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The association between neighborhood social and economic environment and prevalent diabetes in urban and rural communities: The Reasons for Geographic and Racial Differences in Stroke (REGARDS) study

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A R T I C L E I N F O

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A B S T R A C T

Objective: The association between neighborhood disadvantage and health is well-documented. However, whether these associations may differ across rural and urban areas is unclear. This study examines the association between a multi-item neighborhood social and economic environment (NSEE) measure and diabetes prevalence across urban and rural communities in the US.

Methods: This study included 27,159 Black and White participants aged ≥45 years at baseline (2003–2007) from the REasons for Geographic and Racial Differences in Stroke (REGARDS) study. Each participant's residential address was geocoded. NSEE was calculated as the sum of z-scores for six US Census tract variables (% of adults with less than high school education; % of adults unemployed; % of households earning <$30,000 per year; % of households in poverty; % of households on public assistance; and % of households with no car) and within strata of community type (higher density urban, lower density urban, suburban/small town, and rural). NSEE was categorized as quartiles, with higher NSEE quartiles reflecting more disadvantage. Prevalent diabetes was defined as fasting blood glucose ≥126 mg/dL or random blood glucose ≥200 mg/dL or use of diabetes medication at baseline. Multivariable adjusted Poisson regression models were used to estimate prevalence ratios (PR) and 95% confidence intervals (CI) for the association between NSEE and prevalent diabetes across community types.

Results: The mean age was 64.8 (SD=9.4) years, 55% were women, 40.7% were non-Hispanic Black adults. The overall prevalence of diabetes was 21% at baseline and was greatest for participants living in higher density urban areas (24.5%) and lowest for those in suburban/small town areas (18.5%). Compared with participants living in the most advantaged neighborhood (NSEE quartile 1, reference group), those living in the most disadvantaged neighborhoods (NSEE quartile 4) had higher diabetes prevalence in crude models. After adjustment for sociodemographic factors, the association remained statistically significant for moderate density community types (lower density urban quartile 4 PR=1.50, 95% CI=1.29, 1.75; suburban/small town quartile 4 PR=1.54, 95% CI=1.24, 1.92). These associations were also attenuated and of smaller magnitude for those living in higher density urban and rural communities.

Conclusion: Participants living in the most disadvantaged neighborhoods had a higher diabetes prevalence in each urban/rural community type and these associations were only partly explained by individual-level sociodemographic factors. In addition to addressing individual-level factors, identifying neighborhood characteristics

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and how they operate across urban and rural settings may be helpful for informing interventions that target chronic health conditions.

1. Introduction

In the US, 13% of adults have diabetes (Centers for Disease Control and Prevention, 2020). Although overall diabetes prevalence has plateaued since 2010, stark disparities by individual-level race, education, and income have persisted (Beckles & Chou, 2016; Benoit, Hora, Albright, & Gregg, 2019; Geiss et al., 2014). While these disparities by individual-level socioeconomic factors are well-recognized, the neighborhood socioeconomic environment may also affect diabetes burden (Malambo, Kengne, De Villiers, Lambert, & Puoane, 2016), as neighborhood environments have differential resources such that more advantaged neighborhoods may have greater access to supermarkets and physical activity spaces and facilities than disadvantaged neighborhoods. Given that the prevalence of diabetes has been reported to be higher in rural areas than urban areas (O'Connor & Wellenius, 2012) and there are rural-urban differences in built environment features (Ahern, Brown, & Dukas, 2011; Hoehner, Barlow, Allen, & Schootman, 2012), studies investigating the association between neighborhood socioeconomic environment and prevalent diabetes by rural and urban designation are needed.

Prior studies have found that neighborhoods with lower socioeconomic status and less access to physical resources generally have an excess diabetes prevalence (Gebreab et al., 2017; Hill-Briggs et al., 2020; Hu et al., 2020) that persists after accounting for individual-level socioeconomic factors. However, whether these associations may differ across rural and urban areas has not been reported. Findings from a natural experiment in Japan showed that adults in high urban density areas, characterized by greater access to both physical activity facilities and unhealthy food outlets, had worse metabolic health than adults in low urban density areas (Shiba et al., 2020). Additionally, in the Moving to Opportunity Study, adults living in public housing that received a voucher to move to a low-poverty census had lower diabetes prevalence than those that did not receive a voucher, although this study was conducted in densely populated urban areas only (Ludwig et al., 2011).

