The Unequal Impact of AI on Local Labor Markets: Mechanisms, Evidence, and Policy Insights

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Abstract

Artificial intelligence hits local labor markets unevenly, and the reasons go well beyond simple occupational exposure. By synthesizing task-based models, occupational network theory, and research on labor mobility, this review argues that regional resilience depends largely on how densely local jobs are linked by shared skills and whether workers can move---across occupations or across regions. Cities with thicker skill networks tend to absorb automation shocks better, but often at the price of rising wage inequality. Rural areas face a harsher trap: when low-skill jobs vanish, few nearby alternatives exist, and many workers drop out of the labor force entirely. Migration offers partial relief, yet it can also widen the gap between thriving cores and struggling peripheries. For developing economies, weak digital infrastructure and large informal sectors create a structural dependence on the global AI value chain that looks less like automation risk and more like computing colonialism. The paper closes with region-specific policy directions---investing in infrastructure, thickening skill networks, improving migration support, and building fairer global AI governance.

Key words

Artificial intelligence; Labor markets; Regional heterogeneity; Urban resilience; Labor mobility

1. Introduction

Large language models and generative AI are changing where and how people work, but the effects are anything but uniform. A bank teller in rural Ohio and one in downtown Manhattan may hold the same job title, yet their prospects diverge sharply once algorithms start handling the routine tasks behind that title. Understanding why requires moving beyond occupational exposure scores to look at the geography of work itself.

Standard task-based models show that AI displaces some tasks and augments others, while occupational network theory adds that a city's ability to withstand shocks depends on how tightly its jobs are linked by shared skills [1-3]. Labor mobility---workers moving across regions or occupations---has received far less attention in this conversation, even though it is arguably the channel that determines whether a local shock becomes a temporary adjustment or a permanent collapse. Recent reviews note that static task models miss exactly the dynamic reallocation processes that network and mobility perspectives could help illuminate, yet these three literatures have rarely been integrated [4]. That disconnect is the starting point here.

The evidence already hints at what a unified view might reveal. Italian data show cities absorbing automation by upgrading skills, but wage gaps widening; rural areas saw low-skill workers leave the labor force [5]. In the US, commuting zones with denser occupational networks weathered the Great Recession with smaller unemployment spikes [3]. Cross-country evidence from emerging economies suggests that AI adoption tends to cut low- and medium-skill employment while nudging average wages up, consistent with skill-biased technical change, though spatial variation remains striking [4]. Meanwhile, developing countries face a paradox: directly automatable jobs make up a tiny share of their employment, yet weak digital infrastructure, huge informal sectors, and limited data sovereignty leave them structurally dependent on the global AI value chain [6,7].

These patterns point to blind spots in current research. Studies of AI displacement have focused heavily on occupational-level exposure, paying little attention to how the same job title involves different tasks in different places. Work on occupational networks has explored resilience mainly during financial crises, not during AI-driven structural change. And the labor mobility literature has rarely been brought into conversation with AI-specific dynamics. To bridge these gaps, the paper pulls task theory, network analysis, and mobility research into a single spatial framework, then compares the evidence across cities and rural areas, rich and poor countries, and high- and low-resilience regions. The final sections turn to policy, with the caveat that easy answers ignore real trade-offs.

2. Theoretical Mechanisms: Tasks, Networks, and Mobility

2.1 Task-Based Models and Their Spatial Extension

Task-based models provide the natural starting point. The core idea is that production consists of many tasks, and firms decide whether to have a worker or a machine perform each task based on relative costs [1,2]. As AI costs decline, more tasks shift from people to machines, producing a displacement effect. Simultaneously, AI can create entirely new tasks, generating a reinstatement effect. The net effect on employment depends on which force dominates [2].

However, this framework has a conspicuous blind spot when it comes to geography. The same occupation can involve radically different tasks in different locations. Cross-country evidence from the IMF shows that jobs highly exposed to AI in advanced economies—clerical and professional roles, for instance—often have different task compositions in emerging economies, where similar positions may involve more physical or interpersonal components [4]. Thus, even within the same occupational category, AI exposure can vary by location. This finding cautions against naively applying U.S. exposure scores to other countries.

2.2 Occupational Network Resilience and Skill Space

Moro et al. borrow the concept of resilience from ecology and apply it to labor markets [3]. They construct an occupational network in which nodes represent jobs and edges represent similarities in skill requirements. Cities with more tightly connected occupational networks experienced smaller increases in unemployment during the 2007–2009 financial crisis, suggesting that higher connectivity provides stronger buffering capacity.

