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How do social capital and HIV/AIDS outcomes geographically cluster and which sociocontextual mechanisms predict differences across clusters?

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Abstract

Background—Place of residence has been associated with HIV transmission risks. Social capital, defined as features of social organization that improve efficiency of society by facilitating coordinated actions, often varies by neighborhood, and hypothesized to have protective effects on HIV care continuum outcomes. We examined whether the association between social capital and two HIV care continuum outcomes clustered geographically and whether sociocontextual mechanisms predict differences across clusters.

Methods—Bivariate Local Moran's *I* evaluated geographical clustering in the association between social capital (participation in civic & social organizations, 2006, 2008, 2010) and (5-year [2007–2011] prevalence of late HIV diagnosis and linkage to HIV care) across Philadelphia, PA census tracts ($N = 378$). Maps documented the clusters and multinomial regression assessed which sociocontextual mechanisms (e.g., racial composition) predict differences across clusters.

Results—We identified four significant clusters (high social capital-high HIV/AIDS, low social capital–low HIV/AIDS, low social capital-high HIV/AIDS, and high social capital-low HIV/

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Compliance with Ethical Standards

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AIDS). Moran's I between social capital and late HIV diagnosis was ($I=0.19$, $z=9.54$, $p<.001$) and linkage to HIV care ($I=0.06$, $z=3.274$, $p=0.002$). In multivariable analysis, median household income predicted differences across clusters, particularly where social capital was lowest and HIV burden the highest, compared to clusters with high social capital and lowest HIV burden.

Discussion—The association between social participation and HIV care continuum outcomes cluster geographically in Philadelphia, PA. HIV prevention interventions should account for this phenomenon. Reducing geographic disparities will require interventions tailored to each continuum step and that address socioeconomic factors such as neighborhood median income.

Keywords

Social Capital; Social Determinants; HIV/AIDS; Neighborhoods; United States; HIV Care continuum

BACKGROUND

More than 50% of persons diagnosed with HIV are not retained in care [1]. Substantial geographical disparities in HIV care continuum indicators such as diagnosis, linkage, and treatment exists within the United States (US) [2, 3]. For instance, the average lifetime risk of HIV diagnosis for a US adult is 1% (i.e., 1/99), yet the risk is as high as 7.8 % (i.e., 1/13) for individuals in Washington D.C and as low as 0.14% (i.e., 1/670) for individuals in North Dakota [4]. Metropolitan areas and particularly racial and ethnic minorities are disproportionately affected [5].

Social and structural factors at the neighborhood or census tract level may play an important role in these outcomes. For example, geographic areas (e.g., neighborhoods) with high prevalence of persons diagnosed with HIV in the advanced stages of AIDS (i.e., late HIV diagnosis) and suboptimal rates of retention in HIV care may elevate HIV acquisition risks for residents [6, 7]. Persons diagnosed late and not linked to care miss timely opportunities to benefit from antiretroviral therapy; this may also hinder community-level virologic suppression [8–10] [11], which impacts future HIV incidence and acquisition [12, 13].

Social capital, defined here as features of social organization that improve efficiency of society by facilitating coordinated actions [14], has been hypothesized to have a protective effect on HIV population-level HIV transmission dynamics [15, 16]. Indicators based on this theoretical perspective include membership in social and civic community organizations (i.e., social participation) and trust among neighbors [17].

Social capital can improve HIV prevention by facilitating the political capital and power [18] necessary to address substandard housing, access to HIV testing and other prevention services, and improving economic conditions [19], all factors which structure the risk environments that ultimately affect HIV infection in the population [20, 21]. Social capital can also improve HIV prevention by promoting positive psychological health among individuals [22] and communities [23]. For instance, higher social capital (e.g., participation in formal community groups) has been linked to changed social norms from HIV stigma to solidarity and support [24, 25], which has enabled families of HIV-infected individuals to

access HIV care and also empower infected individuals to improve antiretroviral therapy adherence [26].

