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Measuring the Sensitivity of Local Skill Structures to AI Substitution Risks Based on Occupational Task Decomposition

Dingyuan Liu

School of Engineering and Applied Science, University of Pennsylvania, 220 S 33rd St, Philadelphia, PA 19104

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***Abstract*:** This study proposes a task–skill–place framework to quantify how sensitive U.S. local labor markets are to AI substitution risks. Building on task-based theories of technological change, we argue that modern AI - especially generative AI and multimodal foundation models - affects employment primarily by reshaping task portfolios within occupations, and therefore by reweighting the skills embedded in local economies. We integrate O*NET's occupational task decomposition and skill-importance structure with leading AI exposure measures that map current AI capabilities onto tasks (LLM/GPT task exposure, ability-based AI Occupational Exposure, and AI patent–task overlap). Using BLS Occupational Employment and Wage Statistics (May 2024) as local employment weights, we define a Local AI Skill Substitution Sensitivity (LASSS) index that measures the exposed share of each locality's skill bundle, not merely its exposed jobs. Nationally, the exposure baseline is broad: GPT-class models are estimated to affect at least 10% of tasks for roughly four-fifths of U.S. workers and at least half of tasks for about one-fifth, with exposure concentrated in language- and analysis-heavy occupations. The exposed skills cluster in written comprehension and expression, inductive/deductive reasoning, information ordering, complex problem solving, and programming-adjacent systems analysis, whereas physical dexterity, equipment operation, in-person caregiving, and embodied services show lower near-term substitutability. Aggregating to place reveals steep geographic dispersion: U.S. Treasury evidence shows a four-to-one gap between the most- and least-exposed local areas, with dense, highly educated metros - especially in the Northeast corridor - embedding far more of the exposed analytic-communication skill bundle than rural or manufacturing- intensive regions. Interpreting exposure through LASSS clarifies that AI may widen regional inequality unless complemented by place-aware skill buffering in high-LASSS metros and diffusion-oriented adoption policies in low-LASSS regions.

1. Introduction

Artificial intelligence has moved from automating narrowly defined, routine operations to performing or accelerating complex cognitive tasks in language, vision, code generation, and decision support. Large language models (LLMs) and multimodal systems can now draft, summarize, search, translate, write code, and interpret documents with a quality that makes them usable in many office and professional workflows. This evolution implies that technology affects work mainly within occupations—by reshaping which tasks humans do—rather than replacing whole occupations at once. In the United States, this task-level disruption has a strong geographic dimension because local labor markets differ in occupational mix and therefore in the skill bundles embedded in employment. A metro dominated by professional services and headquarters functions embeds high levels of analytic reasoning, written communication, and information-processing skills; a rural region weighted toward construction, logistics, health support, and in-person services embeds more physical dexterity, equipment operation, and interpersonal care. Recent U.S. task-exposure evidence for generative AI indicates that exposure is broad nationally—about 80% of workers are in occupations where at least 10% of tasks are exposed to GPT-class models, and roughly 19% are in occupations where at least half of tasks are exposed. Yet U.S. Treasury analysis shows a steep spatial gradient: occupational AI exposure is about four times larger in the most-exposed local areas (Public Use Micro Areas) than in the least exposed, with cities more exposed than rural regions and especially high exposure along the Washington–Boston Northeast corridor. These patterns invert the geography of earlier routine automation waves, which were concentrated in manufacturing-intensive regions. The central question is therefore not only "where are jobs exposed," but "where are local skill structures sensitive to AI substitution?" This paper develops a task–skill–place framework to measure that sensitivity using occupational task decomposition, and it interprets the U.S. geography of AI risk through the lens of local skill bundles rather than occupation lists alone.

2. Data, Task Decomposition, and Local Skill Structures

2.1. Task-Based Technological Change and Substitution

The task-based tradition in labor economics emphasizes that technology substitutes for some tasks while complementing others, leading to reallocation of human effort within occupations and to new equilibrium patterns in wages and employment. Classic routine-biased technological change models predict that codifiable, repetitive tasks are easiest to automate, while nonroutine analytic and interpersonal tasks are complemented by computers. This view helped explain polarization in the U.S. labor market during the 1980s–2010s. However, occupation-level risk scoring (for example, early computerization probability estimates) treated occupations as monolithic and missed heterogeneity in task content, which is crucial when new AI systems can perform some elements of professional work but not others. The contemporary shift toward generative and multimodal AI further complicates "routine vs. nonroutine" binaries because tasks involving reading, writing, summarizing, or pattern extraction—previously seen as nonroutine—are increasingly machine-performable. Hence, task decomposition is necessary to identify which parts of work are at risk of substitution, which are likely to be accelerated, and which remain anchored in human judgment or physical presence.

