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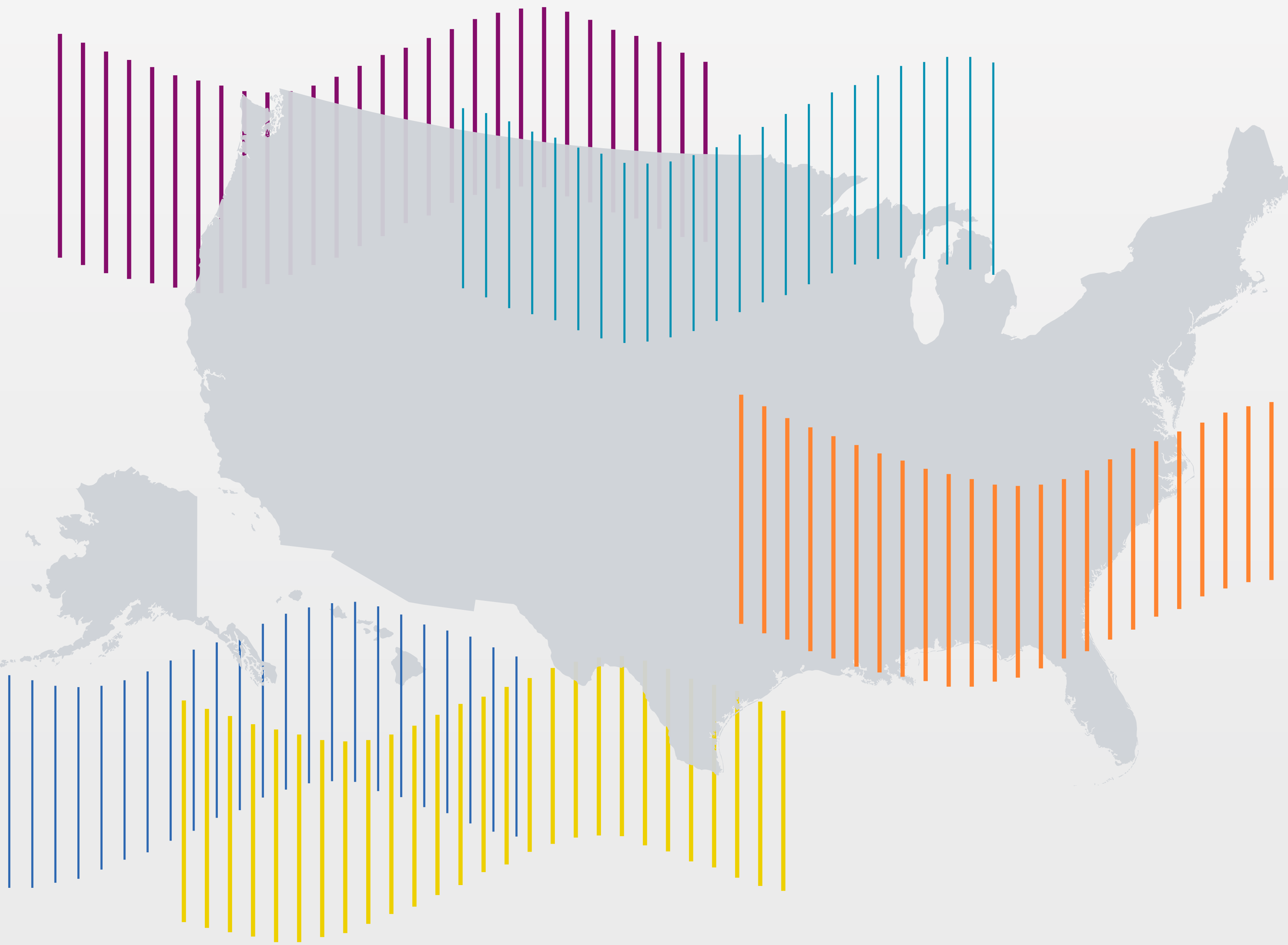
The Community Explorer

Using County-Level Data on US Diversity Effectively to Inform Policy

Claude Lopez, PhD, Hyeongyul Roh, PhD, and Maggie Switek, PhD



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ABSTRACT

The Community Explorer provides new insights and data on the characteristics and diversity of the US population. Using machine-learning methods, it synthesizes the information from 751 variables across 3,142 counties from the US Census Bureau's American Community Survey into 17 communities. Each one of these communities has a distinctive profile that combines demographic, socioeconomic, and cultural behavioral determinants while not being geographically bounded.

Five categories summarize the main features of these profiles.

URBAN AMERICA captures four community profiles that represent 74 percent of the US population across 819 urban-core, suburban, and small metro counties.

Urban Core → Prosperous, ethnically and linguistically diverse large metro areas with substantial disparities between their highly educated (largely White[1]) and less educated (largely Black or African American) residents (26 percent of the population).

Lower-Middle Class → Less populous suburban and small metro counties that are not as economically prosperous as the rest of Urban America (18 percent of the population).

Affluent Suburbs → Affluent and more populous (but less diverse) suburban and small metro counties that jointly represent the profile with the highest median income (16 percent of the population).

Middle Class → Middle-class communities with a largely White population that resides in large- to medium-sized suburban and small metro counties (14 percent of the population).

INDUSTRY-DRIVEN AMERICA captures five community profiles that include 17 percent of the US population across 1,507 counties where employment is concentrated in one industry that shapes all aspects of the population's profile.

College Towns → College towns with a relatively young, highly educated, and highly geographically mobile population (5.4 percent of the population).

Manufacturing Midwest → Counties primarily located in the Midwest that form the profile with the highest proportion of the White population working in the manufacturing sector (5.2 percent of the population).

Low-Wage Manufacturing → Low-wage workers in the manufacturing and chemical industries located largely in the South and Northeast regions of the country, with an above-average proportion of the population living below the poverty line (4.9 percent of the population).

Hispanic Agriculture → Highly agricultural communities with a higher than average concentration of Hispanic or Latino population residing mostly in the West and South (1.2 percent of the population).

The Great Plains → Agricultural counties located in the Great Plains with a high proportion of the White population (0.3 percent of the population).

GRAYING AMERICA captures two community profiles that include 5.1 percent of the US population across 378 counties and jointly represent the profiles with the highest concentration of population aged 65 years or older.

Retiree Communities → Retiree communities with adequate household incomes and access to economic resources (4.5 percent of the population).

Isolated Seniors → Isolated seniors with high disability rates and relatively low incomes (0.6 percent of the population).

EXTREMELY VULNERABLE AMERICA captures four community profiles that include 3.5 percent of the US population across 424 counties and form the profiles with the lowest levels of income.

Hispanic Southern Border → Counties mostly located along the US southern border with a majority of a relatively young Hispanic or Latino population living in extreme poverty (1.4 percent of the population).

Black South → Southern counties with the highest proportion of Black or African American population and lowest median household income of all profiles (1.3 percent of the population).

White Appalachia → White communities in Appalachia with the third-highest level of unemployment rates and second-lowest household income of all profiles (0.7 percent of the US population).

American Indian Reservations → American Indian Reservation communities living in extreme poverty, with more than one-third of the population with income below the poverty line (0.1 percent of the population).

NONCONTIGUOUS AMERICA captures two community profiles that include 0.42 percent of the US population across 34 counties, combining all Hawaiian and nine Alaskan counties.

Hawaii → The Aloha State with high racial and ethnic diversity, high income, and relatively low income inequality (0.4 percent of the population).

Native Alaska → Alaskan communities with large economic gaps between the White and Alaska Native populations (0.02 percent of the population).

INTRODUCTION

Black Lives Matter and other social justice movements have increased the general awareness of the diversity of the US population and the need for societal changes. Diversity awareness is becoming an essential element of many policy efforts, from access to health care and financial inclusion to initiatives addressing systemic racism and inequities. Yet most of these discussions and initiatives overlook the complexity of diversity in the United States. Instead, they focus on a few essential dimensions, such as race and ethnicity, gender, and age.

Such simplification is necessary to bring attention to the urgency of changes. However, identifying the changes and related actionable solutions requires a more refined understanding of the challenges. This starts with a granular understanding of a population's characteristics, allowing tailored and more effective policies and initiatives to be designed.

While data on the multidimensionality of US diversity exists, the challenge stands in making sense of it. How can we account for race and ethnicity, gender, age, income, education, and other relevant dimensions while presenting the data in a format suited to inform decision-making?

With the Community Explorer, we synthesize the information related to the different dimensions of US diversity into a few communities. Using the Census Bureau's American Community Survey (ACS) data, we apply machine-learning techniques to identify population-characteristic patterns across the 3,142 counties.[2] The county location is not part of the dimensions considered, which allows for identifying similarities across counties, regardless of their proximity. As a result, each community has a distinctive profile that combines demographic, economic, and many other behavioral determinants while not being geographically bounded.

We first presented this novel approach in *The Community Explorer: Informing Policy with County-Level Data*. Using 26 behavioral, economic, and social factors, we sorted the 3,142 US counties into eight community profiles, each grouping counties that share a combination of behavioral determinants while not being geographically bounded.

In this report, we extend the number of dimensions considered to 751 variables for the 3,142 counties. The extra 725 variables add tremendous granularity to the analysis, resulting in 17 community profiles that emerge from the data. The Community Explorer dashboard provides the location of these profiles, allowing for targeted deployment of community interventions and, more broadly, increasing the understanding of socioeconomic gaps withing the US. We have identified four main benefits of our approach:

- **Lets the data speak:** We use an agnostic approach to recognize the interactions among a wide range of factors at the county level. The resulting profiles provide an objective snapshot of how communities can be described based on the Census data, without imposing any assumptions or restrictions.
- **Leverages the data granularity when aggregating its information:** Our approach uses the county dimension as the aggregation unit, not as a geographic restriction. As a result, communities are defined by the core characteristics of their population. In contrast, most analyses either impose a geographic dimension and pool the data at the state or regional level, or ignore it by pooling the information at the national level.

- **Allows for peer-counties comparison and insightful benchmarking:** Counties in each profile have more in common, based on the variables considered, than with the rest of the US or the other profiles. As a result, comparing the performance of two counties within the same profile or using the profile average as a benchmark, in addition to the state and the national levels, provides new insights toward actionable solutions.
- **Performs as a great visualization tool:** The Community Explorer dashboard provides an interactive map with the location of the profiles and graphs, with additional statistics for the US, the profiles, and each county. This allows users to explore visually and download information on the profiles, and to compare county-level data to the averages for each county's profile and for the US.

DATA

We used the US Census Bureau's ACS five-year data, which pools 2015-2019 yearly estimates including all US counties, to ensure equally reliable information for the 3,142 counties in this report.

We obtained two types of information from the 2015-2019 data: the most frequently requested social, economic, housing, and demographic characteristics,[3] and additional microlevel information such as means of transportation to work, educational attainment, bachelor's degree field, disability characteristics, median income, employment status, characteristics of health insurance coverage, types of computers and internet subscriptions, among much else.[4] The combined data included 4,017 variables; we used the 751 variables pertinent to our analysis for the population profiles.[5]

METHOD

We synthesized the information from 751 variables across 3,142 counties into a few communities. The number of communities was defined endogenously from the following two-step approach, which relies on machine-learning techniques: First, we dealt with the variables that did not add new information, ultimately reducing the number of variables, then we clustered the counties with similar characteristics.

VARIABLE REDUCTION

We identified the variables that were correlated or that implicitly contained the same information. Not controlling for that double counting would have put too much emphasis on those dimensions and misled the clustering outcome.

We determined the variables essential to our analysis based on the degree of their redundancy or irrelevance. First, we used a density-based spatial clustering algorithm of applications with noise (DBSCAN) to pinpoint highly correlated variables (Ester et al., 1996). DBSCAN enables the clustering of variables while preventing the outliers from influencing the main clusters' profiles. For our analysis, we kept the outliers as variables, as they were poorly correlated with one another.[6] Second, on the basis of the clusters found by DBSCAN, we addressed highly correlated variables in a cluster in one of the following three possible ways:

- Remove apparent redundancy. For example, several variables in different tables represent household/family income statistics: per capita income, mean family income, median household income, and so on. We used only median household income for our analysis.
- Combine if the details are not critical. For example, percentages of households with income less than $10,000, $10,000-$14,999, and $15,000-$24,999 are highly correlated. The same is true for percentages of households with incomes of $150,000-$199,999 and $200,000 or more. We combined the highly correlated ranges and generated two new variables: the percentages of households with incomes less than $25,000 and those with $150,000 or more.
- Keep if each of the correlated variables still gives specific information. For example, the percentage of the Hispanic or Latino population in a county is significantly correlated with overall English fluency (a -0.82 correlation coefficient) and the population speaking a language other than English at home (a 0.9 correlation). Unemployment rate, poverty rate, disability, population percentage without a high school diploma, lack of digital access, and portion of single female parents are highly correlated. Likewise, higher educational attainment is correlated with the prevalence of lucrative industries, such as finance and information, and high-income households. Despite the high correlations between these variables, all provide valuable and distinct information. Therefore, we kept them all to develop more granular county profiles.

Using one of the above methods, we reduced 751 variables to 199 while effectively retaining all necessary information. Table 1 summarizes the variables used, sorting them under 11 main categories.[7]

TABLE 1: LIST OF VARIABLES

Category	Variables (#)	Variables (Descriptions)
Demographic	10	Sex ratio, Median age, Race (White, Black or African American, American Indian and Alaska Native, Asian, Native Hawaiian and Other Pacific Islander, Some other race, Two or more races, and Hispanic or Latino).
Social	5	Civilian veterans, Foreign-born population, Non-US citizens, Language at home: not English; English fluency: not very high.
Income	26	Income distribution (less than $25,000, $25,000-$34,999, $35,000-$49,999, $50,000-$74,999, $75,000-$99,999, $100,000-$149,999, $150,000 or more), Median household income, Receiving Food Stamps/SNAP benefits, Income below the poverty level (family and individuals), Median Income by race (White, Black or African American, Asian, Two or more races, Hispanic or Latino, White), Median Income by age (15 to 24 years, 25 to 44 years, 45 to 64 years, 65+), Median Income: single male and female parents, Gini index, Gender wage gap, Racial income gap.
Employment Status	22	Armed forces, Unemployment rate, Unemployment rate by race (White, Black or African American, Asian, Two or more races, Hispanic or Latino, White), Unemployed male and female, Unemployed: below/above poverty, Unemployment with a disability, Unemployment by education (less than high school, high school, college/associate's, bachelor's), Unemployment by age (less than 25, 25-64, 65+), Unemployment: racial difference.
Housing	24	Residence one year ago: same/different/abroad, vacant housing units, homeowner vacancy rate, rental vacancy rate, owner-occupied, renter-occupied, no vehicles available, lacking complete plumbing facilities, lacking complete kitchen facilities, no telephone service available, housing costs (SMOCAPI with a mortgage <20%, 20-30%, 30-35%, over 35%, SMOCAPI without a mortgage <10%, 10-30%, 30-35%, over 35%, GRAPI <15%, 15-30%, 30-35%, over 35%).
Employment Sectors	22	Five occupation types and 13 different employment industries categorized by the US Census Bureau (see endnote 9 for more details), profile of workers (private wage and salary workers, government workers, self-employed, unpaid family workers).
Education	28	Educational attainments (less than 9th grade, 9th to 12th grade, no diploma, high school graduate, some college, no degree, associate's degree, bachelor's degree, graduate or professional degree), median earnings by education level (less than high school graduate, high school graduate, college/associate's, bachelor's, graduate/professional), bachelor's or higher by race (White, Black, Asian, two or more races, Hispanic or Latino), poverty rate by education (less than high school, high school graduate, college/associate's, bachelor's or higher), Field of bachelor's degree: science and engineering, science and engineering related, business, education, arts, humanities and others, racial gap for higher education.
Household Type	17	Population, married-couple family, cohabiting couple, single male and female, single male and female parent, male and female householders living alone, senior male and female householders living alone, households with residents under 18 years, households with residents aged 65+, grandparents responsible for grandchildren, school enrollment: elementary school (1-8), high school (9-12), college or graduate school.
Health Insurance/ Disability	22	With health insurance, disability by race (White, Black, Asian, two or more races, Hispanic or Latino), disability type (hearing, vision, cognitive, ambulatory, self-care, independent living difficulty), uninsured seniors (65+), uninsured people with a disability, uninsured and unemployed, disability by age (under 18, 18-64 years, 65+), racial gap by health insurance.
Digital Access	17	With a computer, with a broadband internet subscription, no internet with a computer, no internet by age (under 18 years, 18 to 64 years, 65+), no internet by education (less than high school, high school, bachelor's or higher), no internet unemployed, no computer by age (under 18 years, 18 to 64 years, 65+), no computer unemployed, no internet: racial gap, no computer: racial gap.
Commuting	6	Commuting (drive alone, carpool, public transportation, walk), work from home, mean travel time to work (minutes).

Notes: Variables (#) shows how many variables are in a category. SMOCAPI = selected monthly owner costs as a percentage of household income. GRAPI = gross rent as a percentage of household income.