The preponderance of evidence documenting a protective association between social capital and HIV risks and HIV care continuum outcomes has been among international populations [25, 27–31] and there are only a handful of ecological studies on the topic in the US [32–35]. One state-level ecological study using data from year 1999 showed that higher social capital was associated with lower AIDS case rates [34]. A census-tract ecological study in Philadelphia, PA using aggregate data between 2007 to 2011 showed that higher social participation was associated with higher linkage to HIV care but, paradoxically, to higher late HIV diagnosis [33].

Whether and how social capital affects outcomes in the HIV care continuum in the US is not sufficiently understood. Given recent studies documenting the important role that place of resident may play in elevating HIV acquisition risks [36, 37], geographic analysis investigating how social capital in relation to HIV varies across place and space can inform strategies to reduce racial and geographic disparities in HIV/AIDS [38, 39].

Place in health research considers the distribution of aggregate characteristics of individuals, opportunity structures in the physical and social environment, and shared norms, typically within rigid geographic boundaries [40]. Research focused on place alone is limited because rigid boundaries assume individuals in an area or an area's characteristics are static [41]. Space in health research considers the dynamic relations of individuals across geographic areas and an area's characteristics can be influenced by relative position and proximity with another area's characteristics [41–43].

One primary method that incorporates place and space is cluster analysis [44]. Once clusters are identified between social capital and HIV care continuum, the next step is to analyze what sociocontextual mechanisms distinguish those clusters. Sex distribution, racial composition, socio-economic position, access to treatment, and elements of the built environment such as alcohol outlets, which can suggest neighborhood disorder, are sociocontextual factors that influence the distribution of social capital [45–49] as well as HIV/AIDS outcomes [50–52]. Therefore, those are important mechanisms to analyze in relation to geographic clustering.

To explore the relationship between social capital and HIV care continuum outcomes, in this study, we characterize *bivariate* geographic cluster patterns between social capital and late HIV diagnosis, and linkage to HIV care, in the city of Philadelphia, PA. We then analyze whether and which sociocontextual mechanisms predict differences across clusters. We selected Philadelphia, PA because the city has HIV infection rates; in 2014 among Blacks (66.7 per 100,000) was five times higher than the US national average (12.3 per 100,000) [53, 54]. Philadelphia also has wide geographic variations in HIV care continuum outcomes and has a late HIV diagnosis rate as high as the US national average [55]. Finally, in Philadelphia, PA, we had access social capital and HIV data for neighborhoods.

METHODS

HIV/AIDS Outcomes

Through HIVcontinuum.org, we obtained de-identified aggregate ZIP code-level HIV surveillance data from Philadelphia, PA on the 5-year (2007–2011) prevalence of late HIV diagnosis and linkage to HIV care, among adults and adolescents. Displayed through maps, HIVcontinuum.org contains HIV surveillance data from local health departments across five cities with high HIV burden [56]. These data are population-based data reported as of 12/31/2012. Cases without ZIP codes at HIV diagnosis were excluded. Following methods established from ours [33] and other research [57], we spatially interpolated the data onto the Census 2010 tract boundaries ($N = 384$) using areal interpolation and re-aggregation techniques [58].

The two study outcomes are: (a) late HIV diagnosis (defined as an AIDS diagnosis within three months of a newly received HIV diagnosis), and (b) linkage to HIV care (defined as newly diagnosed with HIV and a reported CD4/viral load within three months of HIV diagnosis).

Social Capital

Social capital data were collected in the Southeastern Pennsylvania Household Health Survey (SPHHS), administered by the Public Health Management Corporation [59]. SPHHS is a random digit dialing household landline and cell phone survey that contains health, social, and behavioral items asked of persons 18 years and older in the five major counties in the greater Philadelphia, PA area. We only used data from individuals living in Philadelphia County, which coincides exactly with the city limits. We combined data from survey years 2006, 2008 and 2010 yielding a total of 12,986 participants from whom social capital was calculated. The sample characteristics across the years were similar so combining these data did not threaten temporal variability. SPHHS data are de-identified and available through the University of Pennsylvania Library [60].

