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# Identifying neighborhood characteristics associated with diabetes and hypertension control in an urban African-American population using geolinked electronic health records

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#### ABSTRACT

For health care providers, information on community-level social determinants of health is most valuable when it is specific to the populations and health outcomes for which they are responsible. Diabetes and hypertension are highly prevalent conditions whose management requires an interplay of clinical treatment and behavioral modifications that may be sensitive to community conditions. We used geo-linked electronic health records from 2016 of African American patients of a network of federally qualified health centers in Philadelphia, PA to examine cross-sectional associations between characteristics of patients' residential neighborhoods and hypertension and diabetes control (n = 1061 and n = 2633, respectively). Hypertension and diabetes control were defined to align with the Health Resources and Services Administration (HRSA) Uniform Data System (UDS) reporting requirements for HRSA-funded health centers. We examined associations with nine measures of neighborhood socioeconomic status (poverty, education, deprivation index), social environment (violent crime, perceived safety and social capital, racial segregation), and built environment (land-use mix, intersection density). In demographics-adjusted log-binomial regression models accounting for neighborhood-level clustering, poor diabetes and hypertension control were more common in highly segregated neighborhoods (i.e., high proportion of African American residents relative to the mean for Philadelphia; prevalence ratio = 1.27[1.02–1.57] for diabetes, 1.22 [1.12–1.33] for hypertension) and less common in more walkable neighborhoods (i.e., higher retail land use). Neighborhood deprivation was also weakly associated with poor hypertension control. An important consideration in making geographic information actionable for providers is understanding how specific community-level determinants affect the patient population beyond individual-level determinants.

#### 1. Introduction

Prominent health policy and funding initiatives increasingly emphasize community-level social determinants of individual and population health. For example, the US Department of Health and Human Service's Healthy People 2020 initiative includes indicators of community poverty, food insecurity, education, safety, and civic engagement (Office of Disease Prevention and Health Promotion and Social Determinants of Health, n.d.). A 2014 Institute of Medicine report recommended incorporating information about social determinants of

health, including community-level determinants, into electronic health record systems as a means of promoting coordination between clinical, public health, and community resources to improve population health (IOM (Institute of Medicine), 2014).

There is no consensus, however, on how best to integrate community-level information with patient records (Cantor and Thorpe, 2018). For health care providers, information on community-level social determinants of health is most valuable when it is specific to the populations and health outcomes for which they are responsible. An important consideration in making this information actionable is

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understanding how specific community-level determinants affect the patient population beyond individual-level determinants. In this way, information on community-level determinants can serve as an additional resource—distinct from information on patient-level determinants—for informing clinical decision-making and population-level intervention efforts.

We used electronic health record (EHR) data from a network of federally qualified health centers (FQHCs) in Philadelphia, PA, to examine associations between characteristics of patients' residential neighborhoods and hypertension and diabetes control among patients with these diagnoses. We focused on these outcomes because hypertension and diabetes are highly prevalent (Shay et al., 2015) and confer high risk for future morbidity and mortality (Lloyd-Jones et al., 2010; Wong et al., 2012a; Wong et al., 2012b), because control of these conditions generally involves both clinical treatments and behavioral modifications that may be influenced by community-level characteristics (Shay et al., 2015), and because preventing complications arising from poor control of these conditions is a public health as well as clinical priority (Rutledge et al., 2018; National Center for Chronic Disease Prevention and Health Promotion, 2017).

We hypothesized that lower neighborhood socioeconomic status, a worse social environment (higher crime, less perceived safety and social capital, high segregation), and lower walkability would be associated with higher prevalence of poor hypertension and diabetes control.

We restricted our analysis to non-Latino black patients, who make up the large majority (87%) of patients at the network, to more specifically explore variation within this population. Residents' experiences living in a given neighborhood, and how neighborhood characteristics relate to health, can vary by race and ethnicity (Osypuk et al., 2009; Das et al., 2017). Within-group comparisons therefore help hone in on salient neighborhood characteristics, and important sources of variability in those characteristics, for a given group.

