Analysis of Industrial Job Uptake in Louisiana: Technical Note

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As a supplement to the **executive summary**, this technical note provides additional detail on data limitations and other nuances that shape how many jobs can be linked to industry and our ability to measure them. We also summarize the data sources and methodology used for the analysis.

Methodological challenges in assessing job impacts

Accurately measuring the employment impacts of industrial investments with readily available data presents several challenges, including:

- **Data limitations and privacy**: Existing data systems often prevent the direct assignment of specific jobs to individual employers. This is partly by design to protect worker privacy and employer trade secrets.
- **Gross versus net job creation**: New project announcements typically report gross employment creation, but changes in employment levels over time typically reports net employment change. New jobs may be cancelled out by less publicized job losses elsewhere, and the constant process of employment churn means that new workers can find employment without any change in the number of jobs.
- **Establishing a counterfactual**: Rigorous measurement of impact requires understanding what economic conditions would have prevailed in the absence of the investment. Developing such a credible counterfactual scenario is difficult for specific projects or places.
- **Granularity and trade-offs in employment data**: Employment data is typically reported using broad units and categories (e.g., by geography and industry). There are inherent trade-offs in the level of detail available. For instance, data that is more geographically granular often provides less granularity regarding industry classifications, and vice-versa.
- **Static data vs. dynamic employment processes**: Most available employment data is presented as aggregate totals at specific points in time. However, employment is a dynamic process, with individuals regularly moving between jobs and, at times, relocating in response to new opportunities. Most readily available data sources do not fully capture the complex flows that define labor market change, especially at a locally granular level, and data that does capture employment dynamics tends to be less detailed by industry and geography.
- **Ambiguity in where jobs are counted**: Where and how jobs are "counted" in official datasets is based on the location of a business establishment. For project-based employment, particularly in the construction phase, the location can be unclear (in terms of location or industry). Though often a minor consideration, these issues may be more common for large construction projects involving intricate management and contracting

structures (similar situations also may arise for manufacturing employers where a portion of their workforce is subcontracted or otherwise related to a non-local corporate structure).

- **Ambiguity in defining interrelated industries**: Industries critical to economic development in Louisiana often fail to align neatly with the standardized industry codes (NAICS) used in employment data. For example, the "oil and gas industry" could reasonably be defined to encompass a wide range of activities in the natural resources, construction, manufacturing, and transportation industry sectors, as well as services industries. Thus, industry-based definitions are often debatable and vary from place to place.

Acknowledging these inherent challenges, while this analysis presents specific numbers and localized employment maps, emphasis is placed on identifying general patterns and trends revealed by the data, rather than asserting definitive job creation counts that are specific to a project, industrial area, or parish.

Defining "industry-scale employment" and the scope of the study

Industrial employment is a vital component of state and local economies. Industries like manufacturing are critical because they produce goods for trade beyond the immediate region where they are located and, in doing so, support a network of other local industries involved in the supply chain. The economic impact of such employment is often quantified through:

- **Direct jobs**: Those created during the construction phase or for ongoing operations.
- **Indirect jobs**: Employment generated as the initial investment creates additional demand throughout the local supply chain.
- **Induced jobs**: Additional employment resulting from increased local spending by households whose incomes are boosted by the direct and indirect jobs.

Many economic impact studies estimate these **multiplier effects** before an investment occurs, relying on historical data on relationships between different sectors of the economy. However, these *a priori* studies typically do not directly measure whether the projected jobs are actually created after the initial investment, nor do they typically assess the extent to which any new positions are filled by local workers.

In contrast, the current study adopts a retrospective approach. We examine employment trends and patterns in the recent past, focusing on commuting data within areas where employment in major industry sectors (manufacturing or construction linked to manufacturing) is concentrated, rather than on the impacts of specific, individual projects. While the small-area (census tract and parish) data we analyze technically captures direct employment and a small, highly localized portion of indirect and induced jobs, the quantification of the multiplier effect itself is not the central focus of our investigation. Multiplier effects are relatively small when bounded to single parishes and narrow industrial corridors, which are our focus. Instead, we aim to understand the observable employment changes after periods of significant changes in the level of industrial employment – such as local industrial construction booms that have occurred in different parts of Louisiana since the early 2010s. By mapping residential locations linked to employment in key industrial corridors, the analysis is suggestive of where the induced effects of worker spending are likely to occur. However, our analysis is not directly comparable with multiplier-based estimates.