Social participation is one unique indicator within the broader construct of social capital [61]. Although the SPHHS contains other social capital indicators, we selected social participation, which is derived from a single-item question: “How many local groups or organizations in your neighborhood do you currently participate in such as social, political, religious, school-related, or athletic organizations?” We created the measure following the Empirical Bayes regression procedures described previously [33] by aggregating individual’s responses to the Census tract. We selected social participation because it is a valid indicator of features of the social organization within the city that can facilitate collective action towards a community goal, which is a primary pathway proposed between social capital and health [14, 62]. Second, we wanted to better understand the findings in our recent study [33] where social participation, among two other social capital variables (social cohesion and collective engagement), was positively associated with the late HIV diagnosis and with linkage to care. Hereafter, we use the term social capital to reflect the broader concept through which the measure is derived.

Sociocontextual mechanisms

We included male to female ratio, black racial composition (percent of persons identifying as black/African American), unemployment rate (percent of individuals 16 years and older unemployed), poverty level (percentage of families in poverty), education level (percent 25 years older with college education or higher), median household income (2011 inflation adjusted dollars), and income inequality (GINI coefficient). All the aforementioned continuous variables were retrieved from Social Explorer [63] based on the American Community Survey (ACS) 5-year estimates for 2007–2011 for Philadelphia Census tracts.

HIV testing/treatment access was created through methods described previously [33]. Briefly, HIV testing sites were retrieved from the National HIV and STD Testing website [64] and geographic locations of Ryan White HIV treatment centers were retrieved from OpenDataPhilly.org [65]. The Philadelphia AIDS Activities Coordinating Office validated the centers that were present before year 2007, yielding a list of $N = 75$ centers after removing duplicates. Because of a strong association with HIV risk, alcohol outlets are being considered as potential sites for HIV interventions [66]. However, higher alcohol outlet density may hinder development of social capital [67].

The count of alcohol outlets for year 2007 was retrieved from Business Analyst [68] for both on- and off-premises establishments (North American Industry Classification Codes: 722410 and 445310). We created density of HIV testing/treatment sites and density of alcohol outlets per square mile in each Census tract using the *Kernel Density* Tool in ArcGIS 10.2. All sociocontextual factors were standardized with a mean of zero and standard deviation of 1.

Statistical Analysis

Spatial statistics—After merging the social capital, HIV/AIDS, and sociocontextual variables, a total of $N = 378$ Census tracts were available for analysis. To achieve the first study aim, we performed bivariate spatial cluster analysis of social capital (x) with the two HIV care continuum outcomes (y) separately, using the Local Moran's I tool in GeoDa software [69]. A positive Moran's I indicates that high values are surrounded by high values whereas a negative coefficient indicates high values are surrounded by low values. We assessed statistical significance of the clusters and Moran's I at the $\alpha = 0.05$ level based on 499 permutations. A spatial weights matrix of $k = 7$ nearest neighbors was used. The bivariate cluster analysis identifies patterns, which are locations where groups of neighboring Census tracts cluster. The cluster indicators have five values: 0 for not significant, 1 for high-high, 2 for low-low, 3 for high-low and 4 for low-high [70]. The clusters represent high social capital-high late HIV diagnosis, low social capital-low late HIV diagnosis, high social capital-low late HIV diagnosis, and low social capital-high late HIV diagnosis. The coding pattern is similar for linkage to HIV care. The cluster indicators were then imported into STATA 14.1 for statistical analysis [71]. We considered the reference or “priority” clusters as census tracts with high social capital-low late HIV diagnosis and high social capital-high linkage to HIV care.

