AIDS and Behavior (2019) 23:2795–2802
https://doi.org/10.1007/s10461-019-02609-2

ORIGINAL PAPER

Location of Pre-exposure Prophylaxis Services Across New York City Neighborhoods: Do Neighborhood Socio-demographic Characteristics and HIV Incidence Matter?

Byoungjun Kim[1] · Denton Callander[1] · Ralph DiClemente[2] · Chau Trinh-Shevrin[1] · Lorna E. Thorpe[1] · Dustin T. Duncan[1]

Published online: 18 July 2019

Abstract

Despite an increasing pre-exposure prophylaxis (PrEP) use among populations at highest risk of HIV acquisition, comprehensive and easy access to PrEP is limited among racial/ethnic minorities and low-income populations. The present study analyzed the geographic distribution of PrEP providers and the relationship between their location, neighborhood characteristics, and HIV incidence using spatial analytic methods. PrEP provider density, socio-demographics, healthcare availability, and HIV incidence data were collected by ZIP-code tabulation area in New York City (NYC). Neighborhood socio-demographic measures of race/ethnicity, income, insurance coverage, or same-sex couple household, were not associated with PrEP provider density, after adjusting for spatial autocorrelation, and PrEP providers were located in high HIV incidence neighborhoods ($P < 0.01$). These findings validate the need for ongoing policy interventions (e.g. public health detailing) vis-à-vis PrEP provider locations in NYC and inform the design of future PrEP implementation strategies, such as public health campaigns and navigation assistance for low-cost insurance.

Keywords Pre-exposure prophylaxis (PrEP) · Neighborhoods · Spatial analysis · Spatial epidemiology

Introduction

Despite a recent overall decrease in HIV incidence in the United States (U.S.), new HIV infections remain high among certain populations, including racial and ethnic minorities and low-income populations [1–3]. While black and Hispanics account for 12.3% and 17.6% of the U.S. population, respectively, they comprise 44% and 26% of all HIV diagnoses in 2016 [1]. The disproportionate burden of HIV among minorities is predominantly driven by marked social disparities and other behavioral factors, and some evidence suggests that racial/ethnic segregation may play an important role in this HIV epidemic [4]. Many studies have identified disparities in health outcomes, health behaviors, and access to healthcare services in segregated neighborhoods [5, 6]. Sexually transmitted infections, of which HIV is one, have also been found to be associated with such residential segregation [7, 8], but only a handful of studies have investigated local segregation of HIV care/prevention resources [9].

Pre-exposure prophylaxis (PrEP) is an effective HIV prevention strategy [10–13]; however, access to PrEP is often limited among racial/ethnic minorities and low-income populations [14–19]. Studies have reported that PrEP acceptability among at-risk black and Hispanic populations, such as gay, bisexual, other men who have sex with men (MSM), and transgender women, is similarly high to other populations [20], yet rates of PrEP uptake among such racial, sexual, and gender minority groups have remained much lower relative to their white counterparts [21, 22]. Studies have proposed possible explanations for PrEP access disparities, including healthcare availability, income, education, and barriers associated with geography [17–19, 23].

The present study describes geographic variation in access to PrEP providers in New York City (NYC), and examines the relationship between geographic access,

✉ Byoungjun Kim
byoungjun.kim@nyulangone.org

1 Department of Population Health, School of Medicine, New York University, 180 Madison Ave, 3rd Floor, New York, NY 10016, USA

2 Department of Social and Behavioral Sciences, College of Global Public Health, New York University, New York, NY, USA

neighborhood socio-demographics, healthcare provider availability, and HIV incidence, using spatial analytic methods for spatial autocorrelation. Spatial autocorrelation refers to interdependencies among observations in variables. The presence of spatial autocorrelation violates the major assumption of independence of observations and can lead to biased estimates of parameters [24–27]. In this study, we hypothesized that neighborhoods with certain socio-demographic profiles (e.g., higher percent Black, Hispanic, or poverty) and a high HIV incidence would have limited access to PrEP providers in NYC.