The use of natural experiments and randomized quasi-experimental study designs may help account for the non-random selection of individuals into neighborhoods, but this also highlights methodological challenges for observational studies investigating the health effects of neighborhood environments. Some of these challenges include structural confounding due to lack of sufficient variability in individual-level covariates across strata of neighborhood environment (Diez Roux, 2004; Oakes, 2004, 2006), use of different geographic and administrative boundaries (Boyle & Willms, 1999; Diez Roux, 2004), and limited ability to evaluate neighborhood factors by community type (i.e., urban and rural areas). For example, car ownership may be a basic necessity in a rural community, whereas it may be a luxury item in a highly-dense urban area that has access to public transportation (Reading, Raybould, & Jarvis, 1993), so the neighborhood factor of percent of households without a car may be more likely to reflect disadvantage in rural areas than urban areas (McAlexander et al., 2022). In this current analysis, we sought to address these methodologic challenges by using a multi-item neighborhood social and economic environment (NSEE) measure created using census-tract level data and scaled within strata of community type (higher density urban, lower density urban, suburban/small town, and rural) to investigate its association with prevalent diabetes in a cohort of middle-aged and older adults from the contiguous US.

2. Methods

2.1. Study population

The REasons for Geographic and Racial Differences in Stroke (REGARDS) Study is an ongoing prospective cohort study designed to investigate factors associated with stroke mortality among 30,239 Black and White adults aged ≥45 years from the contiguous US (Howard et al., 2005). By design, the study oversampled Black adults and adults residing in the southeastern US states (North Carolina, South Carolina, Georgia, Alabama, Mississippi, Arkansas, Louisiana, and Tennessee). Sociodemographic information, health behaviors, and previous medical history were collected using a computer-assisted telephone interview (CATI) at baseline (2003–2007). An in-home visit was conducted to obtain anthropometry, blood pressure, electrocardiogram, and blood and urine specimens. Institutional review boards at all participating institutions reviewed and approved the study protocol. Informed consent was obtained from all participants. In the current cross-sectional analysis, participants were excluded for informed consent anomalies (n=56), missing geocoding status (n=277), missing prevalent diabetes status (n=1,131), or missing covariate information (n=1,616), resulting in a sample size of 27,159 (Fig. 1).

2.2. Exposure

The primary exposure, NSEE, was determined at the census tract level. Each participant's residential address at baseline was geocoded using ESRI ArcMap software and linked to the 2000 US Census. NSEE was defined by the Diabetes LEAD (Location, Environmental Attributes, and Disparities) network, a CDC funded collaboration between Drexel University, Geisinger-Johns Hopkins University, New York University School of Medicine, and the University of Alabama at Birmingham (Hirsch et al., 2020). The primary goal of the network is to further the understanding of the role of community-level factors and geographic differences in diabetes incidence and prevalence across the US and across demographic groups.

Based on prior work (Xiao, Berrigan, Powell-Wiley, & Matthews, 2018), the NSEE measure was developed using 6 census tract variables from the 2000 US Census: % of adults with less than high school education, % of adults unemployed, % of households earning <$30,000 per year, % of population in poverty, % of households on public assistance, and % of households with no car (De Silva et al., 2018; Logan, Xu, & Stults, 2014). The z-scores for these six variables were summed and scaled (range 0–100) with higher scores reflecting more disadvantage. NSEE was created separately within strata of community type (higher density urban, lower density urban, suburban/small town, and rural) to reflect how its underlying variables may operate differently within community contexts. Therefore, the z-score for the NSEE measure cannot be compared across the community types.

As neighborhood environments may differ according to urban and rural classifications, the Diabetes LEAD network created 4 community types (higher density urban, lower density urban, suburban/small town, and rural) based on a modification of the USDA's Rural Urban Commuting Area (RUCA) system in order to provide a clearer distinction between densely populated urban areas (McAlexander et al., 2021). For this modification, RUCA community types were reclassified primarily based on the proportion of a census tract's land area that was included in federally classified urbanized areas and urban clusters (McAlexander et al., 2021). Urban census tracts (with population >50,000) were further classified based on the land area such that higher density urban tracts were geographically smaller (<40th percentile) and lower density urban tracts were geographically larger (>40th percentile) compared to the US land area distribution. RUCA categories micropolitan and small-town core were grouped into the suburban/small town community type and all remaining RUCA categories were considered rural.

