random-mobility benchmark described in the text (dashed line).

In summary, the estimated model, despite its simplicity, does a solid job at matching the wage distribution and captures important features of the relationship between task-specific skills and job mobility.

4 The Labor Market Effects of LLMs

We are now in a position to use the estimated model to evaluate the distributional wage effects of an automation shock. Section 4.1 explains how we leverage prominent task exposure measures from the literature to identify *which* tasks to shock in the model. Section 4.2 evaluates occupation-level effects and decomposes them following the method derived in Section 2.3.3. Section 4.3 quantifies the consequences of automation at the individual level. Section 4.4 offers a brief discussion of our results.

4.1 Identifying task-specific automation shocks

Quantifying automation-induced earnings effects for technologies currently being rolled out, or adopted in the future, requires knowledge of which tasks are being, or will be, automated. Unlike backward-looking studies, we cannot rely on changes in labor share to measure automation experienced by industries or occupations. Even if such labor share changes could be constructed, they would not reveal which tasks within industries or occupations are automated. As highlighted in Section 2.3.3, this granular knowledge is essential, though, to capture job transformation effects.

Our methodology addresses this challenge by providing a direct mapping to empirical measures of technology-specific, task-level automation exposure from a burgeoning literature using data sources ranging from patent data (Webb, 2019) and capability-specific AI benchmarks (Felten *et al.*, 2021) to expert and machine judgment (Eloundou *et al.*, 2023). Our model can link directly to any exposure measure at the detailed O*NET task level.

Motivated by the rapid diffusion of large language models (LLMs) with increasingly advanced capabilities (Bick *et al.*, 2024), we focus on this technology in our headline analysis. To identify which tasks are most likely automated through LLMs, we draw on Eloundou *et al.* (2023), who quantify O*NET task exposure to LLM automation using human labeling and GPT-4 classifications. We aggregate their scores to our task cluster level by averaging.[27] Figure 8 shows the resulting exposure scores for our task clusters, ordered by descending exposure. The most exposed categories are "Processing and Analyzing Records" and "Maintaining and Managing Records," followed by "Reviewing and Editing Information" and "Producing Technical Documentation." The first two clusters include detailed, occupation-specific tasks such as "Compute payment schedules" and "Prepare reports showing places of departure and destination, passenger ticket numbers, [...]" or "Maintain and update human resources documents, such as

[27] We focus on the automation rubric specifically, rather than the general exposure rubric. Eloundou *et al.* (2023) quantify exposure using five categorical bins. To convert these to numerical scores between 0 and 1, we use the authors' mapping: T0 (no automation exposure) receives a score of 0, T1 receives 0.25, T2 receives 0.5, T3 receives 0.75, and T4 (full automation exposure) receives 1.

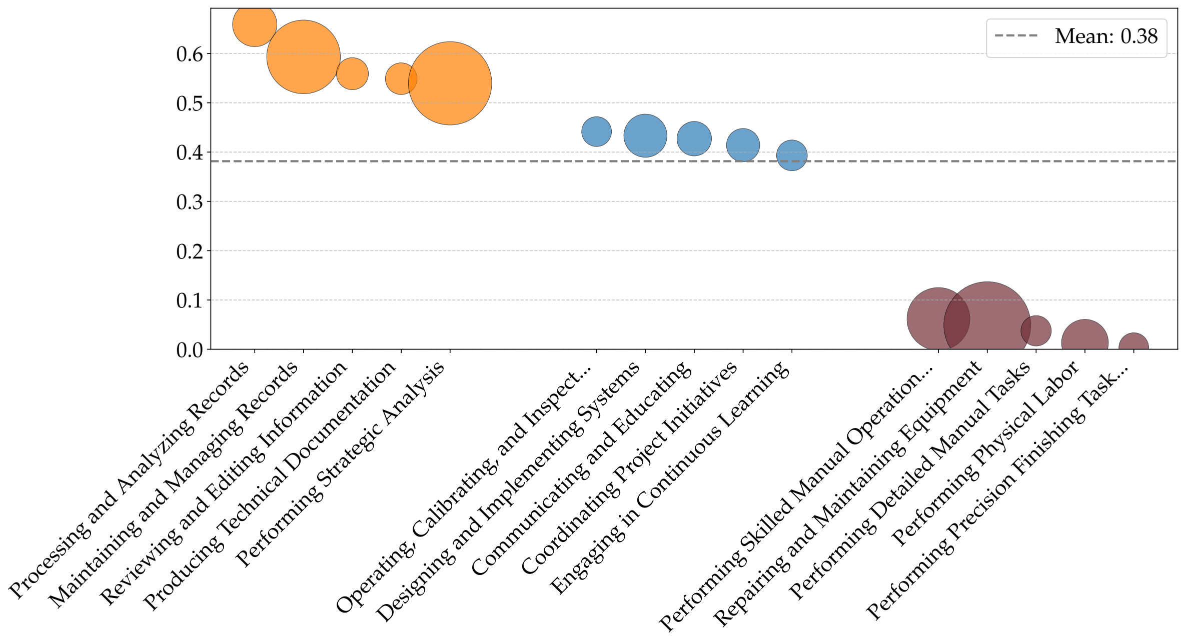


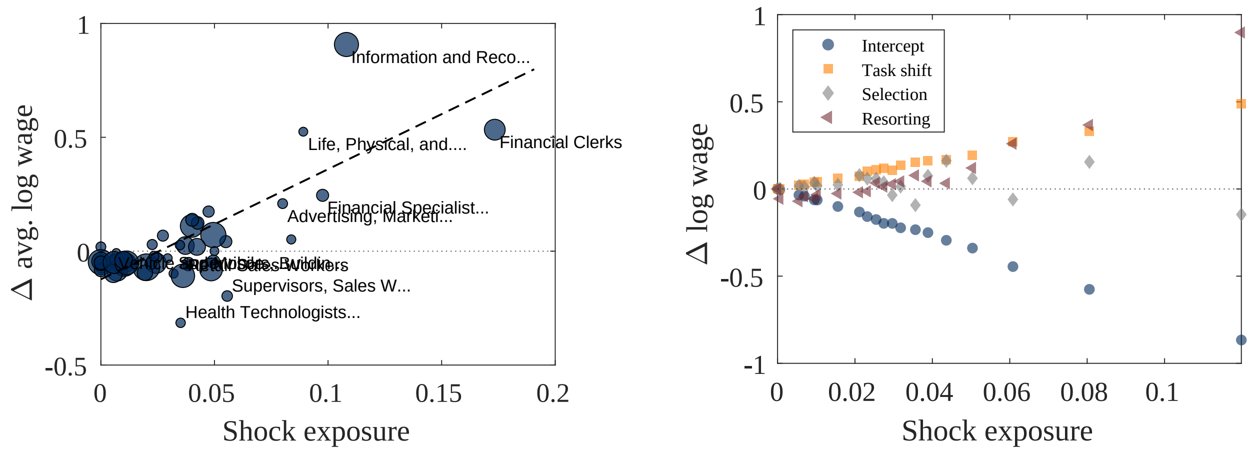
Figure 8: Eloundou *et al.* (2023) exposure scores aggregated to task clusters

Notes. This chart shows the exposure of the task clusters to LLM automation based on the aggregated exposure scores provided by Eloundou *et al.* (2023). . The size of each bubble indicates the number of detailed O*NET tasks contained in each cluster. For example, the two most exposed task clusters are "Processing and Analyzing Records" (a cluster comprising 170 detailed tasks with average exposure of 0.66) and "Maintaining and Managing Records" (470 tasks with average exposure score 0.59).

organizational charts, [...]" and "Organize archival records and develop classification systems to facilitate access to archival materials," respectively.

To contextualize the model-implied labor market consequences of LLMs, we compare them to those from automation by industrial robots. Our approach's flexibility allows us to measure robot automation exposure for our task clusters by linking them to Webb (2019) exposure measures. Webb (2019) construct task automation exposure measures using the overlap between job task descriptions and patent text.[28] This methodology identifies "Performing Detailed Manual Tasks" as the most robot-exposed task cluster—comprising detailed occupation-specific tasks such as "Lubricate moving parts" and "Remove excess materials or impurities from objects, using air hoses or grinding machines"—followed by "Performing Physical Labor," which includes tasks like "Hammer out bulges or bends in metal workpieces" and "Dump refuse or recyclable materials at disposal sites." Appendix B.4 provides more details.

[28]Many thanks to Mike Webb for sharing the exposure scores at the task level.



(a) Effects

(b) Decomposition

Figure 9: LLM automation: occupation-level effects

Notes. Left panel: Each dot is an occupation. The vertical axis measures the average occupational wage change before versus after the shock. The horizontal axis measures shock exposure $A_{o,\tau}$. Dot sizes correspond to pre-shock employment shares. The dotted line is the line of best fit. Right panel: Bin scatter of occupational effect size according to equation (13) by shock exposure $A_{o,\tau}$. Note that the x-axis range differs across the two panels.

4.2 Occupation-level effects & their limits

As a first exercise, we study what happens to occupation-level wages when "Processing and Analyzing Records" is fully automated. Panel (a) of Figure 9 plots occupational wage changes from automating this task against occupational exposure, measured by $A_{o,\tau}$. The figure shows that occupational wage effects tend to be positive. More exposed occupations experience larger wage gains on average. Occupations with the highest loadings on the automated task, such as Financial Clerks and Information and Record Clerks, experience the largest increases in average occupational wages.

The decomposition in equation 13 provides a natural framework to explain these effects. Panel (b) of Figure 9 presents the estimated decomposition terms as a bin scatter, plotting the average magnitude of each effect against occupational exposure. The bin scatter shows that these positive effects are not driven by the productivity and displacement effects captured by $\Delta\mu_o$; indeed, these terms tend to be more *negative* for more exposed occupations. This negative effect, however, is offset by three job transformation effects: task shifting, selection and re-sorting.

First, automating "Processing and Analyzing Records" leads to *task upgrading*, indicated by positive task shift effects. Full automation frees up production time and allows workers to spend more time on tasks where the average worker is more productive. This increases productivity and average occupational wages. The effect is stronger for more exposed occupations, where more time is freed by automation.

Second, selection effects have ambiguous effects on average wages as exposure grows. This shows that selection plays a subtle role: For “Processing and Analyzing Records,” workers regularly select into exposed occupations based on the automated skill but also on skills other than the automated one. When automation occurs, selection effects are thus ambiguous, hurting some workers while benefiting others. Selection effects benefit workers who initially select occupations based on non-automated skills but harm workers who select mainly on automated skills. Appendix C.2 shows this result is somewhat unique to this task: other automation types can generate much more pronounced negative wage effects for most incumbents. Across shocks, selection effects rarely generate wage gains in affected occupations.

Third, re-sorting effects drive much of the average wage gains and are the primary driver for the most affected occupations. This indicates that the shock generates significant labor market "turbulence." The composition of workers in the most exposed occupations changes drastically as automation hits: existing workers leave and new workers enter as the type of work changes.