Descriptive statistics—We computed means and interquartile ranges (IQRs) for social capital, care continuum indicators, and sociocontextual variables across the cluster types. We used Spearman and Pearson correlations to examine potential multicollinearity and to identify variables to include in the multivariable analysis. We mapped the cluster patterns for each social capital and HIV/AIDS indicators in Arc Map 10.2. Each cluster is represented by a different colored shade on the legend. Additionally, we included a map of median income and one that displays the geographic context of Philadelphia, PA.

Multivariable statistics—To achieve the second study aim, we fit a multivariable model by including, in one block, all the sociocontextual mechanisms that were significant in the correlation analysis. For all models, a-priori we included black racial composition and income inequality given a specific interest based on empirical evidence from prior research [50]. We used multinomial logistic regression and selected the “priority” cluster described above as the reference group. Additionally, we excluded the insignificant cluster because comparing this to the priority cluster was uninformative. Relative risk (RR) ratios and 95% confidence intervals (CI) are reported [72]. Relationships are statistically significant at $p < 0.05$.

RESULTS

Spatial statistics and the local setting

Maps showing geographical clustering of social capital and each HIV/AIDS outcome are given in Figure 1. Significant clustering was observed between social capital and late HIV diagnosis (Moran's $I=0.19$, $z=9.54$, $p<0.001$) and linkage to HIV care (Moran's $I=0.06$, $z=3.274$, $p=0.002$), (Moran's I data not shown). Areas with high social capital and low HIV were zoning areas with residential single and two-family attached homes as well as active and passive parks and open space. Areas with high social capital and high HIV were mainly industrial areas.

Descriptive

The prevalence of each HIV care continuum indicator was highest in the “high-high” clusters. The mean social capital levels were highest in the “high-high” clusters for late HIV diagnosis and linkage to HIV care (Table 1). The highest correlation was between median household income and education level ($r=0.65$, $p<0.001$) (Table 2), and the remaining correlations were lower, suggest multicollinearity is not a problem among the sociocontextual variables.

Multivariable

Clustering of social capital and late HIV diagnosis—The reference group (i.e., “priority” cluster) in this multinomial model is high social capital-low late HIV diagnosis ($N = 27$ tracts). We consider low social capital-high late HIV diagnosis the “high-need” cluster ($N = 23$ tracts) because those communities may have limited social resources to address the high HIV burden. A one standard deviation increase in black racial composition ($RR=0.33$, $95\%CI=0.13, 0.85$), median household income ($RR=0.02$, $95\%CI=0.00, 0.15$), and income inequality ($RR=0.16$, $95\%CI=0.05, 0.50$) decreased the relative risk of belonging to a high-

need cluster, controlling for covariates. A one standard deviation increase in education level (RR=0.17, 95%CI=0.03, 0.97) and median household income (RR=0.04, 95%CI=0.01, 0.32) is associated with a decreased risk of being in a low social capital-low late HIV diagnosis cluster ($N=67$ tracts).

Clustering of social capital and linkage to HIV care—The reference group was high social capital-high linkage to HIV care ($N=35$ tracts). We considered low social capital-low linkage to HIV care a high-need cluster ($N=48$ tracts). A one standard deviation increase in median household income (RR=0.01, 95%CI=0.01, 0.03) and income inequality (RR=0.28, 95%CI=0.10, 0.77) decreased the relative risk of belonging to a high-need cluster compared to a priority cluster, controlling for covariates. Similar associations were found for belonging to a low social capital-high linkage to HIV cluster.

Across the models—High income inequality was associated with a priority cluster for late HIV diagnosis and linkage to HIV care. To better understand those findings, which run contrary to the negative effects inequality usually has on health [73], we post-priori explored income inequality in a model without median income, and then median income without income inequality, and then with both excluded. Those analyses reveal that income inequality adjusted for other covariates was *not* significantly associated with being in a priority cluster. Next, the effect size of median income was attenuated when income inequality was added to the model (results not displayed).

