

# The Economic Impacts of Generative AI on the Structure of Work

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## Abstract

We introduce a task-based model of production that responds to automation technologies such as AI, and empirically validate several of its core implications. Production is a sequence of *steps* that firms aggregate into *tasks* and then into *jobs*, each performed by a single worker. A firm can reduce wage costs of jobs by assigning each worker a narrower set of tasks, thereby increasing specialization, but doing so introduces coordination frictions among a larger number of workers. The optimal organizational structure resulting from these aggregations must balance these opposing forces. Production steps may be executed *manually* by humans, *augmented* with AI assistance under human oversight, or *automated* within an AI chain, where multiple consecutive steps are executed by AI and only the final output is verified by a human. A key implication of chaining is that it can overturn simple comparative-advantage logic: a step where a human has an advantage over AI in isolation may nonetheless be optimally automated if it sits adjacent to strong AI performing steps. Productivity gains therefore depend not only on AI quality but also on where AI-suitable steps are positioned within the workflow. We characterize how firms optimally allocate steps between humans and AI in both the short run, when job boundaries are fixed, and the long run, when automation and job design are jointly chosen. This framework yields predictions about task- versus job-level exposure to AI, worker specialization, and the non-linear productivity gains that arise when marginal improvements in AI quality trigger discrete reorganizations of work. Finally, we show how the production functions derived from firm-level cost minimization can map into an aggregate CES production function to study the macroeconomic implications of improving AI quality.

## 1 Introduction

Recent advances in Artificial Intelligence (AI) carry the potential to significantly impact work processes and economic productivity. Questions about the impact of automation technology on production and labor

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are not new, but the rise of generative AI is notable for the breadth of occupational tasks that it might influence, including traditionally white-color knowledge work Eloundou et al. (2023). As generative AI and language models see rapid adoption in the workplace, multiple effects—both local and global—can arise. In the short term, we might expect efficiency gains from individual task-level improvements and partial automation of certain production steps, increasing worker productivity. In the long term, however, it is tempting to imagine larger disruptions to labor as AI usage becomes more widespread. The proliferation of AI tools could potentially enable reorganization of tasks, job responsibilities, and worker skill requirements, with substantial implications for the labor market.

To explore potential long-run impacts of new AI technology, we treat both the definition of worker tasks and the partitioning of tasks into job responsibilities as endogenous market outcomes. A firm seeks to optimize its cost of production by choosing which steps of its production sequence to automate, which steps to assign to human workers, and how to split human labor into jobs with different skill requirements. For example, in the absence of effective automation technology, a firm might hire multiple high-skill workers in different job roles to accomplish distinct steps of its production process, incurring hand-off costs whenever work passes from one worker to another. As AI technology improves, the firm might instead choose to automate many of these steps—lumping them together into one logical task—and then hire a single lower-skill worker to oversee this automation and validate the production outcome. Whether this strategy is effective depends not only on the effectiveness of the AI technology at accomplishing individual production steps, but on the sequential relationship between steps, the relative ease of verification versus manual execution, and hand-off costs between workers.

One might naturally wonder what is special about AI technology in this scenario, relative to other forms of automation. An important feature of AI is its generality: its potential to influence many different tasks, albeit disproportionately. As such, an improvement in AI technology can simultaneously impact automation decisions across multiple points in a production chain, leading to large shifts in overall production strategy. By endogenizing the organization of worker tasks and job assignments, we seek to capture non-local effects that might depend on the sequencing of production steps and their relation to each other.

Table 1: Summary of AI’s Impact in Short and Long Run

Time Horizon	Job Design	Worker Skills and Wages	Automation Strategy	Comments
Short-run	Fixed	Fixed	Optimized within jobs	Productivity gains by automating existing tasks
Long-run	Flexible	Skills and relative wages adjust to job design	Optimized across jobs	Joint optimization of automation and job design to minimize total labor costs

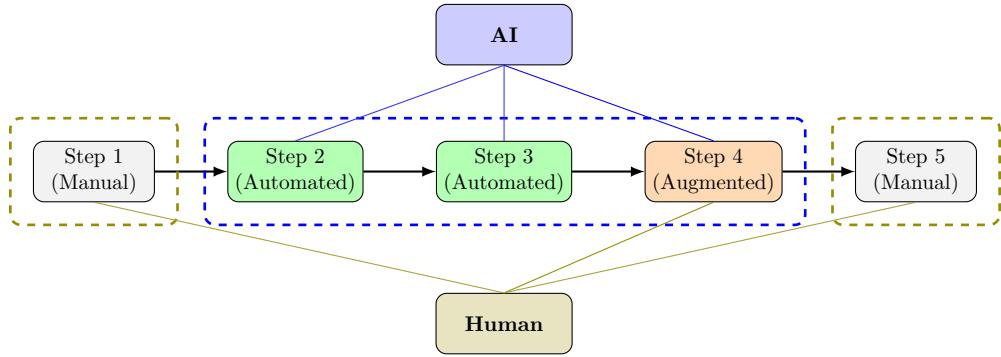
We use our model of automation and labor assignment to explore the effect of AI and the resulting automation of tasks. We investigate how AI advancements affect this division in the short-run—where human capital needs remain fixed but AI is used to increase worker productivity by reducing the time it takes to complete tasks—and in the long-run—where both human capital requirements and firm automation strategies can jointly adjust.

**Automation versus Augmentation.** Central to our model is the distinction between full automation of a production step versus worker augmentation. In our model, three modes of step completion are recognized: manual, augmented, and automated. *Manual* completion of a step means that a human carries out the work without any AI assistance. *Augmented* completion involves a human performing the step with the use of AI, which might (or might not) reduce labor costs. For example, a human describes the parameters of a step to an AI tool, the AI then executes the step, and its output is reviewed and approved by the human. In contrast, we say a step has been *automated* if it is completed by an AI end-to-end without any direct human intervention. We view automation as a way of putting certain production steps “under the hood” of a logical meta-task that a worker is attempting to complete. For example, as part of an AI-augmented request to complete one step (such as writing a report), an AI might also be assigned to complete one or more

preceding steps (such as running a statistical analysis) as part of that single request. Any such preceding step is said to be automated, and the set of all such automated steps, plus the final step that the worker is actively engaged with, can be thought of as a single worker task. By choosing which steps to automate and which to assign either manually or via augmentation, the firm implicitly designs the set of tasks exposed to its workers.

Although augmented and automated production steps both involve AI, they differ in one crucial respect: AI augmentation demands direct human oversight of the AI's output, whereas automation does not. Figure 1 illustrates these concepts using a sequence of five steps. Steps 1 and 5 are performed manually by a human. Steps 2, 3, and 4 form an AI chain and are done using AI. Steps 2 and 3 are automated because their outputs feed directly into subsequent AI tasks without human review. Steps 4 is augmented because its output is evaluated by a human before proceeding. The resulting worker tasks in this job thus become 1, 4 and 5.

Figure 1: Illustrative Example for Division of Labor



*Notes:* This figure illustrates division of labor across five steps: Steps 1 and 5 are manual; Steps 2 and 3 are AI-automated (done without direct human intervention); Step 4 is AI-augmented (done with AI but requires human oversight). Lines from the AI box show which steps involve AI, and lines from the Human box indicate steps requiring human execution or oversight. Dashed boxes group steps according to their task assignments. Steps 1 and 5 are human tasks while Steps 2-4 form an AI chain task.

The decision to deploy AI on a given production step compares the cost of manual execution to the unified AI-based execution cost. At first glance, this might seem like another way of stating that steps get assigned to whichever factor has the comparative advantage in that step, but this is not the case: position within the productive process profoundly changes the optimal allocation of steps between humans and AI. When a single step is performed by an AI as an augmented task, there is always a human requesting the task and evaluating its output in an AI-augmented manner. But with two or more steps it is possible to re-configure production so that an AI completing one step passes its output directly into the next step without human intervention (i.e., the first step is automated). The AI chain (Steps 2–4) in Figure 1 illustrates this case: Steps 2 and 3 are fully automated (their outputs flow from one step to the next without direct human intervention) whereas Step 4 is AI-augmented with human oversight at the end of the chain. This chaining is potentially a source of large productivity gains *but* it requires AIs that can perform each step with a high probability of success. The model's basic setup shares conceptual similarities with the O-ring model of production (Kremer, 1993), and the role humans play in the model as offering judgment on AI outputs is consistent with the emphasis in Agrawal et al. (2019).

A key implication of the model is that chaining steps together into a single task can reverse comparative advantage assignments for individual steps. It can be efficient to deploy an AI on a step even when humans hold a comparative advantage in that step in isolation. A surprising result of chaining is strong AI performance on one step can shift another step from human to AI execution through chaining, even if the AI's capability on the second step is inferior to that of a human. Step 3 in Figure 1 illustrates such a case: with appropriate parameter values, it may be that, *in isolation*, it is more efficient to complete Step 3 manually rather than with the assistance of AI, yet overall production costs are minimized when it is bundled with

Steps 2 and 4 in an AI-automated chain. This might occur if it is especially easy to verify the output of Step 4.

More generally, we should expect the gains from automation to be greatest when highly automatable steps occur together in the production process. Informally, we can think of a job as more or less “fragmented” in its exposure to AI depending on whether the steps on which AI is most effective are mutually coincident or interleaved with steps for which humans hold a strong comparative advantage. In Section 4.1 we define a metric of fragmentation for jobs within our model and show that it approximates the impact of optimal AI deployment.

In our model, with highly capable AIs, the human role shrinks to asking and judging. This perhaps sounds like an uninspiring role but it is not necessarily a low-paid or unimportant one. Consider the famed music producer Rick Rubin, who is not poor, discussing his market value in an interview with Anderson Cooper:

RICK RUBIN: I've no technical ability. And I know nothing about music.

ANDERSON COOPER: Well, you must know something.

RICK RUBIN: I know what I like and what I don't like. I'm decisive about what I like and what I don't like.

ANDERSON COOPER: So what are you being paid for?

RICK RUBIN: The confidence that I have in my taste, and my ability to express what I feel, has proven helpful for artists.

We might be paid for being helpful to AIs. And this help might be valuable, even if we have no ability to do the tasks ourselves. In other words, automation can enable new forms of labor-labor substitution by separating task execution from task evaluation, allowing workers to leverage judgment skills even in domains where they lack execution abilities, potentially upending the allocation of workers to occupations in hard-to-forsee ways (see Autor and Handel (2013) on this human capital-task-wage relationship).

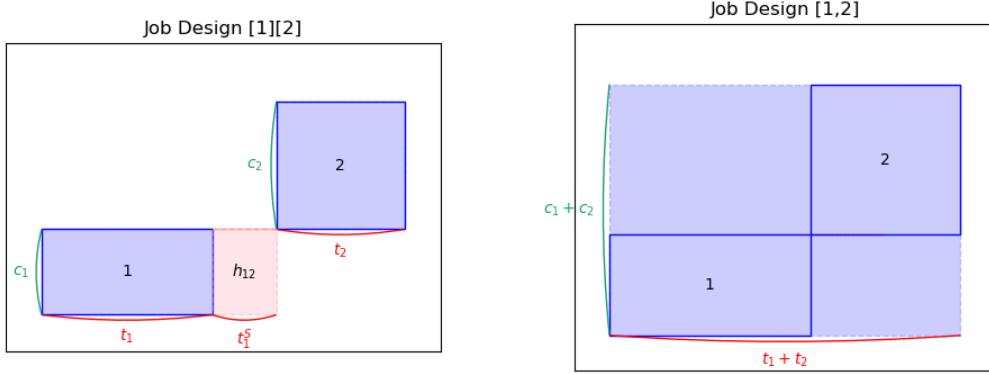
**Jobs and Worker Skill.** In the short-run, the primary impact of AI automation is to modify the amount of time needed for workers to complete their work. But over a longer time horizon, the optimal deployment of AI automation influences not only the time required to complete tasks, but also the level of required worker skill (i.e., the human capital investment required to train labor to be proficient at the task) and even the optimal division of tasks into jobs. To model these effects, we associate with each production step both a time requirement and a skill requirement. To complete a job, a worker must have the skills required of all tasks that make up the job description. The total labor cost (i.e., wage bill) of a job increases proportional to both the time needed to complete all steps and with the total skill level of the worker assigned to the job.

To capture the inefficiencies of fragmenting work into narrowly defined jobs, we introduce a *hand-off cost*, in time, that must be paid whenever output moves from one worker's job to another's. This creates a tension in job design: specialized jobs, containing fewer tasks, align worker skills more precisely with the job's requirements but incur higher hand-off costs. By contrast, generalist jobs, which bundle multiple tasks with different skill needs, reduce hand-off costs but require workers to acquire a broad set of skills, only a subset of which is deployed at any given time.

Figure 2 illustrates the trade-off firms face when deciding how to assign tasks to workers in a production process that aggregates steps into two tasks. In both panels, the shaded regions represent total wage bills. On the left, the firm employs two specialized workers, paying lower wage rates  $c_1$  and  $c_2$  but incurring coordination costs between them. On the right, the firm combines both tasks into one job, avoiding coordination costs altogether but paying a higher per-unit-time wage rate  $c_1 + c_2$  to a more skilled worker.

In some production sequences, adjacent tasks differ sharply in their time and skill profiles—the two cost dimensions that are focal in our model. When a time-consuming, low-skill task is immediately preceded or followed by a short, high-skill task, having a single worker perform both tasks has the unfortunate effect that a necessarily highly skilled individual spends a significant amount of time doing low-skill work. We refer to such tasks as “tent-pole tasks.” The sharp contrast between the skill and time costs of tent-pole tasks creates a friction that has historically driven the division of labor. For instance, rather than having a

Figure 2: Illustration of the Trade-off between Specialization and Coordination in Task Assignment



*Note:* Each task is represented by a rectangle whose height corresponds to its skill requirement ( $c$ ) and width to its time requirement ( $t$ ). The figure contrasts two organizational choices. In the left panel, each task is performed by a separate worker, reducing required skill per worker but introducing a hand-off cost (the pink rectangle) due to coordination and transfer frictions. In the right panel, both tasks are bundled into a single job performed by one worker, eliminating hand-off costs but requiring a worker skilled enough to perform both tasks and compensated with a higher per-unit-time wage.

high-skill worker complete both tasks, it may be more efficient to assign time-consuming, low-skill tasks to a different low-skill worker, even if this incurs extra hand-off costs.

As the deployment of AI automation changes the way worker tasks are defined, and hence changes the profile of time and skill requirements over the course of production, this can in turn influence the economic forces that determine the level of worker specialization. If certain tasks become automated, tent-pole scenarios like the one described above may shift or be avoided altogether, impacting the optimal assignment of production tasks across workers. This, in turn, can influence the relative balance of skilled labor as an input to production, with implications for wages and the distribution of productivity gains. We view this as a potential source of structural deskilling, whereby optimal AI deployment and automation can either increase or decrease the relative demand for skilled labor in a given production process.

**Optimizing Automation and its Implications.** Assigning production steps to factors of production is not a completely trivial optimization problem, even computationally. For a firm with  $m$  steps in its production process, the number of possible production arrangements grows exponentially in  $m$ . For the short-term optimization problem of optimizing the deployment of AI automation to a fixed set of job responsibilities and worker skill levels, we show how to analytically find the optimal automation strategy for an  $m$ -step job in time  $O(m^2)$  using dynamic programming. Long-term optimization—the joint problem of optimizing labor (the division of steps into jobs) and the use of AI automation (including optimal chaining)—can also be solved in polynomial time, subject to an error term that can be made arbitrarily small. Although we do not do it in this paper, this algorithmic approach could be combined with micro-details of task content and composition (as in Frey and Osborne (2017); Felten et al. (2021); Eloundou et al. (2023)) to create rich estimates of how technological change in various tasks would impact workers.

The chaining feature of the model connects to—and potentially reconciles—competing views about automation in production. Despite the emphasis on task-level substitution between AI and labor in most of the AI and labor literature, Autor et al. (2003), Acemoglu and Restrepo (2019) and Bresnahan et al. (2002), among others, argue that that meaningful substitution happens primarily at the system level. One could interpret the model as showing how task-level decisions aggregate into system-level automation through chaining. In our model, there is no Ship-of-Theseus requirement that tasks are automated one by one;

rather, entire chains can be automated all at once—consistent with the Bresnahan et al. (2002) perspective.

This ability for automation to be implemented in large leaps implies that improvements in AI quality can generate nonlinear effects on labor demand and wages. In the short run, higher AI performance reduces task time costs, potentially lowering labor demand. In the long run, however, worker retraining and unrestricted task reallocation can yield new wage schedules that reflect updated human capital and time cost parameters. These threshold effects imply that marginal AI advances may have little impact until they cross a short-run redesign or long-run restructuring tipping point, after which labor demand and job structures may shift abruptly. Our framework thus offers testable predictions on when and how AI-driven productivity gains trigger structural reorganization in labor markets.

Our model implies a form of algorithmic cost function for production, defined implicitly as the solution to an optimization procedure. However, as we show, the solution can also be interpreted as a standard CES production function that can be embedded within a general model of the economy. This allows us to distinguish manual and AI-assisted labor as separate inputs to production and model the aggregate demand for each.

**Empirical Evidence.** While our primary contribution is theoretical, we also bring new empirical evidence for key predictions and economic forces from the theory model. To do so, we assemble a task-level dataset that links O\*NET tasks to human assessments of AI exposure Eloundou et al. (2023), realized execution by AI drawn from Anthropic’s Economic Index Handa et al. (2025), and GPT-generated workflow orderings for each occupation. The dataset allows us to observe not only which tasks are exposed to AI, but where they sit within an occupation’s workflow and whether they are ultimately performed manually, augmented with AI, or automated by AI.

Using this dataset, we test three predictions that follow from the theoretical model. First, we find that tasks executed by AI tend to appear in contiguous blocks within occupations, consistent with the model’s prediction that the main margin of cost savings arises from forming longer AI chains. Second, conditional on level of exposure to AI, occupations whose AI-able steps are more dispersed in their workflow exhibit substantially lower AI execution, in line with the model’s task fragmentation logic. Third, when conceptually similar steps appear across occupations, those adjacent to AI-executed neighbors are significantly more likely to be automated, reflecting the local complementarities created by AI chains. Together, these patterns provide strong empirical support for the central economic forces embedded in the model.

## 2 Model

A firm’s production process consist of a sequence of steps  $\mathcal{S} = (s_1, \dots, s_m)$ . The firm can partition contiguous subsequences of steps into a sequence of tasks  $\mathcal{T} = (T_1, \dots, T_n)$  where  $T_b = (s_i, \dots, s_{i+\ell})$  for some  $i$  and  $\ell$ . The firm can also partition contiguous subsequences of the resulting tasks into jobs  $\mathcal{J} = (J_1, \dots, J_p)$ . Figure 3 provides an illustration for a production process with  $m = 7$  steps,  $n = 5$  tasks, and  $p = 3$  jobs. The cost of any such partitioning depends on the time and skill needed for the component steps, the mode in which the step is completed, and the grouping of steps and tasks. We discuss these in turn.

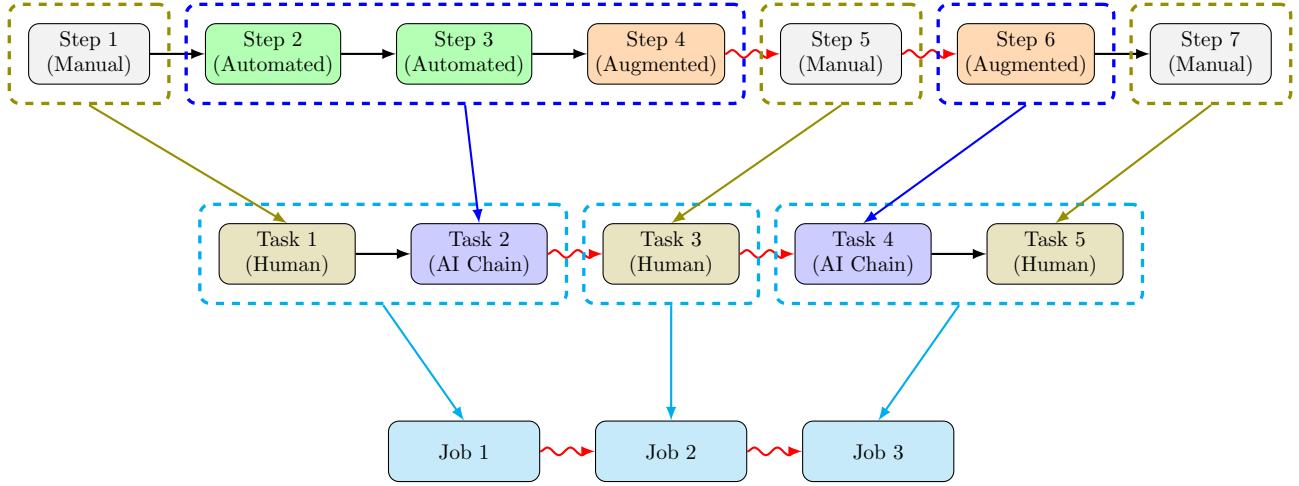
### 2.1 Steps

Each step can be completed with or without the use of AI. If the firm wishes to hire a human worker to complete step  $i$  manually (without AI), it must hire a worker of skill level  $c_i^H$  and pay them for their time  $t_i^H$  spent completing step  $i$ . Alternatively, if the firm wishes to augment a human worker with AI to complete step  $i$ , it must hire a worker of (a potentially different) skill level  $c_i^M$  and pay them for their time  $t_i^M$  spent collaborating with AI<sup>1</sup> to complete step  $i$ . Such a collaboration succeeds independently with some (step-dependent) probability  $q_i = \alpha^{d_i}$  where  $\alpha$  is the quality of the general purpose AI technology and  $d_i$  represents how “difficult” step  $i$  is for AI. The collaboration must be repeated until it succeeds, incurring the time cost of  $t_i^M$  per iteration for a total expected time cost of  $t_i^M/q_i$ .