Source: Milken Institute (2022)

CLUSTERING OF COUNTIES

We used the *k*-means clustering algorithm, which partitions data into '*k*'-mutually exclusive clusters (Lloyd, 1982) to group the counties using information from the 199 variables. While this method is one of the most popular machine-learning algorithms, it (like any statistical method) involves several drawbacks and assumptions. We tackled three relevant limitations of this method by adjusting the algorithm and transforming the data.

- **Data-specific number of clusters:** The *k*-means method entails a predetermined number of clusters *k*. The wrong choice of *k* could yield poor clustering results. We let the data dictate *k* by comparing the clustering solutions for different values of *k* ranging from 2 to 50, based on four widely used clustering evaluation metrics: silhouette values, gap statistics, the Caliński-Harabasz index (also known as the variance ratio criterion), and the Davies-Bouldin index (Rousseeuw 1987; Tibshirani, Walther, and Hastie 2001; Caliński and Harabasz 1974; Davies and Bouldin 1979). The four methods use different algorithms to approximate scores indicating the quality of clusters, and compensate for one another's pitfalls. We chose the best-performing *k* over the four evaluation algorithms.
- **Clusters robust to initial data points:** The *k*-means method begins the clustering process by using a randomly selected set of initial values and finds a solution, thereby offering the possibility of converging to a local minimum solution. To mitigate dependence on the initial values, we repeated the clustering process with 30,000 different, randomly selected initial values and chose the best results.
- **Data standardization:** The *k*-clustering method uses distance-based measurements to determine the similarity between data points; it is sensitive to large numbers and variables with large variance. To deal with this, we standardized the data such that the variables ranged from 0 to 100, and rescaled them according to their standard deviations to ensure a unit variance.

Finally, given the nature of the datasets, a few variables are missing in some counties. For example, in a county without any Asian population, the median income for Asians is missing. Replacing missing values with manipulated values is likely to create unintended bias. Therefore, we modified the distance function to calculate a distance based only on a complete set of variables. Specifically, for a county lacking an Asian population, a distance metric measures the distance from this county to others without considering Asians' median income, even if the other counties have that value.

SEVENTEEN COMMUNITY PROFILES IN THE US

The machine-learning clustering algorithm identifies 17 communities with a distinctive profile that combines demographic, economic, and many other behavioral determinants while not being geographically bounded.

Table 2 summarizes population density, the number of counties, and the average county-level population for each profile. The online appendix further discusses the outstanding features of each profile.

TABLE 2: CLUSTERING RESULT

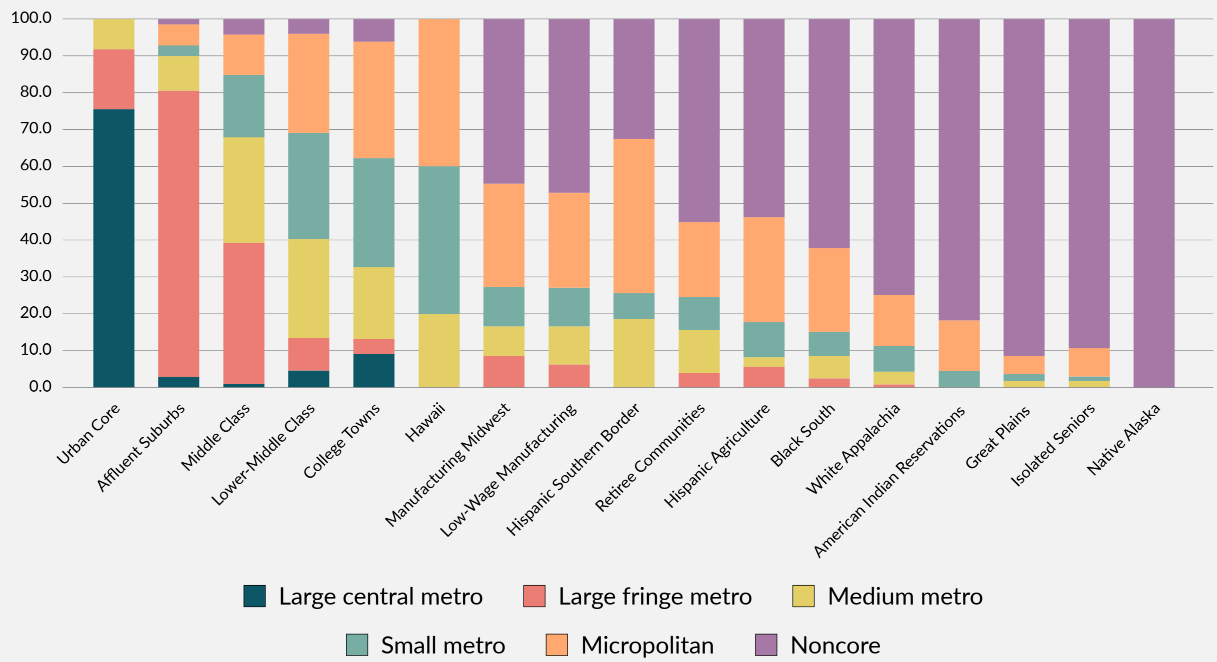
Profile	Population (%)	Number of Counties	Average Population for Counties (thousands)	Group
Urban Core	25.9	49	1,719	Urban America
Lower-Middle Class	18.2	320	185	Urban America
Affluent Suburbs	16.1	139	375	Urban America
Middle Class	13.8	311	144	Urban America
College Towns	5.4	98	178	Industry-Driven America
Manufacturing Midwest	5.2	506	33	Industry-Driven America
Low-Wage Manufacturing	4.9	524	30	Industry-Driven America
Retiree Communities	4.5	256	56	Graying America
Hispanic Southern Border	1.4	43	103	Extremely Vulnerable America
Black South	1.3	198	21	Extremely Vulnerable America
Hispanic Agriculture	1.2	158	25	Industry-Driven America
White Appalachia	0.7	115	20	Extremely Vulnerable America
Isolated Seniors	0.6	168	12	Graying America
Hawaii	0.4	5	284	Noncontiguous America
The Great Plains	0.3	221	4	Industry-Driven America
American Indian Reservations	0.1	22	18	Extremely Vulnerable America
Native Alaska	0.02	9	8	Noncontiguous America

Notes: The table shows population density by profile, the number of counties clustered in each profile, and an average of the county-level population. Different color themes of the shades categorize profile by group.

Source: Milken Institute (2022)

BOX 1. HOW URBAN OR RURAL ARE THE PROFILES?

PERCENTAGE OF URBAN, SUBURBAN, AND RURAL COUNTIES PER PROFILE



We used the National Center for Health Statistics' Urban-Rural Classification Scheme to assess each profile's urban profile, using the six classifications of Ingram and Franco (2014):

1. Large central metro counties—Counties in a metropolitan statistical area (MSA) of 1 million population that (1) contain the entire population of the largest principal city of the MSA, or (2) are entirely contained within the largest principal city of the MSA, or (3) contain at least 250,000 residents of any principal city in the MSA.
2. Large fringe metro—Counties in MSAs of 1 million or more population that do not qualify as large central metro counties.
3. Medium metro—Counties in MSAs with populations of 250,000 to 999,999.
4. Small metro—Counties in MSAs with populations less than 250,000.
5. Micropolitan—Counties in micropolitan statistical areas. Each micropolitan statistical area must have at least one urban cluster of at least 10,000 but less than 50,000 population.
6. Noncore—Nonmetropolitan counties that do not qualify as micropolitan. The Noncore can be thought of as most rural areas.

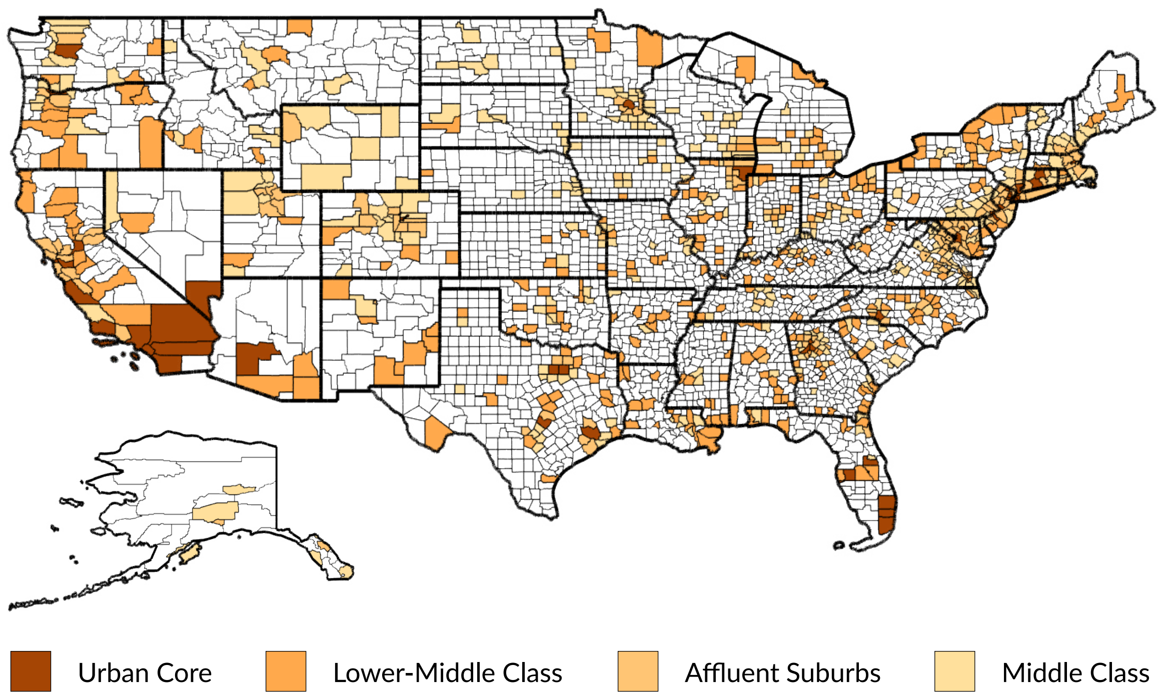
Parker et al. (2018) sort these six categories into three main groups: Urban Core counties as the 53 US metropolitan areas including 68 counties in Large central metro; Suburban and Small metro counties as 1,098 counties in Large fringe metro, Medium metro, and Small metro; and Rural counties as 1,976 counties in Micropolitan and Noncore.

Source: Milken Institute (2022) and the National Center for Health Statistics' Urban-Rural Classification Scheme (2014)

URBAN AMERICA

Two-thirds of the American population live in the Urban Core and the surrounding metropolitan counties. As shown in Box 1, the Urban Core profile groups the largest central metro counties while the Affluent Suburbs profile comprises the large fringe metro counties. The Middle Class profile is a mix of large to medium metro counties, whereas the Lower-Middle Class profile predominantly comprises medium and small metro and micropolitan counties.

FIGURE 1: MAP OF URBAN AMERICA



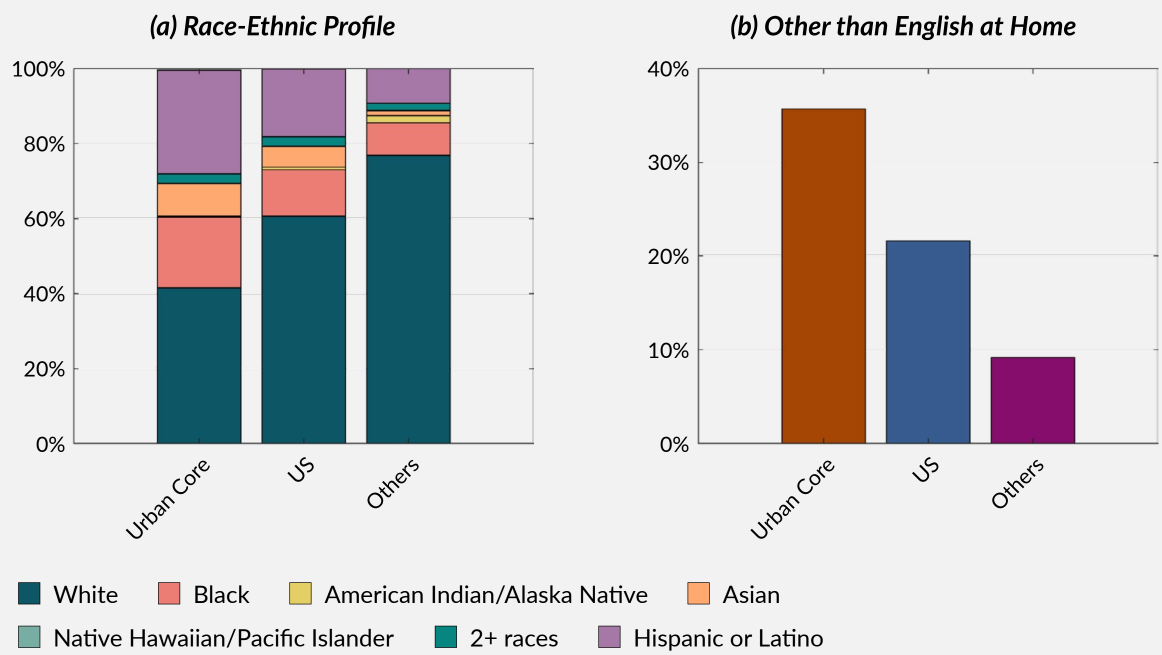
Source: Milken Institute (2022)

URBAN CORE: LARGE METROPOLITAN AREAS

Accounting for the 49 most populous counties and home to 25.9 percent of the population, the Urban Core is one of the most racially and linguistically diverse profiles, with the highest proportion of foreign-born population. Its population is more educated than the rest of the US, with the exception of Hispanics and Latinos. Yet higher education mostly benefits the White population, with Whites being the only racial or ethnic group earning a significantly higher income than the national average for their racial or ethnic category, and more than the other racial or ethnic groups in this profile. The Urban Core's higher-paying jobs also coincide with higher housing costs, more renter-occupied units, and better digital access than most profiles.

The Urban Core's racial and linguistic diversity is a key factor of differentiation from the rest of the US. Only 41.5 percent of the Urban-Core's population is White, which is 19 percentage points less than the nationwide average and 35 percentage points less than the average of counties in the other profiles (see Figure 2[a]). In contrast, the proportions of Asian, Hispanic or Latino, and Black or African American populations in the Urban Core are markedly larger than the other profiles' averages. Figure 2(b) shows the linguistic diversity of the Urban Core: 35.7 percent of the population uses a language other than English at home, which is 14 percentage points more than the national average and 26.5 percentage points more than the average for counties in the other profiles. Furthermore, 14.8 percent of people in this profile report they speak English less than very well, which is 11.6 percentage points more than in the other profiles.

FIGURE 2: RACE-ETHNICITY AND LINGUISTIC DIVERSITY IN THE URBAN CORE

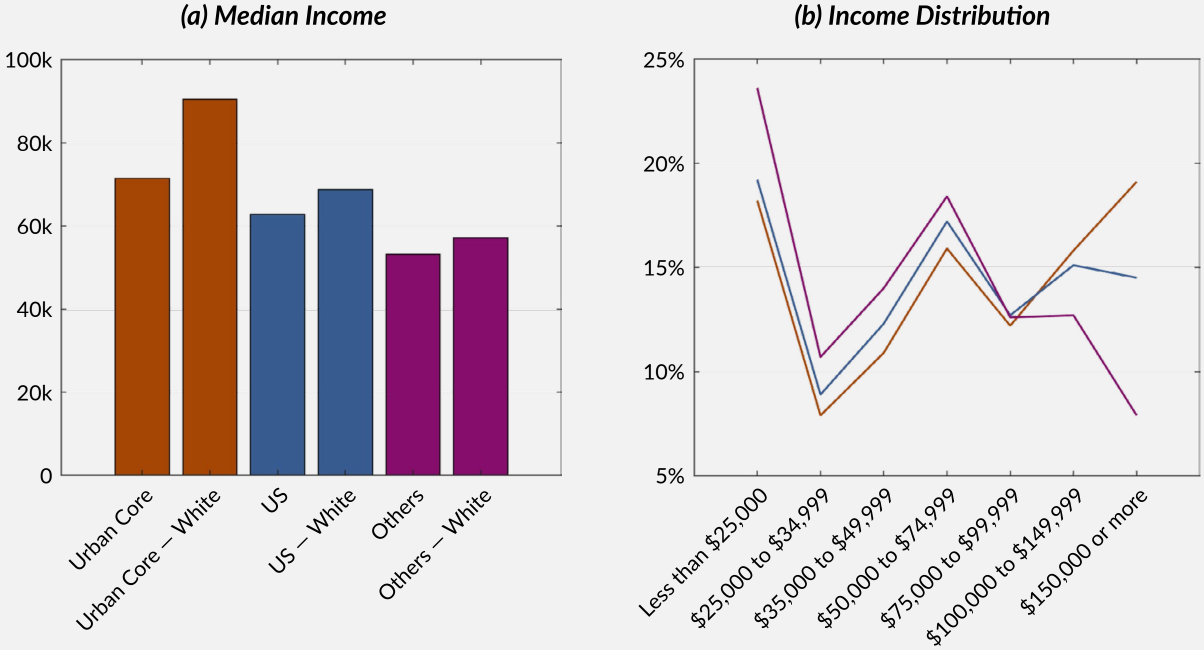


Notes: Panel (a) shows the racial and ethnic profile for the Urban Core, the US, and the average of the counties in all profiles excluding the Urban Core. The percentage counts members of a race-ethnicity who do not identify as Hispanic or Latino to arrive at a total of 100 percent. Panel (b) indicates the percentage of the population that uses a language other than English at home.

