ABSTRACT

LIFE SAVING DRUGS, HEALTH POLICY, AND MENTAL HEALTH

By

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This dissertation has two chapters that broadly fall in the fields of health and public economics. The first paper explores the effect an innovation in HIV/AIDS treatment of the suicide rates of affected population. The second chapter is coauthored with Sherajum Monira Farin and Shyam Raman and explores how states respond to exogenous changes in federal funding for the provision of life-saving HIV/AIDS treatments.

Chapter 1: The introduction of Highly Active Antiretroviral Therapy (HAART) in 1995, transformed the prognosis of an HIV infection from a death sentence to a manageable chronic health condition. Using a difference-in-differences and triple-difference strategy, this paper exploits spatial and demographic variation in HIV incidence at the time HAART treatment was introduced and finds that, in addition to reducing HIV/AIDS deaths, the introduction of HAART led to a disproportionate decrease in suicide rates for men aged 25 to 44. Estimates suggest that HAART saved approximately 500 men aged 25 to 44 from suicide each year following its introduction.

Chapter 2: As part of the Ryan White HIV/AIDS program, the AIDS Drug Assistance Program (ADAP) serves as a payer of last resort for people living with HIV (PLWH) who are uninsured or underinsured and have a low income. ADAP provides recipients with access to life-saving antiretroviral treatments which transforms an HIV diagnosis from a death sentence to a manageable chronic health condition. The ADAP program is funded through a combination of federal and state funds but is administered by the state. I exploit a rule change which was part of the 2006 reauthorization of the Ryan-White Care Act and resulted in an exogenous shock to federal funding for ADAPs. Using this unique setting, the study finds that changes in federal contributions to ADAPs have a near dollar-to-dollar effect on expenditures and increased federal funding results in an increased number of clients served. These findings underscore the importance of federal support for ADAPs in providing critical care for people living with HIV.

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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Chapter 1: An Antidote for Despair: The Effect of Highly Active Antiretroviral Therapy (HAART) on Suicide Rates

1.1 Introduction

The HIV/AIDS crisis represented a particular set of mental health challenges for at-risk communities in the US: heightened homophobia, increased pressure to come out, and the risk of dying from a highly infectious disease. Heightened levels of suicide risk have been found among HIV positive individuals and LGBTQ youth (who are also more likely to contract HIV). Prior to the introduction of effective combination drug therapies, testing positive for HIV was a death sentence. In 1995, the US Food and Drug Administration (FDA) approved the use of Saquinavir in combination with other nucleoside analog medications. This combination proved to be highly effective and marked a new era in combination drug therapy treatments that became known as Highly Active Antiretroviral Therapy (HAART). HAART led to substantial reductions in HIV-related morbidity and mortality and resulted in significant increases in life expectancies of HIV-positive individuals.

Using publicly available mortality data from the US Vital Statistics, this paper finds that the introduction of HAART, not only reduced HIV/AIDS mortality but also saved approximately 500 men aged 25 to 44 from suicide each year following its introduction (NCHS, 1990-2002). There are several ways the introduction of HAART can affect suicide rates for at-risk groups. First, HAART could reduce suicide rates by improving mental health outcomes for HIV positive individuals. There is a significant body of research that highlights the negative mental health effects of testing positive for HIV (Carrico 2010; Kalichman et al. 2000; Schlebusch and Govender 2015; Pelton et al. 2021). Suicide ideation and self-harm are significantly more common among those who test positive for HIV relative to other groups. Given the improved prognosis for people living with HIV infections after the introduction of HAART, we expect lower levels of suicide risk among HIV positive individuals' post-HAART. Secondly, HAART reduced the consequences of testing positive among those who fear infection but are not yet infected with HIV. We see that more people got tested for HIV after HAART, suggesting a potential anticipated negative mental health toll a positive HIV can accompany without treatment (Kellerman et al. 2002). Although HAART is not a cure for the infection, we expect that the treatment would ameliorate heightened fears of death among populations at increased risk of contracting infection, thus improving their mental health outcomes. Third, improved physical and mental health outcomes in the community may have spillover effects on those who are HIV negative. Some reports suggest that the HIV/AIDS crisis was accompanied by rising homophobia and stigma. Gay men routinely mourned the deaths of their friends and fellow community members.[1] Additionally, some evidence indicates that the introduction of HAART coincided with increased acceptance of same-sex couples in areas heavily affected by the HIV crisis. Ferna´ndez et al. (2019) uses data from the General Social Survey to demonstrate that states with higher proportions of HIVpositive individuals experienced a surge in acceptance during this period. Several studies find that decreasing homophobia decreases the risk of suicide among LGBTQ populations (Raifman et al. 2017; Tan et al. 2017).

Despite the clear mechanisms through which the introduction of HAART can impact the mental health outcomes of at-risk individuals, to the best of my knowledge, no study estimates the effects of HAART on suicide rates in the United States. This paper furnishes plausibly causal estimates by exploiting spatial variations in HIV/AIDS incidence prior to the introduction of HAART and comparing suicide rates across the distribution of pre-HAART HIV/AIDS incidence, before and after the introduction of HAART.

[1] In his 1995 book, Odets highlights the emotional and psychological impact of AIDS on the lives of HIV-negative gay men

I use a difference-in-differences event study design to estimate the effects on the group that was most affected by the HIV/AIDS crisis (men aged 25 to 44) across the distribution of pre-HAART HIV/AIDS incidence. I find that counties with a standard deviation higher preexisting HIV incidence rate experiences a 0.9 per 100,00 population decrease is suicides for men aged 25 to 44. This estimate suggests that the introduction of HAART saved approximately 500 men aged 25 to 44 from suicide each year after its introduction.

Expanding my analysis to groups less affected by the introduction of HAART allows me to test for potential spillover effects and provides important control groups. My strategy finds that the introduction of HAART had little or no effect on suicide rates for groups with lower rates of HIV incidence (women, older men aged 65+, and younger men aged 19 or younger). I also employ a triple-difference strategy, where I difference out effects on the suicide rates of less affected groups and find similar estimates, which lends credence to my findings.

I conduct several robustness checks which show that the documented effects are driven by the introduction of HAART. Thereafter, I break down effects by race and find larger effects for HIV-affected white populations compared to HIV-affected nonwhite populations. Additionally, I examine the welfare implications of my research findings, demonstrating that suicides were not simply a substitute for HIV/AIDS deaths within the population that influenced my results. I highlight those improvements in mental health had non trivial implications for the welfare of the affected population.

