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When everyone's doing it: The relative effects of geographical context and social determinants of health on teen birth rates

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ABSTRACT

Geographic disparities in teen birth rates in the U.S. persist, despite overall reductions over the last two decades. Research suggests these disparities might be driven by spatial variations in social determinants of health (SDOH). An alternative view is that "place" or "geographical context" affects teen birth rates so that they would remain uneven across the U.S. even if all SDOH were constant. We use multiscale geographically weighted regression (MGWR) to quantify the relative effects of geographical context, independent of SDOH, on county-level teen birth rates across the U.S. Findings indicate that even if all counties had identical compositions with respect to SDOH, strong geographic disparities in teen birth rates would still persist. Additionally, local parameter estimates show the relationships between several components of SDOH and teen birth rates vary over space in both direction and magnitude, confirming that global regression techniques commonly employed to examine these relationships likely obscure meaningful contextual differences in these relationships. Findings from this analysis suggest that reducing geographic disparities in teen birth rates will require not only ameliorating differences in SDOH across counties but also combating community norms that contribute to high rates of teen birth, particularly in the southern U.S. Further, the results suggest that if geographical context is not incorporated into models of SDOH, the effects of such determinants may be interpreted incorrectly.

1. Introduction

Over the past decade, teen birth rates in the U.S. have consistently fallen, yet large geographic disparities remain (Sedgh et al., 2015). In 2015, county-level teen birth rates varied between 3 and 119 births per 1000 females ages 15–19 years old (Division of Reproductive Health, 2020) with clearly evident clusters of high rates in the southern U.S. and clusters of low rates in the Northeast (Khan et al., 2017; Maslowsky et al., 2019; Romero et al., 2016; Ventura et al., 2001). Recent research has suggested that social determinants of health (SDOH) are a key driver of this spatial variation (SmithBattle, 2012; Viner et al., 2012; Maness et al., 2016). As defined by the World Health Organization, SDOH are "the conditions in which people are born, grow, live, work, and age" (Marmot et al., 2008) and include a multitude of factors, such as poverty, healthcare access, and housing affordability, that can influence health outcomes. These conditions are themselves influenced by, and often the consequence of, more upstream structural, cultural, and place-based factors—what we collectively refer to in this paper as intrinsic geographical contextual effects—that together produce environments that shape individual and community-level behavior (Viner et al., 2012; Koh et al., 2011; Braveman, 2023; Mays, 2021). Disentangling the extent to which each of these sources, the downstream SDOH conditions versus the upstream intrinsic geographical context, influences teen birth rates is important for helping policymakers and health practitioners develop and implement tailored policies and interventions targeted toward addressing the persistent spatial disparities in health outcomes that we observe. We argue here that if the upstream effects of place-based values, belief systems, and cultural norms are not properly incorporated into models linking health disparities to SDOH, such linkages may well be misspecified.

The central argument that geographical context can have a major impact on people's beliefs, preferences, and actions, has been promulgated by many authors in many different application areas (*inter alia*, Agnew, 1996, 2014; Duncan et al., 1998; Enos 2017; Golledge, 1997; Gould, 1991; Harvey and Wardenga, 2006; Pred, 1984; Tuan, 1979; Winter and Freksa, 2012; Link and Phelan, 1995). Several theories have been proposed to account for such a relationship. For instance, a link between place and behavior can arise if a person's actions or beliefs are

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influenced by the people that person talks to on a regular basis ("*social imitation*"), or by the local media, or by long-term conditions that are peculiar to certain locales and which shape a person's outlook on certain issues (Beck et al., 2002; Huckfeldt and Sprague, 1995; Huckfeldt et al., 1995). Equally, traditions, customs, lifestyles, and psychological profiles common to an area can affect social norms, which in turn affect individual behavior. Several studies, for example, have commented on personality differences across regions and how these can explain behavioral differences (*inter alia*, Rentfrow et al., 2015; Rentfrow et al., 2013). These "values, beliefs and norms" (VBN) transcend individual demographic characteristics and can manifest themselves in a variety of ways, such as how people feel about government control, how much they believe in scientific evidence, and to what extent they view teen pregnancy in a negative light (Stern et al., 1999). Within the extensive literature on health and place, neighborhood social environments are often cited as potential pathways through which geographical context might influence health-related outcomes (Diez Roux and Mair, 2010). Features of the neighborhood social environment, such as the strength of social connections, social cohesion, and social capital present in an area, are thought to contribute to the enforcement of certain norms and the transmission of particular behaviors *("social contagion"*) and have been linked to variation in health outcomes, including all-cause mortality, self-rated health, epilepsy, and asthma (Szaflarski, 2014; Gold et al., 2002; Sullivan and Thakur, 2020). More recently, these aspects of the neighborhood social environment along with a broader set of structural factors, including local policies and governance practices, have become known as *structural* determinants of health. Structural determinants of health are thought to influence specific health-related outcomes by creating, configuring, and maintaining social hierarchies that lead to social stratification and ultimately give rise to SDOH (Mays, 2021; Zuckerman, 2021; Diez Roux and Mair, 2010; Viner et al., 2012; Koh et al., 2011; Braveman, 2023).