Both variables, however, contributed to the model fit. For instance, in the social capital and late HIV diagnosis model, without median income and inequality, the Pseudo- R^2 was 26%, which rose to 36% after median income and inequality were included. Next, the model with social capital and linkage to care, the Pseudo- R^2 was 12%, which rose to 33% after included (R^2 results not displayed). We present the results of the fully adjusted model based on our a-priori decisions. McFadden's pseudo R-squared for categorical outcomes is reported in STATA, however, it does not have the same direct interpretation of variance explained as an R-squared from OLS regression [74].

DISCUSSION

This is the first ecological study to document that the association between social capital (specifically, participation in local community groups) and HIV diagnosis and linkage to care—two upstream HIV care continuum outcomes varies across space (i.e., cluster geographically), in Philadelphia, PA. Specifically, we saw that some neighborhoods were characterized by high social capital and high late HIV diagnosis while others characterized by high social capital and low late HIV diagnosis. There were relatively few areas that met the criteria we consider a “priority” cluster—that is where social capital is high and late HIV diagnosis is low. We think the higher proportion of areas that were not a priority cluster could potentially explain the findings from our previous work where high social participation was related to higher late HIV diagnosis prevalence [33]. The broader implication of this study is that HIV prevention interventions that seek to activate social capital in communities may be needed with stronger intensity in non-priority areas. We show where these areas are in the choropleth maps.

Social capital can be intentionally generated through creating new or enhancing current relationships between local community groups and government or other bureaucratic agencies [23]. Next, creating social capital to address HIV can be strengthened by forging partnerships between health care organizations and community organizations [25].

Additionally, social capital can be created, especially in urban cities such as Philadelphia, PA and other poor communities in urban and rural areas by supporting environments that increase political participation [75], which can include fostering stronger relationships to citywide political processes [18]. Increased political participation can balance power relations, for instance, by creating political representation of individuals who reflect the communities disadvantaged by HIV and economic opportunities [75]. Social capital can also be leveraged through investments in infrastructure such as mixed-income and mixed-use housing and other aspects of the built environment such as walkability, which provide opportunities for formal and informal social interactions among individuals [76, 77].

Next, we document that the geographic cluster pattern between social capital and late HIV diagnosis do not overlap with the cluster pattern between social capital and linkage to HIV care. The non-overlap in clusters among HIV care continuum outcomes was also found in one prior Philadelphia, PA study [78]. Together, both study findings suggest that HIV prevention interventions in communities will vary by geography and the HIV care continuum outcome in question. For example, some communities may need interventions focused on reducing late HIV diagnosis while others may need interventions focused on enhancing retention and linkage to HIV care.

We ground our findings within the local geographic context of Philadelphia, PA, in addition to being data driven. For example, we juxtaposed a zoning map of the city to provide visual cues of space. This most recent zoning map (year 2012) show that areas with high social capital and high HIV diagnosis were mainly industrial zones. These areas may have small population density and thus HIV prevalence may be amplified with one new case of a small denominator.

A secondary aim of this study was to identify which sociocontextual factors differentiate any clusters found, which could aid in identifying mechanisms to potentially target. We found that areas with higher median income and income inequality were more likely to be in a high “priority” cluster compared to a low priority cluster (i.e., poor HIV diagnosis and care). That finding is consistent with another Philadelphia study [79], which showed that hotspots with poor viral suppression were more likely to be in economically deprived neighborhoods.

The income inequality finding, however, seemed contrary to theory given that income inequality erodes social capital [80]. Income inequality was not collinear with median household income so we think the paradoxical findings could be that the GINI coefficient does not allow one to distinguish whether it is driven by a higher proportion of high-income residents compared to low-income residents or vice versa. Alternately, the findings may be due to unobserved confounding or interaction with other sociocontextual factors. For example, a recent study in New York City showed that late HIV diagnosis was high in areas

with low black racial concentration and high income inequality and areas with high black racial concentration and low income inequality ^[81].