### 2. Methods

#### 2.1. Study population

EHR data was extracted from three community health centers operated by the Family Practice and Counseling Network (FPCN), a network of federally qualified health centers (The Family Practice and Counseling Network, n.d.). These health centers provide comprehensive primary, behavioral health, and dental care, as well as social services, to medically underserved populations in Philadelphia, PA. They are recognized as "patient-centered medical home" providers by the National Committee on Quality Assurance (NCQA) (National Committee for Quality Assurance. Patient-Centered Medical Home (PCMH), 2018). The study population included adult, non-Latino black patients who had at least one visit to one of the centers during calendar year 2016 and who resided in the City of Philadelphia. For patients with more than one visit during 2016, the most recent visit was used. For each outcome, the analysis sample was defined to align with the Health Resources and Services Administration (HRSA) Uniform Data System (UDS) reporting requirements for HRSA-funded health centers (HRSA Bureau of Primary Health Care, n.d.). For analyses of diabetes control, this included patients aged 18-75 years with a recorded diagnosis of either type 1 or type 2 diabetes (n = 1072). For analyses of hypertension control, patients were included if they were aged 18-85 years and had a recorded diagnosis of hypertension (n = 2706). Patients were excluded if they had missing values on any analysis variables, discussed further below, or an address that could not be geocoded (11 for diabetes; 73 for hypertension), resulting in final analysis samples of n = 1061 for diabetes control and n = 2633 for hypertension control. Data were extracted and analyzed in 2018. The study received Internal Review Board approval.

#### 2.2. Measures

In keeping with the HRSA UDS definition, poor diabetes control was defined as having either a lab value of hemoglobin A1c (HbA1c) > 9% or no record of a HbA1c test during the one-year period prior to the visit. Poor hypertension control was defined as either systolic blood pressure (SBP)  $\geq$  140 mmHg or diastolic blood pressure (DPB)  $\geq$  90 mmHg. Because blood pressure is generally measured at every clinic visit in the network, the number of patients with no recorded blood pressure was very small (n = 41), and we excluded these patients from analyses.

Patient residential addresses were geocoded using ArcGIS 10.5 software with the ESRI Business Analyst 2016 Composite Address Locator. Ninety-eight percent of addresses in the health care network 2016 patient population file were successfully geocoded to the street address level. We used census tracts as proxies for neighborhoods, using boundaries from the 2010 US Census.

We examined nine measures describing three domains of neighborhood characteristics: socioeconomic status (SES), social environment, and built environment. Neighborhood SES variables came from American Community Survey (ACS) 2012–2016 5-year estimates. We used a previously developed weighted factor score of neighborhood socioeconomic deprivation that incorporated 16 ACS-derived measures of tract-level education, occupation, housing value, and income (Christine et al., 2015). We also examined two measures of specific aspects of neighborhood SES: % residents living below the Federal poverty line and % residents aged 25 years or older with a bachelor's degree or higher level of education.

We examined four measures of neighborhood social environment: violent crime rate, perceived safety, social capital, and African American residential segregation. We calculated the annual violent crime rate per 10,000 residents for 2016 using information on numbers of violent crimes (homicides, rapes, aggravated assaults, robberies, and other assaults) recorded by the Philadelphia Police Department and made available on Philadelphia's OpenDataPhilly web portal (OpenDataPhilly, 2018).

Survey-derived measures of residents' perceived neighborhood safety and social capital were created using the Southeastern Pennsylvania Household Health Survey (SEPAHHS), a biennial population-based telephone survey of adult residents of Philadelphia and surrounding counties (Public Health Management Corporation, n.d.). Perceived neighborhood safety was assessed in the 2012 SEPAHHS, with residents who responded both "no" to the question, "In the past month, did you not go someplace during the day because you felt you would not be safe?" and "yes" to the question, "Is there a park or other outdoor space in your neighborhood that you're comfortable visiting during the day?" categorized as perceiving the neighborhood as safe. Social capital information was assessed in the 2014/2015 SEPAHHS; residents were asked to respond on a 4-point scale the extent to which they agreed that 1) people in their neighborhood were willing to help neighbors, 2) most people in their neighborhood could be trusted, and 3) they felt that they belonged and were a part of their neighborhood. For both measures, aggregate tract-level estimates were created using empirical Bayes estimation, adjusted for participant gender and age (Mujahid et al., 2007; Raudenbush and Byrk, 2002). Therefore, the neighborhood safety measure is interpretable as the weighted average proportion of residents who reported that the neighborhood was safe, and social capital as the weighted average score (range 0-3), with higher scores denoting higher social capital.

