Race, place, and police involved deaths

## Abstract

**Objective.** To estimate mortality for police-involved deaths by race and place in the United States.

**Methods.** We use crowdsourced police-involved fatality data to construct Bayesian negative binomial models. We use these models to estimate fatality risk for the Blacks, Latinos and Whites for all counties in the U.S.

**Results.** We estimate that police in the U.S. are involved, on average, in 4.5 deaths per day. Model results show that Black fatality risk is between 0.88 and 1.12 deaths per 100,000 per year, Latino risk is between 0.40 and 0.61, White fatality risk is between 0.36 and 0.42, and total fatality risk is between 0.36 and 0.42 deaths per 100,000 per year. This risk varies substantially across U.S. regions and metro types.

**Conclusions.** The risk of death in an encounter with police is highly sensitive to race and place, and policing is an important social determinant of health. Despite the lack of reliable official statistics, new methods can quantify fatality risk and uncertainty with relatively sparse data.

**Policy Implications.** Efforts to address unequal exposure to police violence should take regional and local variation into account. MORE?

## Introduction

Violent and fatal interactions between law enforcement and people of color are a persistent feature of American social life. 1,2 In response to the shortcomings of federal efforts to systematically document deaths involving police,3 journalists have undertaken a series of systematic efforts to provide comprehensive data on fatalities resulting from interactions between police and the public.4 This analysis utilizes these new data to provide estimates of mortality risk from interactions with police by race and place.

Race, place, and policing are important social determinants of health.5–7 Prior research has clearly established that African Americans are at higher risk of death in interactions with law enforcement 8,9 and has demonstrated clear links between race, place and mortality.10 The legal, cultural, and institutional environments that structure relationships between police and communities of color are tightly coupled with geography,11,12 suggesting that the relationship between policing, race, and mortality may be heterogenous across places. In this paper, we provide the first estimates that show how geography and race interact to produce variable risks for mortality in encounters with law enforcement for people of color using a methodological approach that allows for more predictive precision for rare events, such as law enforcement deaths. Our results suggest that race and place may interact in important ways to increase mortality risk due to police intervention for people of color.

## Background

Disparate exposure to police violence has, historically, been a grievance of African-American led social movements.13,14 Current activists/organizers, notably members of Black Lives Matter, have taken up this point, and argued that the deaths of Michael Brown, Sandra Bland, Philando Castille, Tamir Rice, Laquan McDonald, Eric Garner, Charleena Lyles Anthony Lamar, and many others illustrate a systematic disregard for the well-being of African-Americans among law enforcement, and the broader polity. An increasing volume of social-scientific research has reinforced this claim: empirical studies have, indeed, shown that Blacks are more likely to die in interactions with law enforcement than are Whites,8,15,16 including when those killed are unarmed.17 Because policing and criminal justice regimes vary across places,11,12,18 it is likely that the risk of mortality from interactions with law enforcement are, in part, a function of geography.

## Data

Data on police-involved deaths come from *Fatal Encounters*, a journalist-led project that seeks to document all episodes of fatal police-civilian interactions in the United States for those dates with complete national data, January 1, 2013 through the date of access, May 8, 2017.4 The project relies on contributions of professional and volunteer researchers, compiled from media reports and public records. The universe of cases in *Fatal Encounters* is broader than similar projects, such as *The Washington Post's* compilation of data on police shootings, and has a greater temporal coverage than *The Guardian's* dataset on police-involved deaths. Race data are not reported for all cases in *Fatal Encounters*, because they are often excluded from news reports or public records. Bureau of Justice Statistics analysts noted that *Fatal Encounters* closely matched the proposed inclusion criteria for a BJS redesign of its Arrest-Related Deaths Program.24