The magnitude of re-sorting among the most exposed occupations suggests that occupational averages may lack economic meaning and provide poor guidance for understanding *individual-level* effects. We therefore ask under what conditions re-sorting effects are large. To understand this, we compare all 38 possible full automation shocks by the slope they induce in their respective versions of Figure 9. For each shock, we examine how much more exposed occupations experience larger re-sorting effects. Figure 10 plots these measures against the dispersion of the affected skill. Orange highlights the two tasks most exposed to AI in our aggregation of Eloundou *et al.* (2023). Gray highlights the tasks most exposed to robots in our aggregation of Webb (2019). Figure 10 reveals a clear pattern: shocks affecting highly dispersed skills generate larger re-sorting effects; shocks affecting less dispersed skills produce small re-sorting effects. Equation 13 explains why: shocks to highly dispersed skills feature larger re-sorting effects when negatively correlated with other high-dispersion skills strongly utilized by affected occupations. This holds for our estimated parameters.[29]

Importantly, our estimation suggests AI-exposed tasks ("Processing and Analyzing Records," "Reviewing and Editing Information") tend to feature larger skills dispersion than is the case for tasks automated by industrial robots ("Performing Detailed Manual Tasks," "Performing Physical Labor"). Consequently, occupation-level averages provide a worse guide to worker-level outcomes when considering the ongoing, AI-driven automation compared to the historical case of robots.

In sum, our results suggest that AI-driven automation leads to positive average wage effects for the most exposed occupations, driven by task upgrading and a changing pool of workers. The latter force suggests, however, that pre-shock incumbents of a given occupation may not be the primary beneficiaries of these positive wage changes. To evaluate this conjecture, the next

[29]Appendix C.2 discusses how automation shock properties also affect selection and task-shifting effects.

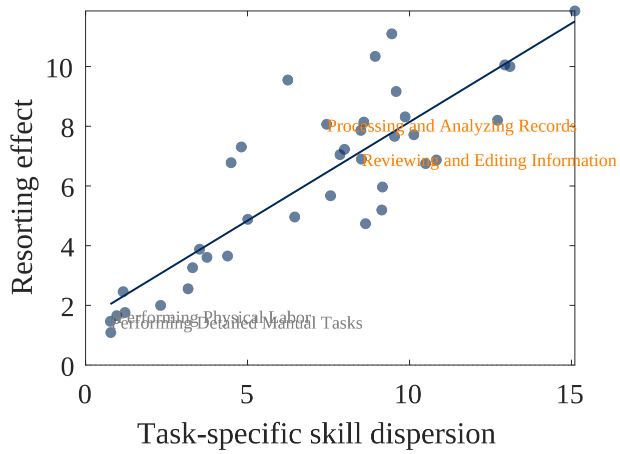


Figure 10: Resorting effect: comparison across tasks

Notes. Each dot corresponds to a task. The horizontal axis displays the estimated skill dispersion of the task, $S_{s,\tau}$. The vertical axis displays the coefficient of a regression that regresses the magnitude of the re-sorting effect from full automation for a given occupation on its exposure $A_{o,\tau}$, weighting coeffcients by pre-shock occupational employment.

section turns to an analysis of individual-level, rather than occupation-level effects.

4.3 Individual-level effects

We now turn to individual-level effects. We classify individuals by their origin occupation before the shock and track their earnings over time. While the individual-level effects do not admit elegant closed-form characterization, many insights from equation 13 carry over.

We begin by showing average wage effects for all incumbent workers by their origin occupation. Figure 11 plots these effects against occupational exposure. The figure reveals a stark contrast between occupation-level wages and incumbent wages: the former rise with exposure (Figure 9), while the latter fall with exposure.

To understand this difference, we decompose incumbent wage effects as follows:

$$\begin{aligned}
&\sum_{o''\in O} \lambda'_{o''}(s_{|o})\mathbb{E}[w'_{o''}|\hat{o} = o] - \mathbb{E}[w_o|\hat{o} = o] \\
&= \underbrace{\mathbb{E}[w'_o|\hat{o} = o] - \mathbb{E}[w_o|\hat{o} = o]}_{\Delta w_o \text{ of incumbents}} + \underbrace{\sum_{o''\in O} \lambda'_{o''}(s_{|o})\mathbb{E}[w'_{o''} - w'_o|\hat{o} = o]}_{\text{Reallocation of incumbents}}. \qquad (16)
\end{aligned}$$

where $\lambda_{o''}(s_{|o})$ denotes the post-automation employment share of occupation o'' for workers initially in o. The first term can be decomposed according to equation 13 into productivity and displacement, task-shift, and selection effects. Since equation 16 describes incumbent wage effects, the "re-sorting" term from equation 13 becomes a term describing incumbent

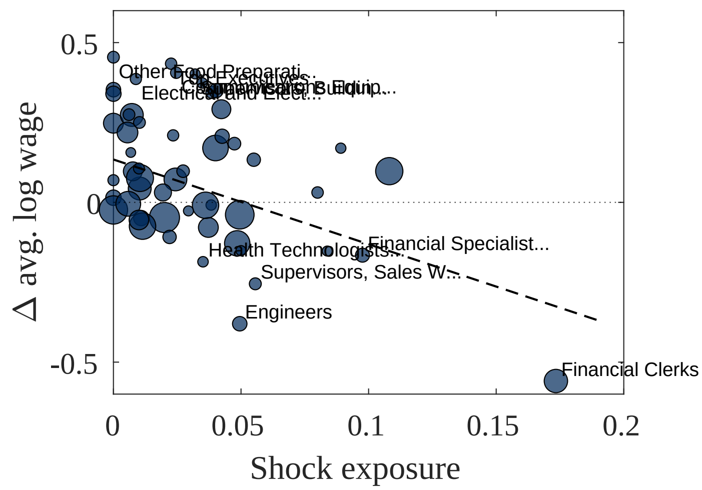


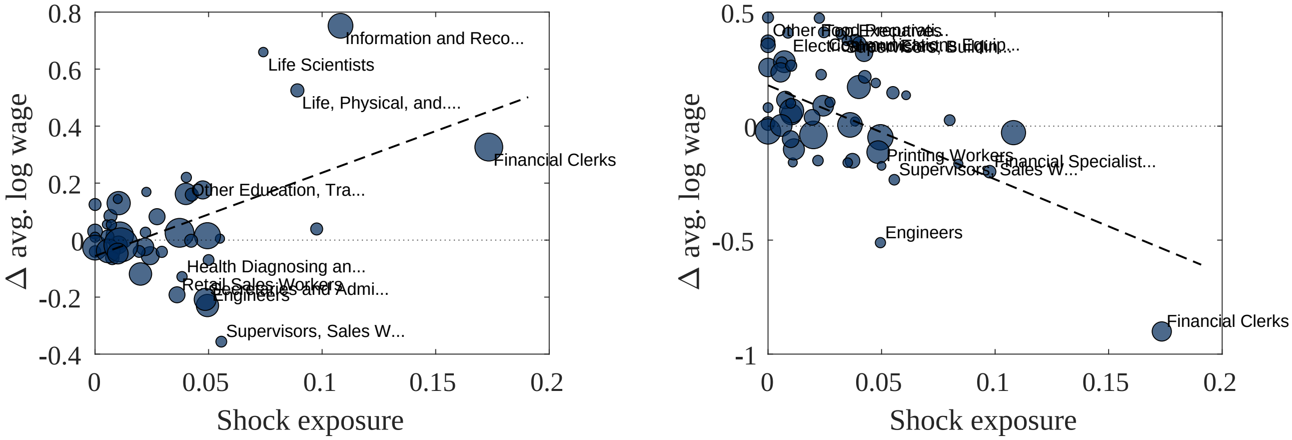
Figure 11: LLM automation: individual-level wage effects for incumbents

Notes. Each dot is an occupation. The vertical axis measures the wage change for initial incumbents of each occupation before versus after the shock. The horizontal axis measures shock exposure $A_{o,\tau}$. Dot sizes correspond to pre-shock employment shares. The dotted line is the line of best fit.

reallocation across occupations. The contrast between occupational averages and the experience of individual incumbents thus arises from two sources: first, wage changes at the occupational level are partly driven by non-incumbents; second, incumbents themselves may move to other jobs with wages that differ from those in their origin occupation. The decomposition in Figure 11 indicates that incumbents in exposed occupations do worse than their occupational average suggests. Thus, their reallocation to new occupations does not successfully insure them against wage losses.

This insight motivates us to distinguish between those who decide to leave their job and those who stay. Figure 12 splits the population of incumbents into these two groups. The figure reveals substantial heterogeneity within occupational incumbents: stayers do much better than leavers. Figure 13 explains why. It plots relative specialization, defined as $s_{o,\tau^\star} - \frac{1}{n_{\text{skill}}}\sum_{\tau\in\mathcal{T}_l} s_{o,\tau}$ for incumbents in low- and high-exposure occupations and, within the latter group, incumbent stayers and incumbent switchers. This contrast shows that selection plays a major role in generating differences between stayers and switchers: switchers are highly specialized in automated tasks, whereas stayers have specialization patterns similar to the general population.

In fact, such heterogeneity within the population of incumbents can be neatly characterized



(a) Incumbent stayers

(b) Incumbent leavers

Figure 12: LLM automation: stayers versus leavers

Notes. Each dot is an occupation. The vertical axis of panel (a) measures the wage change for initial incumbents of each occupation before versus after the shock, including only those who stay in their occupation after the shock. The vertical axis panel (a) measures the wage change for initial incumbents of each occupation before versus after the shock, including only those who leave their occupation after the shock. of The horizontal axis of both panels measures shock exposure $A_{o,\tau}$. Dot sizes correspond to pre-shock employment shares. The dashed line is the line of best fit.

when one focuses on origin-occupation wages:

$$\begin{aligned}
&\text{Var}(\Delta w_{i,o}|\hat{o}=o) = (A'_o - A_o)\Sigma_{s|o}(A'_o - A_o)^\intercal \\
=&(A'_o - A_o)\left(\Sigma_s^{-1} + \nu^{-2}\underbrace{\left(\sum_{o'} h_{o'}(\bar{s}_{|o})A_{o'}^\intercal A_{o'} - \left(\sum_{o'} h_{o'}(\bar{s}_{|o})A_{o'}^\intercal\right)\left(\sum_{o'} h_{o'}(\bar{s}_{|o})A_{o'}^\intercal\right)^\intercal\right)}_{\text{Task intensity dispersion across occupations}}\right)^{-1}(A'_o - A_o)^\intercal,
\end{aligned}$$

which shows that the automation of more dispersed skills tends to lead to more such heterogeneity among incumbents, especially when occupations do not differ much in their exposure and thus induce less initial sorting.