Our measure of racial residential segregation was the Getis-Ord  $G_i^*$  statistic, which produces a z-score quantifying the degree to which the proportion of African American residents in each census tract and its neighboring tracts deviates from the mean for the city of Philadelphia (Getis and Ord, 1992; Kershaw et al., 2015). Using ACS 2012–2016 5-year estimates, we classified census tracts with  $G_i^*$  z-scores  $\geq 1.96$ , denoting a high proportion of African American residents in the census

tract and its neighboring tracts relative to Philadelphia as a whole, as highly segregated.

We used two measures of neighborhood built environment that are associated with walkability, percent retail land use and intersection density; higher values of both denote higher walkability (Brownson et al., 2009; Hirsch et al., 2014; Rodriguez et al., 2009). Land use assigned to parcel boundaries was obtained from the Philadelphia City Planning Commission (Philadelphia Department of Planning and Development, 2014). Percent retail land use was calculated as the proportion of area within the census tract that is categorized as commercial consumer or mixed commercial/residential. Using a street network obtained from ESRI, intersection density was calculated as the count of the number of intersections of three or more road segments divided by the land area of the census tract (ESRI, 2007). Intersections within 10 m of tract boundaries were included to account for differences in the spatial accuracy of the street network and the tract boundaries.

Models were adjusted for age in years, sex (male or female), and insurance type (Medicaid, Medicare, private insurance, or uninsured). We also present models additionally adjusted for clinic site.

#### 2.3. Analysis

All analyses were conducted in SAS version 9.4 software. Analyses for each of the outcomes were conducted separately. We used t-tests and chi-square tests to test bivariate associations of diabetes and hypertension control status with individual- and neighborhood-level characteristics. We then used log-binomial regression models to estimate prevalence ratios of poor diabetes and hypertension control with each neighborhood exposure separately after adjustment for covariates (Coutinho et al., 2008). We used generalized estimating equation (GEE) regression with an exchangeable working correlation matrix and robust standard errors to account for correlated observations between patients living in the same census tract (Hanley et al., 2003). For the continuous neighborhood exposure variables (i.e., all except racial segregation), we used squared terms and models including neighborhood exposure tertile categories to test for nonlinearities in associations with the outcomes. We did not find evidence of meaningful nonlinearities and therefore present models using linear terms.

For each outcome and neighborhood exposure, we used a sequential model building approach where we first adjusted for individual-level covariates (Model 1: age, sex, and insurance status), then added adjustment for clinic site (Model 2), and finally added adjustment for neighborhood SES deprivation score (Model 3). We only ran Model 3 for the neighborhood social environment and walkability measures; the purpose of this model was to test associations of these measures with the outcomes independent of neighborhood SES.

### 3. Results

Overall prevalences of diabetes and hypertension among adult network patients were 13% and 32%, respectively. Table 1 shows characteristics of the overall network adult patient population and the diabetes control and hypertension sample populations. The majority of patients were female and over 70% had public insurance. Patients lived in census tracts that were primarily residential (mean = 5% retail land use). The census tracts in which patients lived were of markedly lower SES and were more likely to be highly segregated than other census tracts in the city (e.g., mean percent of residents living in poverty was 27% in tracts where patients lived vs. 18% in tracts without patients; mean percent African American residents was 60% in tracts where patients lived vs. 16% in tracts without patients [data not shown]). Compared to the overall patient population, those in the diabetes and hypertension control analytic samples were older, more likely to be insured by Medicare, and less likely to be uninsured. They also tended to live in census tracts with slightly lower socioeconomic status (e.g.,

Table 1			
Sample characteristics,	Philadelphia,	PA, 2016.	