Source: Milken Institute (2022)

The economic advantages of the Urban Core areas mainly benefit the highly educated White population. Figures 3(a) and (b) show that the White population's income drives the overall higher income in the Urban Core. At $90,540, the White population's income is the third-largest across all profiles, falling below only the Affluent Suburbs ($98,659) and the White minority in Native Alaska ($100,900) profiles. Most (51.6 percent) of the White population in the Urban Core has a bachelor's degree or higher, and (as discussed later) this higher-than-average education is correlated with the higher income for this population.

FIGURE 3: INCOME AND INCOME DISTRIBUTION IN THE URBAN CORE

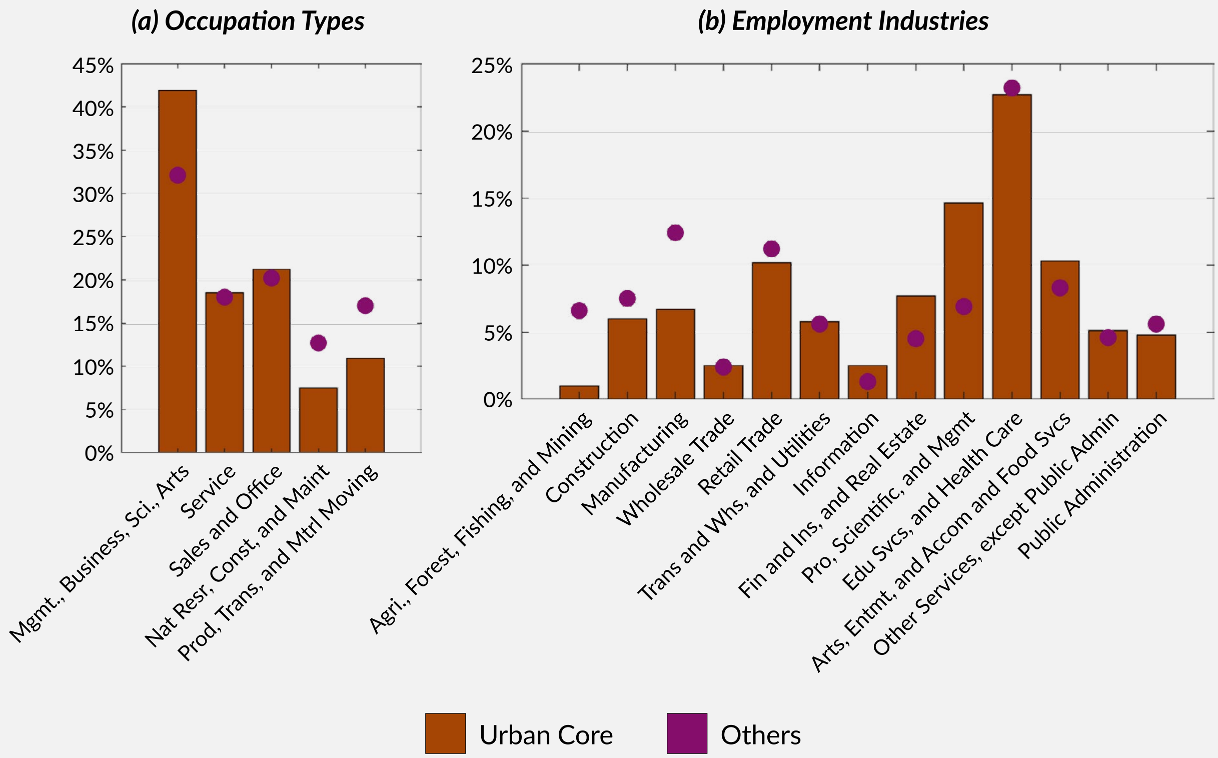


Notes: Panel (a) shows the median income of the Urban Core, the US, and the average of the counties in all profiles excluding the Urban Core. The category "White" shows the median incomes for the White population. Panel (b) reports the population percentages of the Urban Core, the US, and other profiles for each income bracket. The corresponding colors for bars and lines report information for the same group.

Source: Milken Institute (2022)

These counties offer more jobs in high-paying industries. Among all profiles, the Urban Core has the second-largest (after the Affluent Suburbs) portion of employment in white-collar jobs.[8] This is especially true for Management, Business, Science, and Arts jobs (see Figure 4[a]). These jobs are more concentrated in the top three best-paying industries: Professional, Scientific & Management, and Administrative & Waste Management Services; Information; Finance & Insurance, and Real Estate, Rental & Leasing (see Figure 4[b] and Table 3).

FIGURE 4: JOBS AND EMPLOYMENT INDUSTRY IN THE URBAN CORE[9]



Notes: Panel (a) shows percentages of the population per job category in the Urban Core and Others (all profiles excluding the Urban Core). Panel (b) indicates employment per type of industry in the Urban Core and Others.

Source: Milken Institute (2022)

TABLE 3: AVERAGE SALARY BY INDUSTRY

Industry Sector	Average Wage
Agriculture, Forestry, Fishing and Hunting, and Mining	$54,998
Arts, Entertainment & Recreation and Accommodation & Food Services	$26,814
Construction	$54,951
Educational Services, Health Care & Social Assistance	$52,666
Finance & Insurance, and Real Estate, Rental & Leasing	*$84,499*
Information	*$79,359*
Manufacturing	$64,861
Other Services, except Public Administration	$38,552
Professional, Scientific & Management, and Administrative & Waste Management Services	*$75,119*
Public Administration	$66,232
Retail Trade	$37,040
Transportation & Warehousing, and Utilities	$56,463
Wholesale Trade	$66,275

Notes: National average salary for 13 industries in 2019. The top three best-paying industries are italicized.

Source: American Community Survey Public Use Microdata Sample 5-Year Estimate (2019)

The Urban Core has more college graduates than the rest of the US, and they are better compensated for their degrees. However, they also face some of the highest costs of living. Table 4 highlights the higher (relative to other profiles) educational attainments for all races and ethnicities except Hispanics and Latinos in the Urban Core and the gains in income resulting from these post-secondary degrees. It also shows that housing in the Urban Core relies more on renter-occupied units than in the rest of the US, and the related costs are noticeably higher.

The Urban Core has one of the best digital access rates, one of the lowest disability rates, and the longest commutes of all profiles. It has the second-highest rate of access to computers and broadband internet subscriptions and the second-lowest percentage of people with disabilities, all after the Affluent Suburbs.

TABLE 4: EDUCATION, HOUSING, AND INFRASTRUCTURES IN THE URBAN CORE

Category	Variable	Urban Core	*US*	*Other Profiles*
Education	White with bachelor's or higher (%)	51.6***	*35.8*	*24*
	Black or African American with bachelor's or higher (%)	24.7**	*21.6*	*15.2*
	Asian with bachelor's or higher (%)	56.1**	*54.3*	*41.1*
	Hispanic or Latino with bachelor's or higher (%)	19.5	*16.4*	*14.3*
	Median earnings for college/associate's ($)	39,309**	*37,471*	*34,730*
	Median earnings for bachelor's ($)	60,272**	*54,925*	*46,474*
	Median earnings for graduate/professional ($)	80,514**	*74,253*	*58,461*
Housing	Owner-occupied (%)	52.7***	*64*	*71.9*
	Renter-occupied (%)	47.3***	*36*	*28.1*
	SMOCAPI with a mortgage 35% or over (%)	26.2**	*20.9*	*19.1*
	SMOCAPI without a mortgage 35% or over (%)	14.4**	*10.6*	*9*
	GRAPI 35% or over (%)	42.6**	*40.5*	*34.7*
Disability, Computer/ Internet, Commuting	Disability (%)	10.6***	*12.6*	*16*
	With a computer (%)	91.9**	*90.3*	*85.3*
	With a broadband internet subscription (%)	84.7**	*82.7*	*75.3*
	Mean travel time to work (minutes)	30.7**	*26.9*	*23.7*

*Notes: The table compares the average of selected variables with the US average and other profile averages. Different race-ethnicity categories count members of a race-ethnicity who do not identify as Hispanic or Latino. SMOCAPI is an acronym for selected monthly owner costs as a percentage of household income. GRAPI denotes gross rent as a percentage of household income. The asterisks indicate that a profile average is statistically different from the US average (denoted as one asterisk, *), from the other profile average (**), and both (***). All values are shown as percentage of the population except the median earnings ($).*

Source: Milken Institute (2022)

US METROPOLITAN AREAS

These three profiles represent the higher, middle, and lower-middle classes living mostly in the suburban, medium, and small metropolitan areas of the US.

The Lower-Middle Class accounts for 320 counties, primarily in medium, small metropolitan, and micropolitan areas. Less populated and less wealthy than counties in the two other US metropolitan areas (Profiles 3 and 4), the Lower-Middle Class counties are home to 18 percent of the US population. While the overall demographic and housing characteristics of the Lower-Middle Class profile are similar to the national average, its median income is lower as there are fewer jobs in high-paying industries and fewer individuals with bachelor's degrees or higher.

Affluent Suburbs groups the 139 counties with the wealthiest neighborhoods of the large suburban and small metro counties that have at least 1 million residents. Home to 16 percent of the population, these counties are the most affluent in the US, concentrating the population with the highest median income and the highest proportion of university degrees. This population often consists of families who live in an owned house with one adult staying at home and one adult working a white-collar job in a high-paying industry. This profile also has the best digital and health insurance access and the lowest percentage of people with disabilities.

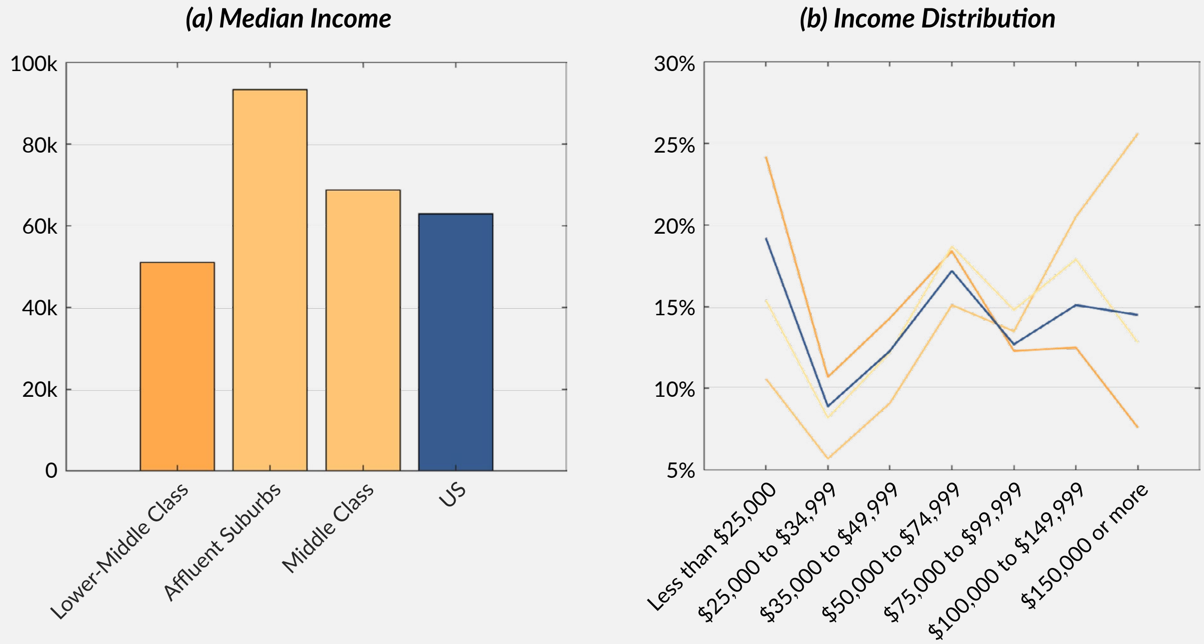
The Middle Class clusters the 311 least racially and ethnically diverse counties of the Urban America profiles. Primarily located in large- to medium-size suburban and small metro counties next to the other US metropolitan areas, they are home to 14 percent of the US population. The Middle Class profile's household income structure is similar to the national average, with lower poverty rates and lower income inequality. More people in this profile own their houses and are married than in the rest of the US.

Six variables explain the difference between these metropolitan profiles: income, jobs and employment industries, educational attainment, health insurance coverage, disability, and digital access.

These counties have levels of income that are at or around the national average. Figure 5 (a) shows that the median household incomes for the US metropolitan areas (Lower-Middle Class, Affluent Suburbs, and Middle Class) are below, above, and at the national median level, respectively. The Affluent Suburbs have the highest median income among all 17 profiles, at $30,447 more than the national median of $62,843.

The income distribution, reported in Figure 5(b), confirms that income distribution in the Affluent Suburbs is more concentrated in the range greater than $100,000. In contrast, the Lower-Middle Class counties have a greater percentage of households with an income of less than $50,000. The Middle Class counties have an income range similar to the national values.

FIGURE 5: INCOME AND INCOME DISTRIBUTION IN US METROPOLITAN AREAS



Notes: Similar colors for bars and lines report the same profile information. Panel (b) indicates what percentages of each profile's population have income falling into specified ranges. Line colors in (b) correspond to columns in (a).

Source: Milken Institute (2022)

Differences exist in employment and education levels across the US Metropolitan Areas. Table 5 shows variables related to education and employment (such as unemployment rates, employment industry and occupation, and educational attainment) for the US metropolitan areas.

The Affluent Suburbs have the lowest unemployment rate among these three profiles and have the highest percentage of Management, Business, Science, and Arts jobs among all 17 profiles. The top three best-paying industries—Professional, Scientific & Management, and Administrative & Waste Management Services; Information and Finance & Insurance; and Real Estate, Rental & Leasing—also occupy a larger share of the labor market in the Affluent Suburbs (Tables 3 and 5). People in this profile are highly educated, with the percentage of the population holding a bachelor's degree or higher at 12 percentage points above the national average.

The Lower-Middle Class profile has significantly fewer jobs in high-paying industries than the rest of the US. Compared to the national average, the Lower-Middle Class counties also have a lower education level, with a smaller proportion (by 8 percentage points) of the population having a bachelor's degree or higher. Finally, the Middle Class counties are the most similar to the national average, with none of the variables (except for one: lowest educational attainment) in Table 5 being statistically significantly different from the national averages, and all of them ranging between the values of the other US metropolitan areas (Lower-Middle Class and Affluent Suburbs).

TABLE 5: EMPLOYMENT AND EDUCATION IN US METROPOLITAN AREAS

Category	Variable	Lower-Middle Class	Affluent Suburbs	Middle Class	*US*
Employment	Unemployment Rate	6.2	3.9*	4.2	*5.3*
	Occupations: Management, Business, Science, Arts	33*	46.3*	37.1	*38.5*
	Industry: Information	1.4*	2.2	1.5	*2*
	Industry: Finance & Insurance, and Real Estate	4.9*	7.6	6	*6.6*
	Industry: Professional, Scientific, & Management	8.2*	14.4	9.3	*11.6*
Education	Less than 9th grade	4.2	3.1	2.9*	*5.1*
	9th to 12th grade, no diploma	8	4.1*	5.7	*6.9*
	High school graduate	31.3	21.3*	29.5	*27*
	Bachelor's degree	15.3*	26.7*	19.2	*19.8*
	Graduate or professional degree	8.9*	17.5	10.6	*12.4*
	White, not Hispanic or Latino, bachelor's or higher	27.1*	47.1*	31.3	*35.8*
	Field of bachelor's degree: Science and Engineering	29.9*	37.5	31.6	*35.1*
	Field of bachelor's degree: Education	17.7*	10.7	16.1	*12.2*

Notes: The table shows averages for selected variables that distinguish the US Metropolitan Areas profiles. The asterisk indicates that a profile average is statistically different from the US average. All values are in percentage of the population.

Source: Milken Institute (2022)

Differences also exist in health insurance, disability, and digital access. Similar patterns emerge from examination of the distributions of health insurance, disability, and computer access across the metropolitan areas (see Table 6). The fraction of people with disabilities is lowest in the Affluent Suburbs and highest in the Lower-Middle Class counties. Similarly, the ratio of households having access to computers, high-speed services, and health insurance is highest in the Affluent Suburbs and lowest in the Lower-Middle Class profile, illustrating the respective affluence (and lack thereof) of these profiles. Again, none of the statistics reported in Table 6 for the Middle Class profile are significantly different from the national averages, and all are within the range of the other US metropolitan profiles.