We reduce race/ethnicity to a three category variable: African American, white, and Latino, which is coded by *Fatal Encounters* contributors. For those cases missing data on victim race/ethnicity, we use names and county of residence to predict victim race26. These criteria yield a total of 7,118 reported deaths involving police over a period of 1588 days. To maximize the information we are able to include in county-level fatality risk estimates, we pool observations to produce counts of deaths by race/ethnicity (Black, Latino, White) for each county or county equivalent unit in the U.S. (3140 counties). Of the 7,118 total police-involved deaths included in the analysis, 1,716 involved Black victims, 1,138 involved Latino victims, and 3,306 involved White victims. *Fatal Encounters* identifies 79 victims who were American Indian/Alaska Native, 124 who were Asian-Pacific Islander, and 14 who were Middle Eastern. We are left with 741 cases that we are unable to classify the race of the victim, about 10 percent of the observations. These cases are included in calculations of total mortality rates, but excluded from race/ethnicity specific models. As such, counts and rates presented below are conservative estimates. All fatality rate and risk estimates presented below are normalized to deaths per 100,000 population per year.

We rely on data from the American Community Survey 5-year 2009 - 2014 population estimates for rate denominators of population by race, ethnicity and county.25 For geographic classification, we rely on the U.S. Census Bureau's 2010 state division classification (see Appendix Table1), and use the National Center for Health Statistics' six category urban-rural county classification scheme for all US counties (see Appendix Table 2). county-level counts of these population estimates to provide exposure population offsets in regression models, urban-rural classification codes to control for county metro type, and a nine category census state division variable to model regional heterogeneity.

## Methods

Because deaths involving police are a relatively rare event in any given county -- zero police deaths were recorded in more than half of US counties -- we construct regression models to pool power and provide predictions of mortality rates by race (African American, Latino, white), by metropolitan status, and by region. These figures provide more reliable estimates of police mortality risk by adjusting for the rarity of this event in places with small populations, and smoothing extreme estimates from the observed data that are driven by outliers.

We estimate Bayesian multilevel negative binomial regressions of police-involved deaths as a function of the race of the victim, metropolitan status, and region. Model intercepts are assigned a weakly informative Normal prior distribution with a mean centered on mortality estimates produced by Krieger and colleagues, 0.37 deaths per 100,000 population for Latinos and whites, and 0.94 deaths per 100,000 population for African Americans.8 These Bayesian models pull mortality risk estimates for places with little observed information toward our prior beliefs about mortality rates, while allowing predictions to draw more weight from the observed data in places where there are more observations, and hence more information.

We then estimate posterior predictive mortality rates for each subset of race by metropolitan status by region. While frequentist inferences may be appropriate for counties with large populations, they greatly distort estimates from places with small populations, where any incident can dramatically effect estimates of per capita rates, or reduce observed rates to zero, though the risk of mortality is almost certainly greater than zero. Bayesian predictive intervals provide more realistic estimates of population mortality risk, because they average over the instabilities that may occur due to idiosyncratic local or annual trends through repeated simulation (GELMAN ET AL 2014, MORE).

Below, we provide a descriptive summary of observed incidents of police-involved mortality by metro type and region. We then demonstrate how Bayesian predictions improve estimation of the rates at which African Americans, Latinos, and whites are killed in interactions with law enforcement across places. Finally, we estimate how racial/ethnic disparities in police-involved mortality vary across regions and county types.

## Findings

Police were involved in the deaths of 0.99 Black people per 100,000, 0.48 Latinos per 100,000, and 0.39 White people per 100,000 per year, and 0.52 total deaths per 100,000 in the U.S. during the 4.4 years between January 1, 2013 and May 8, 2017 as reported by *Fatal Encounters*. These data indicate that there were an average of about 4.5 deaths involving police in the U.S. per day during this time period. Our models quantify uncertainty in the risk of police-involved fatality for each of these groups. We estimate with 95 percent posterior certainty that the risk of Black fatality in interactions with law enforcement is between 0.88 deaths per 100,000 population per year and 1.12 deaths per 100,000 per year. Latinos face a risk of death in interactions with police at the national level at a rate between 0.40 and 0.61 deaths per 100,000 population per year. We estimate that the national White fatality risk rate falls between 0.36 and 0.42 per 100,000 with 95 percent posterior certainty. Our models predict a national fatality risk rate of between 0.49 and 0.58 deaths in interactions with police per 100,000 population. At 2015 population levels, the models predict between 353 and 449 police involved Black deaths, 217 and 329 Latino deaths, 714 and 822 White deaths, and between 1539 and 1834 total police-involved deaths in the U.S. in a year.

