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Occupations, Wages and Artificial Intelligence in the Rio Grande Valley

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THIS BRIEF examines labor market outcomes in the Rio Grande Valley (RGV). Using worker-level data from the American Community Survey (ACS), it first characterizes the distribution of individuals' occupations and their associated wages in the RGV. Then, it integrates occupational skill requirements from the Occupational Information Network (O*NET) to analyze the skill composition of jobs in the RGV and the relationships among these skills. Finally, drawing on measures of occupational-level exposure to artificial intelligence (AI), the brief assesses the extent to which jobs in the RGV are susceptible to AI-related transformation.

Our findings lead to four main conclusions. First, the skills most widely used in the RGV labor market are not always the ones most strongly rewarded through higher wages. Secondly, the most in-demand occupations in the RGV tend to have relatively low exposure to AI. For example, popular occupations in the RGV, such as *Elementary and middle school teachers*, *Nurses and health aides*, and *Drivers and retail workers*, exhibit relatively low levels of AI exposure. In addition, AI exposure is present in occupations that command wage premia and rely heavily on information processing, writing, analysis, and judgment. Finally, exposure to AI does not automatically imply job losses; it may entail the reorganization or automation of some tasks within occupations. Therefore, policymakers can focus on the ability of the labor force to adapt to workplace changes. This adaptation can be nurtured through continued investments in high-level skills in workers, such as reasoning, communication, problem-solving, and digital capabilities.

Skills, Occupations & Technologies: Rethinking Work in the RGV

Artificial intelligence (AI) is reshaping the way work is performed and how skills are valued in the labor market. A growing task-based literature measures jobs' exposure to AI, which reflects the extent to which occupational tasks can be assisted, accelerated, or automated. Although the AI exposure measure is not a direct prediction of job loss, it is a signal of potential task reallocation, productivity gains, and organizational change (see, e.g., Acemoglu et al., 2022; Eloundou et al., 2024). This distinction is particularly important for the RGV, a young and rapidly growing regional economy where employment expansion is driven by education, healthcare, public administration, and trade-linked services, alongside increased integration into cross-border logistics networks (Baker, 2025; Federal Reserve Bank of Dallas, 2025). These sectors are intensive in information processing and human interaction and may be potentially reshaped by the expansion of AI and changes in the supply and demand for skills in the labor market, both of which are changing rapidly. Understanding the economic trajectory of the region, therefore, requires a joint assessment of two forces: the occupations and skills that drive the labor market today and their exposure to AI-driven task transformation.

This brief addresses the above issues by linking worker-level data to occupation-level measures of skill intensity and AI exposure. The analysis is deliberately descriptive and policy-oriented, focusing exclusively on the opportunities and risks within the RGV.

The labor market rewards occupations that rely on higher-order cognitive and interpersonal skills (Slichter et al., 2023). This relationship is broadly aligned with the RGV labor market, where highly-rewarded competencies include critical thinking, creativity, and scientific knowledge, followed by mathematics and communication. Although very well rewarded, skills such as creativity and scientific knowledge have somewhat limited demand in the RGV. At the same time, well-paid occupations in the RGV are associated with greater exposure to AI-related changes in tasks. That said, occupation demand in the RGV is concentrated on those with relatively low AI exposure. Recent evidence suggests that AI technologies disproportionately affect information-rich, text-based, and analytical tasks (Acemoglu et al., 2022; Eloundou et al., 2024). But, as the framework advanced by Autor and Thompson (2025) implies, sustained economic growth will continue to rely on the accumulation of expertise and mastery, even as technological change reshapes how that expertise is deployed. Therefore, it is possible that the implication of AI exposure is not that high-skill jobs will disappear but that they will evolve. Therefore, the future of work in the labor market (and the RGV) will be shaped less by the elimination of occupations than by the transformation of their task content. This evolution places a premium on adaptability, continuous skill development, and the capacity to effectively complement AI systems.