The mechanism behind this is skill proximity. When one occupation is hit by automation, workers can transition into neighboring occupations that use similar skills. Occupations in the dense core—management, finance, office support—are highly connected and therefore more resilient; peripheral occupations such as manual labor and care work are more isolated and thus more vulnerable once automation strikes [8]. Differences across cities in these network structures are the fundamental reason why the same AI shock produces different local outcomes. Similar patterns in large emerging economies support this interpretation: AI adoption has reduced absolute employment in low- and middle-skill occupations without significantly increasing high-skill employment, likely reflecting weaker network connectivity in certain regions.

2.3 Labor Mobility: A Double-Edged Sword

Inter-regional labor mobility is another critical channel. Using data from 22 French regions, Giorgi et al. show that when high-skill workers leave a technologically specialized region, they carry knowledge with them and spark novel technological combinations in their destination regions [9]. In principle, this process should help narrow regional disparities.

But migration can also widen them. Regions that lose talent face reduced innovation, the flight of quality jobs, and a vicious cycle of further out-migration. Meanwhile, prosperous regions enjoy agglomeration effects that attract even more talent, producing a winner-take-all dynamic. Whether migration shrinks or amplifies regional inequality depends heavily on institutions and policy. In developing countries, labor mobility is often constrained by weak infrastructure and informal employment, constraints that block the diffusion of skills [6, 7].

2.4 A Unified Framework

These mechanisms are not independent. AI first substitutes for tasks within occupations, creating an initial shock. Whether that shock translates into persistent unemployment or rapid reallocation depends on two intermediate factors: the local occupational network and the possibility of moving across jobs or regions.

This process can be understood as a cascade. High network connectivity allows workers to shift into skill-adjacent jobs; low connectivity leaves them stranded. Labor mobility then either amplifies or dampens regional effects. Talent flows toward prosperous regions, which benefits those regions but may hollow out peripheral ones.

These individual effects have been documented separately: Moro et al. confirm network effects, while Giorgi et al. document migration effects [3, 9]. The contribution of this paper is to integrate them into a unified analytical framework that examines their interaction. This interaction matters: a region with dense occupational networks but heavy out-migration of high-skill workers may end up worse off than a region with moderate connectivity that manages to retain its talent.

A region's ability to adapt to AI depends not just on the technology itself, but more fundamentally on its local occupational structure, skill mix, and migration patterns. Policies that pull only one lever—retraining, for example, without addressing mobility or network density—are likely to fall short. Most importantly, the same shock can produce starkly different distributional outcomes: resilient cities see rising wage inequality, while vulnerable rural areas see broad-based income declines.

3. Empirical Evidence on Regional Heterogeneity

3.1 Cities Versus Rural Areas

The contrast between urban and rural areas is stark. Using Italian NUTS-3 data from 2009 to 2019, Capello and Lenzi found that automation reduced the employment-to-population ratio everywhere, leaving no place spared [5]. Yet adjustment patterns differed completely.

In non-urban areas, low-skill workers who lost jobs tended to leave the labor force altogether. Their employment rate continued falling, and high-skill employment did not rise to fill the gap. The local economy lacked the higher-skill jobs to absorb displaced workers [5]. In cities, low-skill employment also fell, but high-skill employment expanded and overall labor force participation held steady. This skill upgrading occurred primarily through low-skill workers leaving and high-skill workers moving in, rather than through existing workers learning new skills. Consequently, wage inequality often increased, creating a two-tier labor market.

The US evidence tells a similar story. Moro et al. found that commuting zones with higher occupational network connectivity experienced smaller unemployment increases during the Great Recession [3]. More-over, the more embedded an occupation was in its local network, the higher its average wage. Extending this logic to AI, high-connectivity cities will better absorb automation shocks, though those same highly connected occupations---typically in management and information processing---are also the most exposed to AI [8]. This constitutes the city's paradox: resilience and risk coincide.

3.2 Developed Versus Developing Economies

Turning to cross-country comparisons, the disparities are just as sharp. The IMF reports that almost 40% of global employment is exposed to AI, with advanced economies (60% exposure) facing both greater risks and greater potential benefits than emerging economies (40%) and low-income countries (26%) [4]. The underlying reason is occupational mix. High-income countries have substantially more information-processing, finance, and managerial jobs---precisely the tasks at which generative AI excels. Low-income countries rely more on agriculture, construction, and low-skill services, which are harder to automate [4,10].