Since the early 1990s, a growing body of empirical research has sought to measure the geographical contextual effects on health (*inter alia* Macintyre et al., 2002; Cummins et al., 2007; Diez Roux and Mair, 2010; Decker et al., 2018). Much of the early work in these literatures focused on separating area effects into geographical contextual effects versus compositional effects and often found residual geographical contextual effects on health outcomes after controlling for compositional effects (Decker et al., 2018; Cummins et al., 2007). Within the teen pregnancy literature, several studies have identified significant associations between teen birth rates and various measures of socioeconomic disadvantage, including receipt of public assistance, low levels of education, high unemployment rates, and neighborhood deprivation (Moore, 1995; Penman-Aguilar et al., 2013; Harding, 2003; Sucoff and Upchurch, 1998; Yee et al., 2019; Wei et al., 2005; Fuller et al., 2018). The vast majority of this research has relied on global regression models to assess the relationship between SDOH and teen childbearing (Yee et al., 2019; Orimaye et al., 2021; Bickel et al., 1997; Kirby et al., 2001; Gold et al., 2001), however such models assume that these relationships are constant across space. Despite established theories suggesting that processes by which SDOH influence outcomes might vary spatially and operate at different geographic scales (Cummins et al., 2007), only one study (Shoff and Yang, 2012) to our knowledge has ever examined local variation in the relationships between teen birth rates and SDOH. Using geographically weighted regression (GWR) models, Shoff and Yang (2012) identified spatially nonstationary associations between teen birth rates and several ecological factors, including the demographic composition and rate of religiosity, in both metropolitan and nonmetropolitan counties. Although this work provided crucial insights into how the influence of SDOH on teen birth rates might vary across space, these models relied on a strong and likely incorrect assumption that all measured relationships operated over the exact same spatial scale. As a result, these associations might be biased.

Despite the extensive research into the roles of geographical context, and more recently, SDOH and their influence on health-related behaviors and outcomes, little is still known regarding how much each of these sources contributes to spatial disparities in outcomes and whether these relationships vary not only across space but at different spatial scales, particularly in the context of teen pregnancy. Consequently, what is needed is a means of separating these two potential drivers of geographic variations in teen birth rates (downstream SDOH conditions versus intrinsic geographical context) and to assess the relative contributions of each. Of course, if this can be done for teen birth rates, it could be done for any other health variable that exhibits geographic variation in any country, so the results of this analysis have universal appeal. The general question that needs to be answered, and which is the focus of this analysis, is: "*To what extent are observed health variations due to differences in the SDOH and to what extent are they due to the intrinsic geographical context?"*

Between 2010 and 2015, the U.S. Office of Adolescent Health and the Centers for Disease Control invested considerable resources to help reduce disparities by raising awareness around this connection between SDOH and teen pregnancy (Romero et al., 2016). Research conducted by Fuller et al. (2018) as part of this effort proposed that eliminating disparities in teen birth rates requires addressing SDOH that contribute to teen pregnancy, implying that the geographic variation in teen birth rates could be ameliorated, and possibly reduced altogether, if community-level variations in SDOH were eliminated. However, as discussed above, a great deal of literature across the social sciences suggests that geographical context can affect behavior and that this is upstream and separate from variations in SDOH. Here, we suggest that *both* spatial variations in SDOH and the impacts of geographical context lead to the levels of spatial variation in teen birth rates we observe across the U.S.

What is needed therefore is a means of identifying and quantifying the relative impacts of spatial variations in SDOH and intrinsic geographical context on teen birth rates. To do this, we use a local regression technique, multiscale geographically weighted regression (MGWR), to estimate the effects of SDOH on teen birth rates. MGWR has been used to estimate spatially varying associations in obesity rates (Oshan and Smith, 2020; B Neelon et al., 2017; Chi et al., 2013; Dwicaksono et al., 2018), HIV (Zhou et al., 2015; Nakaya et al., 2005; W Wabiri et al., 2016), and other public health topics (Schooling et al., 2011; Ribeiro and Pereira, 2018; Tu et al., 2012). An important output from MGWR is the estimation of a local intercept, which can be used to identify and measure the intrinsic geographical contextual effects independent from other effects related to SDOH (Fotheringham et al., 2021; Fotheringham and Li, 2023).

By modeling the relationship between SDOH and county-level teen birth rates using MGWR, this paper can thus examine the important question:

> "To what extent can the observed spatial variation in teen birth rates across the U.S. be ascribed to variations in SDOH and to what extent can they be ascribed to intrinsic geographical contextual effects?"

This raises two further intriguing questions which are answered in this paper:

> *"Would disparities in teen birth rates remain if all counties had identical SDOH? That is, if there were no variations in population over space, would we still observe significant, geographically patterned, variations in teen birth rates?";* and

> "*How would teen birth rates be spatially distributed if intrinsic geographic contextual effects played no role in affecting teen behavior? That is, if teen birth rates depended solely on SDOH, what would be the spatial variation in these rates across space – would it be identical to that observed?"*

2. Data

To address these questions, data on county-level teen birth rates for 2017 and 2018 were obtained from the National Center for Health Statistics (2019). Using this information along with data on the number of women ages 15–19 in each county each year, we calculated the two-year teen birth rate for each county by dividing the total number of teen births between 2017 and 2018 by the average number of women ages 15–19 across the two years and multiplying by 1000. We elected to use the two-year teen birth rate, as opposed to the single-year teen birth rate, to minimize the influence of variability in the annual rates, which may fluctuate in response to small changes in the number of births year-to-year. Given the unreliability of rates for communities with small populations, we restricted this analysis to counties with at least 250 women ages 15–19. The final sample included 2475 counties (Fig. 1).

To operationalize the SDOH, county-level data on the socioeconomic, racial/ethnic, and household composition were obtained from the 2018 American Community Survey. Specifically, data on the median income, percent Black, percent Hispanic, and percent of female-headed households with children were included in the analysis. We also included the multidimensional deprivation index, constructed by Glassman (2019), to better measure relative deprivation across counties. The index comprises six dimensions of deprivation, including standard of living, education, health, economic security, housing quality, and neighborhood quality, to capture both monetary and nonmonetary dimensions of deprivation (for more information, see Glassman, 2019). We also controlled for population density by dividing the total population by the total area for each county.