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<sup>1</sup>This could, for example, represent the time spent formulating a prompt for AI and checking the response.

Figure 3: Illustrative Example of a Firm’s Production



*Notes:* This figure illustrates a firm’s production process in three layers. The top layer includes  $m = 7$  steps categorized into Manual (gray), Automated (green), and Augmented (orange) modes of execution. Steps are grouped by dashed boxes colored according to their corresponding task boxes in the layer below. The second layer aggregates steps into  $n = 5$  Tasks, labeled as Human-executed tasks (olive) or AI Chain tasks (blue) depending on the mode of execution. Dashed boxes in this layer are colored cyan to correspond with the jobs layer below. The third layer consolidates tasks into  $p = 3$  jobs, represented in cyan-colored boxes. Vertical colored arrows between layers show aggregation from individual steps into tasks and thenx jobs. Within each layer, horizontal arrows (black and red) show the flow of production. The red curly arrows represent the hand-off costs between jobs, evident from the third layer, that can be traced back to tasks and steps in the upper layers.

Definitions 1 and 2 formalize the two modes of performing a single step explicitly.

**Definition 1** (Manual Step). *A step  $i$  is said to be performed manually if it is executed entirely by a human worker without AI assistance. The associated skill and time costs for a manual step are denoted by  $(c_i^H, t_i^H)$ .*

**Definition 2** (Augmented Step). *A step  $i$  is said to be augmented if it is executed by the AI, after which its output is reviewed and approved by a human worker. The associated skill and (expected) time costs of managing a single augmented step are denoted by  $(c_i^M, \frac{t_i^M}{q_i})$ , where  $q_i \in (0, 1]$  is the AI’s probability of successfully completing the step.*

## 2.2 Tasks

Tasks are the basic unit of work of a human worker. Any step performed in isolation during the production process, either manually or in collaboration with AI augmentation, is a task. The associated skill and time costs for the resulting task are precisely the skill and time costs for the associated step performed in the chosen mode. Steps can also be automated by chaining them together, creating a new aggregate task.

**Definition 3** (Automated Step). *A step is said to be automated if it is executed entirely by AI without direct human intervention, and its output is passed directly to a subsequent augmented or automated step. The direct human costs (in both skill and time dimension) associated with an automated step are zero.*

**Definition 4** (AI Chain). *An AI chain is a contiguous block of one or more sequential steps executed by AI, in which all steps but the final one are automated and the final step is augmented. An AI chain spanning steps  $(s_\ell, \dots, s_r)$  has steps  $(s_\ell, \dots, s_{r-1})$  automated and step  $s_r$  augmented. The skill and time costs of this*

AI chain are given by:

$$\left( c_r^M, \frac{t_r^M}{\prod_{i=\ell}^r q_i} \right),$$

where  $q_i$  denotes the AI success probability for step  $s_i$ .

We can think of an AI chain as a single aggregate task that is being delegated to an AI. Successful completion requires that the AI complete all steps in  $(s_\ell, \dots, s_r)$ . The human worker who manages the AI execution of this chain need only prompt for and evaluate the goal step,  $s_r$ ; all other steps in the chain are assumed to be fully automated “under the hood” and hence beneath the awareness of the human worker. Managing an AI attempt at the chain therefore has the same costs as augmenting step  $s_r$ : namely, skill cost  $c_r^M$  and time cost (per attempt)  $t_r^M$ . Successful completion of the chain requires that the AI complete *every* constituent step successfully. Assuming independent failures, this occurs with probability  $\prod_{i=\ell}^r q_i$ , which we can view as the success probability for the aggregate chained task. Putting this all together yields skill and time costs  $(c_r^M, t_r^M / \prod_{i=\ell}^r q_i)$  for the AI chain, as described in Definition 4.

Note also that since  $q_i = \alpha^{d_i}$ , where recall  $d_i$  is a measure of the difficulty of step  $s_i$ , the probability of successful completion of an AI chain spanning steps  $(s_\ell, \dots, s_r)$  can be written as  $\alpha^{(\sum_{z=\ell}^r d_z)}$ . We can therefore think of  $\sum_{z=\ell}^r d_z$  as the total difficulty of the chain, which aggregates additively over its constituent steps.

To summarize, a task is either a manually-performed step, an AI-augmented step, or an AI chain. A sequence of tasks  $\mathcal{T}$  can be viewed as a partition of step sequence  $\mathcal{S}$  into contiguous subsequences, with each singleton being designated for either manual or augmented execution.

### 2.3 Jobs

A job is a subsequence of tasks that are assigned to a single human worker. Recall that each task  $T_b$  in task sequence  $\mathcal{T} = \{T_1, \dots, T_n\}$  has associated skill and time costs  $(c_b, t_b)$  that can depend on whether the task is being completed manually or with the aid of AI. A job  $J$  is a contiguous subsequence of tasks, say  $J = (T_b, \dots, T_{b+\ell})$  for some  $b$  and  $\ell$ . We say that a partition  $\mathcal{J} = (J_1, \dots, J_p)$  of all tasks into jobs is a *job design*.

The firm hires one worker for each job in its job design  $\mathcal{J}$ . The worker for job  $J_j$  completes all tasks associated with their job. The total time needed to complete all tasks in job  $J_j$  is  $\sum_{T_b \in J_j} t_b$ .

A worker’s wage is determined by the total skill required to complete their job. The total skill required to complete the tasks in job  $J_j$  is  $\sum_{T_b \in J_j} c_b$ . We then assume that a worker’s wage is proportional to the skill level of their job.<sup>2</sup> That is,

$$\text{Wage}_j = \sum_{T_b \in J_j} c_b. \quad (1)$$

The firm must pay workers their wage per unit of time regardless of which tasks they are assigned to complete at any given moment.<sup>3</sup>

While we allow the firm to specialize its job design and partition its production process into distinct jobs, we acknowledge that there are inherent inefficiencies and frictions that are introduced when splitting work among multiple workers. Absent such frictions in our model, it would always be optimal for a firm to

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<sup>2</sup>One motivation for this formulation is workers paying a human capital investment to acquire the skills necessary for a job. This investment must be offset by wages, and we express skill levels in units of their corresponding requisite wage. Rather than formalizing such a wage model here, we impose this as an assumption and provide a more detailed wage formulation in Section 5.

<sup>3</sup>This derivation implicitly assumes a common base wage rate; i.e., all wage differentiation is driven by the human capital cost of acquiring skills. More generally, different tasks  $T_b$  within job  $J_j$  could have different base wage rates  $w_b$  that could be influenced, for example, by the supply of and demand for labor of the corresponding type. One special case, explicitly motivated and discussed in Section 5, assumes manual tasks are executed by human labor at base wage rate  $w_H$ , and AI-assisted tasks are executed by AI management labor at base wage rate  $w_M$ . The formulation in Equation 1 implicitly normalizes these base wage rates to 1, incorporating them into skill costs  $c_b$  for notational simplicity. We maintain this normalization throughout subsequent sections until we explicitly distinguish human labor and AI management labor base wage rates in Section 5.

specialize its workers as much as possible, assigning a distinct worker to each task of its production process. We therefore introduce *hand-off costs* to a job design, as follows. In addition to the time required completing tasks, a worker may need to spend time handing off their work to another worker if  $J_j$  is not the final job in the job design  $\mathcal{J}$ . We will assume throughout that the hand-off time of a worker assigned to job  $J_j$  depends only on the final step of job  $J_j$  (see Figure 3). That is, conditional on where the hand-off occurs in the production process, its cost does not otherwise depend on previous hand-off events. Given step  $s_i$ , we write  $t_i^S$  to denote the additional hand-off time spent by a worker for whom the last step of their job is  $s_i$ . For notational convenience we define the hand-off time for the final step  $s_m$  to be zero:  $t_m^S = 0$ . Also for notational convenience, we will write  $t^S(J_j)$  to denote the hand-off time of job  $J_j$ , which recall is equal to  $t_i^S$  if  $s_i$  is the final step in job  $J_j$ . Thus the total time needed to complete job  $J_j$ , including hand-off costs, is

$$t^S(J_j) + \sum_{T_b \in J_j} t_b.$$

Taking into account both time and skill requirements, the total wage bill paid to a worker assigned to job  $J_j$ , per unit of output, is

$$\text{WageBill}_j = \left( \sum_{T_b \in J_j} c_b \right) \left( t^S(J_j) + \sum_{T_b \in J_j} t_b \right). \quad (2)$$

Equation (2) highlights two opposing forces that shape a job's boundaries. Adding more tasks to a worker's job increases the cumulative skill requirement and thus the wage rate for that worker. However, if tasks are kept separate, workers must incur additional hand-off costs at each job boundary. These two effects—higher wages from combining tasks versus higher hand-off costs from keeping them separate—jointly determine the optimal degree of task aggregation. We explore this trade-off in greater detail in Section 2.5.

## 2.4 Firm's Organizational Structure

Given the sequence of steps  $\mathcal{S} = \{s_1, \dots, s_m\}$ , the firm can design both the partition  $\mathcal{T}$  of steps into tasks and the partition  $\mathcal{J}$  of tasks into jobs. The choice of  $\mathcal{T}$  determines the time and skill requirements of each task. Given  $\mathcal{T}$ , the choice of  $\mathcal{J}$  then determines worker wage rates and time needed per unit of output (including hand-off costs). The full optimization problem faced by the firm can be expressed as

$$\min_{\mathcal{T}} \min_{\mathcal{J}} \text{TotalCost}(\mathcal{J}; \mathcal{T}) = \sum_{J_j \in \mathcal{J}} \text{WageBill}_j = \sum_{J_j \in \mathcal{J}} \left[ \left( \sum_{T_b \in J_j} c_b \right) \left( t^S(J_j) + \sum_{T_b \in J_j} t_b \right) \right] \quad (3)$$

where recall that, for each  $T_b \in \mathcal{T}$ ,  $t_b$  and  $c_b$  are as described in Section 2.2 and can depend on the selected mode of operation for individual steps.

We refer to (3) as the firm's *long-term* optimization problem, as it anticipates the adjustment of worker wages to fit the skill requirements of each job and sets job responsibilities accordingly. We also define a *short-term* optimization exercise in which jobs and worker wages are fixed but the firm may still wish to use AI to maximize worker productivity. This is equivalent to minimizing the time needed for a worker to perform a unit of work in their assigned job. It therefore suffices to optimize for each job separately. Thus, in the *short-term* optimization problem, we can assume without loss of generality that the sequence of steps  $\mathcal{S} = (s_1, \dots, s_m)$  is to be completed by a single worker paid at a (normalized) unit wage. The resulting optimization problem faced by the firm can be expressed as

$$\min_{\mathcal{T}} \sum_{T_b \in \mathcal{T}} t_b \quad (4)$$

where recall that if  $T_b = (s_\ell)$  is a manual task then  $t_b = t_\ell^H$ , and otherwise if  $T_b = (s_\ell, \dots, s_r)$  for some  $\ell \leq r$  then  $t_b = \frac{t_r^M}{\prod_{i=\ell}^r q_i}$  where  $q_i$  is the AI's probability of successfully completing step  $s_i$ .

## 2.5 Hand-off Costs and the Limits of Worker Specialization

Here we discuss how hand-off costs determine the optimal organization of production and limit full worker specialization in the firm's long-run problem (3). We leverage insights from a numerical example as well as a geometric illustrations, which together show how task aggregation balances higher wages against lower coordination costs.

Consider a production process where, for some fixed automation strategy  $\mathcal{T}$ , consists of  $n = 3$  tasks with the following cost parameters:

Task	$c_b$	$t_b$	$t_b^S$
1	3	1	3
2	1	2	0.5
3	2	2	0

With three tasks, there are four ways the firm can design jobs.<sup>4</sup> Denoting jobs by square brackets, with three tasks the four possible job designs are  $\{[1][2][3], [1, 2][3], [1][2, 3], [1, 2, 3]\}$ . The cost of these job designs for the example above is given in Table 2. In the absence of hand-off costs in Panel (a), the optimal

Table 2: Role of Hand-off Costs in Organizational Structure

Panel (a): Without Hand-off Costs

Job Design	Job	Job Tasks	$\sum c_b$	$\sum t_b$	Job Cost	Total Cost	Optimal Design
[1][2][3]	1	{1}	3	1	3	9	✓
	2	{2}	1	2	2		
	3	{3}	2	2	4		
[1,2][3]	1	{1, 2}	4	3	12	16	
	2	{3}	2	2	4		
[1][2,3]	1	{1}	3	1	3	15	
	2	{2, 3}	3	4	12		
[1,2,3]	1	{1, 2, 3}	6	5	30	30	

Panel (b): Including Hand-off Costs

Job Design	Job	Job Tasks	$\sum c_b$	$t_b^S + \sum t_b$	Job Cost	Total Cost	Optimal Design
[1][2][3]	1	{1}	3	4	12	18.5	
	2	{2}	1	2.5	2.5		
	3	{3}	2	2	4		
[1,2][3]	1	{1, 2}	4	3.5	14	18	✓
	2	{3}	2	2	4		
[1][2,3]	1	{1}	3	4	12	24	
	2	{2, 3}	3	4	12		
[1,2,3]	1	{1, 2, 3}	6	5	30	30	

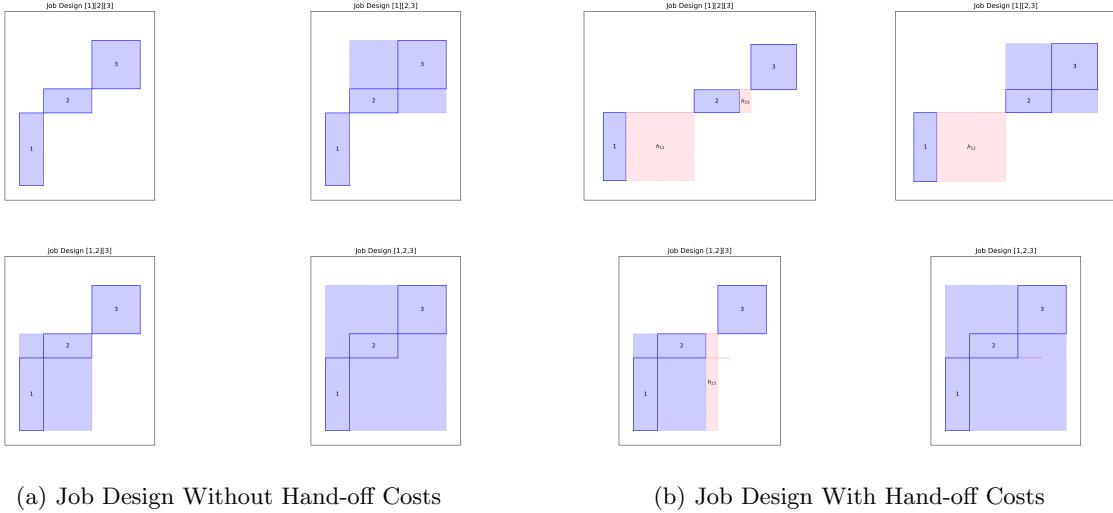
*Notes:* This table reports total production costs for each possible job design in an example production process with a fixed automation strategy and  $n = 3$  tasks. The cost parameters are given by  $(c_b, t_b, t_b^S) = \{(3, 1, 3), (1, 2, 0.5), (2, 2, 0)\}$ . In the absence of hand-off frictions, full specialization, corresponding to job design [1][2][3], is cost-minimizing. Once hand-off costs are taken into account, however, the optimal organizational structure changes to job design [1,2][3], which avoids the large coordination cost between tasks 1 and 2 at the expense of employing a higher-cost (more skilled) worker to complete those tasks.

<sup>4</sup>More generally, a production process with  $n$  tasks has  $2^{(n-1)}$  unique job designs.

job design corresponds to full specialization: each task forms a separate job assigned to a different worker. When hand-off costs are introduced in Panel (b), however, the optimal design changes to one in which tasks 1 and 2 are combined into a single job, while task 3 remains separate. This structure is optimal because it avoids the large hand-off cost that would otherwise arise between tasks 1 and 2 due to the large hand-off time value  $t_1^S = 3$ . By aggregating tasks 1 and 2, the firm pays a higher wage to a more skilled and more versatile worker but eliminates the costly coordination between the two tasks, lowering total production cost. Equation (2) captures this trade-off explicitly: adding more tasks to a worker's job raises the wage rate through the skill term  $\sum_{T_b \in J_j} c_b$ , while keeping tasks separate raises total cost through additional hand-offs  $t^S(J_j)$ . These two effects jointly determine the optimal degree of task aggregation.

The cost of different job designs admits a geometric interpretation as well. Figure 4 visualizes the production process of the example in Table 2 as stacked rectangles, where each rectangle's height corresponds to  $c_b$  and its width to  $t_b$ . Panel (a) depicts the job design when hand-off costs are zero, Panel (b) shows

Figure 4: Geometric Interpretation of Job Designs



*Notes:* Each panel visualizes the production process as stacked rectangles, where the area of each job's bounding box represents its wage bill. Panel (a) sets hand-off costs to zero, in which case it is optimal to assign one task per job. Panel (b) introduces hand-off costs, which alters the cost structure and makes the [1,2][3] design cost-minimizing.

the same process with hand-off costs. Visually, optimal job design balances two opposing forces. Combining tasks into a single job eliminates the pink rectangles representing additional hand-off costs between tasks, but creates inefficiencies due to the higher skill level of the worker required to do the job. Conversely, splitting tasks into separate jobs eliminates the intra-job inefficiencies but incurs hand-off time costs at each job boundary. These boundary costs scale with the cumulative human capital of the switching worker, so the height of the pink hand-off rectangle in Panel (b) equals the sum of human capital heights for that job. Cost-effective job design must balance these effects.

### 3 Optimization

In this section we consider the optimization problems (both short-term and long-term) faced by a firm choosing how to integrate AI automation technology into their production process. We begin by studying the short-term problem of optimizing automation strategy keeping job design and worker wages fixed. We then move on to the joint optimization of automation and labor taking into account long-term wage impacts.

### 3.1 Short-Term Optimization: Automation Design

We begin with a “short-term” optimization problem: the job design and worker wages are assumed to be fixed, so the goal is to find the choice of automation strategy for a single job that minimizes the total time cost. This optimization problem analyzes short-run benefits of AI: where worker skills are fixed but AI automation can still be employed to speed up tasks through some combination of augmentation and automation.

Since the job design and worker wage are fixed, it suffices to optimize for the amount of time spent to complete a unit of work for each job separately. So, from this point onward, we assume that there is a single job  $J$  with  $m$  steps  $\mathcal{S} = (s_1, \dots, s_m)$ , and our goal is to find the sequence of tasks  $\mathcal{T}$  that minimizes total completion time. It turns out that the time-optimal production strategy can be calculated via dynamic programming in  $O(m^2)$  time.

**Proposition 1.** *Given  $m$  steps organized into a single job, the time-optimal automation strategy can be calculated in time  $O(m^2)$  via dynamic programming.*

*Proof.* We first note the following recursive formulation of the optimization problem. For all  $k \leq m$ , let  $C[k]$  denote the minimum time needed to complete a hypothetical job that only includes steps 1 through  $k$ . Note that, because of the way we defined  $C[k]$ , task  $k$  cannot be automated in any minimum-time solution that determines  $C[k]$ ; it can only be augmented or performed manually. Note also that  $C[m]$  is the time cost of our desired optimal solution.

We now show how to calculate  $C[k]$  recursively. As a base case we have  $C[0] = 0$ , as the empty set of steps requires no time to complete. For  $k \geq 1$ ,  $C[k]$  is the lesser of

$$C[k-1] + t_k^H$$

and

$$\min_{\ell < k} \left\{ C[\ell] + \frac{t_k^M}{\prod_{i=\ell+1}^k q_i} \right\}.$$

In other words, we either complete step  $k$  manually (in which case we separately optimize over steps 1 through  $k-1$ ) or we augment step  $k$ . In the latter case, we then optimize over the length of the AI chain that ends with  $k$ . This could be a singleton chain with no automation (corresponding to  $\ell = k-1$ ), or a longer chain that automates one or more steps before step  $k$  (corresponding to a choice of  $\ell < k-1$ ). For any such choice of  $\ell$ , we then separately optimize the production strategy for tasks 1 through  $\ell$ .

Using this formulation, given the values  $(C[0], \dots, C[k-1])$ , we can calculate  $C[k]$  in time  $O(k)$  by considering each potential choice of  $\ell$ . Doing so for each  $k = 1, 2, \dots, m$  yields the value of  $C[m]$  (and the corresponding automation strategy) in total time  $O(m^2)$ .  $\square$

### 3.2 Warm-up to Long-Term Optimization: Job Design without AI

We now move to a broader optimization problem in which the firm can reorganize job requirements and the assignment of tasks to workers. As a warm-up to the full joint optimization of jobs and automation, we first show how to optimize the design of jobs for a fixed task structure. We can interpret this as a labor optimization problem without AI automation, where each step has only a single (i.e., manual) mode of completion and hence the task structure is fully determined.