For clarity, we distinguish between two primary phases of industrial employment (these phases are frequently used to model and describe "direct" employment):

- **Construction phase**: This phase is characterized by temporary, project-based employment, though often at high levels (peak construction for LNG projects is often in the thousands). The jobs are most closely related to the Construction industry sector (NAICS 23). Large and complex construction projects often involve complicated management and contracting arrangements, which can influence how and where these jobs are recorded in publicly available employment data.
- **Operations phase**: This phase involves employment sustained for longer periods of time, though often at lower numbers than the peak construction phase, particularly for highly capital-intensive projects. These jobs are primarily associated with the Manufacturing industry sector (NAICS 31-33), though other industries may also be involved in supporting operations and some industrial operations may not be coded as manufacturing, such as a port or pipeline facility or LNG terminal.[7]

These phases can give a rhythm to employment trends. A rising and falling wave of construction employment – often following a years-long period between initial announcement, design and planning, financing and regulatory approval, and final investment decision – may be followed by a smaller but more sustained rising tide of manufacturing employment when regular operations commence. We see this rhythm in some parish-level employment trends and in the parish vignettes in this report.

Both construction and manufacturing are classified as "goods-producing" industries, alongside natural resources industries (like mining, oil and gas extraction, agriculture, and forestry). This contrasts with "services-providing" industries, which encompass all other forms of employment, from local consumer services to specialized business and professional services. In some of the commuting data utilized in this report, the broad "goods-producing" versus "services-providing" distinction is the most granular industry breakdown available.

Employer locations and the residential locations of workers

In the analysis, we make a key distinction between where workers work and where workers live. We use data that links these two locations to capture commuting relationships. These geographic patterns are shaped by factors that affect the location of industry and by factors that affect the residential locations of workers and their households.

Where industry-scale manufacturing and construction jobs are located reflects a set of processes that lead industries to **cluster** together geographically, often in denser urban areas and in major industrial corridors. Access – to infrastructure and transportation, key industry-specific inputs, and/or skilled workers – can play a large role in where employers locate, and clustering can lead to self-reinforcing, place-based industry specialization. Changing market conditions also can affect where and what kind of investment occurs. For example, changes in the energy economy have fueled additional investment in "downstream" energy-related manufacturing and LNG in Louisiana as employment has fallen in "upstream" oil and gas extraction.

Where manufacturing and construction workers live is determined by a different set of social and economic **sorting** processes. Sorting by place (or neighborhood) and by job type (or occupation) are distinct outcomes that share some overlapping causes. For example, lower-income workers

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[7] There is also ambiguity, and likely inconsistency, in how LNG terminal and liquefaction facilities are assigned to NAICS codes.

tend to work in lower-wage industries and occupations, and they tend to live in lower-income areas where housing options are relatively more affordable. Access to where jobs are located is only one factor in residential location, along with the affordability and availability of housing; preferences for local policies, amenities, and quality of life; historical patterns of residential segregation by race and income; and other demographic, social, and cultural factors. Typically, labor moves more slowly than capital, contributing to spatial mismatches in where people live and where job opportunities are located.

Using small-area data, we map construction and manufacturing employment across the state. Both tend to be concentrated in specific areas, including major manufacturing corridors along the Mississippi River and in Southwest Louisiana, in smaller manufacturing corridors in other metropolitan areas, and in some rural and small-town areas. We investigate some of these areas in the parish vignettes.

Factors influencing job creation and local employment impacts

The translation of large capital expenditures into expectations for local jobs is not always straightforward. Several factors can influence why initial job projections may not fully materialize, or why jobs may not be filled by the local workforce.

