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Associations between Income Inequality, HIV Diagnosis Rate and Primary Care Access: 2008-2013

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2009

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Rollins School of Public Health of Emory University
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Abstract

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By Lauren Ahlschlager

Background: Income inequality has been increasing in the United States for decades, making the U.S. one of the most inequitable nations in the developed world. Previous studies have shown positive associations between income inequality and poor health outcomes, namely mortality, however none have assessed HIV as an outcome in these analyses. In an attempt to identify ways to ameliorate this growing issue, some studies have demonstrated a mediating effect of access to healthcare on the relationship between income inequality and population health.

Objective: This analysis sought to describe the association between HIV diagnosis rates and income inequality among U.S. counties and states and further aimed to detect any presence of a mediating effect of primary care physician supply on this relationship.

Methods: We used publicly available data to examine the association both between HIV diagnosis rate and income inequality as well as all-cause age-adjusted mortality rate and income inequality using log-transformed linear regression. We calculated mean rate ratios (MRR) to describe these relationships at both county and state levels. Further, primary care physician rate was examined as a possible mediator of these associations.

Results: Associations between income inequality and both HIV diagnosis rate and all-cause mortality rate were observed across 499 U.S. counties and 50 states. Higher levels of income inequality were significantly associated with higher HIV diagnosis rates (MRR for a 5 point increase in Gini Index=1.25, 95% CI: 1.17, 1.35). This relationship was also observed at the state level (MRR for a 1 point increase in Gini index=1.19, 95% CI: 1.09, 1.30). Mixed results were obtained for the association between Gini index and mortality rate for both counties and states. The significant associations between income inequality and HIV diagnosis rate did not appear to be mediated by primary care physician supply.

Discussion: Income inequality is a significant independent predictor of HIV diagnosis rates at both the county and state levels. Future analyses should examine the extent to which alternative measures of access to care might mitigate the effect of income inequality on HIV diagnosis rates in order to better inform potential intervention efforts.

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BACKGROUND

Despite its total economic wealth and high standard-of-living, the United States is one of the most unequal countries in the developed world, with income inequality having been on the rise for decades. After remaining relatively stable since 1960 when household wage data were first collected, the top 5% of earners increased their share of overall wealth by about 15% from the early 1980s to 2012 [1]. Differential recovery patterns from the "Great Recession" of 2007-2009 have recently brought increased focus to this issue. From 2009-2012, average household income increased by 6%, however these gains were not evenly distributed, with the top 1% of incomes rising 31.4% while the bottom 99% of incomes rose by less than one half of a percent [2]. This near full recovery on the part of top earners compared to the stagnancy seen elsewhere on the wealth distribution point to an exacerbation of the extant income inequality issue and underscore the necessity of understanding the societal implications of worsening income inequality.

A substantial body of research has been dedicated to uncovering the extent to which income inequality may affect not only the economic health of the nation, but its physical health as well. Various ecological studies have linked income inequality to increased population mortality at the MSA, county, state and national levels and have demonstrated significant associations with other population health indicators such as life expectancy, self-reported general health, cancer mortality and heart disease [3-7].

Despite much contextual evidence for the effect of income inequality on various measures of health, there is debate over the extent to which income inequality affects distal health outcomes, namely mortality, with some suggesting that the relationship only holds for some segments of the mortality distribution [8, 9], while others argue that studies focusing on geographic units of analysis with greater population are more likely to reflect true relationships between inequality and health [9].

HIV continues to be an area of major public health significance in the United States. As of 2011, 1.2 million Americans were living with HIV, with 14% unaware of their infection [10]. From 2006-2009, the United States saw an estimated average of about 50,000 new HIV infections each year [11]. Similar to mortality rate and other important health indicators, rates of HIV diagnosis and prevalence are known to be distributed based on a number of social determinants, including race, geographic region, urbanicity and poverty [9, 12-14]; however, with the exception of national-level comparisons no studies to the author's knowledge have examined the relationship between HIV and income inequality within the United States, although notably one paper has demonstrated a link between state AIDS case rates and income inequality [15].

Adequate access to healthcare has been one factor hypothesized to attenuate any ill-effects of income inequality on mortality. Work done primarily by Shi, Starfield and colleagues has demonstrated that an increase in the rate of primary care physicians (PCP) in an area statistically mitigates levels of mortality within metropolitan areas, counties and states [5-7, 16, 17].

The passage of the Affordable Care Act has expanded coverage to millions of previously uninsured Americans. It has been estimated that the increase in physician utilization due to this expansion would be between 4– 5.2% [18]. The likely increase in the need for primary care physicians coupled with an already anticipated shortage [19] underscores the importance of understanding the impact of adequate access to primary care on population health.

Access and linkage to HIV care services is essential to the effective prevention of HIV transmission, as those who are either HIV-positive and undiagnosed or diagnosed but not receiving care account for 45.2% of the HIV positive population and 91.5% of new infections [20]. Primary care physicians play an important role in the early detection and diagnosis of HIV, as well as linkage to care services which can aid in the control of localized HIV epidemics.

This analysis addresses a gap in the literature regarding the association between HIV and income inequality at sub-national levels in the United States. Using publicly available data, we compared the relationship between income inequality and HIV diagnosis rate to that between income inequality and mortality rate. Further, we assessed the presence of any mediating effect of PCP supply on these relationships.

METHODS

This analysis was designed as an ecologic study aimed at quantifying the effect of income inequality on HIV diagnosis rate at both the county and state levels. For comparison, we examined the effect of income inequality on all-cause age-adjusted mortality rate.

Additionally, we conducted mediation analyses to assess the ability of primary care physician supply to attenuate the relationship between income inequality and either outcome.

Data and Measurements

Table 1 outlines all data sources utilized throughout this analysis. HIV diagnosis data were retrieved from the U.S. Centers for Disease Control and Prevention's (CDC) national HIV surveillance database via AIDSVu, a publicly-accessible online resource created through a partnership between the Rollins School of Public Health at Emory University and Gilead Sciences, Inc. [21]. The outcome variable, HIV diagnosis rate, represents a weighted average of annual rates of diagnosis per 100,000 residents of either a given county or state from 2008 through 2013. In this analysis, HIV diagnosis rate was used as a proxy measure of HIV incidence, which is available only as model-based estimates nationally and occasionally [22].

Mortality data were drawn from the CDC National Vital Statistics System compressed mortality files, made publicly available through CDC WONDER (Wide-ranging Online Data for Epidemiologic Research), an online database containing a wide range of public health data and documentation [23]. Mortality rates at the state and county levels represent population-weighted averages of the number of all-cause age-adjusted deaths per 100,000 from 2008-2013.

Income inequality was measured using the Gini index, a measure common to such studies. The index measures the degree of household income dispersion within a given population, with 100 representing complete inequality and 0 representing a completely equitable distribution of wealth. The Gini coefficient is calculated by first obtaining a Lorenz curve, which depicts the share of total wealth held by a certain proportion of the population (i.e. the actual income distribution curve). The measured area between the Lorenz curve and a line depicting complete income equity (i.e. every household in the population has the same share of total population income) is used to calculate the Gini coefficient, which is then scaled from 1-100 to produce the Gini index [24]. For this analysis, county and state-level Gini data were obtained from the U.S. Census Bureau American Community Survey (ACS), representing a 5-year estimate 2009-2013 [25]. Gini index was included in the analysis as a continuous independent predictor of HIV diagnosis rate and mortality rate.

