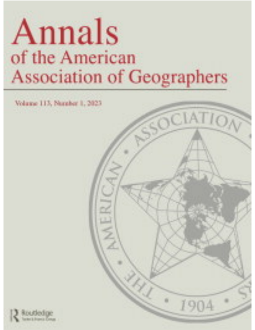

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The COVID-19 pandemic is not only a medical disease outbreak but also a social inequality and health disparity problem. This study analyzed dynamic temporal and spatial associations between confirmed COVID-19 cases and socioeconomic status (SES) variables at the neighborhood level with three case studies to (1) analyze five temporal stages in the County of San Diego, California; (2) compare six U.S. metropolitan areas; and (3) compare SES associations across two spatial scales (counties and zip code units). We identified eleven SES variables as potential contributors to the social determinants of health that influence COVID-19 outbreaks and showed how their correlation coefficients vary over five phases. We found that changes in COVID-19 hot spots and clusters are minimal across the five stages. The consistent spatial patterns through the five outbreak periods imply that the place effects associated with fundamental health disparity factors are persistent and not easily changed. The impact of COVID-19 on SES varies in different local contexts. We also found that Hispanic populations, uninsured groups, Spanish-speaking families, those with less than a ninth-grade education level, and high household densities strongly correlated with COVID-19 cases in all six metropolitan areas. We did not find high scale dependency in SES association patterns between county and zip code spatial units, but analysis at a finer level can provide more association patterns. *Key Words: COVID-19, GIS, health disparity, social determinants of health, spatial analysis.*

Since the outbreak of the COVID-19 pandemic, there have been more than 33.4 million positive confirmed cases and more than 601,000 deaths in the United States as of 1 July 2021 (Centers for Disease Control and Prevention [CDC] 2021). Neighborhood socioeconomic status (SES) variables that have solid associations with confirmed COVID-19 cases might contribute to social determinants of health (SDOH), which are multiple environmental conditions that affect health, well-being, and quality-of-life outcomes and risks. The U.S. CDC employed a social vulnerability index (SVI) to examine the associations between SES and SDOH. Recent research on SDOH and COVID-19 emphasized the health disparities experienced by ethnic groups and comorbidity issues (Abrams and Szefler 2020; Singu et al. 2020) without combining temporal and spatial analysis of SES variables. In addition, the SES variables in the current SVI are not adequate to monitor social vulnerability and determine SDOH. Therefore, researchers constructed alternate indexes incorporating more comprehensive variables for sociodemographics (e.g., race, age, economic stability, education access and quality), health condition and health care access, and environment vulnerability to explore social vulnerability to epidemics (Kiaghadi, Rifai, and Liaw 2020). SES variables, as an important part of analyzing social vulnerability and SDOH, have been widely explored and discussed in the context of pandemics. Specifically, neighborhood SES influences the risk of contracting COVID-19 and treatment outcomes (Singu et al. 2020). Meanwhile, SES variables such as racial or ethnic minority group membership,

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poverty rate, income, and age were disproportionately influenced by COVID-19 (Dasgupta et al. 2020; Maroko, Nash, and Pavilonis 2020; Moise 2020; Fu and Zhai 2021; Islam, Nayak, et al. 2021).

Scale is a critical element when exploring a locational phenomenon. The effects of SES variables vary with local context and different spatial scales can influence the social vulnerability under COVID-19 (Lee and Ramirez 2022; Zhai et al. 2021). Due to COVID-19 data accessibility, some SDOH studies used coarse spatial resolutions, such as U.S. county level, for analyses exploring the SVI (Ramírez and Lee 2020; Neelon et al. 2021) or COVID-19 mortality (Debopadhaya, Erickson, and Bennett 2021) rather than using data sets at detailed scale division (i.e., zip code). Using large scales, at or above the county level, might obscure characteristics of local COVID-19 situations and their associations with socioeconomic variables (Maroko, Nash, and Pavilonis 2020). A few studies combine spatial and temporal analysis of SES variables (e.g., Islam et al. 2021 studies) but some only use existing indexes like the CDC's SVI.

The COVID-19 situation (i.e., number of confirmed cases) fluctuated drastically in response to external factors including government policy changes and viral mutations. A study of the aggregate period might fail to detect the characteristics of the pandemic during specific subperiods. Therefore, it is reasonable to divide the study into phases defined by characteristics of the epidemic at different times. Moreover, different cities exhibit different COVID-19 spread patterns due to their demographic structures, government policies, and so on. Furthermore, COVID-19 spreads more rapidly and with greater effect in metropolitan cities. Because research insights in one city might not fully apply to another, it is important to study disease spread in several representative cities to identify similar and different features. Effective detection and analysis of these socioeconomic factors and their potential impact on COVID-19 cases can help local health agencies improve decision-making processes for intervention and health resource management plans, such as selecting COVID testing sites or vaccination distribution priorities.

This study analyzed temporal and spatial associations between confirmed COVID-19 cases and comprehensive SES variables using three approaches. For our first case study, we selected the County of San Diego, California, as our study area and a zip code level spatial resolution. Given the highly diverse neighborhoods in our study area, analysis at a fine spatial resolution was crucial. The San Diego County Health and Human Services Agency (HHSA) was one of only a few local government agencies to provide comprehensive daily updates of confirmed COVID-19 cases at the zip code level for an extended period. In the first case study, we analyzed temporal and spatial changes for five different outbreak phases over the course of one year. For our second case study, we compared SES associations with COVID-19 data in six U.S. metropolitan areas (San Diego, Chicago, New York, Phoenix, Miami, and San Francisco Bay Area) to identify variations in different local contexts. Finally, our third case study compared SES association results for county and zip code spatial scales in San Diego County.

This study focused on four research questions:

1. How do the statistical associations between SES and COVID-19 confirmed cases vary during different outbreak periods (five stages)? Could these temporal changes reflect the impacts of nonpharmaceutical interventions, such as policy changes, in different stages?
2. What are the spatial distribution patterns of COVID-19 cases during the five stages at the neighborhood level? Do COVID-19 hot spots move during different outbreak periods?
3. Which neighborhood SES variables potentially contribute to the SDOH, in the context of COVID-19 outbreaks? Will different metropolitan areas have similar or unique variable associations? Which variables are more influential in the different metropolitan areas?
4. Are the SES and COVID-19 variable associations scale-dependent? Do the SES correlation patterns change from one spatial scale (i.e., zip code level) to another (i.e., county level)?

Literature Review: Health Disparities in COVID-19 Outbreaks

Health disparities are an important public health concern as they widen social inequality gaps in population health. Factors contributing to health disparities are complex and involve social and structural determinants, including race and ethnicity, SES, and access to health care, especially during the COVID-19 epidemic (Orgera and Artiga 2018; Clark et al. 2020; Hooper, Nápoles, and Pérez-Stable 2020;

Kabarriti et al. 2020). Specifically, SES factors showed close relationships with COVID-19 incidence and vulnerable groups exhibited different sensitivities to the pandemic (Fu and Zhai 2021). Some racial and ethnic minority groups suffered more from COVID-19 than others (Dasgupta et al. 2020; Maroko, Nash, and Pavilonis 2020; Moise 2020; Islam, Nayak, et al. 2021; Huang et al. 2022). Disparities in confirmed COVID-19 cases and mortality are observed among African Americans, Latin Americans, Native Americans, and U.S. immigrants (Clark et al. 2020; Hooper, Nápoles, and Pérez-Stable 2020; Rentsch et al. 2020). African American residents in low-income neighborhoods were highly affected by COVID-19 (Kim and Bostwick 2020; Islam, Lacey, et al. 2021). Counties with a greater percentage of Hispanic residents experienced higher rates of COVID-19 and more negative outcomes (Islam, Lacey, et al. 2021). Possible reasons for disparities among minority groups include higher poverty, higher unemployment rates, and lack of health insurance under the pandemic. Hispanic Americans, Black or African Americans, and American Indians or Alaskan Natives are more likely than White Americans to avoid seeing a doctor due to the cost (21 percent, 17 percent, 19 percent, and 13 percent, respectively; Orgera and Artiga 2018). Low SES compounded by the disproportionate burden of chronic illness has widened disparities in health outcomes (Clark et al. 2020). Among nonelderly populations, uninsured rates are significantly higher for Native Americans, Hispanic Americans, and African Americans as compared to their White counterparts (22 percent, 19 percent, 12 percent, and 8 percent, respectively; Orgera and Artiga 2018).

Research also found that elderly groups were highly influenced by COVID-19. Kiaghadi, Rifai, and Liaw (2020) discovered that residents age forty-five years and older were at a higher risk of COVID-19 in Harris County, Texas, whereas Islam, Lacey, et al. (2021) found that COVID-19 risk for the elderly did not differ among the U.S. counties. Other consistent findings included negative associations between high household income and COVID-19 transmission, reduction of COVID-19 spread after the implementation of stay-at-home orders (Zhai et al. 2021), and disproportionate COVID-19 impact on low-income households (Maroko, Nash, and Pavilonis 2020). The effects of SES variables on COVID-19 varied across the United States (Zhai et al. 2021). Maroko, Nash, and Pavilonis (2020) found significant differences in SES variable associations and COVID-19 risk in Chicago and New York City zip codes. Meanwhile, low SES often clusters spatially, partially due to residential segregation (Sharkey 2013). Residential segregation and socioeconomic clustering converge in specific neighborhoods, leading to resource disparities that shape access to health care (Kwan 2013; Mansour et al. 2022) and the local availability of jobs (Wilson 2011). Consequently, the spatial concentration of disadvantage also has direct associations with poor health (Gibbons et al. 2020; Embury et al. 2022), including the spread of disease (Acevedo-Garcia 2001).