Characteristic	Total adult patient population	Diabetes control sample	Hypertension control sample
	N (%) or mean (SD)	N (%) or mean (SD)	N (%) or mean (SD)
Individual-level <sup>a</sup>			
Total (N)	9499	1061	2633
Age (years)	37.3 (13.9)	49.9 (12.3)	48.7 (12.9)
Female	6758 (71%)	716 (67%)	1810 (69%)
Insurance status			
Medicaid	5747 (61%)	577 (54%)	1434 (54%)
Medicare	865 (9%)	239 (23%)	528 (20%)
Private insurance	1714 (18%)	164 (15%)	471 (18%)
Uninsured	1162 (12%)	81 (8%)	215 (8%)
Neighborhood-level <sup>a</sup>			
Total (N)	353	221	271
Socioeconomic status			
Deprivation score	-0.20 (1.15)	0.07 (0.99)	-0.03 (1.03)
Percent poverty	26.8 (14.8)	31.1 (13.9)	28.9 (14.3)
Percent bachelor's	25.5 (20.4)	19.8 (17.6)	22.0 (18.4)
Social environment			
Violent crime rate <sup>b</sup>	267 (184)	316 (184)	292 (187)
Perceived safety	0.82 (0.11)	0.80 (0.11)	0.82(0.11)
Social capital	1 80 (0 21)	1.77(0.21)	1 78 (0 21)
High segregation <sup>c</sup>	99 (28%)	95 (43%)	98 (36%)
Walkability			
Percent retail land use	5.29 (5.18)	5.07 (4.12)	5.11 (4.74)
Intersection density	108.6 (60.1)	111.1 (52.7)	110.7 (55.5)

 $^{\rm a}$  N (%) for gender, insurance status, and neighborhood high segregation. Mean (SD) for all other characteristics.

<sup>b</sup> Per 10,000 population.

<sup>c</sup> Getis-Ord  $G_i^*$  z-score  $\geq 1.96$  for African American population.

mean = 27% poverty for residential census tracts of the overall patient population vs. 31% and 29% for the diabetes and hypertension control samples, respectively).

Table 2 shows bivariate associations of sample characteristics with diabetes and hypertension control status. Thirty-six percent of patients in the diabetes sample had poorly controlled diabetes. This included 25% who had HbA1c > 9% and 11% who did not have a HbA1c lab value in the past year. Patients with poor diabetes control were younger on average than those whose diabetes was controlled and were more likely to live in neighborhoods that were highly segregated or had lower retail land use (i.e., were less walkable). In the hypertension sample, nearly half (47%) of patients had their hypertension poorly controlled. Those with poor hypertension control were more likely to be male or uninsured, and on average lived in neighborhoods with higher SES deprivation, lower education levels, and more segregation.

Adjusted regression model results were generally consistent with the bivariate associations. After adjustment for individual-level demographic factors, living in a highly segregated neighborhood was associated with 27% higher prevalence of poor diabetes control (Table 3, Model 1; prevalence ratio [PR] = 1.27 [1.02, 1.57]) while living in a neighborhood with higher retail land use was associated with 13% lower prevalence of poor diabetes control (PR = 0.87 [0.77, 0.99] per standard deviation higher retail land use). The associations were only minimally changed by further adjustment for clinic site and neighborhood SES deprivation, although the association for segregation was slightly attenuated, with a slightly wider confidence interval that spanned the null (Table 3, Model 3; PR = 1.25 [0.99, 1.58] for segregation, PR = 0.88 [0.80, 0.98] for retail land use). The other neighborhood exposures were not associated with diabetes control.

Just as for diabetes control, high segregation was associated with a higher prevalence of poor hypertension control (PR = 1.22 [1.12,

#### Table 2

Sample characteristics, by diabetes and hypertension control status, Philadelphia, PA, 2016.