Primary care physician (PCP) rate in this study includes doctors of medicine and osteopathy who were engaged in active patient care in the areas of general practice, family medicine, internal medicine and general pediatrics from 2010-2013. Subspecialties were excluded, as were physicians over 75 years of age and resident physicians. These data were drawn from the Area Health Resource File and represent a weighted average of the rate of physicians per 10,000 population [26]. PCP rate was analyzed as a continuous predictor.

Additional factors known to be consistently associated with both health outcomes were included in the models as categorical covariates. Area minority composition was considered through the use of a variable that measured black population percentage and categorized each county or state as being above or below either the national county-level or state-level 75th percentile. These data represent 2010 U.S. Census estimates. Educational attainment was measured as the percent of a given area's population with less than a high school diploma or its equivalent and was categorized into quartiles. Counties were additionally categorized as being either above or below a 20% poverty rate, the cutoff for the U.S. Department of Commerce's "designated poverty area" classification. States were categorized as being either above or below the 2010 national poverty rate of 15.1%. Data for percent black population, educational attainment and poverty rate were obtained from the Area Health Resource File [26]. Urbanicity was measured using the 2013 National Center for Health Statistics' urban-rural classification scheme, which places counties into 6 categories based on level of urbanicity. These data were obtained from CDC WONDER [23]. For these analyses, the 2 most rural designations (micropolitan and non-core) were collapsed to produce a 5-level rather than 6-level scale.

Design and Analysis

Linear, natural log-transformed linear, and Poisson regression were used to examine the bivariate relationships between Gini index and both outcomes, HIV diagnosis rate and all-cause age-adjusted mortality rate, at both the county and state levels in an effort to determine the best means of analysis for a fully-adjusted model.

Based on the high variance and deviance/df associated with the linear and Poisson models respectively, log-transformed linear regression was identified as the best approach with which to analyze the prediction and mediation models. Given this method of analysis, all adjusted effect estimates represent the mean rate ratio (MRR) for the rate of either HIV diagnosis or mortality corresponding to a given increase in Gini index. At the county level, MRRs represent ratios for a five point increase in Gini index and at the state level, MRRs represent rate ratios for 1 point increases. The decision to examine effects at differing levels of change in income inequality were based on the range of Gini index values for counties and states. That is, Gini has a 24 point range at the county level and less than a 9 point range at the state level.

The four fully-adjusted models predicting county and state level outcomes were analyzed for all possible two-way exposure-covariate interactions using a backward elimination approach with an alpha level of 0.05 as the cutoff for retaining interaction terms in the model. A change-in-estimate all-possible subsets approach was then employed to assess confounding for the four models and a best model for each outcome and geographic level was chosen based on predictive ability and precision of the effect estimate [27]. Changes in effect estimate of greater than 10% either toward or away from the null value of 1.00 were considered confounded. An alpha level of 0.05 was utilized to determine statistical significance of all predictors and effect estimates.

The ratio of primary care physicians to population (PCP) was considered as a potential mediator of the relationship between income inequality and both HIV diagnosis rate and mortality rate. The model-based effect estimates of the four best models before and after the addition of PCP to the models were compared to detect any changes indicative of mediation by primary care physician ratio. Changes of 10% or more toward the null after the addition of PCP indicated a mediation effect.

All analyses were performed using SAS v9.4 (Cary, NC). Due to the exclusive utilization of publicly-available non-identifiable data, this study is exempt from prerequisite IRB approval.

RESULTS

Descriptive Analysis

i. County Description

Due to missingness attributed to data suppression of sparse county-level HIV case counts as well as lack of reporting county-level diagnoses by some states, of the 3,143 U.S. counties and county equivalents (excluding the Virgin Islands and Puerto Rico), only the 499 counties that contributed complete HIV diagnosis data for all 6 years (2008-2013) were retained for analysis.

Table 2 describes the mean, standard deviation, range and distribution of all county-level outcomes and predictors in this study. From 2008-2013, the mean HIV diagnosis rate for counties included in the analysis was 20.25 per 100,000 population (standard deviation=17.91, median=14.15). The mean mortality rate was 785.07 (standard deviation=123.32, median=780.20). County Gini indices ranged from 35.67 to 59.85, with a mean of 45.44 (standard deviation=3.38).

Most counties included in the analysis (n=386, 77%) did not satisfy the HRSA definition of a primary care shortage area [28], yet had PCP levels below the HRSA 2010 predicted PCP requirement of 9.6 primary care physicians per 100,000 population [29]. Ninety four counties met the predicted PCP requirement, with 17 counties being designated as a PCP shortage area, defined as a physician to population ratio of less than 1:3,500 (in this context, a PCP rate of 2.9).

Most counties in the study (n=392, 79%) had poverty rates below the designated poverty area threshold of 20%. Nearly 60% of the counties in the study had a percentage black population that was higher than the national 75th percentile for counties (n=289). Educational attainment, defined as percent of area population over 25 with less than a high school diploma and categorized based on national quartiles, saw a more even distribution compared to the other predictors. Finally, more than 41% of counties in the analysis were defined as either a large metro or large fringe metro area, and under 9% (n=44) being classified as either micropolitan or non-metro areas.

Table 3 examines the distribution of both outcomes as well as the independent variable Gini index and PCP rate at each level of the categorical covariates included in the analysis. HIV diagnoses, mortality rate and Gini index were higher in areas of high poverty, high percent black population and low education. While HIV diagnosis rates and income inequality were highest in the most urban and most rural counties, mortality primarily increased with decreasing levels of urbanicity. PCP rates were highest in areas of low poverty, lower black population, more education and higher urbanicity level.

ii. State Description

Table 4 describes the distribution of state-level outcomes and predictors. States had a mean HIV diagnosis rate of 12.95 (standard deviation=9.11, median=10.83). Overall state mortality rate was 762.97 (standard deviation=86.10, median=746.40). State Gini indices ranged from 41.43 to 50.22 with a mean of 45.49 (standard deviation=1.89).

Table 5 examines the relationship of both outcomes as well as the independent variables Gini index and PCP rate at each level of the covariates. Similar to the county level, at the state level, mortality rate, HIV diagnosis rate and Gini index were higher in states that had higher levels of poverty and larger percentages of black population. HIV diagnosis rates were mostly higher in states with lower percentages of high school completion, while mortality rate was more uniform across quartiles of high school completion. Similar to the county level, PCP rate was higher among states with lower average poverty levels, lower black population and higher levels of high school completion.

Bivariate Analyses

Table 6 outlines the results of the bivariate analysis. For all models at the county level, income inequality was a significant predictor of both outcomes. The county-level linear regression models produced a slope estimate of 2.09 for HIV diagnosis rate ($p<0.0001$, representing the increase in HIV diagnosis rate for every 1 point increase in Gini index) and 4.36 for county mortality rate ($p=0.008$), while explaining over 15% of the variability in the outcome for HIV diagnosis rate and 1% for mortality rate (adjusted $r^2 = 0.154$, adjusted $r^2 = 0.012$, respectively). For county-level log-transformed linear models, Gini index independently predicted a MRR of 1.57 ($p<0.0001$) and explained 19% of the variability in the HIV diagnosis outcome (adjusted $r^2 = 0.193$), while the mortality rate MRR was 1.02

($p=0.029$) with an adjusted r^2 of 0.008. County-level Poisson models had high levels of variance (deviance/DF statistics > 160).

At the state level, Gini index significantly predicted HIV diagnosis rate but did not significantly predict mortality rate using both linear and log-transformed linear regression models. Both the linear and log-transformed state models had high predictive ability for HIV diagnosis rate, accounting for over one third of the total variance in the linear model and over half in the log-transformed linear model (adjusted $r^2 = 0.363$ and adjusted $r^2 = 0.503$ respectively). Similar to the county models, the Poisson models for both HIV diagnosis rate and mortality rate were associated with high variance (deviance/DF statistics > 850).