Currently, many geospatial analyses of health disparities during the COVID-19 pandemic focus on the global, country, and state levels (Cordes and Castro 2020; Harris 2020; Islam et al. 2021; Lieberman-Cribbin et al. 2020). Researchers (Maroko, Nash, and Pavilonis 2020) explored a finer scale (zip code) and found specific groups (low income, high unemployment) were significantly influenced by COVID-19 in Chicago, whereas middle-income groups where people provide service jobs were most vulnerable to COVID-19 in New York City. Although a finer scale (e.g., zip codes, subregional areas, census tracts, block groups) has been explored, the association between SES and COVID-19 at those scales is still worth exploring in different local contexts (Zhai et al. 2021) and even on social networks (Dou and Gu 2022), so further study is required. Some used CDC's SVI to explore the association between social vulnerability and COVID-19. In addition to the SVI, various indexes were developed to identify comprehensive influential factors that have been used in COVID-19-related research. Lee and Ramirez (2021) constructed health and social vulnerability indexes (HSVIs) to characterize health vulnerability toward COVID-19 at the county and census tract level. Moise (2020) constructed a social disadvantage index (SDI) to explore the association between social vulnerability and COVID-19 at the zip code and block group level. The analysis of some of those established indexes seldom explored the impact of COVID-19 on the single SES variable, however, and thus cannot provide recommendations to health agencies about specific groups.

Our research further contributes to the growing number of those studies by examining comprehensive SES variables (including race, age, education, socioeconomic context, etc.) to explore the relationship between social vulnerability and the epidemic in both spatial and temporal aspects. Meanwhile, a finer scale (ZIP code level) is employed to test SES and social vulnerability risk for COVID-19 in San Diego and other metro areas, thus determining the impact of different local contexts on the relation between SES and COVID-19. In addition, each SES variable is examined to explore its association with COVID-19.

The First Case Study: COVID-19 Outbreak in the County of San Diego, California

Temporal Analysis of COVID-19 Outbreak Patterns in San Diego County Zip Code Levels

We selected the County of San Diego, California, for our first case study. Before the wide distribution of vaccinations, the temporal patterns of COVID-19 outbreaks were highly associated with nonpharmaceutical interventions (NPIs) such as social distancing, adherence to masking policies and stay-at-home orders, holiday events, and winter seasonal effects. The implementation of social distancing and stay-at-home measures contained the spread of COVID-19 (Courtemanche et al. 2020). In addition, wearing masks can effectively reduce the growth rate of COVID-19 when combined with social distancing (Li et al. 2020). Holiday events significantly influenced human mobility, however, and increased the spread of the epidemic. The first case study collected a full year of daily COVID-19 confirmed case data (1 April 2020–31 March 2021) at the zip code level and divided the temporal patterns into stages based on seven-day confirmed case averages daily. Based on the visual growth patterns of cases and the possible impacts of NPIs, we ultimately decided on five stages to observe the influence of SES variables on the spread of COVID-19:

- **Stage 1 (1 April –19 June 2020):** Early outbreaks with slow growth rates. On 19 March 2020, the State of California issued a stay-at-home order, followed by the County of San Diego.
- **Stage 2 (20 June–17 August 2020):** Rapid growth rates. The first major "wave" of outbreaks is possibly associated with the official announcement of the County of San Diego policy changes on 12 June 2020 regarding the reopening of gyms, bars, and movie theaters.
- **Stage 3 (18 August–31 October 2020):** Reduced and stable rates, possibly associated with new regulations on 13 July 2020 to reclose indoor operations at gyms, nail salons, and some business sectors.
- **Stage 4 (1 November 2020–15 January 2021):** Rapid growth rates. The second major "wave" of outbreaks is possibly associated with the U.S. presidential election on 3 November 2020 and related demonstration activities, holidays, and the cold winter weather.
- **Stage 5 (16 January–31 March 2021):** Rapidly decreasing rates, possibly associated with a regional stay-at-home order announced on 6 December 2020, the County of San Diego's receipt of vaccines on 13 December 2020 and prompt vaccination plans, and the milestone of 1 million doses of vaccine administered on 5 March 2021.

To calculate the seven-day average number, we combined the daily case number from the target date with those from three days before and after. Using a seven-day average number removes weekly pattern effects like lower case numbers on weekend days. At each stage, we used accumulated confirmed cases for the period for each zip code to compare with SES variables from the American Community Survey (ACS) five-year estimates (2014–2018).

Many COVID-19 temporal graphs use a regular scale to represent the growth patterns of outbreaks. We discovered that the logarithmic (log) expression of case numbers can provide additional details about the temporal patterns. Figure 1 illustrates the two types of graph representations with the following findings.

- The regular-scale chart estimates the impact of COVID-19 outbreaks on public health resources (e.g., hospital and intensive care unit [ICU] beds, testing site capacities) during different stages.
- The log-scale chart reveals detailed temporal pattern changes across the different stages. For example, the early wave (SR1) can be easily identified using the log-scale chart.
- The slope rate (SR) in the log-scale chart effectively represents elevated and reduced rates of COVID-19 cases. For instance, Stage 2's slope rate (SR2) is higher than Stage 4's slope rate (SR3), indicating the growth rate was faster during the Stage 2 outbreak than the Stage 4 outbreak.

In addition to the temporal trend analysis, the first case study also compared descriptive statistical results among the five stages. Table 1 indicates that Stage 4, characterized by the second wave of outbreaks, had

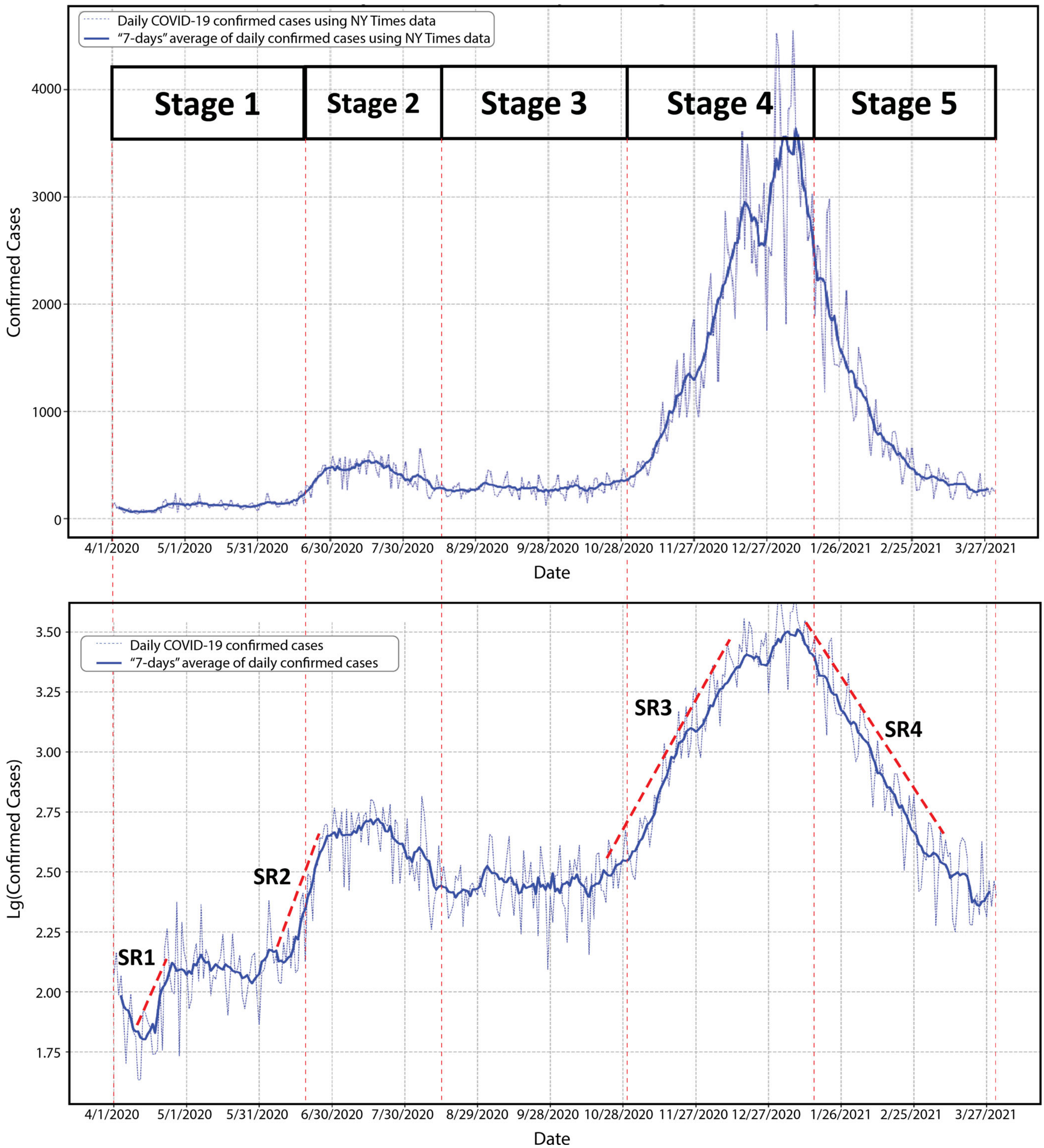

Figure 1. The five stages of COVID-19 outbreaks in the County of San Diego, based on the seven-day average of confirmed cases from 1 April 2020 to 31 March 2021, in regular-scale (top) and log-scale (bottom) charts. *Note:* SR = slope rate.

the highest standard deviation (1,141) which was 8.8 times greater than the standard deviation for Stage 2, defined by the first wave of outbreaks. In addition, Stage 4 had the highest mean value (2,010), which was 4.8 times greater than Stage 2's median. The statistical patterns also reveal that Stage 4 (increasing rates) and Stage 5 (decreasing rates) have the highest daily average (mean) case numbers.