Together, these findings paint a picture of diverging fortunes among individuals in exposed occupations. On the one hand, automation creates losers: Those particularly skilled in the automated task who select into the most exposed occupations precisely because of this specialization. These workers tend to leave after the shock but struggle to find alternative employment at or above their previous wage level. On the other hand, automation also creates winners: workers who selected exposed occupations for reasons other than their skill at the automated task. These

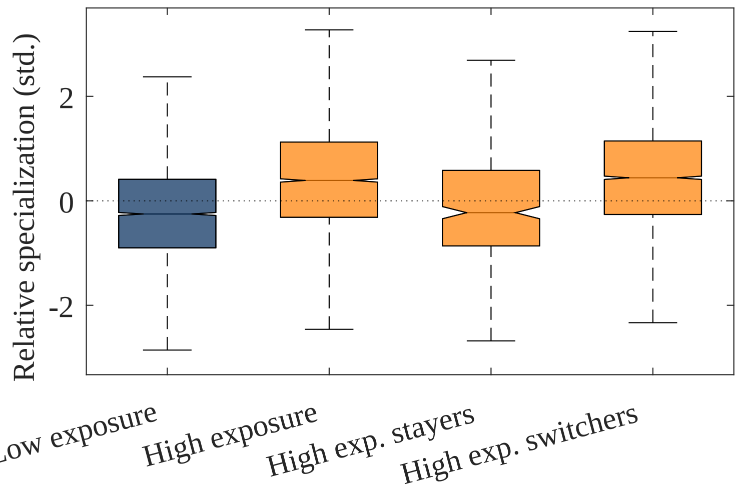


Figure 13: LLM automation: specialization in automated task by worker groups

Notes. Each box plot shows the distribution of $s_{i,\tau^\star} - \frac{1}{n_{\text{skill}}} \sum_{\tau \in \mathcal{T}_l} s_{i,\tau}$ where $\tau^\star$ corresponds to the "Processing and Analyzing Records" task. "Low exposure" ("high exposure") refers to those workers who are in the bottom (top) 10% by exposure, as measured by $A_{o,\tau^\star}$ of their occupation.

workers benefit from task upgrading, typically stay after automation, and realize wage gains.[30]

Incumbent stayers who benefit from task upgrading are not the only winners. As the large re-sorting effect suggests, many workers realize wage gains because automating a task removes entry barriers into occupations they would otherwise qualify for. Figure 14 illustrates this point by comparing wage effects of workers who switch into each occupation against occupational exposure. In-switchers into the most exposed occupations benefit the most. This reflects that these occupations undergo substantial changes in task content and thus attract workers whose skills fit better with the new profile of the transformed occupation.[31]

We thus make out two groups of winners: incumbent workers who stay in exposed occupations and new workers who switch into such occupations; and one group of losers: workers in exposed occupations who tend to be skilled in the automated task and leave their occupation after the shock. For the shock we study, workers whose skills are concentrated in information-processing tasks lose, exiting their incumbent jobs that no longer reward their comparative advantage. However, many other workers, especially in highly exposed office and administrative roles, stay and gain as the content of their work shifts. This is the case for example for those

[30]These model-based findings echo the empirical finding in Dauth *et al.* (2021) that workers who stayed in their firms after the advent of industrial robots tended to experience wage gains and shifted their work to more productive tasks, whereas those who left tended to lose.

[31]Going beyond the specific automation scenario we consider here, an evocative but speculative example of this effect may be the rise of "vibe coding," which may allow individuals who previously would never have worked as software engineers due to a lack of coding skills to enter the profession, as LLM code generation shifts the job toward higher-level tasks like creativity as well as project planning and quality control."

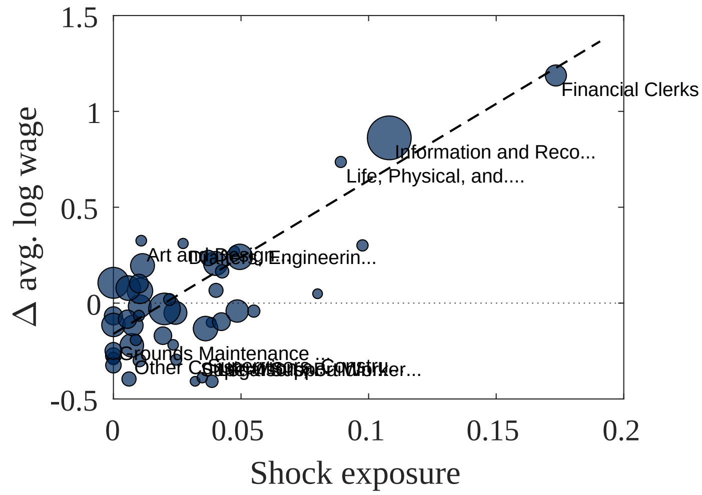


Figure 14: LLM automation: in-switcher wage effects

Notes. Each dot is an occupation. For each occupation, the vertical axis measures the wage change of workers who are *not* incumbents of that occupation but select that occupation after the shock. The horizontal axis measures shock exposure $A_{o,\tau}$. Dot sizes correspond to pre-shock employment shares. The dotted line is the line of best fit.

who stay in occupations such as "Financial Clerks" which has a high weight on customer-facing and coordination tasks. Similarly, those who remain lawyers are typically those whose skills are concentrated in communication ("Communicating and Educating") and negotiation tasks ("Negotiating and Coordinating Contracts") rather than document processing and analysis.

4.4 Discussion

We close by discussing the appropriate interpretation of our quantitative results and potential extensions. As job transformation effects are typically abstracted from in quantitative automation analyses, we made three assumptions to transparently identify these effects. First, formulating our model in partial equilibrium demonstrates that a rich set of distributional effects arises even when occupational prices are fixed. Introducing general equilibrium effects could dampen or amplify their magnitude. Second, the model features no exogenous switching costs or frictions. This assumption traces any non-random job mobility to skill heterogeneity, but may overstate the positive wage gains accruing to the in-switchers we discussed. Third, we assume no heterogeneity along observable dimensions such as age or gender to isolate the effects of skill heterogeneity, but future work should explore how job transformation effects vary with demographic characteristics. In addition, to facilitate estimation and analytical characterization, we assumed skills to be time-invariant. As mentioned previously, this means our results are best interpreted as applying to a horizon of three to five years following the shock.

5 Conclusion

If the historical record—and anecdotal evidence about work reorganization at firms adopting gen-AI at large scale—offers any guidance, job task transformation will play a first-order role in shaping AI's labor market consequences. We develop a framework to analyze these effects, offering both conceptual insights and methodological tools to quantify them.

Our findings challenge the common practice of equating task- or occupation-level automation exposure with negative wage effects. This interpretation of exposure is misleading. Conceptually, job transformation effects create heterogeneous effects at the individual level – workers exposed to the same shock in the same occupation may fare very differently depending on their relative specialization.[32] Quantitatively, our findings underscore that occupation-level averages are especially misleading for AI-induced task automation, because AI automates tasks with larger skill dispersion than in past episodes, prompting larger labor market reallocation flows. Incumbents in the same occupation include winners, who stay and move to higher-productivity tasks, and losers, who are pushed out into lower-paying jobs. In brief, exposure measures provide valuable insights into which tasks specific technologies affect, but deriving implications for earnings requires a structural model that carefully maps exposure into wages.

Our framework offers three attractive properties. First, because it links directly to task exposure measures, including forward-looking ones, it can analyze labor market consequences without waiting for backward-looking exposure data, which is especially useful for policy. Second, our counterfactual analyses avoid first-order approximations, which may not capture a shock's transformative nature, and instead allow for arbitrarily large shocks with potentially non-linear effects. Third, data requirements are limited: worker-level panel data are widely available, and we offer a flexible methodology to measure occupational task weights. Extending the quantitative analysis of job transformation effects to more countries would be valuable future work.

[32] In addition, greater exposure can be positive or negative depending on the relative magnitude of displacement and productivity effects. In our model with task-bundling, positive productivity effects also accrue only to exposed occupations. Worker reallocation and, more generally, general equilibrium effects associated with complementarities across occupational outputs lead to the diffusion of these effects.

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Online Appendix

This appendix contains supplemental material. Any references to sections, equations, figures, tables, assumptions, propositions, lemmas or corollaries that are not preceded by a capital letter refer to the main article.

A Theory appendix

A.1 Derivations

A.1.1 Laplace approximation of the skill posterior

In order to obtain the expressions presented in the main text, it is necessary to compute the posterior skill distribution of workers who choose occupation o in a given period. Because the exact distribution is not tractable, we rely on Laplace approximations. Laplace approximations provide a normal approximation of the true posterior. To apply this method, we write down the exact un-normalized posterior log density of workers in occupation o:

$$\phi_o(s) = -\frac{1}{2}(s-\bar{s})'\Sigma_s^{-1}(s-\bar{s}) + \nu^{-1}\mu_o + \nu^{-1}A_o \cdot s - \log\left(\sum_{o'} \exp(\nu^{-1}\mu_{o'} + \nu^{-1}A_{o'} \cdot s)\right).$$

The Laplace approximation uses the posterior mode as the mean of a multivariate normal and the score of the posterior likelihood as its co-variance matrix. Thus, we need to find the first and second derivative of the un-normalized posterior. Defining the skill-conditional employment share as $h_o(s) = \frac{\exp(\nu^{-1}\mu_{o'}+\nu^{-1}A_{o'}\cdot s)}{\sum_{o''}\exp(\nu^{-1}\mu_{o''}+\nu^{-1}A_{o''}\cdot s)}$, we can write:

$$\nabla\phi_o(s) = -\Sigma_s^{-1}(s-\bar{s}) + \nu^{-1}A_o^{\intercal} - \nu^{-1}\sum_{o'} h_{o'}(s)A_{o'}^{\intercal}$$

$$\nabla^2\phi_o(s) = -\Sigma_s^{-1} - \nu^{-2}\sum_{o'} h_{o'}(s)A_{o'}^{\intercal}A_{o'} + \nu^{-2}\left(\sum_{o'} h_{o'}(s)A_{o'}^{\intercal}\right)\left(\sum_{o'} h_{o'}(s)A_{o'}^{\intercal}\right)^{\intercal}$$

The approximate posterior mean sets the first derivative to zero:

$$\bar{s}_{|o} = \bar{s} + \nu^{-1}\Sigma \overbrace{\left(A_o^\intercal - \sum_{o'} h_{o'}(\bar{s}_{|o}) A_{o'}^\intercal\right)}^{\text{relative task intensity of occupation } o},$$

which implicitly defines $\bar{s}_{|o}$.
The posterior covariance matrix is then

$$\Sigma_{s|o} = -\nabla^2 \phi_o(\bar{s}_{|o})^{-1} = \left(\Sigma_s^{-1} + \nu^{-2} \underbrace{\left(\sum_{o'} h_{o'}(\bar{s}_{|o}) A_{o'}^\intercal A_{o'} - \left(\sum_{o'} h_{o'}(\bar{s}_{|o}) A_{o'}^\intercal\right)\left(\sum_{o'} h_{o'}(\bar{s}_{|o}) A_{o'}^\intercal\right)^\intercal\right)}_{\text{Task intensity dispersion across occupations}}\right)^{-1}.$$

B Empirical appendix

B.1 Clustering of occupation-specific tasks

This section describes in more detail how we construct the task clusters on which our analysis is based. Our starting point is the list of detailed task statements in the O*NET database. We retain only the subset of tasks that O*NET classifies as "core" for any given occupation, dropping "supplemental" tasks that are less relevant and/or important to the occupation.

B.1.1 Extracting skill requirements

For each of the detailed tasks, we extract a core activity and skill requirements using a LLM, specifically openAI's GPT-4o model. The system and user prompts are stated below.[B.1]

Table B.1 provides an illustration of the core activity and required skills this approach extracts for a set of skills; it also indicates the cluster the cluster will eventually be assigned to.