Table 1 shows that the rate of police-involved mortality is associated with place. Large fringe metros--- counties in metropolitan statistical areas (MSA) with populations above 1 million that do not contain, all or most of, said MSA’s principle city (such as Pierce County, which houses Tacoma, WA, in the Seattle-Tacoma MSA) have the lowest rates of police-related fatalities among all metro-types. Note that while the absolute fatality rate among this metro-type varies by division--- from 0.17 per 100,000 in the Middle Atlantic, to 0.66 per 100,000 in the West South Central---its relative, within division rank remains approximately the same in all cases.

Less systematic, but still apparent, patterns can be seen in the other metro-types as well: large central metros (counties in MSAs of over 1 million population that do contain, all or a plurality of, the MSA’s principle city, such as King County, which houses Seattle, WA, in the Seattle-Tacoma MSA) typically have near division-average rates, while medium metros (counties in MSAs of 250,000-999,9999 population, such as Spokane County, WA) and smaller metros, often, have the highest rates of police-related fatalities. Note that, as was the case with large fringe metros, absolute fatality rates shift between Census-divisions: Pacific division counties, for example, have rates that are 1.5 to 2 times larger than equivalent New England counties.

The geographic heterogeneity displayed in Table 1 shows that place matters for understanding police-involved fatalities. To assess how race relates to mortality, we next plot observed (unadjusted observed rates from *Fatal Encounters)*, and model-estimated (predicted from the regression models described above) race-specific police-involved fatality rates for each metro-type and Census-division. Full model predictions by race, division, and metro type are provided in Appendix Table 3.

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| --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 1.** Police related fatalities in the U.S. by metro type and Census division, January 1, 2013 through May 8, 2017, annual rate per 100,000 population in parenthesis | | | | | | | |
| Census Division | Large Central Metro | Large Fringe Metro | Medium Metro | Small Metro | Micro-politan | Noncore | *Total* |
| East North Central | 323  (0.58) | 139  (0.26) | 127  (0.39) | 75  (0.33) | 81  (0.32) | 39  (0.31) | 784  (0.39) |
| East South Central | 84  (0.64) | 39  (0.35) | 120  (0.60) | 83  (0.80) | 82  (0.59) | 97  (0.76) | 505  (0.62) |
| Middle Atlantic | 166  (0.26) | 111  (0.17) | 110  (0.41) | 23  (0.23) | 23  (0.25) | 10  (0.28) | 443  (0.25) |
| Mountain | 240  (0.71) | 57  (0.52) | 188  (0.75) | 110  (0.85) | 76  (0.68) | 39  (0.67) | 710  (0.71) |
| New England | 23  (0.23) | 41  (0.18) | 54  (0.27) | 16  (0.45) | 13  (0.27) | 13  (0.46) | 160  (0.25) |
| Pacific | 685  (0.58) | 179  (0.51) | 309  (0.68) | 98  (0.75) | 58  (0.67) | 21  (0.68) | 1350  (0.60) |
| South Atlantic | 309  (0.57) | 394  (0.42) | 392  (0.61) | 115  (0.45) | 108  (0.62) | 75  (0.51) | 1393  (0.52) |
| West North Central | 107  (0.90) | 91  (0.44) | 123  (0.79) | 64  (0.45) | 59  (0.43) | 63  (0.43) | 507  (0.56) |
| West South Central | 476  (0.80) | 181  (0.66) | 283  (0.76) | 93  (0.69) | 120  (0.81) | 113  (0.90) | 1266  (0.77) |
| *Total* | 2413  (0.57) | 1232  (0.36) | 1706  (0.59) | 677  (0.54) | 620  (0.52) | 470  (0.57) | 7118  (0.52) |
| *Note:* Data from *Fatal Encounters*, accessed 5/9/17 | | | | | | | |

***Figure 1.*** *Violin plots of observed and model estimated race-specific police-related fatalities by metro-type and Census-divisions. Note: rates are per 100,000 population*.

