



The Last Ten Per Cent

How task-level exposure fits into a jobs forecast

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In May 2026, Dario Amodei, the chief executive of Anthropic, offered a compact way to think about artificial intelligence and work: “If you automate 90 percent of the job, then everyone does the 10 percent of the job.”¹

Consider a lawyer who no longer needs to spend hours reviewing routine documents, leaving more time to understand a client’s objectives, test a strategy, and exercise judgment. The service improves and, because the job is done more efficiently, its price falls and demand for it might even grow.

Amodei’s point was that the remaining 10 percent of work could well expand to fill the day while workers become far more productive.² The remark drew attention partly because it sounded more optimistic than Amodei’s earlier warnings about white-collar job loss.³

Of course, something else might happen. Lawyers who have 90 percent of their jobs automated might simply end up with less legal work to do, and thus fewer of them needed to do it.

Amodei’s comment raises real economic questions: *Under what conditions does the last ten per cent become a better and more productive job? When does the job merely become smaller and performed by fewer people?*

Task-level analysis remains the right place to start for understanding AI exposure, or which of the tasks that make up a job might be automated. Trouble begins when a job itself is treated as a checklist and the exposed tasks are crossed out one by one, appearing to simply shrink the amount of work needed to do the job. But once some tasks disappear, the rest of the job may evolve and change character entirely, with the remaining tasks expanding or new tasks emerging to replace the old.

Tasks differ widely. They may be substitutes, complements, bottlenecks, filters for expertise, objects of worker motivation, or parts of an organisational bundle that firms redraw after automation. How a job changes after some of its tasks are automated and new ones emerge depends largely on the nature of those tasks and, especially, how the tasks relate to each other.

Tasks are a useful starting point

The task-based approach used by economists Daron Acemoglu and Pascual Restrepo in their 2019 paper starts with a useful observation: Technology rarely replaces a job title in a single stroke. Instead, it changes who, or what, performs particular activities within production.⁴ Their framework separates a displacement effect (capital takes over tasks previously assigned to labour) from a reinstatement effect (innovation generates new tasks in which people have a comparative advantage). Productivity gains may also increase demand for the resulting goods and services.

This approach is more informative than asking whether an entire occupation is “safe” or “at risk.” An accountant, software engineer, teacher, or nurse performs a bundle of activities. A technology may be well-suited to some activities and poorly-suited to others. Studies of large language models have measured occupational exposure by assessing the tasks for which these systems could reduce completion time.⁵ The resulting measures give us a useful map of technical applicability.

But the map still leaves a difficult step. Once we know where a technology might apply, we need to ask what happens to the human work that remains and its effects on wages and employment. The answer will reflect displacement, reinstatement, and demand. It will also depend on the job’s internal structure.

What happens to expertise?

Economists David Autor and Neil Thompson focus on the type of task that disappears.⁶ Was it among the more expert parts of the occupation, or among the less expert parts? (Autor and Thompson define expert tasks as “problem-solving and decision-making tasks requiring specialized knowledge and training.”) The same activity can be an expert task in one setting and a routine task in another. Once that activity is automated, a worker who remains in the occupation no longer needs the expertise associated with it.

Suppose software removes routine bookkeeping from an accounting clerk’s day. The remaining activities may involve exceptions, problem-solving, and communication with clients. The occupation has become more demanding. Workers with the relevant expertise may become more valuable, while fewer people qualify for the role. Wages can rise as employment falls.

In another occupation, technology might remove the most demanding diagnostic or administrative activity. The remaining role becomes accessible to a broader pool of workers. Employment may rise as wages fall because expertise is less scarce.

For practical analysis, the warning is clear. Wages and employment can move in opposite directions. A task labelled “routine” in one setting may play a different role elsewhere. Autor and Thompson show how automation can replace experts in one context and complement expertise in another. Their framework asks how automation changes the expertise threshold for the remaining tasks.

When the remaining work matters more

Another mechanism appears when the quality of one task affects the value of the others. Michael Kremer's O-ring model captured this idea: Production can depend on several essential activities, and a weak link reduces the value of the whole effort.⁷ In my joint work with Avi Goldfarb, we apply that reasoning to automation when a worker has a fixed amount of time to allocate across essential tasks.⁸ A manager who spends less time scheduling can devote more attention to a difficult negotiation. A radiologist relieved of routine triage can spend more time on integrative diagnosis. A lawyer freed from document review can devote greater care to strategy.

Here, automation has a second effect. A machine takes over one activity, freeing up time for the remaining activities. If the quality of human work depends on attention, the quality of those residual tasks rises. We call this the focus mechanism. At the level of an occupation, it can look like augmentation even though it begins with the automation of a particular task.

This is one way to read Amodei's final ten per cent. The tasks left to people may be the bottlenecks that determine service quality. As auxiliary tasks disappear, those bottlenecks can become more valuable.