System Prompt.

```
<Role> You are an expert in labor economics, job analysis, and task
   classification. </Role>

<Overall goal>
You will be presented with a list of {len(tasks_chunk)}
   occupation-specific task statements. The ultimate goal is to group
   these and thousands of other tasks into clusters based on the type
   of activity and skills utilized, i.e. someone skilled at one task
   in a cluster could perform others in that cluster.

Your overall task is to prepare this clustering step by identifying,
   for each task statement:
```

[B.1] The *temperature* parameter is set to 0.00001, which directs the model to provide its most confident response, minimizing variation across runs. Technically, the LLM predicts the next word in a sequence based on the preceding words and its prior training. Denoting by q_i the logit for candidate token i, the softmax function is used to scale the logits and map them into probabilities: $\frac{e^{q_i/T}}{\sum_{k=1}^{\text{size of vocabulary}} e^{q_k/T}}$. The parameter T is known as *temperature*. A higher temperature value "excites" previously low probability candidates, encouraging creativity, whereas a lower temperature value lowers the smaller outputs relative to the largest outputs. A lower value is thus preferable for contexts requiring high coherence and accuracy. Note, though, that even $T = 0$ does not result in deterministic output in practice, likely due to sources of randomness such as the state of the random-number generator. Moreover, the so-called "reasoning" generation of models does not support a temperature parameter. In practice, we have verified that the time allocation shares are highly comparable across different runs of the model.

```
(i) the fundamental  work activity; and (ii) the most essential skills
   and abilities (up to 5) required to perform this task effectively.

Key requirements for (i) the fundamental work activity:
- Definition: The fundamental work activity is a concise, abstract
   description that encapsulates the core activity  involved in the
   task statement (what is being done).
- Generalization: The activity label should be broad enough that if
   someone can perform one task under this label,
 they'd be expected to handle any task requiring that same underlying
   competency.
- Terminology: Use concise and standardized, domain-agnostic terms
   that capture the core function, phrasing them in clear,
   natural-sounding language.
- Self-explanatory: The label must offer a succinct, self-contained
   summary that includes essential context for standalone
   understanding;
     do not merely reduce the statement to a vague abbreviation.
- Predominant activity: When multiple actions are present, select the
   one that best represents the overall purpose of the task.

Key requirements for (ii) the skills and abilities:
- Definition: skills refer to developed capacities that facilitate
   performance of activities that occur across jobs; abilities refer
   to relatively enduring attributes of an individual's capability for
   performing a particular range of different tasks. A "skill" is not
   simply a rewording of the task/activity description itself, but
   rather answer the question "What underlying capability makes
   someone good at this task?"
So for each skill you identify, ask: 'Would this skill enable
   performance across MULTIPLE different tasks and contexts?' If not,
   it's likely not a true underlying skill.
- Task: Identify the essential skills and abilities required to
   perform this task effectively and list them in descending order of
   importance.
- The number of skills can range from 1 to 5, depending on the
```

```
   complexity of the task; for straightforward ones, only include the
   core skills (at least 1); avoid padding with peripheral skills.
- The "most important skills" can include both capabilities and, where
   critical, knowledge domains, including:
i) Cognitive capabilities
Examples:  strategic planning, statistical analysis, diagnostic
   reasoning, technical writing
ii) Specialized technical capabilities
Examples: programming, surgical technique, database architecture
iii) Interpersonal capabilities, management, and leadership
Examples: negotiation, leadership, instruction, conflict resolution,
   team development, performance evaluation, delegation,
   organizational design, change management,
management of financial resources, management of personnel resources
iv) Physical/sensory capabilities
Examples: fine motor control, spatial awareness, physical endurance
v) Specialized expertise areas
Examples: mathematical modeling, designing scientific experiments,
   legal precedents, medical protocols
- Each skill in the list must follow this format: "Skill Name (Level)"
- Level must be one of "basic", "intermediate", "advanced", or
   "expert" using the following criteria:
basic: requires fundamental knowledge and minimal experience;
   intermediate: requires specialized knowledge and moderate
   experience; advanced: requires deep expertise and substantial
   experience;
expert: requires mastery-level knowledge, typically 8+ years of
   focused experience.
- Critial: When identifying skills, pay particular attention to
   specialized capabilities that typically command higher wages in the
   labor market, such as: Complex analytical or strategic thinking
   skills, Specialized technical expertise that requires extensive
   training, High-stakes decision-making capabilities, Skills
   involving the direction of others' work or significant resources,
   Expertise that is both scarce and in high demand. For high-wage
   occupations, ensure you separately list these skills rather than
```

```
   using generic descriptors.
</Overall goal>

<Detailed instructions>
Step 1) For each task statement, identify and summarize (i) the
   fundamental work activity; and (ii) the most important  skills.
Step 2) Return the output (activity; skills) for all
   {len(tasks_chunk)} task statements in the JSON format specified.
- List the skills in descending order of importance to the task (most
   crucial first).
- Never leave any task blank; if unsure, provide your best guess.
</Detailed instructions>

<Examples>
The following examples illustrate the level of abstraction desired
   (for reference only, do not copy these exact labels unless they
   truly match the task at hand).

Example work activities: "train and teach others at work", "operate
   vehicles", "operate industrial machinery," "provide advice or
   consultation," "coordinate the work of subordinates/peers,"
   "inspect or repair equipment," etc.

Example task: "Review statistical studies, technological advances, or
   regulatory standards and trends to stay abreast of issues in the
   field of quality control."
Activity: evaluate complex technical information
Skills: analytical thinking (expert), research (advanced), statistical
   analysis (advanced), reading comprehension (advanced)

Example task: "Wash glasses or other serving equipment at bars."
- Activity: cleaning
- Skills: manual dexterity (basic)

Example task: "Analyze financial statements to determine company
   valuation"
```

```
Activity: analyze and interpret financial data
Skills: market analysis (expert), numerical reasoning (advanced), data
   analysis (intermediate), financial modeling (advanced)

Example task: "Lead strategic planning for a multinational division
   with $500M annual revenue"
Activity: direct organizational strategy
Skills: leadership (expert), strategic planning (expert), financial
   analysis (advanced), business intelligence (advanced)

Example task: "Train new employees on safety procedures and equipment
   operation"
Activity: train and teach colleagues
Skills: verbal communication (intermediate), technical knowledge about
   equipment (intermediate), instructional planning (basic)

Example task: "Supervise and coordinate the work plan of customer
   service representatives and schedule shifts"
Activity: manage team operations
Skills: operational planning (intermediate), verbal communication
   (advanced), people development (advanced)

Example task: "Develop marketing strategy for new product launch"
Activity: create marketing strategies
Skills: strategic thinking (advanced), business knowledge (expert),
   creativity (intermediate), analytical reasoning (intermediate),
   written communication (advanced)

Example task: "Read operating schedules or instructions or receive
   verbal orders to determine amounts to be pumped."
- Activity: follow operational instructions
- Skills: reading comprehension (basic), verbal communication (basic)
</Examples>
```

User Prompt.

```
<List of task statements>
Here is the list of {len(tasks_chunk)} job task statements to analyze,
   along with their index numbers:

{task_list}
</List of task statements>
```

Task	Activity	Skills	Cluster
Smooth rough spots on walls and ceilings, using sandpaper	smooth surfaces	manual dexterity (basic), attention to detail (basic)	Performing Detailed Manual Tasks
Lubricate moving parts on gate-crossing mechanisms and swinging signals	lubricate moving parts	manual dexterity (basic), attention to detail (basic)	Performing Detailed Manual Tasks
Perform physically demanding tasks, such as digging trenches to lay conduit or moving or lifting heavy objects	perform physical labor	physical endurance (advanced), manual dexterity (intermediate)	Performing Physical Labor
Prepare reports of activities, evaluations, recommendations, or decisions	prepare reports	report writing (advanced), analytical reasoning (intermediate), attention to detail (intermediate)	Processing and Analyzing Records
Confer with officials of public health and law enforcement agencies to coordinate interdepartmental activities.	coordinate interdepartmental activities	collaboration (advanced), project management (advanced), communication skills (intermediate)	Coordinating Project Initiatives

Table B.1: Examples: detailed tasks, extracted characteristics, and cluster assignment

Notes. This table lists examples of detailed tasks (first column), that is the input, as well as the extracted core activity and skill requirements (LLM-generated), and the labeled cluster to which this task is assigned.

B.1.2 Embeddings and clustering

We use Alibaba's `gte-Qwen2-1.5B-instruct` model to create word embeddings of dimension 1,536 for the extracted skills for each task statement. To prepare the embeddings data for clustering, and noting that the HDBSCAN algorithm we are using performs best on data with low to medium dimensionality, we next perform a two-part dimensionality reduction step. We initially perform PCA, retaining 267 principal components that explain 95% of the variance in the embedding space. We then perform a subsequent UMAP step, which is useful to preserve both local and global data structures while shrinking the number of components to a level suited for the

HDBSCAN algorithm. (We use the following hyperparameters for UMAP: `n_components` = 40, `option_umap_n_neighbors` = 40 and `option_umap_min_dist` = 0.1.) Finally, we use the HDB-SCAN algorithms with the following hyperparameters `min_cluster_size` = 70, `min_samples` = 40, `cluster_selection_epsilon` = 0.05. The distance metric er `option_hdbscan_metric` is Euclidean given the preceding UMAP step.

B.1.3 Labeling step & summary output

Finally, we use OpenAI's o3-mini-high model to create natural-language labels and a summary description for each of the task clusters. These cluster-level meta data are useful in two ways: in terms of interpretation, and as inputs to the LLM when constructing the occupation-level time shares across the task clusters. Practically, for each cluster we randomly select ten representative tasks and feed the core activity as well as the skill requirements for these tasks to the LLM, instructing it to generate a cluster label and a brief description, per the following prompts.

Table B.2 details all 38 task clusters, indicating the summary label and description.

System Prompt.

```
 <Role> You are a world-class expert in labor economics, task
    classification and  occupational analysis.  You use concise and
    standardized language that is consistent with established
    terminology in skills/occupational databases like O*NET or PIACC.
</Role>

<Overall goal>
The overarching goal is to create accurate and meaningful summary
    labels for clusters of job tasks.
Each cluster comprises many tasks, which grouped by the type of
    activity (what is being done) and the skills required (capacities
    that facilitate performance of activities); i.e., the general rule
    is that a person proficient in one task in a given cluster should
    also be able to perform others in that cluster.

Given this goal, you will be presented with a list of tasks --
    alongside the most essential skills required to perform each --
    that exemplify a particular cluster.

You primary task is to create an accurate and concise summary label
```

```
   for this cluster of tasks.
Your secondary task is to provide a concise description of this
   cluster, with reference to core skill requirements differentiating
   this cluster from others.

Requirements for the summary label:
- The label summarizes the common core activities (what is being
   done), while remaining specific enough to meaningfully
   differentiate this cluster from others.
- The label focuses on the essential underlying activity rather than
   the specific domain.
- The label is sufficiently specific to allow differentiating between
   occupations that have different skill requirements and wage levels.
- The label is concise (2-5 words),  uses natural sounding language
   aligned with established task/skill terminology,
    and where possible begins with a gerund (verb+ing form).

Requirements for the description:
- The concise description (1 sentence) summarizes the cluster, with
   reference to core skill requirements differentiating this cluster
   from others.
</Overall goal>

<Detailed instructions>
Step 1: Analyze the {len(tasks_chunk)} tasks by identifying the
   fundamental activities involved and core skills utilized across all
   them.

Step 2: Create a summary cluster label that satisfies the requirements
   outlined above.
Test your label to ensure that it meets each of the X requirements;
   revise and iterate until this is the case.

Step 3: Given the label, and considering the skills listed for the
   exemplary rasks, provide a concise description.
</Detailed instructions>
```

```
<Examples of cluster labels>
Here are examples of cluster labels to illustrate the desired level of
   abstraction. These serve for guidance only, you must create
   appropriate task-specific labels.

- Positive example: "Developing and Building Teams" (relevant across
   domains, but specific enough to distinguish from other
   interpersonal tasks)
- Positive example: "Analyzing quantitative data" (relevant across
   different occupations, distinct from qualitative analysis which
   would involve different skills)
- Positive example: "Performing gross motor or heavy manual physical
   labor" (connotes a broad range of tasks with similar skill
   requirements)
- Positive example: "Technical Operation and Maintenance Tasks" (not
   domain specific, connotes a skill requirement distinct from
   advanced technical analysis)
- Negative example: "Getting Information" (too unspecific)
- Negative example: "Performing Administrative Activities" (too broad,
   could involve routine tasks such as processing paperwork or
   advanced managerial tasks, i.e. tasks requiring very different
   skills)
- Negative example: "Communication" (too unspecific, could comprise
   anything from chatting with colleagues to arguing a complex case in
   court)
</Examples>
```