2.2. Measuring AI Exposure from Occupational Tasks

Recent measurement work maps AI capabilities onto tasks using detailed occupational descriptions, principally ONET. Three approaches dominate. First, LLM exposure scores directly rate ONET tasks for whether GPT-class models can substitute or accelerate them; these scores produce the headline national findings that about four-fifths of U.S. workers have at least a tenth of their tasks exposed, and about one-fifth have at least half of tasks exposed, while LLMs alone could speed up roughly 15% of tasks and LLM-powered tools could speed up about 47–56%. Second, ability-based measures (AI Occupational Exposure, AIOE) infer exposure from the alignment between AI progress benchmarks and underlying ONET abilities, yielding stable cross-occupation exposure ranks and allowing geographic aggregation. Third, patent–task overlap indices compare the text of AI patents with ONET task descriptions to capture frontier capability direction. Together these approaches show that AI exposure is unusually high in high-wage, high-education occupations—legal services, business operations, finance, IT, and certain administrative roles—while many physical and in-person service tasks remain less directly exposed in the near term.

2.3. Geography, Skills, and Regional Inequality in the U.S.

A growing U.S. literature examines the geography of AI exposure, finding large metro–rural gaps and strong clustering in elite knowledge hubs. The U.S. Treasury working paper documents that occupational AI exposure is systematically higher in urban areas, with a four-to-one dispersion between the most- and least-exposed local labor markets and a pronounced concentration in Northeastern high-education metros. Regional Federal Reserve work echoes this result and argues that AI may disrupt large diversified service metros more than manufacturing hubs, reversing past automation patterns. These studies, however, primarily measure local exposure at the occupation level. They do not explicitly measure how exposed the skills embedded in local employment are, nor do they identify which local skill clusters are likely to erode, reprice, or instead gain value through augmentation. Since skills determine mobility, training needs, and long-run comparative advantage of regions, a skill-centered local sensitivity metric is required to connect exposure to regional inequality.

Table 1. Data sources and variables used

Dataset	Coverage	Main variables	Use in this study
O*NET (v29+)	~900 U.S. SOC occupations	Task statements & weights; work activities; skill/ability importance	Builds task–skill vectors
LLM/GPT task exposure studies	U.S. SOC occupations	Share of tasks exposed to GPT-class models	Generative AI exposure mapping
Ability-based AIOE/AIGE studies	SOC occupations, counties/states	Ability-AI alignment exposure scores	Broad AI exposure benchmark
AI patent–task overlap studies	SOC occupations	Patent-task similarity exposure scores	Frontier AI capability lens
BLS OEWS May 2024	U.S., states, metros	Employment counts & shares by SOC	Local weighting of exposure

3. Method: Local AI Skill Substitution Sensitivity (LASSS)

3.1. O*NET Task Decomposition and Skill Bundles

ONET provides a hierarchical representation of U.S. occupations that includes (i) detailed task statements describing work performed, (ii) work activities that group tasks into broader functional categories, and (iii) importance/level scores for skills and abilities. This taxonomy supports a task-based decomposition of each occupation into a weighted set of tasks, and a corresponding skill bundle that reflects how intensively each skill is used in that occupation. We use ONET's task weights to represent the internal composition of occupations and its skill importance scores to represent their underlying skill structure. Because O*NET is built for the U.S. Standard Occupational Classification (SOC), it ensures direct alignment with U.S. employment data and provides a consistent basis for cross-occupation and cross-place comparison.