	Diabetes control	ontrol				Hypertension control		
Characteristic <sup>a</sup>	HbA1c > 9	No HbA1c value in past year	Total poor diabetes control	Controlled diabetes		Poor hypertension control	Controlled hypertension	
	N (%) or mean (SD)	N (%) or mean (SD)	N (%) or mean (SD)	N (%) or mean (SD)	p <sup>b</sup>	N (%) or mean (SD)	N (%) or mean (SD)	$\mathbf{p}^{\mathbf{b}}$
Total	265 (25%)	114 (11%)	379 (36%) Individu	682 (64%) al characteristics	-	1239 (47%)	1394 (53%)	-
Age (years)	47.1 (12.5)	47.1 (13.9)	47.1 (12.9)	51.4 (11.6)	< 0.001	48.4 (12.5)	49.0 (13.2)	0.24
Female	168 (63%)	85 (75%)	253 (67%)	463 (68%)	0.71	824 (67%)	986 (71%)	0.02
Insurance status					0.09			< 0.001
Medicaid	142 (54%)	62 (54%)	204 (54%)	373 (55%)		661 (53%)	773 (55%)	
Medicare	45 (17%)	28 (25%)	73 (19%)	166 (24%)		225 (18%)	293 (21%)	
Private insurance	54 (20%)	15 (13%)	69 (18%)	95 (14%)		223 (18%)	248 (18%)	
Uninsured	24 (9%)	9 (8%)	33 (9%)	48 (7%)		130 (10%)	80 (6%)	
Neighborhood socioecono	mic status							
Deprivation score	0.22 (0.74)	0.17 (0.73)	0.20 (0.74)	0.22 (0.70)	0.64	0.26 (0.63)	0.18 (0.73)	0.005
Percent poverty	33.5 (11.4)	33.8 (10.2)	33.5 (11.0)	33.0 (10.8)	0.45	33.0 (10.6)	33.0 (10.9)	0.86
Percent bachelor's	16.1 (13.0)	15.6 (12.3)	15.9 (12.8)	15.6 (11.9)	0.72	14.9 (10.8)	16.0 (12.3)	0.01
degree								
Neighborhood social envir	Neighborhood social environment							
Violent crime rate <sup>c</sup>	349 (165)	363 (164)	353 (165)	354 (162)	0.94	348 (147)	352 (163)	0.45
Perceived safety	0.81 (0.09)	0.80 (0.11)	0.81 (0.10)	0.81 (0.09)	0.61	0.81 (0.08)	0.81 (0.09)	0.22
Social capital	1.74 (0.19)	1.73 (0.18)	1.74 (0.19)	1.74 (0.19)	0.85	1.74 (0.20)	1.74 (0.19)	0.42
High segregation <sup>d</sup>	171 (65%)	73 (64%)	244 (64%)	394 (58%)	0.04	819 (66%)	795 (57%)	< 0.001
Neighborhood walkability	r							
Percent retail land use	4.47 (3.90)	4.97 (4.31)	4.61 (4.03)	5.25 (4.29)	0.02	4.73 (4.08)	4.99 (4.32)	0.11
Intersection density	107.6 (38.5)	115.4 (45.4)	110.0 (40.8)	108.6 (41.3)	0.59	108.8 (39.1)	110.4 (41.2)	0.30
-								

<sup>a</sup> N (%) for total, gender, insurance status, and neighborhood high segregation. Mean (SD) for all other characteristics.

<sup>b</sup> P-value from chi-square test for categorical variables and t-test for continuous variables. *P*-value for diabetes control is for test of total uncontrolled vs. total controlled.

<sup>c</sup> Per 10,000 population.

 $^d$  Getis-Ord  $G_{i^*}$  z-score  $\geq$  1.96 for African American population.

1.33]) while higher retail land use was associated with lower prevalence of poor hypertension control (PR = 0.96 [0.92, 1.00]). For hypertension control the magnitude of the association for retail land use was 4% lower prevalence (vs. 13% for diabetes control) and was marginally statistically significant (p = .06). The association with high segregation was somewhat attenuated after further adjustment for

clinic site and neighborhood SES deprivation (Model 3; PR = 1.12 [1.01, 1.24]) while the association with retail land use was identical. There was also some indication that low neighborhood SES was associated with poor hypertension control. Higher SES deprivation score was associated with a higher prevalence of poor control (PR = 1.09 [1.02, 1.15]) while higher neighborhood education was associated with