Demand matters too. Lower costs may attract more customers, while a better service may draw in people who previously went without it. The history of bank tellers after the spread of automatic teller machines is a useful recollection that work reorganisation and demand expansion often arrive together.⁹

Three cautions follow.

First, average exposure can obscure the job's architecture. Two occupations with the same average exposure may look quite different once we see whether the exposure is concentrated in a few tasks or spread across the whole bundle.

Second, adoption can be lumpy. Automating one task changes the return to automating another, so firms may adopt a package of tools rather than move through a tidy sequence.

Third, better automation can increase the value of retained labour, even as a human bottleneck remains necessary. If full automation becomes credible, the wage effect is less predictable; the worker's contribution may become more valuable even as the firm's outside option improves.

Jobs can be redrawn

Occupations themselves are moving targets. When AI removes part of a job, firms can redesign the human work that survives. Related work on endogenous task bundling studies this organisational margin directly.¹⁰ Consider a radiologist whose pre-AI role combines image classification with physician consultation, while quality assurance and model governance are handled by a separate technical role. If AI begins to read images, the old radiologist's role changes. The hospital has to decide how to recombine the surviving activities.

The hospital might create a broad clinical role that bundles consultation with model governance. Or it might split the work, with a senior clinician focusing on consultation and a governance specialist monitoring the model. The broad role rewards breadth. The specialist arrangement rewards comparative advantage. A skill that carried little weight in the original role can become central after automation, while a skill that anchored the old wage may disappear from the schedule.

For measurement, this matters greatly. A study that holds occupational boundaries fixed can estimate the effect of automation within the old bundle and still miss much of the effect on workers. Where occupations are split into specialist roles, a fixed-bundle estimate may understate the return to comparative advantage. Where tasks are recombined into broader roles, the bias can run in the other direction. Changes in occupational classification belong in the analysis because they record part of the economic response.

What payroll records leave out

Jobs can change even when wage records barely move. Consider a software engineer who uses AI to reduce time spent on documentation, support tickets, and routine debugging, and then devotes additional time to refining a tool they find intrinsically rewarding. Payroll may show little change. The job itself has changed substantially.

Work on enjoyable tasks and contracting shows why this can matter.¹¹ Workers sometimes expand their effort on tasks they value. Two jobs can then have the same hourly wage, paid hours, and wage bill while differing in total time worked and task mix. In some settings, AI reduces recorded hours. In others, it intensifies work, extends the working day or moves effort towards activities beyond formal requirements. Empirical work on AI exposure and the length of the working day points to the importance of this intensive margin.¹²

Enjoyment is one reason for extra effort. Promotion incentives, deadlines, professional norms, and managerial pressure can produce it as well. The practical point is that productivity gains do not automatically translate into shorter hours or better jobs. Payroll records cannot reveal the full quality of the work experience.

Turning exposure into a forecast

Exposure measures still have a clear use: They tell us where to look. Turning exposure into a forecast requires a second layer of analysis. For any occupation, decision-makers should ask at least six questions.

- 1. Which tasks are exposed?** Are they peripheral activities, expert activities, or essential bottlenecks?
- 2. What expertise remains?** Does automation raise or lower the threshold for entering the occupation?

3. **Does freed attention improve quality?** Can workers use the time freed up by AI to perform residual tasks more effectively?
4. **Will firms redraw the job?** Are surviving tasks likely to be rebundled into broad roles or split among specialists?
5. **How elastic is demand?** Will lower costs and higher quality expand the market enough to support additional employment?
6. **What do the available data miss?** Are actual hours, work intensity, worker well-being, and changing job boundaries visible?

The answers are likely to vary across occupations. In professional services, medicine, and management, judgment can remain a bottleneck, leaving room for focus effects. In clerical work, displacement may be more direct, although much still depends on whether AI removes expert or inexperienced tasks. In software and finance, job boundaries may move quickly as firms separate oversight, client interaction, and technical execution. In delegated creative and professional work, payroll may remain stable even as the texture and intensity of work change.

For researchers, this points towards a fairly concrete data agenda. Occupation-level exposure scores should be paired with task-level time use before and after adoption, quality measures for the remaining tasks, evidence of lumpy implementation, vacancy data showing new specialist roles, and worker-reported measures of intensity and well-being.

No single model will fit every setting. The task is to work out which mechanism matters in each case.

Conclusion

What remains after automation can change in several ways. The final ten per cent may become more valuable, more demanding, easier to enter, harder to perform, or newly divided among specialists. AI may displace tasks and reinstate labour elsewhere. It may remove routine work and increase the value of expertise. It may free scarce attention for human bottlenecks, prompt firms to redraw occupational boundaries, or change the intensity of work in ways that payroll does not capture.

For policymakers and business leaders, a useful discipline is to keep asking questions after an exposure estimate is released. What remains? How do the remaining tasks fit together? Who can perform them? How will firms organise the work? Will demand expand? An exposure measure is a starting point for these questions, not the answer.

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