TABLE 6: HEALTH CARE AND DIGITAL ACCESS IN US METROPOLITAN AREAS

Category	Variable	Lower-Middle Class	Affluent Suburbs	Middle Class	*US Average*
Health	With health insurance	90.8	93.9	92.8	*91.2*
	Disability	15.6*	9.5*	12.4	*12.6*
Computer/ Internet	With a computer	87.9	94.5*	91.5	*90.3*
	With a broadband internet subscription	78.8	89.8*	84.1	*82.7*

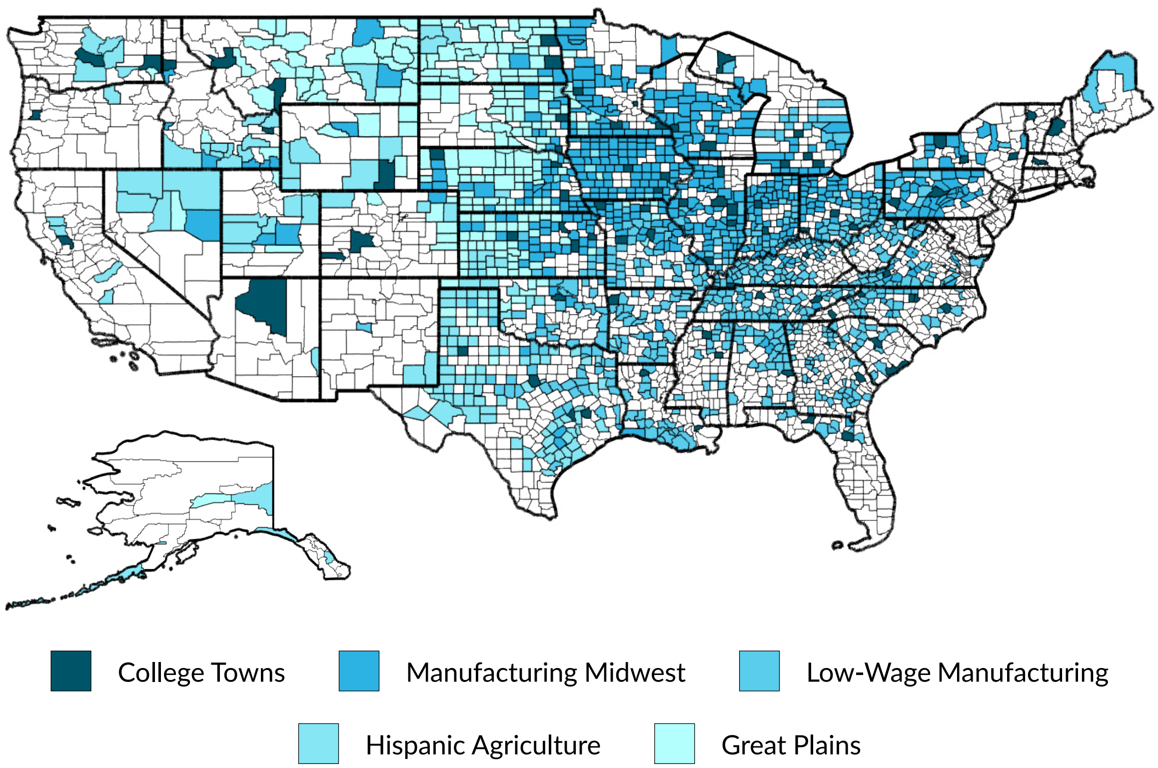
Notes: The table shows averages for selected variables that distinguish the US Metropolitan Areas profiles. The asterisk indicates that a profile average is statistically different from the US average. All values are shown as percentage of the population.

Source: Milken Institute (2022)

INDUSTRY-DRIVEN AMERICA

Figure 6 highlights the 1,507 counties, home to 17.6 percent of the US population, whose industrial concentration shapes their population profiles. Specifically, the occupations driving these profiles are education for College Towns, manufacturing for Manufacturing Midwest and Low-Wage Manufacturing, and agriculture for Hispanic Agriculture and the Great Plains.[10]

FIGURE 6: MAP OF INDUSTRY-DRIVEN AMERICA



Source: Milken Institute (2022)

College Towns groups 98 counties, 5.4 percent of the population, located mostly in suburban and metro areas that are home to the most sizable universities in the country. Almost one-third of the labor force in this profile works in the educational sector, representing the largest concentration of labor in a single employment sector in the US. Because of the large student populations, the residents of this profile are generally young; they often come from another county, state, or country; and their median household income is lower than the national median (significantly lower for Asians). This profile has the highest level of enrollment in post-secondary education and the second-highest educational attainments of all profiles. More of the population in this profile rents their houses than the US average.

Manufacturing Midwest includes 506 mostly Midwestern counties, 5.2 percent of the US population, that represent some of the least diverse areas, with Whites accounting for more than 91 percent of their population. Population in the Manufacturing Midwest is primarily employed in the manufacturing industries, specializing in transportation equipment (motor vehicles and parts, aerospace, and other transportation equipment) and machinery. Residents have more access to job-related benefits, such as health insurance, than the US average, while the levels of qualifications and resulting incomes are lower. These communities maintain low unemployment rates (especially for high school graduates), low housing costs, and less income inequality compared to the average for the country.

Low-Wage Manufacturing clusters 524 counties, 4.9 percent of the US population, with the second-highest concentration of manufacturing jobs after the Manufacturing Midwest (Profile 6). These communities are primarily located in the South with more challenging overall conditions, ranging from lower income and education levels to higher poverty rates and poorer access to digital infrastructure relative to other Industry-Driven America profiles.

Hispanic Agriculture groups 158 counties, 1.2 percent of the US population, that have the second-largest concentration of jobs in the Agriculture; Forestry, Fishing and Hunting; and Mining industries. These communities have a prominent Hispanic or Latino population, representing more than 30 percent of the population. They report below-average levels of education, health insurance coverage, and internet access compared to the US average.

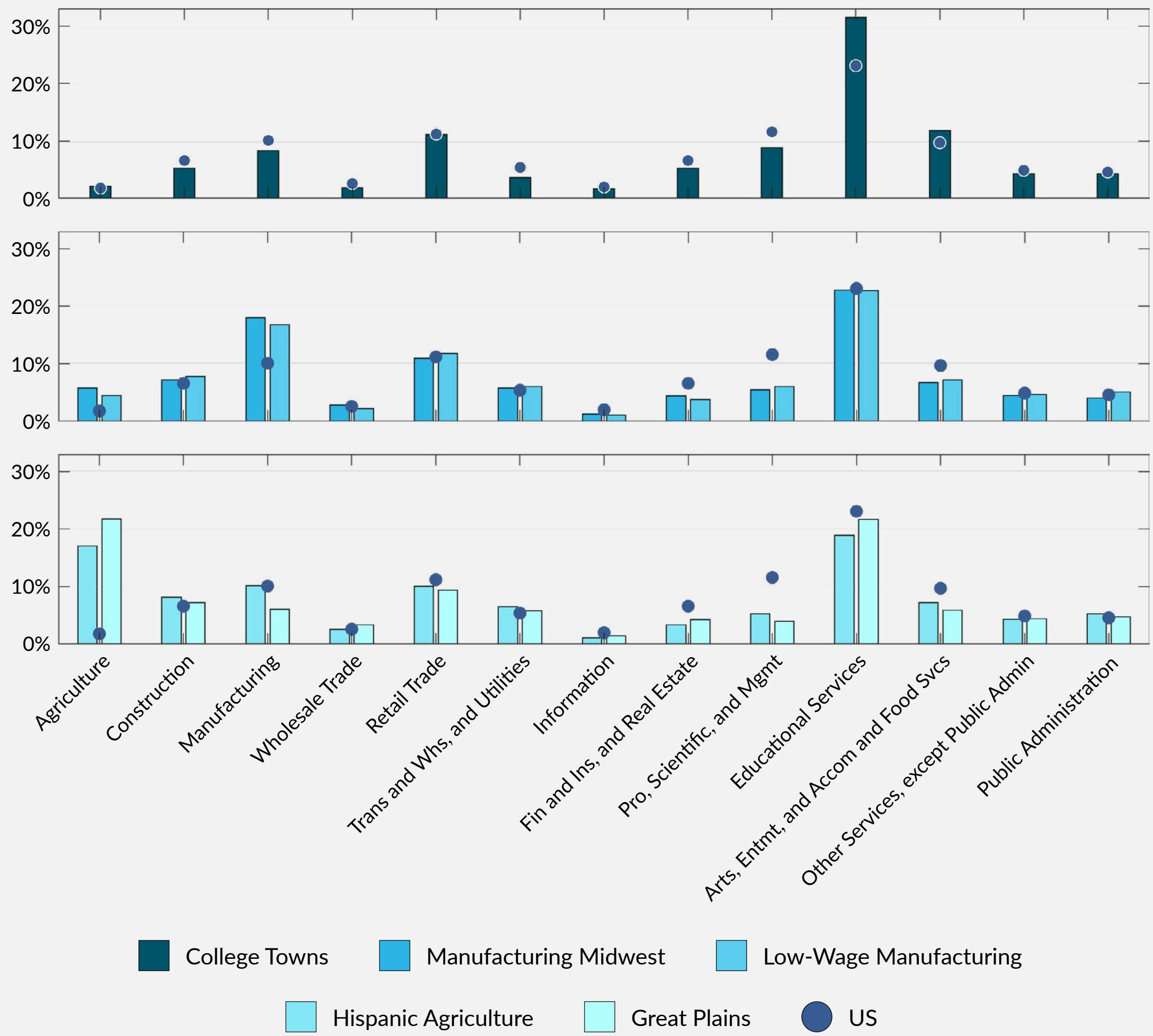
The Great Plains includes 221 counties, with 0.3 percent of the US population, that are rural and primarily located in the Great Plains. These communities have the highest concentration of jobs in wheat production (21.8 percent) and among the highest percentage of jobs in natural resources, construction, and maintenance (46.4 percent). With the second-largest concentration of White population (90.8 percent of the population), these communities have the lowest unemployment rate, the second-lowest ratio (after the Affluent Suburbs) of people receiving the Supplemental Nutrition and Assistance Program (SNAP), and the third-lowest poverty rate of all profiles.

Four variables represent the differences among these five Industry-Driven America profiles: employment industry, race/ethnicity, income, and education. These profiles are also offset by other social and digital components, such as the proportion of foreign-born population and access to a computer.

One industry stands out from the 13 employment industries defined by the US Census Bureau for each profile. Figure 7 summarizes the percentages of workers in a specific industry in each profile and compares them to the national average. As shown in the top panel, College Towns has sizable universities in the counties of the profile, with the highest percentage of the population (31.5 percent) working in education. The distribution of other industries is in line with the national one.

The second panel shows that approximately 18 percent of the population in the Manufacturing Midwest and 17 percent in the Low-Wage Manufacturing profiles work in manufacturing industries, the largest ratios among all profiles. These profiles have a relatively low ratio of workers in the professional, scientific, and management industries, with employment ratios in these industries about 6 percentage points below the national average. Finally, the bottom panel indicates that jobs in the Hispanic Agriculture and Great Plains profiles are concentrated in the agricultural industry.

FIGURE 7: EMPLOYMENT INDUSTRIES[9] IN INDUSTRY-DRIVEN AMERICA



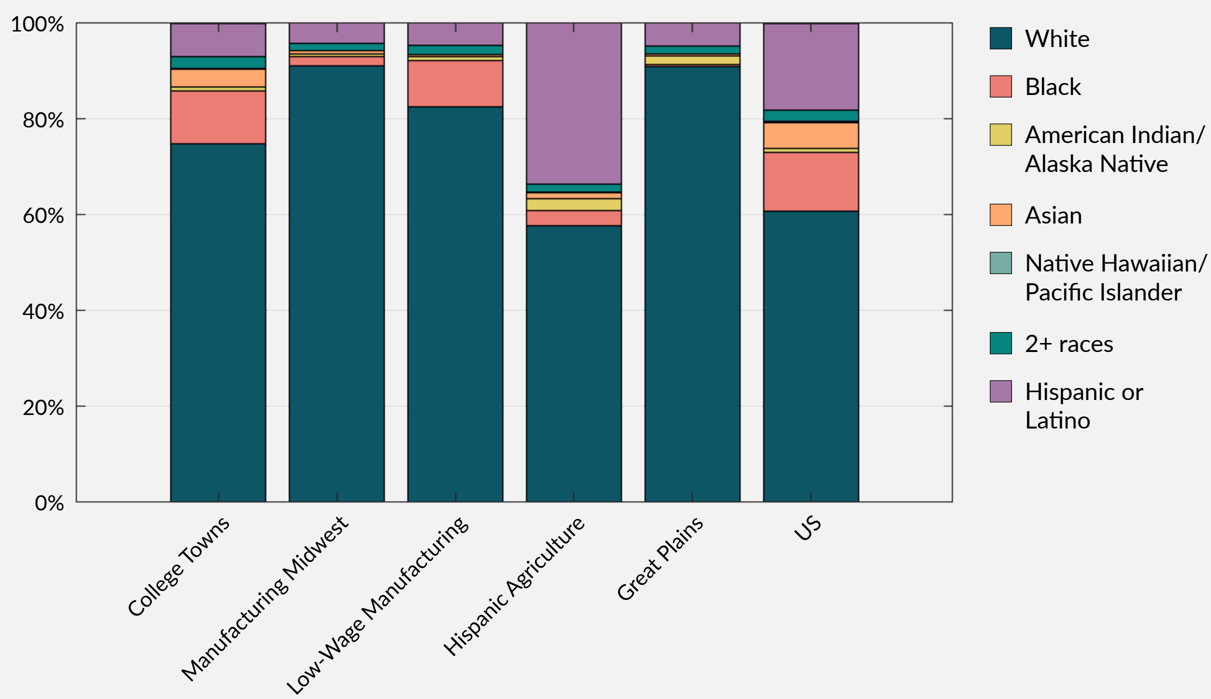
Notes: These figures show the types of industries that employ people in the Industry-Driven America profiles and the total population in the US. Bars denote percentages of adults who work for a specific industry. The 13 employment industries denote Agriculture; Construction; Manufacturing; Wholesale Trade; Retail Trade; Transportation and Warehousing, and Utilities; Information; Finance and Insurance, and Real Estate; Professional, Scientific, and Management; Educational Services; Arts, Entertainment, and Accommodation and Food Services; Other Services except Public Administration; and Public Administration.

Source: Milken Institute (2022)

The Industry-Driven America profiles demonstrate differences in race and ethnicity. Figure 8 shows the racial and ethnic differences across the profiles. Among the manufacturing-driven profiles, the Manufacturing Midwest has a large ratio of the White population (the highest of all profiles), while the Low-Wage Manufacturing profile, which encompasses the South, has a larger percentage of Black or African American population (relative to the Manufacturing Midwest profile). The ratio of Hispanic or Latino population is significantly lower in both profiles than in the US average.

Similarly, the population distribution strongly differs among the agricultural profiles. Communities in the Hispanic Agriculture profile have the second-largest Hispanic or Latino population ratio (33.6 percent) after the Hispanic Southern Border (73.2 percent). In contrast, communities in the Great Plains have the second-largest percentage of the White population (90.8 percent) after the Manufacturing Midwest (91 percent). The racial makeup of communities in the College Towns is similar to the national average, except for an 11 percentage points lower ratio of the Hispanic or Latino population and a higher proportion of the White population.

FIGURE 8: RACE-ETHNICITY IN INDUSTRY-DRIVEN AMERICA



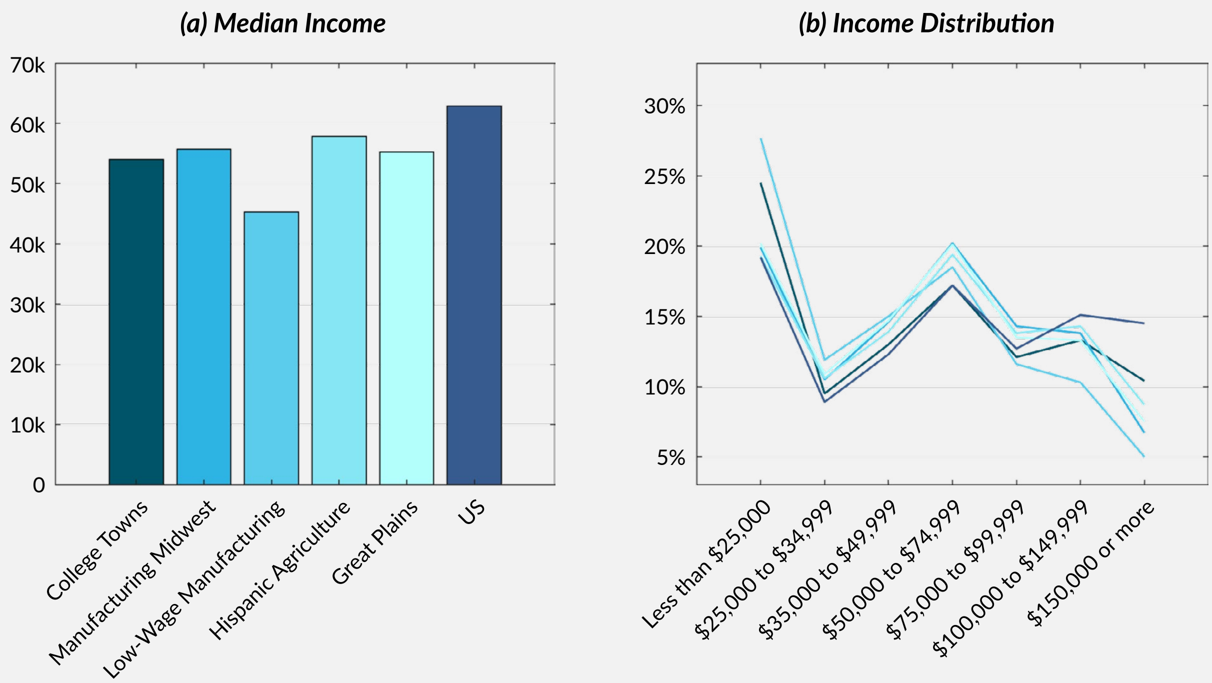
Notes: The percentage counts members of a race/ethnicity who do not identify as Hispanic or Latino in order to reach a total of 100 percent.

