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The geography of generative AI's workforce impacts will likely differ from those of previous technologies

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As the generative AI race heats up, it's important to examine where in the U.S. the technology might boost or harm workers, or if place even matters.

Last fall, Brookings published a report (https://www.brookings.edu/articles/generative-ai-the-american-worker-and-the-future-of-work/) looking at possible patterns of AI involvement in the labor market, focusing on how generative AI appears set to intersect with particular occupations, regardless of their location. There, we found that more than 30% of all workers could see at least 50% of their occupational tasks affected by ChatGPT-4, while 85% of workers could see at least 10% of their tasks affected, with greater impacts possible.

Most notably, our analysis—based on occupation-specific "exposure" data ↗ supplied by ChatGPT creator OpenAI over a year ago—forecasted that for the most part, the greater the education level or pay for an occupation, the greater its likely "exposure" (positive or negative) to generative AI tools will be (albeit with a dip at the very top). That's because generative AI is especially well suited to the cognitive tasks of white collar knowledge work—think coders, writers, financial analysts, engineers, and lawyers. And while generative AI puts at risk the "routine" tasks of customer service and clerical work (often handled by female-staffed call centers, customer service lines, and HR teams, for example), it is currently not equipped to handle the manual work of manufacturing, the skilled trades, construction, and many in-person service industries.

In sum, the workforce impacts of generative AI look at least for now to differ significantly from those of previous forms of automation, which earlier findings (https://www.brookings.edu/articles/automation-and-artificial-intelligence-how-machines-affect-people-and-places/) showed tended to disrupt the work of primarily less-educated, lower-wage workers.

So, what about the geography of generative AI? Does it differ from the impact pattern of earlier automation?

To explore the possible distribution of generative AI impacts across place, we build here on our earlier labor market analysis to leverage AI exposure statistics for occupations as they impact U.S. counties and metropolitan areas. Essentially, we use data on each occupation's share of local employment to calculate county- and metro-level exposure statistics. Such statistics reflect the share of AI-exposed jobs relative to all local jobs in the geographic area. (And it should be said, again, that "exposure" does not speak only to the displacement of workers; it also may involve their "augmentation" through rapidly improving AI tools such as ChatGPT, Claude, and generative AI-powered applications, which can enhance worker productivity and capability.)

What do we find? In short, generative AI is not your grandparents'—or even your parents'—automation. Most notably, the possible impact patterns of generative AI look quite different from those of previous forms of automation.

As noted, Brookings has shown (https://www.brookings.edu/articles/automation-and-artificial-intelligence-how-machines-affect-people-and-places/) that earlier digital or automation technologies—with their facility for replacing rote manual or physical work—tend to impinge most on lower-skill, blue-collar jobs, with corresponding impacts on patterns of regional labor market exposure. As a result, our mapping of earlier automation impacts tended to suggest that workers in small-town, less-educated communities—e.g., in the South and industrial Midwest—encountered much more disruption than workers in larger, more information-oriented cities. This reflects the small-town and more rural locations of much "routine" physical and cognitive work susceptible to earlier forms of automation.

For AI—and specifically, generative AI—the exposure pattern looks very different (https://www.brookings.edu/wp-content/uploads/2019/11/2019.11.20_BrookingsMetro_What-jobs-are-affected-by-

AI_Report_Muro-Whiton-Maxim.pdf#page=12) . AI "upend[s] this paradigm," as we note in the earlier report (https://www.brookings.edu/articles/generative-ai-the-american-worker-and-the-future-of-work/#understanding-generative-ais-potential-impact-on-work-and-workers-866) . By that, we mean that AI excels at supporting or carrying out the highly cognitive, nonroutine tasks that better-educated, better-paid office workers do—tasks such as conducting research, preparing analyses, writing code, creating marketing content, synthesizing data, and drafting presentations. As a result, the more involved workers are in upscale office or information-based work, the more involved they will be with AI.

Figure 1 displays how that looks, with AI exposure rising with wages for the most part.