Why large capital expenditures might yield fewer jobs than anticipated:

- **Capital-intensiveness**: Investments may be heavily weighted towards machinery, automation, and infrastructure rather than labor. Large capital outlays can, in fact, automate tasks previously performed by workers, potentially reducing the overall number of jobs created per dollar invested. Many of Louisiana's leading industrial activities (petroleum refining, chemical manufacturing, LNG, and advanced manufacturing) are capital-intensive and involve massive investments in facilities, machinery, and infrastructure.
- **Leakage**: The economic benefits of an investment can "leak" out of the local economy. This occurs if backward linkages (inputs and supplies for the project) are sourced from outside the region, or if forward linkages (the outputs or products of the facility) do not generate subsequent local economic activity. While more locally integrated supply chains will generally yield greater spillover effects on employment, links to external supply chains are often fundamental to a local industry's competitiveness.
- **Low propensity to consume locally**: If new workers or businesses do not spend a significant portion of their income within the local economy, the anticipated second-order effects of new industry investments may be diminished.
- **Congestion effects and negative externalities**: Large-scale investment in one industry can inadvertently crowd out investment or growth in others. It might also strain local resources, reduce the availability of workers for other sectors, or drive up the costs of labor, materials and other inputs, and housing and transportation. These "congestion effects" can dampen the broader economic impact on the region. Negative externalities of industrial land uses can have a similar effect if they deter other land uses, such as homes or unrelated businesses, from locating nearby.

Why jobs might not accrue to local residents or to specific groups of workers:

- **Specialization for complex projects**: Large, complex construction projects often rely on specialized contractors and a highly skilled workforce that may not be readily available locally, leading to the importation of labor.
- **Hiring practices, information asymmetries, and social networks**: Social and management processes shape hiring and job-seeking behaviors. Established business practices and existing hiring networks can inadvertently favor certain groups while excluding others. Asymmetric information in the job market or specific job requirements (even if not intentionally discriminatory) can have a disproportionate effect in excluding segments of the local workforce.
- **Skills mismatch and training gaps**: Industrial projects frequently demand specialized technical skills. Even with efforts to provide training, there can be a significant time lag before the local workforce is prepared, and training systems may struggle to scale up (and down) at the speed of capital investment and hiring.
- **In-migration and commuting**: Individuals from outside the region may move in to take available jobs, particularly if there's a perceived or actual shortage of qualified local candidates or if recruitment efforts cast a wider net. Workers might also commute long distances for jobs, especially if the compensation is high. Long commutes may be expected, for example, in rural areas with a large industrial footprint but limited residential population, like Cameron Parish or portions of the River Parishes.

When considering racial demographics of the industrial workforce, distance between where the people live and where the jobs are located could also be a factor. Five parishes account for over half of Louisiana's Black population (Orleans, East Baton Rouge, Jefferson, Lafayette, and Ouachita), and these parishes are not necessarily where major manufacturing employers are located. The distance could contribute to the underrepresentation of Black workers in industries like Petroleum and Coal Products Manufacturing and Chemical Manufacturing. On the other hand, Black workers are also underrepresented – and Hispanic workers overrepresented – in construction jobs, which are located more evenly throughout the state. The takeaways are that a complex mix of factors combine to shape access to jobs. Single interventions, like training, are alone unlikely to fill gaps; and efforts to broaden access to jobs should also consider how geography and various other social factors interact with skill demands and the hiring process.

Data and methodology behind the analysis

The employment data used in the analysis comes from four main sources. With each having unique strengths and limitations, we thoroughly reviewed each source to develop the summaries included in the report.

- **Quarterly Census of Employment and Wages** (QCEW, U.S. Bureau of Labor Statistics): This is widely recognized as a benchmark data source on employment levels. The data is mostly derived from quarterly wage reporting to state unemployment insurance systems (UI). As such, it reports "covered" employment, which nearly corresponds with the universe of wage-and-salary employment, or jobs that generate a tax Form W-2. It does not fully capture other types of workers, including many small-business owners, self-employed workers, 1099 contractors, and gig workers. The smallest geography available is the county (parish) level, and it refers to the employer establishment where the job is located, not to where the worker lives.

- **Quarterly Workforce Indicators** (QWI, U.S. Census Bureau): QWI is also based on QCEW. However, through record linking, additional information is reported: employer characteristics, job and employee characteristics, and employment dynamics (hires and separations).
- **Longitudinal Origin-Destination Employment Statistics** (LODES, U.S. Census Bureau): LODES is from the same program as QWI, but it has a different focus. Through record linking, LODES connects places of work with places of residence for UI-covered employment. While it provides less detail on non-geographic aspects of employment than QWI, its greatest advantages are a high level of geographic detail and an ability to describe commuting patterns.
- **American Community Survey microdata** (via IPUMS-USA): Whereas the data sources listed above are based on administrative data, we also use the American Community Survey, the U.S. government's largest annual survey on demographic, socioeconomic, and household characteristics. We use an IPUMS-USA extract to construct a statewide sample of employed workers. A key concern with this data source is the sample size. Estimates are subject to sample error, and estimates for small segments of the population (e.g., workers from a specific demographic group in a specific industry) can be quite noisy. As a result, we pool multiple years together and take other steps described below to manage the tradeoff between the specificity and reliability of estimates.