Table 1. Descriptive statistics of the five-stage COVID-19 outbreaks in the County of San Diego using seven-day average of daily confirmed cases

Confirmed COVID-19 cases	Stage 1 (1 April–19 June 2020)	Stage 2 (20 June–17 August 2020)	Stage 3 (18 August–31 October)	Stage 4 (1 November 2020–15 January 2021)	Stage 5 (16 January–31 March 2021)	All stages (1 April 2020–31 March 2021)
Minimum number	43	182	124	293	178	43
Median	117	419	284	2,019	519	352
Maximum number	258	652	471	4,550	2,980	4,550
SD	47	129	77	1,141	666	918
M (daily average cases)	121	418	293	2,010	809	739
Total accumulated case numbers	9,698	24,678	21,940	152,795	60,642	269,753

SES Variables Correlation Analysis in San Diego

To study the impacts of SES variables as potential contributors of SDOH and COVID-19 outbreaks in San Diego County, we utilized application programming interfaces (APIs) from the U.S. Census Bureau (see https://www.census.gov/data/developers/data-sets.html) to download the ACS five-year estimates (2014–2018) data set at the zip code level. We downloaded fifty-one SES variables including those related to ethnicity, spoken languages, ages, education levels, foreign-born populations, median income, married populations, and populations experiencing disability. Because data for zip codes with low populations might not accurately reflect the characteristics of the residents, we omitted zip codes with fewer than 1,000 residents and selected ninety-four of the County of San Diego's 114 zip codes. The total population of the twenty omitted zip codes is 4,974, just 0.15 percent of the total population of 3,293,730 in the ninety-four selected zip codes. We normalized the explanatory SES variables and COVID-19 accumulative confirmed cases in each stage by the total population in 2018 and tested the data to ensure that the majority followed a normal distribution. To explore the relationships between COVID-19 cases and SES variables, we performed a Pearson's correlation analysis among the fifty-one SES variables and reviewed the significance level of Pearson's correlation coefficient (r). Most SES variables were normalized per capita using the total population in each zip code prior to the correlation analysis.

It is worth noting that correlation does not imply causation. From a scientific perspective, variables with strong correlations could help scientists to form hypotheses and research questions. Actual causative relationships need to be further explored, examined, and validated following scientific procedures. Table 2 illustrates thirty major SES variables in six categories with significant correlation results or representative values. First, we found that total population (TotalPop, $r = 0.394$) and population density ($r = 0.162$) had weak associations with COVID-19 confirmed cases, as more populated areas and high population densities might facilitate disease transmission. These values, however, are not as significant as those for other SES variables. In the ethnicity category, the proportion of Hispanic residents (TotalHispanic) had significant positive associations in all five stages as well as for the cumulative year from 1 April 2020 to 31 March 2021 (all stages, $r = 0.82$). The proportion of non-Hispanic White residents (NonHispWhite) had high negative associations in Stages 1 through 5 and the cumulative year (all stages, $r = -0.728$). In the economic category, the proportion of households receiving federal cash assistance (HouseholdwithCash, $r = 0.724$) and the proportion of unemployed civilians (UnemployedCvilian, $r = 0.558$) had significant positive associations in the all stages period. On the other hand, the normalized values for employees in professional industries (Professional, $r = -0.546$) and married couples (Married, $r = -0.319$) had significant negative associations. For variables related to languages spoken at home (for those five years of age and older), the proportion of English language speakers (Pop5andOlderEnglish, $r = -0.685$) showed significant negative associations, whereas the proportion of Spanish speakers (Pop5andOlder Spanish, $r = 0.789$) had highly significant positive associations across all stages.

Table 2. Pearson's correlation coefficients for the County of San Diego's zip codes ($n = 94$) during Stages 1, 2, 3, 4, and 5 of the COVID-19 pandemic

Social variables (most are per capita)	Stage 1 *r*	Stage 2 *r*	Stage 3 *r*	Stage 4 *r*	Stage 5 *r*	All stages *r*
TotalPop (with original data, not normalized)	0.328*	0.194	0.4***	0.389***	0.388***	0.394***
Population density	0.335***	0.188	0.289	0.138	0.102	0.162
Ethnicity						
White	–0.147	–0.413***	–0.223*	–0.294**	–0.294**	–0.325**
Asian	–0.064	–0.097	–0.092	–0.155	–0.155	–0.159
AmericanIndian	–0.1	0.489***	0.106	0.27**	0.27**	0.288**
TotalHispanic	0.73***	0.601***	0.693***	0.808***	0.725***	0.82***
OtherRace	0.403***	0.407***	0.425***	0.587***	0.587***	0.602***
NonHispWhite	–0.602***	–0.628***	–0.607***	–0.703***	–0.703***	–0.728***
NonHispBlack	0.386***	0.305**	0.308**	0.239*	0.239*	0.312**
Economic						
HouseholdwithCash	0.773***	0.531***	0.533***	0.715***	0.689***	0.724***
Professinal	–0.428***	–0.413***	–0.275***	–0.546***	–0.546***	–0.546***
Married	–0.452***	–0.419***	–0.398***	–0.213*	–0.295**	–0.319**
UnemployedCvilian	0.479***	0.422***	0.523***	0.552***	0.45***	0.558***
PopBelowPoverty	0.279**	0.235*	0.424***	0.321**	0.321**	0.345***
PopUninsurance	0.31**	0.688***	0.521***	0.671***	0.652***	0.69***
Speaking language						
Pop5andOlderEnglish	–0.672***	–0.488***	–0.597***	–0.684***	–0.684***	–0.685***
Pop5andOlderSpanish	0.782***	0.559***	0.684***	0.776***	0.776***	0.789***
Age						
PopAge15_24	0.325**	0.145	0.014	–0.085	–0.085	0.006**
PopAge25_44	0.077	0.104	0.309**	0.155	0.155	0.173**
PopAge65	–0.309**	–0.16	–0.254*	–0.219*	–0.219*	–0.25**
Education						
Pop25OlderLess9	0.64***	0.545***	0.633***	0.782***	0.782***	0.784***
Pop25Older9_12grade	0.43***	0.569***	0.503***	0.683***	0.683***	0.681***
Pop25OlderBachelor	–0.495***	–0.418***	–0.289**	–0.525***	–0.525***	–0.533***
Pop25OlderMaster	–0.539***	–0.514***	–0.408***	–0.64***	–0.64***	–0.655***
Other factors						
MedianIcome	–0.532***	–0.398***	–0.348***	–0.456***	–0.544***	–0.502***
Foreignborn	0.436***	0.346***	0.435***	0.475***	0.475***	0.474***
AveHouseSize	0.17	0.254*	0.342***	0.594***	0.531***	0.528***

*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

When considering the age category, the correlation coefficients for those between fifteen and twenty-four years old (PopAge15_24) changed dynamically from Stage 1 ($r = 0.325$) to Stage 5 ($r = –0.085$), which might indicate that health messages were successfully delivered to young adults in the later stages. The proportion of residents sixty-five-years of age and older (PopAge65/above) had consistently negative associations with COVID-19 in Stages 1 through 5, possibly because these residents belong to a vulnerable group and received a higher level of protection, or took extra precautions, than their younger counterparts. Interestingly, a study found that in Harris County, Texas, seniors were actually at a higher risk of contracting COVID-19 and experiencing negative outcomes (Kiaghadi, Rifai, and Liaw 2020). Although our study finding was different, it does highlight the importance of place and that the effects of SES should be considered within their local contexts, as others have confirmed (Maroko, Nash, and Pavilonis 2020; Chen and Krieger 2021; Islam, Lacey, et al. 2021; Zhai et al. 2021; Lee and Ramírez 2022).