My findings contribute to a growing literature exploring the specific mental health challenges experienced by the LGBTQ community and HIV-positive individuals. Sexual minorities experience elevated levels of suicide risk (Björkenstam et al. 2016; Cochran and Mays 2015; Hottes et al. 2016; Raifman et al. 2017; Clark et al. 2020b). Testing positive for HIV is also associated with heightened suicidal ideation and mortality (Carrico 2010; Kalichman et al. 2000; Schlebusch and Govender 2015; Pelton et al. 2021).

The effect of HAART on HIV-associated morbidity and mortality is well documented (Egger et al. 2002; Keiser et al. 2004). Previous studies have also estimated the effects of HAART on health disparities, labor supply, risky sex, and health-related quality of life indicators (Hamilton et al. 2021; Chan et al. 2016; Pelton et al. 2016; Lakdawalla et al. 2006; Liu et al. 2006). More relevant to this paper, using data from a longitudinal study conducted in Australia, Judd et al. 2000 finds that the introduction of HAART was accompanied by a fall in depressive symptoms amongst HIV positive individuals. Similarly, Keiser et al. 2010 makes use of a cohort of HIV positive individuals who are part of a longitudinal study conducted in Switzerland to find that individuals who are part of the study experience a greater fall in suicides after the introduction HAART than the general population. Although the study finds compelling evidence of differential trends in suicides for HIV positive individuals relative to the general population before and after the introduction of HAART, it only observes a subset of HIV positive individuals in Switzerland and does not make causal claims whereas my design makes use of the distribution of HIV incidence across the United States to estimate the causal effect of HAART on suicide. To the best of my knowledge, no current study estimates the effect of HAART on suicide rates for at-risk populations in the United States.

This study has important implications for measuring the effects of the HIV/AIDS epidemic and HAART treatment. With over 1 million people living with HIV in the US and over 40 million worldwide, understanding the mental health challenges of those living with HIV and those at risk of contracting the virus is important. It is estimated that a total of 700,000 people have died of HIV/AIDS in the United States.[2] This study implies that HIV/AIDS affects mortality in ways other than just HIV/AIDS mortality. Measures of total HIV/AIDS deaths may undercount the effect of the HIV/AIDS crisis. More generally, the findings warn us about the threat of chronic medical issues on mental health outcomes and the benefits of coming up with treatments. By only focusing on the direct impacts of treatment, we miss meaningful aspects of the benefits of innovations in medical treatments.

1.2 Background

In 1981, a mysterious new disease emerged that seemed to affect gay men in New York and California. Similar reports of gay men suffering from a previously unknown disease emerged in other parts of the country, and by the end of the year, the New York Times published an article titled "Rare Cancer Seen in 41 Homosexuals."[3] The number of new cases grew rapidly among gay men and the disease was termed the "gay plague". Although HIV/AIDS also affects heterosexual men and women, the high prevalence of the virus among gay men resulted in many associating the virus with the gay community. Some called the virus "God's Judgement Against Homosexuality."[4] In addition to bearing the brunt of new infections from this virus, gay men also faced heightened discrimination and homophobia in this period.

In the fall of 1982, the CDC defined the disease as Acquired Immune Deficiency Syndrome (AIDS) for the first time (AIDS is the final and most severe stage of the infection). It wasn't until 1983 that scientists identified the virus that caused the development of AIDS, Human

[2] Estimate obtained from KKF: https://www.kff.org/hivaids/fact-sheet/the-hivaids-epidemic-inthe-united-states-the-basics/ last accessed August 24th, 2022

[3] The New York Times, July 3rd, 1981: https://www.nytimes.com/1981/07/03/us/rare-cancerseen-in-41-homosexuals.html

[4] In his book, After the Wrath of God, Petro (2015) documents the role of religious leaders in shaping moral debates surrounding the AIDS crisis in the US.

Immunodeficiency Virus (HIV). Little was known about the virus in its early years and the care of HIV/AIDS patients was largely palliative. Scientists struggled to make progress in combating the new virus and HIV/AIDSrelated deaths continued to rise. Early estimates of total HIV/AIDS cases and deaths are unreliable because misreporting was common, but by 1987, an estimated 40,849 people had died from the virus.[5] Figure 1.1 depicts the recorded rise in cumulative HIV/AIDS deaths from 1981 to 2002. HIV is transmitted through contact with bodily fluids of an HIV-positive individual with a detectable viral load. By 1987, men who have sex with men accounted for over 72 percent of all AIDS cases.[6] Without treatment, HIV usually progresses to AIDS (the final stage of the virus) in 5 to 10 years, and the life expectancy of an untreated AIDS patient is approximately 2 years (Poorolajal et al., 2016).

HIV/AIDS patients and activists grew weary and impatient about the lack of advances made to come up with an effective treatment. Many organized in protest of the government's perceived inaction in combating this crisis.[7] In response to growing pressures to address the crisis, in 1990, Congress passed the Ryan White CARE ACT. The Ryan White program remains the largest federally funded program in the United States aimed at improving access to healthcare for low-income, uninsured, and underinsured people living with HIV. The Act has been reauthorized in 1996, 2000, 2006, and 2009.

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[5] Estimates obtained from HIV/AIDS: Snapshots of an epidemic: https://www.amfar.org/thirtyyears-of-hiv/aids-snapshots-of-an-epidemic/

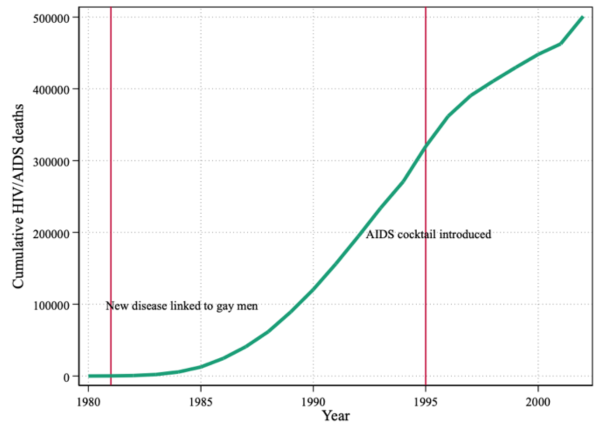
[6] Statistics obtained from November 24, 1995, CDC MMWR weekly report accessed at: https://www.cdc.gov/mmwr/preview/mmwrhtml/00039622.htm00001361.htm

There is some evidence that the proportion of new HIV/AIDS cases represented by men who have sex with men decreased over time and the proportion represented by drug users increased. However, even at the time HAART became available, men who have sex with men made up over 57 percent of HIV/AIDS infections.