Source: Milken Institute (2022)

Differences also exist in income levels that correspond to the various industries that drive these profiles. The household median incomes for the College Towns, Hispanic Agriculture, and the Great Plains profiles in Figure 9(a) are in line with the average industry salaries reported in Table 3. The College Towns' median income is close to the $52,666 shown for Educational Services and Health Care & Social Assistance, and median incomes in the Great Plains and the Hispanic Agriculture profiles are close to the $54,998 for Agriculture; Forestry, Fishing and Hunting; and Mining.

Differences in manufacturing specializations lead to significantly different income levels for the Manufacturing Midwest and Low-Wage Manufacturing profiles, which also differ from the national average (Helper, Krueger, and Wial 2012). The average national salary reported in Table 3 ($64,861) accounts for high-technology manufacturing jobs in computers and electronics, which are not part of the Manufacturing Midwest and Low-Wage Manufacturing profiles. The Manufacturing Midwest specializes in the production of transportation equipment[11] and machinery, which results in a lower median income for this profile at $55,748, or $9,113 less than the national average for the manufacturing sector. Similarly, the Low-Wage Manufacturing profile has a median income of $45,249, or $17,594 lower than the national manufacturing average, reflecting its counties' specialization in low-wage manufacturing industries[12] and chemicals other than pharmaceuticals. Figure 9(b) confirms that the income distribution of the Low-Wage Manufacturing profile is more concentrated in the ranges below $50,000 and much less so in the ranges greater than $100,000 compared to the national distribution. This profile also has higher poverty rates compared to the other Industry-Driven America profiles and the rest of the country.

FIGURE 9: INCOME AND INCOME DISTRIBUTION IN INDUSTRY-DRIVEN AMERICA



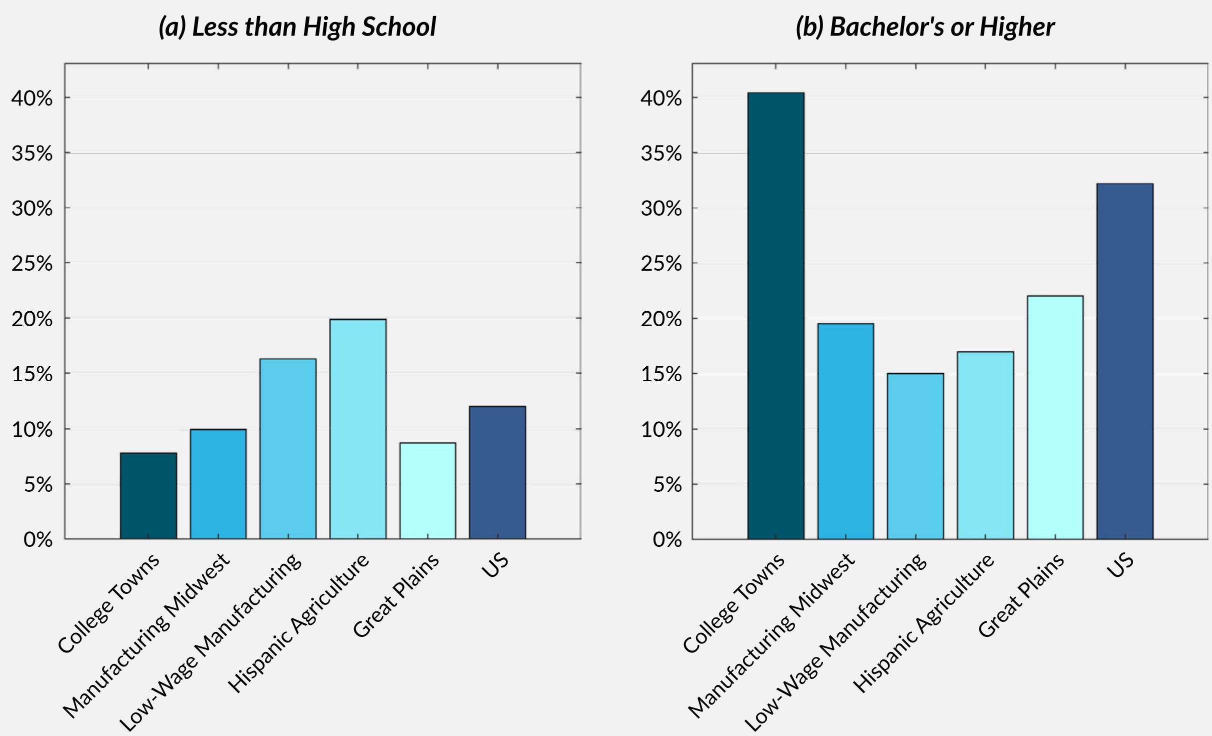
Notes: Panel (a) shows the median income of the Industry-Driven America profiles and the national median. Panel (b) indicates the percentages of the population in each profile that have income within specified ranges. Line colors in panel (b) match the columns in panel (a).

Source: Milken Institute (2022)

Levels of educational attainment differ across the Industry-Driven profiles. Figure 10 highlights the relatively high percentages of the population with a bachelor's degree or higher in College Towns, exceeding the national average. Yet the population with post-secondary degrees in College Towns is less compensated for its high education. The median income in this profile is $44,474 for bachelor's degree holders ($10,451 less than the national average) and $60,134 for graduate degree holders ($14,119 less than the national average).

The Manufacturing Midwest and Low-Wage Manufacturing profiles have relatively high ratios of the population whose highest degree is a high school diploma: 38.2 and 39.8 for the Manufacturing Midwest and Low-Wage Manufacturing, respectively, compared to 27.0 on average for the country. The Hispanic Agriculture profile, with a larger Hispanic or Latino population, has the lowest level of educational achievement among the Industry-Driven America profiles: Almost 20 percent of its residents do not have a high school diploma (8 percentage points more than the country average), and only 17 percent hold a bachelor's degree or higher (15 percentage points less than the national average).

FIGURE 10: EDUCATION IN INDUSTRY-DRIVEN AMERICA



Notes: Panel (a) shows ratios of the population who did not complete high school. Panel (b) indicates the fraction of people who hold a bachelor's degree or higher.

Source: Milken Institute (2022)

These profiles are distinguished by other noteworthy characteristics. The Hispanic Agriculture and College Towns profiles have the first and third-largest ratios among all profiles of foreign-born residents who are not US citizens. However, the College Towns frequently use English at home, with 89.3 percent of homes where English is usually spoken. This is much higher than the percentage of homes primarily using English in the Hispanic Agriculture profile (71.7 percent) and the national average (78.4 percent). Finally, all manufacturing and farming communities have limited digital access.

TABLE 7: OTHER CHARACTERISTICS OF INDUSTRY-DRIVEN AMERICA

Category	Variable	College Towns	Manuf. Midwest	Low-Wage Manuf.	Hispanic Agric.	Great Plains	*US*
Social	Foreign-born population, Not a US citizen	62.7*	52.5	56.5	67.8*	55	*50.4*
	Language at home not English	10.7*	4.8*	4.8*	28.3	5.4*	*21.6*
Household	Married-couple family	42.4	53*	50.9	55.5*	55.4*	*48.2*
Health	With health insurance	92.6	93.4	89.7	83.3*	91.8	*91.2*
	Disability	11.5	14.4	19.2*	13.2	14.1	*12.6*
Computer/ Internet	With a computer	91.7	86.1*	82*	87.1	85.6*	*90.3*
	With a broadband internet subscription	82.7	77.5*	70.7*	75.2*	75.6*	*82.7*

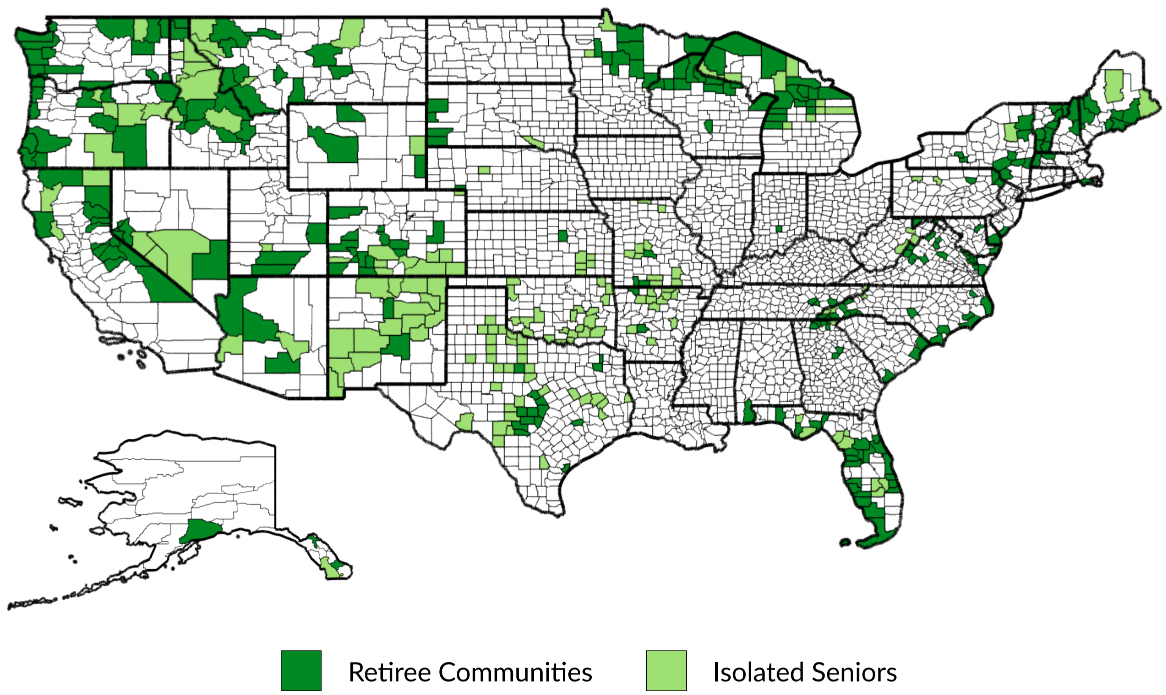
Notes: The asterisk indicates that a profile average is statistically different from the US average. All values are shown as percentage of the population.

Source: Milken Institute (2022)

GRAYING AMERICA

These 424 counties, home to 5.1 percent of the US population, have more than 40 percent of households with people aged 65 and older. The Retiree Communities and Isolated Seniors profiles group these graying communities based on income level and living conditions.

FIGURE 11: MAP OF GRAYING AMERICA



Source: Milken Institute (2022)

Retiree Communities includes 256 counties and 4.5 percent of the US population, where primarily White middle-income retiree communities drive part of the local economy. Among all profiles, these communities have the highest ratio of civilians who formerly served in the military. While the youngest and oldest residents in this profile (men and women ages 15 to 24 years and 65 years and older) have incomes in line with the US average for those age groups, the rest of its population (those 25 to 64 years old) is less well off.

Isolated Seniors consists of 168 counties with 0.6 percent of the US population (2 million people), including a large portion of older households with lower incomes than the rest of the US. These communities report lower levels of education and more low-skilled agricultural jobs compared with the national average. Older people (65 years and older) are more likely to live alone in this than in any other profile. At the same time, the percentage of people living with disabilities is the second-largest (after White Appalachia). Finally, access to digital infrastructure is a concern among the population living in the counties covered in the Isolated Seniors profile.

The Isolated Seniors segment has a higher percentage of rural counties (97 percent) than the Retiree Communities (75.4 percent). Income levels, disability rates, and the percentage of seniors living alone also differentiate these two profiles.

It's not all about Florida. Florida has long attracted retirees and has been one of the nation's grayest states, as Figure 11 confirms. However, our two profiles of Graying America tell more profound stories about retiree havens and pinpoint where the 65-plus population is actually retiring. Table 8 lists the counties with the largest percentage of residents ages 65 and above who comprise the Retiree Communities and Isolated Seniors profiles.

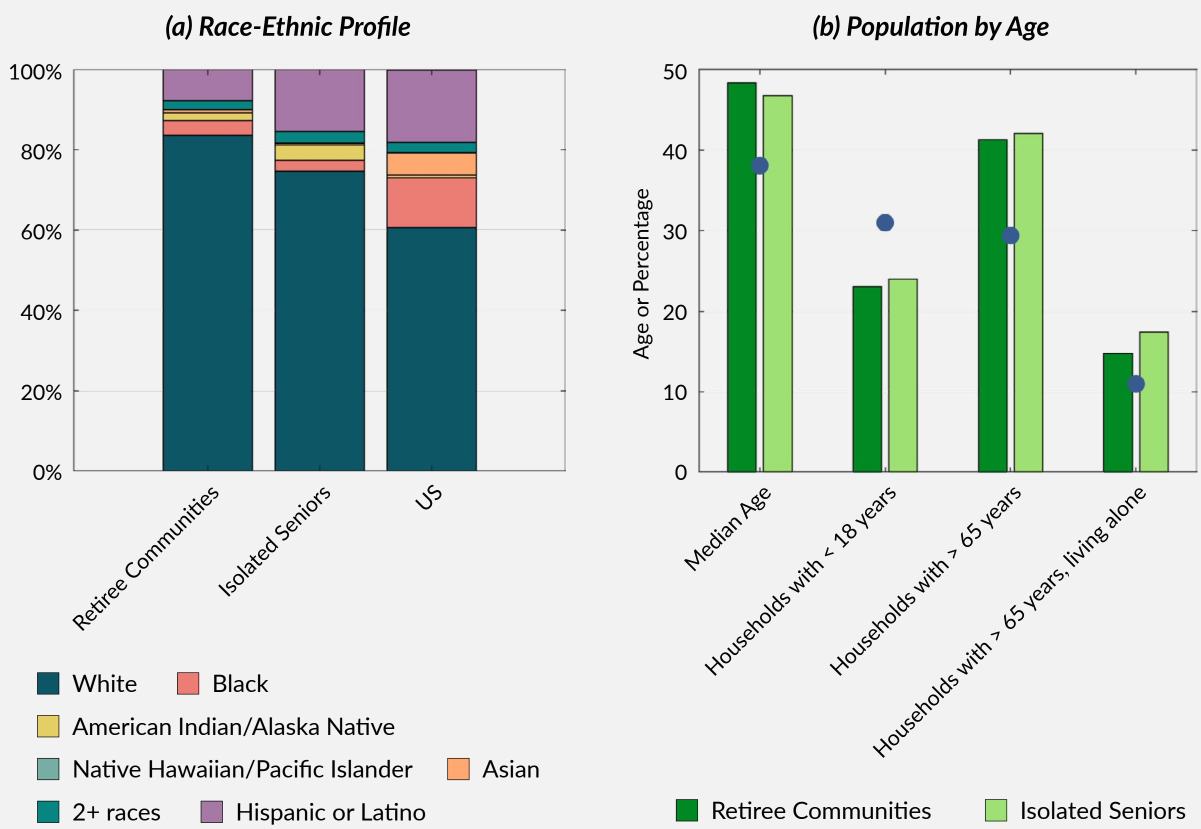
TABLE 8: COUNTIES WITH LARGEST PERCENTAGES OF POPULATION AGES 65+ IN GRAYING AMERICA

County	State	Total Population	Ages 65+ (%)	Profile
Sumter	FL	125,044	56.7	Retiree Communities
Charlotte	FL	181,067	39.6	Retiree Communities
Harding	NM	441	39	Isolated Seniors
Highland	VA	2,204	38.9	Retiree Communities
La Paz	AZ	20,793	38.6	Isolated Seniors
Catron	NM	3,526	37	Isolated Seniors
Northumberland	VA	12,190	36.7	Retiree Communities
Llano	TX	21,047	36.4	Retiree Communities
Citrus	FL	145,169	36.3	Retiree Communities
Lancaster	VA	10,724	36.2	Retiree Communities

Source: Milken Institute (2022)

Differences exist in race, ethnicity, and age distribution between the two Graying America profiles. Figure 12(a) shows that both profiles are predominantly White. Yet the Isolated Seniors profile has a higher percentage of the Hispanic and Latino population, leading to a relatively lower White representation (74.7 percent, compared to 83.6 percent for the Retiree Communities). The Retiree Communities and Isolated Seniors profiles also have the two oldest median ages at 46.8 and 48.4, respectively, which are more than seven years higher than the median age of the total US population. The high median age of these profiles impacts their entire age distributions: Versus the national averages, these profiles have at least 7 percentage points fewer households with residents 18 years and younger, and 12 percentage points more households with residents 65 years and older.

