Issues in Political Economy, Vol 28(2), 2019, 46-67

The Effect of Income Inequality on HIV/AIDS Incidence Rates
Jash Patel, The College of New Jersey

I. Introduction

It is evident that absolute poverty is strongly associated with poor outcomes in health, and there have been countless studies performed to substantiate this claim. Generally speaking, there is a strong association between poverty and ill health, i.e. wealthier countries and wealthier individuals enjoy better health, and many researchers have had the same expectation about human immunodeficiency virus (HIV) and acquired immunodeficiency syndrome (AIDS), which has often been described as a disease of poverty (Subramanian & Kawachi, 2004). However, there is one fundamental difference between HIV/AIDS and other health problems generally linked with poverty. Unlike diseases like tuberculosis and malaria, HIV is a socially transmitted disease and is mostly transmitted through sex. This brings into play the economic perspective around risk and reward, which influences the extent to which individuals are able to make and exercise choices about sexual behavior, and which can be exacerbated by greater poverty (Piot et al. 2007).

While a relationship can be found between simple socioeconomic factors and HIV incidence, there seems to be a myriad of factors that work in conjunction to explain differences in HIV/AIDS incidence in different areas. Global evidence, especially from Africa, suggests that the relationship between poverty and HIV risk is complex, and that absolute poverty on its own cannot be viewed simplistically as a driver of the HIV epidemic. Rather, its role appears to be multidimensional and to interact with a range of other factors, including mobility, social and economic inequalities, and social capital. Studies have found that greater inequality is associated with higher HIV incidence rates in Africa, Latin America, and Asia (Kim et al. 2008). However, the complex and reciprocal relations between macroeconomic policies and HIV/AIDS are only beginning to be explored, especially in the United States, where the epidemic has not been as much of a major concern as in other countries.

In general, most analyses of the links between poverty and HIV/AIDS have focused on examining direct links between income and levels of HIV infection. However, this link is much more unique for the United States because there seems to be a more nuanced picture of the many ways in which risk, environment, and wider circumstances that surround poverty are equally relevant in shaping vulnerability to HIV. These factors combine uniquely for the United States because unlike other countries where HIV/AIDS is more widespread, the United States is highly developed, meaning the risk factors that are present in other countries and make their people more vulnerable to HIV transmission simply are not present in the United States. Additionally, in contrast to the generalized epidemic of sub-Saharan Africa where communities are demographically similar, the US HIV epidemic is concentrated in distinct geographical regions, with most affected Americans either living in urban centers of the east and west coasts or in major cities and small towns throughout the south. Within the cities hit hardest by HIV infection, impoverished neighborhoods are far more affected than are more affluent areas (Pellowski et al 2013). The differences between the countries studied in previous literature and the United States is striking, yet the HIV/AIDS incidence rates between the United States and other countries is comparable, suggesting that while the risk factors that manifest so distinctly in other countries is more nuanced in the United States, those factors may still have an effect on incidence rates in the country, and may explain the disparities in incidence rates that exist in different communities within the United States.

This study will use US Census data as well as HIV/AIDS data from the Center for Disease Control from each of the 50 states from 2010-2016 to attempt to delineate how social determinants of health, in particular income inequality, and the average GDP per household, the proportion of unemployed adults in the labor force, the proportion of people of each race, the proportion of people with different education levels, the proportion of men per women, and the proportion of adults 18 years and older affect HIV incidence rates to determine if there is a significant link between income inequality and HIV/AIDS incidence rates in the United States, and if there is such a link, why unequal societies would be more vulnerable to HIV.

II. Background

HIV transmission is a biological event that is largely dependent on social context and behavioral practices, and it has long been established that HIV transmission is a function of four interrelated factors: local HIV prevalence, individual behaviors, biological factors, and social conditions (Pellowski et al 2013). While HIV/AIDS has been a major concern in the United States for decades and the heath disparities in HIV/AIDS are recognized, they often are not discussed, and when they are, the policies put into place tend to focus largely on individual behaviors and biological factors rather than on social conditions, despite the disease being concentrated overwhelmingly in socially marginalized communities (Pellowski et al 2013). Changing individual-level behaviors can result in some overall change in HIV/AIDS incidence rates, but these changes may be insufficient in aiding the large-scale community. As a result, examining population factors, such as income inequality, may provide insight into the disparate rates of HIV/AIDS incidence rates in different areas of the country. The establishment of a link between population factors such as income inequality and HIV/AIDS incidence rates will also suggest that a policy change is needed to combat socially transmitted diseases like HIV/AIDS, especially since today, President Trump's continued proposals to heavily reduce America's spending on HIV pose a significant threat to the progress that has been made to combat the epidemic to date, and may be especially harmful for poorer populations, who are in most need of access to treatment for the disease.

Income inequality, among other social conditions such as poverty and discrimination, facilitate HIV transmission by influencing local HIV prevalence as well as an individual's risk behaviors. For example, increased economic stress for populations living in communities with high income inequality can cause relationship instability and contribute to sexual partner mixing patterns that foster HIV transmission (Pellowski et al 2013). Additionally, access to health care offers the potential to alleviate multiple sources of HIV transmission risk by reducing infectiousness through antiretroviral therapy and decreasing susceptibility through mental health, substance use, and STI treatment, but impoverished populations living in communities with high income inequality may have limited access to quality health care to alleviate these risks. The United States has undoubtedly worked to combat HIV/AIDS transmission, but by focusing on certain risk factors over others, like income inequality, the country may never be able to completely eradicate the disease.