We also included information from the 2018 County Health Rankings on the chlamydia rate and data on the presence of a health center offering the full range of contraceptive methods obtained from Power to Decide (2020), to control for variation in use of contraceptives and access to comprehensive family planning services, respectively. Finally, we included the rate of total religious adherence in the county from the 2010 Religious Census to control for attitudes related to premarital sex, contraception, and abortion (Grammich et al., 2010). Given the large number of covariates, analyses of the variance inflation factors and local condition numbers were used to assess multicollinearity in the global and local models, respectively, and no significant multicollinearity was observed.

3. Methods

To estimate the role of context on teen birth rates, we calibrate an MGWR model. An ordinary least squares (OLS) model is also calibrated for comparison. Unlike global regression models, MGWR does not assume that the processes being modeled are constant over space. As a result, rather than providing a single estimate of the relationship between a covariate and the outcome, MGWR provides estimates of these relationships for every location in the study region, allowing for a more detailed understanding of how a process varies across space. The MGWR model can be expressed as follows:

$$y_i = \alpha_i + \sum_j \beta_{ij} x_{ij} + \varepsilon_i \tag{1}$$

where y_i is the dependent variable for county i, x_{ij} represents the jth covariate x for county i, α_i is the intercept for county i, β_{ij} is the parameter estimate for the jth covariate for county i, and ε_i is the random error term for county i.

To obtain location-specific parameter estimates, MGWR performs a series of local regressions by borrowing data from nearby locations and weighting them according to how far they are from the regression location; data from locations nearby are weighted more heavily than data from locations farther away. The spatial extent to which data are borrowed varies by covariate and is controlled by a bandwidth parameter, which is estimated from the data by optimizing a goodness-of-fit statistic. A separate bandwidth is estimated for each set of the local parameter estimates, which distinguishes MGWR from GWR, the latter only producing a single bandwidth. The model is calibrated using a backfitting algorithm which is described in greater detail elsewhere (Fotheringham et al., 2021; Wolf et al., 2018; , Li and Fotheringham, 2020; Yu et al., 2020; Li et al., 2020; Oshan et al., 2019).

To calibrate an MGWR model, it is necessary to make decisions about the nature of the weighting function employed, as described elsewhere (Oshan et al., 2019; Li et al., 2020). Here, an adaptive kernel function

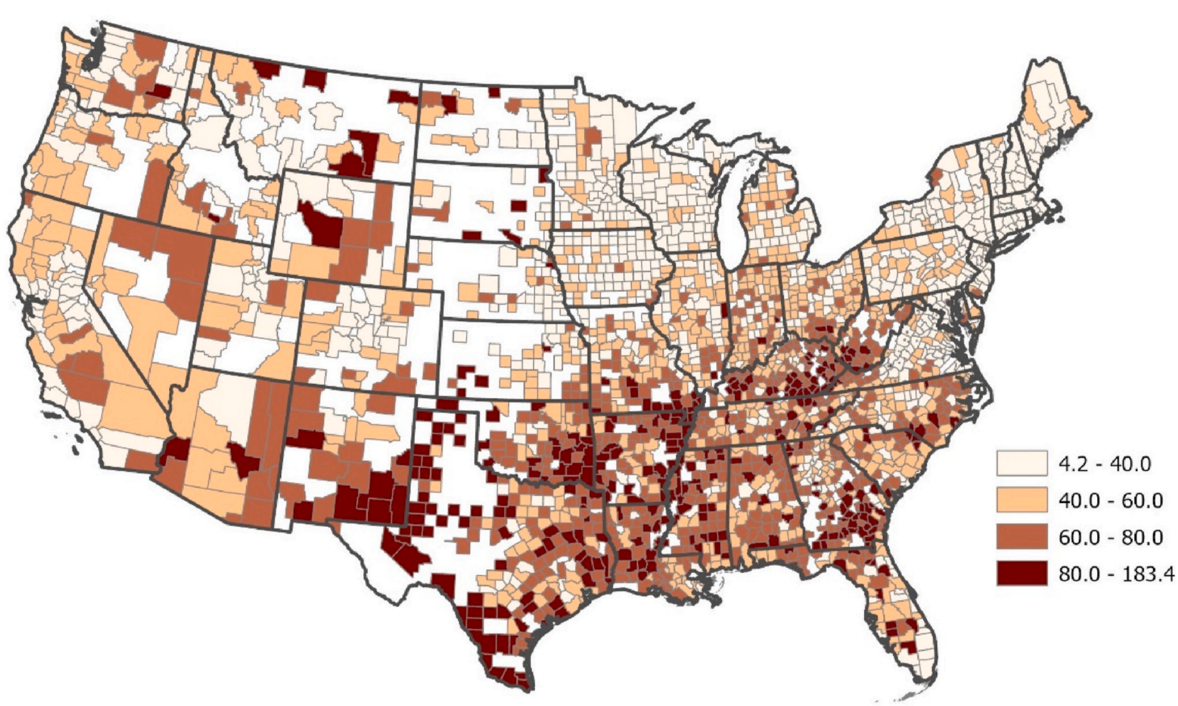

Fig. 1. Two-year teen birth rate (expressed per 1000 females aged 15–19) among counties with at least 250 women ages 15-19.

was used along with a bi-square weighting function of the number of nearest neighbors to calibrate the model, and a golden section search bandwidth selection routine was used to determine the optimal bandwidth for each covariate. In addition, in order to allow a direct interpretation and comparison of the covariate-specific optimized bandwidths, all the variables were standardized to have mean 0 and SD 1 (Fotheringham et al., 2021; Oshan et al., 2019). Consequently, the model calibrated is shown in equation (2):

$$y*_i = \alpha_i + \sum_j \beta_{ij} x*_{ij} + \varepsilon_i \tag{2}$$

where $y*_i = (y_i - y_{mean})/SD_y$ and $x*_i = (x_i - x_{mean})/SD_x$. This model was calibrated using the MGWR 2.2 software freely available at https://sgsup.asu.edu/sparc/mgwr.