State and parish trends

Both QCEW and QWI are derived from UI records, and their smallest scale is the county (parish) level. QCEW is generally accepted as a benchmark source for employment levels. QWI also uses longitudinal record linking and record linking with other data sets to make available dynamic measures of employment (e.g., hires and separations) and demographic breakdowns (e.g., race, age, gender, and educational attainment). Outside of these differentiating features, the data sets are very similar in providing job totals by place of work at a county (parish) level or higher and with industry detail. Both also implement suppression, making many detailed industry-by-parish employment totals unavailable, especially in parishes with lower total employment.

For the state-level breakdowns, we use QCEW to report annual average employment. For the parish-level trends, we use QWI and report quarterly employment. To simplify the parish-level trends and to avoid suppression issues, we focus on the construction and manufacturing sectors; and for comparison, we combine remaining employment into the following industries, unless otherwise noted.

- **Local services**: Retail trade; Educational services; Health care and social assistance; Arts, entertainment, and recreation; Accommodation and food services; Other services (except public administration)

- **Other industries**: Agriculture, forestry, fishing and hunting; Mining, quarrying, and oil and gas extraction; Utilities; Wholesale trade; Transportation and warehousing; Information; Finance and insurance; Real estate and rental and leasing; Professional, scientific, and technical services; Management of companies and enterprises; Administrative and support and waste management and remediation services; Public administration

The state-level trends section includes location quotients and shift-shares, common techniques used to study state and regional economies. A **location quotient** greater than one indicates that an area has more of a certain type of job compared with the national average. Calculated by dividing the industry percentage of total employment in the state or local area by the same percentage at the national level, it is an intuitive measure of concentration or specialization. Values significantly greater than one often indicate a specialized industry that contributes to the state or local area's export base. **Shift-share** analysis is a technique for decomposing employment change in a state or local area into three components: the overall national trend across all industries, the local mix of industries that are fast- and slow-growing nationally, and the unexplained leftover component of change. This unexplained component is the local component, often interpreted as the effect of local competitiveness (net of national trends). We combine the national and industry mix components into "expected change" and highlight its difference with "actual change"—this difference is equivalent to the local component.

Commuting and sub-parish analysis

For analysis that requires greater geographic resolution and investigates commuting flows, we use LODES. We use a variety of LODES tables, including the work area, residence area, and origin-destination files. While the data is provided at the census block level, we aggregate to the census tract level to mitigate significant noise inherent in the block-level estimates (added by the Census Bureau as a confidentiality measure) and to simplify the maps. We note that, due to the way this data is originally generated and then processed by the Census Bureau, tract-level trends are likely less reliable than parish- and state-level trends from QCEW and QWI.

However, the principle and unique advantages of LODES are enhanced geographic detail and the "origin-destination" link between places of work and residence. In exchange, limited industry detail is reported. For the work area and residence area files, industries are provided at the two-digit NAICS code level. For the origin-destination files, only three industry groups are provided, leaving goods-producing industries as the most detailed level of industry available for describing the jobs at the center of the analysis (construction and manufacturing). The case studies thus use a multi-step process.