There are some study limitations. We used HIV/AIDS prevalence data originally obtained at the ZIP code-level. Larger areas lose geographic detail and may limit usefulness in public health planning ^[82]. However, we used spatial re-aggregation techniques to produce a surface map across census tracts. With spatial re-aggregation, we still could not avoid sudden changes in prevalence across boundaries because we did not have raw counts to create smoothed rates based on population denominators ^[82]. Findings are still subject to the modifiable areal unit problem (MAUP), which posits that associations found at one ecological unit may not be the same at another unit ^[83]. Associations could therefore be different across Congressional Districts or Wards, which also designate geographic boundaries in Philadelphia, PA ^[84]. Related, the social capital and HIV/AIDS data were cross-sectional, thus we cannot draw causal inference conclusions.

Our aggregate data contained cases diagnosed in the correctional setting which dominates one area of Northeast Philadelphia where jails for both men and women are located, which prior estimates indicate is approximately 8% ^[78]. However, the Northeast location of the major jail in Philadelphia, PA (Curran-Fromhold Correctional Facility) is situated in an area which exhibited low social capital-low late HIV diagnosis, and low linkage to care. One would expect a higher rate of HIV diagnosis and linkage to care among individuals in an institutional setting. Therefore, we believe that the impact of HIV prevalence in the tracts that includes this group is minimal, especially since an estimated 92% of the sample would be non-institutional and population-based ^[78]. We could not distinguish between non-institutional and institutional populations in our data.

We only analyzed social participation, which is one of several indicators that measure social capital, although others suggest it may not reflect the underlying construct ^[85]. Thus, we cannot generalize the findings to other indicators such as social cohesion or collective efficacy. However, in previous HIV and social capital research, social/civic/political participation was highly positively correlated with other social capital indicators such as collective efficacy, social cohesion, and informal social control ^[32]. We also could not analyze participation by the type of organizations (e.g. athletic club compared to religious or other associations). Next, while we focused on a core group of sociocontextual mechanisms highlighted in the literature to impact both social capital and HIV care continuum indicators, we did not examine access to transportation, ethnic density, or other measures of social disorganization such as crime rates ^[33, 49], which are also potentially modifiable determinants. Nevertheless, despite these potential limitations, this is the first study to analyze the geographic clustering in the association between social capital and care outcomes.

We selected Philadelphia, PA for this analysis because ours and other research demonstrated geographic disparities in HIV outcomes. We also had access to social capital and HIV outcomes data across neighborhoods. However, the spatial and regression methods we used can be replicated across other settings and using other social capital indicators, care continuum outcomes, and sociocontextual mechanisms. For instance, AIDSVu.com ^[86]—an

online interactive website—displays HIV data at the Census tract, ZIP code or neighborhood-level for several other US cities including Atlanta, GA and Chicago, IL. HIV data on AIDSVu.com are publicly available and researchers can download and combine these data with external sources that contain social capital measures to replicate this analysis.

CONCLUSION

Understanding and responding to geographic clustering in the association between social capital and HIV care continuum indicators may have important implications for HIV prevention in urban areas with high rates of HIV infection. For example, some communities may need interventions focused on reducing late HIV diagnosis while others may need interventions focused on enhancing retention and linkage to HIV care. Interventions will also require understanding the distribution of sociocontextual factors such as neighborhood median income across communities. Lastly, the association between social capital and health outcomes such as HIV diagnosis is context dependent [87]. However, given recent studies documenting an association with HIV care continuum outcomes net other traditional contextual factors such as income inequality [32, 88]; we recommend that social capital questions be included and routinely collected in both national and local health or other demographic surveys when possible.

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FIGURE 1.

Bivariate spatial cluster maps of (a) social capital and late HIV diagnosis, (b) social capital and linkage to HIV care, (c) median household income, and (d) base-map of geographic landscape of Philadelphia, PA (Zoning base districts). All shaded clusters for maps (a) and (b) were statistically significant at $p < 0.05$. Philadelphia, PA, Census tracts ($N = 378$), 2007–2011.