To facilitate interpretation of the MGWR parameter estimates, a series of maps was generated, which display the statistically significant local estimates associated with each covariate and the local intercept. Statistical significance was based on adjusted t-statistics, which account for multiple hypothesis testing and spatial dependency of relationships (da Silva and Fotheringham, 2016). To ease interpretation of the MGWR parameter estimate maps, we also spatially interpolated missing values for counties omitted from the analysis using the average value of the 40 nearest counties. This interpolation was done strictly for visualization purposes; all reporting and discussion of the results was based on the analytic results prior to interpolation.

4. Results

4.1. Associations from the OLS model

The OLS model explains about 57% of the variance in county-level teen birth rates, and significant associations are observed for each SDOH (Table 1). Four characteristics exhibit negative conditional associations with teen birth rates: median income (−0.44 ± 0.02), percent black (−0.10 ± 0.02), population density (−0.06 ± 0.01), and presence of a health clinic (−0.05 ± 0.01). The other five characteristics have positive associations with teen birth rates: the deprivation index (0.25 ± 0.02), percent of female-headed households with children (0.20 ± 0.02), percent Hispanic (0.17 ± 0.02), chlamydia rate (0.07 ± 0.02), and total religious adherence (0.07 ± 0.01). Given the variables are all standardized, direct comparison of the absolute values of the parameter estimates suggest that income, deprivation, percent of female-headed households, and percent Hispanic population have the greatest influence on teen birth rates.

Table 1
Ordinary least squares model results.

	Coefficient	Std Error	*p* value
Multidimensional Deprivation Index	0.249	0.017	<0.001
Percent Female-Headed Households with Children	0.197	0.020	<0.001
Chlamydia rate	0.074	0.021	<0.001
Presence of a health center[a]	−0.049	0.014	<0.001
Percent Hispanic	0.173	0.015	<0.001
Population density	−0.059	0.014	<0.001
Median income	−0.439	0.017	<0.001
Rate of religious adherence[b]	0.067	0.013	<0.001
Percent Black	−0.104	0.021	<0.001
Intercept	0.000	0.013	1.000
Model Fit Statistics	Adj R^2 = 0.57	AIC = 4949	AICc = 4951

[a] Presence of a health center offering the full range of contraceptive methods.
[b] Rate of total religious adherence in the county from any religious denomination.

4.2. Associations from the MGWR model

The MGWR model explains 77.3% of the variance in teen birth rates (Table 2) compared to 57% for the OLS model (Table 1) and the AICc value for the former is substantially lower than that for the latter. As shown in Table 2, the MGWR calibration also yields covariate-specific optimized bandwidths which indicate the scale of any spatial heterogeneity in the conditioned associations being modeled. These suggest some determinants of teen birth rates, such as deprivation and female-headed households, have a near-uniform affect whereas others, such as percentage black population, religious adherence, and income, have more locally varying impacts on teen birth rates. These patterns are shown more explicitly in Fig. 2 which describes the spatial pattern of the significant local parameter estimates from each relationship.

These maps of the significant local parameter estimates show a more nuanced influence of various SDOH than would be suggested by the global model. Although deprivation and percentage Hispanic both show almost uniformly positive conditioned associations with teen birth rates and income and percentage black population show almost uniformly negative conditioned associations with teen birth rates, the influence of the other covariates appears to vary spatially, in some cases, quite dramatically. For instance, the distribution of the local parameter estimates for the chlamydia rate shows a cluster of very high positive associations in Montana and Wyoming, clusters of weakly-to-moderately positive associations in the upper Midwest, along the Mississippi delta, and the mid-Atlantic, but a cluster of counties in southern Ohio and West Virginia exhibit moderately negative associations (Fig. 2c). These differences could be due to differences in hormonal contraceptive usage in these areas. In places with lower rates of hormonal contraceptive usage, unprotected sexual intercourse may lead to higher rates of sexually transmitted diseases, such as chlamydia, and higher rates of pregnancy, however in areas with a high uptake of hormonal birth control, unprotected sex may lead to higher rates of chlamydia but not higher birth rates.

Weakly positive associations between the presence of a health clinic

Table 2
MGWR model results.

	MGWR Bandwidth	Mean Coefficient (Min, Max)	Significant local estimates (%)
Multidimensional Deprivation Index	2133	0.068 (0.053, 0.076)	100.0
Percent Female-Headed Households with Children	1412	0.192 (−0.032, 0.376)	69.3
Chlamydia rate	952	−0.020 (−0.459, 0.610)	9.3
Presence of a health center[a]	796	−0.026 (−0.130, 0.058)	15.2
Percent Hispanic	697	0.274 (0.110, 0.447)	99.4
Population density	673	−0.191 (−0.662, 0.053)	36.9
Median income	379	−0.469 (−0.714, −0.180)	100.0
Rate of religious adherence[b]	298	0.051 (−0.035, 0.153)	31.4
Percent Black	74	−0.128 (−0.188, −0.084)	100.0
Intercept	43	−0.105 (−0.974, 1.030)	35.1
Model Fit Statistics	Adj R^2 = 0.77	AIC = 3628	AICc = 3795

Note: MGWR = multiscale geographically weighted regression.
[a] Presence of a health center offering the full range of contraceptive methods.
[b] Rate of total religious adherence in the county from any religious denomination.