Data and Measurement

The analysis uses data from the American Community Survey (ACS) spanning 2005 to 2024, excluding 2020, and focuses on employed individuals aged 21 to 65 years with positive wage and salary income (Ruggles et al., 2025). The sample is restricted to workers residing in the RGV, particularly in Cameron and Hidalgo counties, due to data availability constraints. Occupations are linked to O*NET characteristics, following Slichter et al. (2023), and assigned a value between 0 and 1 that captures the importance of 11 broad skill categories in each job type, including critical thinking, communication, creativity, mathematics, scientific knowledge, social skills, effort, and physical skills. This skill-based framework is well-suited to the present brief because occupations differ not only in wages but also in their task content. As emphasized by Slichter et al. (2023), labor markets reward a multidimensional set of capabilities rather than a single notion of human capital. Their approach allows for detailed O*NET information to be summarized into interpretable skill categories that remain accessible to a broad audience. For other types of skill measurement, we refer the reader to Acemoglu et al. (2022), Autor and Thompson (2025), and the references therein.

In line with recent literature, we assess AI exposure from a task-based perspective. In other words, AI's effect on, or exposure to, occupations depends on the tasks it can perform or significantly accelerate in any occupation (Acemoglu et al., 2022; Eloundou et al., 2024; Autor and Thompson, 2025). We use occupation-level exposure measures based on Eloundou et al. (2024), where exposure is defined as the share of tasks for which AI can reduce completion time by at least 50 percent while maintaining quality. Again, it is worth mentioning that this measure captures the potential for task transformation rather than predicting job displacement.

Occupations and Wages in the RGV

In line with the previous discussion, Figure 1 illustrates the distribution of occupations in the RGV and their relationship with real wages (in 1999 U.S. dollars). We note that the average earnings in the sample are approximately $27,000 and that each occupation includes, on average, 170 surveyed workers. The figure highlights notable variation between occupations, both in terms of wage levels and employment concentration. Two main observations emerge with respect to jobs and wages.

First, education and healthcare occupations are highly prevalent. Among the most common occupations in the RGV are education-related roles, including *Elementary and middle school teachers*, *Teaching assistants*, and *Secondary school teachers*. Similarly, healthcare and care-related occupations, including *Nursing, psychiatric and home health aides*, *Personal care aides*, and *Registered nurses*, are prominently among the 15 most common occupations in the region.

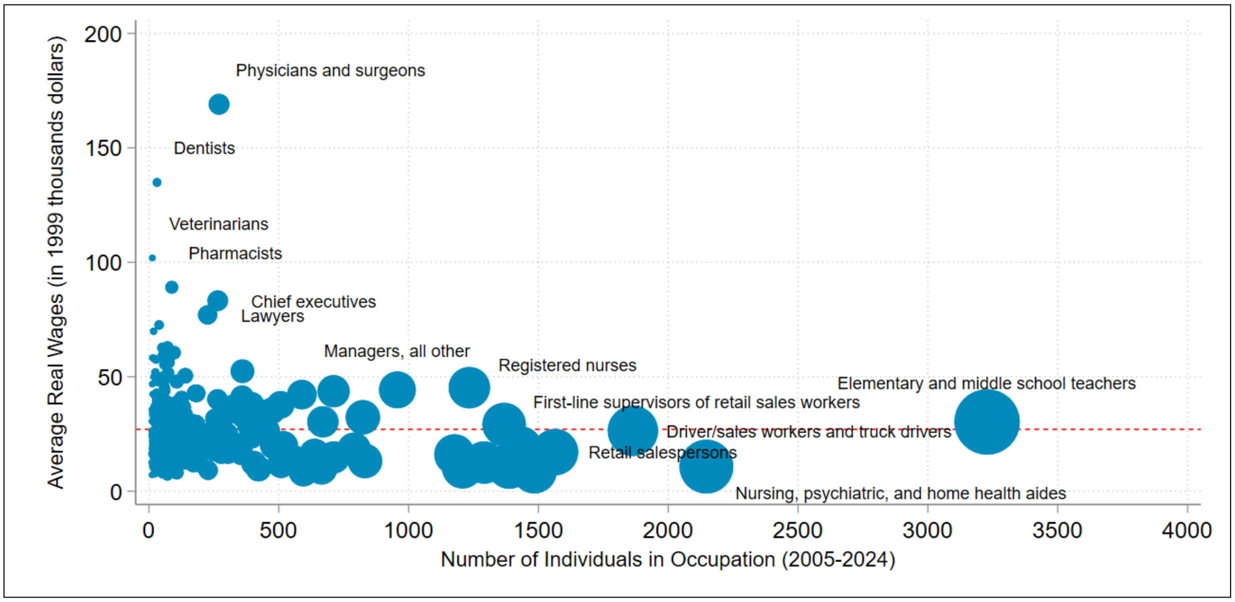
Second, higher wages are concentrated in a limited set of occupations. Among the 15 most common occupations, only about one-third offer above-average wages, including *Registered nurses*, *Managers, all other*, *Secondary school teachers*, *Elementary and middle school teachers*, *First-line supervisors of retail sales workers*, and *Driver/sales workers and truck drivers*. Although less prevalent, many of the highest-paying occupations in the RGV are concentrated in the healthcare sector, such as *Physicians and surgeons*, *Dentists*, *Veterinarians*, and *Pharmacists*. Additional high-paying roles are found in business and legal fields, including *Chief executives* and *Lawyers*.