While HIV/AIDS is certainly an epidemic in the United States, incidence rates, especially in certain states like Montana and Nebraska, are much lower than in countries like Africa and transmission has been contained to certain communities. As a result, incidence rates per 100000 people in a given state were used to measure HIV/AIDS incidence to broaden the application of the data and to more clearly demonstrate any relationships between income inequality and incidence rates.

In measuring economic inequality, the academic community has primarily employed the Gini coefficient. This measure is equivalent to the ratio of two integration calculations on a graph of two curves: one representing actual income inequality and the other, perfect income equality (Figure 1). The first component of the ratio involves the area between the line representing full income equality, where each income decile has an equivalent share of wealth, and the Lorenz Curve, which represents the actual distribution of income in a given society. When taken as a fraction of the entire area underneath the curve representing full equality, the resulting ratio is termed the Gini coefficient, which is expressed as a decimal that can range from 0 to 1, with a higher value signifying greater inequality. The simplicity of the calculation broadens its application, with numerous studies showing the benefits of using such a measure in conjunction with health outcomes, cementing the coefficient's credibility as an analytical tool.

The Gini coefficient has also been the chief measure in a number of studies assessing the relationship between income inequality and mortality as well as with self-rated health (Lopez, 2004). One inherent shortcoming of this measure, however, lies in the scope of what it measures. While as an overall measure, it "incorporate[s] the range and distribution of incomes with the extent of inequality," it cannot give a complete picture as to whether other moderating factors such as race, ethnicity and socioeconomic status (among other variables) play a role in the association (Karriker -Jaffe, Roberts & Bond, 2013). Considering its well-established usage, adding controls for such variables into any model of income inequality and health outcomes consequently proves imperative to understanding the power of such a relationship.

In this particular study, the final model controlled for race and ethnicity and found a significant correlation between HIV/AIDS incidence and the proportion of Asians living in a given state. The Asian population was looked at specifically because in many Asian cultures, sex is seen as taboo, and many people in Asian communities refrain from getting involved in sexual relations. If they do, they are mostly contained within their own Asian communities (Choi et al. 1998). Because HIV/AIDS is transmitted sexually, one would expect transmission rates to be much lower in areas with higher Asian populations. In terms of socioeconomic status, average GDP per capita, the proportion of people who were uninsured, and the proportion of people who were unemployed were used to control for any effects from absolute poverty and barriers to prevention of HIV/AIDS transmission. Differences in education level were also added, as individuals with lower education tend to have lower incomes and subsequently are more impoverished than individuals who go on to pursue higher education. Finally, as HIV/AIDS has been known to be more prevalent in males than in females and in adults rather than in children, the sex ratio and the proportion of people who were 18 years and older in a given state were used to control for any additional effects on HIV/AIDS transmission.

III. Literature Review

Although the evidence of associations between socioeconomic status and the spread of HIV/AIDS in different settings and at various stages of the epidemic is still rudimentary, especially in the United States, there have been several studies that have attempted to find a relationship between income inequality and HIV incidence in different African countries using the Gini Coefficient as the independent variable and HIV incidence as the dependent variable. For example, Stuart Gillespie found that HIV incidence generally tends to raise as the Gini coefficient, and thus income inequality, rises (Gillespie et al. 2007). However, the paper concluded that the association between the two variables is much more complex and context-specific than implied by the model. While it is true that poor individuals and households are likely to be hit harder by the downstream impacts of HIV/AIDS, their chances of being exposed to HIV in the first place are not necessarily greater than wealthier individuals or households. Instead, it is clearer that approaches to HIV prevention need to cut across all socioeconomic strata of society and they need to be tailored to the specific drivers of transmission within different groups, with particular attention to the dynamic nature of the relationship between socioeconomic status and HIV.

Further studies into this dynamic nature have shed more light on the link between social determinants like income inequality and HIV incidence and the theories and models that fit the link. Different mechanisms through which income inequality affects HIV have been constructed as a result of these studies, with three major hypotheses proposing potential pathways from income inequality to increased HIV/AIDS transmission.

The first potential pathway is that income inequality leads to HIV through the economics of sexual behavior. Oster created an economic theory and model of sexual behavior to explain why poor people would be less inclined to adjust their behavior when facing the risk of HIV, basing her idea on the presumption that utility is maximized by an individual over two periods, and the chance of surviving to the second period is determined by the risk of being infected with HIV in the first period, as well as by other mortality risks not related to HIV (Oster 2012). Poor people are more exposed to a high risk of dying for reasons unrelated to HIV, a circumstance that decreases the expected loss associated with the risk of being infected by HIV. Similarly, being richer and having fewer mortality risks means that an individual places greater value on his life in the second period, and thus is less inclined to put it at risk during the first period. Looking at Oster's theory in context of the United States, while there are populations that are poorer than others, the American people are generally more well off than populations in places like Africa. Because wealthier people would be less willing to put their life at risk, it would follow that US populations would be more willing and able to rapidly change their sexual conduct as HIV became known and would explain why HIV continues to run rampant in places like Africa, where people are relatively worse off, but seems to be somewhat contained in the US. As a result, income inequality in the US could have a limited effect on HIV/AIDS incidence rates because the general wealth level in the US puts the American people in a position where they can easily change their behavior, regardless of their relative wealth level in the country.