1. We identify tracts with high industrial employment as tracts where the sum of the following industries exceeds 800 in the work area file: Mining, Quarrying, and Oil and Gas Extraction (NAICS 21), Utilities (22), Construction (23), Manufacturing (31-33). We make some modifications to this set of tracts based on our knowledge of the areas and examining mapping websites as a reference for the location of large industrial employers. These tracts serve as destinations in the commuting analysis.
2. We map the current employment in those tracts using the origin-destination data. As the data has limited detail, we map goods-producing and services employment separately. Note that, in a typical urban or suburban tract, goods-producing employment could include a range of small businesses. In a tract that houses major industrial employers, employment in goods-producing industries is much more likely to align with the "industry-scale" employers at the center of the study, like major construction projects and manufacturing facilities.
3. We identify periods when a significant number of jobs were added beyond typical rates of annual change. This is based on examining the QWI and QCEW data from each parish used in the case studies. We identify a "pre" year when employment was relatively stable and a "post" year – either a momentary peak or a stable period of elevated employment beyond previous levels. Though we focused on parish-level trends in construction and

manufacturing, these trends tend to be concentrated in the tracts with high industry employment identified previously. Cameron Parish showed by far the clearest "spike" in employment, though reasonable pre- and post- periods were identified for other parishes.

4. We map the differences in the place of residence (origin) employment between these two periods, focusing on employment where the place of work (destination) is in census tracts with high industry employment. Subtracting the "pre" employment level before a dynamic period from the "post" level afterward gives net change in employment. We analyze these "net new jobs" by comparing where the workers live at a time of peak employment ("post") and at an earlier time of lower employment ("pre"). Mapping the difference shows where the workers in newly created jobs tend to live. Note that this is still an aggregate comparison of employment before and after a period of significant change in employment. A difference of zero could result from, e.g., 100 new jobs in a census tract cancelled out by 100 lost jobs; but the difference will be positive if the number of new jobs exceeds the number of lost jobs.

The parish vignettes focus our interpretation on the "pre-post" comparison to describe net new jobs in industrial areas during periods of localized employment growth. As noted above, the parish vignettes also show similar origin-destination maps but only for employment in the most recent year of data (2022) without the pre-post comparison and thus without the interpretation of "net new jobs." In addition to the maps, we also use charts to summarize the tract-level pre-post comparison at higher levels of geography that are tailored to each location. These show pre and post levels of employment for the parish, nearby parishes, the rest of Louisiana, Texas, and other states. The differences shown on the charts can be interpreted as net new jobs or net lost jobs by place of residence for jobs located in the parish(s) main industrial areas. While the maps help to illustrate granular geographic commuting patterns, the charts give a clearer indication of the total number of jobs.

Spatial analysis involving census tracts, land use patterns, and commuting relationships. Several of the breakdowns reporting LODES data make an implicit or explicit comparison between jobs in goods-producing industries and jobs in services industries, in part due to the limited industry detail in the LODES origin-destination data.[2] However, because the analysis focuses on tracts with high industry employment, it is essentially selecting on tracts with a high number of jobs in goods-producing industries. In many cases, these areas also contain a concentration of heavy industrial land uses, which are often not the same tracts as the parish's main sites of office buildings, restaurants, retail, and other land uses associated with places of work in services industries. This pattern varies across the study area, e.g., large portions of Ascension and Calcasieu are denser and more urbanized with a more diverse economy than Cameron and the River Parishes, but the larger tracts and lower population densities in those smaller parishes may lead to greater relative land use diversity within the census tracts with high industrial employment.

Thus, as caveats, we note that services employment in tracts with high industry employment may not represent patterns in at the parish or metro level; and in general, census tracts are drawn to reflect land use patterns associated with residential population totals and not places of employment. Nonetheless, our choice to focus on these tracts is justified as a more probable reflection of other relationships. First, using the same tracts of work for goods-producing and services industry jobs helps to control for differences in commuting distance that interact in

[2] LODES only offers three industry categories, one of which is goods-producing industries.

complex, place-specific ways with transportation networks and land use patterns.[3] This makes the interpretation that workers commute longer distances for goods-producing jobs more credible. Second, it is plausible that services industry employers in heavily industrial areas are more likely to be linked with industrial activities than most services industry employers in other types of predominantly commercial or residential areas. While not technically goods-producing industries, some services employers located near major industrial areas may have direct or indirect ties to industrial activity – and thus reflective of agglomeration effects, supply-chain multiplier effects, and other issues relevant to industry-scale employment opportunities.

In concluding this brief discussion of the intricacies of interpreting data on commuting patterns, we underscore that the underlying real-world processes that generate the data we see are in fact complex. As noted above, they reflect an interaction between the processes of industrial clustering and residential sorting, both of which vary from place to place. These interactions are further mediated by distance, the geography of road networks and housing supply, and other spatial relationships. In short, given the nature of the data and the underlying processes that generate it, we should expect to find complex commuting patterns, and comparisons such as those made in this analysis should be made carefully.