User Prompt.

```
 <List of tasks to analyze>
Here is the list of {len(task_descriptions)} tasks that are
   representative of the task cluster under consideration alongside
   the most important skills required to perform them:

{task_list}
</List of tasks to analyze>
```

Cluster label	Description
Performing Detailed Manual Tasks	This cluster involves executing precise, hands-on operations—ranging from cleaning and lubricating to marking and packaging—that rely on basic manual dexterity and careful attention to detail.
Performing Precision Finishing Tasks	This cluster encompasses tasks that involve fine manual adjustments and finishing operations—such as aligning, smoothing, and testing components—requiring intermediate manual dexterity and attention to detail.
Preparing and Planning Meals	This cluster involves tasks that span cooking, menu planning, and overseeing food safety and service, requiring strong culinary skills, dietary knowledge, and attention to detail.
Maintaining Records and Inventory	This cluster involves routine operational support tasks that require diligent record keeping, inventory management, and clear communication to sustain documentation, asset tracking, and service functions.
Coordinating Detail-Oriented Operations	This cluster involves routine tasks such as sorting, record-keeping, material distribution, and facility upkeep that require meticulous attention to detail and basic to intermediate organizational skills.
Delivering Public Presentations	This cluster involves speaking in formal and public settings—ranging from project briefings and lectures to courtroom testimonies—requiring advanced public speaking, communication, and subject matter expertise.
Documenting Technical Information	This cluster focuses on capturing and recording technical details and processes using advanced technical writing, documentation, and attention to detail.
Performing Clinical Procedures	This cluster involves executing patient-focused clinical tasks that combine advanced diagnostic reasoning, technical equipment operation, interpersonal communication, and therapeutic interventions to assess and treat medical conditions.
Providing Customer Service	This cluster involves direct customer interactions that require strong interpersonal, communication, time management, and organizational skills to assist, guide, and support various client needs in service-oriented settings.
Administering Regulatory Compliance	This cluster involves interpreting policies, reviewing and enforcing regulatory standards, and developing procedures, all requiring advanced regulatory knowledge, analytical reasoning, and communication skills.
Coordinating Emergency Response	This cluster involves executing and managing emergency procedures, crisis communication, threat monitoring, and strategic planning, requiring advanced emergency response and situational awareness skills.
Maintaining and Managing Records	This cluster involves systematically updating, retrieving, and organizing diverse records and data through strong attention to detail and organizational skills.
Reviewing and Editing Information	This cluster involves accurately reviewing, editing, and verifying various forms of information—from written materials to operational data—requiring advanced attention to detail and precision.
Ensuring Regulatory Compliance	This cluster involves meticulous inspection, record management, and analytical review to verify adherence to regulatory standards and operational protocols.
Performing Physical Labor	This cluster encompasses physically demanding tasks that require manual dexterity, physical endurance, and fundamental technical and safety skills across diverse settings including construction, cleaning, material handling, animal care, and exercise instruction.
Creating Technical Visual Representations	This cluster involves transforming data, technical specifications, and artistic ideas into precise visual media by integrating advanced drafting, design, and multimedia editing skills.
Designing and Implementing Systems	This cluster centers on planning, designing, and integrating technical systems across diverse fields, emphasizing advanced project management, engineering design, and technical expertise.
Processing and Analyzing Records	This cluster involves tasks focused on maintaining, recording, and evaluating data—including financial, production, and medical records—where strong numerical reasoning, analytical skills, and meticulous attention to detail are essential.
Operating, Calibrating, and Inspecting Equipment	This task cluster involves technical operations focused on handling electronic recording, imaging, and sound equipment, requiring precise calibration, systematic inspections, and adept problem-solving skills.
Inspecting and Evaluating Quality	This cluster involves detailed inspections and analyses that rely on advanced analytical reasoning and attention to detail to assess product, site, and process quality, ensuring standards and performance are met.
Performing Skilled Manual Operations	This cluster involves executing diverse manual tasks—ranging from assembly, finishing, and equipment maintenance to operation and cleaning—that require intermediate to advanced manual dexterity, attention to detail, and technical proficiency.
Negotiating and Coordinating Contracts	This cluster involves engaging stakeholders through advanced negotiation and communication skills to secure agreements and manage procurement activities while coordinating legal, regulatory, and project management requirements.
Repairing and Maintaining Equipment	This cluster encompasses preventative maintenance, technical repair, and equipment installation tasks that require advanced system knowledge, manual dexterity, and safety awareness.
Managing Safety Operations	This cluster involves overseeing operational activities with a strong emphasis on safety compliance, hazard assessment, and technical oversight across diverse industrial, emergency, and technical settings.
Monitoring and Inspecting Systems	This cluster involves actively operating, adjusting, and inspecting automated processes and equipment by employing advanced technical troubleshooting, precision measurement, and quality control skills to ensure optimal system performance.
Analyzing and Optimizing Systems	This cluster involves applying advanced technical analysis, simulation, and maintenance skills to assess performance, recommend design changes, and ensure operational integrity across diverse systems.
Analyzing Natural Phenomena	This cluster involves applying advanced scientific analysis, technical expertise, and data interpretation to evaluate, classify, and redesign natural and biological systems across diverse domains.
Instructing and Training	This cluster involves delivering instruction, training, and mentorship across diverse subject areas, relying on advanced instructional techniques, verbal communication, and subject matter expertise.
Mediating and Consulting Clients	This cluster involves interpersonal guidance tasks—including counseling, referrals, conflict investigation, and dispute resolution—that require advanced communication, empathy, and problem-solving skills to address diverse client issues effectively.
Developing and Delivering Instruction	This cluster encompasses tasks centered on planning, designing, and conveying educational programs and curricula, leveraging advanced instructional design, curriculum development, and communication skills across varied content areas.
Communicating and Educating	This cluster involves effectively conveying information, instructions, and feedback through verbal channels, integrating clear reporting, problem-solving, and instructional skills across diverse contexts.
Engaging in Continuous Learning	This cluster encompasses tasks that require ongoing research, information synthesis, and professional development to remain current with industry trends, technology advancements, and scientific progress.
Collaborating Across Functions	This cluster comprises tasks requiring effective teamwork, communication, and coordination across diverse professional areas to address problems, manage operations, and support technical and client-oriented activities.
Coordinating Project Initiatives	This cluster involves planning, overseeing, and collaborating on diverse project tasks, leveraging advanced project management, communication, and leadership skills.
Coordinating Administrative Tasks	This cluster encompasses planning, scheduling, and organizing a range of administrative operations, requiring strong organizational, communication, and project management skills.
Coordinating Strategic Initiatives	This cluster involves planning, organizing, and supervising diverse activities—ranging from educational events to disaster recovery and recruitment—requiring advanced leadership, strategic planning, and team management skills.
Producing Technical Documentation	This cluster involves drafting and compiling technical reports, proposals, and documentation through advanced technical writing, analytical reasoning, and data presentation skills, with elements of programming and research support.
Performing Strategic Analysis	This cluster involves advanced quantitative research, financial and cost analyses, and strategic planning to assess deviations, forecast outcomes, and drive management recommendations.

Table B.2: Task cluster labels and descriptions

B.2 LLM-generated time diaries

This section describes how, given the task clusters, we construct the occupational task weight matrix. In addition, we detail validation exercises.

B.2.1 Methodology

To generate the time diaries we use the latest version of GPT-o3-mini-high for this step. We loop over each occupation using the following prompts. These are designed to break the complex task into clear sequential steps, draw on high-quality inputs, and convert the qualitative assessment into a numerical output.

System Prompt.

```
You are an expert in occupational classification (the system being
   used is {occ_system} at the {occ_level}-digit level) and analyzing
   occupational time allocation.
You combine precision in classification with deep knowledge of how
   different occupational groups allocate their time across tasks.
You focus on accurate, structured data output, and your time share
   predictions MUST sum to exactly 1.0. You are precise and
   conscientious.
```

User Prompt.

```
<Objective and context>
We want to accurately estimate what percentage of their work time
   workers in a specific occupation group spend on various tasks.
The occupation group is {occ_title}, as classified following the
   occupational classification system {classification_description}.
The reference period to consider is the {option_timeperiod}.
</Objective and context>

<List of tasks>
The tasks to consider are as follows:

{task_list}
</List of tasks>
```

```
<Instructions>
Follow these steps to generate accurate time allocation estimates:

1. Analyze core functions, activities and responsibilities of
   {occ_title}
2. For each task listed above:
  - Review the task carefully
  - Assess the importance and frequency of this task for {occ_title}
   in the {option_timeperiod}, drawing on high-quality evidence,
   expert knowledge and statistical data.
3. Having done this for all tasks, convert assessments to time
   allocation shares:
    For each task:
  - Convert assessment to percentage of work time
  - Translate to decimal (e.g., 25%  0.2500)
  - Document: task_name: 0.XXXX
  - Add to running_sum
4. Verification (required):
  Calculate total_sum to 4 decimals
  If total_sum != 1.0000:
  - Calculate scaling = 1.0000/total_sum
  - Multiply EACH share by scaling
  - Recalculate sum
  STOP: Submit shares only if sum = 1.0000

Critical Requirements:
- Use 4 decimal precision throughout
- Show calculations
- Final shares MUST sum to 1.0000
- No rounding of intermediate values
- Calculate time shares for all {task_count} tasks.
</Instructions>
```

In rare instances, the LLM does not generate time shares that sum to 1, despite the above instructions. This is reminiscent of human responses in time diary surveys. We therefore programmatically normalize the LLM-predicted shares, just as we do using the conventional, human survey responses discussed below. Over the course of the project we moved from openAI 4o to o3-mini-high, which dramatically reduced the need for this ex-post normalization of time shares.

B.2.2 Validation

This section describes four complementary approaches that collectively demonstrate the robustness of the LLM-based measurement of the occupational task weights.

Comparison to aggregated O*NET task ratings. O*NET 29.2 provides for each O*NET-SOC-2019 8-digit occupation a list of detailed task statements categorical ratings on a scale from 1-5 that indicate the importance of that task to the occupation. In this section we use these ratings and the mapping from tasks to our clusters to construct an alternative A matrix and compare it to our baseline.