An extension to Oster's model is that there would also be a link between income inequality and risky sexual conduct if there were an element of economic transaction, such as prostitution, involved (Holmqvist 2009). To further explain, a utility-maximizing individual would engage in transactional sex as a "seller" if the utility of the benefits, i.e. the transactional sex income, outweighs the expected utility lost, which is partially determined by the risk of being infected and therefore not surviving to the second period. The marginal utility of income is higher the pooper people are, so the transactional sex income has greater weight in the utility function of the poor. Being poorer also entails a higher mortality risk due to factors other than HIV/AIDS in the second period, as mentioned previously, and hence is associated with a lower expected loss from being infected in the first period. More poverty thus leads to more people being ready to engage in risky behavior, such as transactional sex, and facing a greater likelihood of contracting diseases like HIV/AIDS (Holmqvist 2009). On the other hand, people engage in transactional sex as a "buyer" if the pleasure they derive from it outweighs the lost utility from it, which is determined by the price for transactional sex plus the expected utility loss from increased risk of not surviving to the second period. As a result, the wealthier a person is, the more likely they are to act as the "buyer" because being richer means being able to afford more transactional sex without being hurt as much economically. Therefore, with higher levels of income inequality, it is expected that more poor people are ready to engage in transactional sex for a given price, and perhaps also that more rich people are able and ready to enter the transactional sex market as buyers.

Looking at the United States, while the illegal nature of transactional sex makes it difficult to gather population-level data on HIV risk, it has been found that the risk of HIV, among other sexually transmitted diseases, is high among people who engage in transactional sex due to a multitude of sexual risk factors that exist exclusively for people who engage in transactional sex. The "sellers" may receive more money for sex without a condom and may use condoms less often with regular clients, who would more likely be part of a wealthier population, than with one-time clients. The power dynamics present in transactional sex, especially within communities where income inequality are highest, may also make it difficult for people who "sell" sex to negotiate condom use. As a result, communities with higher income inequality create an intersection for all of these risks, subsequently increasing the risk of spreading HIV.

While determining the precise strength of the link between risk behavior and HIV is demanding because of issues of both data availability and reverse causality, Holmqvist was able to create a model that establishes a link from income inequality to risky sexual behavior (Holmqvist 2009). He found that income inequality is significantly and positively correlated with many indicators of risk behavior, such as having multiple partners or having commercial sex. When substituting HIV incidence for an indicator of risky behavior as a dependent variable, Holmqvist was also able to confirm income inequality as a significant predictor of HIV incidence.

The second pathway suggests that reduction in social capital can also lead to higher HIV incidence. Social capital has been related to a number of important public health variables such as child welfare, mortality, and health status. However, the relation of social capital to infectious diseases, such as HIV, has received relatively little attention. There are numerous ways of defining social capital, but the elements usually included in the definitions are trust, norms, reciprocity, and cooperation among members of a social network, enabling collective action in pursuit of a shared goal (Barnett and Whiteside 2006). Socially cohesive societies are assumed to be better able to mobilize resources in pursuit of joint goals and to avoid or control risk. In regards to HIV transmission, this could mean establishing common norms in a community to uphold certain rules of sexual behavior for socially cohesive societies and shared values being lost as a result of social divides and mutual support mechanisms being undermined in socially non-cohesive societies (Barnett and Whiteside 2006). In other words, societies with greater income inequality may be more likely to have many more social divisions in place, resulting in fewer common norms and support systems for diseases like HIV/AIDS, perhaps making them more vulnerable to increased transmission rates. The relation between social capital is especially interesting to explore because while social capital would seem to build the social infrastructure for a community to prevent and respond to infectious disease outbreaks, higher levels of trusting social interactions also could lead to increased opportunities for disease transmission.

The link between social capital and income inequality is quite well established empirically, but the link between social capital and HIV is more problematic, as with sexual behavior, the causal relationship is likely to work in both directions (David 2010). Studies have concluded that a relationship between social capital and HIV exists, though the variables used to measure HIV and social capital may not have been of the best quality. Studies based on US states have confirmed a social capital-HIV link while in places like South Africa, the results have been mixed, depending on the character of the group or network (David 2010). While these studies are very rudimentary because of limited access to information, in the future, larger samples and access to a wider range of indicators of social capital should be available, in addition to instrumental variables or time series data to address the issue of direction of causality.

Finally, some models have proposed that income inequality may lead to higher HIV incidence through poor public sector performance. Inequality is associated with lower tax revenue and hence lower public expenditures, and so one hypothesis could be that an inequality-health link operates through a weakened public sector performance in delivering social services (Mellor and Milyo 2002). In regards to HIV incidence, a weak public health system might be less able to organize efficient HIV testing, to treat STDs, and to manage successful public awareness campaigns, all of which are believed to be important in counteracting the spread of HIV (Mellor and Milvo 2002).