2.3. Outcome

The primary outcome was prevalent diabetes, defined as fasting blood glucose (FBG) $\geq$ 126 mg/dL ($\geq$7 mmol/L) or random blood glucose (RBG) $\geq$ 200 mg/dL ($\geq$11.1 mmol/L) or self-reported use of any diabetes medication.

2.4. Covariates

Covariates included self-reported age, sex, race, education ($\leq$high school, >high school), annual household income (<$20,000; $20,000–$34,999; $35,000–$74,999; $\geq$$75,000), and health insurance. Geographic region of residence was classified as stroke belt (Tennessee, Louisiana, Mississippi, Arkansas, Alabama, Georgia, North Carolina and South Carolina), stroke buckle (coastal areas of Georgia, North and South Carolinas) and outside stroke belt/buckle (rest of the contiguous US).

2.5. Statistical analysis

NSEE was categorized into quartiles within each community type (higher density urban, lower density urban, suburban/small town, and rural) based on the number of unique census tracts where REGARDS participants resided. As NSEE was community-specific, Poisson regression (Zou, 2004) with robust standard error estimation was used and accounted for potential correlation between participants residing in the same census tract. Prevalence ratios (PR) were estimated for the association of NSEE quartile with prevalent diabetes, separately for each community type. Additionally, differences in prevalence were estimated using %nlmeans macro in SAS (support.sas.com/kb/62/362.html" title="http://support.sas.com/kb/62/362.html"). Models were crude and adjusted for individual-level sociodemographic factors (age, race, sex, education, annual household income, health insurance, and geographic region).