Model Selection

i. Interaction Assessment

After assessing all possible two-way interactions between the independent variable Gini index and all covariates, significant interaction was detected only in the model predicting log-transformed county mortality rate. Here, the interactions between Gini index and percent black population, Gini index and poverty, and Gini index and education were found to be significant (Table 7).

ii. County HIV Diagnosis Rate Confounding Assessment and Model Selection

The addition of social determinants as covariates to create a fully adjusted, "gold standard" model produced a MRR of 1.25 (95% CI: 1.17, 1.35) and served to increase the predictive ability of the model from the bivariate 19% to 57% (adjusted $r^2 = 0.572$). Thus Gini index alone accounted for nearly one-third of the total explanatory power of the fully adjusted model.

Fourteen reduced models predicting county-level HIV diagnosis rate were analyzed for confounding (Table 8). All single covariate models, as well as the two covariate model that removed the percent black population and urbanicity variables, produced MRR estimates that were more than 10% different from those of the fully-adjusted model and therefore were considered confounded.

The model which retained just the percent black population and education covariates (removing the poverty and urbanicity variables) was the only model in which all variable coefficients were significant. Dropping the black population variable from the model consistently resulted in the largest drops in predictive ability of the model, while removal of the percent poverty covariate resulted in the smallest declines in predictive ability. The reduced model that removed only the poverty variable saw the lowest drop in adjusted r^2 relative to the gold standard (0.569 versus 0.572, respectively). This observation, coupled with the lack of any significant interaction between Gini index and poverty suggests that not only is there a lack of confounding by poverty, but that HIV diagnosis rates vary independently of county poverty levels when income inequality is considered.

Among the models without confounding of the Gini-HIV relationship, while the model that removed urbanicity, the model that removed poverty, and the model that removed both urbanicity and poverty all saw modest gains in precision of the unconfounded effect estimate, none conferred precision improvements substantial enough to replace the fully-adjusted model as the designated best model. While three of the four indicator variables for urbanicity were non-significant in this fully-adjusted gold standard model, it was chosen over the reduced model that dropped urbanicity due to retention of greater explanatory power and urbanicity's demonstrated importance in previous county-level population studies of HIV [13].

ii. County Mortality Rate Confounding Assessment and Model Selection

After the addition of covariates, the fully adjusted model accounted for over 42% of the variation in the outcome (adjusted $r^2 = 0.425$), indicating that while GINI may be a statistically significant independent predictor of mortality, other social determinants of health play a much larger role in elucidating the potential pathway to poor mortality outcomes at the population level.

Given the interaction present for the model predicting county mortality rate, the urbanicity covariate was the only variable eligible to be dropped from the model. Thus, only 2 models - the fully adjusted model and the reduced model which dropped urbanicity were assessed for confounding (Table 8). All MRRs for the reduced model were within a 10% threshold of the gold standard model. Because the reduced estimates offered no gains in precision, the fully adjusted "gold standard" model was determined to be the final model.

Using the lowest percentile of population lacking a high school education as the referent, the MRR for a 1 point increase in Gini index at the county level was highest where both percent black population and percent in poverty were high (MRR=1.07, 95% CI: 1.01, 1.14), and lowest when both percent black population and percent poverty were low (MRR=0.94, 95% CI: 0.90, 0.97). All other MRRs were nonsignificant.

While the model predicting county mortality did produce some significant associations, given that the two significant results fell on either side of the null value of 1 coupled with the modest size of the effect estimate, there exists some skepticism as to whether or not income inequality affects mortality to an extent that is statistically significant in some cases yet practically insignificant overall.

iii. State HIV Diagnosis Rate Confounding Assessment and Model Selection

Gini index predicted over 50% of the variation in HIV diagnosis rate at the state level in a crude analysis (adjusted $r^2 = 0.5023$), and resulted in a MRR of 1.32 (95% CI: 1.22, 1.42) for a 1 point increase in Gini index (Table 6). After addition of all covariates, the fully adjusted model resulted in a MRR of 1.19 (95% CI: 1.09, 1.30) and attained an additional 18% in explanatory power of the outcome (adjusted $r^2 = 0.681$) (Table 10). These results show that while income inequality alone is a significant independent predictor of HIV diagnoses at the state level, the unadjusted MRR is confounded and other population risk factors for HIV diagnoses must be accounted for.

Six reduced models predicting state-level HIV diagnosis rate were assessed for confounding (Table 10). The model which retained just the poverty variable as a covariate resulting in confounding up and away from the null (MRR=1.33, 95% CI: 1.22, 1.46). Similar to the county level HIV diagnoses predictions, removal of the percent black variable resulted in the largest relative drops in predictive ability of the model (>0.10 change in adjusted r^2 in each case where black was removed from the model), while removal of the education variable, the poverty variable, or both simultaneously resulted in the smallest drops in predictive ability of the model (<0.05 change in adjusted r^2 in each case).

While the model which removed the education variable and the model which removed both education and poverty did produce unconfounded estimates with modest improvements in confidence interval precision, the final best model was determined to be the fully adjusted gold standard model.

iv. State Mortality Rate Confounding Assessment and Model Selection

The bivariate association between Gini index and state mortality rate produced a MRR of 1.01 (95% CI: 1.00, 1.03) and served to account for well under 1 percent of the variability in the outcome (adjusted r^2 <0.001). Upon addition of percent black population, percent in poverty and percent with high school education as covariates, the predictive ability of the model rose substantially to 46% (adjusted r^2 = 0.458) and resulted in a MRR of 0.97 (95%

CI: 0.96, 0.99); an indication that, similar to the county level mortality estimates, social determinants play a much larger role in the prediction of mortality compared to prediction of HIV diagnoses.

Six reduced models predicting state-level mortality rate were assessed for confounding. None of the reduced models considered resulted in effect estimates that fell further than 10% from the fully-adjusted model and therefore all results were considered unconfounded (Table 10). The model that removed the education variable as well as the model that removed both education and percent black population resulted in modest gains in precision, but both produced nonsignificant effect estimates with large declines in explanatory power of the model (>15% point drop in adjusted r^2 values compared to the fully adjusted model). Additionally, the model that removed both education and poverty also resulted in a nonsignificant effect estimate.

As no reduced models offered significant, unconfounded effect estimates with gains in confidence interval precision, the fully adjusted gold standard model was determined to be the final "best" model. However, similar to the county level mortality predictions, the fully adjusted and reduced models produced results on either side of the null, of which many were nonsignificant relationships. Additionally, Gini index itself was not a significant independent predictor of mortality in the bivariate association. Therefore, while some significant relationships may exist, overall income inequality may represent a practically nonsignificant predictor of mortality at the state level.

Mediation Analysis

Upon addition of PCP rate to the fully adjusted models predicting HIV diagnosis rate at the county and state levels, effect estimates rose up and away from the null, indicating the lack of any mediating effect by PCP rate (Table 11). For models predicting mortality rate, addition of PCP to the fully adjusted models resulted in changes of the effect estimate that were up and toward the null and changed by less than a 10% threshold, similarly indicating a lack of mediation by the PCP variable.