**Proposition 2.** *Given a fixed sequence of tasks  $\mathcal{T} = (T_1, \dots, T_n)$  with skill and time costs  $c = (c_1, \dots, c_n)$  and  $t = (t_1, \dots, t_n)$ , the cost-minimizing job design  $\mathcal{J}$  can be computed in time  $O(n^2)$  by dynamic programming.*

*Proof.* We first note the following recursive formulation of the optimization problem. For all  $k \leq n$ , let  $C[k]$  denote the minimum cost of a job design for tasks 1 through  $k$ , *including hand-off costs for task  $k$* . Note then that  $C[n]$  is the cost of the optimal job design for all tasks, recalling that the hand-off cost for the final job (i.e., the job that includes task  $n$ ) is always 0.

We now show how to calculate  $C[k]$  recursively. As a base case we have  $C[0] = 0$ . For  $k \geq 1$  we have

$$C[k] = \min_{s < k} \left\{ C[s] + \left[ \left( \sum_{i=s+1}^k c_i \right) \left( t_k^S + \sum_{i=s+1}^k t_i \right) \right] \right\}.$$

In other words, we optimize over the choice of the final job  $\{s+1, \dots, k\}$ , accounting recursively for the optimal job design for remaining jobs. Note that we make implicit use of the assumption that the handoff cost  $t_k^S$  depends on the final task  $T_k$  of this final job but is otherwise independent of the job design. Using this formulation, we can calculate each  $C[k]$  in time  $O(k)$  by considering each potential choice of  $s$ . Doing so for each  $k = 1, 2, \dots, n$  yields the value of  $C[n]$  (and the corresponding optimal job design) in total time  $O(n^2)$ .  $\square$

### 3.3 Full Long-Term Optimization

We now consider full joint optimization of job design and automation strategy, accounting for both time and skill costs of workers assigned to the resulting jobs. In other words, the firm's goal is to choose both the set of AI chains to implement—yielding a vector of skill and time costs—along with a job design for the resulting tasks.

#### 3.3.1 Recursive Formulation of Optimization Problem

Here we present a recursive formulation of the firm's cost minimization problem. In Section 3.3.2 we propose an approach to calculate an approximation of the optimal solution via dynamic programming.

Consider a production process with  $m$  steps  $\mathcal{S} = \{s_1, s_2, \dots, s_m\}$ . For  $0 \leq i \leq m$ , let  $V(i)$  denote the minimum cost required to complete steps 1 through  $i$  using one or more jobs, including any hand-off costs to a subsequent worker. Note then that  $V(m)$  is the solution to the desired optimization problem, recalling that the hand-off time for the final job will always be 0. Note also that it is implicitly assumed in the definition of  $V(i)$  that it optimizes over job designs for steps 1 through  $i$  in which the final job terminates after the completion of step  $i$ .

It will also be helpful to consider optimal designs for steps 1 through  $i$  in which the final job doesn't necessarily terminate after the completion of step  $i$ , but rather continues onward to subsequent steps. To that end, we introduce an auxiliary function  $W(i, c, t)$ . This function denotes the minimum cost of completing steps 1 through  $i$ , as well as some additional (but unspecified) set of tasks that have already been assigned as a single job to a single worker (referred to as the “active worker”). It is assumed that the tasks assigned to the active worker have total time cost  $t$  and total skill cost  $c$ . The time cost  $t$  is assumed to already include any hand-off cost for this active worker (which recall depends only on the final step of the worker's final task). Crucially, the minimum is taken over all automation strategies and job designs, including those that expand the number of tasks assigned to the active worker (e.g., by including step  $i$  in the active worker's job). In this sense,  $W(i, c, t)$  captures the minimum cost across all feasible job designs and automation strategies that may potentially expand the active worker's task assignment.

Note that, for all  $i \leq n$ , we have

$$V(i) = W(i, 0, t_i^S).$$

This is because, in  $V(i)$ , all job designs must end with a job that completes at step  $i$  and hands off to the following worker. Consequently, the hand-off cost associated with step  $i$  must be incurred by the final worker. Equivalently, this can be thought of as assigning the active worker an additional task with zero skill requirement but a time cost equal to the hand-off cost of step  $i$  right after step  $i$  itself. This scenario is represented explicitly by  $W(i, 0, t_i^S)$ .

Also note that, for the base case  $i = 0$ , we have

$$W(0, c, t) = c t, \quad \text{for all } c, t.$$

This is because, if  $i = 0$ , then there are no further steps to add to the job of the active worker. The active worker's skill and time requirements are therefore determined entirely by the steps they have already been assigned.

We are now ready to describe a recursive formulation of the function  $W(i, c, t)$  for  $i \geq 1$ . We emphasize that in the definition of  $W(i, c, t)$ , the active worker has not been assigned step  $i$ ; we can think of step  $i$  as the highest-indexed step that has not yet been assigned to a worker.

**Proposition 3** (Recursive Formulation of Job Design Problem). *For each  $i \geq 1$ , the minimum cost function  $W(i, c, t)$  satisfies the following recursive relation:*

$$W(i, c, t) = \min \left\{ \begin{aligned} & ct + V(i), \\ & W(i-1, c + c_i^H, t + t_i^H), \\ & \min_{r < i} W \left( r, c + c_i^M, t + \frac{t_i^M}{\prod_{s=r+1}^i q_s} \right) \end{aligned} \right\}.$$

The cost of the optimal joint automation and job design for a given sequence of  $m$  steps is then  $V(m) = W(m, 0, 0)$ .

The recursive formulation in Proposition 3 evaluates the minimum cost among three distinct alternatives at each step:

- **Option (1):** The term  $ct + V(i)$  corresponds to not adding any further steps to the job of the active worker. All steps 1 through  $i$  will be completed by other workers. The active worker's total cost is then  $ct$ , and  $V(i)$  is the total cost of completing steps 1 through  $i$  (including hand-off costs to the active worker).
- **Option (2):** The term  $W(i-1, c + c_i^H, t + t_i^H)$  corresponds to designating step  $i$  for manual completion, and adding the corresponding (singleton) task. In this case, the manual execution costs  $(c_i^H, t_i^H)$  of step  $i$  are added to the accumulated costs of tasks already assigned to the active worker, extending their job to include step  $i$  as well.
- **Option (3):** The term  $\min_{r < i} W \left( r, c + c_i^M, t + \frac{t_i^M}{\prod_{s=r+1}^i q_s} \right)$  corresponds to creating an AI chain task for steps  $r+1$  through  $i$ , with step  $i$  being augmented and steps  $r+1$  through  $i-1$  automated, and assigning the resulting task to the job of the active worker. Step  $i$  is thus chained with zero or more preceding (automated) steps, and the associated AI management costs are added to the active worker's skill and time costs. The index  $r$  corresponds to the highest-index step that is not added to this AI chain, which can be any value between 0 and  $i-1$ .

Note that in evaluating option (3) of the recursive step for  $W(i, c, t)$ , step  $i$  can only be augmented (rather than automated) as each step of the recursion adds a full AI chain to an active worker's job. Automation strategies in which step  $i$  is automated are considered when performing task calculations  $W(r, c, t)$  with  $r > i$ .

### 3.3.2 Calculating an Approximately Optimal Solution

Given our recursive formulation, we wish to use dynamic programming to solve for the jointly optimal job design and automation strategy by filling in the values of  $W(i, c, t)$  for all  $i, c$ , and  $t$ . Since  $c$  and  $t$  take on continuous values, we will discretize all skill costs  $c$  and time costs  $t$  to appropriate powers of  $(1 + \epsilon)$ , where  $\epsilon > 0$  is an arbitrarily small error term. We obtain the following result.

**Proposition 4.** *Fix any sequence of  $m$  steps  $S = (s_1, \dots, s_m)$  for which all skill costs, time costs, and hand-off costs lie in  $[1/B, B]$  for some  $B > 0$ . Then for any  $\epsilon > 0$ , an approximately cost-minimizing pair*

of automation strategy  $\mathcal{T}$  and job design  $\mathcal{J}$  minimizing expression (3) to within a factor of  $(1 + \epsilon)$  can be computed in time  $O(m^2\epsilon^{-2}\log^2(mB))$  by dynamic programming.

*Proof.* The first step of proving Proposition 4 is to determine the range of powers of  $(1 + \epsilon)$  that we must consider in our discretization. Suppose that all manual and augmented skill and time costs, as well as all hand-off costs, lie in  $[1/B, B]$  for some  $B > 0$ . That is, these parameters require  $O(\log B)$  bits to represent. In this case, note that any subsequence of steps could be completed at a total cost of at most  $2mB^2$  by performing them all manually by different workers, incurring a time and handoff cost of at most  $B$  each for a total time of  $2B$ , and a skill cost of at most  $B$  for a total cost of  $2B^2$  for each of the  $m$  tasks. We therefore need not consider any solution containing a job with total cost greater than  $2mB^2$ . In particular, since any non-zero skill cost for any job is at least  $1/B$ , we need not consider any job design in which a job has total time cost greater than  $2mB^3$ . Furthermore, each job has total skill cost lying between  $1/B$  and  $mB$  (as skill costs combine additively) and time cost at least  $1/B$  (as each step's manual cost is at least  $1/B$ , and any AI chain's time cost is at least the management cost of its final step which is also at least  $1/B$ ).

We conclude that when filling table  $W(i, c, t)$ , it suffices to consider skill costs  $c$  lying in the range  $[1/B, mB]$  and time costs  $t$  lying in the range  $[1/B, 2mB^3]$ . There are  $O(\epsilon^{-1}\log(mB))$  powers of  $(1 + \epsilon)$  in each of these ranges, so our table will have  $O(m\epsilon^{-2}\log^2(mB))$  total entries. Each entry can be filled in time  $O(m)$  by considering the recursive formulation in Proposition 3, for a total runtime of  $O(m^2\epsilon^{-2}\log^2(mB))$ .

Note that while the table formally describes only the cost of a solution and not the solution itself, one can also read off the corresponding task and job design as well. Indeed, by recording which of the options described in Proposition 3 achieves the minimum for each table entry  $W(i, c, t)$ , one can trace out the corresponding task and job designs starting with  $V(m) = W(m, 0, 0)$ . The pair of automation strategy  $\mathcal{T}$  and job design  $\mathcal{J}$  can therefore be computed in time  $O(m^2\epsilon^{-2}\log(mB))$ , the same as the time required to fill the table.

It remains to bound the error introduced by our discretization. Consider the recursive formulation in Proposition 3 and suppose that  $c$  and  $t$  are rounded down to the nearest power of  $(1 + \epsilon)$ . Since time and skill costs are multiplied together to calculate the total cost of a proposed job, this discretization introduces a multiplicative error of at most  $(1 + \epsilon)^2$  into our cost calculation for the first option when minimizing in the recursive definition of  $W(i, c, t)$ . For the other two options, note that we accumulate time and skill costs additively when chaining tasks together for a single worker. As  $c$  and  $t$  are rounded to a power of  $(1 + \epsilon)$ , adding additional (accurate) skill and time costs and subsequently rounding maintains a multiplicative error of at most  $(1 + \epsilon)$  on the total time and skill costs.

We conclude that if we fill in our table for all  $W(i, c, t)$  where  $i \leq m$  and  $c$  and  $t$  are discretized into powers of  $(1 + \epsilon)$ , rounding down to nearest values of  $(1 + \epsilon)$  on recursive calls into the table, we obtain a  $1 + O(\epsilon)$  approximation to the optimal solution. An appropriate change of variables (scaling  $\epsilon$  by a constant) yields a  $(1 + \epsilon)$  approximation factor in total runtime  $O(m^2\epsilon^{-2}\log^2(mB))$ , as claimed in Proposition 4.  $\square$

## 4 Discussion

### 4.1 Job-level AI Exposure and the Fragmentation Index

For a single step in isolation, the decision whether or not to deploy AI augmentation depends simply on whether the manual execution cost exceeds the AI management cost. That is, the optimal choice of whether to use AI assistance depends only on the AI exposure of the step in question. For two or more steps, however, the optimal deployment of AI depends on more than the exposure of each step in isolation. This can arise because of the benefits of automating multiple steps together in an AI chain. Even if one step can be completed more effectively through manual work, it may be preferable to automate it as part of a larger collection of steps that can be jointly delegated to AI. Whether this occurs in the optimal automation strategy depends on the relationship between other nearby steps in the production process.

Returning to the short-run optimization problem described in (4) and Section 3.1, we can interpret job-level AI exposure as the extent to which an optimal automation strategy employs AI automation and augmentation. Intuitively, a run of *consecutive* steps in the production process that an AI can perform

effectively is a natural candidate for an AI chain. A job that contains such runs of consecutive steps are therefore likely to benefit most from AI automation. On the other hand, a job for which AI-friendly steps are separated by intermediate steps that an AI is likely to fail is less exposed to large-scale automation, even though its task-level exposure to AI may appear high.

**Example 1.** Consider a job consisting of  $m$  steps, where  $m$  is even. Each step takes time 5 to complete manually and has an AI management time of 1, but the steps vary in how difficult they are for an AI to complete: odd-numbered steps can be successfully completed by an AI with probability 1, whereas even-numbered steps will be successfully completed with probability only 0.1, as shown below:

$$(\text{Easy})_1 \rightarrow (\text{Hard})_2 \rightarrow (\text{Easy})_3 \rightarrow \dots \rightarrow (\text{Hard})_{m-2} \rightarrow (\text{Easy})_{m-1} \rightarrow (\text{Hard})_m$$

In this scenario, it is suboptimal to attempt to use AI on any of the even-numbered steps, even as part of a chain. The optimal automation strategy is to employ AI-augmentation on the odd-numbered steps (for a cost of 1 each) and perform even-numbered steps manually (for a cost of 5 each), resulting in an overall time cost of  $3m$ .

**Example 2.** Next suppose that easy and hard steps are not interleaved, but rather the first  $m/2$  steps can each be completed by AI with probability 1 and the last  $m/2$  steps can each be completed with probability 0.1, as follows:

$$(\text{Easy})_1 \rightarrow (\text{Easy})_2 \rightarrow \dots \rightarrow (\text{Easy})_{\frac{m}{2}} \rightarrow (\text{Hard})_{\frac{m}{2}+1} \rightarrow \dots \rightarrow (\text{Hard})_{m-1} \rightarrow (\text{Hard})_m$$

In this case, the optimal strategy chains together the first  $m/2$  steps into a single automated AI chain, for a combined cost of 1. The remaining  $m/2$  steps are then performed manually. This results in an overall time cost of  $1 + 5m/2$ , which is strictly less than  $3m$  as long as there are four or more steps.

To make this intuition more precise, let us return to the short-run optimization problem described in (4) and Section 3.1. Recall that in this short-run problem we are fixing a single job assigned to a worker with a fixed wage, so our focus is on optimizing the time cost of production. Consider the special case where AI management costs are normalized:  $t_i^M = 1$  for all  $i$ . That is, each step of production requires the same amount of time to prompt and manage one attempt by an AI process. Under this assumption, we will define a measure of the dispersion of AI-exposed tasks in a production process, which we refer to as the *fragmentation index* of a job. We then show that the fragmentation index of a job approximates (up to constant factors) the time cost of an optimal automation strategy for that job. In other words, jobs for which the fragmentation index is high will tend to yield less benefit from AI automation in the short-term where worker wages and job boundaries are fixed. Notably, this intuition makes heavy use of the short-run assumption that worker wages are fixed and independent of task skill requirements; we discuss examples where this intuition fails when describing long-run effects in Section 4.2.

To define the fragmentation index, consider a random process in which each step  $s_i$  succeeds independently with probability  $q_i$ ; any task that does not succeed is said to fail. Write  $F$  for the set of steps that fail, and  $\mathcal{C} = \{C_1, \dots, C_k\}$  for the random variable representing the collection of maximal connected components of non-failed steps. The weight of each  $C_j \in \mathcal{C}$  is defined to be  $\omega(C_j) = \min\{1, \sum_{i \in C_j} t_i^H\}$ . That is, each  $C_j$  has weight 1 unless the sum of the manual time costs for each of its steps is less than 1 (due to our assumption that AI management costs are normalized to 1).

Given a realization of  $\mathcal{C}$  and  $F$ , we define the realized fragmentation to be

$$\sum_{i \in F} \min \left\{ t_i^H, \frac{t_i^M}{q_i} \right\} + \sum_{C_j \in \mathcal{C}} \omega(C_j). \quad (5)$$

The *fragmentation index* is defined to be the expected value of the realized fragmentation.

Intuitively, we expect the fragmentation index to be lower when highly automatable steps (that is, those for which the AI are likely to succeed) are clustered together, since a large cluster of highly automatable steps are more likely to realize as a single connected component when failures are realized.

We will show that the fragmentation index is within a constant factor of the cost of the optimal (short-term) automation strategy for a given fixed job's step sequence.

**Proposition 5.** *Fix a single job with a sequence of  $m$  steps  $\mathcal{S} = \{s_1, \dots, s_m\}$ , each with  $t_i^M = 1$ . Let  $FI$  denote its fragmentation index and let  $OPT$  denote the minimum time cost over all automation strategies. Then  $\frac{1}{8}OPT \leq FI \leq \frac{5}{4}OPT$ . If we further assume  $t_i^H \geq 1$  for all  $i$ , then  $\frac{1}{4}OPT \leq FI \leq \frac{5}{4}OPT$ .*

We prove Proposition 5 in Appendix A. The key take-away from Proposition 5 is that jobs with high fragmentation index—i.e., those for which the expected number of *consecutive* successful step executions by an AI is low—will tend to have higher time costs even under optimal use of AI chaining. A key driver of efficiency gains via AI automation is therefore not simply the expected number of steps that can be automated effectively, but the number of *adjacent* steps in the production process that have high exposure to AI.

## 4.2 Impact of AI Deployment on Worker Skill and Specialization

While the fragmentation index captures the short-run impact of AI deployment on task completion time, in the long run automation also alters the skill requirements of workers and the degree of specialization within the workforce. This can dampen or even reverse the short-run intuition that gains from AI derive primarily from time savings, as the following example shows.

**Example 3.** *Consider a job consisting of a single step. This step has manual time and skill requirements  $(t^H, c^H) = (5, 5)$ . Suppose that, under AI augmentation, this step has an AI management time of 1 (per attempt), an AI management skill requirement 1, and probability 1/8 of successful completion. Despite the task taking longer to complete with AI (due to the low likelihood of success on any individual attempt), the reduced skill requirement of managing the AI process means that it is firm-optimal to employ AI augmentation.*

The impact of AI on worker skill reflects two common narratives about the impact of AI on work: first, that AI can automate mundane or repetitive tasks and allow high-skill workers to concentrate more of their time on meaningful high-skill tasks; second, that AI could lead to deskilling as high-skilled labor for manual task completion is replaced with low-skill AI management. Our framework unifies these two perspectives by endogenizing (a) the nature (i.e., time and skill requirements) of work to be automated and (b) how the automation strategy impacts requisite worker skill. If replacing a given sequence of production steps in given job with an AI chain is beneficial, in the long term, then either the total time needed to complete the steps is shortened, the total skill needed to manage the AI automation is reduced relative to completing the steps manually, or both. For an example of the latter, a step with low skill requirement but high time requirement (such as Step 2 in Figure 4) may be optimally augmented by AI even when doing so increases the skill needed for AI management, if the time savings are substantial enough. In this case, the skill required to complete the same job might increase: AI augmentation can be viewed as complementing worker capabilities. Alternatively, it may also be beneficial to employ AI on production steps with high skill requirements (such as Step 1 in Figure 4) even if this results in an AI-assisted task that takes longer to complete, as long as it requires substantially less worker skill to manage the AI. This can ultimately lead to a deskilling of the labor force assigned to the job as AI capital substitutes for high-skilled human work.

This discussion has so far focused on impacts within a single job. Our framework likewise captures the impact of AI automation on job design, and specifically on worker specialization across tasks. Consider again the example from Figure 4, which illustrates how hand-off costs and the structure of tent-pole tasks<sup>5</sup> can influence the partition of production steps into specialized jobs. As AI automation influences the time and skill profile of tasks, the incentive to specialize workers likewise changes.

To predict the direction of this effect, one hypothesis is that AI automation will tend to have a normalizing effect on tasks, reverting both skill requirements and time requirements toward the mean and making tasks more “square-like” (in terms of our geometric interpretation of job design costs). If so, and if hand-off

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<sup>5</sup>Recall that a tent-pole task refers to a high-skill but short-duration task that is adjacent to a low-skill but long-duration task.

time costs remain unaffected, then (roughly speaking) tent-pole inefficiencies due to grouping tasks together into the same job would be reduced. This suggests that the adoption of AI automation may reduce worker specialization.

**Example 4.** Consider a two-step production process, with manual skill and time costs  $(c_1^H, t_1^H) = (2, 4)$  and  $(c_2^H, t_2^H) = (4, 2)$  and hand-off cost  $t_1^S = 5$ . That is, the first step is low-skill but time-intensive and the second step is high-skill but can be completed quickly. In this example, combining both steps into a single job (at a labor cost of  $(2+4)(4+2) = 36$ ) is strictly worse than separating into two specialized jobs with a handoff (at a total cost of  $(2)(4+5) + (4)(2) = 26$ ). However, if each step of production could be augmented separately via AI to yield effective skill and time costs of  $(2, 2)$  for each, then the optimal design combines both augmented steps into a single job at a total cost of  $(2+2)(2+2) = 16$ , which is better than separating into two distinct jobs (incurring cost  $(2)(2+5) + (2)(2) = 18$ ).