FIGURE 1

Generative AI exposure by occupation group

Source: Authors analysis of data from OpenAI and BLS

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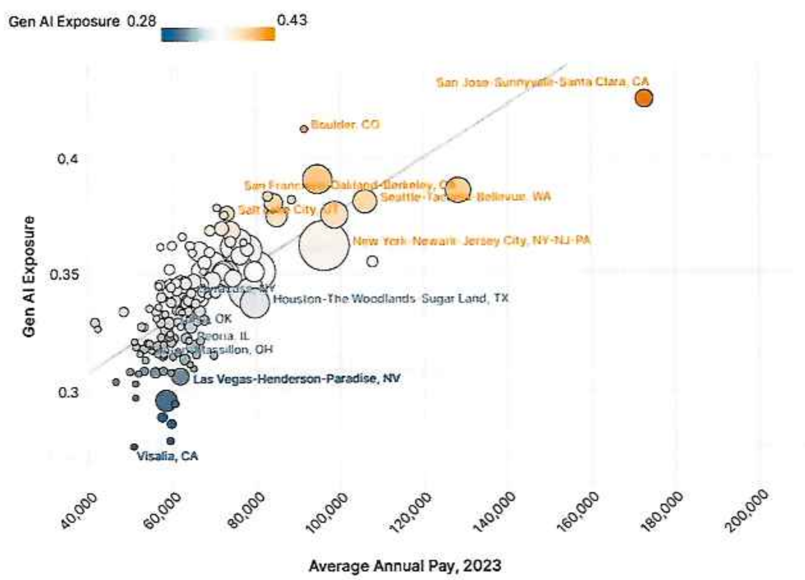
This has implications for places, as generative AI's broad pattern of impacts on occupation groups drives its own pattern of local labor market exposure. Given that, highly educated, high-paying, white collar metro areas previously considered to be at relatively low risk of automation look to be the places that will be the most exposed to generative AI—meaning that they will both gain the most from the potential it unlocks as well as shoulder the greatest burdens of any worker displacement and disruption it causes.

In this respect, the urban geography of generative AI starkly contrasts with the geography of previous automation technologies such as digital enterprise systems and robotics. As those technologies spread over the last decade, they tended to impact workers in lower-paid, less educated metro areas much more than those in higher-tech, office-oriented metro areas (who tended to benefit from them).

Now, the higher-end workers and regions only mildly exposed to earlier forms of automation look to be most involved (for better or worse) with generative AI and its facility for cognitive, office-type tasks. In that vein, workers in high-skill metro areas such as **San Jose, Calif.; San Francisco; Durham, N.C.; New York;** and **Washington D.C.** appear likely to experience heavy involvement with generative AI, while those in less office-oriented metro areas such as **Las Vegas; Toledo, Ohio;** and **Fort Wayne, Ind.** appear far less susceptible. For instance, while 43% of workers in San Jose could see generative AI shift half or more of their work tasks, that share is only 31% of workers in **Las Vegas.**

FIGURE 2

Generative AI exposure level and annual pay by metro



Source: Authors' analysis of task exposure data from OpenAI and employment data from Lightcast
Note: Exposure estimates the share of each occupational group's tasks for which ChatGPT-4 can reduce the time for humans to complete by 50% or more