Looking at the United States specifically, the healthcare system in place overwhelmingly supports wealthier populations in favor of impoverished ones. While programs like Medicare and Medicaid exist to support impoverished populations, recipients of the programs often only have access to certain hospitals and doctors' practices, and they often live in areas in which the institutions and programs they have access to are not nearly the same high-quality access wealthier populations have. Additionally, routine HIV/AIDS testing is optional in a number of US states, so states with greater income inequality may opt not to cover HIV/AIDS testing under Medicaid because of lack of funding from lower tax revenues (Holtgrave and Crosby 2003). This may place impoverished communities at more risk of spreading HIV because they may contract and spread the disease without ever knowing they have it.

IV. Data

This study analyzes the relationship between HIV/AIDS incidence rates and state-level Gini coefficient data across the United States in recent years. Gini coefficient data and demographic information were extracted from data collected by the U.S. Census Bureau from the years 2010 through 2016. The US Census Bureau collects data from all 50 states via a comprehensive survey covering a range of topics, including information on health behaviors, medical service usage, and socioeconomic characteristics. HIV outcome measures were obtained from the Center for Disease Control.

A. Dependent Variables

The dependent variable in this model is HIV incidence. Data was collected through cross-sectional data obtained from the Center for Disease Control, showing HIV incidence per 100,000 people in each state in a given year, as HIV incidence is relatively rare in the United States.

B. Independent Variables

The US Census Bureau provides an extensive set of variables for control purposes, including sex, age, race, health insurance status, education level, and household size, all of which have been correlated in previous studies with general health. Race and ethnicity were controlled for using the percent of the population that fell under each of the standard classifications (White, Black, Asian, Alaska native/American Indian, Native Hawaiian/Pacific Islander, or Other, which included individuals who identified as multiracial) in each state. Education and employment variables were stratified into separate categories based on the highest level of degree acquired (No High School, Some High School, High School Graduate, Some College, College or More). GDP per capita was taken as the average household income in each state to control for absolute poverty in each state. The percent of habitants in each state who were uninsured further controlled for income's effect on each health outcome. Sex was controlled for by using the sex ratio, the number of males per 100 females, in each state, as HIV has been predominantly transmitted within the male community. Unemployment data was taken from the Bureau of Labor Statistics as the percent of the labor force unemployed in each state during each year. A squared term of the Gini Coefficient was also added to determine if the relationship between income inequality and HIV/AIDS incidence changed as income inequality increased.

C. Sample and Methods

ID values were created for each state and year in the study to more easily study any relationships while controlling for state and year effects. Because HIV is relatively scarce in some areas of the United States, there was not enough data available for HIV incidence rates in certain states (North Dakota, Vermont, and Wyoming), and so any variables associated with those states were dropped. Additionally, any variables associated with Washington D.C. were dropped, as the HIV incidence rates associated with the area were much higher than in any other state, creating outliers in the dataset. Any data collected from off-shore U.S. territories were excluded from the sample as well. After cleaning the dataset, a total of 323 observations from 46 states over the years 2010 to 2016 were collected. Additionally, after running preliminary tests, many of the control variables used were found to have statistically insignificant relationships with HIV/AIDS incidence rates but were kept in the model to avoid any omitted variable biases. The final general model for HIV incidence rates included 16 control variables. The model was eventually specified as follows:

$$(1) \quad HIVINC_{st} = \beta_0 + \beta_1 GINI_{st} + \beta_2 GINISQU_{st} + \beta_3 GDPPERCAPITA_{st} + \beta_4 UNINSURED_{st} + \beta_5 OLDERTHAN18_{st} + \beta_6 SEXRATIO_{st} + \beta_7 UNEMPLOYED_{st} + \beta_8 RACE_{st} + \beta_9 EDUCATION_{st} + \beta_9 YEARTREND_s + \beta_{10} STATECONTROLS_t + a_s + E_{st}$$

where *HIVINC* is the HIV incidence per 100,000 people in state *s* at time *t* and a_s accounts for any fixed effects due to variables not related to any explanatory variable. The *RACE* and *EDUCATION* terms represent individual variables for each classification as outlined in greater detail in the Appendix. As HIV/AIDS incidence seems to depend entirely on social context, factors that affect social context, as the ones included in the model, should affect incidence rates.

A fixed effects model was used in favor of a random effects model because a random effects model assumes that any unmeasured variables are not correlated with the independent variables included in the regression model. However, as previous literature has suggested, there seem to be a myriad of factors that work in conjunction to affect HIV/AIDS incidence rates, meaning it is more probable that they are correlated with each other. The Hausman Test for Random Effects, which rejected the null hypothesis that a random effects model was appropriate to use at the 0.05 significance level, was used to confirm the use of a fixed effects model. The Hausman Test detects if there is endogeneity, or a correlation between the error terms and the dependent variables in the model, with the null hypothesis stating that there is no correlation, suggesting that a random effects model is preferred, and the alternate hypothesis stating that there is a correlation, suggesting that a fixed effects model is preferred. Endogeneity in a model suggests that an omitted variable is confounding both independent and dependent variables, or that the independent variables are measured with too much error. The Hausman Test confirmed that the random effects model exhibited endogeneity, making it an unfit model when compared to a fixed effects model. While using a fixed effects model makes it harder to generalize the results beyond this study, it was proven to create a better model.