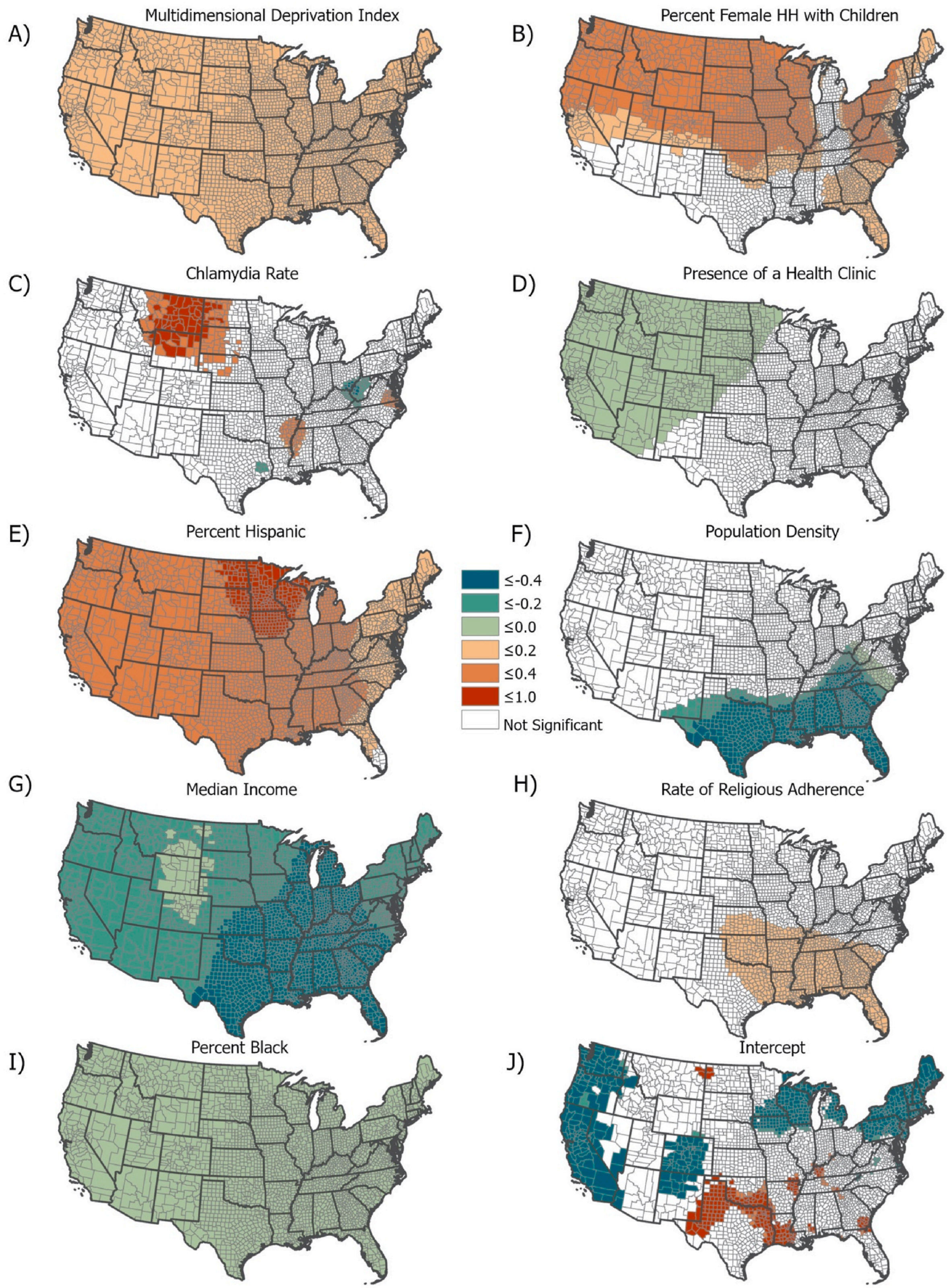

Fig. 2. County-specific parameter estimates from the MGWR model. **Note:** Spatial interpolation was performed to impute missing values for counties omitted from the analysis using the average value among the 40 nearest counties. Values are presented as rates per 1000.

and teen birth rates are observed throughout the western U.S., while no significant associations are present elsewhere (Fig. 2d). This regional variation is likely due to counties in the east being smaller than those in the west, which reduces the importance of residing in a county with a health clinic, as clinics in adjacent counties are also accessible.

The county-specific parameter estimates for population density are significantly negative across the south, and not significant elsewhere (Fig. 2f). These findings imply that within the south, teen birth rates are lower in urban areas than rural ones, *ceteris paribus,* which could be due to differences in access to healthcare or contraception.

The local parameter estimates for the rate of religious adherence are uniformly positive, however, these relationships are only significant in the southeast, an area commonly referred to as the Bible Belt (Fig. 2h). Because this model examines associations with teen birth rates, as opposed to pregnancy rates, these positive associations may be due to differences in access or attitudes towards abortion. Even if the rate of teen pregnancy were identical across counties, if religious beliefs reduced the likelihood of terminating a teen pregnancy, we would expect the birth rate to be higher in places with those beliefs.

Finally, there is considerable variation in the local intercept parameter estimates (Fig. 2j). The local intercept estimates from MGWR have a useful interpretation. Because all the variables are standardized prior to calibration (equation (2)), the local intercepts show the unmodeled geographic variation, which represents the intrinsic values of teen birth rates when all the covariates are equal to the mean across the country (i.e. zero). Consequently, the local intercepts indicate the intrinsically raised or lowered rates of teen birth rates that would be observed if all the counties had the same SDOH composition. Strong positive values are concentrated in the south, specifically in counties around the Texas border and in Louisiana, suggesting these counties have intrinsically higher teen birth rates, *ceteris paribus*. In contrast, significant negative values of the local intercept estimates are observed in New England, in New York and Pennsylvania, in Colorado, all down the West Coast, and in Wisconsin and Minnesota suggesting that counties in these states have intrinsically low rates of teen births, *cetris paribus*. We explore these findings in more detail below.