DISCUSSION

Income Inequality is a Significant Predictor of HIV Diagnosis Rates

This analysis illustrated that income inequality is a strong predictor of HIV diagnosis rate, independent of the other modeled social determinants, and that states and counties with higher Gini indices have significantly higher rates of HIV diagnosis. While these associations were significant at both the county and state levels, income inequality was more predictive at the state level. This finding is consistent with the tendency for larger geographical units of analysis such as states or nations to be more likely to find an effect of income inequality compared to smaller units such as MSAs or counties [9]. Two previously hypothesized reasons for this tendency are that state-level analyses better capture and reflect the full spectrum of social class differentiation within a society, and similarly that more unequal societies exhibit greater levels of residential segregation; thus, the smaller the unit of analysis is, the more likely one is to find a more homogenous population and consequently reduced potential for inequity within it. [9, 30]

Given the fact that the impact of income inequality has proven more difficult to detect at the county level, the significant relationship between county-level income inequality and HIV diagnosis rate uncovered in this analysis is notable. While state-level associations are practically important given that health and economic policy decisions are more likely to be carried out at the state and national levels, the broad impacts of social determinants of health take root on a smaller scale, therefore county-level analyses such as this are essential to the description of how social determinants impact health at a more micro level and further, to hypothesize what might be done to mitigate their deleterious effects.

While this study was not designed to test the causal relationships between income inequality and HIV diagnosis rate, the results support previously hypothesized mechanisms. For example, some have posited that greater income inequality in a community leads to the erosion of social norms, aiding an increase in high risk behaviors such as injection drug use and unprotected sexual encounters [31]. A common view is that in general, higher income inequality in a community weakens levels of social cohesion, stifling the ability and political will to implement and invest in social safety nets such as public welfare programs and other services. In practice, these services could otherwise serve to help manage and reduce HIV transmissions within an area [32]. Other hypothesized pathways implicate income inequality as damaging to an individual's own psychosocial environment, which leads to strain on social relationships and general support, ultimately leading to poorer health outcomes [7].

While the state and county models predicting HIV diagnosis rates were highly predictive, neither was able to explain more than 70% of the total variability in the outcome. This suggests the presence of other predictors, confounders, or significant interactions that may help to explain the outcome but that were not considered in this analysis, for example the distribution of high-transmission-risk groups, sexual network structure, and prevalence rates of sexually transmitted infections that serve as risk factors for HIV transmission [33, 34].

Not only does this analysis represent the first of its kind in regard to linking income inequality to HIV diagnosis rate at the county and state level, it also represents the only analysis known to the author to examine associations between health outcomes and income inequality in the U.S. during a mid and post-recession timeframe. As previously discussed, the recession of 2007-2009 is thought to have worsened an already increasing level of income inequality, and therefore this analysis represents the examination of a timeframe which is characterized by some of the worst levels of income inequality on record. These higher levels of income inequality may have assisted in the detection of county-level effects which, as discussed, are less frequently found to be significant compared to effects detected among larger geographic units of analysis.

Income Inequality is a Better Predictor of HIV Diagnosis Rate than Mortality Rate

As previously discussed, income inequality has been shown to be a significant predictor of many health outcomes in the literature. Our results demonstrated that while some significant associations were detected between income inequality and mortality, income inequality was a much stronger and more significant predictor of HIV diagnosis rates at both the state and county levels.

This is likely in part an artifact of the differing range of both outcome variables; for example, at the county level, HIV diagnosis rate ranged from 1.94 to 156.79 (mean=20.25, standard deviation=17.91) while mortality rate ranged from 495.03 to 1,182.75 (mean=785.07, standard deviation=123.32). There is much greater variability in HIV diagnosis rates among U.S. counties compared to mortality rates, offering a wider spectrum within which to be able to detect strong associations.

Similarly, differences in the very nature of the two outcomes considered have implications on the extent to which social determinants of health can explain their variability. Death is an outcome that may occur with some differing frequency relative to other geographic units of analysis, but nonetheless occurs with some frequency in all counties and states. In contrast, HIV diagnosis is not an inevitable outcome and its presence or lack thereof in a given area is much more likely to be closely tied to aspects of the societal landscape and thus more heavily concentrated in some areas relative to others of differing social makeup.

Previous studies illustrating the association between mortality and income inequality have been robust to several measures of mortality, different timeframes and varying analytical approaches; however, as noted the results seen from this analysis appear to reflect a significant yet somewhat muted association at the county level and curiously a slight protective effect of high income inequality on mortality at the state level. One reason for these findings may be that the impact of income inequality has been shown to vary across the spectrum of mortality, with the association disappearing at certain points on the distribution [8]. This analysis focused only on the mean rate ratio for mortality, and therefore potentially stronger effects of income inequality at various locations on the spectrum of mortality rate may be obscured. Other methods of analysis such as the utilization of quantile regression may have be able to detect such associations within these data.

Associations between HIV Diagnosis Rate and Income Inequality Were Independent of Poverty Level

For both county and state-level HIV diagnosis rate, poverty was the least important covariate in terms of assisting in the explanatory ability of the models. In fact at the state level, the addition of poverty to the bivariate model actually lowered the adjusted explanatory power of the model. While absolute measures of poverty such as household income level and poverty rate have long been associated with poor health outcomes, these findings are consistent with current scholarship suggesting that in more developed societies, it is the inequitable distribution of wealth that has the greater impact on population health, conferring poorer health overall for both the rich and poor [35].

Primary Care Supply Did Not Mediate the Impact of Income Inequality on HIV Diagnoses

We hypothesized that intervening on the primary care physician supply in a given area could reduce the impact of income inequality on HIV diagnoses. While previous studies have shown that the presence of more primary care physicians can mitigate the effect that income inequality has on certain health outcomes [7, 17], our results did not show that this relationship holds for HIV diagnoses.

Part of the hypothesized impact of primary care physician supply on HIV diagnoses centered around the assumption that an area with a higher density of primary care physicians may have a better overall health infrastructure, and thus is better equipped to handle HIV infections via early detection of incident cases as well as strong linkage to and retainment in care; however, our measure of primary care did not include physicians who specialize in infectious disease that typically provide this type of ongoing care. It may be possible that some areas with a high density of primary care services do not also have levels of specialized HIV care services sufficient to adequately manage the epidemic in the community.

Additionally, detection bias related to both the use of HIV diagnosis rate as an outcome and primary care physician supply as a predictor may have been an issue in this analysis. Primary care physician supply may be a measure more closely tied to the ability to simply test and detect new cases, but have less of a role in actually stemming new community infections, because infectious disease physicians are often most typically and proximally engaged in the provision of ART for improving health and reducing transmissions. This may mean that HIV diagnosis rates are higher in areas where more primary care physicians are simply because those physicians test and diagnose more patients, but not because HIV incidence is truly higher in that area. In this analysis, HIV diagnosis rate serves as a proxy measure for HIV incidence, which can only be estimated, however it is possible that an estimated incidence measure could have produced different results.

Limitations

There are a few important limitations of this study to consider. First, as mentioned above, the use of HIV diagnosis rate has been used here to stand in for HIV incidence rate. It should be noted however that the extent to which HIV diagnoses estimates HIV incidence depends heavily on the varying availability of testing, which can fluctuate between states and counties due to differing health infrastructure, allocation of public funds and laws regarding consent to test.

Similar considerations should be made for use of the primary care variable. In this study the rate of primary care physicians stands in as a proxy measure of an area's general access to healthcare, however this may be problematic. The presence of primary care physicians in an area does not necessarily mean that equitable access to these physicians exists for all residents of a given geographic unit. Additionally, it should be noted that though this analysis examined the impact of income inequality while considering well-evidenced social determinants of health, there is potential for confounding by other factors which were unmeasured and not included in these models.