Which Skills Pay in the RGV?

Given the patterns observed in Figure 1, one potential explanation for the relatively low wages in the RGV is that the most prevalent occupations in the region are associated with skills that command lower returns in the labor market. To examine this hypothesis, Table 1 reports, for each skill category, its relative importance and its correlation with average real wages across occupations in the RGV. Two main conclusions emerge.

First, consistent with Slichter et al. (2023), the labor market places a strong premium on idea-generating and problem-solving capabilities. In particular, *Critical Thinking*, *Scientific Knowledge*, and *Creativity* are all positively

Figure 1: Occupation Distribution in the Rio Grande Valley and Average Real Wages



Notes: the figure displays the number of observations in a given occupation on the x-axis and the occupation's average real wages (in 1999 thousands of dollars) on the y-axis. The size of bubbles represents how common an occupation is in the RGV (i.e., the number of individuals in that occupation that are observed in the sample). Average occupations' earnings are $27,000 (signaled with a red line). The average number of individuals in an occupation is 170. *Source:* The data are drawn from the 2005–2024 American Community Survey (ACS), excluding 2020, and restricted to employed individuals aged 21–65 earning a wage or salary income residing in Cameron and Hidalgo counties. These data are matched to occupation-level skills information from Slichter et al. (2023), and the sample is restricted to occupations with more than 10 observed individuals, resulting in 59,165 observations across 346 occupations.

and strongly correlated with wages in the RGV. By contrast, *Physical* skills, basic *Cognitive* skills, and *Technology*-related skills (defined here as knowledge and abilities associated with the use or maintenance of complex or advanced equipment; e.g., machinery, computers, or aircraft) tend to be negatively correlated with wages. This pattern suggests that occupations that are more dependent on manual dexterity, physical effort, and routine cognitive tasks are disproportionately concentrated in lower-paying segments of the local labor market.

The above trends are not unique to the RGV. A broad body of evidence shows that modern labor markets place a premium on aforementioned idea-generating and problem-solving capabilities in environments shaped by technological change and increasing task complexity (Autor, Levy, and Murnane, 2003; Acemoglu and Autor, 2011; Deming, 2017; Slichter et al., 2023). Interestingly, *Communication*, which is highlighted by Slichter et al. (2023) as an important skill, does not rank as highly in the RGV. One plausible explanation is the multilingual structure of the RGV labor market, where communication skills are widely held and often constitute a baseline requirement rather than a scarce form of human capital, thereby limiting their ability to generate wage premia (Fry and Lowell, 2003; López, 2023).