[Figure 1 here]

Figure 1 illustrates the differences between observed and model-predicted values. For example, the difference between the observed and model-based rates of police-involved mortality among Blacks in Pacific, noncore metros is sizeable (approximately 3.8 and 1.1 per 100,000, respectively). Here, the, extremely, high observed mortality rate is the product of a sparse Black population/mortality count. While this outcome is striking, and the circumstances that generated it are certainly worth further consideration, there is uncertainty around whether this observed rate is a “true” underlying risk of mortality. The model predicted rates attempt to account for this uncertainty by pulling weakly supported points toward the prior. In places where more data exists--- large and medium metros across divisions---we have more trust that data reflects true underlying risks. In these cases, predicted values lie closer to observations from the data.

Figure 1 shows that race-specific fatalities rates are, like pooled rates, contingent upon Census-division. Among Whites, for instance, individuals in the West South Central division--- Arkansas, Louisiana, Oklahoma, and Texas--- have the highest risk of police-related mortality (with predicted rates of 0.5 to 0.7 deaths per 100,000), while individuals in the Middle Atlantic--- New Jersey, Ney York, and Pennsylvania---appear to have the lowest risk (with rates of about 0.1 to 0.2 fatalities per 100,000 population). In contrast, for Blacks, individuals in the Pacific (Alaska, California, and Washington) and West North Central (Iowa, Kansas, and Missouri ) divisions have the highest risk of mortality (with predicted rates of approximately 1.0 to 1.6 deaths per 100,000), while individuals in the Middle Atlantic and South Atlantic (Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, Washington DV, and West Virginia) states have the lowest risks. Latino mortality risk is highest in the West South Central, and Mountain (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming) divisions have the highest estimated risks of police-related mortality, while individuals in the Atlantic divisions, again, have among the lowest.

Figure 1 also shows that for Blacks, police-involved fatality risk depends on metro-type. The shapes (“violins”) that envelope the point-estimates in Figure 1 summarize the distribution of rates, across divisions, for a given metro-type; metros with more “violin-mass” further up the x-axis represent metros with higher average mortality risk across divisions. Police-related mortality is, generally, highest for Blacks in medium metros: the lowest rate among this metro-type (in the Middle Atlantic, at 0.9 per 100,000) is approximately equal to the highest rate among large fringe metros (in the West North Central at 1.0 per 100,000); and most of the mass of this distribution lies near, or above, the top of the distribution of smaller-metros. The violins of large central metros and medium metros mostly overlap, though the peak of the latter distribution lies slightly above the peak of the former.

Though Figure 1 illustrates that the degree of *racial disparity* in police-related deaths varies by place, we can make a more explicit assessment by predicting and plotting differences in race-specific rates. Figure 2 plots the model-predicted (1) Black rates of police-related mortality minus White rates of police related mortality, and (2) Latino rates minus White rates, for each metro-type and Census Division.

[Figure 2 here]

***Figure 2:*** *Predicted differences in rates of police-mortality, by Census-division and metro-type. Note: Rate differences above 0 indicate that a given racial group has a higher, estimated, rate of police-mortality than Whites. Estimates represented by a circle indicate that an estimate uncertainty/confidence interval does not include zero.*

Figure 2 shows that while Black-White disparities exists in police-related fatalities across the country, the severity of this inequality is contingent upon place. Among the East North Central, Pacific, and West North Central states, Black-White disparities appear to be the most severe. Depending on the metro-type, Black individuals in the East North Central are 0.6 to 1.3 points more likely to be killed by the police than Whites living in the same county. Black-White disparities are, generally, lowest among the South Atlantic and New England counties, where rate differences vary between 1 and 3 across metro-types. Figure 2 makes clear racial inequality in mortality by metro-type as well. Blacks in large central metros, and medium metros have the highest rates of police-related mortality. Large fringe metros have rate differences that approximate small-metro, micropolitan, and noncore metro-types. Our results suggest that there are no clear differences between Latino police-involved mortality risk and White police-involved mortality risk across Census divisions and metro types.