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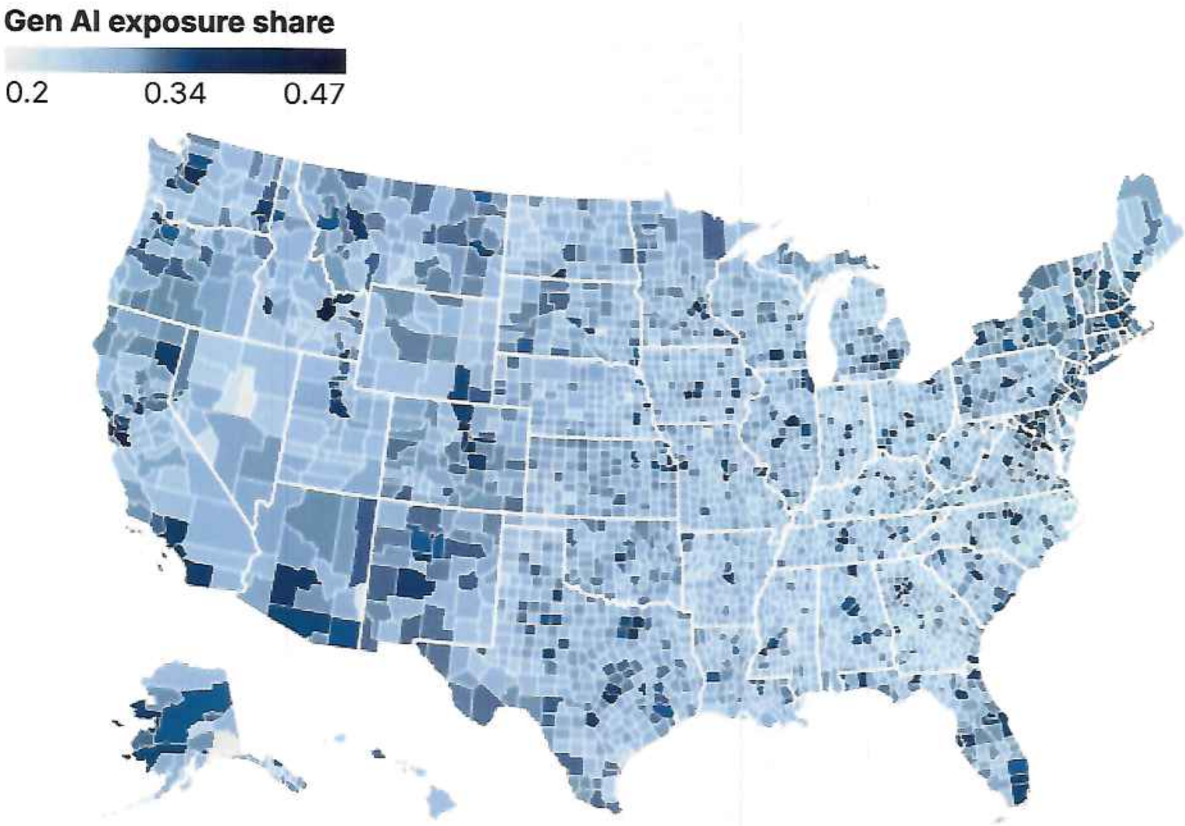
At the county level, exposure to AI varies widely, from elevated exposure rates of around 40% or more in high-paying tech, business, and finance locales such as **Santa Clara County, Calif.; King County, Wash.;** and **New York County,** to rates in the 30% range and even the 20% range in small and rural heartland counties.

MAP 1

Exposure to generative AI across US counties



Source: Authors' analysis of task exposure data from OpenAI and employment data from Lightcast U.S. Census Bureau 2021 boundaries. Simple Maps.