It is also technically possible in our model for AI automation to increase the amount of specialization in an optimal job design. This could happen if AI-augmented steps have higher skill requirements than the corresponding manual steps, leading to an increased need for high-skill workers. Even if AI management is assumed to require no more skill than manual completion, an increased use of AI automation can lead to more responsibilities being combined into a single job, leading to a higher worker skill requirement, as the following example shows.

**Example 5.** Consider a different two-step production process, with manual skill and time costs  $(c_1^H, t_1^H) = (c_2^H, t_2^H) = (3, 3)$  and hand-off cost  $t_1^S = 5$ . The optimal job design separates these into two separate jobs at a total cost of  $(3)(3+5) + (3)(3) = 33$ , with each job requiring a worker of skill 3. Suppose AI augmentation can allow each step to be completed with an AI management skill of 2, a management time of  $1/4$ , and an AI success probability of  $1/8$ , for a total expected execution time of  $(1/4) \times (1/8)^{-1} = 2$ . In this case, the optimal design employs AI augmentation in each step and combines the two steps into a single job, resulting in a total cost of  $(2+2)(2+2) = 16$  and requiring a worker of skill 4. Note that this is preferable to combining the two steps into a single AI chain, which would result in a total cost of  $(2)((1/4) \times (1/8)^{-1} \times (1/8)^{-1}) = 32$ .

### 4.3 Non-Linear Impacts of AI Improvements

Improvements to AI technology naturally lead to improvements in the overall cost of production, but these effects need not be linear. The full economic impact of a disruptive general-purpose technology can take significant time and investment to materialize, with notable historical examples ranging from the steam engine to electricity to computers. In each case, a new technology enables modest short-term improvements to existing production processes, but the full impact is not felt until large-scale reorganization of production is enabled. This drives a potentially non-monotone marginal value from technology improvements, where major improvements are only unlocked after surpassing a threshold of capability at which they become feasible.

Our framework captures such non-monotonicities in the marginal value of technological improvements. This arises in our model via optimization over different automation and job design strategies. One can think of parameter  $\alpha \in (0, 1]$  in our model as metric of the quality of a general purpose AI technology, taken to be the probability that a task of normalized difficulty 1 is completed successfully. We can then model general technology improvements as increasing the value of  $\alpha$ . For a given fixed automation strategy (described by a task sequence  $\mathcal{T}$ ) and job design (described by job sequence  $\mathcal{J}$ ), the total cost can be expressed as a polynomial in  $(1/\alpha)$ . As a result, the cost of  $\mathcal{T}$  and  $\mathcal{J}$  shifts in a continuous and smooth manner as  $\alpha$  increases, with monotone marginal gains to technology improvements. However, the optimal choice of design (expressed as optimization problem (3)) involves taking the minimum-cost solution over many possible automation and job designs. Automation strategies with a higher degree of AI chaining will naturally involve higher powers of  $1/\alpha$  in their cost expressions, meaning that they are more sensitive to changes in  $\alpha$  and become preferable only at higher values of  $\alpha$  (i.e., as AI becomes more effective as a tool). This naturally leads to scenarios where the productivity improvements of AI integration are modest at low levels of quality but can grow sharply past a certain inflection point, as we describe in the following example illustrated in Figure 5 below.

**Example 6.** Consider a production process with two steps. The first step is short but high-skill and difficult for AI tools to perform correctly. Specifically, its manual skill cost is  $c_1^H = 5$ , its manual time cost is  $t_1^H = 1$ , and its hand-off time is 1. Its AI difficulty score,  $d_1$ , is 6, meaning that an AI can successfully complete the step with probability  $q_1 = \alpha^6$ . The AI management skill and time requirements are the same as the manual execution requirements:  $(c_1^M, t_1^M) = (5, 1)$ .

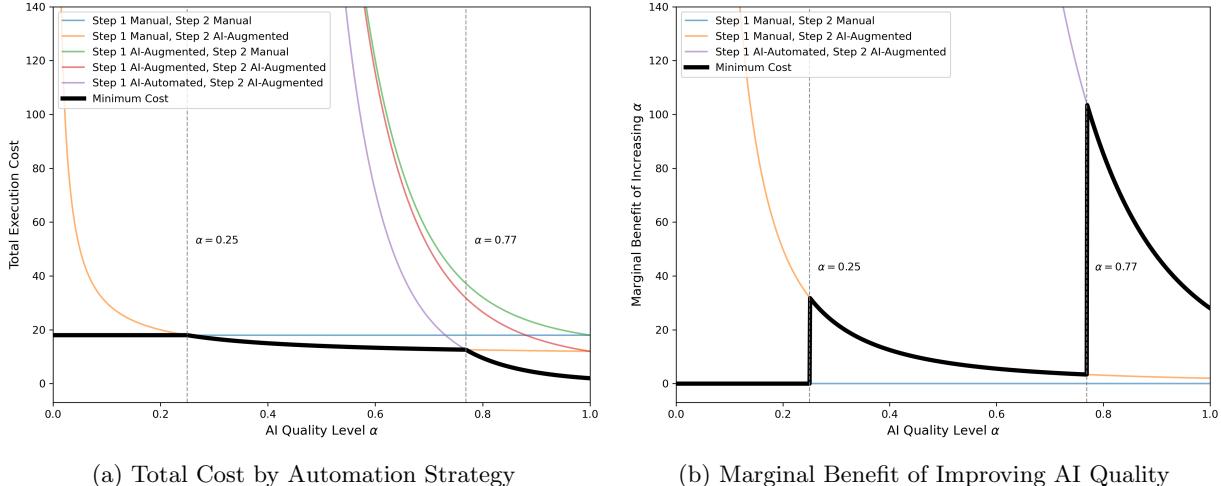
The second step is low-skill and timely to execute manually, but easy for AI. It has  $(c_2^H, t_2^H) = (2, 4)$  and AI difficulty score 1. The skill needed to manage the AI is also 2, but the time needed to manage the AI is reduced to 1:  $(c_2^M, t_2^M) = (2, 1)$ .

Consider the optimal automation strategy and job design for this example as a function of  $\alpha$ , the general AI quality metric. The costs of different automation strategies are plotted in Panel (a) of Figure 5. For  $\alpha < 0.25$ , it is optimal to complete each step manually as a separate task, and to separate the two tasks into separate specialized jobs. This incurs a total cost of  $(5)(1+1) + (2)(4) = 18$ . As this strategy does not employ AI, the cost is not affected by improvements to  $\alpha$  in this range, which is evident in Panel (b) of the figure.

For  $\alpha \in (0.25, 0.77)$ , the optimal automation strategy changes: it is better to use AI augmentation for the second step, reducing that step's total completion cost from  $(2)(4)$  to  $(2)(1/\alpha)$ . As  $\alpha$  increases, the total execution cost drops gradually from 18 (at  $\alpha = 0.25$ ) to  $10 + 2/\alpha \approx 12.5$  (at  $\alpha \approx 0.77$ ). This gradual improvement is visible as a modest slope in Panel (b).

However, once  $\alpha$  grows larger than 0.77, the optimal automation strategy and job design changes more dramatically. At this point, it is better to combine both steps into a single AI chain, automating step 1, and to assign the resulting aggregate task to a single low-skill worker. The completion cost of this strategy is  $(2)(1/\alpha^7)$ . This cost starts at approximately 12.5 at  $\alpha = 0.77$  but drops sharply, eventually converging to a total cost of 2 at  $\alpha = 1$ . This sharp drop indicates substantial marginal benefits from incremental improvements in AI quality in this region, illustrated by the pronounced jump in the slope in Panel (b) at  $\alpha \approx 0.77$ .

Figure 5: Cost Analysis of Automation Strategies in Example 6



*Notes:* Panel (a) shows total execution costs under various automation strategies as AI quality ( $\alpha$ ) improves. Panel (b) illustrates the marginal reduction in optimal costs associated with increased AI quality. Dashed vertical lines indicate thresholds where optimal automation strategies shift.

## 5 Macro-level Production Function

So far, the mode has focused on individual firm decision-making: how a firm allocates production steps among automation, augmentation, and manual execution, and how its micro-level choices of task assignment and job design determine internal productivity and costs. Ultimately, however, our interest extends beyond the firm to the broader economy. Improvements in AI quality not only alter how individual firms organize production but also affect the composition of inputs used across the economy and the aggregate relationship between labor, capital, and output. Yet the firm-level optimization framework developed above prevents direct analysis of these aggregate effects and also makes our approach distinct from the large literature in which production is modeled directly at the task level and then aggregated to the economy level (e.g., Acemoglu et al. (2022, 2024); Acemoglu (2025); Autor and Thompson (2025)). To bridge this gap, this section examines whether the micro-level cost-minimization problem of firms can be aggregated into well-behaved firm- and economy-level production functions. In particular, we show that the detailed, many-input Leontief representation of production at the task level can be reduced to a more compact formulation with only a small number of effective inputs, and that aggregating across heterogeneous firms(in terms of AI quality level) yields a macro-level production function with a CES form. This provides a tractable link between micro-level organization decisions and macroeconomic implications of improving AI quality.

We begin by showing how firm's micro-level decisions can be explicitly represented by a Leontief production function at the task level. Next, we demonstrate how, for the purposes of analyzing labor allocation within a firm, this detailed task-level production function can be simplified into a Leontief production function with just two aggregate inputs: skill-adjusted AI management labor and skill-adjusted human labor (we will describe what we mean by "skill-adjusted" below). Finally, we explore how the production functions of numerous individual firms, which differ in their AI quality levels, can be aggregated into a single, economy-wide CES production function. In this macro-level representation, the inputs are economy-wide aggregates of the corresponding micro-level inputs from individual firms, thereby facilitating clearer insights into the overall labor allocation in the economy.

Before the aggregation analysis, let us first describe the setup of production. A firm uses two production inputs: (1) skill-adjusted AI management labor (to complete AI-assisted tasks), and (2) skill-adjusted human labor (to perform manual tasks). These two types of labor demand different compensations: executing an AI-assisted task with skill and time cost of one demands  $w_M$ , while completing a manual task with similar skill and time requirements commands a compensation of  $w_H$ . We call  $w_M$  and  $w_H$  base wage rates for AI management and human labor, respectively.

Firms use these two inputs to complete tasks. Recall that the skill and time requirements of tasks are determined by the firm's automation strategy  $\mathcal{T}$ , while the aggregate skill requirements of jobs depend jointly on the automation strategy and job design  $\mathcal{J}$ . Specifically, the per unit of time compensation of a worker employed to do tasks of a job is determined by all tasks in that job. Consider Job 1 in Figure 3 for example. The worker assigned to perform Job 1 is required to obtain not only the skill required for manual Task 1,  $c_1^H$ , but must also possess the required skill for AI-assisted Task 2,  $c_2^M$ , as the worker's total compensation per unit of time is determined at the job level, and equals  $c_1^H + c_2^M$ . Therefore, the more tasks firm includes in a job, the higher required compensation for every task in that job.

In order to produce, the firm hires human labor to perform manual tasks and AI management labor for AI-assisted tasks. Therefore, the total compensation of a job will be a weighted average of skill costs of the job's tasks, with weights being the base wage rates of each type of labor. Specifically, the compensation for job  $J$  will be:

$$w_H \left( \sum_{T_b^H \in J} c_b^H \right) + w_M \left( \sum_{T_b^M \in J} c_b^M \right), \quad (6)$$

which is composed of the sum of contributions of skill costs from its manual tasks denoted by set  $T_b^H$  (each weighted by  $w_H$ ) and its AI-assisted tasks denoted by set  $T_b^M$  (each weighted by  $w_M$ ).<sup>6</sup>

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<sup>6</sup>Notice that this formulation is essentially equivalent to the original definition of wage in (1), as pointed out in Footnote 3. If we multiply each skill cost in (6) by its respective base wage rate and redefine the task's skill cost as the resulting product,

Next, we define skill-adjusted labor, which is the unit of work in our analysis. Let  $J(b)$  denote the job to which task  $b$  belongs, and  $O(b)$  be the mode of execution of task  $b$  (i.e.,  $O(b) = H$  if  $b$  is a manual task, or  $O(b) = M$  if  $b$  is an AI chain). Define the skill-adjusted time requirement of task  $b$  as:

$$\tau_b = \frac{w_H \left( \sum_{T_\ell^H \in J(b)} c_\ell^H \right) + w_M \left( \sum_{T_\ell^M \in J(b)} c_\ell^M \right)}{w_{O(b)}} t_b.$$

Note that the fraction appearing behind  $t_b$  represents an effective skill adjustment factor, as the numerator captures the total compensation of the job task  $b$  belongs to, while the denominator normalizes by the base wage rate for the specific mode of execution. The resulting fraction thus has units of skill intensity. This characterization becomes useful later as it allows expressing the (expected) wage bill paid for task  $b$  simply as  $w_M \tau_b \alpha^{-d_b}$  if it is AI-assisted or as  $w_H \tau_b$  if it is executed manually.

## 5.1 Within-Firm Aggregation: Leontief to Leontief

We now consider the firm's production. To produce output, each firm must complete requirements of all  $m$  production steps  $s_1, \dots, s_m$ . This naturally results in a Leontief production structure with multiple inputs.<sup>7</sup> Although firms choose whether to execute each step manually or by the help of AI, we show that analyzing labor allocation can be simplified. Specifically, production function of the firm can be represented by a Leontief function with only two firm-level aggregate inputs: AI management labor and human labor.

Suppose the firm solves the long-run cost minimization problem (3) for a given AI quality level  $\alpha$ , and obtains the optimal automation strategy  $\mathcal{T}$  and job design  $\mathcal{J}$ . Let  $|\mathcal{T}| = n$ , implying the original  $m$  production steps are organized into  $n$  distinct tasks, and  $|\mathcal{J}| = p$ , indicating these  $n$  tasks are grouped into  $p$  jobs. Given the fixed automation strategy, the execution mode for each production step is predetermined. This lets us consider and work directly with tasks rather than individual steps. Furthermore, with the job design held fixed, each firm takes the job boundaries and the total skill requirements within jobs as given.

We assume hand-offs are performed manually by the worker who completes the final task of each job. This allows us to simplify the analysis in two ways: (1) Since job design is fixed, we know exactly which steps occur at the job boundaries and thus incur hand-off time costs. Therefore, hand-off of job  $J_j$  can be treated as a standalone, human-executed task with time requirement  $\tau^S(J_j)$  and skill requirement equal to the total skill requirement of job  $J_j$ .<sup>8</sup> (2) The order of tasks—including the newly defined hand-off tasks—can be rearranged within the production sequence. Specifically, we relabel tasks such that tasks 1 to  $k$  are AI-assisted and thus require AI management labor, while tasks  $k+1$  to  $n$ , along with the hand-off tasks  $n+1$  to  $n+p-1$ , are executed manually and require human labor.<sup>9</sup>

The firm's task-level production can be expressed in the following Leontief form:

$$x = \min \left\{ \frac{l_1}{\tau_1^M \alpha^{-d_1}}, \dots, \frac{l_k}{\tau_k^M \alpha^{-d_k}}, \frac{l_{k+1}}{\tau_{k+1}^H}, \dots, \frac{l_n}{\tau_n^H}, \frac{l_{n+1}}{\tau^S(J_1)}, \dots, \frac{l_{n+p-1}}{\tau^S(J_{p-1})} \right\}. \quad (7)$$

The  $x$  on the left-hand side represents the firm's output while  $l_b$  is the amount of labor assigned to task  $b$ . All other variables remain as previously defined.

Since the automation strategy and job design are fixed the required amount of skill-adjusted time to spend on each task in the denominators of (7) are fixed, and the firm takes them as given. In equilibrium, allocation of labor to tasks satisfies

$$x = \frac{l_1}{\tau_1^M \alpha^{-d_1}} = \dots = \frac{l_k}{\tau_k^M \alpha^{-d_k}} = \frac{l_{k+1}}{\tau_{k+1}^H} = \dots = \frac{l_n}{\tau_n^H} = \frac{l_{n+1}}{\tau^S(J_1)} = \dots = \frac{l_{n+p-1}}{\tau^S(J_{p-1})}.$$

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we arrive at the original formulation given in (1). The formulation in (6) allows tasks to contribute differently to the job's wage depending on their mode of execution and type of labor that need to perform them.

<sup>7</sup>Different automation strategies and job designs lead to different input proportions but share the same fundamental Leontief form.

<sup>8</sup>Denote the skill-adjusted time cost of hand-off task of job  $J_j$  with  $\tau^S(J_j)$ .

<sup>9</sup>Recall that the final job  $p$  requires no hand-off by definition. The last hand-off thus occurs at the end of job  $p-1$ .

Notice that the ratio of labor allocated to any two tasks  $a$  and  $b$  is independent of output level and wage rates (regardless of whether tasks  $a$  and  $b$  are executed manually or by the help of AI), and solely depends on their relative skill-adjusted time requirements, which are fixed given  $\mathcal{T}$  and  $\mathcal{J}$ . The fixed ratio of labor inputs implies that the rate of substitution between any pair of tasks is independent of the labor allocated to other tasks:

$$\frac{\partial}{\partial l_z} \left( \frac{\frac{\Delta x}{\Delta l_a}}{\frac{\Delta x}{\Delta l_b}} \right) = 0, \quad \forall z \neq a, b. \quad (8)$$

A necessary and sufficient condition to aggregate the firm's production function from a Leontief with one input per task into a Leontief with (firm-level) aggregate human labor and AI management labor is that the rate of substitution between any two tasks within the same aggregate input type is independent of all tasks in the other aggregate input type (Leontief (1947); Fisher (1965); Felipe and Fisher (2003)). In other words, the relative amount of labor allocated to any two human-executed (AI-managed) tasks should depend exclusively on tasks within the human-executed (AI-managed) group.

The condition expressed in (8) satisfies the aggregation requirement above.<sup>10</sup> Thus, the firm's production function can be represented as:

$$x = \min \left\{ \frac{\bar{\alpha} l_M}{\tau_M}, \frac{l_H}{\tau_H} \right\}. \quad (9)$$

Here,  $l_M$  and  $l_H$  represent respectively the firm-level aggregate AI management labor and human labor. Moreover, the aggregate skill-adjusted AI and human time requirements,  $\tau_M$  and  $\tau_H$ , are defined as the sum of skill-adjusted time requirements of tasks in their respective groups:

$$\tau_M = \sum_{b=1}^k \tau_b^M, \quad (10)$$

$$\tau_H = \sum_{j=1}^{p-1} \tau^S(J_j) + \sum_{b=k+1}^n \tau_b^H. \quad (11)$$

Finally,  $\bar{\alpha}$  is the firm's effective AI quality level defined as

$$\bar{\alpha} = \frac{\sum_{b=1}^k \tau_b^M}{\sum_{b=1}^k \tau_b^M \alpha^{-d_b}}, \quad (12)$$

so that the following relationship holds:

$$\frac{\tau_M}{\bar{\alpha}} = \sum_{b=1}^k \tau_b^M \alpha^{-d_b}.$$

In short, (9) allows us to analyze labor allocation using the simpler two-input Leontief production function for a given automation strategy  $\mathcal{T}$  and job design  $\mathcal{J}$ . This firm-level aggregate Leontief function implies the equilibrium condition:

$$x = \frac{\bar{\alpha} l_M}{\tau_M} = \frac{l_H}{\tau_H}. \quad (13)$$

The representation in (9) helps us gain clearer insights into the allocation between human and AI management labor at the firm level by removing the need to deal with the complex, many-input production function (7) at the level of steps.

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<sup>10</sup>In fact, this condition is stricter than necessary. It not only guarantees labor independence across aggregated input types, but also imposes a stronger condition: that the rate of substitution between tasks within the same aggregate input type is independent even of other tasks within the same aggregate type.

## 5.2 Cross-Firm Aggregation: Leontief to CES

Next, we analyze whether Leontief production functions of many firms can be collectively represented by a single economy-wide production function, where each input in the macro function aggregates the corresponding inputs from the micro functions. To do so, we draw on the extensive literature on aggregation theorems in production theory, which establishes conditions for the existence of an aggregate production function based on individual firms' production functions. The central idea is to introduce an appropriate form of heterogeneity across firms, allowing micro-level production functions to be smoothed into a well-behaved aggregate function (See Sato (1975), Chapters 2 and 4, for existence conditions).<sup>11</sup> While most existence results in this literature do not yield a closed-form functional representation, we show here that under certain conditions on firm heterogeneity, firm-level Leontief production functions can be aggregated into an economy-wide CES production function.

Consider a unit mass of firms in the economy, each producing output with AI management labor, human labor, and capital. We assume capital is a fixed input, so firms make labor decisions conditional on their given capital stock. Moreover, we impose a Leontief structure between capital and labor inputs, normalizing the production process so that exactly one unit of capital is required per unit of output produced.<sup>12</sup> Firms do not know their individual effective AI quality levels before production occurs; instead, they share a common prior belief regarding the distribution from which these quality levels are drawn.

Production unfolds in two stages. In the first stage, firms solve the long-run cost minimization problem (3), committing to an automation strategy  $\mathcal{T}$  and a job design  $\mathcal{J}$  based on their *expected* AI quality levels. Since firms hold the same expectations about the distribution of effective AI quality, they choose identical automation strategies and job designs. In the second stage, firms learn their realized effective AI quality levels, hire the required labor and capital, and begin production.<sup>13</sup> The resulting Leontief production function, determined by the previously selected automation strategy, job design, and the firm's realized effective AI quality, takes a form similar to (9).