3.2. AI Task Exposure Indices and Harmonization

We triangulate across three exposure lenses that are all grounded in O*NET and therefore SOC-compatible. LLM/GPT task exposure assigns task-level probabilities of substitution or acceleration by GPT-class models and yields the national estimates noted above. Ability-based AIOE associates exposure with the importance of abilities for which AI benchmarks show rapid progress, capturing broad AI substitution risk beyond language tasks. Patent–task overlap measures exposure to frontier AI innovation as reflected in patents. Each index emphasizes a different slice of AI capability (current generative performance, broad ability progress, and frontier direction), so convergence in results increases robustness. We harmonize indices to common SOC versions using published crosswalks, and we interpret exposure as potential substitution/acceleration under technological feasibility, not as a direct forecast of job loss.

3.3 Local Employment Weights from BLS OEWS

To translate occupational exposure into local sensitivity, we use the BLS Occupational Employment and Wage Statistics for May 2024, which reports employment by SOC for the nation, states, and metropolitan/nonmetropolitan areas. For each locality, OEWS employment provides occupational shares that weight exposure. This step links technology to geography: a locality with large employment shares in exposed occupations automatically inherits high local exposure. The key extension beyond existing local exposure metrics is that we carry task exposure through to skill exposure before aggregation, so the final Local AI Skill Substitution Sensitivity (LASSS) index measures the exposed portion of a place's skill bundle, not merely its exposed jobs.

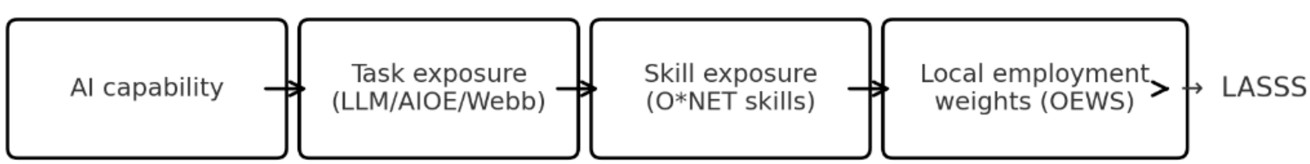

Figure 1. Conceptual task – skill – place

4. U.S. Findings: National Exposure, Skill Drivers, and Geographic Gradients

4. Empirical Patterns and Local Sensitivity in the United States

4.1. National Exposure and Skill Drivers

At the national level, AI exposure is widespread and concentrated in cognitive–linguistic tasks. LLM-based assessments indicate that around 80% of U.S. workers are in occupations where at least 10% of tasks are exposed, while about 19% are in occupations where at least 50% of tasks are exposed; average task exposure within occupations is meaningful even without full software integration. Exposure is highest in tasks involving reading and synthesizing information, drafting and editing text, searching and organizing knowledge, coding and debugging, compliance checking, and structured analytic reporting. The most exposed skills therefore include written comprehension and expression, inductive/deductive reasoning, information ordering, critical thinking, systems analysis, and programming-adjacent skills. By contrast, tasks requiring physical dexterity in unstructured environments, in-person caregiving and emotional support, real-time equipment operation, and high-stakes embodied interaction are less directly exposed in the near term. Ability- and patent-based measures confirm this ranking, showing stable high exposure for analytic–communication skill families and lower exposure for physical and interpersonal-care skill families.

4.2. Local Skill Substitution Sensitivity (LASSS) and the Metro–Rural Gradient

When we aggregate skill exposure using local occupational weights, the U.S. exhibits a steep LASSS gradient. Treasury evidence shows a four-to-one spread in occupational AI exposure between the most- and least-exposed local areas, with higher average exposure in cities than in rural regions and a particularly high concentration in Northeastern metros along the Washington–Boston corridor. LASSS interprets this as a difference in local skill bundles: elite and dense metros embed large shares of professional services, finance, government, and tech work that intensively uses analytic reasoning and written communication skills—exactly the skill families most exposed to LLM substitution and acceleration—so their local skill sensitivity is high. Conversely, many interior and rural labor markets embed larger shares of construction, transportation, healthcare support, manufacturing operations, and in-person service occupations, which rely on physical, presence-based, or environment-sensitive skills that are less substitutable by today's AI, so their LASSS is lower. This geographic pattern suggests that AI may create a new form of regional inequality that differs from past automation shocks.