FIGURE 12: RACE-ETHNICITY AND AGE IN GRAYING AMERICA



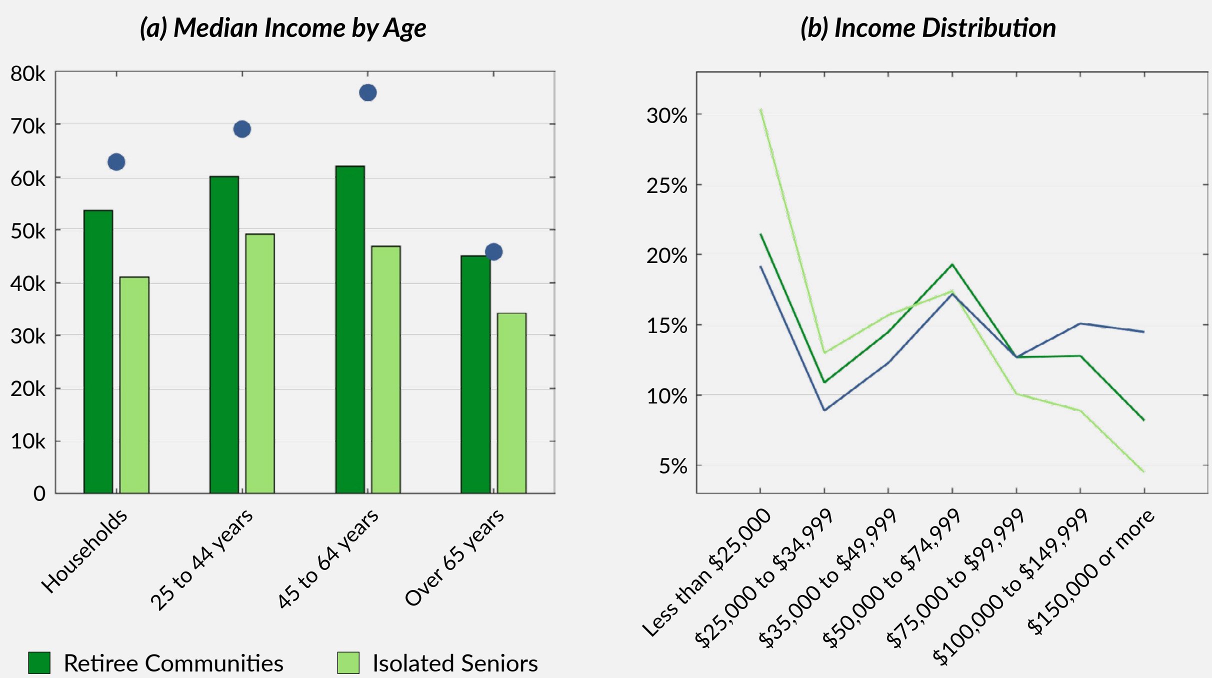
Notes: Panel (a) shows race-ethnicity for the Graying America profiles and the US. The percentage counts members of a race-ethnicity who do not identify as Hispanic or Latino, to achieve a total of 100 percent. Panel (b) indicates the median age and the ratio of households with residents aged <18 years or >65. It also denotes the percentage of households with seniors living alone.

Source: Milken Institute (2022)

Income differences also exist across these two profiles. Figure 13(a) indicates that the median income of the working-age group (ages 25 to 64) in the Retiree Communities is lower than the national average, whereas the median income for seniors ages 65 and older is in line with the national average. In contrast, the median household income in the Isolated Seniors profile is lower than the national median income for all age categories, with a higher concentration of incomes below the poverty line.

Figure 13(b) highlights the difference in income distributions between the two profiles: 30.4 percent of the Isolated Seniors households have an income below $25,000, which is 11 percentage points more than the national average and 9 percentage points more than the average of the Retiree Communities. The flipside of the same pattern emerges for the higher income range: 13.4 percent of the Isolated Seniors population has an income higher than $100,000, which is 16 percentage points less than the national average and 8 percentage points less than the average of the Retiree Communities.

FIGURE 13: DEMOGRAPHY AND INCOME IN GRAYING AMERICA



Notes: Panel (a) shows median household income overall and by age. Panel (b) indicates percentages of the population in each profile who have income within specified ranges. Line colors in (b) correspond to columns in (a).

Source: Milken Institute (2022)

More people are self-employed in these profiles. The Isolated Seniors profile has fewer private wage and salary workers than the Retiree Communities, as more government employees and self-employed workers reside in the counties within the Isolated Seniors profile. Both profiles have significantly fewer (relative to the national average) jobs in the top three high-paying industries: Information; Finance & Insurance and Real Estate, Rental & Leasing; Professional, Scientific & Management, and Administrative & Waste Management Services (see Tables 3 and 9).

Post-secondary degrees are less common and less rewarded than in the rest of the country. The Isolated Seniors profile has 8.6 percentage points fewer bachelor's degree holders and 6.9 percentage points fewer graduate degree holders than the US average. Compensation for higher degrees in both profiles is significantly less than the national median: Earnings with a bachelor's degree are $11,605 and $14,504 below the national median in the Retiree Communities and Isolated Seniors profiles, respectively. Holders of graduate or professional degrees earn significantly less than the corresponding national median, with earnings of $17,625 and $24,897 below the national median, respectively. The median earnings for all levels of higher education among residents of the Isolated Seniors profile are the lowest among all profiles.

TABLE 9: INDUSTRY AND EDUCATION IN GRAYING AMERICA

Category	Variable	Retiree Communities	Isolated Seniors	*US*
Employment	Information	1.5	1*	*2*
	Finance & Insurance and Real Estate	4.8*	3.7*	*6.6*
	Professional, Scientific, & Management	8.3*	5.5*	*11.6*
	Private wage and salary workers	72.8*	67.7*	*80.2*
	Government workers	17.2	21.7*	*13.7*
	Self-employed	9.7*	10.2*	*5.9*
Education	Bachelor's degree	16.2	11.2*	*19.8*
	Graduate or professional degree	9.4	5.5*	*12.4*
	Median earnings with some college/ associate's	32,835*	29,223*	*37,471*
	Median earnings with bachelor's	43,320*	40,421*	*54,925*
	Median earnings with graduate/ professional	56,628*	49,356*	*74,253*

Notes. The asterisks indicate that a profile average is statistically different from the US average. All values median earnings ($) are shown as percentage of the population.

Source: Milken Institute (2022)

More veterans live in these profiles and disability rates are high. Table 10 shows that both profiles have a significantly larger veteran population than the rest of the country; the Retiree Communities have the highest percentage of the veteran population among all the profiles.

Residents of the Isolated Seniors profile communities are more likely to be living with disabilities as the rates—overall and for four of the six types of disabilities surveyed by ACS—are the second-highest after White Appalachia (which represents predominantly White communities with high poverty levels). Isolated Seniors also have significantly less access to computers and high-quality internet services than the rest of the country. Finally, housing vacancy rates for both profiles are among the highest of all profiles.

TABLE 10: OTHER CHARACTERISTICS OF GRAYING AMERICA

Category	Variable	Retiree Communities	Isolated Seniors	*US Average*
Social	Civilian veterans	11.2*	10.7*	*7.3*
Housing	Vacant housing units	31.3*	34.4*	*12.1*
	Owner-occupied	75.6*	74.7*	*64*
Household Type	Grandparents responsible for grandchildren	42.4	55.8*	*34.1*
	Enrollment, elementary school (g1-8)	44.8	47.6*	*40.4*
Disability, Computer/ Internet	With health insurance	90.6	87.3	*91.2*
	Disability	17*	21.8*	*12.6*
	Hearing difficulty	6.1*	8*	*3.6*
	Vision difficulty	2.9	4.6*	*2.3*
	Cognitive difficulty	6.1	7.9*	*5.1*
	Ambulatory difficulty	9.2*	12.9*	*6.9*
	Self-care difficulty	3.2	4.2*	*2.6*
	Independent living difficulty	6.8	9*	*5.8*
	With a computer	88.1	80.9*	*90.3*
	With a broadband internet subscription	78.8	66.8*	*82.7*
	No computer, 65+ years	17.1	27.2*	*18.1*

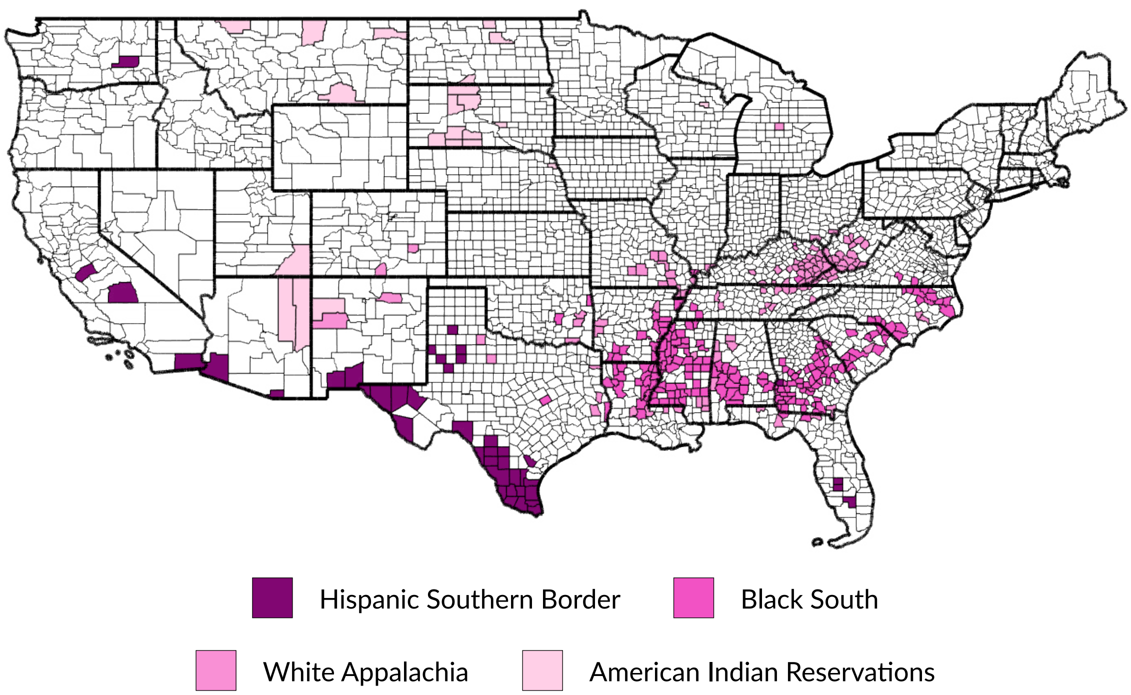
Notes: The table shows averages of selected variables that distinguish the Graying America profiles. Asterisks indicate a profile average statistically different from the US average. All values are shown as percentage of the population.

Source: Milken Institute (2022)

EXTREMELY VULNERABLE AMERICA

These 378 counties, where 3.5 percent of the US population resides, are primarily rural (85 percent of their population), with widespread poverty. The Extremely Vulnerable America profiles (Hispanic Southern Border, Black South, White Appalachia, and American Indian Reservations) significantly lag the rest of the US regarding income, education, employment, and essential infrastructures. Racial-ethnic differences characterize these profiles, which are in regions with above-average percentages of disadvantaged groups from diverse ethnic backgrounds.

FIGURE 14: MAP OF EXTREMELY VULNERABLE AMERICA



Source: Milken Institute (2022)

Hispanic Southern Border includes 43 counties harboring 1.4 percent of the US population, primarily located close to the US southern border. These young, mostly Hispanic or Latino communities have the lowest English proficiency, among the lowest income levels, and the lowest attainments in compulsory education of all profiles. Compared to other profiles, more workers in these communities have low-skilled jobs in the service and agricultural industries. The communities have low access to digital infrastructure and health insurance.

Black South clusters 198 counties, 1.3 percent of the US population, located mostly in the South, encompassing a stretch of counties from Virginia down through the Deep South and including parts of Arkansas. These largely Black or African American communities (46.3 percent on average) are historically poor. They remain extremely vulnerable, with lower education levels, and the lowest income and highest income inequality of all profiles. Compared to other profiles, more workers in these communities have low-skilled jobs in the manufacturing industry. The communities have poor access to digital infrastructure and health insurance. Finally, among all profiles, the Black South has the second-lowest ratio of married-couple families and the highest ratio of single female parents.

White Appalachia groups 115 counties, 0.7 percent of the US population, populated by primarily White communities (84.7 percent on average). These communities have the second-lowest median income, a high poverty rate, and a very high unemployment rate—third-largest after the American Indian Reservations and Native Alaska profiles. White Appalachia has the highest unemployment rates among the White population of all profiles. More people have blue-collar jobs in the agriculture and manufacturing industries and lower educational attainments than the national average. The percentage of people living with disabilities is the highest among all profiles, and access to digital infrastructure is very limited.

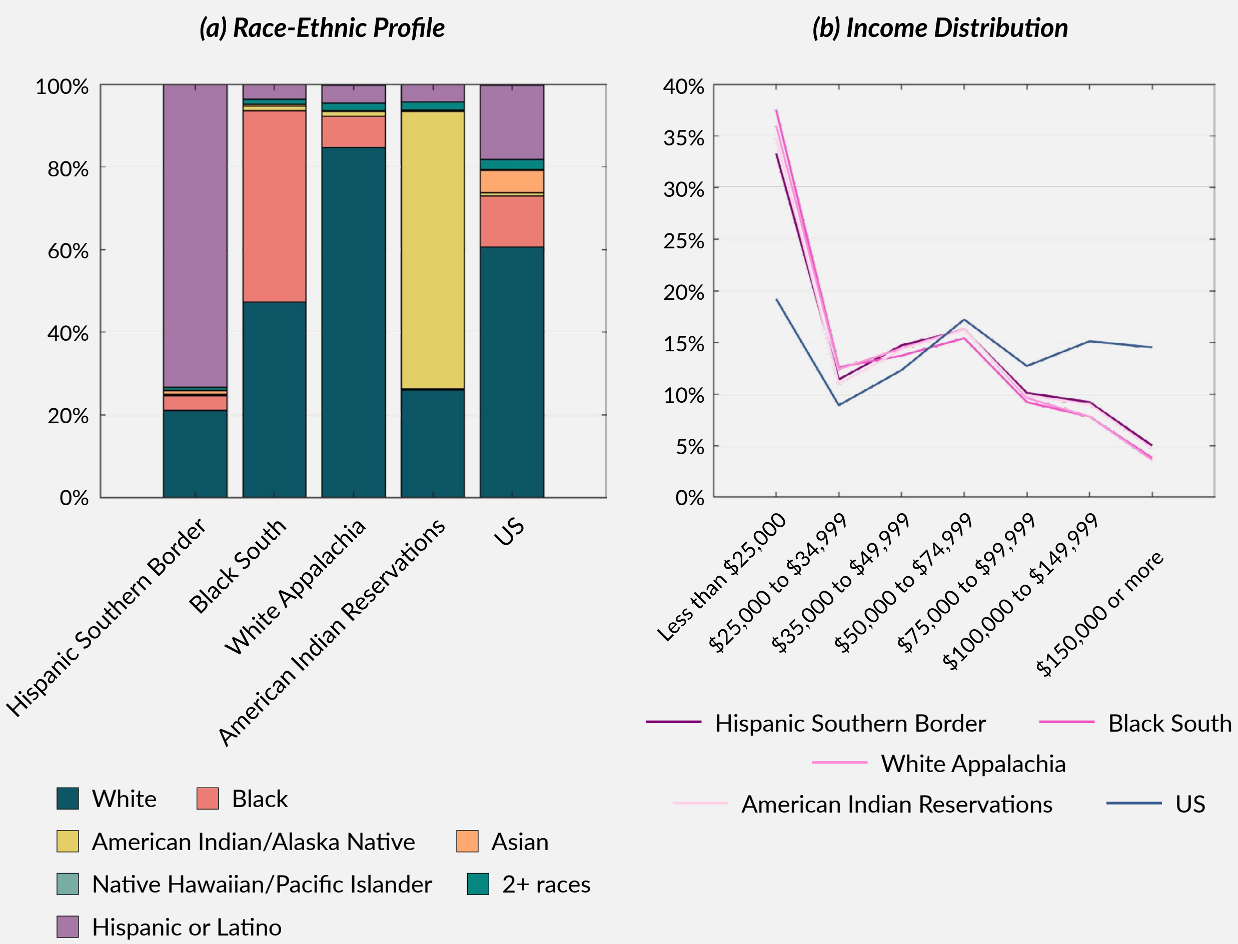
American Indian Reservations comprises 22 counties, 0.1 percent of the US population, where the majority (67 percent) of the population belongs to the American Indian or Alaska Natives racial or ethnic category. These communities have the highest poverty rates among all the profiles (36 percent for individuals and 29 percent for families) and the second-highest percentage of households receiving SNAP benefits (26 percent). The unemployment rate is the second-highest at 13 percent, falling below only that of the Native Alaska profile (whose unemployment rate is 16 percent). An unusually large percentage of the population in the American Indian Reservations profile works for the government (43.4 percent). These communities have the lowest health insurance coverage and digital access in the US.