Second, the skills that are most prevalent in the RGV occupations are not necessarily those that command the highest returns. With the exception of *Critical Thinking*, the most intensively used skills in the region (such as *Physical* and *Social* skills) tend to exhibit either weak or negative correlations with wages. This pattern aligns with evidence that routine, manual, and service-oriented tasks are generally less rewarded in the wage distribution, particularly in regions where such occupations are abundant (Autor and Dorn, 2013; Goos, Manning, and Salomons, 2014). These findings reveal that the skills most widely used in the RGV labor market are not always the most rewarded.

Occupations and AI Exposure

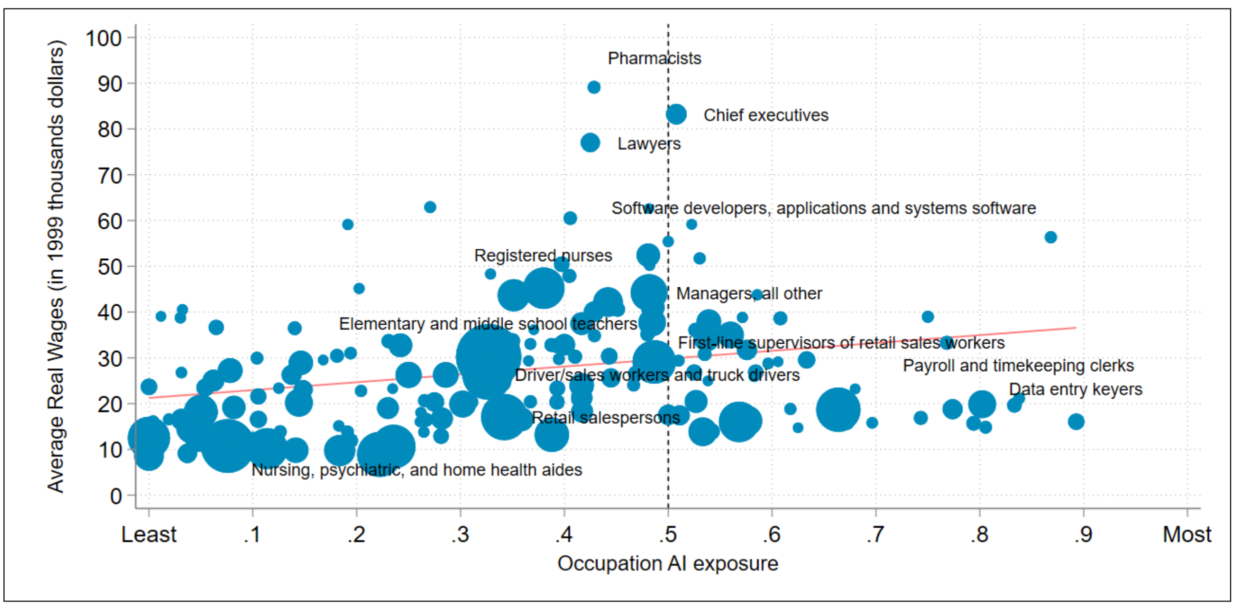
Although wages provide a useful benchmark for ranking skills and occupations, they do not fully capture the dynamics of a labor market shaped by rapid technological change and the growing adoption of AI. The effect of automation on the labor market depends critically on the expertise content of the tasks that remain after technology

Table 1: Skill Importance and Average Real Wages in the Rio Grande Valley

Skill category	Importance of Skill	Correlation with Average Real Wages
Critical Thinking	11.04%	0.514
Scientific Knowledge	4.73%	0.458
Creativity	3.45%	0.390
Math	2.58%	0.208
Communication	12.79%	0.200
Other Knowledge	10.70%	0.148
Social	10.71%	0.031
Effort	10.22%	-0.093
Technology	8.45%	-0.140
Other Cognitive	9.39%	-0.151
Physical	15.95%	-0.368