Methods

Data

The present study used the PrEP Locator Database provided by the Centers for Disease Control and Prevention National Prevention Information Network (CDC NPIN) [28]. The PrEP Locator is a national database of PrEP-prescribing clinics, hospitals, and organizations, providing a unified and vetted source of PrEP providers across the U.S. The data collection process included web searches, referrals, and outreach to state health departments, and the dataset was consistently reviewed by an advisory board and staff of CDC NPIN. Details of the database's methodology for data collection and maintenance have been described elsewhere [29]. We chose NYC as our study site, as the largest urbanized city in the U.S. with high concentrations multi-racial/ethnic populations. Also, NYC has one of highest HIV incidence and prevalence in the U.S. [1]. By October 2018, there were 154 registered PrEP providers in NYC. Five-year cumulative new HIV diagnosis case data were obtained by ZIP code tabulated area (ZCTA)-level from the NYC Department of Health and Mental Hygiene (NYC DOHMH) [30] via AIDSVu [31]. The new diagnosis cases represent people newly diagnosed HIV infection regardless of the stage of disease (stage 0, 1, 2, 3 [AIDS], or unknown) reported to the NYC DOHMH from January 1, 2012 to December 31, 2016. The HIV incidence was calculated as an incidence rate per person-year. Socio-demographic data were retrieved from the 2013–2017 American Community Survey by ZCTA level, including: the percentage of Hispanic, non-Hispanic black, Asian, white, the percentage of people with annual incomes below the federal poverty level, the percentage of people without health insurance, and the percentage of same-sex couple household as a proxy of gay population. In addition, the availability of general healthcare providers was calculated as density per 100,000 population. Data for public and private healthcare providers were accessed through the Health Facility General Information provided by New York State Department of Health, and the number of hospitals, diagnostic and treatment centers, mobile diagnostic and treatment centers, and their extensions were divided by population by ZCTA. There were a total 211 ZCTAs in NYC.

The PrEP providers' addresses were geocoded using a common geocoding method, ArcGIS (ESRI, Redlands, CA, USA) [32]. The number of point locations of all PrEP providers in NYC was counted by ZCTA level, and the number of PrEP providers per population of 100,000 were calculated as a marker of PrEP provider density. A total of 47 ZCTA with a small number of new HIV diagnoses (less than 5) and/or population size (less than 500) had missing incidence data due to confidentiality issue thus excluded from the analysis. One isolated ZCTA was also excluded due to a limitation of spatial autocorrelation analysis for zero neighbors. A total of 163 ZCTAs in NYC with valid HIV incidence, socio-demographics, healthcare availability, and PrEP provider density were included in the final analyses. Spatial data processing were done in ArcGIS 10.6 (ESRI, Redlands, CA, USA).

Statistical Analysis

We examined spatial autocorrelation of all socio-demographics, healthcare provider availability, HIV incidence, and PrEP provider location variables using the Global Moran's I. Previous health research assessing neighborhood characteristics and built environments applied similar spatial approach [33–36]. In this study, we employed a row-standardized binary contiguity spatial weight matrix based on first-order Queen criteria, which is commonly used with areal data [37]. The Queen's contiguity spatial weights matrix defines neighbors as ZCTAs that share a common boundary or a corner. A pseudo P value for the Moran's I was calculated using a Monte Carlo simulation of 999 random trials. Moran's I values range between -1 to 1, and a value near 1 suggests clustered similarities and positive spatial autocorrelation. We also tested Spearman correlations adjusting for the spatial autocorrelation between study variables and PrEP provider density. Non-spatial bivariate and multivariate models were specified with various Lagrange Multiplier (LM) tests for spatial autocorrelation on the residuals of these fitted non-spatial ordinary least squares (OLS) models. The LM tests are diagnostics to assess spatial dependence based on Lagrange Multiplier principle, and those can be used when Moran's I is statistically significant [24, 38, 39]. Finally, as appropriate, spatial error models (SEM) or spatial lag models (SLM) were developed to account for spatial autocorrelation [24–27], and we evaluated the goodness-of-fit for each model using Akaike Information Criterion (AIC) [40, 41]. We used R statistical software 3.5.1 (R Core Team, 2018).