The use of a six year timespan over which to analyze these relationships presents a few important areas for consideration. First, it is reasonable to believe that some counties or states could have seen substantial improvements in testing availability over this timeframe which may have impacted these results but would not be discernible in the weighted average measure of HIV diagnosis used. Second, this study design did not take into consideration the potential for time-lagged effects on the outcome measures due to income inequality. That is, an increase in income inequality in a given timeframe would not be expected to result in an immediate or simultaneous increase in HIV diagnoses; rather, if income inequality affects health outcomes through a pathway comprised of various social determinants, it is more likely that effects related to changing levels of income inequality would be observed after some period of time.

Additional key limitations of this study center on the use of counties as geographic units of analysis. Crossover bias is of particular concern for the use of the primary care variable at the county level, as residents of certain counties may not necessarily access care in their county of residence. Additionally, the ability of county-level measures to accurately depict life in a given location may vary depending on county size and region. As an illustrative comparison we can reference the level of subdivision between two states. The state of Georgia has a population of just over 10 million and is divided into a relatively large number of counties at 159 total, with the state's largest metro area of Atlanta being subdivided into 14 counties. California's population of nearly 39 million is divided into just 58 counties, with Los Angeles county alone accounting for about one third of the state's total population. It is reasonable to think that county-level measures of social determinants in Georgia better reflect the reality for a greater proportion of residents as compared to California, where counties are more inclusive and thus county-level measures are less likely to be able to accurately describe reality for a majority of residents.

Use of states as geographic units of analysis may correct for some of the above limitations related to the analysis of counties, however the sample size of 50 states limited the statistical power of these analyses and similarly restricted the ability to add additional covariates to the models considering state-level effects.

Finally, the retaining of a subset of all U.S. counties for analysis based on those which reported unsuppressed data for all 6 years of the study timeframe elicits questions around possible selection bias. The sample size of 499 U.S. counties of 3,143 total counties skewed the data toward a higher proportion of urban counties, which tend to have the greatest levels of income inequality; however, it should be noted that these counties account for 71.64% of all U.S. population and 95.48% of all reported new HIV diagnoses from 2008-2013. Additionally, this method of county retention consequently resulted in counties with more HIV diagnoses being more likely to be included than those with low diagnoses which were more likely to be suppressed and excluded from analysis. State level estimates may be less subject to suppression and thus may capture data from a wider portion of total counties.

Future Directions

Achievement of viral suppression via linkage to and retainment in specialized HIV care is essential to reducing incident cases of HIV in the United States [20]. Reforms passed in an effort to make healthcare more affordable and expand Medicaid through the Affordable Care Act (ACA) were implemented during the timeframe of this study. In this analysis, primary care access was averaged over the course of the 6 year study timeframe, but future studies should examine any potential impact that certain ACA reforms may have had in expanding access to care, such as measures making private insurance more affordable. Additionally, future analyses should examine any impact that the selective expansion of

Medicaid in some states may have had on the HIV epidemic at both the state and county levels.

Given the issues noted around the use of primary care access as an indicator of access to care, future analyses may consider the inclusion of alternate or additional measures related to access to care, such as density of infectious disease physicians or other specialized HIV-related care services. Analyses relating the ability of an individual in a given area to attain specialized HIV care at differing levels of income inequality could shed light on how the epidemic is being differentially controlled in areas of high and low income inequality. Finally, spatial analyses surrounding proximity to care with considerations of functional barriers such as transportation and social capital indices could provide a clearer picture of true access to care services.

Finally, as previously discussed, the six year timespan of this study includes a time when the U.S. underwent and subsequently began to recover from the worst recession in decades, that potentially served to worsen an existing upward trend in income inequality. Future analyses may consider a study design that allows for the description of how changes in income inequality over time impact health rather than one summary measure. As mentioned above, the inclusion of time-lagged outcome variables may be an important additional consideration in such a design.

REFERENCES

1. Cynamon, B.Z. and S.M. Fazzari, Inequality, the Great Recession, and Slow Recovery. Cambridge Journal of Economics, 2016. 40: p. 373-399.

2. Saez, E., Striking It Richer: The Evolution of Top Incomes in The United States (Update Using 2006 Preliminary Estimates). 2015, University of California, Department of Economics.

3. Lopez, R., Income inequality and self-rated health in US metropolitan areas: a multi-level analysis. Soc Sci Med, 2004. 59(12): p. 2409-19.

4. Lynch, J.W., et al., Income inequality and mortality in metropolitan areas of the United States. American Journal of Public Health, 1998. 88(7): p. 1074-80.

5. Shi, L. and B. Starfield, Primary care, income inequality, and self-rated health in the United States: a mixed-level analysis. Int J Health Serv, 2000. 30(3): p. 541-55.

6. Leiyu Shi, D., MBA, et al., The Relationship Between Primary Care, Income Inequality, and Mortality in US States, 1980–1995. Journal of the American Board of Family Medicine, 2003. 16(5).

7. Shi, L., et al., Primary care, social inequalities and all-cause, heart disease and cancer mortality in US counties: a comparison between urban and non-urban areas. Public Health, 2005. 119(8): p. 699-710.

8. Yang, T.-C., et al., Using quantile regression to examine the effects of inequality across the mortality distribution in the U.S. counties. Social Science & Medicine, 2012. 74(12): p. 1900-1910.

9. Wilkinson, R.G. and K.E. Pickett, Income inequality and population health: A review and explanation of the evidence. Social Science & Medicine, 2006. 62(7): p. 1768-1784.

10. Centers for Disease Control and Prevention; Monitoring selected national HIV prevention and care objectives by using HIV surveillance data—United States and 6 dependent areas, 2012. 2014, US Department of Health and Human Services: http://www.cdc.gov/hiv/pdf/surveillance_report_vol_19_no_3.pdf. p. 61.

11. Prejean, J., et al., Estimated HIV Incidence in the United States, 2006?2009. PLoS ONE, 2011. 6(8): p. e17502.

12. Denning, P. and E. DiNenno. Communities in crisis: is there a generalized HIV epidemic in impoverished urban areas of the United States. in XVIII international AIDS conference. 2010. Vienna.

13. Vaughan, A.S., et al., Connecting race and place: a county-level analysis of White, Black, and Hispanic HIV prevalence, poverty, and level of urbanization. Am J Public Health, 2014. 104(7): p. e77-84.

14. Johnson, A.S., et al., Trends in diagnoses of HIV infection in the United States, 2002-2011. JAMA, 2014. 312(4): p. 432-4.

15. Holtgrave, D.R. and R.A. Crosby, Social capital, poverty, and income inequality as predictors of gonorrhoea, syphilis, chlamydia and AIDS case rates in the United States. Sex Transm Infect, 2003. 79(1): p. 62-4.

16. Leiyu Shi, D., MBA and M. Barbara Starfield, MPH, The Effect of Primary Care Physician Supply and Income Inequality on Mortality Among Blacks and Whites in US Metropolitan Areas. American Journal of Public Health, 2001. 91(8).

17. Leiyu Shi, D., MBA, et al., Income Inequality, Primary Care, and Health Indicators. The Journal of Family Practice, 1999. 48(4).

18. Petterson, S.M., et al., Projecting US Primary Care Physician Workforce Needs: 2010 -2025

Annals of Family Medicine, 2012. 10(6).

19. Dill, M.J. and E.S. Salsberg, The Complexities of Physician Supply and Demand: Projections Through 2025. 2008, Association of American Medical Colleges.

20. Skarbinski, J., et al., Human immunodeficiency virus transmission at each step of the care continuum in the United States. JAMA Intern Med, 2015. 175(4): p. 588-96.

21. AIDSVu. Emory University, Rollins School of Public Health: www.aidsvu.org.

22. Hall, H.I., et al., Estimation of HIV Incidence in the United States. JAMA : the journal of the American Medical Association, 2008. 300(5): p. 520-529.