Local government policies toward seniors, prevalence of comorbidities, health care accessibility, and senior income levels could contribute to differences in confirmed COVID-19 case rates and outcomes. The education category includes data for residents twenty-five years of age and older. The proportion of the population with less than a ninth-grade

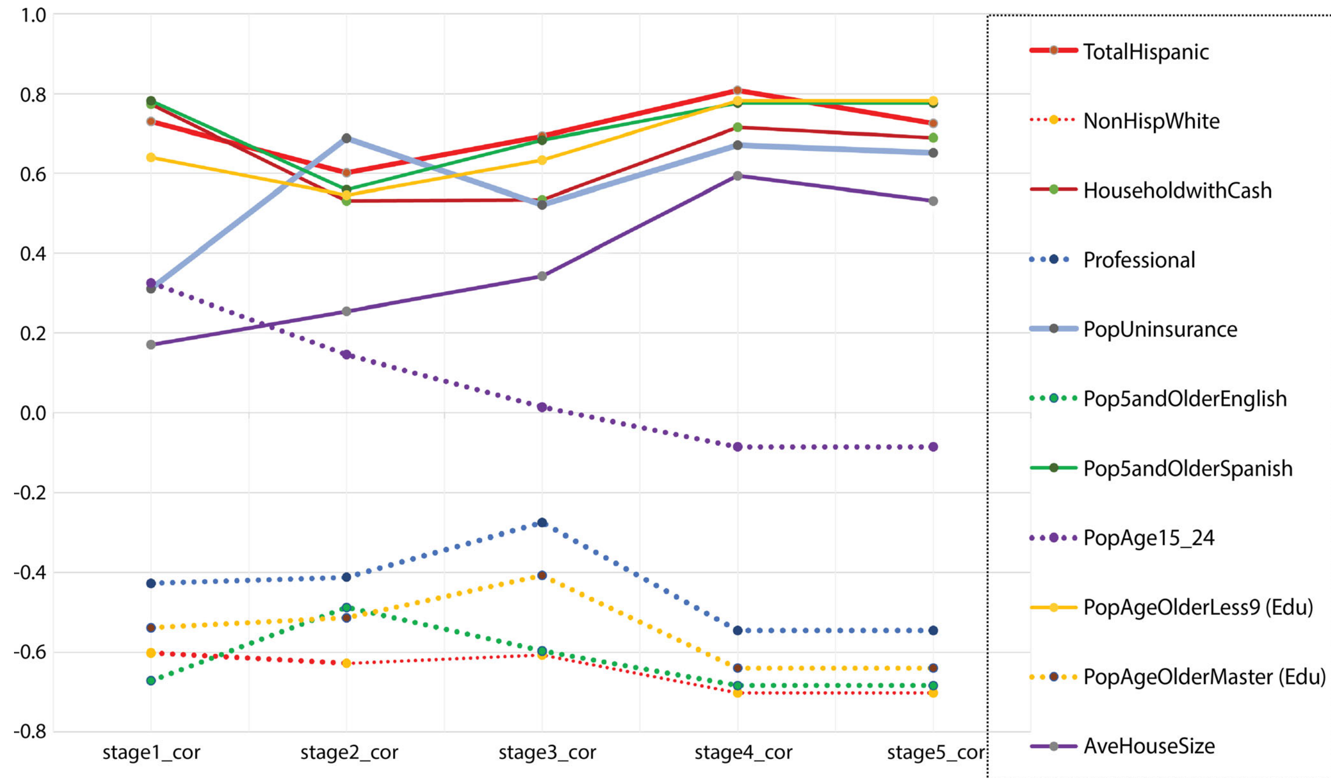

Figure 2. Pearson's correlation coefficient (r) trend lines for selected socioeconomic status variables in five stages of COVID-19 outbreaks. Solid lines indicate consistently positive associations ($r \geq 0$), dashed lines indicate negative associations ($r \leq 0$), and dotted lines display unique trend patterns.

education (Pop25OlderLess9, $r = 0.784$) showed strong positive associations in all stages. On the other hand, the proportion of the population with a bachelor's degree (Pop25OlderBachelor, r = –0.533) or master's degree (Pop25OlderMaster, r = –0.655) had significant negative associations in all stages. Among the other factors, median household income (MedianIncome, r = –0.52) had significant negative associations with COVID-19 cases, consistent with findings from Zhai et al. (2021). The proportion of foreign-born residents (Foreignborn, $r = 0.474$) and the average household size (AveHouseSize, $r = 0.528$) both had significant positive associations with COVID-19 cases.

To investigate the impact of NPIs during different outbreak stages, we identified eleven significant SES variables, indicated in bold in Table 2, as potential contributors to the SDOH and COVID-19 outbreaks, then illustrated their correlation coefficient trend lines over the five stages (Figure 2). In the top group, the solid lines in Figure 2 have a consistently positive association ($r \geq 0$), whereas the dashed lines in the bottom group have negative association values ($r \leq 0$). The other three dotted lines (red, blue, and purple) display unique trend patterns. The following observations are our key findings.Four strong positive associations (solid lines; TotalHispanic, Household withCash, Pop5andOlderSpanish, Pop25OlderLess9) decreased in Stage 2 (the first wave) and then increased in Stage 3 and Stage 4 (the second wave). Other studies confirm the disparate COVID-19 burden felt by racial and ethnic minority groups (Dasgupta et al. 2020; Maroko, Nash, and Pavilonis 2020; Moise 2020; Islam, Lacey, et al. 2021). Specifically, Hispanic communities have positive relationships with COVID-19 rates (Islam, Lacey, et al. 2021).Four negative associations (dashed lines; Education with master's degree, Professional, English-speaking population, and NonHispanic White) had the lowest values in Stage 3 (the stable stage) and the highest negative values in Stage 4 (the big wave). Overall, numerous studies found that non-Hispanic White communities suffered less during the pandemic (Dasgupta et al. 2020; Maroko, Nash, and Pavilonis 2020; Moise 2020; Islam, Lacey, et al. 2021).PopUninsurance (blue solid line) had the highest positive value in Stage 2, corresponding to the reopening of gyms, bars, and so on. One explanation is that those without insurance are more likely to work in industries that remained open to the public during the pandemic (Adamkiewicz et al. 2011; Raifman and Raifman 2020).

AveHouseSize (dark purple solid line) had a low positive association ($r = 0.17$) in Stage 1 that increased to a maximum during Stage 4 ($r = 0.594$) and then slightly decreased in Stage 5 ($r = 0.531$). Households with more members were more vulnerable to COVID-19 during the first and the second wave of outbreaks. These households might be more crowded or multigenerational, thereby escalating exposure to health risks and limiting options for following social distancing and quarantine guidelines (Adamkiewicz et al. 2011; Raifman and Raifman 2020).PopAge15-24 had a positive association at the beginning of the pandemic (Stage 1, $r = 0.325$), that decreased to its lowest value in Stages 4 and 5 ($r = -0.085$). Awareness of COVID-19 risks might have increased among younger populations as the pandemic progressed. Further study should be conducted to explore the mechanisms behind this consistent decrease.

We suggest that the eleven SES variables, illustrated in Figure 2, could be potential SDOH and indicators of COVID-19 outbreaks. Based on these results, public health researchers and practitioners can form hypotheses to study the mechanisms behind these dynamically changing associations. Local public health agencies can use these findings to recommend appropriate social interventions and mitigate health disparities. For example, we found that zip codes with higher proportions of Hispanic and Spanish-speaking residents had the strongest positive associations with COVID-19 cases. We recommend that local public health agencies provide more Spanish-language media (e.g., television advertisements, flyers, social media) and recruit more Spanish-speaking community health workers to work in these neighborhoods. We also identified that economic factors such as receipt of federal cash assistance, unemployment status, and uninsured rates (HouseholdwithCash, UnemployedCvilian, and PopUninsurance) had strong positive associations with COVID-19 outbreaks. Economically vulnerable groups might need more financial support from the emergency relief funds provided by federal and local government agencies.

Spatial Patterns and Hot Spot Analysis of the COVID-19 Pandemic in San Diego

We used geographic information system (GIS) software (ArcGIS Pro) to visualize COVID-19 spatial clusters in the County of San Diego and to conduct a hot spot analysis for the five stages using confirmed COVID-19 cases. Among the ninety-four zip codes, we adopted equal interval classification to form twenty classes (Figure 3). For this portion of the study, we did not normalize accumulated case numbers by zip code population because our focus is on spatial cluster patterns rather than infection rates.

The pattern of spatial clusters remains consistent during the five temporal stages. All the submaps in Figure 3 show a major cluster of zip codes with high numbers of confirmed COVID-19 cases located in southern San Diego's South Bay region, including zip codes 92154, 91911, 91910, and 91950. The spatial distribution of confirmed COVID-19 cases spread to East County zip codes (e.g., 92021, 92020) and North County zip codes (e.g., 92027, 92084) in Stages 4 and 5. One exception to the general trend is the local outbreak in the neighborhood surrounding San Diego State University (zip code 92115) during Stage 3.

For our hot spot analysis, we used the Getis–Ord Gi* statistic function provided by ArcGIS Pro. There are two output variables in the Getis–Ord Gi method. The z scores indicate the spatial clustering values. High positive z values indicate clustered high values representative of a hot spot, whereas low negative z values are indicative of clustered low values associated with a cold spot. The p values indicate the statistical significance with a 90 percent, 95 percent, or 99 percent confidence level. In Figure 4, the blue-colored areas are cold spots and the red areas are hot spots.