However, low exposure does not imply low risk. As Chigbu points out, developing countries face a distinct vulnerability: structural dependence [6]. The high-value segments of the AI value chain---algorithm design, chip fabrication, foundation model training---remain concentrated in the United States, China, and a handful of other countries. Most of the Global South supplies data, labels training examples, and consumes AI services. Gray and Suri call this *ghost work*: millions of data labelers, content moderators, and data entry workers earn poverty wages to keep AI systems running, with little labor protection [11].

Infrastructure gaps compound these challenges. Lehdonvirta et al. show that many developing countries are compute deserts: they lack the reliable electricity, high-speed internet, and affordable computing power needed to train or even run advanced AI models [7]. They are forced to rely on foreign cloud platforms and technology vendors, eroding their digital sovereignty [6,7]. This structural inequality in compute access further entrenches global AI divides, with only a handful of countries hosting advanced GPU infrastructure. The compute infrastructure dimension remains perhaps the most underappreciated aspect of the AI debate.

The pattern also varies considerably across the developing world. In Southeast Asia, economies such as the Philippines built large business process outsourcing sectors on routine voice and back-office work---precisely the tasks that generative AI handles best---so millions of service jobs are exposed even where direct automation risk once appeared low [10,13]. In Africa, countries such as Kenya have become hubs for data annotation and content moderation, yet the work is low-paid, insecure, and easily relocated, while unreliable electricity and limited broadband keep much of the continent in the compute desert [7,11]. In Latin America, informal employment accounts for roughly half of all jobs, so displaced workers have little institutional cushion, and weak digital infrastructure outside major cities limits participation in AI-driven gains [6,10]. These contrasts suggest that developing countries face not a single predicament but several distinct ones, each calling for different policy responses.

3.3 High-Resilience Versus Low-Resilience Regions Within Countries

Resilience also varies sharply within countries. Using US county-level job posting data from 2014 to 2023, Andreadis et al. found enormous geographic inequality in AI-related job shares [12]. Slope County, North Dakota, and Santa Clara County, California, had AI job shares of 10% and 8.2% respectively, while many rural counties had virtually none. The strongest predictors of AI job growth were the share of STEM degrees, local labor market tightness, and patenting activity; manufacturing intensity was negatively associated with AI job growth [12]. Evidence from East Asia reinforces this pattern: AI-related job growth and resilience are highly concentrated in coastal regions with stronger innovation capacity and digital infrastructure.

In low-resilience regions---old manufacturing belts, resource-dependent areas---automation shocks can lead to persistent unemployment and scarring effects: workers lose skills and motivation, dropping out of the labor force entirely [5]. In high-resilience regions---college towns, diverse metropolitan areas---the shock is absorbed mainly through occupational switching and skill upgrading, so total employment remains steady. The distributional consequences diverge completely: resilient regions see rising wage inequality, while fragile regions see broad-based income decline and withdrawal from the labor market [3,5]. These divergent outcomes suggest that no region is fully insulated from adverse effects; the pain simply takes different forms.

4. Labor Mobility and Regional Outcomes

4.1 High-Skill Migration and Knowledge Diffusion

When skilled workers move across regions, they carry knowledge with them. Giorgi et al. linked French worker mobility data to patent records and showed that workers coming from regions that specialized in a technology significantly increased the production of novel technological combinations in that technology at their destination [9]. The effect was stronger when the destination region already possessed some strength in that technology, highlighting complementarity between external knowledge and local capability.

Applied to AI, this suggests that migration of AI talent from leading hubs such as Silicon Valley to follower regions can help those regions build their own AI capacity. However, in practice, migration is centripetal: talent flows toward a few superstar hubs rather than diffusing to the periphery [12]. Consequently, migration may actually reinforce, rather than reduce, regional concentration.

4.2 Occupational Switching and Skill Reallocation

Geographic mobility is not the only adjustment channel; moving between occupations matters too. In Moro et al.'s occupational network, workers flow more readily between occupations that share similar skill requirements [3]. When one occupation shrinks, workers tend to move into the most skill-similar alternatives. This means that the damage from AI-driven job loss depends not only on how many jobs are lost but also on how many skill-adjacent jobs exist to absorb displaced workers.

In regions with sparse occupational networks---small towns dominated by a single industry---few nearby options exist, so a shock can cause lasting unemployment. In dense networks---big metropolitan areas---workers can reallocate across occupations, muting the impact [3]. This explains why identical automation shocks can produce very different unemployment durations in different places. Cross-country evidence suggests that college-educated workers are significantly more likely to transition into high-complementarity occupations than non-college workers [4]. This finding raises important concerns for policymakers addressing rising inequality.

4.3 The Costs of Mobility: Polarization and Hollowing Out

Migration is not costless. For sending regions, net out-migration of skilled workers can mean brain drain: less innovation, lower growth, and a downward spiral. For receiving regions, an influx of high-skill workers boosts innovation but also pushes up housing prices, raises the cost of living, and widens the gap between high- and low-skill wages [5].