## Table 3

'oor diabetes control			Poor hypertension cont					
el 1 <sup>a,b</sup>	Model 2 <sup>a,b</sup>	Model 3 <sup>a,b</sup>	Model 1 <sup>a,b</sup>	odel 1 <sup>a,b</sup> Model 2 <sup>a,b</sup>				
95% CI) I	PR (95% CI)	PR (95% CI)	PR (95% CI)	PR (95% CI)	PR (95% CI)			
Neighborhood socioeconomic status								
3 (0.84, 1.13)	0.97 (0.83, 1.13)	-	1.09 (1.02, 1.15)**	1.06 (1.00, 1.12)*	-			
4 (0.92, 1.17)	1.02 (0.89, 1.15)	-	1.00 (0.95, 1.06)	1.02 (0.96, 1.08)	-			
4 (0.90, 1.20)	1.05 (0.91, 1.22)	-	0.92 (0.87, 0.98)**	0.95 (0.89, 1.01)*	-			
Neighborhood social environment								
3 (0.88, 1.09)	0.96 (0.86, 1.07)	0.97 (0.86, 1.08)	0.99 (0.94, 1.04)	0.98 (0.93, 1.03)	0.97 (0.92, 1.02)			
) (0.89, 1.13)	1.02 (0.90, 1.15)	1.01 (0.89, 1.15)	1.02 (0.97, 1.08)	1.01 (0.96, 1.07)	1.02 (0.96, 1.08)			
) (0.90, 1.11)	1.01 (0.91, 1.12)	1.00 (0.89, 1.12)	0.98 (0.92, 1.04)	1.00 (0.94, 1.06)	1.01 (0.95, 1.07)			
(1.02, 1.57)**	1.21 (0.96, 1.53)*	1.25 (0.99, 1.58)*	1.22 (1.12, 1.33)**	1.14 (1.03, 1.25)**	1.12 (1.01, 1.24)**			
(0.77, 0.99)** (	).88 (0.80, 0.97)**	0.88 (0.80, 0.98)**	0.96 (0.92, 1.00)*	0.96 (0.92, 1.00)**	0.96 (0.92, 1.00)*			
4 (0.81, 1.09)	0.91 (0.78, 1.05)	0.90 (0.78, 1.04)	0.97 (0.91, 1.04)	1.01 (0.95, 1.09)	1.01 (0.94, 1.09)			
	all 1a,b N   21 1a,b N   25% CI) F   3 (0.84, 1.13) (0.92, 1.17)   4 (0.92, 1.17) (0.90, 1.20)   3 (0.88, 1.09) (0.89, 1.13)   9 (0.90, 1.11) (1.02, 1.57)**   (0.77, 0.99)** (0.81, 1.09)	analytics control   21 1 <sup>a,b</sup> Model 2 <sup>a,b</sup> 25% CI) PR (95% CI)   3 (0.84, 1.13) 0.97 (0.83, 1.13)   4 (0.92, 1.17) 1.02 (0.89, 1.15)   5 (0.90, 1.20) 1.05 (0.91, 1.22)   6 (0.88, 1.09) 0.96 (0.86, 1.07)   0 (0.90, 1.13) 1.02 (0.90, 1.15)   0 (0.90, 1.11) 1.01 (0.91, 1.12)   (1.02, 1.57)** 1.21 (0.96, 1.53)*   (0.77, 0.99)** 0.88 (0.80, 0.97)**   4 (0.81, 1.09) 0.91 (0.78, 1.05)	Habetes control   Model 2 <sup>a,b</sup> Model 3 <sup>a,b</sup> 21 1 <sup>a,b</sup> Model 2 <sup>a,b</sup> Model 3 <sup>a,b</sup> 25% CI)   PR (95% CI)   PR (95% CI)     3 (0.84, 1.13)   0.97 (0.83, 1.13)   -     4 (0.92, 1.17)   1.02 (0.89, 1.15)   -     4 (0.90, 1.20)   1.05 (0.91, 1.22)   -     4 (0.98, 1.09)   0.96 (0.86, 1.07)   0.97 (0.86, 1.08)     0 (0.89, 1.13)   1.02 (0.90, 1.15)   1.01 (0.89, 1.15)     0 (0.90, 1.11)   1.01 (0.91, 1.12)   1.00 (0.89, 1.12)     (1.02, 1.57)**   1.21 (0.96, 1.53)*   1.25 (0.99, 1.58)*     (0.77, 0.99)**   0.88 (0.80, 0.97)**   0.88 (0.80, 0.98)**     (0.81, 1.09)   0.91 (0.78, 1.05)   0.90 (0.78, 1.04)	Inductes control Inductes control Inductes control   Inductes control Model $2^{a,b}$ Model $3^{a,b}$ Model $1^{a,b}$ Model $2^{a,b}$ Model $3^{a,b}$ Model $1^{a,b}$ Model $2^{a,b}$ PR (95% CI) PR (95% CI) PR (95% CI)   PR (95% CI) PR (95% CI) PR (95% CI) PR (95% CI)   Image: Control (0.92, 1.17) 1.02 (0.89, 1.13) - 1.09 (1.02, 1.15)^{-1}   Image: Control (0.90, 1.20) 1.05 (0.91, 1.22) - 0.92 (0.87, 0.98)^{-1}   Image: Control (0.90, 1.20) 0.96 (0.86, 1.07) 0.97 (0.86, 1.08) 0.99 (0.94, 1.04)   Image: Control (0.90, 1.13) 1.02 (0.90, 1.15) 1.01 (0.89, 1.15) 1.02 (0.97, 1.08)   Image: Control (0.90, 1.11) 1.01 (0.91, 1.12) 1.00 (0.89, 1.12) 0.98 (0.92, 1.04)   Image: Control (0.92, 1.57)^{-1} 1.21 (0.96, 1.53)^{-1} 1.25 (0.99, 1.58)^{-1} 1.22 (1.12, 1.33)^{-1}   Image: Control (0.77, 0.99)^{-1} 0.88 (0.80, 0.97)^{-1} 0.88 (0.80, 0.98)^{-1} 0.96 (0.92, 1.00)^{-1}   Image: Control (0.91, 1.09) 0.91 (0.78, 1.05) 0.90 (0.78, 1.04) 0.97 (0.91, 1.04)	Indects Control Indects Control   Indects Control Model $2^{a,b}$ Model $3^{a,b}$ Model $1^{a,b}$ Model $2^{a,b}$ Model $3^{a,b}$ Model $1^{a,b}$ Model $2^{a,b}$ Model $2^{a,b}$ Model $2^{a,b}$ S% CI) PR (95% CI)   S (0.84, 1.13) 0.97 (0.83, 1.13) - 1.09 (1.02, 1.15)^{**} 1.06 (1.00, 1.12)^{*}   S (0.92, 1.17) 1.02 (0.89, 1.15) - 1.00 (0.95, 1.06) 1.02 (0.96, 1.08)   S (0.90, 1.20) 1.05 (0.91, 1.22) - 0.92 (0.87, 0.98)^{**} 0.95 (0.89, 1.01)^{*}   S (0.88, 1.09) 0.96 (0.86, 1.07) 0.97 (0.86, 1.08) 0.99 (0.94, 1.04) 0.98 (0.93, 1.03)   S (0.89, 1.13) 1.02 (0.90, 1.15) 1.01 (0.89, 1.15) 1.02 (0.97, 1.08) 1.01 (0.96, 1.07)   S (0.88, 1.09) 0.96 (0.86, 1.07) 0.97 (0.86, 1.08) 0.99 (0.94, 1.04) 0.98 (0.93, 1.03)   S (0.88, 1.09) 0.96 (0.86, 1.07) 0.97 (0.86, 1.08) 0.99 (0.94, 1.04) 0.98 (0.93, 1.03)   S (0.88, 1.09) 0.96 (0.94, 1.10) 1.01 (0.96, 1.57) 1.21 (0.96, 1.53)^{*} 1.22 (1.12, 1.33)^{**} 1			