A CAUSALTRT procedure (PROC CAUSALTRT) was also administered to estimate any causal treatment effects between income inequality and HIV/AIDS incidence rates. PROC CAUSALTRT combines some of the functionalities of the randomization process to compute the causal effect for an observational study, and so in terms of this study, the procedure was used to find the causality of income inequality on HIV/AIDS incidence rates. The CAUSALTRT procedure estimates two types of causal effects for a binary treatment on an outcome, where the outcome can be continuous or binary. These two types are the average treatment effect (ATE), which is the causal effect of the treatment within the entire study population, and the average treatment effect for the treated (ATT), which is the causal effect of the treatment within the subset of the study population that is in the treatment condition. In an observational study, such as this one, the subjects are assigned to treatments through a non-randomized process. In this study, the treatment consisted of two levels of inequality where one was deemed as “control”, while the other was treated as the “treatment”. The average Gini coefficient value of 0.458 was used as the threshold value to determine any differentiating effects of income inequality on HIV/AIDS incidence rates between values above and below this value, with values above the threshold being placed in the control group and values below the threshold being placed in the control group. A value of 1 was given to any values above this threshold value and a value of 0 was given to any values below this threshold. All statistical testing was performed using SAS 9.4.

V. Results & Discussion

Descriptive statistics (mean, standard deviation, minimum, and maximum) for each of the dependent and independent variables employed are shown in Table 1, with a further explanation of the variable definitions in the Appendix. Coefficient estimates for the panel estimation with fixed effects, along with their standard errors, sample sizes and adjusted R^2 values are displayed in Table 2 for the panel estimation, and individual state effects are outlined in Table 3, giving further support to previous hypotheses about the relationship between income inequality and HIV/AIDS incidence rates. Results from the CAUSALTRT procedure, demonstrating any causal effects, are given in Table 4.

After controlling for the appropriate measures, HIV/AIDS incidence rate was found to have a positive relationship with the Gini coefficient and a negative relationship with the squared term of the Gini coefficient, both significant at a 0.01 significance level. Specifically, a one point increase in the Gini coefficient was expected to correlate with a 964.24 person increase in HIV/AIDS incidence rates per 100000 people (Table 2). As the Gini coefficient was scaled between 0 and 1 and the Gini coefficients were all within 0.1 point of each other, a more apt interpretation would be that a 0.01 point increase in the Gini coefficient was expected to correlate with an 9.642 person increase in HIV/AIDS incidence rates. A one point increase in the squared term of the Gini coefficient was expected to correlate with a 1014.5 person decrease in HIV/AIDS incidence rates per 100000 people (Table 2). Again, a more suitable interpretation would be that a 0.01 increase in the squared term was expected to correlate with a 10.15 person decrease in HIV/AIDS incidence rates. When used in conjunction, these two relationships demonstrate that while HIV/AIDS incidence rates are expected to rise as income inequality and the Gini coefficient rise, it does so at a decreasing rate, being affected less at higher values of the Gini coefficient than at lower values.

Interestingly, when running the CAUSALTRT procedure to determine any significant differences between lower and higher values of the Gini coefficient, a negative estimate was found for both the average treatment effect (ATE), for the entire sample, and the average treatment effect for the treated (ATT), for higher values of the Gini coefficient. The ATE estimate was -2.3910 and was significant at the 0.001 significance level, indicating that on average, a state with a Gini coefficient above the threshold value of 0.458 would decrease the HIV/AIDS incidence rates in that state by approximately 2.391 people per 100000 people (Table 4). The ATT estimate was -0.3789 and while it was statistically insignificant, the negative values still suggests that even when looking at only high values of the Gini coefficient, HIV/AIDS incidence rates are still expected to fall for higher values of the Gini coefficient (Table 4). This is particularly surprising given the literature and this study indicating a positive relationship, but may be explained by the limitations of data points available as well as the low variability in the Gini coefficient independent variable.

VI. Conclusion

There have been several studies focused on the effect of income inequality on general health, all finding convincing empirical support and a very strong correlation between higher income inequality and a lower quality of health. Using 2010-2016 CDC data and state-level Gini coefficient data from the US Census Bureau as well as control variables used in previous studies to determine relationships between income inequality and health, this study was able to generalize the effect of income inequality on HIV/AIDS incidence rates. The data suggest that a strong positive relationship exists between income inequality on HIV/AIDS incidence rates, with the effects of income inequality decreasing for increasing values of the Gini coefficient. As public policy has focused on eradicating the HIV/AIDS epidemic in the United States, especially recently, the results of this study suggest that perhaps an effective preventative measure would be to implement policies that eradicate income inequality present in certain communities rather than polices that plan to eradicate the disease itself, which seem to have proved to be futile. This would mean implementing more policies that plan to reduce the persistent barriers to social and monetary mobility that lower income individuals face, which could at least in the short-term, lead to lower HIV/AIDS incidence rates.