[7] Organizations such as ACT UP mobilized the gay community and held protests bringing attention to the government's slow response to the crisis.

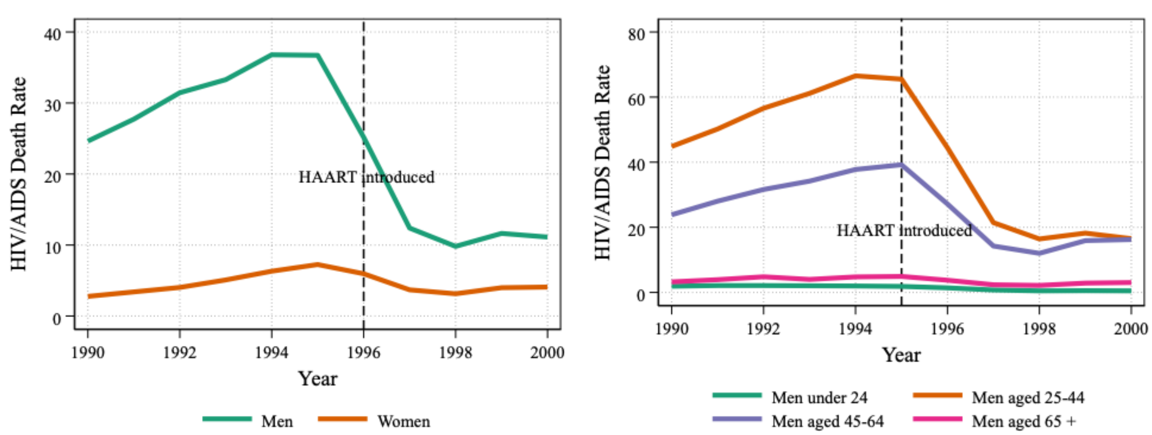
The crisis became a hotly contested political debate. In the early years, President Reagan refused to address the crisis altogether. In the 1992 presidential election, gay-related issues were discussed in great detail.

Figure 1. 1: Cumulative HIV/AIDS Deaths Over Time



In 1995, the FDA approved Saquinavir, the first protease inhibitor. This ushered in a new era of combination drug therapies which became known as the "AIDS Cocktail" and later, as Highly Active Antiretroviral Therapy (HAART). HAART was a game changer in this epidemic and led to a substantial reduction in HIV-associated mortality. Figure 1.2 shows the rapid fall in HIV/AIDS death rates after the introduction of the AIDS cocktail. From 1995 to 1997, men's HIV/AIDS death rate fell by over 60%.

Figure 1. 2: HIV/AIDS Death Rates Over Time



1.3 Data

1.3.1 Suicide & HIV/AIDS-Related Mortality Data

I use publicly available data from the 1990-2002 US Vital Statistics National Center for Health Statistics Multiple Cause of Death Files in order to calculate Suicide and HIV/AIDS-related mortality rates NCHS (1990-2002). The mortality data includes all deaths that occurred in the United States and is abstracted from death certificates filed in the vital statistics departments of each state and the District of Colombia.

A large portion of the analysis in this article is based on county, sex, and age group-specific mortality rates. For the years 1989 onwards, county codes are only provided for counties with a population above 100,000. Therefore, smaller counties are dropped from my data set.[8] To discern suicide and HIV/AIDS-related mortality, I use the International Classification of Disease (ICD) Code provided under the primary cause of death. Records from 1990-1998 are based on ICD-9 codes, whereas records from 1999 onwards use ICD-10 codes. Appendix A.1 provides which ICD codes are associated with suicide and AIDS-related mortality. Although physicians became aware of a disease that was later classified as HIV back in 1981, HIV did not join the list of communicable diseases, and therefore is not visible in the mortality data until 1987. Although we do not have reliable estimates of HIV/AIDS-related mortality rates before 1987, this does not affect my analysis. I only use HIV/AIDS deaths before the introduction of combination drug therapy in 1995 as a proxy for HIV incidence.

I calculate the number of suicides and HIV/AIDS-related deaths per 100,000 population. Sex and age group-specific suicide deaths and population levels are used to calculate suicide rates for men aged 25-44. I chose this group for my main analysis because this group was most affected

[8] Although I do not see a large number of smaller counties, I still observe over 60% of deaths since most Americans live in larger counties.

by the HIV/AIDS crisis. For example, from 1993 to 1995, HIV/AIDS was the leading cause of death for men aged 25 to 44 in the United States. I also calculate mortality rates for women aged 25 to 44, men over 65, and men under 25, in a triple-difference analysis to verify my findings. Since HIV/AIDS death rates are only used as a measure of pre-HAART HIV incidence in a county and I am exploiting differences in HIV incidence across demographic groups, I calculate overall county HIV/AIDS mortality per 100,000 population instead of sex and age-specific rates.

Figure 1.2 shows national HIV/AIDS-related death rates in the mortality data from 1980 to 2002. As mentioned above, HIV/AIDS-related deaths were not recorded before 1987. From 1987, we see a steep rise in HIV-related mortality peaking in 1995. In 1995, the FDA approved the use of Saquinavir to be used in combination with other nucleoside analogue medications. This combination proved to be highly effective and marked a new era in combination drug therapy treatments that scientists began to call highly active antiretroviral therapy (HAART). HAART became widely available in 1996 and there was a significant fall in HIV/AIDS-related deaths thereafter.

There are important variations in HIV/AIDS-related death rates by sex and age group. As depicted in Figure 2, men between the aged of 25 and 44 were significantly more likely to contract and die from HIV compared to women. HIV/AIDS death rates were significantly lower for young (under 24) and older men (over 65) compared to men aged 25 to 44.

1.3.2 Population and Controls Data

I obtain census estimates of county population and demographics using a data set constructed by the Survey of Epidemiology and End Results SEER (2020). This dataset is based on annual population estimates as per the decennial census. Unemployment may play an important role in determining suicide rates. I use county unemployment data from the Bureau of Labor Statistics

BLS (1990-2002). Population density has been identified as an important factor in determining suicide rates (Kegler et al. 2017; Ivey-Stephenson et al. 2017). I calculate population density using population and land area data obtained from the 2000 census. Religious adherence may be another factor explaining some of the variation in suicide rates especially in response to HIV/AIDS tests or the risk of being "outed" to the religious community as a result of positive HIV test. I obtain county-level religious adherence data for the Church and Church Membership study conducted by the Glenmary Research Center (Grammich et al., 2018).