## Discussion

These results provide new precision in estimating the risk of fatality in interactions with law enforcement, and demonstrate the utility of Bayesian methods for incorporating prior information to smooth estimates of important public health indicators in contexts of relatively sparse data. We show that the risk of death in an interaction with police is sensitive both to race and to place. Nationally, Black fatality risk is between 2.4 and 2.7 times greater than White fatality risk, and Latino fatality risk is between 1.1 and 1.45 times greater than White fatality risk. Both the risk of death by race and racial disparities in the risk of death in interaction with police vary substantially across U.S. regions and across metro types. Black fatality risk is most pronounced in large central and medium metros and in the Pacific and West North Central states. Latino fatality risk is highest in the Mountain and West South Central states, and is generally highest in medium metros and noncore rural metros.

GIVEN THAT THESE NEEDS TO BE A BIG SOCIAL DETERMINANTS DISCUSSION, CAN HEDY AND MIKE DO MORE WORK TO TIE THIS IN TO RACE/GEO/HEALTH?

Big takeaway: the posterior predictive estimates smooth out the extremes in estimates from small population counties. They also provide more reasonably estimates for the counties with zero observed estimates. For reasonable estimates of population risk, these posterior estimates are superior to the frequentist alternative. MIKE – WANT TO PULL THIS OUT – LECTURE ON UTILITY OF BAYES?

These results raise provocative questions about how local and regional policing regimes may affect mortality risk. Latinos are most vulnerable to police-involved death in rural counties and medium-sized urban and suburban counties, and in a contiguous set of states in the Southwest and Mountain West. African Americans are at highest risk in cities and in West coast and Midwestern states. Prior research on policing suggests that variation in policing regimes may help to explain these pronounced spatial differences (CITE JACOBS, FAGAN, EPP, WEAVER/SOSS). It is likely that local relationships between elites, communities of color, and the police play an outsized role in determining the frequency of fatal encounters between police and people of color.

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## Appendix

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| Appendix Table 1. States in Census Divisions | |
| Division Name | States Included |
| East North Central | IL, IN, OH, MI, WI |
| East South Central | AL, KY, MS, TN |
| Middle Atlantic | NJ, NY, PA |
| Mountain | AZ, CO, ID, MT, NM, NV, UT, WY |
| New England | CT, MA, ME, NH, VT |
| Pacific | AK, CA, HI, OR, WA |
| South Atlantic | DE, FL, GA, MD, NC, SC, VA, WV |
| West North Central | IA, KS, MN, MO, ND, NE, SD |
| West South Central | AR, LA, OK, TX |
| ADD CITATION | |

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| Appendix Table 2. Description of NCHS Urban-Rural County Classification | | |
| County Type | Description | Number of Counties |
| Large Central Metro | counties in MSA of 1 million population that: 1) contain the entire population of the largest principal city of the MSA, or 2) are completely contained within the largest principal city of the MSA, or 3) contain at least 250,000 residents of any principal city in the MSA. | 68 |
| Large Fringe Metro | counties in MSA of 1 million or more population that do not qualify as large central | 368 |
| Medium Metro | Medium metro counties in MSA of 250,000-999,999 population. | 372 |
| Small Metro | Small metro counties are counties in MSAs of less than 250,000 population. | 358 |
| Micropolitan | Nonmetropolitan counties: Micropolitan counties in micropolitan statistical area | 641 |
| Noncore | Noncore counties not in micropolitan statistical areas | 1333 |
| Citation: https://www.cdc.gov/nchs/data/series/sr\_02/sr02\_166.pdf | | |