This two-stage structure mirrors realistic firm behavior. Firms initially decide how to structure operations and post job vacancies. Only after making these structural commitments do they hire workers and acquire machines to begin production. Once hiring occurs, firms discover the actual productivity levels of inputs, which necessitates operating under their previously chosen organizational structures.

In what follows, we demonstrate that the heterogeneity in effective AI quality level can be structured so that micro-level Leontief production functions (9) aggregate into a macro-level CES production function, in which the CES inputs are aggregates of the micro-level inputs (Levhari (1968)). Suppose specifically that the macro-level production function takes the form:

$$X = (\theta_M M^\rho + \theta_H H^\rho + (1 - \theta_M - \theta_H) K^\rho)^{\frac{1}{\rho}}, \quad (14)$$

where  $X$  represents (economy-wide) aggregate output,  $M$  denotes aggregate AI management labor,  $H$  denotes aggregate human labor,  $K$  is aggregate capital, and parameters  $\theta_M$  and  $\theta_H$  represent the weights of corresponding inputs. Since the measure of firms in the economy is normalized to 1, aggregate capital is also normalized to 1, making the third term in (14) effectively constant at  $1 - \theta_M - \theta_H$ .

To link the macro production function above to the micro production functions, we must relate aggregated firm-level inputs  $l_M, l_H$  from (9) to the economy-wide aggregates  $M, H$  in (14). This requires either determining macro parameters from the distribution of heterogeneity, or specifying the form of heterogeneity given a set of macro-level parameters. We adopt the latter approach and derive the output probability density function in terms of effective AI quality, denoted by  $\phi(\bar{\alpha})$ , as a function of  $\theta_M, \theta_H, \rho$ . Throughout, we assume that  $\rho < 0$  (which implies elasticity of substitution  $\sigma < 1$ ), indicating that macro-level production exhibits some degree of complementarity.

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<sup>11</sup>For instance, Houthakker (1955) studies aggregation from micro Leontief functions to a macro Cobb-Douglas function; Levhari (1968) investigates aggregation from micro Leontief functions to a macro CES function; and Sato (1969) explores aggregation from micro CES to macro CES functions. See Baqae and Farhi (2019) for a broader formulation of this problem.

<sup>12</sup>This normalization can be interpreted as assuming identical capital productivity across firms. Since we introduce firm-level heterogeneity through variations in AI quality, we abstract away from additional sources of heterogeneity across firms.

<sup>13</sup>As production depends on the realized effective AI quality level,  $\bar{\alpha}$  also determines firms' sizes.

Normalize the output price to  $p = 1$ , so that  $w_M$  and  $w_H$  can be interpreted as real wage rates for a unit of skill-adjusted AI management and human labor, respectively. A firm produces only if it earns nonnegative profits:

$$w_M l_M + w_H l_H \leq x.$$

Substituting for  $l_H$  and  $x$  from (13) into the profitability condition yields:

$$w_M l_M + w_H \frac{\tau_H \bar{\alpha} l_M}{\tau_M} \leq \frac{\bar{\alpha} l_M}{\tau_M}.$$

Rearranging terms and canceling  $l_M$  gives the lower bound of firms' effective AI quality level:<sup>14</sup>

$$\bar{\alpha} \geq \frac{w_M \tau_M}{1 - w_H \tau_H}.$$

This lower bound implies that only firms with realized effective AI quality level above this threshold will produce in equilibrium and others exit the market. Moreover, observe from (12) that for  $d_b \geq 0$  the upper bound of  $\bar{\alpha}$  is 1 and is achieved when  $\alpha \rightarrow 1^-$ . Therefore:

$$\frac{w_M \tau_M}{1 - w_H \tau_H} \leq \bar{\alpha} \leq 1. \quad (15)$$

Let  $\phi(\bar{\alpha})$  be the distribution of output across firms according to their effective AI quality level. A firm with effective AI quality  $\bar{\alpha}$  thus produces output  $x = \phi(\bar{\alpha})$  by definition. From equation (13), it directly follows that the AI management labor and human labor used by this firm are:  $l_M = (\tau_M/\bar{\alpha})\phi(\bar{\alpha})$ , and  $l_H = \tau_H \phi(\bar{\alpha})$ . Consequently, aggregate output  $X$ , aggregate AI management labor  $M$ , and aggregate human labor  $H$  can be expressed as:

$$X = \int_{\frac{w_M \tau_M}{1 - w_H \tau_H}}^1 \phi(\bar{\alpha}) d\bar{\alpha}, \quad (16)$$

$$M = \int_{\frac{w_M \tau_M}{1 - w_H \tau_H}}^1 \tau_M \frac{\phi(\bar{\alpha})}{\bar{\alpha}} d\bar{\alpha}, \quad (17)$$

$$H = \int_{\frac{w_M \tau_M}{1 - w_H \tau_H}}^1 \tau_H \phi(\bar{\alpha}) d\bar{\alpha}. \quad (18)$$

Substituting the aggregated variables from the micro-level equations (16, 17, 18) into the aggregate production function (14), we obtain:

$$\int_{\frac{w_M \tau_M}{1 - w_H \tau_H}}^1 \phi(\bar{\alpha}) d\bar{\alpha} = \left( \theta_M \left( \tau_M \int_{\frac{w_M \tau_M}{1 - w_H \tau_H}}^1 \frac{\phi(\bar{\alpha})}{\bar{\alpha}} d\bar{\alpha} \right)^\rho + \theta_H \left( \tau_H \int_{\frac{w_M \tau_M}{1 - w_H \tau_H}}^1 \phi(\bar{\alpha}) d\bar{\alpha} \right)^\rho + (1 - \theta_M - \theta_H) \right)^{\frac{1}{\rho}}. \quad (19)$$

Solving for  $\phi(\bar{\alpha})$  in terms of  $\theta_M, \theta_H, \rho$  we obtain the following distribution for effective AI quality:

$$\phi(\bar{\alpha}) = \frac{(1 - \theta_M - \theta_H)^{\frac{1}{\rho}} (1 - \theta_H \tau_H^\rho)^{\frac{\rho}{\rho-1}} (\theta_M \tau_M^\rho)^{\frac{1}{1-\rho}}}{1 - \rho} (\bar{\alpha})^{\frac{1}{\rho-1}} \left[ 1 - \theta_H \tau_H^\rho - (1 - \theta_H \tau_H^\rho)^{\frac{\rho}{\rho-1}} (\theta_M \tau_M^\rho)^{\frac{1}{1-\rho}} (\bar{\alpha})^{\frac{\rho}{\rho-1}} \right]^{-\frac{1+\rho}{\rho}}. \quad (20)$$

See Appendix B for derivation details.

This completes the production function aggregation procedure. The derived distribution (20) characterizes firm-level heterogeneity in the effective AI quality level required to support a macro CES production function of the form (14), with economy-wide aggregate human and AI management labor inputs and parameters  $\theta_M, \theta_H, \rho$ , obtained from micro-level Leontief production functions of the form (9).

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<sup>14</sup>We assume the parameters  $w_M, w_H, \tau_M, \tau_H$  are such that  $0 < (w_M \tau_M)/(1 - w_H \tau_H) < 1$ .

## 6 Empirical Evaluation

In this section, we empirically test and validate several predictions of the model. To do so, we construct a task-level dataset that records three attributes of each task: its AI exposure status (exposed or unexposed to AI), its realized mode of execution (manual, AI-augmented, or AI-automated), and its position in the production sequence. We combine data from four sources to create this dataset: (1) the O\*NET 27.3 database (May 2023), (2) human-generated labels for AI exposure of all O\*NET tasks from Eloundou et al. (2023), (3) the actual AI execution mode of O\*NET tasks reported in Anthropic’s Economic Index dataset Handa et al. (2025), and (4) a GPT-generated task ordering for each O\*NET occupation.

The structure of our theoretical framework is closely aligned with the structure of the O\*NET dataset. In our framework, each step corresponds to an O\*NET task, and each job corresponds to an O\*NET occupation. Once the mode of execution of a step (that is, an O\*NET task) is realized, it becomes a task in the sense of our theoretical framework. Throughout this section, we use the terms O\*NET task and task to refer to steps in the model, and we use the terms manual task and AI task to refer to tasks whose mode of execution has been specified. For brevity, we do not repeatedly restate this mapping and instead assume the reader keeps it in mind. Whenever the mode of execution is not mentioned, either it is not important (or can be inferred from context), or, if it is important, the reader should interpret the object as a step in the theoretical framework. We similarly use the terms job and occupation interchangeably.

We use the May 2023 release of O\*NET, which contains roughly 18,000 tasks assigned to more than 850 U.S. occupations. AI-exposure measures come from Eloundou et al. (2023), which provides human-generated labels for all O\*NET tasks and several alternative exposure metrics. We adopt their most conservative measure, treating tasks with a human-assigned E1 label as exposed to AI and those with E0 or E2 labels as unexposed.<sup>15</sup>

To obtain task execution labels, we use Anthropic’s Economic Index dataset, which classifies millions of Claude conversations into six categories: “Validation”, “Task Iteration”, “Learning”, “Directive”, “Feedback Loop”, and “Filtered”. Conversations in the first three categories (Validation, Task Iteration, Learning) are treated by Anthropic as AI augmenting activities, while those in Directive and Feedback Loop are recognized as AI automating activities. The sixth category, Filtered, corresponds to conversations that either could not be classified or whose actual category could not be disclosed for privacy reasons.

Anthropic also reports the subset of O\*NET tasks to which these conversations are matched, along with the share of each task’s conversations falling into the six categories. In total, conversations are linked to 3,364 tasks, of which 1,017, about one third, have 100% of their conversations filtered, leaving 2,347 tasks with at least one non filtered conversation. Following Anthropic’s definitions of AI augmenting and AI automating activities, we assign each task an AI execution label based on the majority share of its non filtered conversations across the augmenting versus automating categories. Table C.2 provides several examples of this labeling procedure.

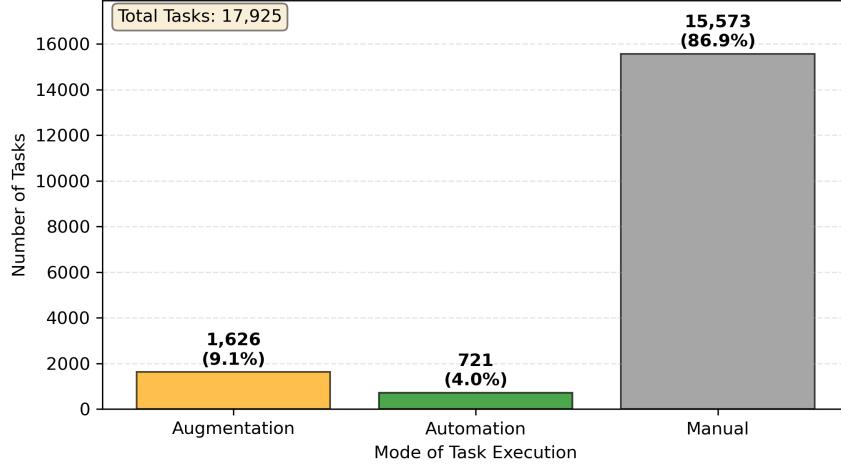
Finally, we treat tasks that do not appear in the Anthropic dataset, as well as those with 100% filtered conversations, as manual tasks. Figure 6 shows the distribution of task execution modes in the matched dataset. About two thirds of O\*NET occupations (555 of the 872) contain at least one AI-executed task. Figure 7 shows the distribution of occupations by the fraction of their tasks that are executed by AI.

As the final input into our empirical analysis, we use GPT-5-mini to generate a task sequence for every O\*NET occupation through Expected Parrot Horton and Horton (2024). The prompt used to generate these sequences is given in Appendix E. Appendix Figures D.1, D.2, and D.3 show the resulting task sequences for three example occupations: *Computer Programmers* (occupation code 15-1251), which has a high share of its tasks executed by AI, *Public Relations Specialists* (occupation code 27-3031), which has a moderate share, and *Electronic Equipment Installers and Repairers, Motor Vehicles* (occupation code 49-2096), which has no tasks executed by AI.

A noteworthy feature of these task sequences is that the realized execution modes are broadly consistent with, but do not perfectly satisfy, our model’s assumptions about AI chains. In particular, in the model an

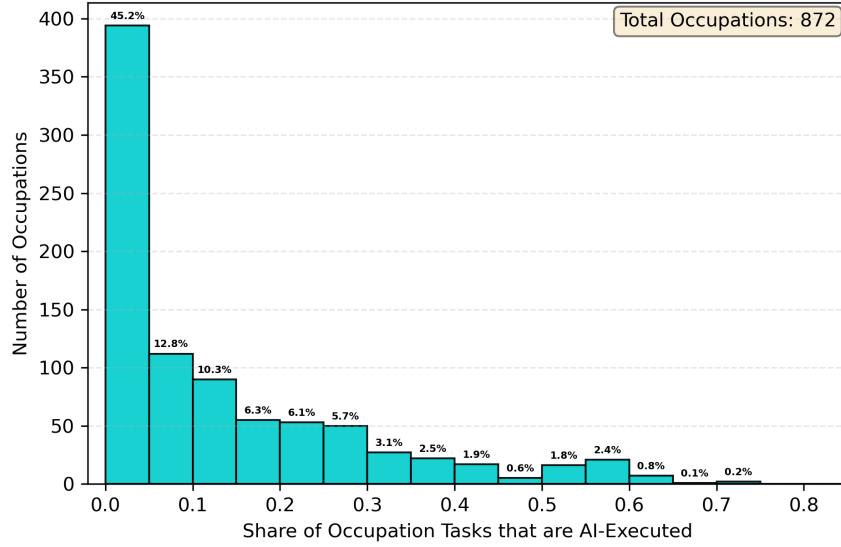
<sup>15</sup>Eloundou et al. (2023) define E1 tasks as those that an AI can perform in at least half the time required by a human while preserving human-level output quality. E2 tasks meet the same time-saving and quality thresholds but require additional software or tools to fully leverage AI capabilities. Any task that is neither E1 nor E2 is labeled E0.

Figure 6: Distribution of Modes of Task Executionin the Matched Dataset



*Notes:* Tasks are from the May 2023 extract of O\*NET dataset. The automation and augmentation labels are from Anthropic's Economic Index.

Figure 7: Distribution of Occupations by Fraction of AI-executed Tasks



*Notes:* Percentages above bars denote fraction of observations corresponding to that bar out of all 872 occupations.

automation task can only be followed by another AI-executed task, either automated or augmented, whereas in the data we occasionally observe an automation task followed by a non AI task. Task 5 in Appendix Figure D.1 and Task 3 in Appendix Figure D.2 are two such instances.

Before discussing the findings, it is worth emphasizing that our procedure yields a conservative measure of AI involvement in task execution. Recall that we label tasks with fully filtered conversations as manual, even though we know that all of them were executed in some way using Claude. These tasks account for

roughly one third of all Anthropic mapped tasks, and excluding them limits our statistical power. However, the remaining two thirds are nonetheless sufficient for revealing the patterns predicted by our framework.

One might also worry that workers rely on different AI tools for different purposes, for example Claude for writing and ChatGPT for coding. This would imply that the true set of AI-executed tasks is likely larger than what is recorded in Anthropic’s data. Although evidence from a single tool do not allow us to confirm or refute such heterogeneous tool use, our results seem unlikely to be driven by idiosyncrasies of Claude usage alone. Such concerns would require believing that no person anywhere used Claude for a given type of task during the period covered by Anthropic’s analysis, which seems implausible. Nevertheless, to mitigate these concerns we control for Standard Occupational Classification (SOC) codes in our analyses whenever applicable and show that our findings are not driven by a narrow subset of occupations. The patterns we document are present within different occupation groups, even though they may appear stronger in some groups than in others. This reduces the risk that our results merely reflect patterns specific to any particular tool or to tailored Claude usage.

## 6.1 Prediction #1: Tendency to Have Runs of Consecutive AI-executed Tasks

The first prediction of the model that we test is that AI tasks tend to appear next to each other in contiguous blocks, forming AI chains. This follows from our definition of AI chains (Definition 4), which requires every automated step to be followed by another automated or augmented task, and from the fragmentation argument, which suggests that AI chains are more likely to emerge when AI-easy tasks are clustered together in the workflow.

Instances of this pattern are evident in the task sequences of the occupations shown in Appendix Figures D.1 and D.2. To test this prediction systematically, we compute the average AI chain length and the average number of AI chains in the data and compare them to two placebo reshuffles of the original dataset. In the first placebo, we randomize the positions of tasks within each occupation’s task sequence. In the second, we randomize the assignment of AI execution labels to tasks across the entire dataset.

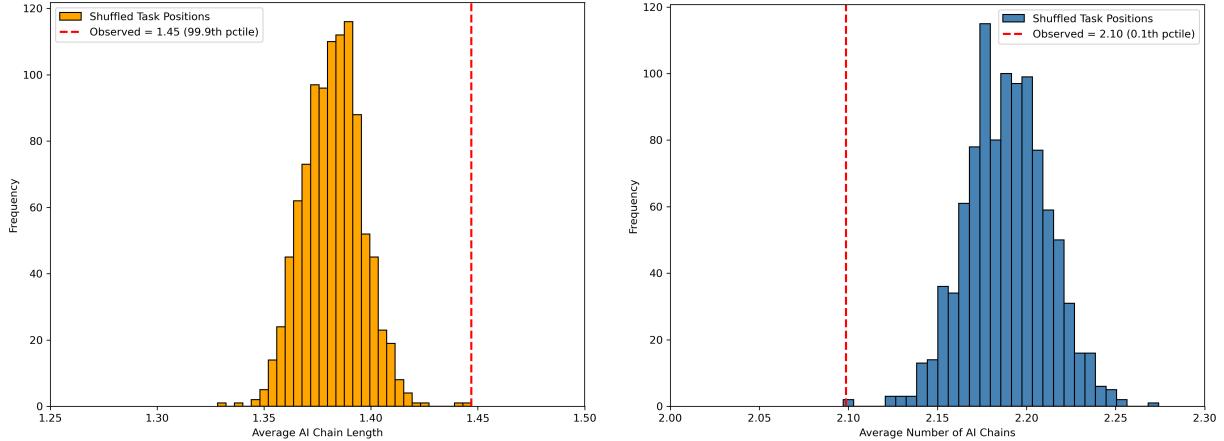
The randomized task position placebo tests whether the GPT generated task sequences contain meaningful structure or are effectively random. If the sequences were random, we would expect to see similar clustering patterns after arbitrarily re-ordering tasks within each occupation. The results from the within occupation permutations show that this is not the case, and the task sequences we obtain are indeed meaningful. The execution label reassignment placebo addresses a different concern, namely that Anthropic’s AI execution labels might be randomly scattered across tasks in the dataset. If so, the co-occurrence of AI-executed tasks within an occupation, and thus the formation of AI chains, could simply reflect chance. The results from this test indicate that the observed clustering of AI-executed tasks is substantive and not an artifact of random label assignment, further ensuring that the pattern we observe are meaningful.

For measurement, we slightly deviate from the model’s definition of AI chains and treat all automated and augmented tasks as a single type of AI task, with any consecutive run of AI-executed tasks constituting an AI chain. We adopt this modified definition for two reasons. First, given the limited number of automation tasks overall, our power to meaningfully measure chains under the strict definition of the model is limited. Second, because some automation tasks appear out of order, the reshuffling exercises mechanically place these tasks next to other AI tasks and artificially inflate measured chain lengths in the placebo datasets. Because it is already difficult to meaningfully identify real AI chains under the strict definition, the random assignment causes placebo AI chains to occur too frequently, making it harder to distinguish actual chains from artificial ones induced by out-of-order AI automation tasks. In other words, the out-of-order automation tasks not only fail to contribute to “real” AI chains but also cause over representation of AI chains in placebo tests once they appear next to other AI tasks in random permutations. Treating all automated and augmented tasks symmetrically as AI tasks yields a more sensible measure of AI chains given our data limitations.