In a first step, we collapse occupations to the SOC-2019 minor group level and create occupation-cluster weights that correspond to the shares of the detailed tasks associated to that occupation group that belong to a given cluster, weighted by importance ratings. That is, the weight occupation o puts on cluster c is greater if a large fraction of the detailed tasks associated to o are linked to c or if those tasks have especially high importance weights. [B.2] Next, the SOC-2019 occupations are cross-walked to the SOC-2000 classification used in our analysis using the official crosswalks available from https://www.onetcenter.org/taxonomy.html.

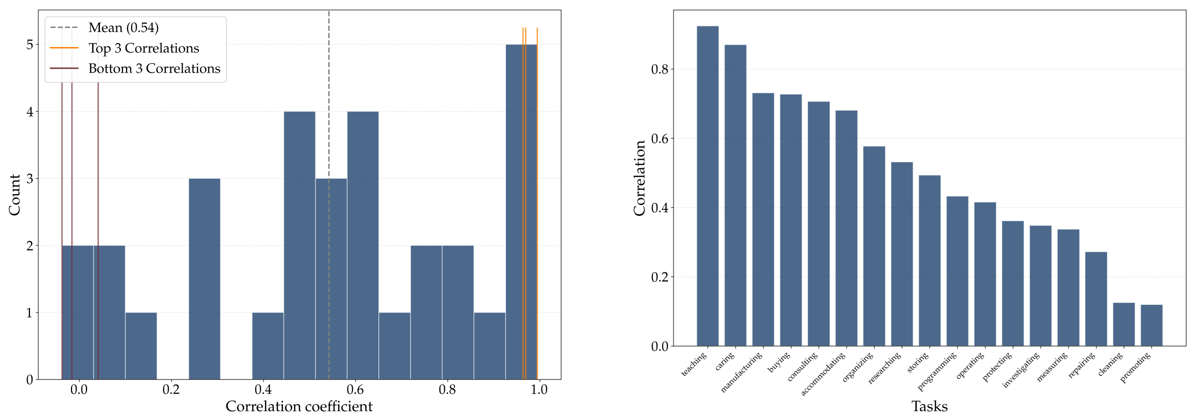
Comparing the occupational task weights thus obtained to our baseline, we find that they exhibit a strong, positive correlation (0.45). The task ratings yield an A matrix with a higher degree of concentration, in that the average occupation-level Herfindahl Index is 0.18 compared to 0.11 in our baseline. We prefer our baseline approach, because it relies on cardinal time shares that identify the entries of the A matrix in a model-consistent way, but in principle the A matrix based on O*NET task ratings is a viable alternative.

BIBB time diaries. We use a supplemental survey conducted for the 2012 Employment Survey carried out by the German Federal Institute for Vocational Training (Bundesinstitut fuer Berufsbildung, BIBB) and the and the German Federal Institute for Occupational Safety and Health (BAuA). This survey asks a subset of surveyed workers to report their allocation of time to a pre-specified list of tasks such as “teaching” and “cleaning” on a given day.[B.3]

We proceed in three steps. First, we construct occupation-task level time allocation shares from the BIBB. We consider the sample of individuals in West Germany aged 15-65 who have

[B.2] In addition to “importance,” O*NET also provides scales for “relevance” and “frequency,” which in principle could be used in the weighting also.

[B.3] The full list of 17 tasks is as follows: ’investigating’, ’organizing’, ’researching’, ’programming’, ’teaching’, ’consulting’, ’buying’, ’promoting’, ’repairing’, ’accommodating’, ’caring’, ’cleaning’, ’protecting’, ’measuring’, ’operating’, ’manufacturing’, ’storing’



(a) Occupation-level correlations

(b) Task-level correlations

Figure B.1: Comparison of LLM-generated task weights & BIBB survey

Notes. The left panel plots the distribution of occupation-level correlations between the LLM-predicted task weights and those constructed from the BIBB. The right panel shows the task-level correlations across occupations instead.

completed their training and who report a valid occupation ISCO-08 2-digit occupation. For each individual, we normalize the time shares to sum to one. Then we average time shares across occupations and retain those occupations comprising least ten surveyed workers. Second, we re-run the same LLM-based process as in the main analysis, but now requiring responses for the same set of tasks considered in the BIBB and looping over ISCO-08 2-digit occupations. Third, we compare the BIBB-based and LLM-based responses.

Overall, the two different approaches yield highly comparable results. Figure B.1a shows correlations at the level of occupations; the mean correlation is 0.54, the standard deviation is 0.31. The lowest correlations are reported for "Customer Service Clerks," "General and Keyboard Clerks" and "Numerical and Material Recording Clerks." A major source of discrepancy is that for these occupations, survey respondents in the BIBB put substantial weight on the task "programming" (which in the original German language context could also be interpreted as "using a computer"). With further clarification on the interpretation of tasks, we expect that the LLM and BIBB would yield results that are more comparable still. Figure B.1b reports task-level correlations of weights across occupations. The tasks with the lowest overlap are "promoting" and "cleaning," while the alignment is greatest for "teaching" and "caring."

Comparison to O*NET importance weights for GWAs. Next, we compare LLM-generated time allocation shares with O*NET occupation-level importance weights for Generalized Work Activities (GWAs). We use the GWAs from ONET 5.0, as this database aligns with the SOC-2000 classification used in our main empirical analysis. We construct relative importance weights for each GWA by occupation and aggregate to the minor-group level. We then generate LLM-based time allocation shares for identical GWAs across the same occupational categories and compare the resulting two A matrices.

Figure B.2 displays the distribution of occupation-level correlations between LLM-generated time shares and O*NET importance weights. The distribution is markedly right-skewed, with a central tendency around 0.6-0.7, indicating substantial alignment between our LLM-based approach and established occupational measurements. Figure B.3 presents task-specific correlations across occupations, grouped by correlation strength. Tasks involving cognitive and managerial functions show the strongest correspondence (correlations >0.75), while more specialized technical tasks exhibit moderate alignment. Even the lowest-correlating tasks maintain coefficients above 0.2, suggesting our approach captures meaningful variation across the entire task spectrum.

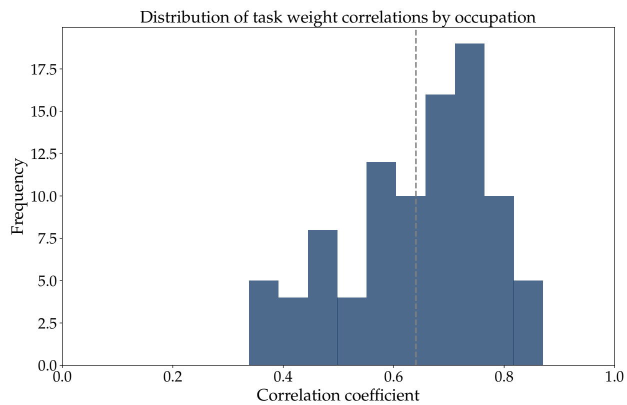


Figure B.2: GWAs: LLM-time shares correlate with O*NET importance weights

LLM consistency in aggregation across occupational hierarchies. Figure **??** demonstrates the strong consistency of the LLM generated task weights across different levels of occupational aggregation. We compare weights derived directly from major occupational groups with those constructed by averaging across their constituent minor occupational categories (using unweighted means). The very high correlation coefficient (0.89) confirms that our task allocation approach maintains consistency regardless of aggregation level.

B.3 Occupational labor shares

To construct occupation-level labor shares – i.e., compensation over value-added – we take the following approach, where industries are indexed by j and occupations by o:

(i) Construct weights s_{oj} corresponding to the share of industry-j payments to labor going to occupation o:

$$s_{oj} = \frac{(\text{wage payments to } o \text{ in } j)}{\sum_o (\text{wage payments to } o \text{ in } j)} \tag{B.1}$$

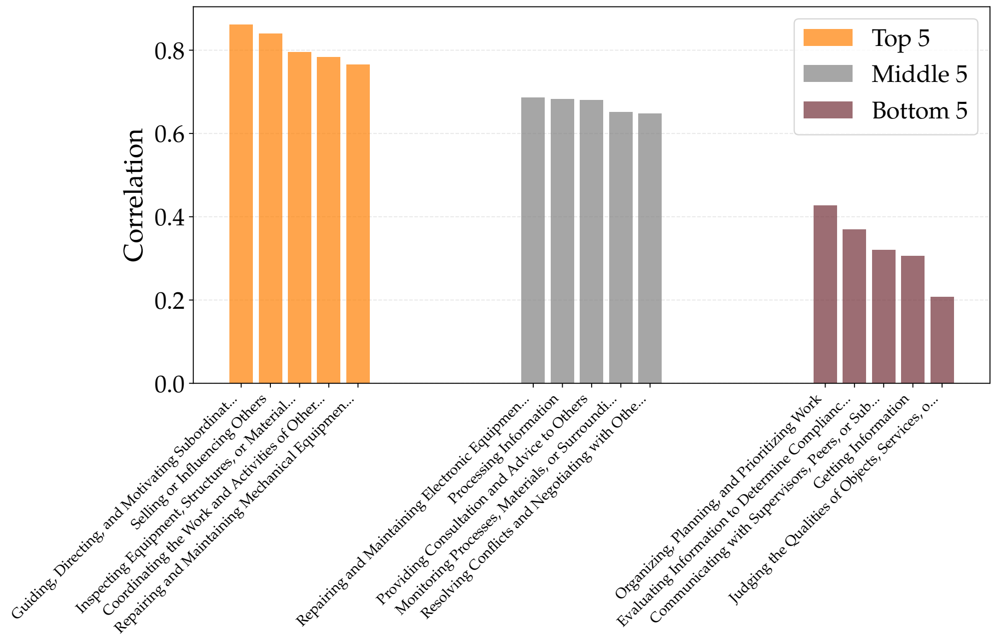


Figure B.3: Correlation across occupations by task

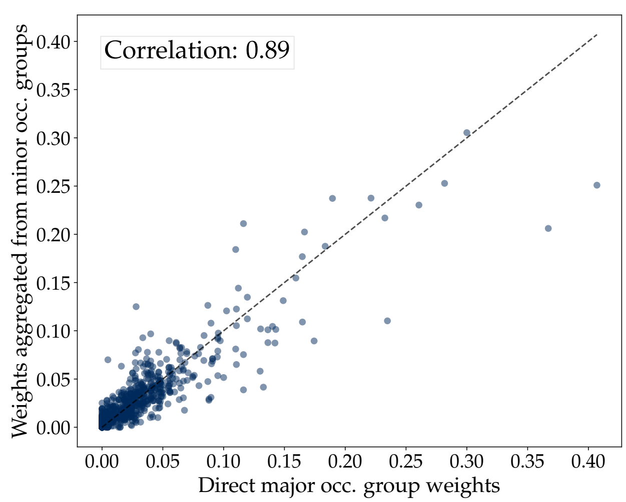


Figure B.4: Comparison of task weights at different occupational levels of aggregation *(ii)* Assume that value-added in j due to o is proportional to s_{oj}:

$$\mathrm{VA}_{oj} = s_{oj} \cdot \mathrm{VA}_j \tag{B.2}$$

(iii) Compute

$$\mathrm{LS}_o = \frac{\sum_j \text{wage payments to } o \text{ in } j}{\sum_j \mathrm{VA}_{oj}} \tag{B.3}$$

In the empirical implementation, we use the 2002 wave of the BLS Occupational Employment and Wage Statistics (OEWS) to construct s_{oj}. This wave uses the same SOC-2000 occupational classification as our (harmonized) NLSY dataset and NAICS-2002 industry codes. Data on VA_j come from the BEA-BLS Integrated Industry-level Production Accounts (1987-2020). In addition, to construct the numerator of equation (B.3) we use the same apportionment method as in equation (B.2).[B.4] Industry-level data are averaged across sample years. We then link the OEWS data on s_{oj} with the BEA/BLS industry-level data by merging at the 2-digit NAICS level, retaining only those industries with a 1:1 mapping.[B.5]

The (unweighted) average labor share across occupations is 0.61, with a minimum of 0.49 (Farming, Fishing, and Forestry Occupations) and a maximum of 0.75 (Legal Occupations).