23. Centers for Disease Control and Prevention (CDC) and National Center for Health Statistics (NCHS); Compressed Mortality File 1999-2014 on CDC WONDER Online Database. 2008-2013: http://wonder.cdc.gov/.

24. Jones Jr., A.F. and Weinberg, D.H.; The Changing Shape of the Nation's Income Distribution, in Consumer Income, U.S.C. Bureau, Editor. 2000, U.S. Department of Commerce: www.census.gov. p. 11.

25. U.S. Census Bureau; American Community Survey, A.C.S.-Y.E., Table B19083; generated by Lauren Ahlschlager; using American FactFinder; <Error! Hyperlink reference not valid. (December 2015).

26. Area Health Resources Files (AHRF). 2014-2015. US Department of Health and Human Services, Health Resources and Services Administration, Bureau of Health Workforce, Rockville, MD.

27. Kleinbaum, D. and M. Klein, Logistic Regression: A Self-Learning Text. 3rd ed. Statistics for Biology and Health. 2010: Springer-Verlag New York. 702.

28. Code of Federal Regulations (CFR), C., Part 5, Appendix A (October 1, 1993, pp. 34-48) Criteria for Designation of Areas Having Shortages of Primary Medical Care

Professionals [45 FR 76000, Nov. 17, 1980, as amended at 54 FR 8737, Mar. 2, 1989; 57 FR 2480, Jan. 22, 1992].

29. Services, U.S.D.o.H.a.H., The Physician Workforce: Projections and Research into Current Issues Affecting Supply and Demand. 2008: bhpr.hrsa.gov.

30. Pickett, K.E. and R.G. Wilkinson, Income inequality and health: A causal review. Social Science & Medicine, 2015. 128: p. 316-326.

31. Lim, T.W., et al., Community-level income inequality and HIV prevalence among persons who inject drugs in Thai Nguyen, Vietnam. PLoS One, 2014. 9(3): p. e90723.

32. Holmqvist, G; HIV and Income Inequality: If There is a Link, What Does it Tell Us? Stockholm: Institute for Futures Studies International Policy Centre for Inclusive Growth. 2009.

33. Cohen, M.S., Sexually transmitted diseases enhance HIV transmission: no longer a hypothesis. The Lancet. 351: p. S5-S7.

34. Galvin, S.R. and M.S. Cohen, The role of sexually transmitted diseases in HIV transmission. Nat Rev Micro, 2004. 2(1): p. 33-42.

35. Pickett, K. and Wilkinson, R; The Spirit Level: Why Greater Equality Makes Societies Stronger. 2011: Bloomsbury Press.

TABLES AND FIGURES

Table 1. Data sources for all outcomes, predictors and covariates

Variable (Variable Name)	Data Source	Comments
HIV Diagnosis Rate (DXRATE)	Aidsvu.org	Average rate of new HIV diagnoses per 100,000 population, 2008-2013
Mortality Rate (MORTRATE)	CDC Wonder	All-cause age-adjusted mortality rate, 2008-2013
Income Inequality (GINI)	American Community Survey 5-Year Estimates	Average GINI index, 2009-2013
Primary Care Physician Rate (PCP)	Area Health Resource File	Primary care physicians engaged in active patient care, including family medicine, general practice, internal medicine and general pediatrics excluding residents, physicians over 75 years and all other subspecialties, 2010-2013
Poverty Rate (POV)	Area Health Resource File	Average percent of the population living in poverty, 2008-2013
Minority Composition (PCTBLACK)	2010 United States Census	Percent black population, 2010
Educational Attainment (EDU)	Area Health Resource File	Percent of the population with less than a high school education or equivalent, 2009-2013
Urbanicity (URB)	National Center for Health Statistics (NCHS)	Based on the NCHS 2013 Urban-Rural Classification Scheme

Table 2. Characteristics of Outcomes, Exposure and Covariates for All Counties included in Analysis

	n	% in category	mean (SD)	range
HIV diagnosis rate per 100,000, 2008-2013	499	100	20.25 (17.91)	1.94, 156.79
All-cause mortality per 100,000 population, 2008-2013	499	100	785.07 (123.32)	495.03, 1,182.75
Gini Index, National County Quartiles 2009-2013	499	100	45.44 (3.38)	35.67, 59.85
> 75th percentile	219	43.89		
50th - 75th percentile	146	29.26		
25th-50th percentile	75	15.03		
<= 25th percentile	59	11.82		
Primary Care Physicians per 10,000 residents	499	100	7.33 (2.88)	0.76, 18.87
Meets HRSA projected 2010 requirement	94	18.91		
In between	386	77.67		
Below the HRSA shortage area threshold	17	3.42		
Average Poverty Level, 2008-2013	499	100	16.11 (6.15)	3.67, 38.28
20% and above (designated poverty area)	107	21.44		
Less than 20%	392	78.56		
Percent Black, 2010	499	100	17.92 (15.90)	0.45, 79.11
> national 75th percentile (county-level)	289	57.92		
< national 75th percentile (county-level)	210	42.08		
Percent 25+ with less than a HS education, 2009-2013	499	100	14.10 (5.87)	4.00, 38.20
> 75th percentile (> 19.8%)	81	16.23		
50th - 75th percentile (14.1 - 19.8%)	118	23.65		
25th-50th percentile (10.2 - 14.1%)	171	34.27		
<= 25th percentile (<10.2%)	129	25.85		
Urbanicity	499	100	-	-
Large Central Metro	68	13.63		
Large Fringe Metro	139	27.86		
Medium Metro	164	32.86		
Small Metro	84	16.83		
Micropolitan (non-metro)	44	8.82		

Table 3. County-Level Outcome, Independent Variable and Mediating Variable Values by Covariate Levels

		HIV Diagnosis Rate		Age-Adjusted Mortality Rate		Gini Index		Primary Care Physician Rate	
	n	mean (SD)	range	mean (SD)	range	mean (SD)	range	mean (SD)	range
Percent population in poverty									
20% and above	107	31.76 (20.35)	5.23, 117.59	884.24 (122.18)	604.50, 1182.75	48.01 (2.75)	41.85, 55.31	6.16 (2.66)	0.76, 14.68
Less than 20%	392	17.11 (15.81)	1.94. 156.79	758.00 (109.07)	495.03, 1103.65	44.74 (3.20)	35.67, 59.85	7.65 (2.85)	1.47, 18.87
Percent black population									
>= county 75th percentile	289	27.07 (20.17)	6.15, 156.79	829.76 (117.92)	495.03, 1182.75	46.08 (3.63)	36.30, 59.85	7.21 (2.96)	0.76, 18.87
< county 75th percentile	210	10.87 (7.10)	1.94, 62.17	723.57 (102.54)	501.20, 1015.40	44.55 (2.79)	36.40, 53.90	7.49 (2.75)	1.47, 16.96
Adults 25+ with < high school education									
> 75th percentile	81	30.12 (23.02)	5.48, 118.48	863.98 (110.83)	573.72, 1182.75	46.81 (2.67)	36.69, 54.06	5.06 (1.82)	1.18, 10.19
50th - 75th percentile	118	24.84 (18.29)	3.32, 117.59	838.98 (110.83)	501.20, 1050.30	46.09 (3.61)	39.07, 55.31	6.56 (2.40)	0.76, 14.68
25th - 50th percentile	171	18.57 (16.65)	4.43, 156.79	779.61 (99.28)	531.05, 1103.65	45.32 (3.25)	37.30, 59.85	7.65 (2.50)	1.97, 15.40
<= 25th percentile	129	12.08 (9.50)	1.94, 84.55	693.86 (76.69)	495.03, 900.74	44.13 (3.28)	35.67, 53.88	9.03 (3.11)	2.90, 18.87
Urbanicity									
Large Central Metro	68	34.47 (25.85)	8.80, 156.79	743.43 (113.19)	531.05, 1050.30	48.03 (3.27)	41.01, 59.85	8.68 (2.18)	4.04, 15.40
Large Fringe Metro	139	16.82 (16.61)	1.94, 118.48	740.77 (117.93)	495.03, 1082.16	43.09 (3.12)	35.67, 53.31	7.30 (3.14)	1.47, 18.80
Medium Metro	164	15.96 (11.63)	3.17, 64.84	782.37 (105.35)	501.20, 1103.65	45.56 (2.62)	39.44, 53.91	7.63 (2.91)	0.76, 18.87
Small Metro	84	17.06 (13.58)	4.43, 91.35	827.01 (116.30)	581.86, 1040.88	45.69 (2.76)	39.79, 54.57	6.73 (2.59)	2.13, 16.96
Micropolitan & non-metro	44	31.21 (18.63)	6.37, 116.80	919.37 (111.08)	638.77, 1182.75	47.89 (3.02)	40.50, 54.06	5.40 (1.99)	1.18, 10.19