The hot spot analysis results are consistent across the five temporal stages, and are similar to the previously identified spatial clusters. The major hot spot regions are located in the South Bay region of southern San Diego, meaning that COVID-19 cases are highly clustered in this area. By contrast, wealthy neighborhoods in Camel Valley, Rancho Santa Fe, Del Mar, and Carlsbad are the major cold spot regions, where COVID-19 cases remained low. This polarized distribution feature became more obvious as the pandemic evolved. By Stages 4 and 5, the hot spot areas spread to East County and Escondido (zip code 92027).

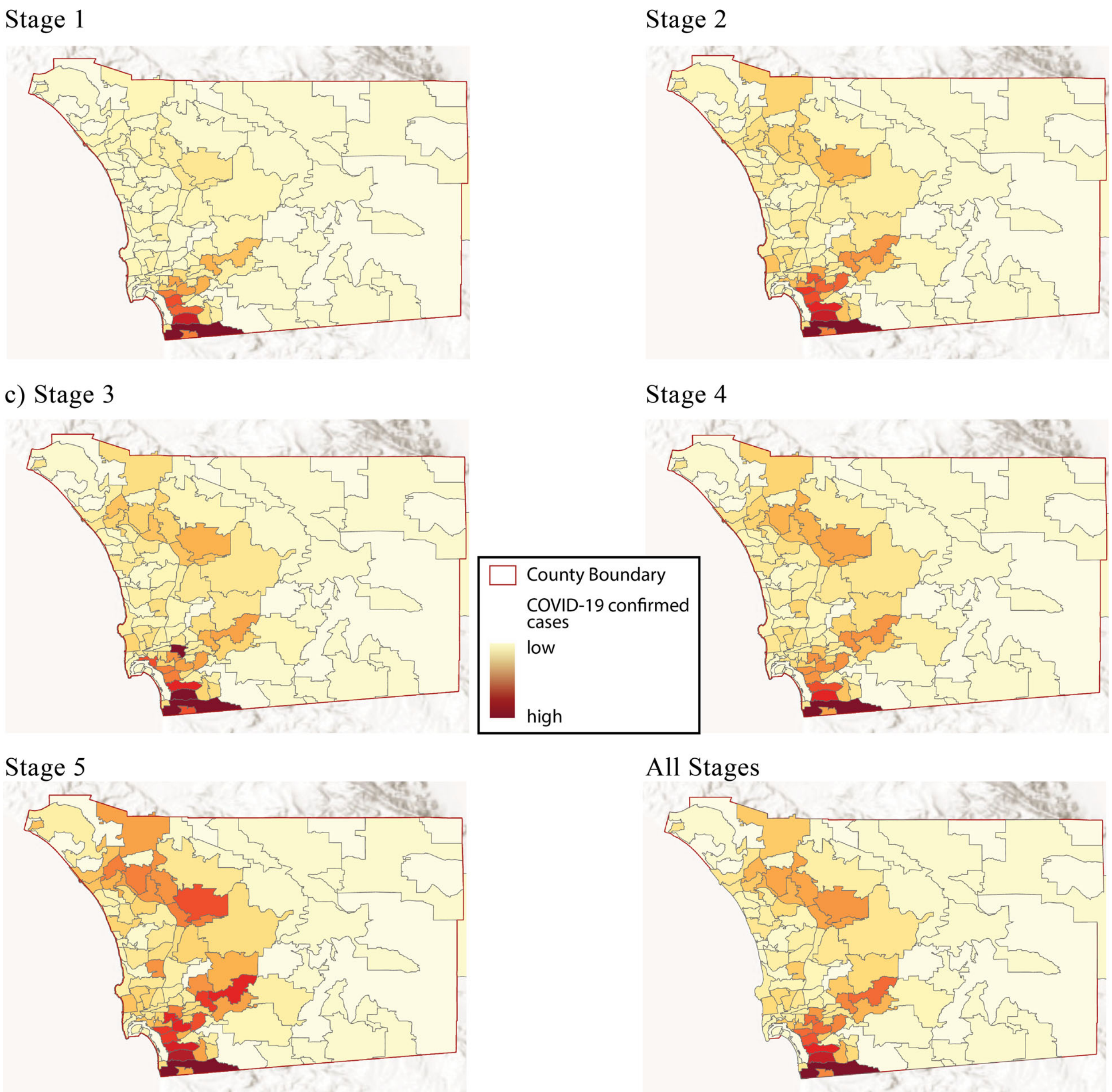

Figure 3. The spatial pattern of COVID-19 confirmed cases in the County of San Diego during the five pandemic stages of outbreaks.

When compared to the dynamic temporal changes of confirmed COVID-19 cases over five stages (Figure 1), the spatial changes of COVID-19 hot spots and clusters are minimal. South Bay, North County (Escondido), and rural areas to the east had major clusters of confirmed COVID-19 cases from Stage 1 to Stage 5. The consistent spatial patterns throughout the year might imply that the "place effects" associated with the factors of fundamental health disparity are strong and difficult to change. We need to study the implications of place effects and the potential SDOH on COVID-19 outbreaks to design and provide effective intervention and prevention methods that can mitigate and even resolve future COVID-19 outbreaks in these neighborhoods. For example, public health officials in the county can use the maps in Figures 3 and 4 to aid in the development of health resource management plans such as where to locate COVID-19 testing sites or distribute COVID-19 vaccines at different stages.

We explored the distribution of SES variables and any overlaps with common hot spot areas (95 percent confidence interval) in Figure 5. We found that some variables (e.g., proportion of Hispanic residents, proportion of residents with earnings below

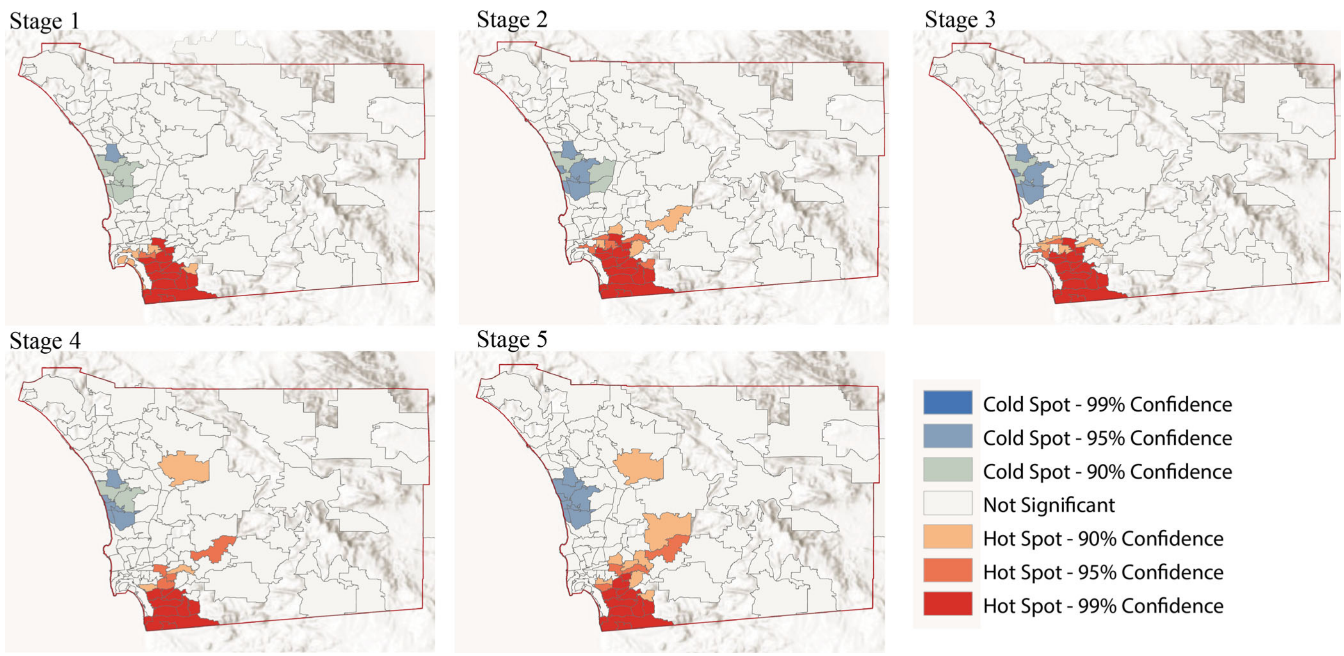

Figure 4. The hot spot (red) and cold spot (blue) analysis of COVID-19 in the County of San Diego during the five outbreak stages, using Getis–Ord Gi* statistics and ArcGIS Pro. The light, medium, and dark shades of red and blue indicate p values with 99 percent, 95 percent, and 90 percent confidence levels, respectively.

the poverty line, proportion of residents ages fifteen to twenty-four) that displayed high positive correlations with COVID-19 also shared a clustering distribution with confirmed COVID-19 cases. For instance, zip codes with high proportions of residents earning below the poverty line are clustered in high COVID-19 risk areas. Other variables (e.g., proportion of non-Hispanic White residents, civilians employed in professional industries, proportion with a master's degree) that were negatively correlated with COVID-19 are not significantly clustered in low-risk, cold spot areas, however.