1.3.3 Summary Statistics

For my main analysis, I use a continuous treatment measure of the 1994 HIV/AIDS death rate as an indicator of HIV incidence in a county before the introduction of HAART. My analysis is based on comparing changes in suicide rates over time between high and low HIV counties. High and low HIV counties have some different observable characteristics. Table 1.1 provides summary statistics by pre-HAART HIV/AIDS death rates. Here, I divide counties across quartiles of pre-HAART HIV/AIDS death rates.

High HIV/AIDS counties have significantly different characteristics compared to low HIV/AIDS counties. Although I attempt to explicitly control for many of these characteristics, it is important to note these differences are a limitation to my study. Counties with higher pre-HAART HIV/AIDS death rates experience higher rates of unemployment, are racially more diverse, and have higher population densities than other counties. Unsurprisingly, they are also significantly more likely to be eligible for Ryan White Title 1 funding because Title 1 eligibility is determined by cumulative AIDS cases. Interestingly, there are little differences in religious adherence, percentage evangelical and age distributions.

Table 1.1: Summary Statistics

	4th Quartile	3rd Quartile	2nd Quartile	1st Quartile
Male Suicide Rate	20.39	18.48	19.03	17.77
	(7.42)	(7.97)	(8.58)	(8.57)
Female Suicide Rate	5.17	4.72	4.57	3.94
	(2.68)	(2.74)	(3.04)	(3.40)
Male HIV Death Rate	43.70	15.77	8.50	4.47
	(55.49)	(15.95)	(9.81)	(6.04)
Female HIV Death Rate	5.07	1.81	0.78	0.41
	(10.25)	(2.87)	(1.56)	(1.10)
1994 HIV Death Rate	28.85	11.06	5.34	2.40
	(20.02)	(2.26)	(0.96)	(0.85)
Male Fire Arm Suicide Rate	12.26	11.19	12.07	11.06
	(5.78)	(6.06)	(6.74)	(6.25)
Female Fire Arm Suicide Rate	1.94	1.67	1.57	1.33
	(1.66)	(1.77)	(1.82)	(1.92)
Male Non Fire Arm Suicide Rate	8.12	7.29	6.96	6.71
	(4.43)	(4.19)	(4.62)	(5.12)
Female Non Fire Arm Suicide Rate	3.23	3.06	3.00	2.61
	(1.87)	(2.08)	(2.41)	(2.65)
Eligible for Title 1 funding by 1996	0.74	0.43	0.43	0.35
	(0.44)	(0.49)	(0.50)	(0.48)
Unemployment Rate	6.82	6.25	6.26	6.53
	(1.98)	(2.33)	(2.55)	(3.35)
Population Density	2,484.85	1,305.59	704.97	519.17
	(2,849.46)	(1,160.48)	(613.32)	(539.54)
Percentage Pop Male	48.68	48.71	48.81	49.12
	(1.13)	(1.13)	(0.96)	(1.21)
Percentage Pop White	74.42	84.81	89.78	93.77
	(12.56)	(7.89)	(6.35)	(5.41)
Percentage Pop aged b/w 0 and 24	35.95	35.68	36.12	37.45
	(3.28)	(3.63)	(3.58)	(4.72)
Percentage Pop aged b/w 25 and 44	33.95	32.90	32.91	32.36
	(2.43)	(2.38)	(2.88)	(3.12)
Proportion Evangelical Protestant	0.11	0.11	0.12	0.10
	(0.10)	(0.11)	(0.09)	(0.07)
Proportion Adherents to a Religion	0.57	0.59	0.56	0.62
	(0.11)	(0.15)	(0.15)	(0.16)
Observations	1980	2040	1960	1820

1.4 Methodology

The CDC multiple causes of death data do not provide information about an individual's HIV/AIDS status unless the individual dies because of the HIV infection. I observe county, gender, and age identifiers for all deaths. There are large geographic, age, and gender variations in HIV/AIDS incidence. I exploit geographic and demographic variations in county pre-HAART HIV/AIDS incidence to estimate the effect of HAART on suicide rates. There are several ways to measure pre-HAART HIV/AIDS incidence. We might gauge HIV prevalence by positive HIV tests, AIDS statistics (the final and most severe stage of HIV infection), and HIV/AIDS deaths. Reliable testing data is unavailable for this period and differences in testing availability across counties would result in testing data being plagued with selection issues.

Although AIDS data is available through the AIDS public use data set, the data set only records AIDS cases in cities with populations that exceed 500,000 people, according to the latest available official U.S. Bureau of Census estimates. HIV/AIDS death data is available through the US vital statistics. Although county codes are only provided for counties with populations above 100,000 and I must drop counties with smaller populations, this is less restrictive than using the AIDS data.

For my main analysis, I use the HIV/AIDS death rate in 1994 as a measure of pre-HAART HIV incidence.[9] This is an imperfect measure of HIV/AIDS incidence because it reflects some combination of incidence, access and quality of medical care, and correct identification of cause of death. It may also underestimate HIV/AIDS incidence for younger groups who are at the earlier phases of their HIV/AIDS infection.

[9] In appendix A.2, I repeat the analysis by changing the HIV incidence measure to the AIDS case rate in 1994 as per the AIDS public use data set and find similar effects.

Although the most convincing specification estimated in this study is a triple difference where I exploit both geographic and demographic variation in HIV/AIDS death rates, I first restrict my sample to men aged 25 to 44 and estimate the effect of HAART on this group. Thereafter, I measure the effects on groups that are less affected by the HIV/AIDS crisis, and therefore less affected by the introduction of HAART. Finally, I conduct a triple difference analysis where I compare effects across demographic groups to estimate the causal effect of HAART on suicide rate.

1.4.1 Event Study

I choose an event study design to estimate the effects of HAART on suicide rates for several reasons:

1. The event study shows time-varying treatment effects, where suicide rates may change in response to the introduction of combination drug therapy over time. Suicide may be linked to the affected population's expectations and beliefs about the effectiveness of the therapy and these are expected to change over time.
2. Examining the period leading up to the introduction of combination drug therapy tests whether suicide rates were on a pre-existing trend before the introduction of the treatment.