Future research could attempt to see if these relationships hold up in different countries. While this study was originally focused on determining the effect of income inequality on HIV/AIDS incidence rates in developing countries versus already developed countries, enough data could not be found for enough countries to provide any meaningful results. By following the same procedures as done in this study, different relationships between the two variables could be found in different countries and perhaps shed more light on how different factors work in conjunction to spread the HIV/AIDS epidemic. As HIV/AIDS seems to even be contained within certain communities within certain states, a further study could use Gini coefficient data from different cities, further isolating the impact of income inequality, and providing a more accurate representation of the relationship between income inequality and HIV/AIDS incidence rates.

VII. References

Berndt, Donald J., Fisher, John W., Rajendrababu, Rama V., & Studnicki, James. "Measuring healthcare inequities using the Gini index." *Proceedings of the 36th Annual Hawaii International Conference on System Sciences*, (2003)

Choi, K.-H., Yep, G. A., & Kumekawa, E. "HIV Prevention Among Asian and Pacific Islander American Men Who Have Sex With Men: A Critical Review of Theoretical Models and Directions for Future Research." *AIDS Education and Prevention 10*, no. 3 (1998): 19-30.

David, Antonio C and Li, Carmen. "Exploring the Links Between HIV/AIDS, Social Capital and Development." *The Journal of International Development 2*, no. 4 (2010)

Gant, Z et al. "A Country-Level Examination of the Relationship Between HIV and Social Determinants of Health: 40 States, 2006-2008" *open AIDS journal 6* (2012): 1-7.

Gillespie, Stuart et al. "Is Poverty or Wealth Driving HIV Transmission?" *AIDS 3* (2007).

Grönqvist, Hans et al. "Income Inequality and Health: Lessons from a Refugee Residential Assignment Program." *Journal of Health Economics 31*, no. 4 (2012): 617-629.

Holmqvist, Göran. "HIV and Income Inequality: If There is a Link, What Does it Tell Us?" *International Policy Centre for Inclusive Growth* 2 (2009).

Holtgrave, D and Crosby, R. "Social Capital, Poverty, and Income Inequality as Predictors of Gonorrhea, Syphilis, Chlamydia, and AIDS Case Rates in the United States." *Sexually Transmitted Infections 79* (2003): 62-64.

Karriker-Jaffe, K. J., CM Roberts, S., & Bond, J. (2013). "Income Inequality, Alcohol Use, and Alcohol-Related Problems." *American Journal of Public Health 103*, no. 4 (2013): 649-656.

Kim, Julia et al. "Exploring the Role of Economic Empowerment in HIV Prevention" *AIDS 22*, no. 22 (2008): 57-71.

Lachaud, Jean-Pierre. "HIV Incidence and Poverty in Africa: Micro- and Macro-Econometric Evidences Applied to Burkina Faso." *Journal of Health Economics 26*, no. 3 (2007): 483-504.

Lim, Travis W et al. "Community-Level Income Inequality and HIV Incidence Among Persons who Inject Drugs in Thai Nguyen, Vietnam." *PLOS Medicine 9*, no. 3 (2014).

Lopez, R. "Income Inequality and Self-Rated Health in US Metropolitan Areas: A Multi- Level Analysis." *Social Science & Medicine 59*, no. 12 (2004): 2409-2419.

Mellor, Jennifer M and Milyo, Jeffrey. "Income Inequality and Health Status in the United Sates: Evidence from the Current Population Survey." *The Journal of Human Resources 37*, no. 3 (2002): 510-539.

Oster, Emily. "HIV and Sexual Behavior Change: Why Not Africa?" *Journal of Health Economics 31*, no. 1 (2012): 35-49.

Pellowski, J.A. et al. (2013). "A Pandemic of the Poor: Social Disadvantage and the US HIV Epidemic". *The American Psychologist 68*, no. 4 (2013): 197-209.

Piot, Peter et al. "Squaring the Circle: AIDS, Poverty, and Human Development" *PLOS Medicine 21*, no. 2 (2007): 5-16

VIII. Tables

Table 1. Summary Statistics

Variable	Mean	Standard Error	Min	Max
Dependent Variable				
HIV Incidence	10.395	5.663	1.7977	25.915
Independent Variables				
Scaled Gini Coefficient	0.458	0.019	0.410	0.510
Scaled & Squared Gini Coefficient	0.210	0.017	0.164	0.260
GDP per Capita	44030.1	7525.28	30948	69547
Uninsured	16.782	6.446	4	32
18 and Older	76.733	1.965	68.5	80.9
Sex Ratio	97.313	2.919	93.1	111.2
Unemployed	6.832	2.048	2.9	13.5
Asian	4.387	6.161	0.656	42.44
White	80.59	11.942	27.97	96.49
Black	11.02	9.077	0.38	36.07
American Indian/Alaska Native	1.62	2.614	0.22	13.7
Native Hawaiian	0.37	1.337	0.03	9.43
Other Race	0.02	0.026	0.01	0.19
No High School	4.75	1.617	1.9	10.5
Some High School	7.41	1.85	4.1	12.4
High School Graduate	29.06	4.07	20.5	41.6
Some College	21.73	2.928	15.5	29.9
College or More	37.07	6.7	22.3	55.4
N	323			