The Second Case Study: Comparison of Six Metropolitan Areas at the Zip Code Level

Our second case study compared zip-code-level SES variable associations for six U.S. metropolitan areas: County of San Diego, California; Chicago, Illinois; New York, New York; Phoenix, Arizona; Miami, Florida; and the San Francisco Bay Area, California. First, we removed zip codes with populations less than 1,000. We collected the COVID-19 case data on 23 April 2021, so values represent total accumulated cases from the start of the pandemic in early 2020 to the collection date. Pearson's correlation coefficients (r) between SES variables and confirmed COVID-19 cases are listed in Table 3. The primary objective of this analysis was to compare the results from different metropolitan areas to better understand both general and unique patterns of association between SES variables and COVID-19 outbreaks. The following are our key findings.

County of San Diego and the San Francisco Bay Area, both in California, have similar patterns for all SES variables, with some minor differences in the proportion of Hispanic residents per zip code (TotalHispanic; San Diego, $r = 0.793$; San Francisco Bay Area, $r = 0.474$), uninsured rates (PopUninsurance; San Diego, $r = 0.673$; San Francisco Bay Area, r = 0.304), and proportion of foreign-born residents (ForeignBorn; San Diego, $r = 0.457$; San Francisco Bay Area, r = 0.247). Hispanic residents comprise 33 percent (1,105,152 of 3,298,704) of the San Diego County population, but only 23.6 percent (1,812,607 of 7,686,624) of the population in the San Francisco Bay Area. One possible explanation for the differences in the observed variable associations is that the San Francisco Bay Area has a lower proportion of Hispanic residents, lower uninsured rates, and a smaller foreign-born population than the County of San Diego.

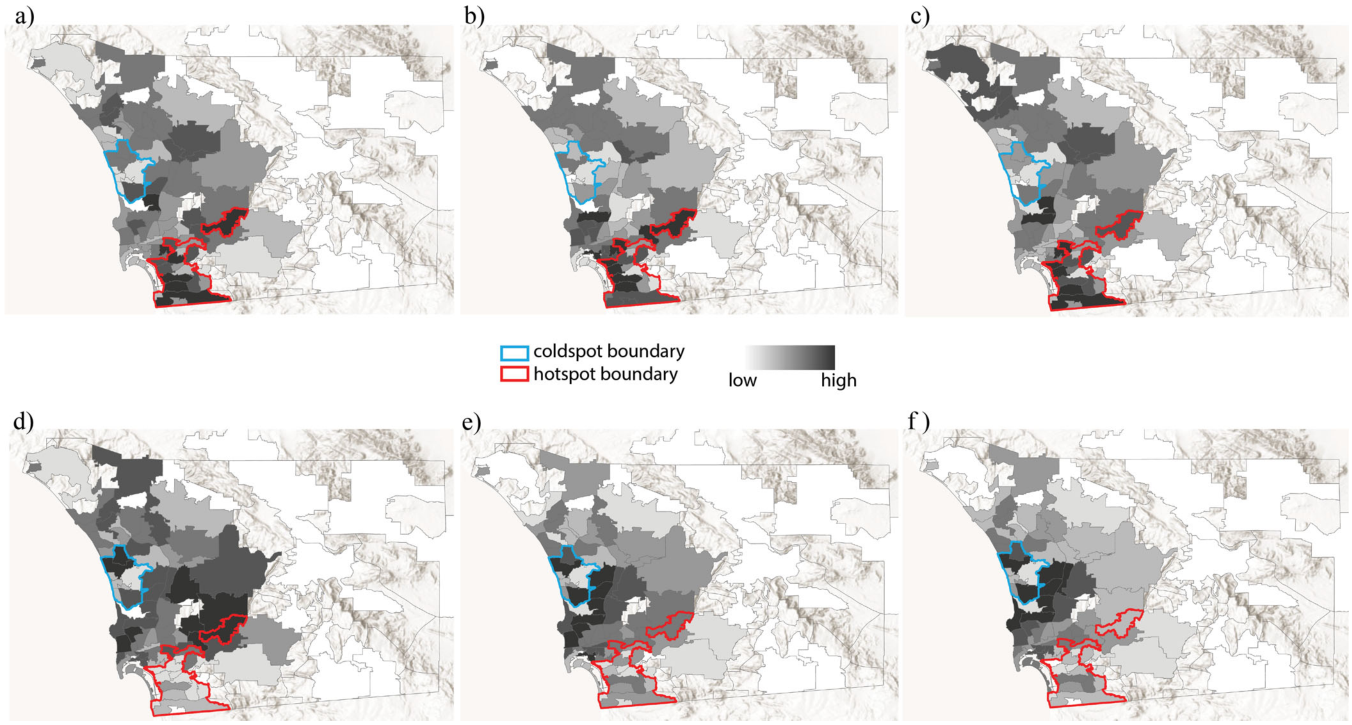

Figure 5. Selected socioeconomic status variable distribution and overlapping hot spots (red boundary) and cold spots (blue boundary), using 95 percent confidence levels, in the County of San Diego. (A) Proportion of Hispanic residents. (B) Proportion of residents with earnings below the poverty line. (C) Proportion of residents between fifteen and twenty-four years old. (D) Proportion of non-Hispanic White residents. (E) Proportion of civilians employed in professional industries. (F) Proportion of residents with a master's degree.

In general, Phoenix also has an SES association pattern similar to the County of San Diego. Exceptions include SES variables representing the proportion of residents fifteen to twenty-four years old (PopAge15_24; San Diego, $r = 0.08$; Phoenix, $r = 0.391$), average household size (AveHouseSize; San Diego $r = 0.523$; Phoenix, $r = 0.223$), and total population per zip code (TotalPop; San Diego, $r = 0.412$; Phoenix, $r = -0.169$). Possible explanations for the discrepancies include Phoenix's relatively low number of highly populated zip codes, its smaller average household size, and its higher numbers of accumulated COVID-19 cases among teenagers and young adults in 2020, as compared to the County of San Diego.

Chicago and the County of San Diego have similar SES association patterns except for proportion of non-Hispanic White residents (NonHispWhite; San Diego, $r = -0.706$; Chicago, $r = -0.101$), proportion of non-Hispanic Black or African American residents (NonHispBlack; San Diego, $r = 0.353$; Chicago, $r = -0.326$), proportion of households receiving federal cash assistance (HouseholdwithCash; San Diego $r = 0.544$; Chicago $r = 0.184$), and proportion of unemployed civilians (UnemployedCvilian; San Diego, $r = 0.301$; Chicago, $r = -0.008$). The socioeconomic profiles for different racial and ethnic minority groups vary a lot between Chicago and the County of San Diego. Also, in Chicago, COVID-19 cases were not always associated with low-income zip codes. This is consistent with findings from Maroko, Nash, and Pavilonis (2020) that indicate that the lowest income groups in New York City were not affected the most by COVID-19. Because the accumulated COVID-19 case rates in Chicago (9.99 percent) are higher than in the County of San Diego (7.82 percent), another possible hypothesis is that the COVID-19 outbreaks in Chicago were more severe for all residents, regardless of SES.

Miami is a unique city with an SES association pattern that is markedly different from those of the other five metropolitan areas. There are some similarities between Miami and New York City, which could relate to their locations on the U.S. East Coast: proportion of Hispanic residents (TotalHispanic), proportion of non-Hispanic White residents (NonHispanWhite), uninsured rates (PopUninsurance), proportion of English-speaking residents (Pop5andOlderEnglish), proportion of

Table 3. Pearson's correlation coefficients (r) between confirmed COVID-19 confirmed cases, as of 23 April 2021, and socioeconomic variables in six metropolitan areas at the zip code level

Social variables (most are per capita)	San Diego (94 zip codes)	San Francisco Bay Area (296 zip codes)	Chicago (56 zip codes)	Miami (55 zip codes)	New York City (177 zip codes)	Phoenix (43 zip codes)
TotalPop	0.412 *	0.336 ***	0.353 **	–0.232	0.142	–0.169
Ethnicity						
TotalHispanic	0.793***	0.474 ***	0.804 ***	0.392 ***	0.375 ***	0.617 ***
NonHispWhite	–0.706***	–0.528 ***	–0.101	–0.108	–0.281 ***	–0.629***
NonHispBlack	0.353**	0.253 **	–0.326 *	–0.328*	0.051	0.455**
Economic						
HouseholdwithCash	0.544***	0.7***	0.184	–0.099	0.419***	0.489***
Professional	–0.367**	–0.363***	–0.352**	0.127	–0.713***	–0.35*
UnemployedCvilian	0.301*	0.207***	–0.088	–0.139	0.134	0.39**
PopUninsurance	0.673***	0.304***	0.497***	0.105	0.316***	0.533***
Speaking language						
Pop5andOlderEnglish	–0.678***	–0.479***	–0.654***	–0.228	–0.32***	–0.552***
Pop5andOlderSpanish	0.782***	0.8***	0.773***	0.351**	0.334***	0.588***
Age						
PopAge15_24	0.08	–0.053	–0.102	–0.137	0.375***	0.391**
PopAge65	–0.263**	–0.333***	–0.084	0.053	0.065	–0.453 **
Education						
Pop25OlderLess9	0.792***	0.652***	0.63***	0.35**	0.392***	0.608***
Pop25OlderBachelor	–0.534***	–0.504***	–0.351**	0.06	–0.675***	–0.453**
Pop25OlderMaster	–0.663***	–0.52***	–0.471***	–0.008	–0.692***	–0.425**
Other factors						
MedianIcome	–0.158 **	–0.122	–0.148	0.061	–0.254 ***	0.1
Foreignborn	0.457**	0.247 **	0.339*	0.331*	0.248***	0.469**
AveHouseSize	0.523***	0.508***	0.683***	–0.331*	0.595***	0.223