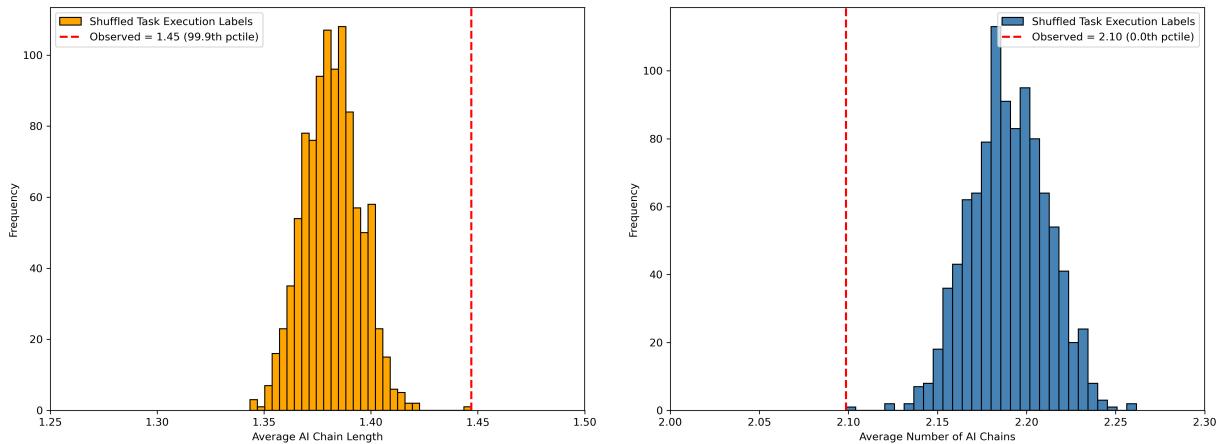
Given the modified definition of AI chains, the average chain length in the original dataset is 1.45, and the average number of AI chains per occupation is 2.1. Figure 8 plots these observed values alongside histograms of the same two statistics calculated from 1,000 task position reshuffles (Panel A) and 1,000 random execution label assignments (Panel B) of the original dataset. Comparing the observed values with the distribution generated by random task position assignments in the left graph of Panel (A), we find that the average AI

Figure 8: Observed Average AI Chain Length and Average AI Chain Counts Against Placebo Tests

Panel (A): Random Task Position Assignment



Panel (B): Random Execution Label Assignment



*Notes:* Red dashed lines show the observed average AI-chain length (graphs of the left) and average AI-chain count (graphs on the right) in the actual dataset under the modified definition of AI chains. Panel (A) shows the histogram of the two statistics for 1,000 placebo datasets in which the positions of tasks within each occupation are randomized. Panel (B) shows the histogram of the two statistics for 1,000 placebo datasets in which the mode of task execution in the entire dataset is randomized. The percentile of the reshuffled distributions in which the observed value falls is reported in the label of the observed value in each graph.

chain length in the original data is noticeably larger than in the placebo distribution. This shows that the GPT produced task sequences embed genuine structure rather than reflecting random task orderings within occupations. Comparing the observed values with the distribution generated by random execution label assignments in the left graph of Panel (B), we again find that the observed average AI chain length lies well above what would be expected under random assignment of labels. Taken together, the left-hand graphs of Panels (A) and (B) indicate that AI-executed tasks tend to cluster within occupations, forming longer AI chains than would arise under either type of random assignment. The results for the number of AI chains tell a consistent story. Holding fixed the number of AI-executed tasks, longer chains necessarily imply fewer separate chains. Accordingly, the right-hand graphs of Panels (A) and (B) show that the observed number of AI chains per occupation is meaningfully smaller than what would be expected under either form of random assignment.

## 6.2 Prediction #2: Dispersion of AI-able Tasks Affects AI Execution Outcomes

The second prediction of the model that we test is that the intensity of AI task execution in an occupation depends not only on the overall share of its AI-exposed tasks, but also on how these AI-able tasks are distributed within the occupation’s workflow. To examine this, we ask whether occupations with similar shares of AI-exposed tasks exhibit different shares of realized AI-executed tasks depending on how dispersed their AI-able tasks are in the production sequence. We estimate the following regression:

$$\text{ai\_fraction}_o = \beta_0 + \beta_1 \text{ai\_exposure}_o + \beta_2 \text{fragmentation\_index}_o, \quad (21)$$

where  $\text{ai\_fraction}_o$  is the share of tasks executed by AI in occupation  $o$ ,  $\text{ai\_exposure}_o$  is the share of E1-exposed tasks, and  $\text{fragmentation\_index}_o$  measures how dispersed the AI-able tasks are across the occupation’s workflow.

The model predicts that occupations with higher AI exposure should have a higher share of tasks executed by AI ( $\beta_1 > 0$ ). Conditional on exposure, it also predicts that when AI-able tasks are more dispersed in the workflow, the share of realized AI-executed tasks should be lower ( $\beta_2 < 0$ ). The intuition is that, for a given level of AI quality (parameter  $\alpha$  in the model), AI chains are more likely to form when AI-easy steps appear next to each other, as illustrated in Examples 1 and 2 in Section 4.1. When such clustering occurs, nearby steps that would otherwise remain manual may instead be automated as part of a chain.

To construct an empirical fragmentation measure, we abstract from differences in tasks’ underlying cost profiles, which are unobserved in our data, and focus solely on task position within the workflow. We define the fragmentation index of an occupation as the number of tasks in the sense of our theoretical framework divided by the total number of steps in the occupation, which we take to be the raw count of O\*NET tasks. For example, consider an occupation with 5 tasks. If all 5 are executed manually, then the number of tasks in the theoretical sense is 5 and the fragmentation index equals  $5/5 = 1$ . If two consecutive tasks form an AI chain, the number of tasks in the model falls to 4 and the fragmentation index becomes  $4/5 = 0.8$ . Thus, the measure decreases as more steps merge into longer AI chains.

In practice, while the number of steps in an occupation is fixed, the realized mapping of those steps into AI chains or manual tasks may vary. Because we observe only one realization of each occupation’s task execution, we construct four versions of the fragmentation index to ensure that our findings do not depend on a specific definition or realization. First, we use the model’s strict definition of AI chains in Definition 4, in which a chain begins with an automated or augmented task and ends after the first augmented task. Second, we adopt a more relaxed definition that treats automated and augmented tasks as a single type of AI task and counts any consecutive run of AI-executed tasks as a chain. This avoids distortions caused by out of order automation tasks in the data. Third, we construct potential AI chains by replacing realized execution outcomes with AI exposure labels and treating all E1 tasks as identical for chaining. Fourth, we expand this exposure based definition to include both E1 and E2 tasks and apply the same chaining logic.

The results from estimating (21) using these four fragmentation measures are reported in Table 3. For each measure, we estimate three specifications: without controls (columns 1, 4, 7, and 10), with SOC major group fixed effects (columns 2, 5, 8, and 11), and with SOC minor group fixed effects (columns 3, 6, 9, and

Table 3: Effect of AI-able Task Fragmentation on Share of AI-executed Tasks in Occupation

	FI Definition 1			FI Definition 2		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A: Definitions 1 &amp; 2</i>						
AI Exposure	0.43*** (0.03)	0.20*** (0.04)	0.15*** (0.05)	0.26*** (0.02)	0.13*** (0.03)	0.11*** (0.03)
Fragmentation Index	-2.58*** (0.12)	-1.97*** (0.15)	-1.68*** (0.17)	-1.48*** (0.05)	-1.29*** (0.05)	-1.24*** (0.06)
R-squared	0.65	0.74	0.80	0.84	0.87	0.90
Adj. R-squared	0.65	0.74	0.77	0.84	0.87	0.88
	FI Definition 3			FI Definition 4		
	(7)	(8)	(9)	(10)	(11)	(12)
<i>Panel B: Definitions 3 &amp; 4</i>						
AI Exposure	0.66*** (0.08)	0.20** (0.08)	0.18** (0.08)	0.33*** (0.06)	0.14** (0.06)	0.12** (0.06)
Fragmentation Index	0.04 (0.20)	-0.15 (0.16)	-0.01 (0.16)	-0.23*** (0.03)	-0.21*** (0.04)	-0.14*** (0.04)
R-squared	0.31	0.63	0.73	0.37	0.66	0.74
Adj. R-squared	0.31	0.62	0.70	0.37	0.65	0.71
Observations	872	872	872	872	872	872
SOC Group Fixed Effect		Major	Minor		Major	Minor

Standard errors in parentheses. \* :  $p < 0.1$ , \*\* :  $p < 0.05$ , \*\*\* :  $p < 0.01$ .

*Notes:* The dependent variable in all specifications is share of AI-executed tasks in occupation (ai\_fraction). The variable ai\_fraction is the share of AI-exposed (E1) tasks in occupation and fragmentation\_index measures how dispersed AI-able tasks are in the occupation workflow. The fragmentation index is measured in four versions to ensure robustness to different definitions.

12). Inclusion of SOC fixed effects ensures that the estimated relationships are not driven by a particular family of occupations, so that the remaining variation reflects the relative positioning of tasks within a typical job.

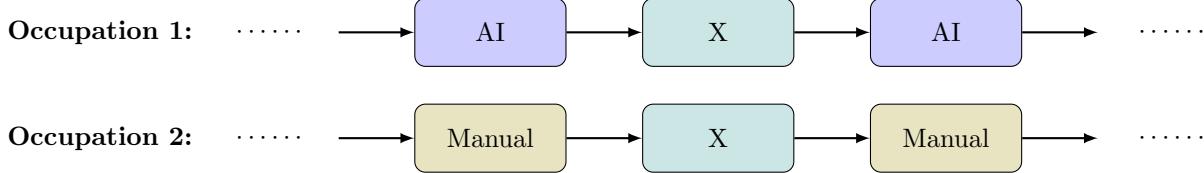
We find that a 10 percent increase in occupation-level AI exposure is associated with a 1 to 6.5 percent increase in the share of tasks executed by AI, depending on the specification. Across nearly all definitions, the coefficient on the fragmentation index is negative, consistent with the model's prediction that greater dispersion of AI-able tasks reduces realized AI execution. The only exception is when we use the strictest exposure based definition (Definition 3) without SOC controls. In that case, and more generally with this conservative measure, estimates are imprecise and statistically insignificant because the definition sharply limits which tasks can potentially form an AI chain. When we move to the more permissive exposure based definition in Definition 4, which allows additional tasks to be considered as potential chain members, we again obtain negative and statistically significant coefficients. These results are consistent with those based

on fragmentation measured using realized AI execution outcomes in Definitions 1 and 2.

Taken together, these findings support the model’s prediction that higher AI exposure increases realized AI task execution, while greater fragmentation of AI-able tasks reduces it.

### 6.3 Prediction #3: Adjacency to AI Tasks Increases Likelihood of AI Execution

The final prediction of the model that we test is that when the same task appears in two occupations, in one sitting between strong AI performers and in the other located between manual tasks, it is more likely to be executed by AI in the first occupation. Intuitively, when a task is surrounded by AI-executed steps, there are gains from automating it jointly with its neighbors as part of an AI chain. For example, task X is more likely to be automated in the first occupation below than in the second:



Testing this prediction requires identifying tasks that appear across different occupations. Because O\*NET tasks are occupation-specific, no single task is shared across occupations. Instead, we rely on O\*NET’s broader categories of Detailed Work Activities (DWAs), which group conceptually similar tasks across occupations. Panel (A) of Appendix Table C.3 provides examples of DWAs, the tasks associated with them in different occupations, and the execution modes of those tasks.

For the empirical analysis, we restrict attention to DWAs that contain tasks appearing in more than one occupation. For each such DWA, we ask GPT-5-mini to select the subset of tasks that are most similar in terms of skill requirements and execution complexity. The prompt used for this is given in Appendix E. This procedure produces, for each DWA, a set of highly comparable tasks that occur in different occupational contexts. Panel (B) of Appendix Table C.3 lists the tasks that survive this operation for the DWAs shown in Panel (A). We treat these as instances of the same underlying task appearing across occupations and estimate the following regression:

$$\Pr(\text{is\_automated}_t = 1 | X_t) = \Lambda\left(\beta_0 + \beta_1 \text{prev2\_is\_ai}_t + \beta_2 \text{prev\_is\_ai}_t + \beta_3 \text{next\_is\_ai}_t + \beta_4 \text{next2\_is\_ai}_t\right), \quad (22)$$

where  $\Lambda(z) = \frac{e^z}{1+e^z}$  is the logistic CDF and  $\text{is\_automated}_t$  indicates whether task  $t$  is automated. The variables  $\text{prev2\_is\_ai}_t$  and  $\text{prev\_is\_ai}_t$  equal 1 if the task two positions before or immediately before task  $t$  is AI-executed, respectively, and  $\text{next\_is\_ai}_t$  and  $\text{next2\_is\_ai}_t$  are defined analogously for the tasks immediately after and two positions after task  $t$ . In the implementation we also control for the task’s AI-exposure status and number of tasks in the occupation task  $t$  appears.

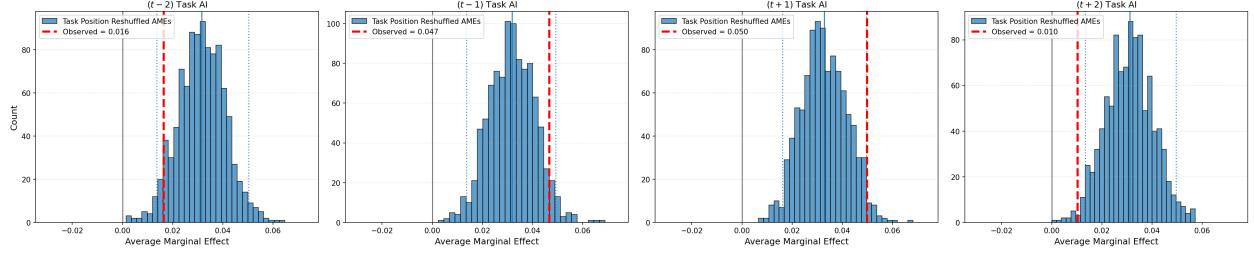
The average marginal effects (AMEs) from estimating (22) are reported in Table 4. Interpreting the magnitudes in isolation is difficult, since there is no natural benchmark indicating whether a given effect is large or small. To better understand the results and to assess whether the observed patterns could arise by chance, we conduct a robustness exercise in which we repeat (22) on 1,000 placebo datasets constructed by randomizing the positions of tasks within occupations.

The results are shown in Figure 9. In each panel, the red dashed line marks the observed AME from the actual data reported in Table 4. The blue bars in Panel (A) report AMEs from the 1,000 reshuffled datasets estimated using the baseline specification. Panels (B) and (C) show the distributions when SOC major group and SOC minor group fixed effects are included.

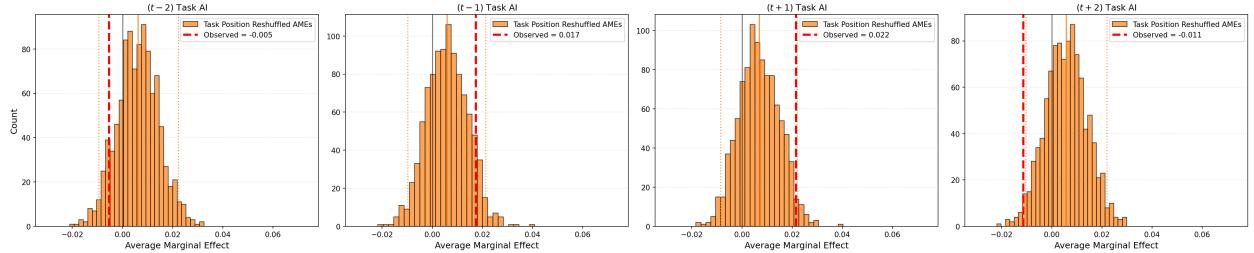
Several patterns emerge from the figure. First, across all four neighbor indicators and all three specifications, the randomized distributions are centered at similar means and have similar shapes. This indicates that if position of tasks in the workflow had no effect on automation outcomes, each neighbor position would contribute similarly, on average, to the automation probability of a task.

Figure 9: Effect of Neighboring Tasks' AI Execution Status on Task's Automation

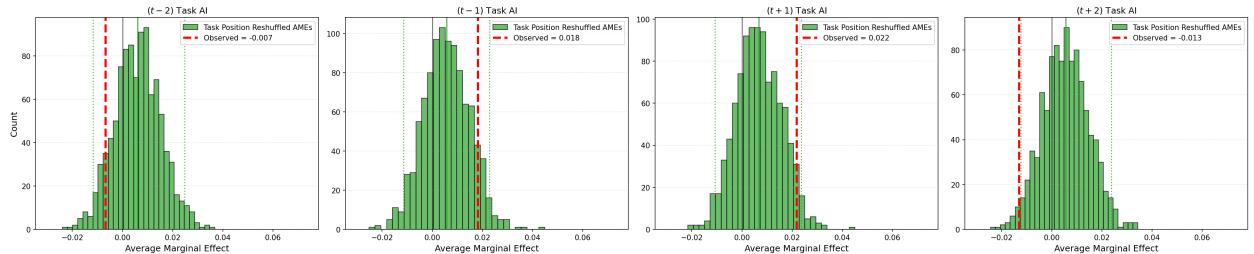
Panel (A): No Fixed Effects



Panel (B): SOC Major Group Fixed Effects



Panel (C): SOC Minor Group Fixed Effects



*Notes:* The red dashed line in each graph indicates observed average marginal effect in the actual dataset reported in Table 4. Thin black lines show zero for baseline comparison. Histograms show frequency of average marginal effects in 1,000 randomized task position reshuffles of the original dataset. Panel (A) reports outcomes of specification 22. Panels (B) and (C) respectively add SOC major group and SOC minor group controls to the baseline specification.

Table 4: Average Marginal Effects of Neighbors' Execution Status on Task's Automation

Specification	(1)	(2)	(3)
( $t - 2$ ) Task AI	0.02*	-0.01	-0.01
	(0.01)	(0.01)	(0.01)
( $t - 1$ ) Task AI	0.05***	0.02**	0.02**
	(0.01)	(0.01)	(0.01)
( $t + 1$ ) Task AI	0.05***	0.02***	0.02**
	(0.01)	(0.01)	(0.01)
( $t + 2$ ) Task AI	0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)
Pseudo $R^2$	0.039	0.107	0.105
Adj. Pseudo $R^2$	0.035	0.091	0.063
Observations	6,675	6,662	5,961
SOC Group Fixed Effects	Major	Minor	

Robust standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

*Notes:* The dependent variable in all specifications is the indicator for whether task  $t$  is AI-automated (is\_automated). All specifications control for AI exposure status of task  $t$  and number of tasks in task  $t$ 's occupation.

Second, in all panels, the observed marginal effects for immediate neighbors (the middle columns) lie to the right of the randomized distributions, while the observed effects for farther neighbors (the outer columns) tend to lie to the left. This pattern suggests that immediate neighbors exert a stronger positive influence on a task's automation likelihood than would be expected under random assignment, while farther neighbors exert less influence once the contribution of immediate neighbors is accounted for.

Third, once SOC major group and minor group fixed effects are included, the estimated effect of farther neighbors collapses to essentially zero in Panels (B) and (C), whereas the effects of immediate neighbors remain positive and distinct from their placebo distributions. The absence of meaningful effects from farther neighbors is consistent with the relatively short AI chains observed in the data. Recall that the average AI chain length is only 1.45, implying that tasks two positions away rarely fall within the same chain. As AI quality improves, longer chains may become more common, in which case the execution status of farther neighbors may begin to meaningfully influence automation outcomes.

Finally, because the dataset contains relatively few automated tasks, and because some automated tasks appear out of order, one might worry that our analysis of AI automation does not fully exploit the information in the data. We therefore repeat the exercise, this time treating both augmented and automated tasks as a single kind of AI-executed task. In this version, the dependent variable in (22) is an indicator for whether task  $t$  is AI-executed, that is, is\_ai <sub>$t$</sub> . The results, reported in Appendix Table C.1 and Appendix Figure D.4, display qualitatively similar patterns, with stronger effects for immediate neighbors and weaker effects for farther neighbors relative to the AI automation analysis presented here.

## 7 Conclusion

This paper develops a task-based framework for understanding how advances in AI reshape automation, the division of labor, and production more generally. By modeling production as a sequence of steps that can be aggregated into tasks and then into jobs, we show how firms optimally allocate work between humans and AI when doing so requires trading off gains from specialization against coordination frictions. A central

feature of the model is the possibility of AI chains, in which multiple steps are executed by AI and only the final output is verified by a human. Chaining can overturn step-level comparative advantage and amplify the effects of local improvements in AI quality.

We characterize short-run automation decisions when job boundaries, and therefore the set of tasks assigned to each worker, are fixed, and the long-run joint optimization of job design and automation strategy. We show that improvements in AI quality can induce discrete reorganizations of work. A key implication is that marginal increases in AI quality may generate little or no cost savings until a threshold is crossed, after which the optimal task and job structure reorganizes discontinuously. This helps explain why firms invest so heavily in AI capabilities even when short run returns appear limited, and is consistent with the J-curve pattern of technology adoption Brynjolfsson et al. (2021) in which early adoption raises costs before the anticipated gains from reorganization are realized.

We also show how the production functions derived from firm-level cost minimization can be mapped into a CES production function at the aggregate level when firms differ in how they deploy a common, general-purpose AI technology. The framework therefore links micro level production to macro implications for labor demand and aggregate productivity.

We complement the theoretical analysis with empirical tests of three core mechanisms implied by the model. Using a task-level dataset of AI exposure and AI execution outcomes, we find that AI-executed steps tend to appear in contiguous AI chains, that occupations with more fragmented AI-able steps in their workflow exhibit lower realized AI execution conditional on exposure levels, and that when comparable steps appear across occupations those adjacent to AI-executed neighbors are significantly more likely to be AI automated. These patterns align with the central economic forces highlighted by the model: the importance of positional relationships among steps, the role of AI-able step dispersion in shaping execution outcomes, and the local complementarities created by AI chains.

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## A Technical Details - Fragmentation Index

In this appendix we prove Proposition 5, which relates the cost of the optimal short-term automation strategy for a fixed job to the fragmentation index of that job. Intuitively, we expect a production process in which automatable tasks are clustered together will benefit more from automation than one where steps with high and low levels of automation are interspersed. This is due to the potential benefits from AI chains.

First recall the definition of fragmentation index for a given step sequence  $\mathcal{S} = (s_1, \dots, s_m)$ . As a reminder, we assume for Proposition 5 that  $t_i^M = 1$  for all  $s_i$ . Consider a random process in which each step  $s_i$  succeeds independently with probability  $q_i$ ; any step that does not succeed is said to fail. Write  $F$  for the set of steps that fail, and  $\mathcal{C} = \{C_1, \dots, C_k\}$  for the random variable representing the collection of maximal connected components of non-failed steps. The weight of each  $C_j \in \mathcal{C}$  is defined to be  $\omega(C_j) = \min\{1, \sum_{s_i \in C_j} t_i^H\}$ . That is, each  $C_j$  has weight 1 unless the sum of the manual time costs for each of its steps is less than 1 (due to our assumption that AI management costs are normalized to 1).