Table 2. Panel Estimation for Dependent Variable with Fixed Effects Model

	HIV Incidence
Scaled Gini Coefficient	964.24**
	(281.4)
Squared and Scaled Gini Coefficient	-1014.5**
	(437.2)
GDP per Capita	-0.00007
	(0.00008)
Uninsured	0.0491^{+}
	(0.027)
18 and Older	0.622*
	(0.269)
Sex Ratio	0.798***
	(0.021)
Unemployed	-0.075
	(0.131)
Asian	-1.144***
	(0.38)
White	-0.072
	(0.09)
Black	-0.118
	(0.0918)
American Indian/Alaska Native	-0.399*
	(0.199)

Table 2. Panel Estimation for Dependent Variable with Fixed Effects Model (Continued)

	HIV Incidence
Native Hawaiian	-1.352
	(0.874)
Other Race	41.514
	(33.716)
No High School	-0.54319
	(1.017)
Some High School	-0.27992
	(1.017)
High School	-0.36032
	(0.999)
Some College	-0.60616
	(0.999)
College or More	-0.66325
	(0.985)
Constant	-239.22**
	(89.928)
N	323
Adjusted R^2	0.973

Notes: 1. Standard errors are shown in parentheses
2. $^+$ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table 3. Panel Estimation of Individual State Effects

State	HIV Incidence
Alabama	9.332***
	(0.846)
Alaska	1.024
	(1.16)
Arizona	7.025***
	(0.75)
Arkansas	5.599***
	(0.787)
California	11.376***
	(0.895)
Colorado	3.308***
	(0.735)
Connecticut	7.446***
	(1.008)
Delaware	7.307***
	(0.655)
Florida	22.624***
	(0.894)
Georgia	21.351***
	(0.856)
Hawaii	3.371***
	(0.632)
Idaho	-1.933*
	(0.932)
Illinois	8.74***
	(0.835)

Table 3. Panel Estimation of Individual State Effects (Continued)

State	HIV Incidence
Indiana	4.244***
	(0.637)
Iowa	-0.798
	(0.69)
Kansas	0.014
	(0.695)
Kentucky	4.079***
	(0.815)
Louisiana	20.219***
	(0.93)
Maine	0.342
	(0.81)
Maryland	17.424***
	(0.66)
Massachusetts	8.746***
	(0.877)
Michigan	3.734***
	(0.733)
Minnesota	1.443*
	(0.644)
Mississippi	10.996***
	(0.877)
Missouri	4.077***
	(0.734)
Montana	-1.459^{+}
	(0.957)

Table 3. Panel Estimation of Individual State Effects (Continued)

State	HIV Incidence
Nebraska	0.412 (0.729)
Nevada	11.433*** (0.655)
New Hampshire	-1.162 (0.843)
New Jersey	9.061*** (0.825)
New Mexico	3.845*** (0.825)
New York	20.276*** (1.336)
North Carolina	11.139*** (0.816)
Ohio	3.946*** (0.761)
Oklahoma	3.724*** (0.765)
Oregon	1.714* (0.712)
Pennsylvania	4.752*** (0.775)
Rhode Island	5.817*** (0.828)

Table 3. OLS Estimates for Individual State Effects (Continued)

State	HIV Incidence
South Carolina	10.826***
	(0.788)
Tennessee	9.725***
	(0.848)
Texas	14.262***
	(0.871)
Utah	0.255
	(0.771)
Virginia	7.751***
	(0.769)
Washington	3.561***
	(0.664)
West Virginia	0.117
	(0.773)
Wyoming	-24.22**
	(8.923)
N	323
Adjusted R^2	0.973

Notes: 1. Washington, D.C., North Dakota, Vermont, and Wyoming are excluded
2. Standard errors are shown in parentheses
3. $^{+}$ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