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| Appendix Table 3. Posterior police related mortality by race/ethnicity, census region, and metro type, 95 percent credible intervals | | | |
| **County Name** | **Black** | **Latinx** | **White** |
| East North Central |  |  |  |
| - Large Central Metro | 1.1 (0.4, 2.4) | 0.3 (0, 0.8) | 0.2 (0.1, 0.5) |
| - Large Fringe Metro | 0.7 (0.2, 1.6) | 0.2 (0, 0.7) | 0.2 (0.1, 0.4) |
| - Medium Metro | 1.2 (0.4, 2.7) | 0.3 (0.1, 1) | 0.3 (0.1, 0.6) |
| - Small Metro | 0.8 (0.3, 1.8) | 0.3 (0, 0.8) | 0.3 (0.1, 0.6) |
| - Micropolitan | 0.9 (0.3, 2) | 0.3 (0.1, 0.9) | 0.3 (0.1, 0.6) |
| - Noncore | 0.8 (0.3, 1.8) | 0.3 (0.1, 1) | 0.3 (0.1, 0.6) |
| East South Central |  |  |  |
| - Large Central Metro | 0.9 (0.3, 2.1) | 0.2 (0, 0.8) | 0.4 (0.1, 0.9) |
| - Large Fringe Metro | 0.6 (0.2, 1.4) | 0.2 (0, 0.7) | 0.4 (0.1, 0.8) |
| - Medium Metro | 1.1 (0.4, 2.3) | 0.3 (0.1, 1) | 0.5 (0.2, 1.1) |
| - Small Metro | 0.7 (0.2, 1.6) | 0.2 (0, 0.8) | 0.5 (0.2, 1.1) |
| - Micropolitan | 0.8 (0.3, 1.7) | 0.2 (0, 0.8) | 0.5 (0.2, 1.2) |
| - Noncore | 0.7 (0.2, 1.6) | 0.3 (0.1, 1) | 0.5 (0.2, 1.2) |
| Middle Atlantic |  |  |  |
| - Large Central Metro | 0.8 (0.3, 1.8) | 0.2 (0, 0.5) | 0.1 (0.1, 0.3) |
| - Large Fringe Metro | 0.5 (0.2, 1.2) | 0.1 (0, 0.4) | 0.1 (0.1, 0.3) |
| - Medium Metro | 0.9 (0.3, 2) | 0.2 (0, 0.6) | 0.2 (0.1, 0.4) |
| - Small Metro | 0.6 (0.2, 1.3) | 0.2 (0, 0.5) | 0.2 (0.1, 0.5) |
| - Micropolitan | 0.6 (0.2, 1.5) | 0.2 (0, 0.5) | 0.2 (0.1, 0.5) |
| - Noncore | 0.6 (0.2, 1.4) | 0.2 (0, 0.6) | 0.2 (0.1, 0.5) |
| Mountain |  |  |  |
| - Large Central Metro | 1.1 (0.4, 2.6) | 0.6 (0.1, 1.7) | 0.4 (0.2, 1) |
| - Large Fringe Metro | 0.7 (0.2, 1.7) | 0.5 (0.1, 1.5) | 0.4 (0.1, 1) |
| - Medium Metro | 1.2 (0.4, 2.8) | 0.8 (0.2, 2.2) | 0.6 (0.2, 1.3) |
| - Small Metro | 0.8 (0.3, 1.9) | 0.6 (0.1, 1.8) | 0.6 (0.2, 1.3) |
| - Micropolitan | 0.9 (0.3, 2.1) | 0.6 (0.1, 1.8) | 0.6 (0.2, 1.4) |
| - Noncore | 0.8 (0.3, 2) | 0.7 (0.1, 2.2) | 0.6 (0.2, 1.4) |
| New England |  |  |  |
| - Large Central Metro | 0.9 (0.3, 2) | 0.3 (0.1, 1.1) | 0.2 (0.1, 0.4) |