Table 4. Characteristics of Outcomes, Exposure and Covariates for All States

	n	% in category	mean (SD)	range
HIV diagnosis rate per 100,000, 2008-2013	50	100	12.95 (9.11)	2.43, 42.04
All-cause mortality per 100,000 population, 2008-2013	50	100	762.97 (86.10)	598.60, 957.90
Gini Index, National State Quartiles 2009-2013	50	100	45.59 (1.89)	41.43, 50.22
> 75th percentile	12	24.00		
50th - 75th percentile	13	26.00		
25th-50th percentile	13	26.00		
<= 25th percentile	12	24.00		
Primary Care Physicians per 10,000 residents	50	100	7.56 (1.26)	5.28, 10.93
Meets HRSA projected 2010 requirement	3	6.00		
In between	47	94.00		
Below the HRSA shortage area threshold	0	0.00		
Average Poverty Level, 2008-2013	50	100	14.45 (3.09)	8.78, 22.58
Above 2010 National Poverty Rate (15.1%)	23	46.00		
Below 2010 National Poverty Rate (15.1%)	27	54.00		
Percent Black, 2010	50	100	10.33 (9.56)	0.41, 37.02
> national 75th percentile (state-level)	12	24.00		
< national 75th percentile (state-level)	38	76.00		
Percent 25+ with less than a HS education, 2009-2013	50	100	12.41 (3.24)	7.65, 18.83
> 75th percentile	12	24.00		
50th - 75th percentile	13	26.00		
25th-50th percentile	13	26.00		
<= 25th percentile	12	24.00		

Table 5. State-Level Outcome, Independent Variable and Mediating Variable Values by Covariate Levels

		HIV Diagnosis Rate		Age-Adjusted Mortality Rate		Gini Index		Primary Care Physician Rate	
	n	mean (SD)	range	mean (SD)	range	mean (SD)	range	mean (SD)	range
Percent population in poverty									
>= 2010 national poverty rate	23	15.81 (9.18)	2.76, 36.07	812.73 (95.58)	646.80, 957.90	47.03 (1.41)	43.40, 50.50	6.93 (0.87)	5.28, 9.04
< 2010 national poverty rate	27	10.51 (8.46)	2.43, 42.04	720.58 (46.76)	598.60, 828.40	44.98 (1.90)	41.40, 49.20	8.10 (1.31)	5.64, 10.93
Percent black population									
> state 75th percentile	25	24.61 (8.76)	15.24, 42.04	812.68 (97.33)	666.30, 957.90	47.32 (1.64)	44.20, 50.50	6.96 (0.94)	5.28, 8.82
< state 75th percentile	26	9.27 (5.39)	2.43, 22.92	747.27 (77.12)	598.60, 943.00	45.48 (1.87)	41.40, 49.20	7.75 (1.30)	5.64, 10.93
Adults 25+ with < high school education									
> 75th percentile	12	16.64 (7.09)	5.35, 31.65	721.06 (30.31)	657.80, 760.20	43.73 (1.34)	41.40, 45.30	6.55 (0.78)	5.64, 10.93
50th - 75th percentile	13	18.65 (8.51)	9.11, 36.07	719.85 (59.70)	598.60, 821.20	45.66 (1.72)	43.20, 49.20	7.31 (0.93)	6.08, 10.31
25th - 50th percentile	13	11.71 (9.77)	3.29, 42.04	760.53 (73.55)	666.30, 915.10	46.95 (1.59)	44.20, 50.50	8.14 (1.00)	6.31, 9.28
<= 25th percentile	12	4.44 (1.47)	2.43, 7.53	721.06 (30.31)	657.80, 760.20	43.73 (1.34)	41.40, 45.30	8.21 (1.57)	5.28, 7.69

Table 6. Bivariate Relationships between Gini Index and Outcomes, County and State Level

	Effect Estimate[a]	Gini Variable Coefficient	Standard Error	p value	adjusted r^2	Log Likelihood	Deviance /DF
County HIV Diagnosis Rate							
Linear	2.09	2.09	0.218	<.0001	0.1537		
Log-Linear	1.57	0.09	0.008	<.0001	0.1928		
Poisson	1.83	0.12	0.001	<.0001		1,531,887	161
County Mortality Rate							
Linear	4.36	4.36	1.624	0.0075	0.0123		
Log-Linear	1.02	0.00	0.002	0.0291	0.0076		
Poisson	1.00	0.00	0.000	<.0001		90,451,536	405
State HIV Diagnosis Rate							
Linear	2.96	2.96	0.551	<.0001	0.3634		
Log-Linear	1.32	0.27	0.039	<.0001	0.5026		
Poisson	1.20	0.19	0.001	<.0001		2,252,910	856
State Mortality Rate							
Linear	10.79	10.79	6.406	0.0985	0.0362		
Log-Linear	1.01	0.01	0.008	0.1246	0.0286		
Poisson	0.99	-0.01	0.000	<.0001		1,656,682,112	3,254

[a] The linear regression effects presented are the slopes of the linear association, which represent the change in outcome for a 1 point increase in Gini index. Log-linear effect estimates are presented as the mean rate ratio (MRR) which represents the ratio of the outcome variable for a 5-point increase in Gini index for county estimate and a 1-point increase in Gini for state estimates. Poisson effects presented represent the rate ratio (RR) for a given increase in Gini index. All county associations represent 5 point increases in Gini index, while state effects represent changes or ratios of a 1 point increase.