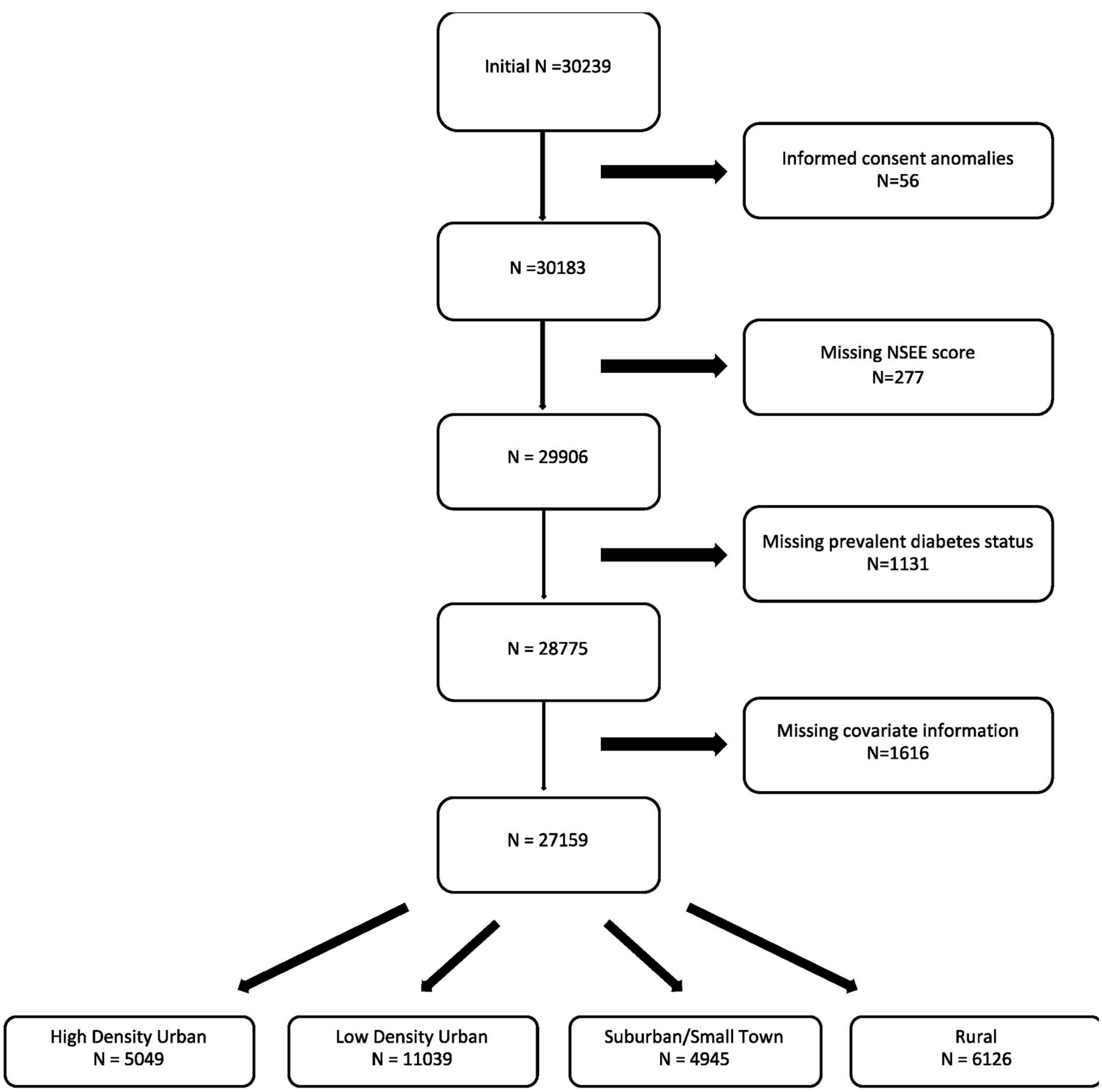

Fig. 1. Exclusion flowchart for REGARDS Study.

3. Results

Participant characteristics are presented in Table 1. Overall, 40.7% of participants lived in lower density urban areas, 22.6% in rural areas, 18.6% in higher density urban areas, and 18.2% in suburban/small town areas. Participants residing in higher density urban areas were more likely to be Black adults (70.7%), women (59.7%), and have an annual household income <$20,000 (23.1%). Participants in rural areas were more likely to be White adults (78.5%), have high school education or less (45.2%), and reside inside the stroke belt or buckle geographic areas. Diabetes prevalence was highest for participants living in higher density urban areas (24.5%) followed by those living in lower density urban (20.7%), rural (20%), and suburban/small town areas (18.5%).

The crude and adjusted models for the association between NSEE quartiles and prevalent diabetes by community type are presented in Table 2. Within each community type, NSEE quartile 1 (reference category) represents the most advantaged neighborhoods. Compared with participants living in the most advantaged quartile, participants in more disadvantaged neighborhoods had higher diabetes prevalence in crude analyses. The magnitude of these associations generally increased as disadvantage increased, with participants in the most disadvantaged neighborhoods (quartile 4) having a higher diabetes prevalence in each community type in crude models (higher density urban PR=1.86, 95% CI=1.58–2.19; lower density urban PR=2.29, 95% CI=2.00–2.63; suburban/small town PR=2.26, 95% CI=1.86–2.75; and rural areas PR=1.90, 95% CI=1.58–2.27). Adjustment for individual-level sociodemographic factors attenuated these associations, with a 16%–54% higher prevalence of diabetes remaining for the most disadvantaged neighborhoods (quartile 4) across the community types (higher density urban PR=1.16, 95% CI=0.97, 1.38; lower density urban PR=1.50, 95% CI=1.29, 1.75; suburban/small town PR=1.54, 95% CI=1.24, 1.92; and rural PR=1.21, 95% CI=0.99, 1.48).

In additional analyses investigating absolute measures of association, there were significant differences in prevalence between NSEE quartiles for all community types in crude models. After adjusting for individual-level sociodemographic factors, differences in prevalence were observed for participants residing in lower density urban, suburban/small town and rural communities but not those in higher density urban communities (Supplemental Table 1).

4. Discussion

In this study of middle-aged and older adults, participants living in the most disadvantaged neighborhoods had higher diabetes prevalence in crude models than those living in the most advantaged neighborhoods within all community types. These associations were generally attenuated after adjustment for sociodemographic factors, and the magnitude of the associations was stronger in the most disadvantaged neighborhoods in lower density urban and suburban/small town areas than higher density urban and rural areas.