*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

Spanish-speaking residents (Pop5andOlderSpanish), proportion of residents age sixty-five or older (PopAge65), proportion of residents with less than a ninth-grade education (Pop25OlderLess9), and proportion of residents born outside of the United States (ForeignBorn). When compared to the County of San Diego, SES variables with unique patterns in Miami are total population (TotalPop; San Diego, $r = 0.412$; Miami, r = –0.232), proportion of non-Hispanic White residents (NonHispWhite; San Diego, r = –0.706; Miami, r = –0.108), proportion of non-Hispanic Black or African American residents (NonHispBlack; San Diego, $r = 0.353$; Miami, r = –0.328), proportion of households receiving federal cash assistance (HouseholdwithCash; San Diego, r = 0.544; Miami, r = –0.099), proportion of residents with a bachelor's degree (Pop25OlderBachelor; San Diego, r = –0,534; Miami, $r = 0.06$), and average household size (AveHouseSize; San Diego, $r = 0.523$; Miami, r = –0.331). The proportion of non-Hispanic White residents showed a weak negative correlation with COVID-19 cases in Miami. The average household size in Miami has a moderate negative association. These findings indicate that racial or ethnic and gender disparities contribute more significantly to COVID-19 than income. Whereas the proportion of non-Hispanic White residents ($r = 0.061$), median household income ($r = 0.061$) and age ($r < 0.15$) were not statistically significant in Miami, the proportion of Hispanic and Latino residents ($r = 0.392$) showed a significant association with COVID-19, as other studies have found (Taylor et al. 2021).

The SES association patterns for New York City and the County of San Diego differ for variables related to the proportion of different racial or ethnic groups, proportion of employees working in professional industries (Professional; San Diego, r = –0.367; New York City, r = –0.713), proportion of Spanish-speaking residents (Pop5andOlderSpanish; San Diego,

Table 4. Pearson's correlation coefficients (r) at two spatial scales: 50 California counties versus 94 County of San Diego zip codes

Variables	50 counties in California (31 March 2021)	94 zip codes in San Diego (31 March 2021)
TotalPop	0.234	0.394 ***
Ethnicity		
TotalHispanic	0.732***	0.82***
NonHispWhite	–0.626***	–0.728***
NonHispBlack	0.351**	0.312**
Economic		
HouseholdwithCash	0.535***	0.724***
Professional	–0.363**	–0.546***
UnemployedCivilian	0.296*	0.555***
PopUninsurance	0.222	0.69***
Speaking language		
Pop5andOlderEnglish	–0.579***	–0.685***
Pop5andOlderSpanish	0.703***	0.789***
Age		
PopAge15_24	0.429***	0.006
PopAge65	–0.617***	–0.25**
Education		
Pop25OlderLess9	0.64***	0.784***
Pop25OlderBachelor	–0.482***	–0.533***
Pop25OlderMaster	–0.484***	–0.655***
Other factors		
MedianIcome	–0.099	–0.154 ***
Foreignborn	0.336**	0.474***
AveHouseSize	0.621***	0.528***

*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

$r = 0.782$; New York City, $r = 0.334$), unemployment rates (San Diego, $r = 0.301$; New York City, $r = 0.134$), and proportion of residents with less than a ninth-grade education (Pop25OlderLess9; San Diego, $r = 0.792$; New York City, $r = 0.392$). Unlike Chicago, where the low-income zip codes suffered the most due to COVID-19, middle-income zip codes with lower unemployment rates were highly influenced by COVID-19 in New York City and the County of San Diego, perhaps because service jobs in those areas pay above the poverty line (Maroko, Nash, and Pavilonis 2020).

We found out that the variables most consistent among the six metropolitan areas were proportion of Hispanic residents (TotalHispanic), uninsured rates (PopUninsurance), proportion of Spanish-speaking residents (Pop5andOlderSpanish), proportion of residents with less than a ninth-grade education (Pop25OlderLess9), and proportion of residents born outside of the United States (ForeignBorn). These variables indicate that local Hispanic communities with Spanish-speaking families, as well as communities with high proportions of foreign-born and less educated residents have a higher risk of COVID-19 infections as well as greater vulnerability during fast-growing outbreak periods.

The Third Case Study: Comparison of SES Associations at County and Zip Code Spatial Scales in California

The primary objective of our third case study is to compare neighborhood SES variable associations between two different spatial scales in California (fifty counties vs. ninety-four zip codes). COVID-19 case data at both scales were collected on 31 March 2021 so values represent total accumulated cases from the beginning of the pandemic in early 2020 to that date. Pearson's correlation coefficients (r) between SES variables and confirmed COVID-19 cases are listed in Table 4. The purpose of this analysis was to assess whether SES and COVID-19 variable associations vary from one spatial scale to another. The following are our key findings.

The SES association patterns between California's fifty counties and the County of San Diego's ninety-four zip codes share more similarities than the six metropolitan areas, from the second case study, for variables in the categories of race or ethnicity, language spoken at home, education, and miscellaneous factors. The impact of SES variables on COVID-19 is observed at both county and zip code levels, with an identical pattern (Chen and Kreger 2021). Regions with higher average household sizes, greater proportions of racial or ethnic minorities, and lower income levels are disproportionately affected by COVID-19. We did not find high scale dependency in SES association patterns between the two spatial units.

There are minor differences in the economic and age group variables, including proportions of residents working in professional industries (Professional; CA counties, $r = -0.363$; County of San Diego zip codes, $r = -0.546$), uninsured rates (PopUninsurance; CA counties, $r = 0.222$; County of San Diego zip codes, $r = 0.690$), proportion of residents between fifteen and twenty-four years old (PopAge15_24; CA counties, $r = 0.429$; County of San Diego zip codes, $r = 0.006$), and proportion of residents sixty-five years of age or more (PopAge65; CA counties, $r = 0.429$; County of

San Diego zip codes, $r = 0.006$). Analysis at finer levels can provide important information about the impact of SES variables on COVID-19 (Chen and Kreger 2021). California has a relatively large number of rural counties, whereas the County of San Diego has relatively few rural zip codes. Therefore, the observed association patterns might reflect the characteristics of rural areas in counties of California, with lower uninsured rates and higher proportions of seniors over age sixty-five.

Discussion and Limitations

This study provides a comprehensive spatial and temporal analysis of COVID-19 outbreaks, which includes identifying COVID-19 outbreak stages, exploring potential SDOH for COVID-19 using hot spot and correlation analyses, and finding similarities and differences of association between SES variables and COVID-19 for different metropolitan areas and at different spatial scales. COVID-19 disproportionately affected racial and ethnic minority groups (Dasgupta et al. 2020; Maroko, Nash, and Pavilonis 2020; Moise 2020; Islam, Lacey, et al. 2021). In our research, we found that Hispanic communities were most heavily burdened by the COVID-19 pandemic. The impact of COVID-19 on senior citizens varied with local context due to differing social structures and local policies (Zhai et al. 2021). Whereas Kiaghadi, Rifai, and Liaw (2020) stated that seniors were at a higher risk of COVID-19 in Harris County, Texas, our study showed that senior groups were well protected in the County of San Diego. Moreover, elevated poverty rates and household densities displayed consistently positive associations with COVID-19. Although there is variability found in the relationship between lower SES and COVID-19, the disproportionate disease burden compounded by lower SES has widened health disparities overall (Clark et al. 2020), as minorities with lower SES were more likely to work in industries that remained open to the public and to live in crowded areas and multigenerational households, thereby escalating exposure to health risks and limiting options for following recommended guidelines such as social distancing and quarantines (Adamkiewicz et al. 2011; Raifman and Raifman 2020). Analysis at finer levels can provide important information about the impact of COVID-19 on SES variables (Chen and Krieger 2021).

To make this study more broadly applicable, we designed a research framework for studying future COVID-19 health disparities and SDOH. It expands the existing research variables into three broad areas: human, place, and time (HPT). The human factors include social profiles (individuals), human mobility, cultural factors, and health preconditions (e.g., obesity and hypertension associated with a high risk of COVID-19 hospitalization and death). The place factors include neighborhood SES, building environments, the impacts of local policies, health care accessibility, and spatial scales and units. Finally, the time factors include the dynamic changes of outbreak stages (with daily infected, hospitalized, or death case numbers) and the impacts of intervention methods during different stages (e.g., stay-at-home orders, masks, vaccination) and special events (e.g., elections, holidays). Although the focus of this research was limited to confirmed COVID-19 cases in the County of San Diego, the six selected metropolitan areas, and California's fifty counties, researchers can apply the framework to other cities and regions in the United States if appropriate data sets are available at the fine scale.