Difference-in-Differences: Formally, I estimate the following equation:

$$\text{Suicide Rate}_{ct} = \alpha + \sum_{\substack{m \neq -1994 \\ m=-1990}}^{2002} \beta_m (Pre - HIV/AIDS\ deathrate_c \times 1[t = m]) + X_{ct}\gamma + a_c + \mu_{st} + \epsilon_{ct}$$

(1.1)

where Suicide Rate$_{ct}$ measures the number of suicides per 100,000 population in county c at year t. Pre-HIV/AIDS deathrate$_c$ is the number of HIV/AIDS deaths per 100,000 population in 1994 and serves as a measure of the level of HIV incidence before the introduction of combination drug therapy. I use the standardized form of the HIV/AIDS death rate. $1[t = m]$ is an indicator variable that equals 1 when the observations time period is m years relative to 1995.[10]

I control for some county characteristics $\mathbf{X}_{ct}$ such as county unemployment rate, percentage of the population that is white, eligibility for Ryan White Title 1 funding, percentage of the population that is Evangelical Protestant, and percentage of the population that adheres to a religion.[11] I control for time fixed effects (η_t) and county fixed effects (a_c). I also control for the interaction of state and time fixed effects (μ_{st}) which accounts for any changes in policy at the state level.[12] I have a panel of data with complete controls from 1990 to 2002. I use all these years of data in my analysis and can observe 5 years before the introduction of combination drug therapy, and 8 years after. First, I restrict my sample to men aged 25-44. This group is the most likely to be affected by HIV/AIDS. I then estimate Equation 1.1 for groups that are less affected by the HIV/AIDS crisis (women aged 25 to 44, men over 65, and men 19 and under). This allows me to test for any spillover effects, and these groups also serve as control groups in my

[10] I use 1995 as my first post-HAART year and 1994 as my reference year because Saquinavir was first made available on the market in 1995, and through 1995 newspapers such as the New York Times and San Francisco Chronicle published articles highlighting the promise of combination drug therapies and results from clinical trials (David Perlman, June 22, 1995; Sullivan, Nov 21, 1995; Altman, Feb 02, 1995). Over the next couple of years, the medical community made several changes in drug formulation and other combinations of drug therapies were introduced, but Saquinivir was the first of its kind.

[11] Some recent evidence suggests that Medicolegal Systems can affect Suicide rates (Fern´andez et al., 2019; Klugman et al., 2013). I explore the possibility of my results being contaminated by the introduction of Medical examiner systems in Appendix A.4.3

[12] In the appendix A.5 I make certain alterations to the control variables and fixed effects used. First, I drop all control variables and find that my estimates do not change. Then, I remove my interaction of state and time fixed effects and only include county and time fixed effects. I find that my estimates are similar.

analysis. Estimates are weighted by group-specific populations and standard errors are clustered at the county level.

Triple-Difference: To verify these findings, I also employ a triple-difference approach. In addition to spatial and temporal variation, I difference out effects on suicide rates for women aged 25 to 44, men over 65, and men 19 and under. These groups are less likely to contract HIV, and therefore less likely to be affected by the introduction of combination drug therapy.

Formally, I estimate the following equation:

$$\begin{aligned}\text{Suicide Rate}_{jct} &= \alpha \\ &+ \sum_{\substack{m \neq -1994 \\ m=-1990}}^{2002} \beta_m \left(Pre - HIV/AIDS\ deathrate_c \times 1[t = m] \times Men\ 25-44_j \right) + \theta_{ct} + \iota_{jc} \\ &+ \delta_{sjt} + \epsilon_{ctj}\end{aligned}$$

(1.2)

where $SuicideRate_{jct}$ measures group-specific suicide rates.[13] Men 25-44$_j$ is a dummy variable that measures whether the observation represents suicide rates for men aged 25 to 44. In my triple-difference analysis, I compare effects on men aged 25 to 44 to women aged 25 to 44, men over 65, and men 19 and under. Pre-HIV/AIDS deathrate$_c$ and $1[t = m]$ are the same as Equation 1.1. Estimates are weighted by group-specific populations and standard errors are clustered at the county level.

[13] Given the differences in suicide rates across demographic groups, I also consider percentage changes of the outcome variable. In Appendix A.3, I change my outcome variable to represent the inverse hyperbolic sine of suicide rates and find similar effects.

With the triple-difference specifications, I can control for the interaction of time and county fixed effects (θ_{ct}), sex and county fixed effects (ι_{jc}), and sex and time fixed effects (κ_{jt}). I also control for the interaction of state, sex, and time-fixed effects (δ_{sjt}). This controls for any state-level changes in policy during the period of analysis that may have affected men aged 25 to 44 differently from other groups.

1.4.2 Specifications Without Time Variations in Treatment Effect

Standard Difference-in-Differences: To summarize my findings, I also consider a standard difference-in-differences specification where I focus on the impact of the introduction of combination drug therapy in a grouped post period. Formally, I estimate the following equation:

$$Suicide\ Rate_{ct} = \alpha + \beta(Pre - HIV/AIDS\ deathrate_c \times Post_t) + X_{ct}\gamma + a_c + \eta_t + \mu_{st} + \epsilon_{ct}$$

(1.3)

where $Post_t$ is a dummy variable that is equal to one after the introduction of combination drug therapy. This is a restricted version of Equation 1.1. All other features of this equation are the same as that of Equation 1.1. Grouping pre and post-periods also provides a convenient way of presenting results in table form.[14]

Standard Triple-Difference: I also consider a triple-difference specification where I focus on the impact of the introduction of combination drug therapy on 25 to 44-year-old

[14] I follow Kirill and Xavier 2017 and do not include linear-in-unit time trends

men's suicide rate relative to suicide rates of other groups in a grouped post period. Formally, I estimate the following equation:

$$Suicide\ Rate_{ct} = \alpha + \beta\left(Pre - HIV/AIDS\ deathrate_c \times Post_t \times Men25 - 44_j\right) + \theta_{ct} + \iota_{jc} + \delta_{sjt} + \epsilon_{ctj}$$

(1.4)

where $Post_t$ is a dummy variable that is equal to one after the introduction of combination drug therapy. This is a restricted version of Equation 1.2 and all other features of this equation are the same as that of Equation 1.2.