Notes: This table reports the correlation of the relative importance of skill categories with average real wages (in 1999 thousands of dollars). Skill importance is constructed using the categories defined in Slichter et al. (2023) and O*NET's occupation-level skill importance measures. For each occupation, importance scores for individual skills are aggregated within each category and expressed as a percentage of the total importance across all skills, with values between 0-100% reflecting the prominence of each skill category within occupations. *Source:* The data are drawn from the 2005–2024 American Community Survey (ACS), excluding 2020, and restricted to employed individuals aged 21–65 earning a wage or salary income residing in Cameron and Hidalgo counties. These data are matched to occupation-level skills information from Slichter et al. (2023), and the sample is restricted to occupations with more than 50 observed individuals, resulting in 55,092 observations across 189 occupations.

Figure 2: Occupation-Level AI Exposure and Average Wages in the Rio Grande Valley



Notes: The figure plots the occupation-level AI exposure index on the x-axis and average real wages by occupation (in 1999 thousands of dollars) on the y-axis. The AI exposure index ranges from 0 (least exposed) to 1 (most exposed), capturing the degree to which an occupation is affected by AI. The gray vertical line is the midpoint of the index (0.5). The red line is the fitted relationship between AI exposure and wages. Bubble size reflects the number of observations within each occupation. *Source:* The data are drawn from the 2005–2024 American Community Survey (ACS), excluding 2020, and restricted to employed individuals aged 21–65 earning a wage or salary income residing in Cameron and Hidalgo counties. These data are matched to occupation-level skills information from Slichter et al. (2023), and the sample is restricted to occupations with more than 50 observed individuals. Occupations are then linked to AI exposure indices from Eloundou et al. (2024), resulting in 53,245 observations across 179 occupations. The construction of the AI exposure measure follows Manning and Aguirre (2026); see their work for additional details.

is introduced (Autor and Thompson, 2025). In other words, the wage outcomes are determined not only by the exposure of a job to technology, but also by whether the residual tasks become more or less skill-intensive.

To examine this dimension, we combine the AI exposure estimates at the occupation level of Eloundou et al. (2024) with the RGV data. Figure 2 reveals a modest positive relationship between AI exposure and wages between occupations in the RGV, consistent with broader evidence that higher-wage occupations tend to involve tasks that are more exposed to AI-related technologies (Acemoglu et al., 2022; Eloundou et al., 2024). Two important dynamics emerge in the RGV.

First, AI exposure is not concentrated solely in traditionally low-wage or low-skill occupations. Rather, it is also present in occupations that command wage premia and rely heavily on information processing, writing, analysis, and judgment. This pattern is consistent with a central finding in the recent AI literature, which documents that higher-wage and better-educated occupations often contain a larger share of tasks exposed to large language models and related technologies (Eloundou et al., 2024). This reflects the fact that AI is particularly effective in tasks involving text generation, coding, classification, summarization, information retrieval, and routine analytical processes.

Importantly, a higher level of AI exposure in an occupation should not be interpreted as a threat to high-skill employment in that sector. The ultimate effect of AI will depend on how tasks are reorganized within occupations. In some cases, AI substitutes for labor in specific tasks; in others, it complements labor by improving productivity and reshaping the allocation of tasks (Acemoglu et al., 2022). Autor and Thompson (2025) further show that the wage effects of automation depend on whether technology displaces relatively expert or relatively inexpert tasks. When the remaining tasks require greater expertise and judgment, wages may increase even as some tasks are automated; when the opposite occurs, wages may decline.

In general, these insights suggest that AI is unlikely to uniformly reduce employment in exposed occupations. Instead, it is more likely to alter the composition of tasks within jobs. In the RGV, this distinction is particularly relevant, as many of the highest-paying occupations already rely heavily on tasks most susceptible to AI-driven transformation.