\*\* p < .05.

\* p < .10.

<sup>a</sup> Generalized estimating equation (GEE) logbinomial model accounting for clustering by census tract.

<sup>b</sup> Model 1 adjusted for age, sex, and insurance status. Model 2 = Model 1 + clinic site. Model 3 = Model 2 + neighborhood SES deprivation score.

<sup>c</sup> Per standard deviation (see Table 1).

 $^d~$  Getis-Ord  $G_i{}^*$  z-score  $\geq 1.96$  for African American population.

a lower prevalence of poor control (PR = 0.92 [0.87, 0.98]). However, these associations were small in magnitude and were not robust to further adjustment for clinic site (see Table 3, Model 2).

#### 4. Discussion

Among African American patients of an urban community health center network, we found that poor diabetes and hypertension control were more common in highly segregated neighborhoods and less common in more walkable neighborhoods (as measured by retail land use). We also found weak associations between poor hypertension control and lower neighborhood SES. Other measures of neighborhood SES, social environment, and walkability were not associated with diabetes or hypertension control. Thus, we found associations (in some cases only suggestive) of neighborhood characteristics with the outcomes across multiple domains (SES, social environment, walkability), yet there was no domain in which all measures were consistently associated with the outcomes. This suggests complex, multi-faceted relationships of neighborhood conditions with diabetes and hypertension control in this population.