1.5 Results

Figure 1.3 depicts the impact of the introduction of combination drug therapy on suicide rates for men aged 25 to 44. The figure implies that there is approximately a 1 per 100,000 population decrease in suicide rates for men in counties that have a 1 standard deviation higher pre-HAART HIV/AIDS death rate. The first column of Figure 1.4 depicts effects on groups less affected by the introduction of HAART. Effects on women aged 25 to 44, men over 65, and men 19 and under appear to be close to zero. Coefficients for women and older men are negative but statistically insignificant. This may represent some spillover effects. Although other groups had significantly lower rates of HIV/AIDS, they were still affected by the virus. Rates of HIV infection were low for these groups, but they were not zero. Members of these groups may also have friends and family members who are HIV positive, and therefore it is reasonable to find some negative effects on suicidality for this group following the introduction of HAART. These results correspond with those produced in the difference-in-differences table presented in Table 1.2. My findings are further verified by observing similar estimates in the triple-difference analysis depicted in the second column of Figure 1.4. I observe small immediate effects that grow over time. This may be a result of increasing trust in the efficacy of HAART treatment and increasing access to life-saving medications. This is in line with other studies which find falling suicide rates amongst HIV-positive individuals over time even after the introduction of HAART Ruffieux et al. (2019).

Taken together, the estimates suggest that the introduction of HAART reduced suicide rates by 0.9 per 100,000 population in counties that have a 1 standard deviation higher pre-HAART HIV/AIDS death rate. A 0.9 per 100,000 population reduction in suicide rates represents approximately 4% change since the average suicide rate for the population of interest is 24 per 100,000 population. Some back of the envelope calculations would reveal that HAART saves approximately 500 men aged 25 to 44 from suicide each year following its introduction.[15]

To further contextualize the magnitude of these results, I compare effects across the distribution of Pre-HAART HIV/AIDS incidence. I divide counties into deciles of Pre-HAART HIV incidence and re-estimate Equation 1.1 where Pre-HAART HIV is now a dummy variable equal to 1 when looking at the highest decile of Pre-HAART incidence and equal to zero when looking at the lowest three deciles. Here, I am trying to consider the most extreme case so I drop the deciles in between. The first two panels of Figure 1.5 show effects on men and women. Here,

[15] HIV/AIDS death rate went down by approximately 1.3 standard deviations after the introduction of HAART (HIV/AIDS death rate is 26 per 100,000 in 1994, 8 per 100,000 in 1998, and 1 standard deviation of 1994 HIV/AIDS death rate is approximately 14). Therefore, suicide rates should decrease by 1.17 per 100,000 and the population of men aged 25 to 44 is approximately 42 million.

I see a 4 per 100,000 reduction in suicide rates in the top decile of HIV incidence when compared to the bottom 3 deciles for men. This represents an approximate decrease in 25-44-year-old men's suicide rate by 20%. When comparing these counties, I see small but significant negative effects on women's suicide rate. I find similar but slightly smaller effects in my triple difference analysis depicted in the third panel of Figure 1.5.

Due to the large magnitude of estimates, I must convince the reader that these effects are reasonable. Since this is the first study of its kind, it's difficult to make direct comparisons to other studies. Keiser et al. (2010) estimates suicide rates among HIVpositive men and women in Switzerland before and after the introduction of HAART. They find that amongst HIV-positive men, suicide rates fell from 447.4 per 100,000 person-years to 90.1 person-years after the introduction of HAART. On average there were approximately 20 HIV-positive individuals in 1994 for every reported HIV/AIDS death.[16] Therefore, I can infer that a 1 standard deviation increase in HIV/AIDS death rate is associated with a 240 increase in the HIV positivity rate (defined as HIV-positive individuals per 100,000 population).[17]

If I assume that this HIV positivity rate remained constant before and after the introduction of HAART, estimates from (Keiser et al.; 2010) would suggest that the overall suicide rate for men would go down by 0.85 per 100,000 driven entirely by a fall in suicide rates amongst HIV positive individuals. Although we cannot discern whether our effects are driven by a reduction in suicide rates amongst HIV-positive individuals or through other mechanisms (such as reduced consequences of infection for uninfected people or reductions in homophobia), finding similar estimates to those in the Switzerland study suggests that the effects may largely be a result of falling suicide rates amongst HIV positive individuals.

Figure 1. 3: Estimates from Equation 1.1

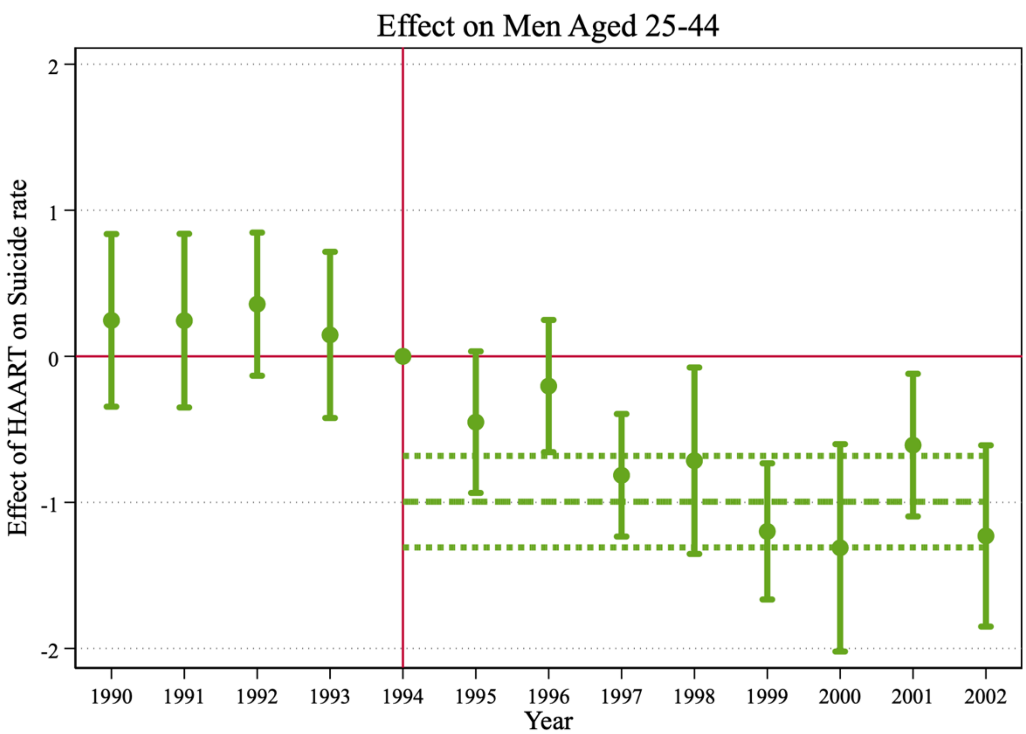


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Figure 1. 4: Estimates from Equation 1.1 and 1.2