The observed associations in this study are consistent with findings from prior studies that reported that residents from the most disadvantaged neighborhoods were more likely to have diabetes (Corriere et al., 2014; Garcia et al., 2015; Hu et al., 2020; Mirowsky et al., 2017; Rachele, Giles-Corti, & Turrell, 2016; Sheets et al., 2017). In the Gulf Coast Long-Term Follow-up Study of adults primarily in the southeastern US, the association between neighborhood disadvantage and diabetes prevalence remained statistically significant after accounting for individual-level education, income, and employment (Hu et al., 2020). Similar associations between neighborhood disadvantage and

Table 1
Participant characteristics by community type, the REGARDS Study (2003–2007).

Characteristics	Higher Density Urban (N=5,049)	Lower Density Urban (N=11,039)	Suburban/Small Town (N=4,945)	Rural (N=6,126)
Neighborhood Social and Economic Environment (NSEE)[a]				
Mean (SD)	28.6 (12.9)	20.2 (12.9)	15.4 (10.0)	24.6 (9.7)
Median (IQR)	27.9 (18.2–37.3)	17.7 (9.8–28.5)	12.6 (8.0–21.1)	24.0 (17.2–31.2)
Age (years)	65.2 (9.6)	65.2 (9.5)	64.5 (9.2)	63.9 (9.1)
Race (%)				
Black	70.7	44.5	25.6	21.5
White	29.4	55.5	74.4	78.5
Gender (%)				
Men	40.3	46.2	46.7	45.5
Women	59.7	53.8	53.3	54.5
Education (%)				
College graduate and above	31.9	38.6	38.5	29.9
Some college	27.2	27.7	26.6	24.9
High school graduate	25.6	23.2	24.4	31.2
<High school	15.3	10.5	10.5	14.0
Annual household income (%)				
<$20,000	23.1	16.5	13.9	18.2
$20,000–$34,999	25.8	23.7	21.7	25.6
$35,000–$74,999	26.4	30.9	32.2	29.8
>=$75,000	12.5	17.4	19.6	14.8
Refused	12.1	11.5	12.6	11.6
Has health insurance (%)	92.8	93.7	94.6	92.6
Geographic region (%)				
Stroke Buckle	3.4	15.7	30.6	36.9
Stroke Belt	9.8	38.8	41.4	43.8
Outside Stroke Belt/Buckle	86.8	46.1	28.0	19.3
Clinical Factors[b]				
Current smoking status (%)	16.9	14.1	13.0	14.1
Body mass index (kg/m^2)	29.8 (6.5)	29.2 (6.1)	28.9 (5.9)	29.3 (6.1)
Waist circumference (cm)	96.8 (15.2)	95.8 (15.2)	95.0 (15.4)	96.1 (15.2)
Total cholesterol (mg/dL)	193.6 (41.2)	191.7 (39.6)	191.4 (39.7)	192.4 (40.6)
Systolic blood pressure (mmHg)	129.9 (17.7)	127.3 (16.2)	126.1 (16.2)	126.9 (16.6)
Diastolic blood pressure (mmHg)	78.0 (10.0)	76.4 (9.6)	75.7 (9.4)	76.2 (9.6)
Use of antihypertensive medications (%)	64.0	58.9	55.8	56.9
Prevalent diabetes at baseline (%)	24.5	20.7	18.5	20.0

[a] NSEE measure was developed and scaled within each community type, so its values are not comparable across the community types.
[b] Clinical factors are presented for descriptive purposes and are not included in models given their role in the pathway between NSEE and diabetes.

Table 2
Prevalence ratios (PR) for the association of neighborhood social and economic environment (NSEE) quartile with prevalent diabetes, stratified by community type in the REGARDS Study.