We now introduce some notation: for each  $s_i$ , write  $c_i = \min\left\{t_i^H, \frac{t_i^M}{q_i}\right\}$ . That is,  $c_i$  is the minimum cost to implement step  $s_i$  individually (whether manually or through AI augmentation). Given a realization of  $\mathcal{C}$  and  $F$ , we define the realized fragmentation to be

$$\sum_{s_i \in F} c_i + \sum_{C_j \in \mathcal{C}} \omega(C_j).$$

The *fragmentation index* is defined to be the expected value of the realized fragmentation.

We now fix the sequence  $\mathcal{S} = (s_1, \dots, s_m)$ , write  $FI$  for the fragmentation index of  $\mathcal{S}$ , and let  $OPT$  be the cost of the optimal (i.e., time-minimizing) task structure for those steps.

We begin by showing that  $FI$  is not much larger than  $OPT$ .

**Proposition 6.**  $FI \leq \frac{5}{4}OPT$ .

*Proof.* Fix an arbitrary task sequence  $\mathcal{T} = (T_1, \dots, T_n)$ . Partition this into two sets of tasks:  $\mathcal{T}_H$  containing all (singleton) tasks that are completed manually, and  $\mathcal{T}_M$  containing all other tasks (consisting of AI-augmented singletons and AI chains). We first claim that

$$FI \leq \sum_{T_j \in \mathcal{T}_M} \left( 1 + \sum_{s_i \in T_j} (1 - \alpha^{d_i})(1 + c_i) \right) + \sum_{(s_i) \in \mathcal{T}_M} t_i^H.$$

To see why, first note that for any human-executed task  $(s_i) \in \mathcal{T}_H$ , either the task fails in the realization of  $F$  (in which case it contributes  $c_i \leq t_i^H$  to  $FI$ ), or it succeeds (in which case it appears in some connected component  $C_j$ , contributing at most  $t_i^H$  to the component's weight  $\omega(C_j)$ ).

Next consider the machine-assisted tasks. For any  $T_j \in \mathcal{T}_M$ , consider the set of steps in  $T_j$  that fail in any given realization of  $F$ . If no steps in  $T_j$  fail, then  $T_j$  collectively contributes at most 1 to the realized fragmentation (since all  $s_i \in T_j$  lie in the same connected component of non-failed tasks). Otherwise, each failed task  $s_i \in T_j$  contributes  $c_i$  to the realized fragmentation (for itself, recalling that  $c_i$  is the minimal cost of executing  $s_i$  on its own) plus an additional value of at most 1 for the weight of a potential new connected component of non-failed tasks. As each task  $s_i \in T_j$  fails independently with probability  $(1 - \alpha^{d_i})$ , we get that the contribution of tasks in  $T_j$  to the fragmentation index is at most  $1 + \sum_{s_i \in T_j} (1 - \alpha^{d_i})(1 + c_i)$  as claimed.

On the other hand, recall that if we take  $\mathcal{T}$  to be the cost-minimizing task sequence, then

$$OPT = \sum_{T_j \in \mathcal{T}_M} \alpha^{-d(T_j)} + \sum_{(s_i) \in \mathcal{T}_H} t_i^H$$

by definition, where we write  $d(T_j) = \sum_{s_i \in T_j} d_i$  for the total difficulty of steps in task  $T_j$ .

Comparing our expression for  $OPT$  with our bound on  $FI$ , we see that each task in  $\mathcal{T}_H$  contributes the same amount to each, whereas each  $T_j \in \mathcal{T}_M$  contributes  $\sum_{s_i \in T_j} (1 - \alpha^{d_i})(1 + c_i)$  to the former and  $\alpha^{-d(T_j)}$

to the latter. We will show that, for each  $T_j \in \mathcal{T}_M$ ,  $1 + \sum_{s_i \in T_j} (1 - \alpha^{d_i})(1 + c_i) \leq \frac{5}{4}\alpha^{-d(T_j)}$ , which will complete the proof.

First, since  $c_i \leq \alpha^{-d_i}$  for each  $s_i \in \mathcal{S}$ , we have  $1 + \sum_{s_i \in T_j} (1 - \alpha^{d_i})(1 + c_i) \leq 1 + \sum_{s_i \in T_j} (1 - \alpha^{d_i})(1 + \alpha^{-d_i})$ .

Next note that for any  $x, y \in [0, 1]$ ,  $(1 - xy)(1 + \frac{1}{xy}) \geq (1 - x)(1 + \frac{1}{x}) + (1 - y)(1 + \frac{1}{y})$ . (This can be checked by expanding and taking derivatives.) Repeatedly applying this fact, we get that  $1 + \sum_{s_i \in T_j} (1 - \alpha^{d_i})(1 + \alpha^{-d_i}) \leq 1 + (1 - \alpha^{d(T_j)})(1 + \alpha^{-d(T_j)}) = 1 + \alpha^{-d(T_j)} - \alpha^{d(T_j)}$  for any  $T_j \in \mathcal{T}_M$ . The ratio between this expression and  $\alpha^{-d(T_j)}$  is maximized at  $\alpha^{-d(T_j)} = 1/2$ , achieving a value of  $5/4$  as claimed.  $\square$

Note that this bound of  $5/4$  is tight. Suppose we have 3 steps in  $\mathcal{S}$ : the first and last always succeed, and the second succeeds with probability  $1/2$  and has a manual cost of 2. Then the optimal policy automates all three together for an expected cost of 2, whereas the fragmentation index is  $(1/2) \times 1 + (1/2) \times (1+2+1) = 5/2$ .

We next argue that  $F$  is not much smaller than  $OPT$ . We begin with an analysis under the assumption that  $t_i^H \geq 1$  for all  $s_i \in \mathcal{S}$ . That is, for each step  $s_i$ , completing the step manually is at least as costly as managing an AI tool to complete the step in a single attempt (with guaranteed success).

**Proposition 7.** *Suppose  $t_i^H \geq 1$  for all  $s_i \in \mathcal{S}$ . Then  $FI \geq \frac{1}{4}OPT$ .*

*Proof.* Consider the following task sequence. Beginning with the first step  $s_1$ , consider the maximal contiguous sequence of steps  $T$  whose success probability  $\alpha^{d(T)}$  is greater than or equal to  $1/2$ . If that set is empty (i.e., the first step has success probability strictly less than  $1/2$ ) then the first step is set to be completed individually, either manually or automated, whichever is cheaper. In this case, we'll say the resulting singleton task is completed *individually*. Otherwise, the sequence  $T = (s_1, \dots, s_\ell)$  (which could still be a singleton task) is added to the task sequence as an AI chain; we call this a *non-individual* task. This process is then repeated beginning with the next step (which is  $s_2$  in the former case, or  $s_{\ell+1}$  in the latter case), until all steps have been added to a task. Call the resulting task sequence  $\mathcal{T}$ .

Let  $ALG$  denote the cost of the task sequence  $\mathcal{T}$ . Note that we must have  $ALG \geq OPT$ . We will argue that  $FI \geq ALG/4$ , which will prove the claim.

We first define some notation. Write  $\mathcal{T}_I$  for the set of individual tasks in  $\mathcal{T}$  and  $\mathcal{T}_{NI}$  for the set of non-individual tasks. Note that  $\alpha^{d_i} < 1/2$  for all  $(s_i) \in \mathcal{T}_I$ , by construction. Note also that  $\mathcal{T}_H \subseteq \mathcal{T}_I$  (recalling that  $\mathcal{T}_H$  is the set of all singleton tasks executed manually), and this containment may be strict if  $\mathcal{T}_I$  contains singleton tasks that are augmented. We emphasize that  $\mathcal{T}_{NI}$  may still include singleton tasks, but any singleton task  $(s_i) \in \mathcal{T}_{NI}$  must have the property that  $\alpha^{d_i} \geq 1/2$ .

If the final task  $s_m$  from  $\mathcal{S}$  is contained in some  $T_j \in \mathcal{T}_{NI}$ , we say that  $T_j$  is the *terminal* task. All other tasks in  $\mathcal{T}_{NI}$  are non-terminal tasks. Note that if the final step is a singleton task in  $\mathcal{T}_I$  then no task is terminal. For each non-terminal task  $T_j \in \mathcal{T}_{NI}$ , we'll write  $\bar{T}_j$  to denote  $T_j$  plus the first step that follows  $T_j$ . For example, if  $T_j = (s_i, \dots, s_\ell)$ , then  $\bar{T}_j = (s_i, \dots, s_\ell, s_{\ell+1})$ . The set  $\mathcal{T}_{NI}$  then has the property that for each task  $T_j \in \mathcal{T}_{NI}$  we have  $\alpha^{d(T_j)} \geq 1/2$ , and for each non-terminal  $T_j \in \mathcal{T}_{NI}$  we have  $\alpha^{(d(\bar{T}_j))} < 1/2$ .

We are now ready to relate  $FI$  and  $ALG$ . Let  $k = |\mathcal{T}_{NI}|$  be the number of non-individual tasks. Note first that

$$ALG = \sum_{T_j \in \mathcal{T}_{NI}} \alpha^{-d(T_j)} + \sum_{(s_i) \in \mathcal{T}_I} c_i \leq 2k + \sum_{(s_i) \in \mathcal{T}_I} c_i.$$

This is because  $\alpha^{d(T_j)} \geq 1/2$  for each  $T_j \in \mathcal{T}_{NI}$ , and hence  $\alpha^{-d(T_j)} \leq 2$ .

Next we bound  $FI$ . Note that the assumption  $t_i^H \geq 1$  implies that, in any realization of the connected components of non-failed steps  $\mathcal{C} = (C_1, \dots, C_\ell)$ ,  $\omega(C_j) = 1$  for all  $j$ . This implies that the realized fragmentation is equal to 1 plus, for each  $s_i \in F$  (i.e., each step  $s_i$  that fails), a contribution of  $c_i$  plus an additional 1 in the event that  $i > 1$  and the task immediately preceding  $s_i$  did not fail. (This additional cost of 1 accounts for creating a new connected component of non-failed steps ending with  $s_{i-1}$ .)

We claim that  $FI \geq k/2 + \frac{1}{2} \sum_{(s_i) \in \mathcal{T}_I} c_i$ . We will show this by charging the realized fragmentation to tasks in  $\mathcal{T}_{NI}$  and  $\mathcal{T}_I$ , so that each  $T_j \in \mathcal{T}_{NI}$  is charged at least 1 with probability at least  $1/2$ , and each  $(s_i) \in \mathcal{T}_I$  is charged at least  $c_i$  with probability at least  $1/2$ .

To see this, let  $E_j$  denote the event that some step in  $\bar{T}_j$  fails, for each non-terminal  $T_j \in \mathcal{T}_{NI}$ . Note that  $E_j$  occurs with probability at least  $1/2$ , since  $\alpha^{d(\bar{T}_j)} < 1/2$ . Also, if  $E_j$  occurs, then either a step  $s_i \in T_j$  fails, or no step in  $T_j$  fails but the step immediately following  $T_j$  does. In the former case, we will charge the  $c_i \geq 1$  contribution of  $s_i$ 's failure to  $T_j$ . In the latter case, it must be that the step immediately preceding the failed task did not fail; so we will charge the additional contribution of 1 from  $s_i$ 's failure (as described above) to  $T_j$ . Additionally, if there is a terminal  $T_j$  in  $\mathcal{T}_{NI}$ , then we charge the baseline 1 from the calculation of  $FI$  to that terminal  $T_j$ . Aggregating over all these cases, we have that at least 1 is charged to each set  $T_j \in \mathcal{T}_{NI}$  with probability at least  $1/2$ . Finally, for each  $(s_i) \in \mathcal{T}_I$  that fails (which occurs with probability at least  $1/2$ , by construction), we charge the  $c_i$  portion of its contribution to task  $(s_i)$ . We conclude that  $FI \geq k/2 + \frac{1}{2} \sum_{(s_i) \in \mathcal{T}_I} c_i$  as claimed.

But now since  $FI \geq k/2 + \frac{1}{2} \sum_{(s_i) \in \mathcal{T}_I} c_i$  and  $ALG \leq 2k + \sum_{(s_i) \in \mathcal{T}_I} c_i$ , we conclude  $FI \geq ALG/4$  as claimed.  $\square$

Can the approximation factor in Proposition 7 be improved? While we do not have a matching lower bound of 4, we do know that the approximation factor is at least  $\frac{2}{3}(2 + \sqrt{2}) \approx 2.276$ . Here is an example. Suppose the problem instance is a sequence of  $m$  steps, each with success probability  $1/\sqrt{2}$  and manual cost  $\sqrt{2}$ . The task sequence described in the proof of Proposition 7 then handles each task separately, for a total cost of  $m\sqrt{2}$ . The optimal task sequence must therefore perform at least this well. The fragmentation index is such that each task contributes  $\sqrt{2}$  if it fails, plus 1 if the preceding task did not fail, for a total contribution of  $(1 - 1/\sqrt{2})(\sqrt{2} + 1(1/\sqrt{2})) = \frac{3}{2}(\sqrt{2} - 1) \approx 0.6213$ . As  $m$  grows large, the ratio between  $m\sqrt{2}$  and  $1 + m \times 0.6213$  approaches  $\frac{2}{3}(2 + \sqrt{2}) \approx 2.276$ .

We can relax the assumption in Proposition 7 that  $t_i^H \geq 1$  for all  $s_i$ , but at the cost of a worse approximation factor.

**Proposition 8.** *For general  $t_i^H$  (i.e., allowing  $t_i^H < 1$  for some steps  $s_i$ ),  $FI \geq \frac{1}{8}OPT$ .*

*Proof.* The argument follows the proof of Proposition 7, with the following changes.

First we make a slight change in the definition of the task sequence  $\mathcal{T}$  that defines  $ALG$ . If a constructed task  $T_j$  has the property that  $\sum_{s_i \in T_j} t_i^H < 1$  (which implies it is cheaper to run all steps of  $T_j$  manually than as an AI chain that is guaranteed to succeed), we switch to running the tasks of  $T_j$  manually in the task sequence. In our analysis, we still consider  $T_j$  to be a set in  $\mathcal{T}_{NI}$ ; but its cost is taken to be  $\sum_{s_i \in T_j} t_i^H$ .

This modification changes our upper bound on the total cost of  $ALG$  to the following:

$$ALG \leq 2 \sum_{T_j \in \mathcal{T}_{NI}} \min \left\{ 1, \sum_{s_i \in T_j} t_i^H \right\} + \sum_{(s_i) \in \mathcal{T}_I} c_i.$$

Then, to bound  $FI$ , we claim that

$$FI \geq \frac{1}{4} \sum_{T_j \in \mathcal{T}_{NI}} \min \left\{ 1, \sum_{s_i \in T_j} t_i^H \right\} + \frac{1}{2} \sum_{(s_i) \in \mathcal{T}_I} c_i$$

which would prove the claim.

To see why this bound on  $FI$  holds, we employ a charging argument as before. Recall that for each non-terminal  $T_j \in \mathcal{T}_{NI}$ , the event  $E_j$  occurs with probability at least  $1/2$ . When it does, we charge to  $T_j$  the contribution  $c_i$  to  $FI$  from any  $s_i \in F$  that lies in  $T_j$ . Furthermore, when  $E_j$  occurs, for each connected component  $C_\ell$  that intersects  $T_j$  we additionally charge the contribution  $\omega(C_\ell)$  from  $FI$  to  $T_j$ . Crucially, the contribution from each  $C_\ell$  can be charged to at most two different tasks  $T_j$  in this way: once for the leftmost  $T_j$  that it intersects, and once for the rightmost  $T_j$  that it intersects. (The reason is that if some  $T_j$  is a subset of  $C_\ell$ , then by definition no step of  $T_j$  fails and hence  $E_j$  did not occur. So this charging can only occur for a task  $T_j$  that intersects  $C_\ell$  but is not a subset of  $C_\ell$ , of which there are at most two.)

Moreover, this charging to  $T_j$  adds up to a total value of at least  $\min \left\{ 1, \sum_{s_i \in T_j} t_i^H \right\}$ . Since the charging occurs with probability 1/2 for each  $T_j \in \mathcal{T}_{NI}$ , and we are at most double-counting each  $\omega(C_\ell)$ , we conclude that the expected sum of all  $\omega(C_\ell)$ , plus  $c_i$  for all failed tasks  $s_i$  that lie in some  $T_j \in \mathcal{T}_{NI}$ , is at least 1/4 of  $\sum_{T_j \in \mathcal{T}_{NI}} \min \left\{ 1, \sum_{s_i \in T_j} t_i^H \right\}$ .

The charging for  $(s_i) \in \mathcal{T}_I$  remains unchanged: the value  $c_i$  is charged in the event that step  $s_i$  fails, which occurs with probability at least 1/2.

Taken together, we obtain our desired 8 approximation.  $\square$

We suspect the factor of 8 in Proposition 8 is not tight. But, as we now show, the factor is strictly greater than the factor 4 from Proposition 7, so the assumption that  $t_i^H \geq 1$  for all  $s_i$  is necessary for Proposition 7 to hold.

Consider a step sequence  $\mathcal{S}$  that alternates between (a) steps of manual cost 0 and success probability  $1/\sqrt{2} - \epsilon$  where  $\epsilon$  is vanishingly small, and (b) steps of manual cost 1 and success probability 1. Suppose there are  $K > 1$  such pairs. The task sequence described in the proof of Proposition 8 above groups the steps into pairs of two-step tasks, for a total cost of  $K\sqrt{2}$  (ignoring  $\epsilon$ ). The fragmentation index is 1 plus 1 for each task that fails, which is  $1 + K(1 - 1/\sqrt{2})$  (again ignoring the impact of  $\epsilon$ ). As  $K$  grows large, the ratio tends to  $2(\sqrt{2} + 1)$  which is strictly greater than 4.

## B Technical Details - Derivation of Effective AI Quality Heterogeneity Distribution

In this Appendix we describe how to obtain the analytical formula for distribution of heterogeneity  $\phi(\bar{\alpha})$  expressed in (20) by extending the work of Levhari (1968).

Define  $u = (w_M \tau_M)/(1 - w_H \tau_H)$  and rewrite equation (19) as:

$$\left( \int_u^1 \phi(\bar{\alpha}) d\bar{\alpha} \right)^\rho = \theta_M \left( \tau_M \int_u^1 \frac{\phi(\bar{\alpha})}{\bar{\alpha}} d\bar{\alpha} \right)^\rho + \theta_H \left( \tau_H \int_u^1 \phi(\bar{\alpha}) d\bar{\alpha} \right)^\rho + (1 - \theta_M - \theta_H). \quad (23)$$

Our goal is to solve for  $\phi(\bar{\alpha})$  in the equation above as a function of  $\theta_M, \theta_H, \rho$ . Define:

$$\Gamma(u) = \int_u^1 \phi(\bar{\alpha}) d\bar{\alpha}, \quad (24)$$

and

$$\Psi(u) = \int_u^1 \frac{\phi(\bar{\alpha})}{\bar{\alpha}} d\bar{\alpha}. \quad (25)$$

Note that  $\Gamma'(u) = -\phi(u)$  and  $\Psi'(u) = -\phi(u)/u$ . Rewrite equation (23) as:

$$\Gamma^\rho(u) = \theta_M \tau_M^\rho \Psi^\rho(u) + \theta_H \tau_H^\rho \Gamma^\rho(u) + (1 - \theta_M - \theta_H).$$

Rearranging terms, we obtain:

$$(1 - \theta_H \tau_H^\rho) \Gamma^\rho(u) = \theta_M \tau_M^\rho \Psi^\rho(u) + (1 - \theta_M - \theta_H). \quad (26)$$

Differentiating equation (26) with respect to  $u$  yields:

$$(1 - \theta_H \tau_H^\rho) \Gamma^{\rho-1}(u) = \theta_M \tau_M^\rho \Psi^{\rho-1}(u) u^{-1}.$$

Rearrange this to solve for  $\Psi^{\rho-1}(u)$  as a function of  $u$  and  $\Gamma^{\rho-1}(u)$ :

$$\Psi^{\rho-1}(u) = \frac{(1 - \theta_H \tau_H^\rho)}{\theta_M \tau_M^\rho} \Gamma^{\rho-1}(u) u.$$

Finally, express  $\Psi(u)$  in terms of  $\Gamma(u)$ :

$$\Psi(u) = (1 - \theta_H \tau_H^\rho)^{\frac{1}{\rho-1}} (\theta_M \tau_M^\rho)^{\frac{1}{1-\rho}} u^{\frac{1}{\rho-1}} \Gamma(u). \quad (27)$$

Substituting  $\Psi(u)$  from equation (27) into equation (26), we have:

$$(1 - \theta_H \tau_H^\rho) \Gamma^\rho(u) = (1 - \theta_H \tau_H^\rho)^{\frac{\rho}{\rho-1}} (\theta_M \tau_M^\rho)^{\frac{1}{1-\rho}} u^{\frac{\rho}{\rho-1}} \Gamma^\rho(u) + (1 - \theta_M - \theta_H).$$

Rearranging terms to solve for  $\Gamma(u)$ , we get:

$$\Gamma(u) = (1 - \theta_M - \theta_H)^{\frac{1}{\rho}} \left[ 1 - \theta_H \tau_H^\rho - (1 - \theta_H \tau_H^\rho)^{\frac{\rho}{\rho-1}} (\theta_M \tau_M^\rho)^{\frac{1}{1-\rho}} u^{\frac{\rho}{\rho-1}} \right]^{-\frac{1}{\rho}}.$$

Recall that  $\Gamma'(u) = -\phi(u)$ . Differentiating  $\Gamma(u)$ , we obtain:

$$\begin{aligned} \Gamma'(u) &= \frac{\partial}{\partial u} \left[ (1 - \theta_M - \theta_H)^{\frac{1}{\rho}} \left[ 1 - \theta_H \tau_H^\rho - (1 - \theta_H \tau_H^\rho)^{\frac{\rho}{\rho-1}} (\theta_M \tau_M^\rho)^{\frac{1}{1-\rho}} u^{\frac{\rho}{\rho-1}} \right]^{-\frac{1}{\rho}} \right] \\ &= \frac{(1 - \theta_M - \theta_H)^{\frac{1}{\rho}} (1 - \theta_H \tau_H^\rho)^{\frac{\rho}{\rho-1}} (\theta_M \tau_M^\rho)^{\frac{1}{1-\rho}}}{\rho - 1} u^{\frac{1}{\rho-1}} \left[ 1 - \theta_H \tau_H^\rho - (1 - \theta_H \tau_H^\rho)^{\frac{\rho}{\rho-1}} (\theta_M \tau_M^\rho)^{\frac{1}{1-\rho}} u^{\frac{\rho}{\rho-1}} \right]^{-\frac{1+\rho}{\rho}}. \end{aligned}$$

Thus, we have:

$$\phi(\bar{\alpha}) = \frac{(1 - \theta_M - \theta_H)^{\frac{1}{\rho}} (1 - \theta_H \tau_H^\rho)^{\frac{\rho}{\rho-1}} (\theta_M \tau_M^\rho)^{\frac{1}{1-\rho}}}{1 - \rho} (\bar{\alpha})^{\frac{1}{\rho-1}} \left[ 1 - \theta_H \tau_H^\rho - (1 - \theta_H \tau_H^\rho)^{\frac{\rho}{\rho-1}} (\theta_M \tau_M^\rho)^{\frac{1}{1-\rho}} (\bar{\alpha})^{\frac{\rho}{\rho-1}} \right]^{-\frac{1+\rho}{\rho}}, \quad (28)$$

which is the formula provided in (20) in the main text.