Results

Descriptive and Spatial Statistics

The mean ZCTA-level PrEP provider density was 1.89 per 100,000 (standard deviation (SD) = 3.13, range = 0 to 16.7) for the analytic sample of 176 ZCTAs (Table 1). Mean HIV incidence rate was 0.007 per person-year (7/1000-person year) (SD = 0.005, range = 0.0 to 0.03). A large range exists for the neighborhood socio-demographics, especially for ZCTA percent non-Hispanic black and white (Table 1).

The Global Moran's *I* for PrEP provider density was 0.49 ($P < 0.01$) (Table 1). We also identified positive significant global spatial autocorrelation in all of the neighborhood characteristics and HIV incidence rate (Global Moran's *I* range from 0.51 to 0.75, all $P < 0.01$). Figure 1 shows maps of the spatial distribution of PrEP provider density, key neighborhood characteristics, and HIV incidence rate by ZCTA level.

Correlation between Neighborhood Socio-demographics, Healthcare Availability, HIV Incidence and PrEP Provider Density

Table 2 shows the traditional Spearman correlation and Spearman correlation accounting for spatial autocorrelation. From conventional correlation analyses, percentage Asian ($r_s = -0.21$, $P < 0.01$), below poverty ($r_s = 0.22$, $P < 0.01$), same-sex couple household ($r_s = 0.44$, $P < 0.01$), health care provider density ($r_s = 0.53$, $P < 0.01$), and HIV incidence ($r_s = 0.44$, $P < 0.01$) were significantly correlated with PrEP provider density. The spatially adjusted analyses showed that only percentage same-sex couple household ($r_s = 0.44$, $P < 0.01$), healthcare density ($r_s = 0.53$, $P < 0.01$) and HIV incidence ($r_s = 0.44$, $P < 0.01$) were correlated with PrEP density of ZCTAs. Only percentage of non-Hispanic Asian variable showed a negative correlation between PrEP provide density from conventional correlation test ($r_s = -0.21$, $P < 0.01$). The magnitudes of correlation were largest for healthcare provider density ($r_s = 0.53$), and HIV incidence as well as percentage of same-sex couple household (both $r_s = 0.44$), suggesting those three variables were powerful predictors of PrEP provider density.

Spatial Regression Analyses of the Relationship between Neighborhood Socio-demographics, Healthcare Availability, HIV Incidence, and PrEP Provider Density

We found that HIV incidence was positively associated with PrEP provider density in all non-spatial and spatially adjusted bivariate models (Table 3). The percent of the population that was non-Hispanic Asian was negatively correlated with PrEP provider density from the non-spatial bivariate model, but from multivariate models the association did not attain statistical significance (Table 3). The Moran's *I* for the non-spatial multivariate OLS regression residual was positive and significant (Moran's $I = 0.07$, $P < 0.05$) (Table 3). The LM test was significant for spatial lag model (LM error $P = 0.19$, LM lag $P < 0.01$), confirming the need for SLM, and since the p-value of LM lag was smaller, robust SLM would be regarded as better model fitting [42]. Table 3 also shows the result of multivariate models including the SLM. In the SLM, the coefficients of all socio-demographics variables were not statistically significant, and only healthcare density ($b = 0.13$, $P < 0.01$), and HIV incidence ($b = 211.3$, $P < 0.01$) remained strong positive predictors of PrEP provider density. For example, one person-year increase in HIV incidence is associated with 211 increase in PrEP provider density (/100,000) in a ZCTA in NYC. As examined from LM tests, the SLM had smaller AIC than SEM, suggesting a better model fit (data now shown).