Extreme poverty is a common factor, while the racial and ethnic profiles differ. Each of the profiles is characterized by the prominence of one racial or ethnic group: The Hispanic or Latino population represents 73.2 percent of the Hispanic Southern Border, the Black and African American population represents 46.3 percent of the Black South, the White population represents 84.7 percent of White Appalachia, and the American Indian or Alaska Native population represents 67.0 percent of the American Indian Reservations (see Figure 15[a]). Except for White Appalachia, these profiles comprise the most congregate levels of racial or ethnic minorities in the contiguous states. White Appalachia's relatively large White population ratio also stands out compared to the average US racial composition.

Figure 12(b) shows the similarity of income distributions across these four profiles: About 35 percent of the population has income below $25,000, and close to half the population has income below $35,000 in all four profiles. The Extremely Vulnerable America profiles also have the highest poverty rates (for both families and individuals) among all profiles. Table 11 shows that the percentages of households receiving SNAP benefits in these four profiles are the highest after the Native Alaska communities.

Low-wage jobs and high unemployment are at the core of poverty. Unemployment rates for the Native American Reservations and White Appalachia profiles (13.0 percent and 9.6 percent, respectively) are the second- and third-highest among all profiles (after the Native Alaska profile). Unemployment rates in the Hispanic Southern Border and Black South profiles are higher but not significantly different from the national average unemployment rate. In addition, these four profiles rely more on blue-collar jobs in relatively low-paying industries. For example, workers in these profiles are among the least likely (across all profiles) to find jobs in the top three high-paying industries: Information; Finance & Insurance, and Real Estate, Rental & Leasing; Professional, Scientific & Management, and Administrative & Waste Management Services (see Tables 4 and 11). Government workers represent about 40 percent of the labor market in the Native American Reservations profile.

FIGURE 15: RACE-ETHNICITY AND INCOME IN EXTREMELY VULNERABLE AMERICA



Notes: The percentage in panel (a) counts members of a race-ethnicity who do not identify as Hispanic or Latino to arrive at a total of 100 percent. Panel (b) indicates percentages of the population that have income within specified ranges. Line colors in (b) correspond to columns in (a).

Source: Milken Institute (2022)

TABLE 11: POVERTY RATES AND EMPLOYMENT[9]

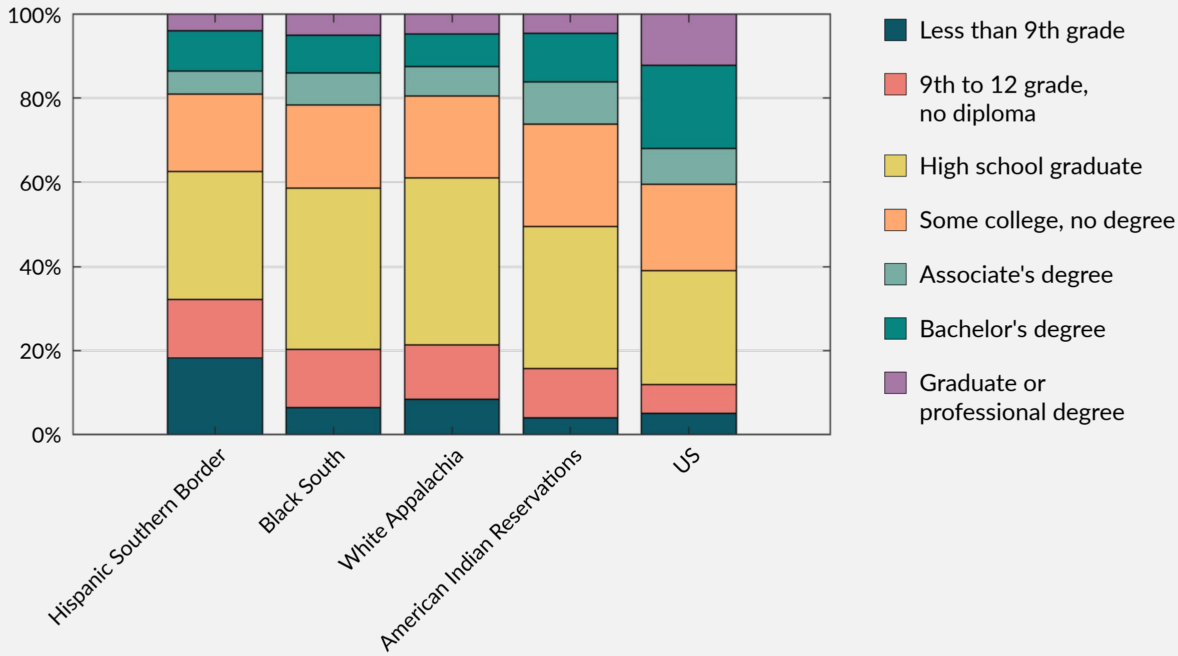
Category	Variable	Hispanic Southern Border	Black South	White Appalachia	American Indian Reservations	*US Average*
Income	With Food Stamp/SNAP benefits	23.4*	22.4*	23.3*	26.1*	*11.7*
	Below poverty level - family	20.9*	20.4*	18.9*	28.9*	*9.5*
	Below poverty level - individuals	25.4*	26*	24.1*	35.9*	*13.4*
Employment Status	Unemployment rate	8.1	8.5	9.6*	13.3*	*5.3*
Employment	Management, Business, Science, Arts jobs	24.1*	26.6*	27.9*	36.7	*38.5*
	Service jobs	23.1*	19.8	19.5	22.6	*17.8*
	Natural Resources, Construction, and Maintenance jobs	18.2*	12.2	14*	12*	*8.9*
	Production, Transportation, and Material Moving jobs	15	21.7*	18.5*	9.9*	*13.2*
	Agriculture, Forestry, Fishing, and Mining	14.1*	5.8*	6.4*	11.6*	*1.8*
	Manufacturing	5.3*	15.5	11.7	2.7*	*10.1*
	Information	0.9*	0.8*	1.2	0.9*	*2*
	Finance and Insurance, and Real Estate and Rental and Leasing	3.3*	3.4*	3.5*	3.5*	*6.6*
	Professional, Scientific, and Management	5.4*	5.5*	5.8*	3.2*	*11.6*
	Private wage and salary workers	72.7*	74*	73.4*	46.3*	*80.2*
	Government workers	19.7*	19.8*	19.4*	43.4*	*13.7*

Notes: The table shows averages of selected variables that distinguish these profiles from the rest. The asterisk indicates that a profile average is statistically different from the US average. All values are a percentage of the population.

Source: Milken Institute (2022)

These profiles are characterized by low educational attainments and deep poverty. Figure 16 highlights the prevalence of educational inequality in these profiles, which correlates with incomes considerably lower than the national average. Compared to the national average, the ratio of the population without compulsory education (all grades through high school) is notably high. The Hispanic Southern Border has the lowest educational attainments of these profiles across all categories, which aligns with almost a quarter of its population's not having a good command of English. In addition, the percentages of the population holding post-secondary degrees in the Hispanic Southern Border, Black South, and White Appalachia profiles are the lowest among all profiles.

FIGURE 16: EDUCATIONAL ATTAINMENTS IN EXTREMELY VULNERABLE COMMUNITIES



Notes: Bars indicate ratios of the population attaining certain educational levels in the Extremely Vulnerable America profiles, compared to US ratios.

Source: Milken Institute (2022)

High disability rates, low health insurance coverage, and lack of digital access are worrisome. Significantly more residents live with disabilities in the group of counties comprising the Extremely Vulnerable America profiles than in the rest of the US. White Appalachia has the highest disability rate among all profiles, which correlates with an older population relative to the other Extremely Vulnerable America profiles (see Table 12). The Hispanic Southern Border and American Indian Reservations profiles have among the lowest health insurance coverages. In contrast, the Black South deviates less from the US average, and White Appalachia has coverage close to the national average. Finally, access to digital services, from owning a computer to having access to high-quality internet, is a significant concern for all these profiles.

Several other prominent characteristics are correlated with deep poverty in these profiles. Female single-parent households are prevalent in Extremely Vulnerable America: The Black South, American Indian Reservations, and Hispanic Southern Border profiles have the first- to third-highest percentages of single-mother households, respectively. Lack of English proficiency is an issue: More than half of the Hispanic Southern Border profile's population does not use English at home, almost a quarter of the population does not speak English very well, and foreign-born non-US citizens comprise a large fraction of the population (66 percent). All four profiles have a high vacancy rate for housing units, around 10 percentage points higher than the national rate.

TABLE 12: OTHER CHARACTERISTICS OF EXTREMELY VULNERABLE AMERICA

Category	Variable	Hispanic Southern Border	Black South	White Appalachia	American Indian Reservations	*US Average/ Median*
Demography	Median age	33.9*	40.6	43.2*	30.5*	*38.1*
Social	Foreign-born population, Not a US citizen	66*	59.9	56.9	58.3	*50.4*
	Language at home not English	59.1*	4*	4.4*	17.2*	*21.6*
	Language at home not English - Speak English less than very well	23.1*	1.6*	1.3*	3.1*	*8.4*
Housing	Vacant housing units	21.5*	22.7*	22.4*	23.4*	*12.1*
	No telephone service available	2.5	3.2	2.9	8.3*	*1.9*
Household Type	Married-couple family	48.9	40.1*	48.3	39.7*	*48.2*
	Female householders, no spouse, with children	7.9*	8.3*	4.9	8.3*	*5.3*
	Households with people under 18 years	37.6	29	29	42.2*	*31*
	Households with people 65 years and over	33.9	34.9*	35.7*	29.1	*29.4*
	Grandparents responsible for grandchildren	42.2	54*	59*	61.8*	*34.1*
Health Insurance/ Disability	Married-couple family	48.9	40.1*	48.3	39.7*	*48.2*
	Female householders, no spouse, with children	7.9*	8.3*	4.9	8.3*	*5.3*
	Households with people under 18 years	37.6	29	29	42.2*	*31*
	Households with people 65 years and over	33.9	34.9*	35.7*	29.1	*29.4*
	Grandparents responsible for grandchildren	42.2	54*	59*	61.8*	*34.1*
Computer/ Internet	With a computer	78.9*	74.6*	77.9*	70.7*	*90.3*
	With a broadband Internet subscription	64.9*	59.7*	66.8*	57.2*	*82.7*

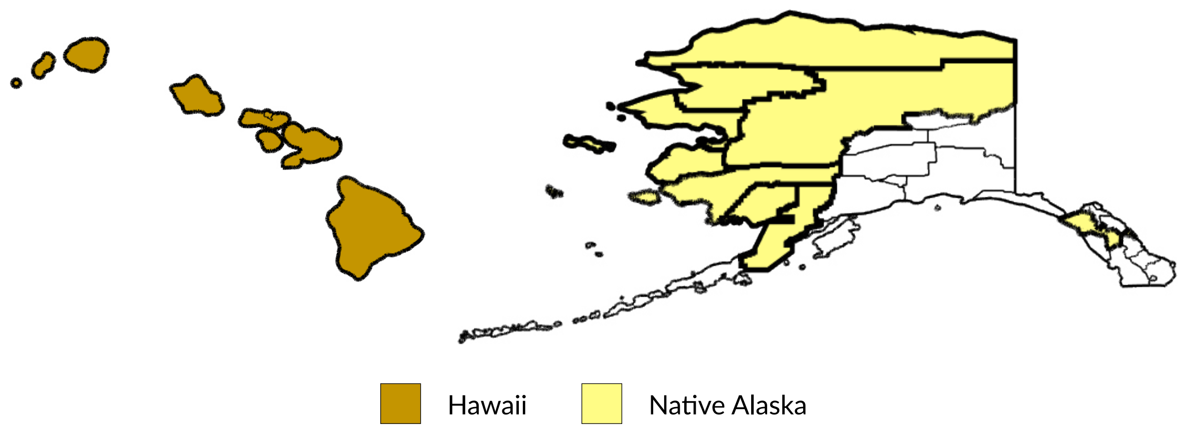
Notes: Averages of selected variables that distinguish these profiles from the rest. Asterisk indicates a profile average statistically different from the US average. All values except median age are a percentage of the population.

Source: Milken Institute (2022)

NONCONTIGUOUS AMERICA

These 14 counties, where 0.46 percent of the US population resides, are located in the two noncontiguous states: The Hawaii profile accounts for the five counties of Hawaii, and the Native Alaska profile accounts for nine of Alaska's 29 counties (the other 20 counties are widely spread across Affluent Suburbs, Middle Class, Retiree Communities, Hispanic Agriculture, Isolated Seniors, and The Great Plains).

FIGURE 17: MAP OF NONCONTIGUOUS AMERICA



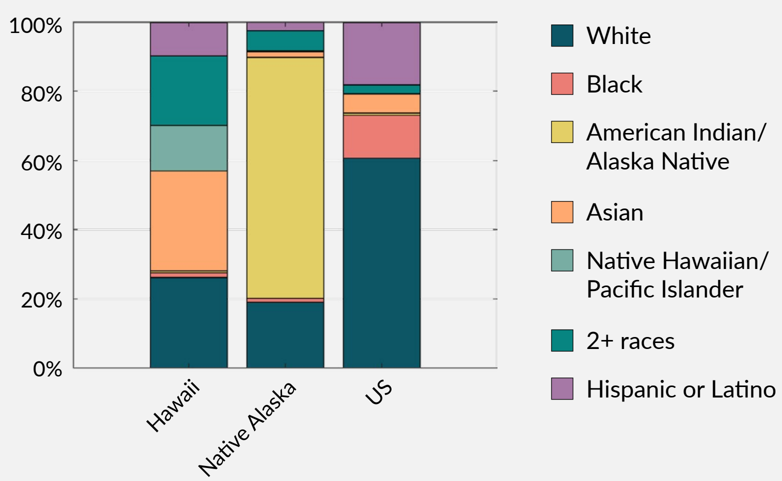
Source: Milken Institute (2022)

Hawaii comprises 0.4 percent of the US population. Hawaii has the second-smallest White population (26.2 percent), higher only than the White population of the Native Alaska profile. The Hawaii profile also has the highest proportions of Asian, Native Hawaiian and Pacific Islander, and Two or More Races populations of all profiles. Household incomes are higher in Hawaii than the national average, and the median income for people aged 25 to 44 is among the highest. But the residents face expensive housing markets. Compared to other profiles, this profile has the largest portion of jobs in the hospitality industry (Arts & Entertainment, and Accommodation & Food Services). There is a gap in the average education levels between the White and Asian populations: Compared to their racial or ethnic groups in other profiles, the percentage of the population with a post-secondary degree is the second-highest for the White population, whereas for Asians it is the second-lowest.

Native Alaska accounts for 0.02 percent of the US population that lives in counties where a majority of the population (69.6 percent) belongs to the American Indian or Alaska Native racial or ethnic category. Yet in this profile the local White minority is better off, with the highest median income for its racial or ethnic category ($100,900) and one of the lowest unemployment rates (2.4 percent) among all profiles. In contrast, Alaska Natives have low median incomes ($43,049) and suffer the most considerable unemployment rate (23.2 percent) among all profiles. Similarly, the Native Alaska profile has the highest percentage of households receiving SNAP benefits. Finally, the Native Alaska profile's access to high-quality internet and health insurance coverage is one of the lowest in the country.

One or two national minorities comprise the largest racial or ethnic groups in the Noncontiguous America profiles. In Hawaii, the Asian population (29 percent) exceeds the White population by 3 percentage points. For two other racial or ethnic groups—Two or More Races and Native Hawaiian and Pacific Islander—their shares are higher in this than in any other profiles. The Native Alaska profile's population belongs predominantly to the American Indian and Alaska Native racial or ethnic groups (69.6 percent of the population), though it's to be expected that most of this population is Alaska Native, since all these counties are located in Alaska.

FIGURE 18: RACE-ETHNICITY IN NONCONTIGUOUS AMERICA



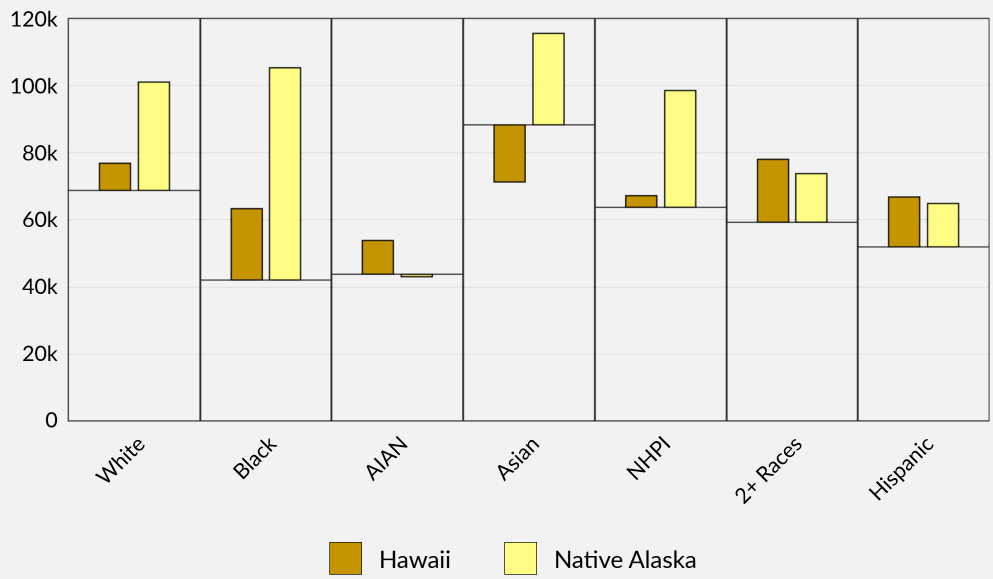
Note: The percentage counts members of a race-ethnicity who do not identify as Hispanic or Latino to arrive at a total of 100 percent.