4.3. Relative effects of geographic context and SDOH

To this point, we have raised the distinction between teen births being a product of varying SDOH and also of geographical contextual effects. Although we cannot identify exactly what factors might be causing a geographical contextual effect on teen births, we can see its presence from the map of the significant local intercepts in Fig. 2j. It would be useful to further identify just how much an effect on the spatial variation in teen births across the U.S. is caused by geographical context and how much is caused by spatial variations in SDOH levels. This we can do by rearranging the terms in Eq. (2). Specifically, we can rewrite Eq. (2) as:

$$y_i = \bar{y} + \alpha_i\sigma_y + \sigma_y\sum_j \beta_{ij}\left(x_{ij} - \bar{x}_j\right) \Big/ \sigma_{x_j}, \tag{3}$$

where $\bar{y}$ is the mean teen birth rate across all counties, σ_y is the standard deviation of y, the observed teen birth rate, σ_{x_j} is the standard deviation of the jth covariate x, $\alpha_i\sigma_y$ represents the proportion of the teen birth rate due to location or geographic context, and $\sigma_y\sum_j \beta_{ij}(x_{ij} - \bar{x}_j) / \sigma_{x_j}$ is the proportion of the teen birth rate due to the particular combination of SDOH within a county. When we map each of these terms (Fig. 3), we can visually and quantitatively separate the three effects to assess the relative strength of each on the overall county-level teen birth rate for each county in the U.S.

The average two-year teen birth rate across counties was approximately 50 births per 1000 females ages 15–19 (Fig. 3a), which is higher than the national two-year teen birth rate of 36 births per 1000 due to the large number of rural counties in the U.S. that tend to have much higher incidence of teen births. Fig. 3b depicts the change in the teen birth rate due solely to intrinsic geographical context. This map is based on the distribution of the local intercepts, but the numbers are converted to percentages which can be added or subtracted from the national average. Much of the south and most of Montana and Wyoming have a predisposition for higher teen birth rates independent of SDOH. While for most counties this intrinsic geographical contextual effect is relatively small and translates to increasing the county birth rate by fewer than 10 births per 1,000, there are counties in Texas and Louisiana where the effect is twice as high. A pronounced north-south split also emerges in the distribution of estimated effects of SDOH on the county-specific teen birth rate (Fig. 3c). Not only do nearly all counties in the South, including those in the Southwest, have a tendency for higher teen birth rates due to their levels of SDOH, in some counties this effect exceeds 100 births per 1000.

Another way of looking at these findings is to consider: (1) what the teen birth rate would be if each county had the same SDOH composition; and (2) what the teen birth rate would be if geographical context had no impact on teen births. By summing the percentages in Fig. 3a and b, we can answer the first question, as illustrated in Fig. 4a. By summing the percentages in Fig. 3a and c, we can answer the second question, as shown in Fig. 4b. In both cases, geographical disparities in the teen birth rate persist although the patterns are quite different. For example, if all counties shared the same SDOH composition (Fig. 4a), counties in the southwest would have substantially lower teen birth rates than currently observed. If we compare these counterfactual maps with the distribution of the actual two-year teen birth rate (Fig. 4c), it is possible to see how the contextual effects combine with those from variations in SDOH to produce the observed rates. Interestingly, in parts of the northeast and California, the contextual effects moderate the effects from SDOH keeping the observed rates lower than would be expected given the composition of SDOH. The opposite effect is present in parts of the Southwest, where the effects from the SDOH appear to dominate the geographic contextual effects.

5. Discussion

This analysis explores the relative roles of geographical context and SDOH on teen birth rates. Contrary to research that suggests reducing variation in SDOH alone will ameliorate geographic disparities in teen birth rates (Ventura et al., 2001; Fuller et al., 2018; CDC, 2021), findings from this analysis indicate that even if all counties had identical SDOH compositions, geographic disparities would still persist. In particular, communities in the South, especially those in Texas and the Mississippi delta would continue to have high rates of teen births, while counties in the Northeast, West Coast, and the Great Lakes regions would have lower rates.

These results are suggestive of the importance of place in moderating the effects of SDOH on teen birth rates. Although SDOH capture important risk factors, such as higher levels of deprivation, lower levels of education, and lack of access to healthcare, that contribute to higher rates of teen birth, these risk factors alone do not explain the persistent spatial variation in teen birth rates that we observe. Instead, as argued by Link and Phelan (1995), we must contextualize these risk factors to better understand when SDOH will likely contribute to higher rates of teen birth and when they will not. Our analysis indicates that the local conditions or geographical contextual factors present in parts of the Western U.S., including most counties in California and Oregon, lead to a weakening of the relationship between SDOH and teen birth rates (Fig. 3b), whereas the geographical contextual factors present in the South, especially in Texas, lead to a strengthening of this relationship.

While our analysis does not identify the specific geographical contextual factors that differ between these places, one possible explanation for why places with similar SDOH are likely to exhibit different rates of teen births is related to differences in values, beliefs, and norms across communities in the U.S. Several studies, for instance, have demonstrated the role of community norms and attitudes toward teen childbearing in influencing teen behavior and perceptions regarding teen births (Kearney and Levine, 2012; South and Baumer, 2000; Warner et al., 2011; Baumer and South, 2001; Brewster, 1994). Among economically disadvantaged communities, such as those in the South, research shows that supportive pro-childbearing attitudes and support for premarital teen childbearing create permissive environments that