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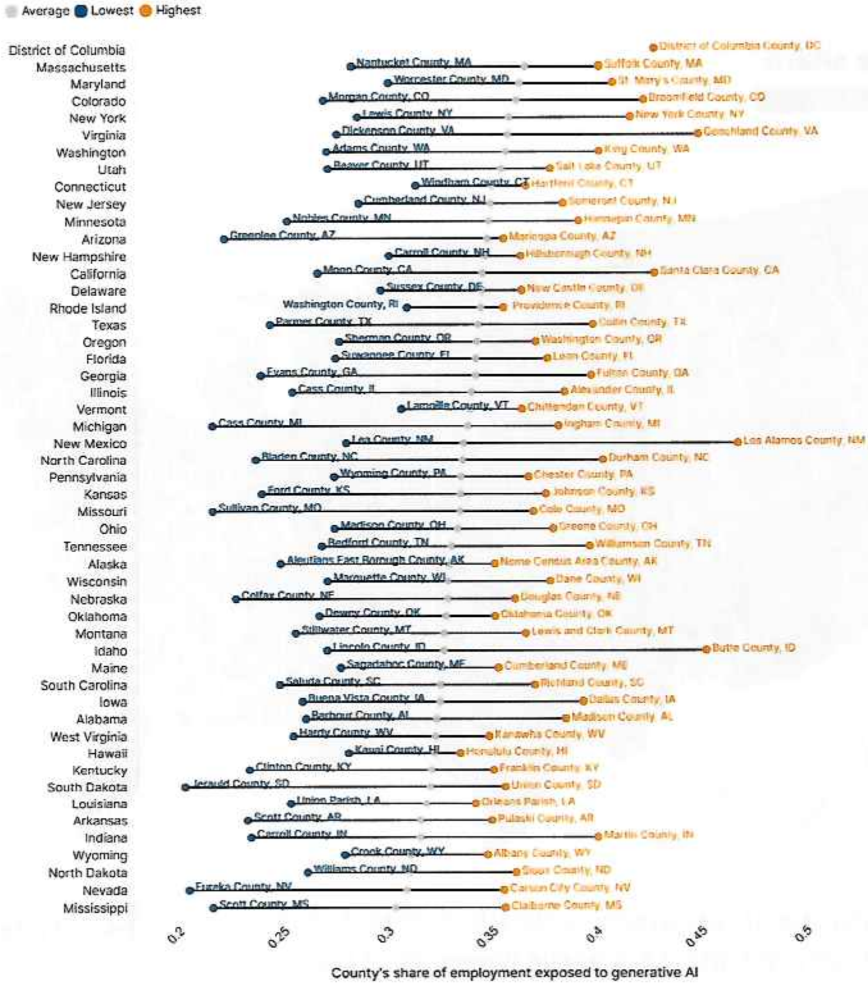
Generative AI exposure varies dramatically even within the same state, shaped by the industry makeup of individual counties. For example, California shows high intra-state variation due to the presence of both urban tech counties and less educated exurban or rural ones. Labor market exposure to generative AI in the state ranges from as much as 42.8% in Santa Clara County to as little as 26.7% in Mono County. By contrast, other lower-exposure states without large information-oriented metro areas—such as North Dakota and Mississippi—exhibit much narrower ranges of exposure, reflecting more uniform lower exposure across their largely agriculture- and manufacturing-dependent counties.

FIGURE 3

Range of generative AI exposure across counties in US states



Source: Authors' analysis of task exposure data from OpenAI and employment data from Lightcast
Note: Exposure estimates the share of each occupational group's tasks for which ChatGPT-4 can reduce the time for humans to complete by 50% or more

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Looking across the entirety of the nation's counties, average variations flatten out a bit. Reflecting the fact that many metro areas aren't particularly tech- or information-saturated, the average local AI exposure level varies modestly from 35% in the nation's 821 highly urban counties to 30% in its 1,053 rural counties. Overall, the metropolitan exposure rate is 35% and the nonmetro rate is 30%.

In sum, then, the new landscape of AI—reshaped by generative AI—reflects a dynamic in which the people and places who were initially the least exposed to automation technology may now be the most involved.

In this respect, generative AI looks likely to impact a different set of workers compared to previous technologies. It is now big-city information workers who will gain the most from generative AI—and bear its most challenging displacements. By the same token, the communities that past waves of automation hit hardest look like they will be the ones most insulated from the risks of AI. With that said, such regions also look likely to be left out of the biggest gains.

Given that, what the Organisation for Economic Co-operation and Development (OECD) calls a "changing landscape" ↗ of automation suggests the need for policy adaptations to address different and emerging groups of workers and places. Policymakers need to better track the emergence of new and different exposure patterns, often in the biggest, highest-tech cities. They will also need to do much more to identify AI-relevant skills competencies, and leverage that to develop new and more proactive upskilling and re-skilling efforts for workers in danger of displacement. Likewise, strong efforts will be needed to mitigate economic and social disparities that may arise as some people and places pull ahead thanks to the likely productivity benefits of AI technologies.

In any event, the geography of AI exposure looks like it will be exactly opposite of what it was for previous automation bouts, ensuring it will present new and different riddles.

Method

1. Of the 858 occupations with exposure ratings from OpenAI (Eloundou et al., 2023), 738 unique Standard Occupational Codes (SOC) match the Occupational Employment and Wage Statistics (OEWS) data.
2. The exposure ratings are disaggregated by detailed SOC occupation titles, while the OEWS codes group these titles together. To align the ratings with the OEWS data, we calculate an average exposure rating for each grouped SOC code.
3. The share of exposed jobs in each geographic region is then calculated by multiplying the average exposure rating for each SOC code by the local occupational employment figures, followed by aggregating the results.

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