Characteristics of individual workers

To examine details about the demographic and socioeconomic characteristics of workers, we rely on an ACS sample from IPUMS-USA (Ruggles et al. 2025). As we use a household survey to report on the characteristics of workers, this differs from the other data sources, which are based on administrative records. The advantage of ACS microdata is the level of detail and flexibility to describe workers and their experiences, but the disadvantage is relatively small samples for detailed subgroups of workers. As such, many of our methodological decisions were driven by the effort to manage sample size and meaningful differences in industry categories.

When the outcome is for employed workers, we generally define the sample population as follows unless otherwise noted:

- We use a sample for the years 2015-2022, excluding 2020. We exclude 2020 due to issues with data collection driven by the pandemic and to give a regular picture of the labor market unaltered by the pandemic's disruption to employment levels.
- Employment measures are limited to the employed civilian workforce (excluding Armed Forces). They do not include unemployed workers or individuals who did not report participating in the labor force.
- We exclude individuals for whom the variables in question are not reported, such as wage or educational attainment.
- Employed workers include wage-and-salary employees and self-employed workers. We report earnings, which includes wage-and-salary earnings as well as business earnings from self-employment.

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[3] For example, a resident of Baton Rouge can more easily commute via I-10 to work in a commercial area in Gonzales or Prairieville than to an industrial area in St. Gabriel or Donaldsonville.

- When reporting by race and ethnicity, we recode into mutually exclusive categories, such that White, Black, and Asian imply non-Hispanic ethnicity, and Hispanic can be of any reported race.
- We adjust all dollar values to constant 2022 dollars, the most recent year of available data at the time of the analysis, using CPI-U.
- We also report wages and annual employment numbers for the "top 10 occupations" in different industry categories. These use a different four-year sample (2018, 2019, 2021, and 2022) because of changes to SOC 2018 coding. Note that we use a crosswalk developed by IPUMS-USA that is related to but may not exactly match SOC 2018.

These estimates have sample uncertainty. We do not report margins of error unless they are large enough to potentially affect the interpretation, but we do review these margins to inform how the data is presented and to prevent unreliable interpretations. Margins of error are estimated using the replicate weights method suggested in IPUMS-USA documentation.

In reporting breakdowns by industry, we combine industries into categories as follows. These groupings are based primarily on differences in the workforce and earnings levels. Generally, the ACS industry codes provided by IPUMS-USA align with three-digit NAICS codes except for the "M" codes for "miscellaneous."

- *Construction* (NAICS 23 is the most detailed level available from ACS data)
- *Manufacturing: Petroleum and Coal Products* and *Manufacturing: Chemical* are equivalent to their three-digit definitions (324 and 325)
- *Manufacturing: Food, textile, apparel, wood, paper, furniture* includes several three-digit codes, including a miscellaneous code (311, 312, 313, 314, 315, 316, 31M, 321, 322, 323, 337, 339)
- *Manufacturing: Plastic, metal, mineral, electronics, transportation equipment* includes several three-digit codes, including a miscellaneous code (326, 327, 331, 332, 333, 334, 335, 336, 33M)
- *Utilities* is equivalent to its two-digit definition (22)
- *Services* includes all other two-digit industries besides those listed above and Agriculture, forestry, fishing and hunting (11) and Mining, quarrying, and oil and gas extraction (21)

For some breakdowns with multiple dimensions (e.g., race by industry by education), we use categories that are further aggregated, partially to manage sample size for disaggregated estimates:

- *Energy-related and heavy manufacturing* combines *Manufacturing: Petroleum and Coal Products*, *Manufacturing:* Chemical, Manufacturing*: Plastic, metal, mineral, electronics, transportation equipment*
- *Light manufacturing* is the same as *Manufacturing: Food, textile, apparel, wood, paper, furniture*
- *Construction* and *Services* are the same

For charts and tables involving wages for specific occupations ("Employment by occupational earnings levels" and "Top 10 occupations" by industry), we calculate earnings percentiles for workers in the occupation across all industries, not only for the occupation within the specific industries reported. Again, this choice mitigates small cell sizes for more reliable estimates, but the results suggest a distribution of wages that is somewhat lower than the earnings percentiles reported for the industry without considering occupations, as in “Median, 20th, and 80th percentile earnings for selected industry categories.”