Table 1 Descriptive statistics and global spatial autocorrelation (N = 163)

	Mean (SD)	Range	Moran's *I*	P-value
PrEP provider density (/100,000)	1.89 (3.13)	0.0–16.7	0.49	0.001
Percent non-Hispanic Black	21.4 (24.3)	0.4–90.8	0.73	0.001
Percent Hispanic	27.6 (19.6)	5.6–74.3	0.75	0.001
Percent non-Hispanic Asian	14.1 (13.9)	0.0–72.7	0.67	0.001
Percent non-Hispanic White	33.7 (25.5)	0.6–84.3	0.64	0.001
Percent below poverty	18.1 (9.8)	3.2–46.4	0.67	0.001
Percent uninsured	9.2 (4.3)	0.8–26.3	0.51	0.001
Percent same-sex partner household	0.51 (0.65)	0.0–3.4	0.54	0.001
Healthcare provider density (/100,000)	10.0 (9.9)	0.0–56.8	0.21	0.001
HIV incidence rate (/person-year)	0.007 (0.005)	0.0–0.03	0.65	0.001

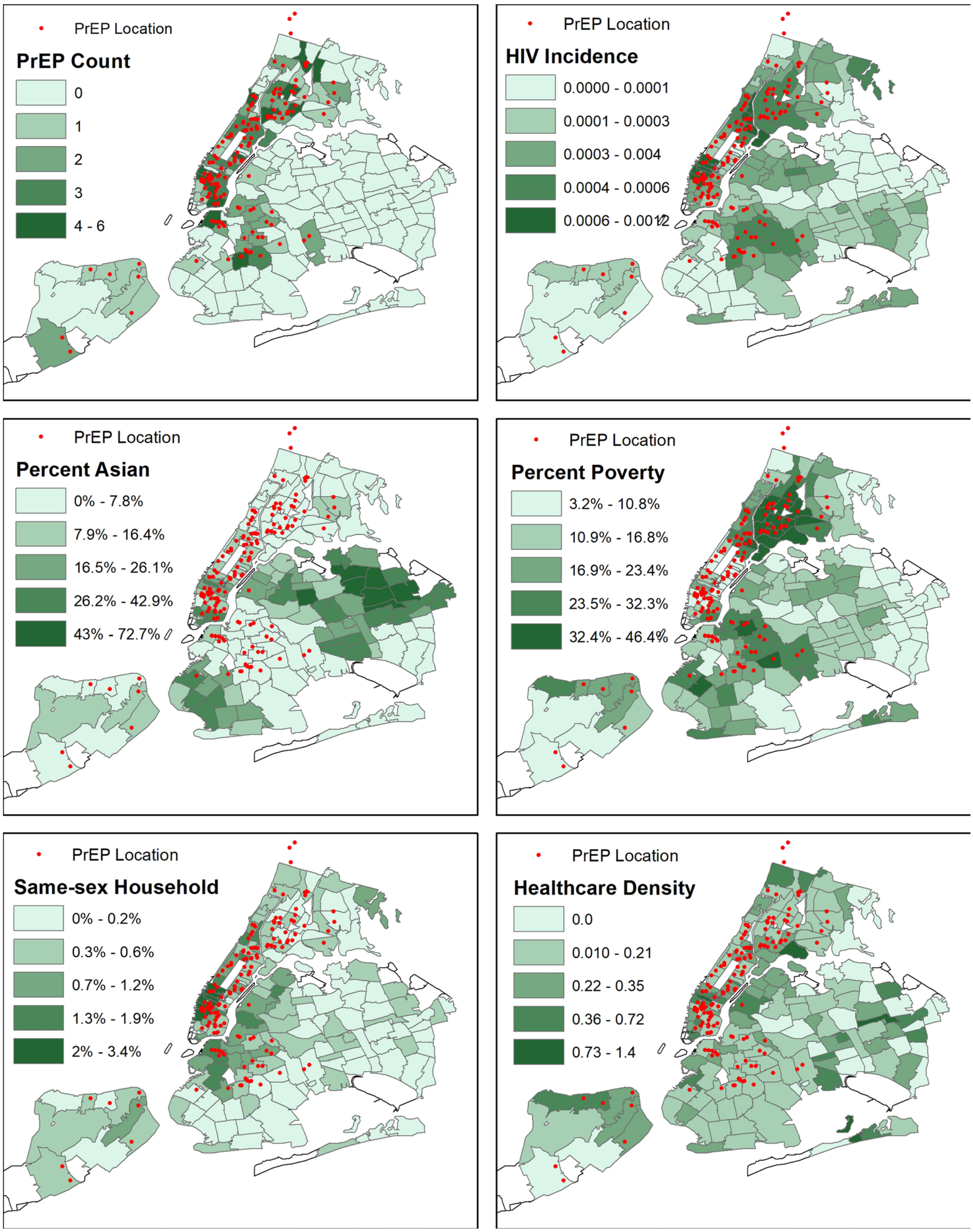

Fig. 1 Spatial distribution of PrEP provider, HIV incidence rate, socio-demographics, and healthcare availability in New York city (ZCTA Level). 47 ZCTAs were excluded from the map due to small a number of new HIV diagnose (less than 5) and/or population size (less than 500)