A special concern in the AI era is telework polarization. The OECD shows that exposure to generative AI is much higher in cities than in rural areas, and remote jobs are especially exposed [13]. The irony is hard to miss: the jobs that are geographically portable---and thus could help spread opportunity to remote places---are precisely the ones most at risk of automation. Rural areas thus get the worst of both worlds: they miss out on the dispersion of high-skill work and lack the infrastructure to participate in AI-driven productivity gains.

5. Policy Implications

5.1 Build Regional Resilience: Strengthen Occupational Networks

Occupational network connectivity matters for absorbing shocks, so policy should aim to increase skill diversity and connectivity within regions. Concrete starting points include building regional skill maps that show which occupations share similar skills, funding cross-occupational training programs, and attracting anchor occupations to thicken the local network [3]. For manufacturing-dependent regions, digital and AI literacy training can help move production workers toward adjacent roles like equipment maintenance or data analysis.

5.2 Turn Brain Drain into Brain Circulation

A fundamental tension emerges in this domain. Attracting AI talent to lagging regions is desirable, but doing so may accelerate brain drain from even poorer areas. Policy should therefore seek to convert one-way brain drain into two-way brain circulation by coordinating skill certification and portable social benefits, promoting remote work models that allow skilled workers to stay in their home regions while working for firms elsewhere, and creating innovation enclaves in lagging regions---branch offices of leading universities or companies [9,13]. The challenge is to avoid a scenario where only a handful of superstar cities benefit while the periphery empties out. This trade-off has no clean resolution.

5.3 Close Infrastructure Gaps: Computing and Data Sovereignty

For the Global South and for lagging regions within wealthy countries, the compute desert is a binding constraint [7]. Policy should invest in regional computing infrastructure---including green data centers and public AI compute platforms---support open-source AI models, and establish data sovereignty frameworks that prevent local data from being extracted without fair compensation [6,7]. At the international level, developing countries should push for data-benefit-sharing rules and a more multipolar AI governance architecture [6,11]. Priorities also differ by region: Southeast Asian economies may gain most from upskilling business process outsourcing workforces toward AI-complementary services; African economies need investment in basic electricity, connectivity, and computing capacity before almost anything else; and Latin American economies should pair infrastructure investment with portable social protection for their large informal workforces [6,7,10]. Without such measures, the global AI divide will continue to widen.

5.4 Differentiate Social Protection by Local Conditions

Because AI's impacts vary substantially by place, social protection should not be one-size-fits-all. In high-resilience regions---large metros---priority goes to mitigating within-city inequality: expanding unemployment insurance, mandating algorithmic transparency and appeal rights [14]. In low-resilience regions---old industrial belts---the priority should be given to active labor reallocation and community renewal: training accounts, relocation assistance, and investment in alternative industries [5].

Informal workers require particular attention. In developing countries, they constitute the majority of the labor force, yet they remain largely invisible in AI policy debates [6]. Portable benefits and skill certification systems designed for informal workers are urgently needed. The ILO has emphasized that without deliberate policy interventions, informal workers will remain excluded from AI-driven productivity gains [10,15]. This is not a peripheral issue but central to any equitable AI transition.

6. Conclusion

What emerges from this review is less a single headline than a set of interconnected patterns. Occupational network connectivity is not merely correlated with regional resilience; it appears to be a structural determinant, shaping how quickly displaced workers can slide into skill-adjacent jobs. Cities and rural areas adjust in almost opposite directions: the former absorb shocks through occupational switching and in-migration of high-skill workers, but wage inequality rises; the latter see broad-based withdrawal from the labor force when low-skill jobs disappear and nothing comparable replaces them. Labor mobility, often celebrated as an equalizer, proves to be a conditional force---capable of closing regional gaps when institutions support circulation, yet equally capable of hollowing out peripheries when talent flows one-way toward superstar hubs. Perhaps most urgent, developing countries face a low-exposure, high-risk dilemma that has little to do with their own technology adoption and everything to do with their position in the global AI value chain.

These observations also highlight where the evidence remains thin. Most network studies come from wealthy economies; Africa, South Asia, and other developing regions are largely missing. The literature is dominated by short-term snapshots, and longitudinal data on career trajectories, wage dynamics, and regional convergence as AI diffuses are still scarce. Informal employment---central to any equitable transition in the Global South---has barely entered the discussion. And the interaction between AI and climate change in reshaping regional labor markets remains almost entirely unexplored.

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