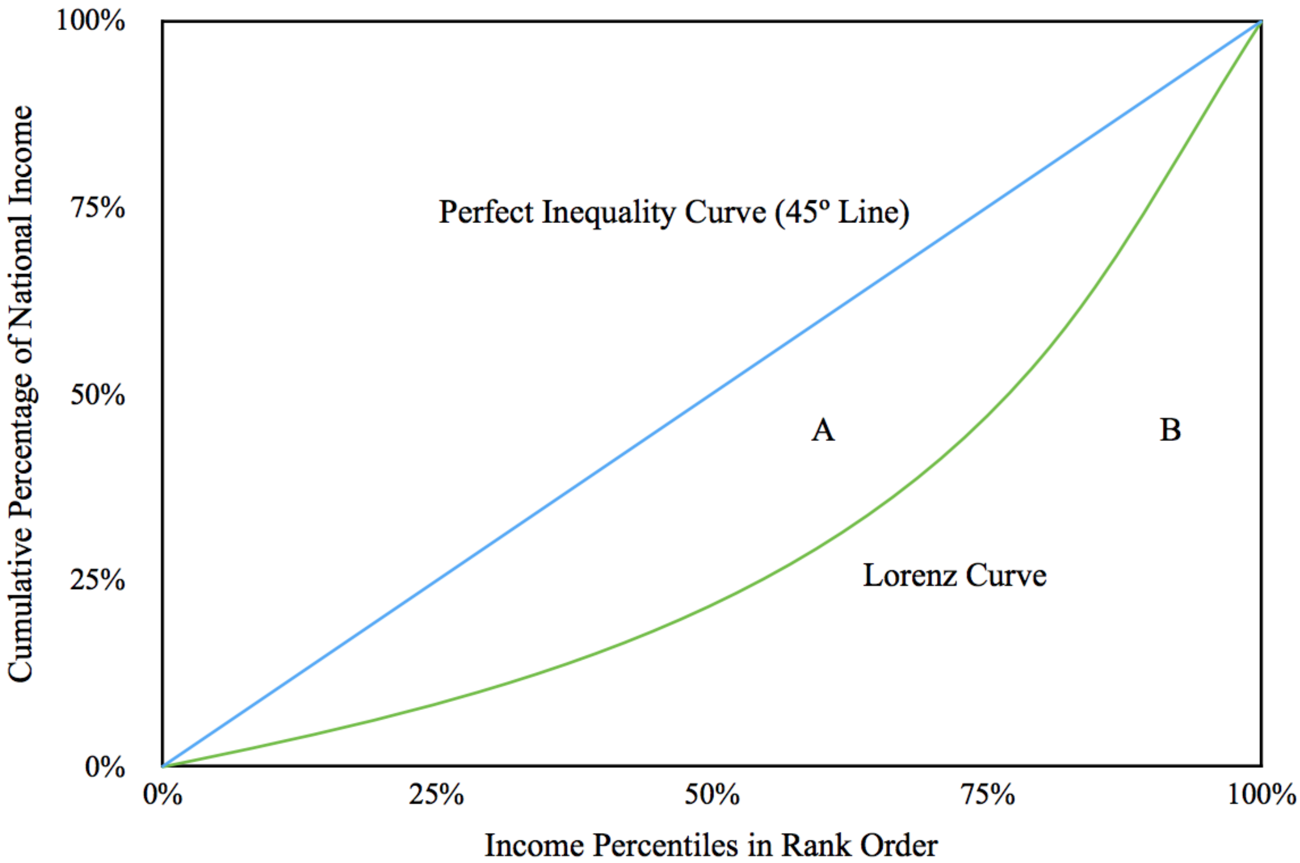
Table 4. CAUSALTRT Analysis of Causal Effects

	HIV Incidence	
	Control Group (Gini < 0.458)	Treatment Group (Gini > 0.458)
Scaled Gini Coefficient	69.153***	238.7***
	(23.6212)	(37.7811)
Squared and Scaled Gini Coefficient	-743.192**	184.29**
	(239.129)	(24.102)
GDP per Capita	0.00066***	-0.00018***
	(0.0001)	(0)
Uninsured	0.2446***	0.48***
	(0.0681)	(0.1013)
18 and Older	0.952***	0.2226
	(0.131)	(0.4022)
Sex Ratio	1.0391***	-1.2252***
	(0.1408)	(0.1995)
Unemployed	1.0761***	0.4493*
	(0.1658)	(0.1995)
Asian	-0.2310***	-0.5053***
	(0.034)	(0.1123)
Constant	110.9***	1.0235
	(22.9703)	
	ATE: -2.391***	ATT: -0.3789
	(0.6817)	(0.8891)

Notes: 1. Standard errors are shown in parentheses
2. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

IX. Figures

Figure 1. Gini Coefficient Calculation = (A)/(A+B)



X. Appendix

Dependent Variable

HIV incidence	Number per 100,000 people who are infected or diagnosed with HIV/AIDS in a given state during a given year

Independent Variables

Scaled Gini Coefficient	State-level Gini coefficient scaled from 0 to 1
Scaled & Squared Gini Coefficient	State-level Gini coefficient scaled from 0 to 1 and then squared
State	ID for each state (including Washington D.C. in alphabetical order (i.e. Alabama = 1, Wyoming = 51)
Year	ID for each year in study (2010-2016)
GDP per Capita	Average state-level economic output per household
Uninsured	State-level percentage of population who are uninsured
Asian	State-level percentage of population who self-identify as Asian
White	State-level percentage of population who self-identify as White
Black	State-level percentage of population who self-identify as Black
American Indian/Alaska Native	State-level percentage of population who self-identify as American Indian/Alaska Native
Native Hawaiian	State-level percentage of population who self-identify as Native Hawaiian
Other Race	State-level percentage of population who self-identify as a race other than those specified
No High School	State-level percentage of population who did not attend high school
Some High School	State-level percentage of population who attended, but did not graduate high school

High School Graduate	State-level percentage of population who graduated high school or received a GED
Some College	State-level percentage of population who attended, but did not graduate college or technical school
College or More	State-level percentage of population who graduated college or technical school
18 and Older	State-level percentage of population who are 18 years or older
Sex Ratio	State-level number of males per 100 females
Unemployed	State-level percentage of population in the labor force who are unemployed