B.4 Automation exposure measures: Webb (2019)

Figure B.5 shows the average standardized exposure score of each task cluster for the three types of technology considered by Webb (2019): AI, Robots, and Software.

It can be observed that the task cluster identified as most exposed to AI in Webb (2019) is "Analyzing Natural Phenomena" which, according to the LLM's summary description, involves "applying advanced scientific analysis, technical expertise, and data interpretation to evaluate, classify, and redesign natural and biological systems across diverse domains." By contrast, "Processing and Analyzing Record," our primary example of a task category exposed to LLMs has a close to average exposure score.

This difference is indeed to be expected. The technology cluster labeled by Webb (2019) as "AI" comprises a broader set of tools, including neural networks and deep learning algorithms more broadly, compared to the study by Eloundou *et al.* (2023), which explores task-level exposure to LLMs more specifically. Thus, it is indeed to be expected that different tasks would be exposed

[B.4] Using the wage bill information from the OEWS instead suffers from the problem that magnitudes of compensation differ from those in the BEA-BLS accounts; using the latter is, therefore, internally more consistent.

[B.5] The BEA/BLS data provide a crosswalk from the "production account classes" to NAICS-2007; NAICS-2007 and NAICS-2002 are identical at the 2-digit level.

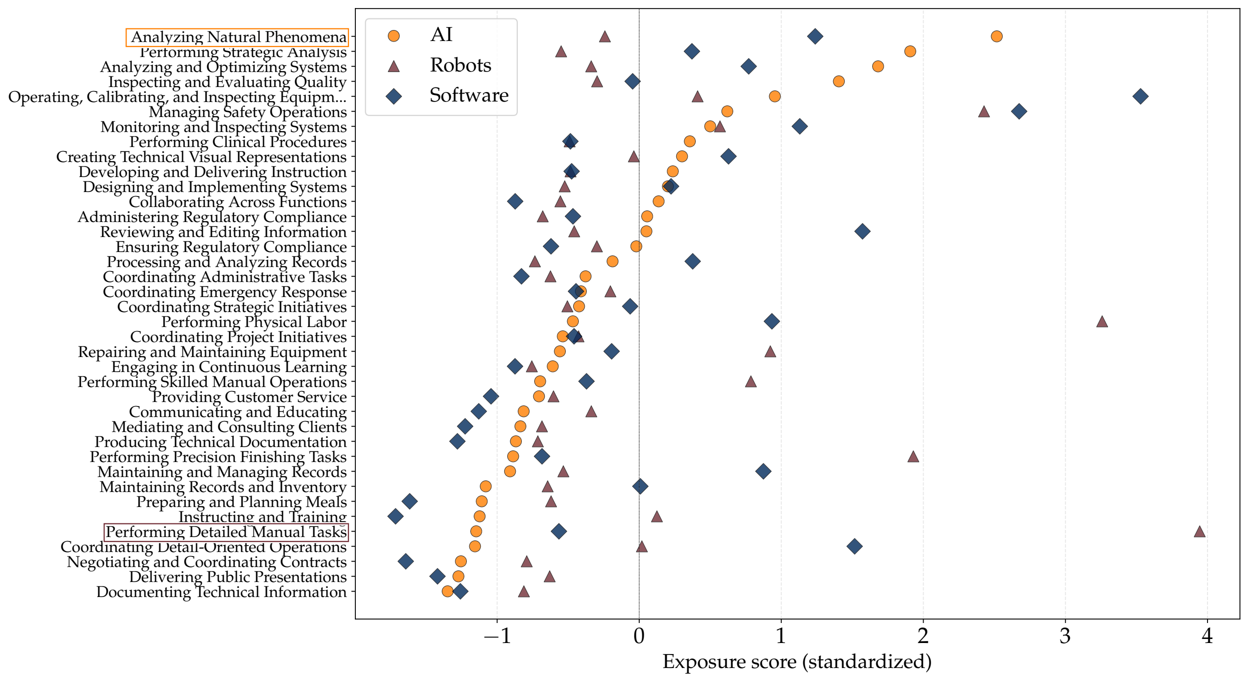


Figure B.5: Technology-specific exposure scores at the task level (Webb, 2019)

Notes. This chart shows for each of three technologies the standardized exposure score for our task clusters based on the results of Webb (2019). In Webb's approach, AI patents are identified by terms like "neural network," "deep learning," or "generative model" in titles or abstracts. Software patents contain terms such as "software" or "program" while excluding hardware-related terms like "chip" or "circuit." Robot patents are selected through the inclusion of the term "robot" in titles or abstracts.

to the two technologies, respectively. Our framework suggests that this difference is potentially important, even if the degree of automation of two distinct tasks, as measured by the decline in the labor share, for instance, may carry labor market consequences that differ in important ways depending on the bundles of tasks the exposed tasks form part of and the distribution of task-specific skills.

C Quantitative appendix

C.1 Methodology

C.1.1 Stochastic gradient descent

To estimate the model parameters, including the joint distribution of skills, the following stochastic object has to be maximized:

$$\hat{\mathcal{L}}_i(w_{i,\hat{o}_{i,\cdot},\cdot}, \hat{o}_{i,\cdot}|\nu, \varsigma, \bar{s}, \Sigma_s) = \left(\frac{1}{n_0}\sum_j \prod_t P(\hat{o}_{i,t}|w_{j,\cdot,t}, \nu)\right) \cdot f(w_{i,\hat{o}_{i,\cdot},\cdot}|\varsigma, \bar{s}, \Sigma_s)$$

To do this, we can write exploit the fact $s_i|w_{j,\hat{o}_{i,\cdot},\cdot}$ is normal and thus any can be written as

$$s_i = \mu_s^{cond} + L_s^{cond} \cdot u$$

for some easy to compute $(\mu_s^{cond}, L_s^{cond})$ and $u \sim \mathcal{N}(0, I)$. u is drawn once and then held constant throughout the maximization procedure, while μ_s^{cond} and L_s^{cond} depend on model parameters. We therefore proceed as follows:

(i) For each worker i, generate n_0 draws of u that remain fixed

(ii) Compute $s_i = \mu_s^{cond} + L_s^{cond} \cdot u$

(iii) Compute $\varepsilon_{i,t} = w_{i,\hat{o}_{i,t},t} - \mu_o - A_{o,\cdot} \cdot s_i$

(iv) Use these draws to obtain a sample $w_{j,\cdot,\cdot}$ of wages in every occupation-period cell.

(v) Compute $\hat{\mathcal{L}}_i(w_{i,\hat{o}_{i,\cdot},\cdot}, \hat{o}_{i,\cdot}|\nu, \varsigma, \bar{s}, \Sigma_s)$

We then employ stochastic gradient descent. That is, starting with some guess, we update our parameters as follows:

$$\theta_{t+1} = \theta_t - \eta \cdot \nabla\left(-\hat{\mathcal{L}}(\theta_t)\right)$$

for some sufficiently small $\eta > 0$. To further ease the computational load, we evaluate the likelihood at a subsample B only. To do this, we iterate over epochs. In each epoch, we randomly partition individuals into n groups:

$$\{1, 2, \ldots, I\} = B_1 \cup B_2 \cup \ldots \cup B_n, \quad B_i \cap B_j = \emptyset$$

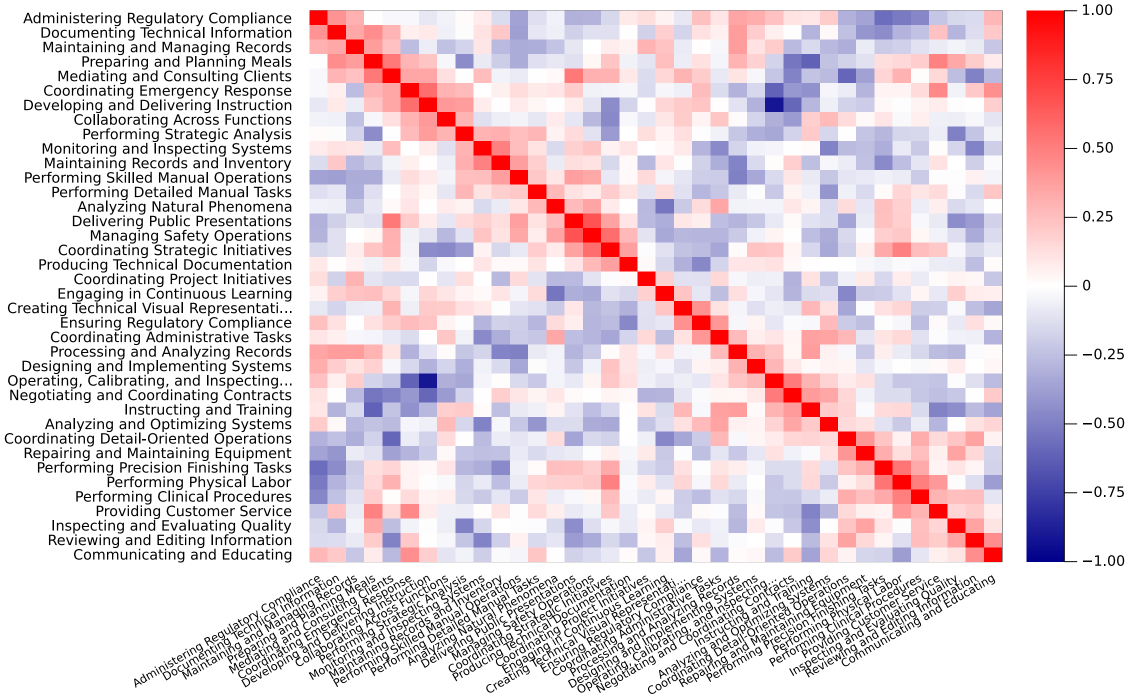


Figure C.1: Correlation matrix C_s

Notes: Heatmap of the correlation matrix C_s. Each cell corresponds to one entry of the matrix.

and, on each iteration within an epoch, evaluate the likelihood based on batch $B_1, \ldots, B_n$ only. Using parallelization over individuals and auto-differentiation techniques, this reduces the computation time of the likelihood maximization procedure substantially and allows us to solve this problem even when the parameter space is very large.

C.2 Additional results

C.2.1 Additional estimation results

The co-variance matrix of our baseline estimate is plotted in Figure C.1.

C.2.2 Additional simulation results

Sorting. Figure C.2 illustrates sorting on the basis of comparative advantage, using the skill of "Coordinating Strategic Initiatives" for the occupation of "Top Executives" as an example. Since the task of "Coordinating Strategic Initiatives" is heavily utilized within this occupation, the occupation features a worker pool that is on average more skilled in this task.