Source: Milken Institute (2022)

The White population may be a smaller fraction of the overall population, but it retains economic advantages. Figure 19 indicates the difference between the median income for each racial or ethnic group in the Noncontiguous America profiles compared to the national medians. For the Native Alaska profile, White, Black or African American, and Asian populations have the highest median incomes within their racial or ethnic groups among all profiles ($100,900, $105,267, and $115,372, respectively). These relatively high incomes also show clear departures from the overall national median income. The median incomes for American Indians and Alaska Natives, at $43,049, remain in line with the national median for this group.

Hawaii's median incomes for all seven racial or ethnic groups are not statistically significantly different from their respective national median incomes.

FIGURE 19: INCOME BY RACE-ETHNICITY IN NONCONTIGUOUS AMERICA

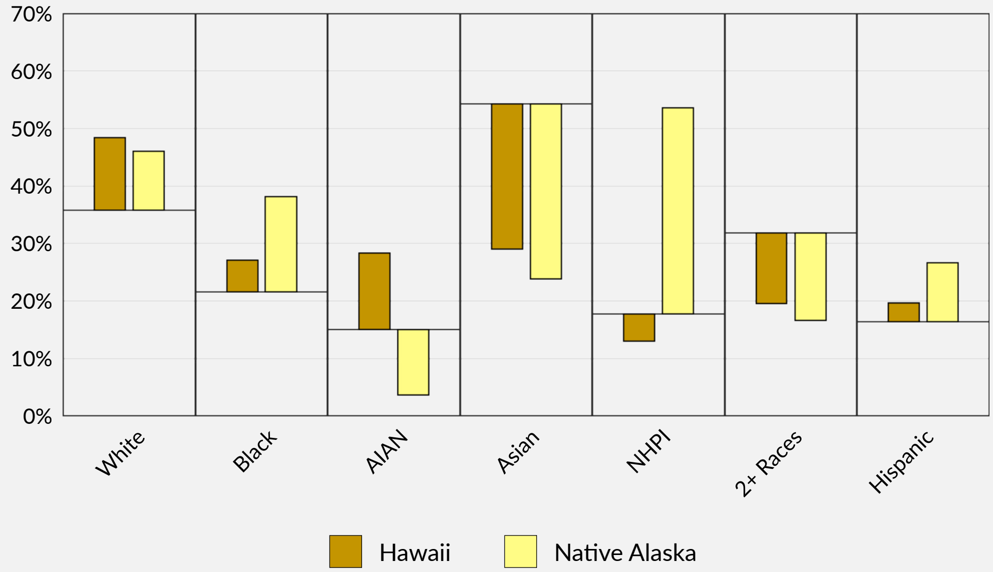


Notes: The bars show, for each race-ethnicity, how the profile's median income deviates from the US median income (or from the median income for its respective group). Bar baseline denotes the US median. AIAN = American Indian and Alaska Native. NHPI = Native Hawaiian and Other Pacific Islander.

Source: Milken Institute (2022)

A significant gap in educational achievements divides the White and non-White prominent racial groups compared to their national averages. The White populations in the Hawaii and Native Alaska profiles have higher than national average educational achievements. In contrast, Hawaii's most prominent populations other than White—Asian and Two or More Races—and the Native Alaska profile's American Indians and Alaska Natives lag significantly in educational attainment relative to the national averages for their racial or ethnic groups (see Figure 20).

FIGURE 20: EDUCATION BY RACE-ETHNICITY IN NONCONTIGUOUS AMERICA



Notes: The bars show, for each race-ethnicity, how the profile's percentage of population with bachelor's or higher degrees deviates from the US average and from the average for the respective group. Bar baseline denotes the US average. AIAN= American Indian and Alaska Native. NHPI = Native Hawaiian and Other Pacific Islander.

Source: Milken Institute (2022)

These profiles have similar labor markets but different social infrastructures. Table 13 shows that the Arts, Entertainment, Recreation, and Accommodation and Food Services (linked to service jobs) and Government Workers occupations lead Hawaii's labor market. Likewise, the government employs about half (45.6 percent) of the Native Alaska profile's residents, the most significant percentage among all profiles.

Health insurance coverage in the Hawaii and Native Alaska profiles is at opposite ends of the spectrum: Hawaii has the highest and the Native Alaska profile has the second-lowest coverage. Finally, significantly fewer residents of the Native Alaska profile have access to high-quality internet services compared to the national average.

TABLE 13: OTHER CHARACTERISTICS OF NONCONTIGUOUS AMERICA

Category	Variable	Hawaii	Native Alaska	*US*
Employment	Service jobs	29.5*	19.6	*17.8*
	Arts, Entertainment, Recreation, and Accommodation and Food Services	19.9*	5.9*	*9.7*
	Private wage and salary workers	67.5	50.2*	*80.2*
	Government workers	24.8*	45.6*	*13.7*
Health Insurance, Computer/ Internet	With health insurance	96.4*	76.5*	*91.2*
	With a computer	88.1	84.1	*90.3*
	With a broadband internet subscription	79.9	67.5*	*82.7*

Notes: The table shows averages of selected variables that distinguish these profiles from the rest. The asterisks indicate that a profile average is statistically different from the US average. All values are shown as percentage of the population.

Source: Milken Institute (2022)

CONCLUDING REMARKS

The latest Census confirms that the US population will continue to change in many dimensions. To name just a couple of dimensions, the population will get older, and the White population will shrink to less than 40 percent of the whole by the year 2060, while the Hispanic and Latino population will continue to rise with all the other minorities except for the Black or African American population. In light of these likely changes, we cannot ignore the multidimensionality of diversity when tackling issues related to inequalities.

With the Community Explorer, we propose a new approach to policy that effectively leverages county-level data produced by the Census to inform decisions related to equity across the US.

In this report we have already explained the benefits of clustering information into communities defined by the populations' characteristics rather than their location. This approach allows for insightful benchmarking when determining or assessing the impact of an initiative, thus permitting comparison across peer counties even if they are not within the same state or region. It also identifies the main factors that differentiate one community from another.

We would like to share some final remarks on this novel and informative policy and visualization tool.

- It identifies correlations. The combination of information related to a specific topic with the community profiles highlights patterns across the US but does not provide causal insights.
- It allows states to leverage the complexity of their populations' diversity to produce tailored and flexible policies. The 254 counties of Texas are spread across 14 profiles, whereas the 58 counties of California are spread across nine. The Community Explorer can help states align their policies with their diversity while allowing for economies of scale or scalability in policy implementation. The same reasoning applies to policy within a region and on a national level.
- It goes beyond the rural-versus-urban differentiation. The profiles provide informative nuances beyond the rural-versus-urban dimensions. To illustrate, let's compare the Great Plains with the Black South. Both are highly rural, with 96 percent and 85 percent of their respective populations living in non-core and micropolitan areas. The Great Plains profile represents a group of relatively well off, middle-class counties with a dominant non-Hispanic White population (90.8 percent) working largely in agriculture. In contrast, the Black South profile groups economically vulnerable counties with a large Black or African American population (47.3 percent) working in low-skilled manufacturing jobs. Similar contrasts can be drawn across urban counties, some of which represent the Affluent Suburbs with a mostly non-Hispanic population, while others belong to the ethnically diverse Urban Core.

As an accompaniment to this report, the Community Explorer dashboard provides an appealing and intuitive visual tool that allows users to explore the wealth of information discussed here. Users can also download the graphs and information provided in the dashboard for use in their own research and analyses.

ENDNOTES

1. Here and throughout the report we refer to racial or ethnic descriptions as recorded by the US Census Bureau. All racial or ethnic groups include only the non-Hispanic population (except for the Hispanic or Latino group, which includes Hispanic population of any race).
2. In 2019, Valdez-Cordova Census Area in Alaska was divided into two, making the number of counties 3,143 for the 2020 Census.
3. Table identification codes for the four tables in ACS are DP02, DP03, DP04, and DP05.
4. Table identification codes for the 11 tables in ACS are S0802, S0804, S1501, S1502, S1810, S1903, S2301, S2701, S2801, S2802, and B19083.
5. Pertinent variables include all information related to the communities' socioeconomic characteristics. A few examples of variables that we considered non-pertinent are population counts (as we included the percentages), detailed information on the types of household computing devices (such as having a desktop or laptop), and the number of available vehicles in a household.
6. The algorithm needs two parameter specifications: a search radius (ϵ) and a minimum number of samples. If the distance between two data points is below the threshold ϵ, the two points are considered neighbors. The points in the same neighborhood comprise a cluster only if the cluster has the minimum number of samples that a user defines. Otherwise, the data points are classified as outliers. We set the minimum number of samples as 3 to identify any redundant variables. One strategy for estimating a value for ϵ is to generate a k-distance graph for the input data, in which k is 3 in our case. For each point in the data, this method finds the distance to the k^{th} nearest point, and plots sorted points against this distance. The resulting graph contains a knee, at which the distance rapidly increases. Based on the knee, we chose 10 as the distance. However, for robustness, we also repeated the whole process with widely ranging ϵ, from 1 to 1000, and the minimum number of samples, ranging from 2 to 10. We found the solutions of our method to be very robust over different sets of parameters.
7. See the online appendix for more details.
8. We define white-collar jobs as including the Management, Business, Science, and Arts and Sales and Office jobs categories as classified by the US Census Bureau.
9. The US Census Bureau divides occupations into five categories: Management, Business, Science, and Arts occupations; Service occupations; Sales and Office occupations; Natural Resources, Construction, and Maintenance occupations; and Production, Transportation, & Material Moving occupations. Also, employment industries are divided into 13 categories: Agriculture, Forestry, Fishing and Hunting, and Mining; Construction; Manufacturing; Wholesale Trade; Retail Trade; Transportation & Warehousing, and Utilities; Information; Finance & Insurance, and Real Estate and Rental & Leasing; Professional, Scientific, & Management, and Administrative and Waste Management Services; Educational Services, and Health Care & Social Assistance; Arts, Entertainment, and Recreation, and Accommodation & Food Services; Other services except Public Administration; Public Administration.
10. Helper et al (2012) identify six broad groups defined by common patterns of manufacturing industry employment composition. Each group is defined by an anchor industry or combination of industries, in which all metropolitan areas in the group are relatively strongly (usually highly)

specialized, and by another industry in which all metropolitan areas in the group are less specialized. The six anchor manufacturing industries are computers and electronics (West in general; California, Colorado, New England), transportation equipment (including motor vehicles and parts, aerospace, and other transportation equipment), low-wage manufacturing industries (a broad category that combines food, textile mills, textile product mills, apparel, leather, wood, and furniture), chemicals, machinery, and food.

11. This includes manufacturing of motor vehicles and parts, aerospace, and other transportation equipment.
12. This broad category combines manufacturing of food, textiles, textile products, apparel, leather, wood, and furniture.

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ABOUT THE AUTHORS

Claude Lopez, PhD, is the head of the Research Department at the Milken Institute. She leads data-driven efforts to influence global policy issues on international finance (systemic risk, financial stability, ESG investing, tech, capital flows, G20 topics), health economics (public health risks, health disparities), and regional economics (regional competitiveness, innovation, labor-market disparities). She is an active member of the T20 task force on international financial architecture for stability and development, an advisory committee to the G20. Lopez has over 20 years of experience in academic and policy research in the US and abroad. Before joining the Institute, Lopez headed multiple research teams at the Banque de France, the nation's central bank, and was a professor of economics at the University of Cincinnati. She has an MS in econometrics from Toulouse School of Economics and a PhD in economics from the University of Houston.

Hyeongyul Roh, PhD, is a senior research analyst specializing in applied economics within the Research Department at the Milken Institute. The core of his research interests is to assess empirically the efficiency of markets and identify optimal economic decisions based on the empirical setting. His recent work focuses on energy industry organization and clean energy policy by employing economic theory and diverse machine learning methods. Before joining the Institute, Roh was a postdoctoral fellow at the Duke University Energy Initiative. Roh holds a PhD in economics from North Carolina State University and an MS in mathematical finance from Boston University.

Maggie Switek, PhD, is director of regional economics in the Research Department at the Milken Institute. Before joining the Milken Institute, Switek worked in academia and consulting, developing a broad range of expertise in antitrust, intellectual property, labor, public policy, and well-being. Her experience in antitrust includes working with counsel and enforcement agencies to evaluate the impacts of mergers, acquisitions, price-fixing, and other competition matters. In research, Switek's interests include well-being, migration, and regional economics. She has published studies on the effects of public social spending on quality of life in Latin America, the effects of rapid economic growth (and accompanying economic changes) on well-being in China, and migration patterns among young adults in Sweden.

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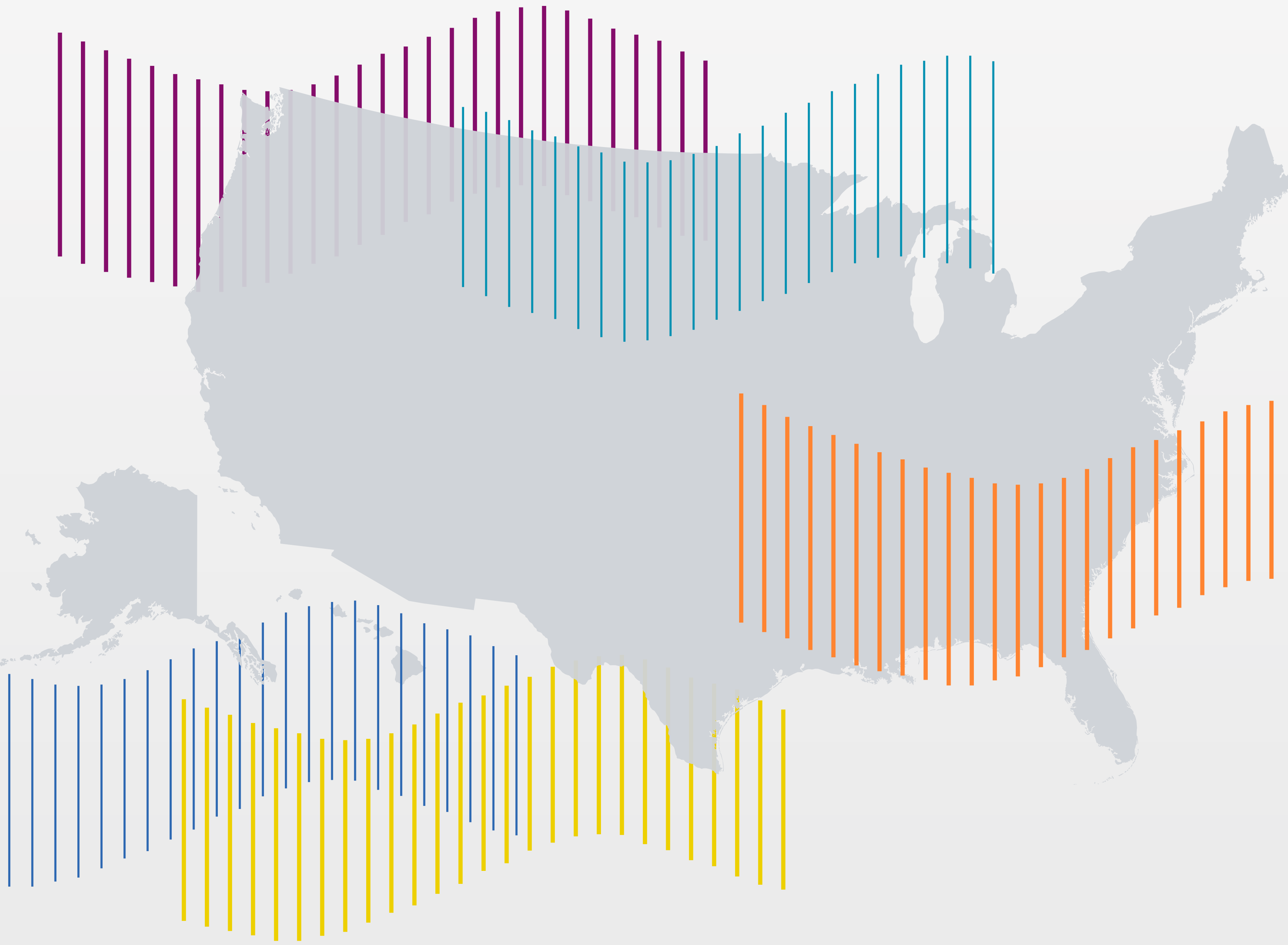

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