Discussion

Our findings suggest that PrEP providers in NYC are effectively distributed in high HIV incidence neighborhoods. Contrary to our hypothesis, neighborhoods with a high percentage of black, Hispanic, and a population below federal poverty level, were not associated with lower levels of PrEP provider density. Although percentages of Asian and uninsured population were negatively associated with PrEP density from our bivariate model, the associations did

Table 2 Spearman correlation between ZCTA level socio-demographics/HIV prevalence and PrEP density (N = 163)

	r_s	Conventional P-value	Spatially adjusted P-value
Percent non-Hispanic Black	0.12	0.12	0.29
Percent Hispanic	0.02	0.83	0.92
Percent non-Hispanic Asian	**−0.21**	**0.01**	0.13
Percent non-Hispanic White	0.07	0.38	0.68
Percent below poverty	**0.22**	**0.01**	0.13
Percent uninsured	−0.13	0.09	0.33
Percent same-sex partner household	**0.44**	**0.00**	**0.01**
Healthcare provider density (/100,000)	**0.53**	**0.00**	**0.00**
HIV incidence rate (/person-year)	**0.44**	**0.00**	**0.00**

Bold values denote statistical significance at the $p < 0.05$ level

not retain significance in our spatially adjusted multivariate model. Previous individual-level studies have identified ease of physical access to PrEP providers as a PrEP access barrier [43, 44], but in NYC, we found a relatively high concentration of PrEP providers in neighborhoods with a population groups who may seek PrEP subscriptions. Public efforts including stakeholder engagement and public health detailing to increase utilization of PrEP prescription in high-risk and/or vulnerable areas could play important roles in this balanced PrEP location. From 2014, NYC DOHMH began marketing PrEP directly to clinicians in a project funded jointly by the CDC and the municipality, as public health detailing to address PrEP disparities. In fact, the NYC DOHMH had a deliberate strategy to increase PrEP providers in high prevalence areas and prioritized medical practices that diagnosed HIV among people of color based on surveillance data [45].

These findings can guide future PrEP implementation strategies to target populations disproportionately impacted by the HIV epidemic, including blacks and Hispanics. In addition to geographical access to PrEP

Table 3 Model estimations of the relationship between ZCTA level socio-demographics, healthcare availability, HIV incidence rate, and PrEP density with model diagnostics for spatial autocorrelation and goodness-of-fit (N = 163)

	Non-spatial OLS		Spatial lag model	
	Coefficient (SE)	P-value	Coefficient (SE)	P-value
Bivariate estimation				
Percent non-Hispanic Black	−0.11	0.91	0.3	0.7
Percent Hispanic	−0.28	0.83	−0.07	0.94
Percent non-Hispanic Asian	**−4.14**	**0.02**	−1.64	0.24
Percent non-Hispanic White	1.66	0.08	0.32	0.68
Percent below poverty	4.23	0.09	2.26	0.26
Percent uninsured	**−15.1**	**0.01**	−5.35	0.24
Percent same-sex partner household	**210.0**	**0.00**	**126.07**	**0.00**
Healthcare provider density	**0.19**	**0.00**	**0.14**	**0.00**
HIV incidence rate (/person-year)	**320.0**	**0.00**	**206.54**	**0.00**
Multivariate estimation				
Percent non-Hispanic Black	−1.33	0.82	−0.72	0.89
Percent Hispanic	−1.33	0.82	−0.95	0.86
Percent non-Hispanic Asian	−1.65	0.79	−0.97	0.87
Percent non-Hispanic white	−0.22	0.97	−0.26	0.96
Percent below poverty	−0.8	0.77	−1.55	0.54
Percent uninsured	−7.61	0.22	−4.56	0.44
Percent same-sex partner household	43.75	0.33	33.22	0.42
Healthcare provider density	**0.15**	**0.00**	**0.13**	**0.00**
HIV incidence rate (/person-year)	**261.4**	**0.00**	**211.3**	**0.00**
Multivariate model diagnostic				
Global moran's I	**0.07**	**0.02**	–	–
LM spatial error model P-value	1.73	0.19	–	–
LM spatial lag model P-value	9.78	**0.00**	–	–
Robust LM P-value	–	–	–	0.00
AIC	722		714	