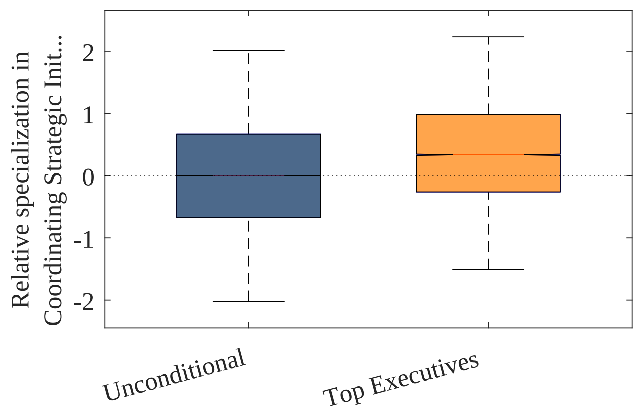


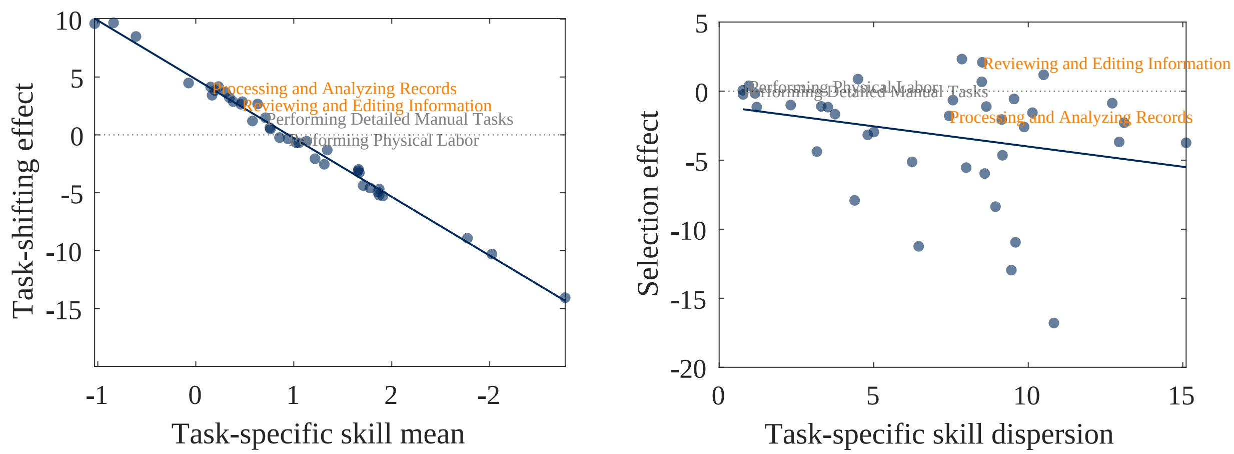
Figure C.2: Selection based on comparative advantage: example

Notes. This figure displays the standardized distribution of relative specialization in a focal task τ^* defined as $s_{i,\tau^\star} - \frac{1}{n_{\text{skill}}} \sum_{\mathcal{T}_l} s_{i,\tau}$, where τ^* is the task "Coordinating Strategic Initiatives," comparing the unconditional distribution that the distribution conditional on having selected into the occupation "Top Executives."

Task shift and selection effects. In the main text, we showed that the dispersion of worker skills is positively related to the magnitude of the re-sorting effect. In this appendix, we conduct a comparative analysis of different task automation shocks to understand the determinants of task shift and selection effects. One way to assess the role of these effects with rising exposure is to regress their effect size onto the exposure $A_{o,\tau}$ of every occupation $o \in \mathcal{O}$.[C.1]. Figure C.3 plots the slope of the corresponding regression line against simple measures that plausibly determine the size - the skill mean $\bar{s}$ for the task-shift effect and the skill dispersion S_s for the selection effect. Panel (a) shows that the task shift effect increases faster in occupational exposure when $\bar{s}$ is smaller. This is not surprising: Automating low productivity skills tends to lead to more powerful task upgrading effects. The figure also indicates that the task upgrading effect for tasks associated with the rise of AI ("Processing and Analyzing Records", "Reviewing and Editing Information") tend to be larger than those for skills associated with robots ("Performing Detailed Manual Tasks", "Performing Physical Labor"). Panel (b) shows that selection effects typically put more downward pressure on wages when the affected skill is more dispersed. Again, this is not too surprising, as more dispersed skills tend to be more dominant in determining sorting patterns and thereby exacerbate the correlation between occupational exposure and specialization in the automated task. What is more surprising is that the most affected tasks in the case of AI appear to be outliers from this pattern. Selection effects may therefore play a more important role in alternative scenarios of AI automation.

Alternative shock. Figure C.4 reproduces Figure 12 from the main text for an alternative shock

[C.1]We weight these regressions by pre-shock occupational employment shares



(a) Task-shifting **(b)** Selection

Figure C.3: Decomposition of task-shifting & selection effects: comparison across tasks

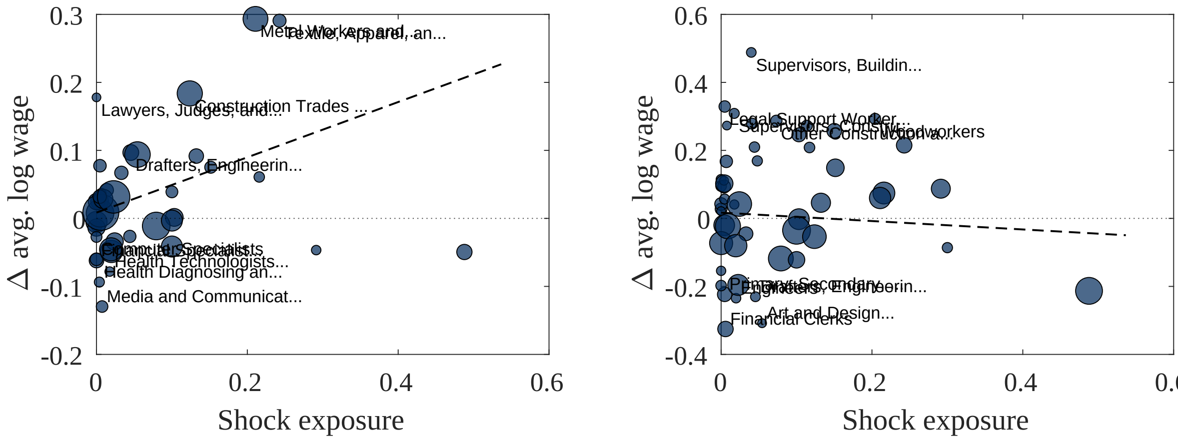
Notes. In both panels, each dot corresponds to a task. In the left panel, the horizontal axis displays the (standardized) estimated skill mean of the task, $\bar{s}_\tau$. The vertical axis displays the coefficient of a regression that regresses the magnitude of the task-shift effect from full automation for a given occupation on its exposure $A_{o,\tau}$, weighted by pre-shock employment. In the right panel, the horizontal axis displays the estimated skill dispersion of the task, $S_{s,\tau}$. The vertical axis displays the coefficient of a regression that regresses the magnitude of the selection effect from full automation for a given occupation on its exposure $A_{o,\tau}$, weighted by pre-shock employment.

to the second most affected skill, "Maintaining and Managing Records". The results remain qualitatively unchanged.

C.2.3 Robustness: returns to occupational experience

As mentioned in the main text, a limitation of our baseline model is that it under-predicts workers' tendency to stay in the same occupation (cf. Figure 6). One likely reason is that the model abstracts from occupational tenure effects, which are important in the data (e.g., Traiberman, 2019, Figure 3). In this section, we we show that our model can be extended to feature a type of learning in the form of returns to occupational experience. Reassuring e found that the

This version of the model is identical to our baseline except that a worker's productivity depends on their tenure in occupation o. Here, we consider the simplest such case, where productivity is greater whenever a worker has at least one year of experience in the occupation. We thus assume that workers who in period t choose occupation $o \in \mathcal{O}$ have a productivity that depends on whether they worked in occupation o in period $t-1$: If they did not work in o in $t-1$, their productivity is 1. If they did work in o in $t-1$, their productivity is $\exp(\Delta)$ with $\Delta > 0$



(a) Incumbent stayers **(b)** Incumbent leavers

Figure C.4: Stayers versus leavers

Notes. See notes for Figure 12.

The worker's decision problem can be characterized as follows: Let

$$w^e_{i,o}(0) = \mu_o + A \cdot s_i$$
$$w^e_{i,o}(1) = \mu_o + \Delta + A \cdot s_i$$

be the expected wages of a worker with skills s_i. Then the worker's (expected) value function satisfies:

$$V_o(0) = w^e_{i,o}(0) + \beta\nu \log\left[\exp\left(\frac{V_o(1)}{\nu}\right) + \sum_{o'\neq o} \exp\left(\frac{V_{o'}(0)}{\nu}\right)\right]$$
$$V_o(1) = w^e_{i,o}(1) + \beta\nu \log\left[\exp\left(\frac{V_o(1)}{\nu}\right) + \sum_{o'\neq o} \exp\left(\frac{V_{o'}(0)}{\nu}\right)\right]$$

and thus that $V_o(1) = V_o(0) + \Delta$. This can be calculated via value function iteration and is simple enough to be handled by our estimation algorithm.

We do not report the full set of results for this specification but note that, as illustrated in Figure **??**, this version of the model yields substantially greater levels of occupational persistence.

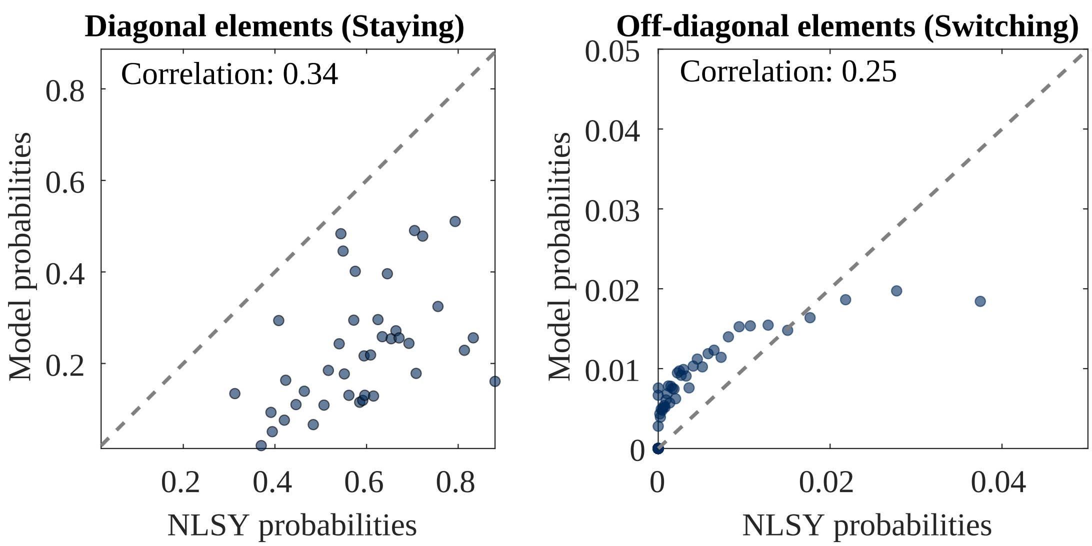


Figure C.5: Occupational transition patterns in the model with learning

Notes. See notes for Figure 6.