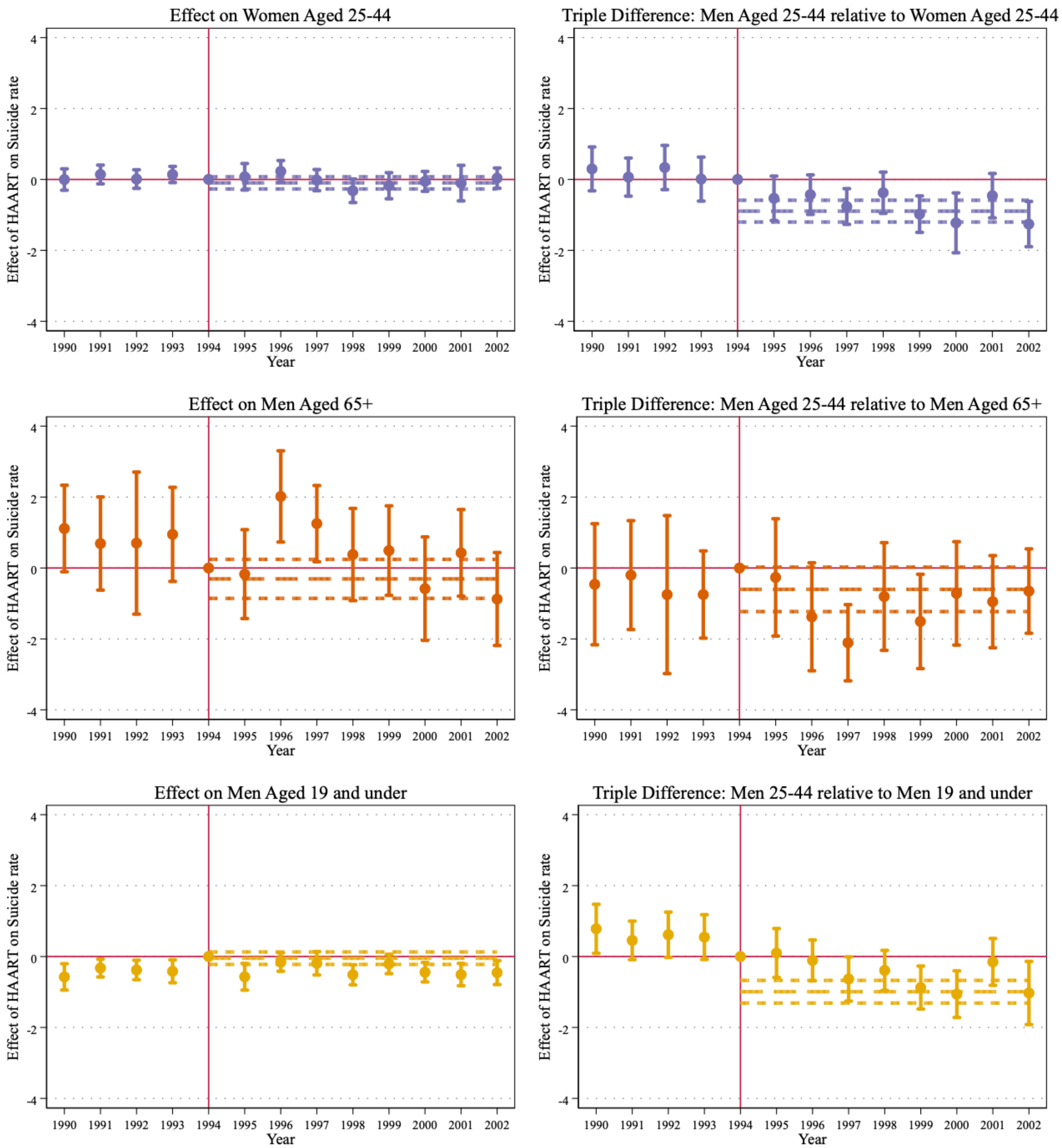


Figure 1. 5: Effect Across Distribution

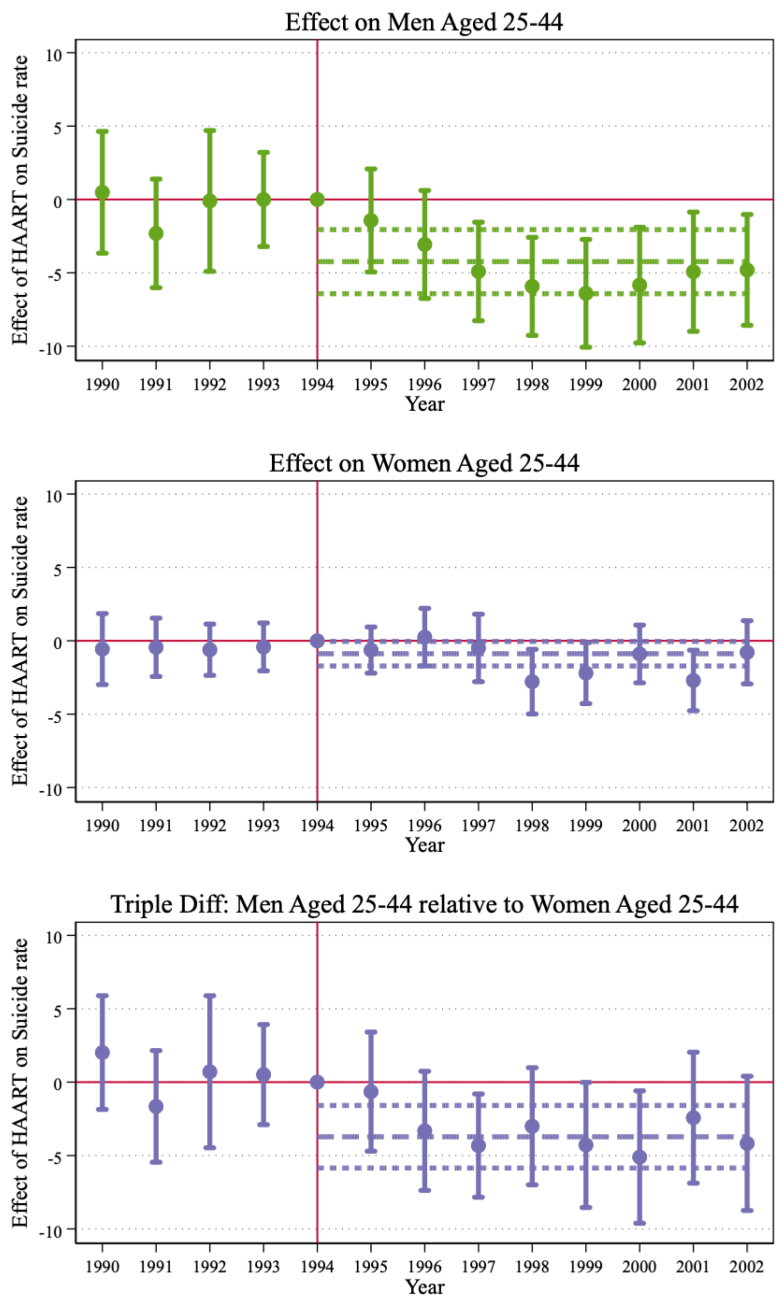


Table 1.2: Difference in Differences: Men Aged 25 to 44 and Women Aged 25 to 44

	Men 25-44			Women 25-44		
	(1)	(2)	(3)	(4)	(5)	(6)
Post=1 × Stdz 1994 HIV death rate	-1.03379***	-0.95096***	-0.99522***	-0.07506	-0.05912	-0.09614
	(0.147)	(0.174)	(0.159)	(0.079)	(0.081)	(0.087)
Population Density		-0.00204	0.00061		-0.00030	-0.00024
		(0.002)	(0.002)		(0.001)	(0.001)
Unemployment Rate		0.26256**	-0.03912		0.01567	0.03712
		(0.124)	(0.156)		(0.060)	(0.084)
Percentage Pop White		0.03613	0.14017		-0.00961	0.07815
		(0.109)	(0.120)		(0.053)	(0.049)
Proportion Pop Evangelical		18.90438	17.47253		-1.89047	15.10848**
		(15.915)	(17.849)		(7.376)	(6.691)
Proportion Pop Religious		-2.62522	1.05753		0.11764	0.69799
		(3.177)	(2.944)		(1.939)	(1.686)
Title 1 Eligible=1		-1.02496**	-0.99244*		-0.58575**	-0.23886
		(0.479)	(0.526)		(0.234)	(0.245)
Observations	5070	4970	4866	5070	4970	4866
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	Yes	Yes	No
State X Time FE	No	No	Yes	No	No	Yes

Table 1.3: Difference in Differences: Men Aged 65+ and Men Under 19

	Men 65+			Men Under 19		
	(1)	(2)	(3)	(4)	(5)	(6)
Post=1 × Stdz 1994 HIV death rate	-0.16355	0.00197	0.03455	-0.06766	-0.05533	-0.04581
	(0.323)	(0.263)	(0.201)	(0.084)	(0.085)	(0.089)
Population Density		-0.00569***	-0.00477***		-0.00035	0.00040
		(0.002)	(0.002)		(0.000)	(0.001)
Unemployment Rate		0.12260	0.12563		-0.09411	-0.07339
		(0.206)	(0.300)		(0.057)	(0.067)
Percentage Pop White		-0.17883	-0.16314		-0.05438	-0.00933
		(0.164)	(0.210)		(0.044)	(0.052)
Proportion Pop Evangelical		49.33260**	0.91073		-7.07499	-15.17962**
		(19.131)	(21.295)		(6.799)	(7.705)
Proportion Pop Religious		-10.62841**	-3.39449		3.88390**	3.76248*
		(5.154)	(5.692)		(1.783)	(1.993)
Title 1 Eligible=1		-1.08891	-1.65386*		-0.14091	0.05084
		(0.755)	(0.859)		(0.210)	(0.250)