Table 7. Main Exposure and Covariates Interaction Assessment

Model	Results
County Level HIV Diagnosis Rate	No Significant Interaction
County Level Mortality Rate	Significant Interaction Present
GINI and Black Interaction	$p = 0.001$
GINI and Poverty Interaction	$p = 0.012$
GINI and Education Interaction	$p = 0.021$
State Level HIV Diagnosis Rate	No Significant Interaction
State Level Mortality Rate	No Significant Interaction

Table 8. County Confounding Assessment Results

Covariates in the Model	Dropped Terms	adjusted r^2	MRR [a]	95% CI
County HIV Diagnosis Rate				
PCTBLACK, POV, EDU, URB (Full Mode	none	0.5716	1.25	(1.17, 1.35)
PCTBLACK, POV, EDU	URB	0.5178	1.29	(1.21, 1.39)
PCTBLACK, POV, URB	EDU	0.5303	1.25	(1.16, 1.35)
PCTBLACK, EDU, URB	POV	0.5690	1.28	(1.19, 1.37)
POV, EDU, URB	PCTBLACK	0.3856	1.31	(1.20, 1.43)
PCTBLACK, POV	EDU, URB	0.4806	1.31	(1.22, 1.41)
PCTBLACK, EDU	POV, URB	0.5179	1.31	(1.22, 1.40)
PCTBLACK, URB	POV, EDU	0.5094	1.32	(1.22, 1.42)
POV, EDU	PCTBLACK, URB	0.3016	1.39	(1.28, 1.50)
POV, URB	PCTBLACK, EDU	0.3291	1.31	(1.20, 1.43)
EDU, URB	PCTBLACK, POV	0.3748	1.36	(1.25, 1.48)
PCTBLACK	POV, EDU, URB	0.4623	1.39	(1.30, 1.48)
POV	PCTBLACK, EDU, U	0.2462	1.41	(1.30, 1.54)
EDU	PCTBLACK, POV, UI	0.2953	1.43	(1.32, 1.54)
URB	PCTBLACK, POV, EI	0.2811	1.42	(1.30, 1.55)
County Mortality Rate [b]				
PCTBLACK, POV, EDU, URB (Full Mode	none	0.4246		
Black=1, Pov=1, HS=0			1.07	(1.01, 1.14)
Black=1, Pov=0, HS=0			1.00	(0.97, 1.03)
Black=0, Pov=1, HS=0			1.01	(0.94, 1.08)
Black=0, Pov=0, HS=0			0.94	(0.91, 0.97)
BLACK, POV, HS	URB	0.3757		
Black=1, Pov=1, HS=0			1.08	(1.01, 1.15)
Black=1, Pov=0, HS=0			1.00	(0.97, 1.03)
Black=0, Pov=1, HS=0			1.03	(0.96, 1.10)
Black=0, Pov=0, HS=0			0.95	(0.92, 0.99)

[a] MRR represents a 5 point increase in Gini index

[b] County Mortality Rate models include all significant interaction terms, including GINI*PCTBLACK, GINI*POV and GINI*EDU. The urbanicity variable (URB) was the only covariate eligible to be dropped for the confounding assessment order to ensure a hierarchically well formed final model.

Table 9. Effect of Gini index and Covariates on HIV Diagnosis Rate and Age-Adjusted Mortality Rate, Based on Best Model Determinations

	County HIV Diagnosis Rate adjusted r^2 = 0.5716			County Mortality Rate adjusted r^2 = 0.4246		
	MRR	(95% CI)	p value	MRR	(95% CI)	p value
Gini Index [a]						
Main effect model	1.25	(1.17, 1.35)	<.001			
Interaction model						
Black=1, Poverty=1, Education=0				1.07	(1.01, 1.14)	0.021
Black=1, Poverty=0, Education=0				1.00	(0.97, 1.03)	0.865
Black=0, Poverty=1, Education=0				1.01	(0.94, 1.08)	0.811
Black=0, Poverty=0, Education=0				0.94	(0.91, 0.97)	0.001
Percent Black	23.87	(15.61, 36.51)	<.001	0.10	(0.02, 0.53)	0.007
Percent Poverty	1.92	(1.01, 3.64)	0.048	0.05	(0, 0.6)	0.019
Education	2.32	(1.83, 2.94)	<.001	3.65	(1.5, 8.91)	0.005
Urbanicity						
Large Central Metro Indicator	6.34	(2.48, 16.22)	0.000	0.53	(0.41, 0.69)	<.001
Large Fringe Metro Indicator	1.79	(0.70, 4.53)	0.223	0.61	(0.48, 0.78)	<.001
Medium Metro Indicator	0.61	(0.26, 1.42)	0.251	0.77	(0.61, 0.97)	0.029
Small Metro Indicator	0.49	(0.20, 1.19)	0.115	0.91	(0.71, 1.15)	0.417
Gini Index and Black Interaction				1.07	(1.03, 1.11)	0.001
Gini Index and Poverty Interaction				1.07	(1.02, 1.13)	0.012
Gini Index and Education Interaction				0.98	(0.96, 1)	0.021

	State HIV Diagnosis Rate adjusted r^2 = 0.6805			State Mortality Rate adjusted r^2 = 0.4582		
	MRR	(95% CI)	p value	MRR	(95% CI)	p value
Gini Index [b]	1.19	(1.09, 1.30)	<.001	0.97	(0.96, 0.99)	0.004
Percent Black	1.86	(1.38, 2.51)	<.001	1.04	(0.98, 1.11)	0.182
Percent in Poverty	0.70	(0.52, 0.94)	0.021	1.07	(1.01, 1.14)	0.019
Education	1.05	(1.05, 1.44)	0.014	1.06	(1.03, 1.10)	<.001

[a] GINI estimates at the county level represent a 5 point increase in GINI index.

[b] GINI estimates at the state level represent a 1 point increase in GINI index.

Table 10. State Confounding Assessment Results

Covariates in the Model	Dropped Terms	adjusted r^2	MRR [a]	95% CI
State HIV Diagnosis Rate				
PCTBLACK, POV, EDU (Full model)	none	68.05%	1.19	(1.09, 1.30)
BLACK POV	HS	64.17%	1.26	(1.17, 1.37)
BLACK HS	POV	64.78%	1.17	(1.07, 1.28)
HS POV	BLACK	57.22%	1.22	(1.10, 1.35)
BLACK	HS POV	63.29%	1.23	(1.14, 1.32)
HS	BLACK POV	55.27%	1.20	(1.09, 1.33)
POV	BLACK HS	49.53%	1.33	(1.22, 1.46)
State Mortality Rate				
PCTBLACK, POV, EDU (Full model)	none	45.82%	0.97	(0.96, 0.99)
BLACK POV	HS	29.84%	0.99	(0.97, 1.01)
BLACK HS	POV	40.01%	0.98	(0.96, 0.99)
HS POV	BLACK	44.83%	0.97	(0.96, 0.99)
BLACK	HS POV	11.66%	1.00	(0.99, 1.02)
HS	BLACK POV	38.45%	0.98	(0.96, 1.00)
POV	BLACK HS	25.46%	1.00	(0.98, 1.01)

[a] MRR represents a 1 point increase in Gini index.

Table 11. Analysis of Mediating Effect of Primary Care on HIV Diagnosis Rate and Age-Adjusted Mortality Rate

	Full Model			Mediation Model			Change in MRR
	MRR	(95% CI)	p value	MRR	(95% CI)	p value	
County HIV Diagnosis Rate	1.25	(1.16, 1.35)	<.0001	1.33	(1.22, 1.44)	<.0001	5.6%
County Mortality Rate							
Black=1, Poverty=1, Education=0	1.01	(1.01, 1.14)	0.021	1.07	(1.02, 1.16)	0.0064	5.6%
Black=1, Poverty=0, Education=0	1.00	(0.97, 1.03)	0.865	1.00	(0.99, 1.06)	0.2119	0.2%
Black=0, Poverty=1, Education=0	1.00	(0.94, 1.08)	0.811	1.01	(0.95, 1.09)	0.5452	0.7%
Black=0, Poverty=0, Education=0	0.99	(0.91, 0.97)	0.001	0.94	(0.92, 0.99)	0.0223	-5.0%
State HIV Diagnosis Rate	1.23	(1.09, 1.38)	<.001	1.25	(1.10, 1.42)	0.0015	1.8%
State Mortality Rate	0.97	(0.95, 0.99)	0.004	0.98	(0.96, 1.00)	0.0253	0.7%