## C Appendix Tables

Table C.1: Average Marginal Effects of Neighbors' Execution Status on Task's AI Execution

Specification	(1)	(2)	(3)
( $t - 2$ ) Task AI	0.04*** (0.01)	-0.00 (0.01)	-0.02 (0.01)
( $t - 1$ ) Task AI	0.12*** (0.01)	0.07*** (0.01)	0.05*** (0.01)
( $t + 1$ ) Task AI	0.14*** (0.02)	0.09*** (0.01)	0.08*** (0.01)
( $t + 2$ ) Task AI	0.05*** (0.01)	0.01 (0.01)	-0.01 (0.01)
Pseudo $R^2$	0.043	0.074	0.082
Adj. Pseudo $R^2$	0.042	0.067	0.057
Observations	6,675	6,675	6,470
SOC Group Fixed Effects		Major	Minor

Robust standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Notes:* The dependent variable in all specifications is the indicator for whether task  $t$  is AI-executed (is.ai). All specifications control for AI exposure status of task  $t$  and number of tasks in task  $t$ 's occupation.

Table C.2: Example O\*NET Tasks Associated with Claude Conversations, and Calculated Augmentation vs. Automation Outcomes

O*NET Task	Share of Claude Conversations (%)								Label
	Validation	Task Iteration	Learning	Directive	Feedback Loop	Filtered	Augmentation	Automation	
Provide road information to assist motorists.	0.00	11.47	44.39	33.42	5.74	4.99	<b>55.86</b>	39.15	Augmentation
Calculate costs of orders, and charge or forward invoices to appropriate accounts.	0.00	0.00	0.00	68.00	0.00	32.00	0.00	<b>68.00</b>	Automation
Process data for analysis, using computers.	4.23	18.60	31.40	25.79	16.38	3.59	<b>54.23</b>	42.18	Augmentation
Adapt text to accommodate musical requirements of composers and singers.	0.00	40.00	0.00	58.26	0.00	1.74	40.00	<b>58.26</b>	Automation
Provide system design and integration recommendations.	2.13	29.75	39.98	21.23	5.80	1.11	<b>71.87</b>	27.02	Augmentation
Communicate traffic and crossing rules and other information to students and adults.	0.00	0.00	0.00	65.52	0.00	34.48	0.00	<b>65.52</b>	Automation
Prepare, manipulate, and manage extensive databases.	0.00	25.89	22.34	23.40	24.47	3.90	<b>48.23</b>	47.87	Augmentation
Prepare, administer, and grade tests and assignments to evaluate students' progress.	7.64	20.94	7.39	58.13	3.94	1.97	35.96	<b>62.07</b>	Automation
Conduct statistical analyses to quantify risk using statistical analysis software or econometric models.	0.00	25.23	31.53	17.12	18.92	7.21	<b>56.76</b>	36.04	Augmentation
Assemble, typeset, scan and produce digital camera-ready art or film negatives and printer's proofs.	0.00	21.88	0.00	77.34	0.00	0.78	21.88	<b>77.34</b>	Automation
Conduct searches to find needed information, using such sources as the internet.	1.31	5.53	58.30	23.14	3.57	8.15	<b>65.14</b>	26.71	Augmentation
Compile data and create statistical reports on library usage.	0.00	0.00	0.00	64.86	0.00	35.14	0.00	<b>64.86</b>	Automation
Create custom illustrations or other graphic elements.	0.00	48.17	3.17	43.82	2.74	2.10	<b>51.34</b>	46.56	Augmentation
Confer with clients to obtain and provide information when claims are made on a policy.	0.00	0.00	45.45	0.00	0.00	54.55	<b>45.45</b>	0.00	Augmentation

*Notes:* Augmentation percentage is the sum of Validation, Task Iteration, and Learning types of conversation whereas as Automation percentage is the sum of Directive and Feedback Loop types of conversation. Whichever mode between Augmentation and Automation has a higher share is selected as the task's mode of AI execution, ignoring the share Filtered.

Table C.3: Example DWAs with Tasks in Multiple Occupations and the Subset of Tasks Surviving the “Finding Similar Tasks” Procedure

Panel (A)

O*NET DWA Title	O*NET Task Title	O*NET Occupation Title	Execution Label
Analyze operational or research data.	Analyze or manipulate bioinformatics data using software packages, statistical applications, or data mining techniques.  Conduct quality analyses of data inputs and resulting analyses or predictions.	Bioinformatics Technicians	Augmentation
	Analyze research data to determine its significance, using computers.  Collect and analyze data, such as studying old records, tallying the number of outpatients entering each day or week, or participating in federal, state, or local population surveys as a Census Enumerator.	Astronomers	Augmentation
	Analyze data to determine answers to questions from customers or members of the public.  Compute and analyze data, using statistical formulas and computers or calculators.	Interviewers, Except Eligibility and Loan  Receptionists and Information Clerks	Manual  Augmentation
Prepare research or technical reports on environmental issues.	Write reports or articles for Web sites or newsletters related to environmental engineering issues.  Prepare technical and research reports, such as environmental impact reports, and communicate the results to individuals in industry, government, or the general public.  Prepare scientific atmospheric or climate reports, articles, or texts.  Prepare charts or graphs from data samples, providing summary information on the environmental relevance of the data.  Write reports or academic papers to communicate findings of climate-related studies.	Environmental Engineers  Biologists  Atmospheric and Space Scientists  Environmental Scientists and Specialists, Including Health	Manual  Manual  Automation  Augmentation
	Prepare study reports, memoranda, briefs, testimonies, or other written materials to inform government or environmental groups on environmental issues, such as climate change.  Prepare technical and research reports, such as environmental impact reports, and communicate the results to individuals in industry, government, or the general public.  Produce environmental documents, such as environmental assessments or environmental impact statements.	Climate Change Policy Analysts  Industrial Ecologists  Transportation Planners	Manual  Manual  Manual
Document events or evidence using photographic or audiovisual equipment.	Take photographs and motion pictures for use in lectures and publications and to develop displays.  Create data records for use in describing and analyzing social patterns and processes, using photography, videography, and audio recordings.  Create photographic recordings of information, using equipment.  Use photographic or video equipment to document evidence or crime scenes.	Park Naturalists  Anthropologists and Archeologists  Geological Technicians, Except Hydrologic Technicians  Forensic Science Technicians	Manual  Automation  Automation  Manual

Panel (B)

O*NET DWA Title	O*NET Task Title	O*NET Occupation Title	Execution Label
Analyze operational or research data.	Analyze or manipulate bioinformatics data using software packages, statistical applications, or data mining techniques.  Analyze research data to determine its significance, using computers.  Compute and analyze data, using statistical formulas and computers or calculators.	Bioinformatics Technicians  Astronomers  Statistical Assistants	Augmentation  Augmentation  Augmentation
Prepare research or technical reports on environmental issues.	Prepare technical and research reports, such as environmental impact reports, and communicate the results to individuals in industry, government, or the general public.  Prepare scientific atmospheric or climate reports, articles, or texts.  Prepare charts or graphs from data samples, providing summary information on the environmental relevance of the data.  Prepare study reports, memoranda, briefs, testimonies, or other written materials to inform government or environmental groups on environmental issues, such as climate change.  Prepare technical and research reports, such as environmental impact reports, and communicate the results to individuals in industry, government, or the general public.  Produce environmental documents, such as environmental assessments or environmental impact statements.	Biologists  Atmospheric and Space Scientists  Environmental Scientists and Specialists, Including Health  Climate Change Policy Analysts  Industrial Ecologists  Transportation Planners	Manual  Automation  Augmentation  Manual  Manual  Manual
Document events or evidence using photographic or audiovisual equipment.	Take photographs and motion pictures for use in lectures and publications and to develop displays.  Create data records for use in describing and analyzing social patterns and processes, using photography, videography, and audio recordings.  Create photographic recordings of information, using equipment.	Park Naturalists  Anthropologists and Archeologists  Geological Technicians, Except Hydrologic Technicians	Manual  Automation  Automation

Notes: Panel (A) shows three example detailed work activities (DWAs) and tasks associated with them in the O\*NET dataset. Entries highlighted with a red font are those that do not survive the “finding similar tasks” procedure described in text. Panel (B) shows the set of tasks for DWAs of Panel (A) that successfully survive the “finding similar tasks” procedure.

## D Appendix Figures

Figure D.1: Task sequence of Computer Programmers occupation (high share of AI-executed tasks)

1	Consult with managerial, engineering, and technical personnel to clarify program intent, identify problems, and suggest ...	Augmentation
2	Perform systems analysis and programming tasks to maintain and control the use of computer systems software as a systems...	Manual
3	Prepare detailed workflow charts and diagrams that describe input, output, and logical operation, and convert them into ...	Automation
4	Write, analyze, review, and rewrite programs, using workflow chart and diagram, and applying knowledge of computer capab...	Augmentation
5	Write, update, and maintain computer programs or software packages to handle specific jobs such as tracking inventory, s...	Automation
6	Develop Web sites.	Manual
7	Compile and write documentation of program development and subsequent revisions, inserting comments in the coded instruc...	Augmentation
8	Conduct trial runs of programs and software applications to be sure they will produce the desired information and that t...	Manual
9	Investigate whether networks, workstations, the central processing unit of the system, or peripheral equipment are respo...	Augmentation
10	Correct errors by making appropriate changes and rechecking the program to ensure that the desired results are produced.	Automation
11	Perform or direct revision, repair, or expansion of existing programs to increase operating efficiency or adapt to new r...	Automation
12	Consult with and assist computer operators or system analysts to define and resolve problems in running computer program...	Augmentation
13	Write or contribute to instructions or manuals to guide end users.	Manual
14	Train users on the use and function of computer programs.	Manual
15	Assign, coordinate, and review work and activities of programming personnel.	Manual
16	Train subordinates in programming and program coding.	Manual
17	Collaborate with computer manufacturers and other users to develop new programming methods.	Augmentation

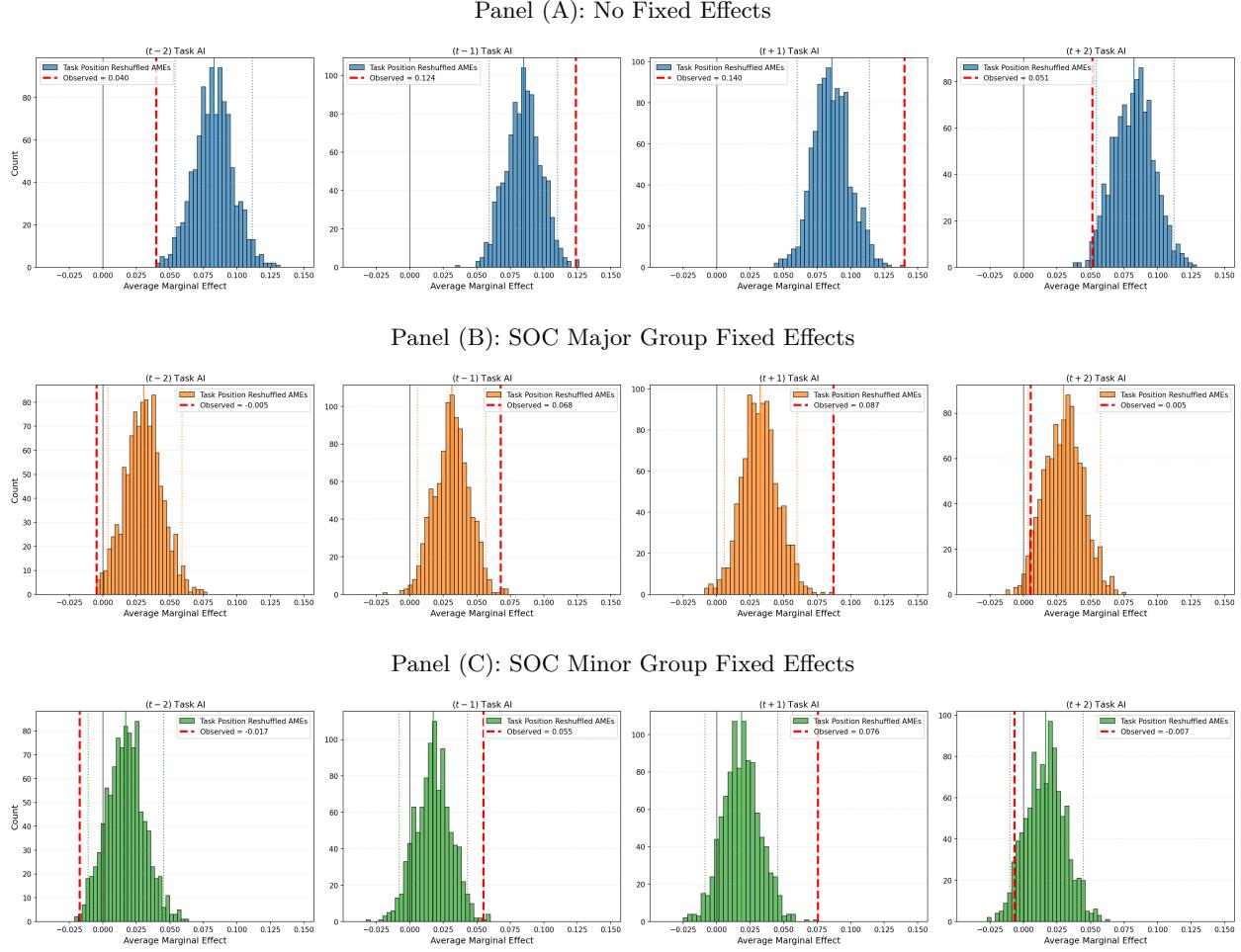
Figure D.2: Task sequence of Public Relations Specialists occupation (moderate share of AI-executed tasks)

1	Study the objectives, promotional policies, or needs of organizations to develop public relations strategies that will i...	Augmentation
2	Confer with other managers to identify trends or key group interests or concerns or to provide advice on business decisi...	Manual
3	Plan or conduct market or public opinion research to test products or determine potential for product success, communica...	Automation
4	Establish or maintain cooperative relationships with representatives of community, consumer, employee, or public interes...	Manual
5	Consult with advertising agencies or staff to arrange promotional campaigns in all types of media for products, organiz...	Manual
6	Confer with production or support personnel to produce or coordinate production of advertisements or promotions.	Manual
7	Purchase advertising space or time as required to promote client's product or agenda.	Manual
8	Develop marketing campaigns for environmental technologies or services.	Manual
9	Develop plans or materials to communicate organizational activities that are beneficial to the environment, public safet...	Manual
10	Plan or direct development or communication of programs to maintain favorable public or stockholder perceptions of an or...	Manual
11	Write press releases or other media communications to promote clients.	Augmentation
12	Prepare or edit organizational publications, such as employee newsletters or stockholders' reports, for internal or exte...	Augmentation
13	Post and update content on the company's Web site and social media outlets.	Manual
14	Arrange public appearances, lectures, contests, or exhibits for clients to increase product or service awareness or to p...	Manual
15	Coach client representatives in effective communication with the public or with employees.	Augmentation
16	Prepare or deliver speeches to further public relations objectives.	Augmentation
17	Coordinate public responses to environmental management incidents or conflicts.	Manual
18	Respond to requests for information from the media or designate an appropriate spokesperson or information source.	Augmentation

Figure D.3: Task sequence of Electronic Equipment Installers and Repairers (zero share of AI-executed tasks)

1	Confer with customers to determine the nature of malfunctions.	Manual
2	Inspect and test electrical or electronic systems to locate and diagnose malfunctions, using visual inspections and test...	Manual
3	Record results of diagnostic tests.	Manual
4	Estimate costs of repairs, based on parts and labor charges.	Manual
5	Diagnose or repair problems with electronic equipment, such as sound, navigation, communication, and security equipment,...	Manual
6	Replace and clean electrical or electronic components.	Manual
7	Remove seats, carpeting, and interiors of doors and add sound-absorbing material in empty spaces, reinstalling interior ...	Manual
8	Cut openings and drill holes for fixtures and equipment, using electric drills and routers.	Manual
9	Build fiberglass or wooden enclosures for sound components, and fit them to automobile dimensions.	Manual
10	Run new speaker and electrical cables.	Manual
11	Splice wires with knives or cutting pliers, and solder connections to fixtures and equipment.	Manual
12	Install equipment and accessories, such as stereos, navigation equipment, communication equipment, and security systems.	Manual

Figure D.4: Effect of Neighboring Tasks' AI Execution Status on Task's AI Execution



*Notes:* The red dashed line in each graph indicates observed average marginal effect in the actual dataset reported in Table C.1. Thin black lines show zero for baseline comparison. Histograms show frequency of average marginal effects in 1,000 randomized task position reshuffles of the original dataset. Panel (A) reports outcomes of specification 22 but with dependent variable `is_ait` instead of `is_automated_t`. Panels (B) and (C) respectively add SOC major group and SOC minor group controls to the baseline specification.

## E GPT-5-mini Prompts

This Appendix provides the GPT-5-mini prompts used to generate a task sequence for each occupation (Prompt 1), and for finding similar tasks across occupations for each DWA (Prompt 2).

### Prompt #1: GPT-5-mini Prompt for Ordering of Tasks in Occupation

```
You are an expert in workflow analysis for the occupation: {{ occupation }}.  
Below is a list of {{ num_tasks }} tasks that are part of this occupation:  
{{ tasks_list }}
```

Provide the typical sequential order in which these tasks are performed in a real-world workflow.

Return your answer as a JSON array where each element has:

- "Task Position": the sequence number (1, 2, 3, etc.).
- "Task Title": the exact task text from the list above.

Format: [{"Task Position": 1, "Task Title": "..."},  
 {"Task Position": 2, "Task Title": "..."},  
 ...]

Only return the JSON array, nothing else.

Prompt #2: GPT-5-mini Prompt for Finding Similar Tasks in Each DWA

You are an expert in workflow analysis for the detailed work activity:  
{{ detailed\_work\_activity }}.

Below is a list of {{ num\_tasks }} task IDs and titles that belong to this detailed work activity and appear across similar or different occupations (tasks and occupations are ordered such that the first task belongs to the first occupation, the second task belongs to the second occupation, etc.).

Tasks IDs: {{ tasks\_ids }}

Tasks list: {{ tasks\_list }}

Occupations list: {{ occupations\_list }}

Occupation Codes list: {{ occupation\_codes\_list }}

Determine which tasks are similar in nature and in terms of their objectives, methods, or required skills. There may be more than one task associated with an occupation. Return only the most relevant task for every occupation. Only look for tasks that are actually similar. Do not feel obliged to return all occupations.

Return the task-occupation pairs you determine as similar as a JSON array where each element has:

- "Task ID": the exact task ID from the list of task IDs above
- "Task Title": the exact task text from the list of tasks above
- "O\*NET-SOC Code": the exact occupation code text from the list of occupation codes above
- "Occupation Title": the exact occupation text from the list of occupations above

Format: [ {"Task ID": 1234, "Task Title": "...",  
"O\*NET-SOC Code": "...", "Occupation Title": "..."},  
 {"Task ID": 5678, "Task Title": "...",  
"O\*NET-SOC Code": "...", "Occupation Title": "..."},  
 ... ]

Only return the JSON array, nothing else.