| - Large Fringe Metro | 0.6 (0.2, 1.4) | 0.3 (0.1, 0.9) | 0.2 (0.1, 0.4) |
| - Medium Metro | 1 (0.3, 2.3) | 0.4 (0.1, 1.3) | 0.2 (0.1, 0.5) |
| - Small Metro | 0.6 (0.2, 1.5) | 0.3 (0.1, 1.1) | 0.2 (0.1, 0.5) |
| - Micropolitan | 0.7 (0.2, 1.6) | 0.3 (0.1, 1.1) | 0.2 (0.1, 0.6) |
| - Noncore | 0.6 (0.2, 1.5) | 0.4 (0.1, 1.4) | 0.2 (0.1, 0.6) |
| Pacific |  |  |  |
| - Large Central Metro | 1.5 (0.5, 3.2) | 0.4 (0.1, 1.3) | 0.4 (0.1, 1) |
| - Large Fringe Metro | 1 (0.3, 2.1) | 0.4 (0.1, 1) | 0.4 (0.1, 1) |
| - Medium Metro | 1.6 (0.5, 3.6) | 0.5 (0.1, 1.6) | 0.6 (0.2, 1.3) |
| - Small Metro | 1 (0.4, 2.4) | 0.4 (0.1, 1.2) | 0.6 (0.2, 1.3) |
| - Micropolitan | 1.2 (0.4, 2.7) | 0.4 (0.1, 1.3) | 0.6 (0.2, 1.4) |
| - Noncore | 1.1 (0.4, 2.5) | 0.5 (0.1, 1.6) | 0.6 (0.2, 1.4) |
| South Atlantic |  |  |  |
| - Large Central Metro | 0.9 (0.3, 2) | 0.2 (0, 0.6) | 0.3 (0.1, 0.7) |
| - Large Fringe Metro | 0.6 (0.2, 1.3) | 0.2 (0, 0.5) | 0.3 (0.1, 0.7) |
| - Medium Metro | 1 (0.3, 2.2) | 0.2 (0.1, 0.8) | 0.4 (0.1, 0.9) |
| - Small Metro | 0.7 (0.2, 1.5) | 0.2 (0, 0.6) | 0.4 (0.1, 0.9) |
| - Micropolitan | 0.7 (0.2, 1.6) | 0.2 (0, 0.6) | 0.4 (0.2, 1) |
| - Noncore | 0.7 (0.2, 1.5) | 0.3 (0, 0.7) | 0.4 (0.2, 1) |
| West North Central |  |  |  |
| - Large Central Metro | 1.4 (0.5, 3.3) | 0.4 (0.1, 1.2) | 0.3 (0.1, 0.6) |
| - Large Fringe Metro | 1 (0.3, 2.2) | 0.3 (0.1, 1) | 0.3 (0.1, 0.6) |
| - Medium Metro | 1.6 (0.5, 3.8) | 0.5 (0.1, 1.4) | 0.4 (0.1, 0.8) |
| - Small Metro | 1.1 (0.4, 2.4) | 0.4 (0.1, 1.1) | 0.4 (0.1, 0.8) |
| - Micropolitan | 1.2 (0.4, 2.6) | 0.4 (0.1, 1.2) | 0.4 (0.1, 0.9) |
| - Noncore | 1.1 (0.3, 2.5) | 0.5 (0.1, 1.4) | 0.4 (0.1, 0.9) |
| West South Central |  |  |  |
| - Large Central Metro | 1.2 (0.4, 2.7) | 0.7 (0.1, 1.9) | 0.5 (0.2, 1.1) |
| - Large Fringe Metro | 0.8 (0.3, 1.8) | 0.6 (0.1, 1.6) | 0.5 (0.2, 1.1) |
| - Medium Metro | 1.4 (0.5, 3.1) | 0.8 (0.2, 2.3) | 0.7 (0.2, 1.4) |
| - Small Metro | 0.9 (0.3, 2) | 0.7 (0.1, 2) | 0.7 (0.2, 1.5) |
| - Micropolitan | 1 (0.3, 2.2) | 0.7 (0.1, 1.9) | 0.7 (0.2, 1.6) |
| - Noncore | 0.9 (0.3, 2.1) | 0.8 (0.2, 2.4) | 0.7 (0.2, 1.6) |