One limitation of this study is that "correlation does not mean causation." The study also faces the challenge of ecological fallacy; although we have identified several important SES variables with strong positive or negative correlation values, readers should not interpret that these variables directly cause COVID-19 outbreaks. For instance, the language variable (e.g., Spanish-speaking) is not the direct cause of COVID-19 outbreaks. Rather, the high family density and poverty among Hispanic families could trigger COVID-19 outbreaks (Chen and Krieger 2021; Islam, Lacey, et al. 2021).

Due to data accessibility, environmental factors that potentially influenced the pandemic (e.g., grocery store accessibility, neighborhood environment, green index) beyond the ACS data are not examined in this study. Variables of health conditions are also significantly considered to affect COVID-19. Specifically, Lee and Ramirez (2021), Moise (2020), and Ong et al. (2021) examined population health contexts, such as diabetes, and chronic health indicators that are associated with COVID-19 incidence. A further study could integrate more potential variables into the HPT framework and explore their association with the epidemic (Mahmoudi et al. 2021).

Another limitation of this research is that vaccination interventions could significantly influence COVID-19 cases, such as when the vaccination started to be distributed at the start of 2021, mildly affecting our analysis at Stage 5. The intervention, however, makes it possible to explore differences in the impact of SES variables on COVID-19 after the pharmaceutical intervention.

In the modeling part, researchers have used multilinear regression (e.g., ordinary least squares) to investigate the relationship between COVID-19 spread and those SES factors; some SES variables show implicit correlations to other SES variables, thus causing multicollinearity and potential bias when building the explanatory model. To address these issues, we will consider implementing methods such as principal component analysis (Kiaghadi, Rifai, and Liaw 2020; Kim and Bostwick 2020; Moise 2020) and orthogonalizing variables to construct new explanatory indexes in our future study. Meanwhile, many special events (e.g., local policy changes and orders, NPIs, social events, and family gatherings during holidays) can affect the analysis of spatiotemporal patterns of COVID-19 (Yang et al. 2020). Therefore, we should develop a new spatially oriented disease spread model to consider and respond to those factors at different temporal stages.

To propose appropriate mitigation measures, we should figure out the hidden challenges. One is the stigma of COVID-19. The stigma of having COVID-19 causes individuals significant psychological distress (Duan, Bu, and Chen 2020; Guo et al. 2020; Peprah and Gyasi 2021) and failure to report important medical history (Peprah and Gyasi 2021). Another hidden challenge is the lack of proper COVID-19 prevention knowledge associated with certain race or ethnicity, age, gender, and SES groups. For example, African Americans and Hispanic Americans, as well as young and lower income groups had less knowledge about COVID-19 than their counterparts (Alsan et al. 2020).

Hence, there has been an increasing need to implement stigma-mitigation strategies and interventions. First, community engagement strategies might effectively facilitate community residents' participation in COVID-19 programs and enhance social cohesion to combat stigma (Duan, Bu, and Chen 2020; Logie and Turan 2020). Second, the lack of knowledge or misinformation is often the cause of fear and stigma (Zhai et al. 2021); thus, educational efforts to increase knowledge are essential. Providing up-to-date knowledge and debunking myths and misperceptions of COVID-19 via media can reduce stigma and promote health-seeking behaviors (Earnshaw et al. 2020). Third, policymakers should consider the disproportionate effects on socially vulnerable groups across space (Zhai et al. 2021). Targeted economic aid can achieve social distancing for vulnerable populations, thus reducing COVID-19 incidence. Such measures should be implemented in a culturally appropriate way, considering the languages and characteristics of stigmatized groups or communities (Peprah and Gyasi 2021). Fourth, spatiotemporal analyses on mitigation measures such as stay-at-home orders and vaccination distribution should be further explored in response to vulnerable groups (Zhai et al. 2021). Since April 2020, our research team has met weekly with public health staff and epidemiologists in the County of San Diego to share our findings and suggestions, which help local health agencies make more effective health resource management and communication strategies.

Conclusion

This study illustrates the important roles of geography and neighborhood SES in understanding the spread of COVID-19 in selected U.S. cities and California counties. The spatial clustering patterns of COVID-19 hot spots can be correlated with unique SES characteristics (e.g., minority groups such as Spanish-speaking families, less educated groups, low-income populations, etc.) as potential SDOH. Current public health orders or NPIs issued by state or local government agencies are typically designed for the whole county or state rather than customized for high-risk local communities or neighborhoods. To provide more effective public health intervention methods for COVID-19, we must create geographically targeted strategies for NPIs based on those identified hot spots and vulnerable population groups to solve fundamental health disparity problems.

The three case studies illustrated in this article are good examples of adopting some components in the HPT framework for COVID-19 health disparities research. The first case study focuses on the time factors in five stages and associated place factors (neighborhood SES and hot spot analysis). The second study focuses on the comparison of the place factors and the human factors in six different U.S. cities. The third case study focuses on the place factors in terms of spatial scales by comparing two different spatial units and their neighborhood characteristics. This framework can be adopted in San Diego local analysis and California county to subcounty analysis.

The COVID-19 pandemic is not only a medical disease outbreak, but also a social inequality and health disparity problem. To resolve these challenging problems of the COVID-19 pandemic, we need to use both medical and socioeconomic approaches. There are many health disparities issues regarding COVID-19 testing, vaccination, treatments, and hospitalizations. Both state and local governments need to implement effective social and economic approaches to improve health resource management associated with the COVID-19 pandemic. For example, local health agencies should adjust their public health orders and interventions considering the actual needs within vulnerable local communities and hot spot areas. By adding more testing and vaccination sites in hot spot regions, providing more financial support and incentives for large families, simplifying clear quarantine procedures and safety guidance for Hispanic and Latino populations, and implementing free high-speed Internet services for quarantined families, public health agencies can help protect these vulnerable communities and make them more resilient to the COVID-19 pandemic.

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Appendix

Table A.1. The full list of 51 American Community Survey variables used in this study: Five-year estimates from 2014 to 2018 at the zip code level

Category	2018	Definition
Individual population	TotalPop	Total population
Sex	Male	Total male population
	Female	Total female population
Race/ethnicity	White	Total White population
	Black	Total Black population
	Asian	Total Asian population
	AmericanIndian	Total American Indian and Alaska Native population
	NativeHawaiianOtherPacificIslander	Total Hawaiian and other Pacific Islander population
	OtherRaceOne	Some other race alone
Hispanic ethnicity	TotalHispanic	Total Hispanic population (including White)
	NonHispWhite	Total not Hispanic or Latino White alone
	NonHispBlack	Total not Hispanic or Latino Black or African American alone
	NonHispAsian	Total not Hispanic or Latino Asian alone
Language	Pop5andOlder	Total population age 5 and older
	Pop5andOlderEnglish	Total population speaking only English, age 5 and older
	Pop5andOlderSpanish	Total population speaking Spanish, age 5 and older
	Pop5andOlderSpanishEnglishWell	Total population speaking Spanish and speaking English well or very well age 5 and older
	Pop5andOlderSpanishEnglishnotWell	Total population speaking Spanish and speaking English not well or not at all age 5 and older
	Pop5andOlderAsian	Total population speaking Asian/Pacific Islander language, age 5 and older
	Pop5andOlderAsianEnWell	Total population speaking Asian/Pacific Islander language and speaking English well or very well age 5 and older
	Pop5andOlderAsianEnnotWell	Total population speaking Asian/Pacific Islander language and speaking English not well or not at all age 5 and older
	Pop5andOlderother	Total population speaking other language, age 5 and older
	Pop5andOlderotherEnWell	Total population speaking other language and speaking English well or very well age 5 and older
	Pop5andOlderotherEnnotWell	Total population speaking other language and speaking English not well or not at all age 5and older
Age	popAge0_4	Total population age 0–4
	popAge5_14	Total population age 5–14
	popAge15_24	Total population age 15–24
	popAge25_44	Total population age 24–44
	popAge45_64	Total population age 45–64
	popAge65	Total population age 65 and over
Education	pop25Older	Population age 25 and older
	pop25OlderLess9	Less than 9th grade; total population age 25 and older
	pop25Older9_12Grade	9th through 12 grade, no diploma; total population age 25 and older
	pop25OlderHighSch	High school graduate, including equivalency, total population age 25 and older
	pop25OlderCollege	Some college, no diploma; total population age 25 and older
	pop25OlderAssociate	Associate's degree; total population age 25 and older
	pop25OlderBachelor	Bachelor's degree; total population age 25 and older
	pop25OlderMaster	Master's degree; total population age 25 and older
Socioeconomic context	HouseholdwithCash	Total households with cash assistance
	HouseHoldwithChildren18	Total households with children under age 18

(*Continued*)

Table A.1. (*Continued*).

Category	2018	Definition
	Professinal	Total professional, scientific, management, administrative employed civilians
	Armedforced	Total population in armed forces
	Married	Total population married
	UnemployedCvilian	Total unemployed civilian population
	PopPivertyDetermined	Total population where poverty was determined
	PopBelowpoverty	Total population below poverty
	MedianIcome	Median income; total household income
	Foreignborn	Total population foreign born
Health	PopInsurance	Total population with health insurance
	PopDisability	Total population with a disability