4.3. Occupation–Skill Profiles and Local Vulnerability Types

Different localities may be "high exposure" for different reasons, and LASSS helps classify these types. A legal–policy hub (e.g., a capital or major law-market metro) is vulnerable because exposed tasks heavily draw on reading, writing, and information ordering; substitution risk is tied to document analysis and drafting, though oversight remains human-responsible. A tech–data hub is vulnerable because many tasks are exposed in coding, testing, and documentation; however, augmentation is also strong because AI tools raise productivity and shift work toward system design and verification. A finance–business-operations hub faces medium-high exposure in reporting, rule checking, and administrative analytics; it may see large back-office automation with smaller impacts on client-facing strategic roles. Low-LASSS regions are not "immune": they may still experience productivity changes through AI-assisted logistics, maintenance, scheduling, or tele-support, but direct substitution of core physical or caregiving skill bundles is more limited in the short run.

Table 2. Illustrative U.S. occupation – skill exposure patterns

Occupation group	Typical exposure level	Skills most exposed	Likely AI relationship
Legal & compliance	High	reading, writing, information ordering	strong substitution + productivity shock
Software & data	High	coding, logic, documentation	heavy augmentation, partial substitution
Finance & business ops	Medium-high	reporting, rule checking, clerical analysis	back-office task automation
Education	Medium	content prep, grading, admin tasks	augmentation dominates
Healthcare support	Low-medium	coordination/documentation > caregiving	limited substitution
Construction/extraction	Low	manual dexterity, equipment operation	low near-term substitution
Food/personal care	Low	in-person service, multitasking	low substitution

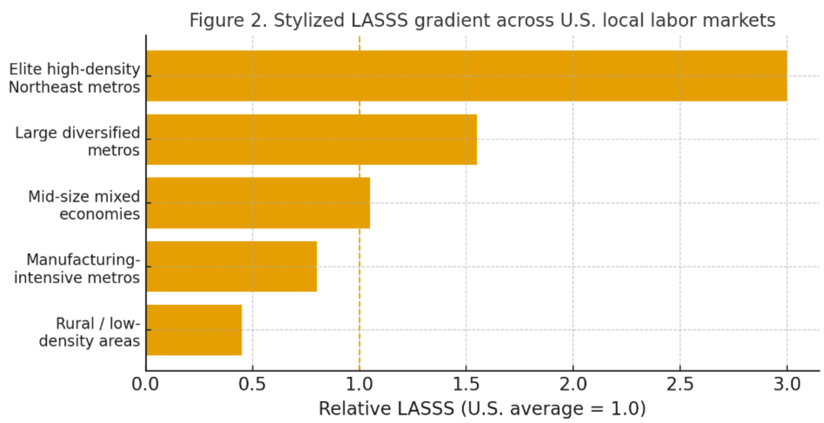

Figure 2. Stylized LASSS gradient across U.S. local labor markets

5. Conclusion and Policy Implications

LASSS reframes AI disruption as a skill reweighting shock with a clear geography. Because generative and broader AI systems are especially competent at language, structured reasoning, and information processing, they expose many tasks in high-education, high-wage occupations, producing broad national exposure and a strong urban concentration. U.S. evidence indicates that most workers have some exposed tasks, yet local sensitivity differs sharply, with elite metro corridors embedding exposed analytic–communication skills and rural/interior markets embedding more resilient physical or in-person skill bundles. These facts imply neither inevitable displacement nor automatic benefit: exposure translates into either substitution or augmentation depending on institutions, firm adoption capacity, complementary capital, and regulation. For high-LASSS metros, policy should build "skill buffers" by pivoting training away from rote production of text or code toward domain-specific reasoning, human-in-the-loop verification, auditing, system design, and accountable decision-making, while also supporting midcareer reskilling to reduce wage compression as exposed tasks are automated. For low-LASSS regions, the priority is capturing complementarity: spreading AI tools that augment logistics, maintenance, agriculture, healthcare coordination, and small-business operations, while investing in broadband and technical support to overcome diffusion barriers. At the federal and state level, modernizing community colleges with short-cycle AI-complementary credentials, creating portable training accounts, and funding place-based AI diffusion can prevent the concentration of productivity gains in already-advantaged metros, limiting new regional inequalities. Overall, occupational task decomposition provides a rigorous path to translate AI capability into local skill sensitivity, and LASSS offers an actionable metric for U.S. workforce and regional policy in the era of generative AI.

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