Bold values denote statistical significance at the $p < 0.05$ level providers, studies have proposed other potential barriers and facilitators to PrEP use, including limited PrEP awareness, lack of culturally-specific marketing and information, and increased concerns about the effectiveness of PrEP, long- and short-term side-effects, adherence to PrEP, and cost of PrEP [17, 18, 44, 46–50]. In NYC, public health campaigns designed to enhance PrEP awareness and knowledge, and to provide information about availability and accessibility of PrEP provider locations, as well as assistance for low-cost health insurance and tailored coordination of healthcare services, could likely further increase the PrEP uptake among at-risk populations such as MSM of color and transgender women.

This study has several limitations. First, the study sample was 163 ZCTAs in NYC with a relatively high density of PrEP providers and easy access to public transportation. Thus, the results may not be generalizable to other cities or rural areas. Second, there are inherent limitations to an ecological study design, including ecological fallacy. Individual-level barriers and facilitators to PrEP use were not accounted for in this study, thus it is possible that areas with high PrEP provider density may not be associated with PrEP uptake and adherence. Third, neighborhood was designed using ZCTA, which is an arbitrary boundary with heterogeneity [5, 51]. Thus, there might be a potential modifiable areal unit problem (MAUP), that the study results may have differed by the neighborhood definition used [52, 53]. However, the smallest geographical level of HIV incidence data was ZCTA, and the ZCTA level was frequently used due to available health information [5, 54]. Fourth, the healthcare provider data did not specify private and public clinics, so we were not able to include proportion of public healthcare facilities in the analysis, which may be relevant to the PrEP provider density. Lastly, there was a temporal mismatch between the datasets used. The HIV incidence data was cumulative number between 2012 and 2016, and the socio-demographics were 5 year estimate between 2013 and 2017. The PrEP provider location data were retrieved as of October 2018.

Despite limitations, the findings suggest that there are effective policy interventions (e.g., NYC DOHMH's public health detailing) vis-à-vis PrEP provider locations within neighborhoods with high HIV incidence in NYC, which may partly explain recent local decreases in HIV incidence [55]. However, while allocating resources to identified high HIV incidence neighborhoods is necessary, it may not be sufficient to effectively curtail the HIV epidemic. As the results indicate, PrEP provider density was not associated with a high percentage of black, Hispanic, low-income, or same-sex couple household neighborhoods. These neighborhoods, while having lower HIV incidence, at this time, may have a high prevalence of risk networks, particularly related to HIV-associated substance use and sexual behavior. Thus, these neighborhoods remain at disproportionate risk of HIV and may benefit from additional PrEP provider locations.

Acknowledgements Mr. Byoungjun Kim was supported in part by the NYU Training Program in Healthcare Delivery Science and Population Health funded by Agency for Healthcare Research and Quality (Grant Number T32HS026120-01; Leora Horwitz, MD and Mark Schwartz, MD, Principal Investigators). Dr. Dustin Duncan was supported in part by grants from the National Institute on Minority Health and Health Disparities (Grant Number R01MD013554), National Institute on Mental Health (Grant Number R01MH112406), National Institute on Drug Abuse (Grant Number R03DA039748) and the Centers for Disease Control and Prevention (Grant Number U01PS005122). We gratefully acknowledge the CDC NPIN for providing the PrEP Locator data. We also wish to thank the anonymous reviewers who offered very helpful comments and suggestions which allowed us to greatly improve our manuscript.

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