Distribution of sociocontextual mechanisms across clusters of social capital and selected indicators along the HIV care continuum in Philadelphia, PA
Census Tracts (N=378), 2007–2011

TABLE 1

Type of clustering	NS	HH	LL	LH	HL
Social capital and late HIV diagnosis					
	Number of Census tracts				
Variable (Inter quartile range)	228	33	67	23	27
Social capital (0.78, 0.99)	0.93	1.00	0.74	0.74	0.98
Late HIV diagnosis (22.48, 28.60)	26.36	35.19	20.00	32.54	20.98
Male to female ratio (0.77, 1.00)	0.89	1.00	0.96	0.91	0.90
Percent black (9.64, 85.17)	48.79	20.22	46.87	32.94	36.93
Percent 16 older unemployed (8.35, 19.24)	13.67	09.63	19.27	11.33	12.57
Percent of families in poverty (7.3, 30.41)	18.76	07.78	31.04	19.90	14.57
Percent 25 years older with college education or higher (9.13, 31.2)	28.15	29.95	10.48	20.47	24.87
Median household income (\$25,084, \$50,732)	\$40,868	\$58,099	\$27,511	\$34,782	\$45,085
Income inequality (Gini coefficient) (0.41, 0.49)	0.46	0.41	0.46	0.43	0.47
Density of HIV testing/treatment centers, per square mile (0, 1.53)	1.50	0.14	1.15	0.33	0.69
Density of alcohol outlets, per square mile (2.10, 7.09)	5.78	2.41	5.62	4.67	4.44
Social capital and linkage to HIV care					
	Number of Census tracts				
Variable (Inter quartile range)	214	35	48	50	31
Social capital (0.78, 0.99)	0.91	1.05	0.77	0.78	1.04
Linkage to HIV care (63.65 69.44)	66.14	73.47	61.45	71.57	61.08
Male to female ratio (0.77, 1.00)	0.91	0.92	0.99	0.88	0.91
Percent black (9.64, 85.17)	43.61	22.71	63.23	41.28	48.07
Percent 16 older unemployed (8.35, 19.24)	13.76	9.66	20.94	13.93	11.25
Percent of families in poverty (7.3, 30.41)	18.67	8.19	34.85	23.52	12.27
Percent 25 years older with college education or higher (9.13, 31.2)	25.89	36.39	10.28	16.37	36.26
Median household income (\$25,084, \$50,732)	\$48,048	\$60,398	\$25,774	\$34,034	\$43,905
Income inequality (Gini coefficient) (0.41, 0.49)	0.46	0.42	0.46	0.43	0.46

Type of clustering	NS	HH	LL	LH	HL
Density of HIV testing/treatment centers, per square mile (0, 1.53)	1.00	0.74	1.26	0.76	2.89
Density of alcohol outlets, per square mile (2.10, 7.09)	5.04	4.80	5.54	5.63	6.63

Social capital: predicted count of participation in social, political, religious or other organizations in neighborhood. Social Capital is X and HIV is Y, for the clustering patterns.

NS= Not significant, HH=High-High, LL=Low-Low, LH=Low-High, HL=High-Low.

TABLE 2
Spearman and Pearson Correlations among the social capital and HIV/AIDS clusters and the sociocontextual mechanisms.

	1	2	3	4	5	6	7	8	9	10	11
1 Social capital and late HIV diagnosis ^a	1										
2 Social capital and linkage to HIV care ^a	0.09	1									
3 Male to female ratio	0.04	-0.01	1								
4 Percent black	-0.11 *	-0.20 ***	-0.15 ***	1							
5 Percent 16 older unemployed	0.05	-0.24 ***	0.06	0.44 ***	1						
6 Percent of families in poverty	0.08	-0.30 ***	-0.17 ***	0.43 ***	0.61 ***	1					
7 Percent 25 years and older with college education or higher	-0.18 ***	0.31 ***	0.03	-0.47 ***	-0.59 ***	-0.55 ***	1				
8 Median household income	-0.09	0.26 ***	0.11 *	-0.50 ***	-0.57 ***	-0.71 ***	0.65 ***	1			
9 Income inequality (GINI coefficient)	-0.09	-0.03	-0.03	0.15 **	0.10 *	0.32 ***	0.20 ***	-0.39 ***	1		
10 Density of HIV testing/treatment centers	-0.13 *	0.22 ***	0.09	-0.15 **	-0.12 *	-0.05	0.38 ***	-0.00	0.31 ***	1	
11 Density of alcohol outlets	-0.08	0.18 ***	0.05	-0.22 ***	-0.14 **	-0.02	0.36 ***	0.05	0.25 ***	0.76 ***	1