	Crude	Model 1	Model 2
	PR (95% CI)	PR (95% CI)	PR (95% CI)
Higher Density Urban (N=5,049)			
Quartile 1 (most advantage)	Reference	Reference	Reference
Quartile 2	1.35 (1.14–1.60)	1.10 (0.93–1.30)	1.06 (0.90–1.25)
Quartile 3	1.61 (1.37–1.89)	1.20 (1.02–1.42)	1.10 (0.93–1.30)
Quartile 4 (most disadvantage)	1.86 (1.58–2.19)	1.33 (1.13–1.58)	1.16 (0.97–1.38)
Lower Density Urban (N=11,039)			
Quartile 1 (most advantage)	Reference	Reference	Reference
Quartile 2	1.37 (1.18–1.61)	1.25 (1.07–1.46)	1.22 (1.04–1.42)
Quartile 3	1.86 (1.61–2.14)	1.55 (1.34–1.79)	1.46 (1.26–1.70)
Quartile 4 (most disadvantage)	2.29 (2.00–2.63)	1.66 (1.43–1.92)	1.50 (1.29–1.75)
Suburban/Small Town (N=4,945)			
Quartile 1 (most advantage)	Reference	Reference	Reference
Quartile 2	1.23 (0.97–1.55)	1.21 (0.96–1.54)	1.16 (0.91–1.47)
Quartile 3	1.50 (1.21–1.87)	1.42 (1.14–1.76)	1.31 (1.05–1.64)
Quartile 4 (most disadvantage)	2.26 (1.86–2.75)	1.74 (1.42–2.15)	1.54 (1.24–1.92)
Rural (N=6,126)			
Quartile 1 (most advantage)	Reference	Reference	Reference
Quartile 2	1.24 (1.00–1.54)	1.21 (0.97–1.50)	1.06 (0.85–1.32)
Quartile 3	1.64 (1.35–2.00)	1.49 (1.22–1.81)	1.27 (1.03–1.56)
Quartile 4 (most disadvantage)	1.90 (1.58–2.27)	1.48 (1.23–1.79)	1.21 (0.99–1.48)

Model 1 – Adjusted for age, race and sex.
Model 2 – Adjusted for Model 1 + education, annual household income, health insurance coverage, and geographic region.

prevalent diabetes were reported in studies of Latino adults from the Sacramento valley area in California (Garcia et al., 2015), older women in Baltimore city (Corriere et al., 2014), and Medicare patients within a single academic healthcare system (Sheets et al., 2017). Our study builds upon the findings from these prior studies by showing that the association between neighborhood disadvantage and prevalent diabetes was generally similar in direction although magnitudes differed across higher density urban, lower density urban, suburban/small town, and rural areas. A study of cardiac catheterization patients in central North Carolina reported that the association between neighborhoods with low poverty levels and prevalent diabetes was more pronounced in urban areas than rural areas (Mirowsky et al., 2017). In our study with participants from across the US, we found that the magnitude of the association between neighborhood disadvantage and prevalent diabetes was present in each community type and generally of stronger magnitude in lower density urban and suburban/small town areas.

Previous research reported a higher burden of diabetes-related mortality in rural and non-metropolitan areas than urban areas, highlighting how disease burden can vary across community types (Singh & Siahpush, 2014). From 1999 to 2016, trends in diabetes mortality showed overall declines in mortality rates, with greater declines observed in urban areas in the Northeast and Midwest regions whereas rural areas had smaller declines or were stagnant, especially in the South (Callaghan, Ferdinand, Akinlotan, Towne, & Bolin, 2020). Few studies have reported on diabetes prevalence or incidence across urban and rural communities, with mixed findings to date. Using data from the Behavioral Risk Factor Surveillance System, the prevalence of self-reported diabetes was lower in rural areas than urban areas (O'Connor & Wellenius, 2012) in an analysis that excluded those living in suburban counties and those living outside the city center. In a study from the Geisinger health system in Pennsylvania that evaluated geographic administrative units (township, borough, and city census tracts) and urban/rural community types (urbanized area, urban cluster, and rural), patients living in city census tracts/urban clusters and city census tracts/urbanized areas had greater odds of new-onset diagnosed diabetes than those living in township/rural areas (Schwartz et al., 2021). In the current study, our descriptive results showed a higher percentage of participants from higher density urban areas had prevalent diabetes compared to those living in rural areas; however, this may be reflective of our study's design that oversampled participants in the southeastern US. Taken together, these findings suggest that diabetes morbidity and mortality may differ across community types and warrant further study.