Second, the occupational structure in the RGV suggests that the most in-demand occupations tend to have relatively low exposure to AI. The correlation between AI exposure and the number of workers in a given occupation is modestly negative (-0.0704). Occupations with relatively high AI exposure, including *Data entry keyers*, *Software developers, applications and systems software*, *Payroll and timekeeping clerks*, and *Insurance claims and policy processing clerks*, are comparatively rare in the RGV (with 158, 76, 69, and 120 observed workers, respectively). By contrast, more prevalent occupations, such as *Elementary and middle school teachers*, *Nursing, psychiatric, and home health aides*, *Driver/sales workers and truck drivers*, and *Retail salespersons*, display exposure levels to AI below the midpoint (0.33, 0.08, 0.33, and 0.34, respectively). In particular, the healthcare sector has relatively limited exposure to AI. In the RGV, *Registered nurses* (a highly paid and in-demand occupation) also have an AI exposure index below the midpoint (0.38). These patterns are consistent with recent evidence highlighting the central role of healthcare and care-related services in current U.S. employment dynamics (Bhattarai and Melgar, 2026). As a core sector in the RGV with relatively low exposure to AI, healthcare is well-positioned to support the region's economic resilience. In addition, the adoption of AI in this sector is more likely to increase worker productivity than to substitute for labor, potentially increasing the demand for healthcare workers, as they can serve a larger patient population.

Adaptation, Policy, and the Future of Work in the RGV

The combination of high returns on cognitive skill and nontrivial exposure to AI points to adaptation as the central policy issue. Recent work by Manning and Aguirre (2026) argues that exposure alone is not enough to identify vulnerability. The ability of workers to adapt depends on a broader set of factors, including financial resources, skill transferability, age, and the density of alternative job opportunities. Even if only a subset of AI-exposed tasks ultimately leads to displacement, workers with weaker adaptive capacity may bear greater transition costs. This perspective is particularly useful for the RGV. Therefore, policymaking may focus on ensuring that workers are prepared for jobs whose task composition is likely to evolve. The evidence here suggests three priorities.

First, workforce and education policies should continue to emphasize analytical reasoning, communication, and problem-solving. These skills are already well rewarded in the RGV labor market, and they are also the ones most likely to remain central as jobs are reorganized around AI. Investments in developing these skills for workers are useful both under current labor-market conditions and in plausible future scenarios.

Second, AI literacy should be treated as a complement to, not a substitute for, core skills. Many exposed occupations involve substantial cognitive and communication content. Workers will increasingly need to know how to use AI systems productively, evaluate their outputs, and integrate them into broader workflows.

Third, local policy should focus on adaptability rather than static job protection. The relevant question is not whether a specific occupation will survive unchanged, but whether workers can move across tasks and roles with limited loss in earnings and job quality. This implies a role for community colleges, universities, employers, and workforce boards in building pathways for re-skilling, mid-career training, and occupational mobility.

Conclusion

In this brief, we document two central features of the Rio Grande Valley (RGV) labor market. First, occupations that rely on higher-order cognitive and problem-solving skills, including critical thinking, creativity, and scientific knowledge, command substantially higher wages but are somewhat less in demand in the RGV. Second, higher-earning occupations are, to some extent, more exposed to AI-driven changes in task content. As documented in recent AI literature, this pattern may not imply a decline in high-skill employment but rather a reorganization of the tasks that define it. Although highly demanded occupations in the RGV are less exposed to changes in the AI-driven labor market, AI-driven structural changes will nevertheless be felt throughout the region. Looking ahead, the future of work in the RGV is likely to be shaped by the transformation of the tasks required across various occupations.

The same skills acquired in higher education that foster higher wages (for example, reasoning, communication, problem-solving, and digital capabilities) are also the ones most likely to enhance the RGV's capacity to adapt to AI. In this sense, policymakers should continue to support the building of human capital, as this will strengthen adaptability, which, in turn, supports both economic resilience and long-term growth in the region.

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