^a Assessed with Spearman Correlation. All other correlation assessed with Pearson statistic.

* p < 0.05,

** p < 0.01,

*** p < 0.001.

TABLE 3

Multivariable assessing which sociocontextual factor predict differences across clusters between social capital and selected indicators along the HIV care continuum in Philadelphia, PA Census Tracts (N=378), 2007–2011

Social capital and late HIV diagnosis				
Type of clustering	HH	LL	LH	HL
Variable (Inter quartile range)	N=33	N=67	N=23	N=27
	IRR (95% CI)			
Male to female ratio (0.77, 1.00)0.89		—		
Percent black (9.64, 85.17)48.79	0.73 (0.29, 1.79)	0.46 (0.20, 1.07)	0.33 (0.13, 0.85)	REF
Percent 16 older unemployed (8.35, 19.24) 13.67		—		
Percent of families in poverty (7.3, 30.41) 18.76		—		
Percent 25 years older with college education or higher (9.13, 31.2)5	2.93 (0.78, 10.93)	0.17 (0.03, 0.97)	2.03 (0.51, 8.09)	REF
Median household income (\$25,084, \$50,732)\$40,868	2.19 (0.48, 10.03)	0.04 (0.01, 0.32)	0.02 (0.00, 0.15)	REF
Income inequality (Gini coefficient) (0.41, 0.49)0.46	1.09 (0.38, 3.10)	0.29 (0.83, 1.46)	0.16 (0.05, 0.50)	REF
Density of HIV testing/treatment centers, per square mile (0, 1.53)1.50		—		
Density of alcohol outlets, per square mile (2.10, 7.09)5.78	0.28 (0.11, 0.70)	2.13 (0.71, 7.50)	1.10 (0.44, 2.73)	REF

Social capital and linkage to HIV care				
Type of clustering	HH	LL	LH	HL
Variable (Inter quartile range)214	N=35	N=48	N=50	N=31
	IRR (95% CI)			
Male to female ratio (0.77, 1.00)1			—	
Percent black (9.64, 85.17)43.61	REF	2.05 (0.94, 4.43)	1.04 (0.52, 2.09)	2.26 (1.10, 4.61)
Percent 16 older unemployed (8.35, 19.24) 13.76			—	
Percent of families in poverty (7.3, 30.41) 18.67			—	
Percent 25 years older with college education or higher (9.13, 31.2) 25.89			—	
Median household income (\$25,084, \$50,732)\$48,0448	REF	0.01 (0.01, 0.03)	0.04 (0.01, 0.14)	0.66 (0.27, 1.58)
Income inequality (Gini coefficient) (0.41, 0.49)0.46	REF	0.28 (0.10, 0.77)	0.28 (0.10, 0.74)	1.27 (0.54, 3.02)
Density of HIV testing/treatment centers, per square mile (0, 1.53)1.00	REF	1.10 (0.38, 3.17)	0.51 (0.17, 1.57)	2.41 (0.91, 6.41)
Density of alcohol outlets, per square mile (2.10, 7.09)5.04	REF	2.48 (0.82, 7.46)	3.12 (1.19, 8.13)	0.74 (0.30, 1.82)

Social Capital is X and HIV is Y, for the clustering patterns. HH=High-High, LL=Low-Low, LH=Low-High, HL=High-Low.

Factors in bold font are statistically significant at $p < .05$