In some cases, we also emphasize Black-White demographic comparisons in the charts and interpretations and do not provide similar estimates for Asian and Other when these estimates are especially noisy due to small cells.

In the slide deck, we report a table with demographic estimates. Here, we reproduce the table with 95% confidence intervals.

	Construction	Energy-related and heavy manufacturing	Light manufacturing	Services
Race/ethnicity				
Asian	0.7% (0.5%-1.0%)	1.6% (1.3%-1.9%)	1.2% (0.9%-1.8%)	2.2% (2.1%-2.2%)
Black	16.3% (15.5%-17.2%)	19.3% (17.9%-20.8%)	32.4% (30.4%-34.6%)	31.0% (30.7%-31.3%)
Hispanic	15.9% (14.9%-16.9%)	4.3% (3.6%-5.1%)	4.7% (3.8%-5.8%)	4.3% (4.2%-4.5%)
Other	2.7% (2.3%-3.2%)	2.0% (1.7%-2.5%)	1.7% (1.2%-2.3%)	2.4% (2.2%-2.5%)
White	64.4% (63.2%-65.5%)	72.8% (71.4%-74.1%)	60.0% (57.7%-62.2%)	60.1% (59.8%-60.4%)
Sex				
Female	11.5% (10.8%-12.3%)	15.6% (14.6%-16.6%)	30.8% (28.6%-33.2%)	57.5% (57.2%-57.8%)
Male	88.5% (87.7%-89.2%)	84.4% (83.4%-85.4%)	69.2% (66.8%-71.4%)	42.5% (42.2%-42.8%)
Educational attainment				
Less than HS	18.8% (17.9%-19.8%)	7.4% (6.5%-8.4%)	10.6% (9.1%-12.4%)	8.3% (8.1%-8.6%)
HS diploma	45.4% (44.3%-46.6%)	36.5% (35.2%-37.8%)	42.4% (40.2%-44.8%)	28.0% (27.5%-28.4%)
Some college	20.1% (19.2%-21.1%)	22.7% (21.5%-24.0%)	22.2% (20.3%-24.3%)	24.7% (24.3%-25.0%)
Associate	4.9% (4.5%-5.4%)	9.9% (9.0%-10.9%)	8.0% (6.7%-9.5%)	7.3% (7.1%-7.5%)
Bachelor	8.8% (8.1%-9.6%)	18.7% (17.7%-19.8%)	13.9% (12.4%-15.5%)	20.0% (19.7%-20.4%)
Graduate or professional degree	1.9% (1.6%-2.3%)	4.7% (4.1%-5.5%)	2.8% (2.3%-3.5%)	11.7% (11.5%-11.9%)
Age				
24 and under	10.9% (10.0%-11.8%)	7.9% (6.9%-8.9%)	9.5% (8.2%-10.9%)	14.8% (14.5%-15.1%)
25-34	24.5% (23.3%-25.7%)	24.1% (22.9%-25.3%)	21.0% (19.3%-22.9%)	24.5% (24.2%-24.8%)
35-44	25.2% (24.0%-26.4%)	24.0% (22.8%-25.3%)	23.9% (22.1%-25.8%)	23.0% (22.8%-23.3%)
45-54	22.7% (21.7%-23.7%)	24.8% (23.7%-25.9%)	24.8% (22.8%-26.9%)	20.6% (20.3%-20.8%)
55-64	16.8% (16.0%-17.7%)	19.2% (18.1%-20.4%)	20.8% (19.0%-22.8%)	17.1% (16.9%-17.3%)
Mean age	41.9 (41.6-42.3)	42.9 (42.5-43.3)	43.7 (43.1-44.3)	41.6 (41.5-41.7)

References

Steven Ruggles, Sarah Flood, Matthew Sobek, Daniel Backman, Grace Cooper, Julia A. Rivera Drew, Stephanie Richards, Renae Rodgers, Jonathan Schroeder, and Kari C.W. Williams. *IPUMS USA: Version 16.0* [dataset]. Minneapolis, MN: IPUMS, 2025. https://doi.org/10.18128/D010.V16.0