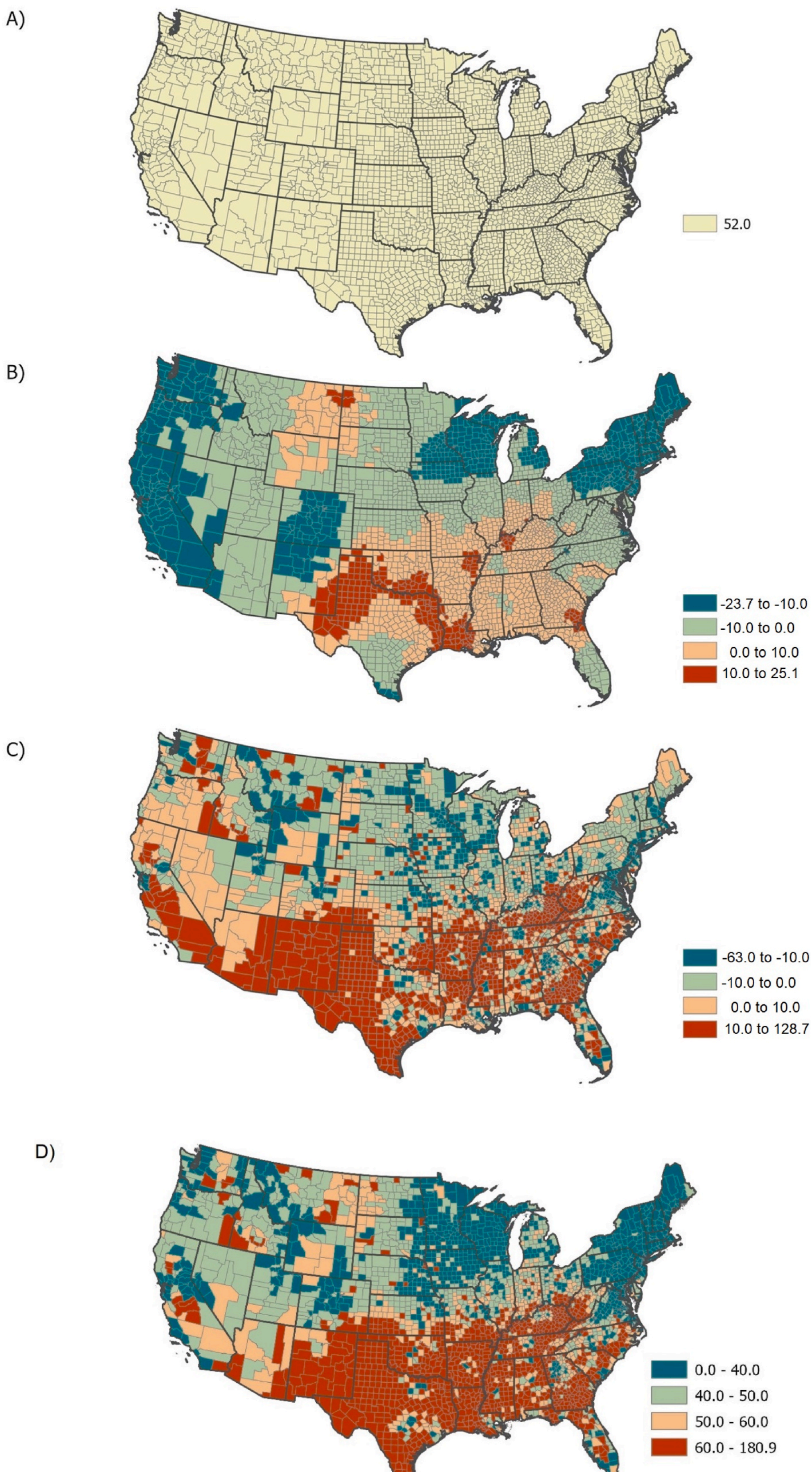

Fig. 3. Contributions to the overall teen birth rate in each county due to (a) mean birth rate. (b) Geographical context, (c) social determinants of health, and (d) the predicted teen birth rate. **Note:** Spatial interpolation was performed to impute missing values for counties omitted from the analysis using the average value among the 40 nearest counties. Values are presented as rates per 1000.