Both high African American residential segregation and percent retail land use were associated with both outcomes, although associations were only marginally statistically significant in some models. Notably, the associations were not explained by neighborhood SES, since they were nearly identical after adjustment for neighborhood SES deprivation score. Residential segregation has been called a fundamental cause of racial health disparities (Williams and Collins, 2001) and has been linked to higher cardiovascular risk and mortality among African Americans (Kershaw et al., 2015; Kershaw and Albrecht, 2015). However, little research examines residential segregation in relation to diabetes control among African Americans. In a recent review, Kershaw and Pender concluded that there was little evidence relating segregation with diabetes prevalence, but that higher segregation was related to higher diabetes mortality (Kershaw and Pender, 2016). Our finding is consistent with this, and points to potential effects of segregation on diabetes severity or management. Several studies have related residential segregation to higher blood pressure or hypertension prevalence, and one found associations between living in a neighborhood with a high percentage of black residents and lower prevalence of hypertension treatment among foreign-born, but not US-born, blacks in New York City (Kershaw and Albrecht, 2015; Cole et al., 2016). Yet some hypothesized mechanisms through which segregation may affect health-such as by promoting socioeconomic deprivation, higher crime, less social capital, or less appropriate medical care (Williams and Collins, 2001)-are not well supported by our data.

One possibility is that our results may reflect differences in the built environment that affect health behaviors such as cost, availability, or quality of food or physical activity resources; housing and street quality; or marketing and availability of alcohol and tobacco. This is supported by our result for neighborhood retail land use. Neighborhood walkability has been related to lower incidence or prevalence of diabetes or hypertension in numerous studies (Bilal et al., 2018; Malambo et al., 2016; Sarkar et al., 2018), but little research has examined how it relates to control of these conditions. Two recent studies have related neighborhood land-use mix and a factor-derived physical activity favorability score to better glycemic control in urban populations with diabetes (Tabaei et al., 2017; Hirsch et al., 2018).

Our study is subject to several limitations. Our cross-sectional study design precludes causal interpretation of the associations we found, and specifically did not allow investigation of the relevant time-frame for potential neighborhood effects on the outcomes. We also used census tracts as proxies for neighborhoods, and did not account for time residents may spend in areas other than their residential neighborhood (Kwan, 2018). We did not have information about health care patients may have received concurrently from other providers, including HbA1c or blood pressure measures that might have been taken and recorded

elsewhere. Our results may not be generalizable to other patient populations or to populations who are not under the care of a medical provider or are receiving care in practices less committed to monitoring and improving the quality of care (Schinasi et al., 2018). Our results may be subject to residual confounding by individual-level SES, as we relied on insurance payer information as a proxy measure of this important potential confounder. With respect to our survey-based social environment measures, some of the social determinants we examined have been associated with health outcomes when considered at the individual level but not as a neighborhood attribute (Leader and Michael, 2013). Finally, we did not investigate the cumulative impact of multiple neighborhood characteristics or potential interactions between neighborhood characteristics. For example, Barber et al. found interactive effects between neighborhood disadvantage and low social cohesion with respect to health effects among African American residents of Jackson, MS. (Barber et al., 2016)

The applications of information about community-level social determinants of health for health care providers vary according to patient and provider needs and capacity. First, information from studies such as ours can provide additional context for understanding the patient population and risk stratification. In this respect, our analysis identified potentially meaningful geographic variation within the network's patient population even though the distribution of residential community characteristics was distinct from, and more homogeneous than, that of the city as a whole. Second, this information may help inform clinical decision-making by identifying community-level barriers to or opportunities for maintaining health for individual patients. Third, this information may inform providers' efforts to forge connections with other organizations to address social determinants of health among their patient population (IOM (Institute of Medicine), 2014; Children's Hospital Association, 2018). Fourth, information about how community-level factors affect patient health provides evidence for multisectoral advocacy and policymaking efforts to improve population health and health equity.

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#### **Declaration of Competing Interest**

None.

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