Although a growing body of studies has reported associations of neighborhood disadvantage with diabetes and other chronic conditions, it remains unclear what underlying factors may explain such associations in certain community types. Access to healthcare facilities, food stores, and obesogenic environment across community types may be possible pathways that can explain the observed associations. For instance, areas with a higher density of grocery stores have been shown to be associated with lower diabetes prevalence outside of, but not within metro areas (Ahern et al., 2011). In a hierarchical clustering analysis, neighborhoods with high levels of disadvantage varied in proximity to roadways which could affect commuting distance (Mirowsky et al., 2017). Increased automobile use and longer commuting distance from home to work were also associated with a higher prevalence of obesity, a risk factor for diabetes, in metropolitan counties (Hoehner et al., 2012). Additional research has shown the association between community factors and diabetes burden may differ across geographic regions. For example, a study using data from the Behavioral Risk Factor Surveillance System showed that the density of recreational facilities was associated with prevalent diabetes in the Southeastern US, whereas, economic context (e.g., poverty, unemployment) had a stronger association with diabetes in regions outside of the Southeastern US (Myers et al., 2017). Thus, further investigation of built environment characteristics may help elucidate the association between neighborhood disadvantage and diabetes burden, particularly across urban and rural community types.

Diabetes prevention is a critical public health focus in the United States. To date, many prevention efforts have focused on individual-level behavioral modifications (Diabetes Prevention Program Research Group, 2002; Mozaffarian et al., 2009; Tuomilehto et al., 2001). However, it remains unclear whether such individual-level behavioral changes will reduce population-level disparities in diabetes, especially for those living in neighborhoods with fewer resources. Examining the neighborhood environment may be important for directing resources in local communities and informing population-level prevention strategies.

Our study has several strengths, including the use of NSEE, a measure developed based on six census-tract level variables within our four designated community types. The multidimensional nature of NSEE and its development within each community type, addresses potential differential item functioning and non-positivity issues (Messer, Jagai, Rappazzo, & Lobdell, 2014). For instance, differential item functioning could occur when investigating the neighborhood factor of percent of households without a car, as this may be more likely to reflect disadvantage in rural areas than urban areas. Non-positivity could occur when only one level of exposure is experienced in some population subgroups such that residents living in high-poverty neighborhoods are not likely to have a high individual-level income (Oakes, 2004, 2006). Further, our analysis included a national sample with participants from the 48 contiguous states, thus covering a wide geographic area. This is an important strength of this study as prior studies were generally limited in their geographic areas included and few investigated associations across urban-rural community types.

We also acknowledge several potential limitations. While census tracts are administrative designations and are relatively stable, they may not represent the participant's perception of their neighborhood. Also, participants may self-select into certain neighborhoods and the factors that affect neighborhood selection may extend beyond the variables available in the current study (Diez Roux, 2004; Oakes, 2004). Another potential limitation is that the results across community types are not directly comparable as the NSEE measure was community-specific. However, this stratified approach takes community-level characteristics into account and will help inform locally targeted diabetes prevention efforts. While we adjusted for individual-level factors when investigating NSEE and prevalent diabetes, other unmeasured neighborhood characteristics such as food stores and access to physical activity facilities were not investigated and may affect observed associations. Additionally, participants with missing covariate data were excluded from this complete case analysis. Participants included and excluded in the analysis were generally similar in age, sex, health insurance, and geographic region, although there were differences by race, education, and income (Supplemental Table 2). Lastly, due to the cross-sectional nature of the analysis, causal inferences cannot be made from the study findings.

5. Conclusion

Our study showed that middle-aged and older adults living in more disadvantaged neighborhoods had a significantly higher prevalence of diabetes than adults living in more advantaged neighborhoods and this association was attenuated after accounting for individual-level sociodemographic factors. The association between NSEE and prevalent diabetes was present across all community types with stronger effect estimates observed in lower density urban and suburban/small town communities. In addition to addressing individual-level factors, identifying neighborhood characteristics and how they operate across urban and rural settings may be helpful for informing interventions that target chronic health conditions.

Author contributions

G.M. conceptualized the study, assisted in statistical analysis, interpreted the data and drafted the manuscript. J.U. interpreted the data and drafted the manuscript. A.P.C. conceptualized the study, interpreted the data and critically revised the manuscript. S.Z. performed statistical analysis, interpreted the data and critically revised the manuscript. D.L.L, N.B., A.C., G.R.D., D.M.C., S.E.J., M.M.S., and E.B.L. interpreted the data and critically revised the manuscript. A.P.C. is the guarantor of this work and, as such, had full access to all the data and takes responsibility for the integrity of the data and the accuracy of the data analysis.

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Declaration of competing interest

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2022.101050.

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