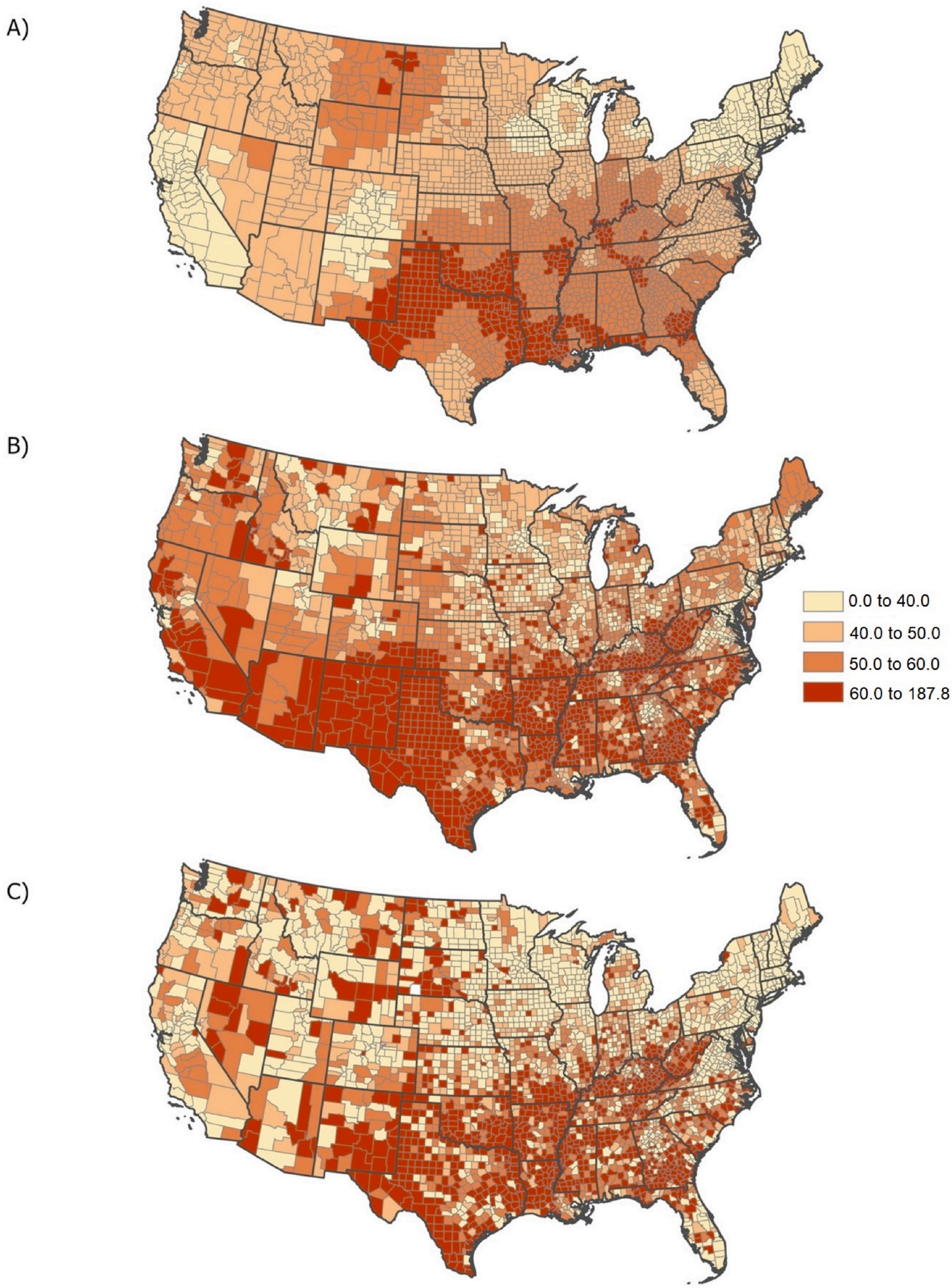

Fig. 4. Spatial variations in teen birth rates (a) if social determinants of health were constant across counties, (b) if geographical context did not matter, and (c) actual teen birth rates. **Note:** Spatial interpolation was performed to impute missing values for counties omitted from the analysis using the average value among the 40 nearest counties. Values are presented as rates per 1000.

normalize these behaviors and increase the likelihood of teen births (South and Baumer, 2000; Warner et al., 2011; Adamek et al., 2019). These place-based cultural factors independent of SDOH create conditions favorable for teen childbearing that may contribute to higher rates of teen birth than may otherwise occur if local attitudes towards teen birth were different. As supported by our findings regarding the relative contribution of geographical context and SDOH on teen birth rates, illustrated in Fig. 4, eliminating geographic disparities in teen birth rates would require not only reducing variations in SDOH but also shifting community mindsets that may promote these behaviors. Without addressing both the contextual and socioeconomic conditions that contribute to these rates, spatial disparities are likely to remain.

In addition to quantifying the effects of geographical context and SDOH on teen birth rates, this research also deepens our understanding of how the influence of individual SDOH on teen birth rates varies over space. Maps of the local parameter estimates show substantial variation, and in some cases opposite effects, across the country. Even covariates with consistently negative, or consistently positive, associations do not always exhibit uniformly strong associations. Population density, total religious adherence, and median income all had stronger effects on teen birth rates across the southern U.S. Consistent with earlier findings from Shoff and Yang (2012), we observe spatially non-stationary and statistically significant positive associations between the teen birth rate and proportion of Hispanic residents in a county and measures of healthcare access. Similar to Shoff and Yang's (2012) findings related to socioeconomic disadvantage, we did not observe significant spatial variation in the relationship between deprivation and teen birth rates. Prior research (Orimaye et al., 2021; Shoff and Yang, 2012) has identified significant rural-urban differences in teen birth rates which are supported by the findings related to population density observed in the current study, although the current analysis indicates that these differences are localized to the southeastern U.S. And, contrary to previous findings suggesting that rates of religiosity are negatively associated with teen birth rates, this research finds the religious adherence is positively correlated with teen birth rates but only at a statistically significant level in the southeastern portion of the U.S. This difference might be due to the fact that Shoff and Yang (2012) partitioned their dataset into metropolitan and nonmetropolitan subsets prior to analysis reducing their power to identify the scale at which relationships varied or because their models assumed that all relationships operated at only a single spatial scale, whereas the current study finds that the influence of individual components of SDOH on teen birth rates varies at local, regional, and global scales. Consequently, future research into SDOH on teen childbearing should continue to employ multiscale local modeling techniques to better model these associations. Without taking intrinsic contextual effects into account, models that relate spatial disparities in health simply to SDOH, risk reporting relationships that contain significant misspecification bias.

While this paper provides policy-relevant insights for addressing disparities in teen birth rates, it is not without its limitations. First, this analysis sought to understand the relationships between SDOH and teen birth rates rather than pregnancy rates. Because not all pregnancies are brought to term, it is possible that the variation in teen birth rates is partially due to differences in awareness, access, or attitudes toward contraceptives and abortion. While we try to control for these differences by including information on the presence of clinics offering comprehensive contraceptive access and rates of religious adherence, it is likely these proxy measures do not capture all relevant differences. Although the MGWR model provides strong explanatory power, additional variables, including the provision of sexuality education, access to contraception, and access and attitudes toward abortion might further improve it. However, because these variables are not consistently available at the county level, it was not possible to incorporate them into the analysis.

6. Conclusion

This paper demonstrates the value of using MGWR to model the associations between SDOH and teen birth rates. The findings suggest that variations in teen birth rates are partially the result of intrinsic contextual geographic differences in addition to variations in SDOH. While addressing differences in SDOH across counties will ameliorate disparities in teen birth rates, it will not eliminate them altogether. As a result, as governments at the federal, state, and local levels seek to address the persistent spatial disparities in teen birth rates, they should aim to not only enact policies related to reducing disparities in SDOH but that also address variations in cultural norms that support, and even promote, teen childbearing across communities, particularly in the South.

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CRediT authorship contribution statement

Sarah Bardin: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **A. Stewart Fotheringham:** Funding acquisition, Writing – review & editing.

Data availability

Data will be made available on request.

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