Observations	5070	4970	4866	5067	4967	4863
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	Yes	Yes	No
State X Time FE	No	No	Yes	No	No	Yes

Table 1.4: Triple Difference: Men Aged 25-44 Relative to Women Aged 25-44

	(1)	(2)	(3)	(4)
Post=1 × male=1 × Stdz 1994 HIV death rate	-0.96243***	-0.95850***	-0.95622***	-0.89336***
	(0.146)	(0.146)	(0.130)	(0.156)
Population Density		-0.00117		
		(0.001)		
Unemployment Rate		0.14168**		
		(0.071)		
Percentage Pop White		0.01491		
		(0.070)		
Proportion Pop Evangelical		8.56835		
		(10.315)		
Proportion Pop Religious		-1.30231		
		(2.137)		
Title 1 Eligible=1		-0.80935***		
		(0.291)		
Observations	10140	9940	10140	9958
County FE	Yes	Yes	No	No
Time FE	Yes	Yes	No	No
County X Time FE	No	No	Yes	Yes
Time X Sex FE	No	No	Yes	Yes
Sex X County FE	No	No	Yes	Yes
Time X Sex X State FE	No	No	No	Yes

Table 1.5: Triple Difference: Men aged 25-44 Relative to Men Over 65 and Men Under 19

	Relative to: Men over 65		Relative to: Men Under 19	
	(1)	(2)	(3)	(4)
Post=1 × Men 25-44=1 × Stdz 1994 HIV death rate	-0.87495**	-0.92818***	-1.01339***	-0.97783***
	(0.358)	(0.349)	(0.147)	(0.156)
Observations	10140	9958	10134	9952
County FE	No	No	No	No
Time FE	No	No	No	No
County X Time FE	Yes	Yes	Yes	Yes
Time X Age FE	Yes	Yes	Yes	Yes
Age X County FE	Yes	Yes	Yes	Yes
Time X Age X State FE	No	Yes	No	Yes

1.6 Robustness Tests

This study depicts falling suicide rates amongst men aged 25 to 44 in high HIV/AIDS counties relative to low HIV counties. It shows little to no effects on groups less affected by the HIV/AIDS virus and finds that estimates are robust after differencing out effects on low HIV/AIDS demographic groups. Back-of-the-envelope calculations reveal that the estimates suggested in this paper are reasonable when comparing them to a longitudinal study of HIV-positive populations in Switzerland.

Despite these findings, this study has several limitations and I conduct a series of robustness checks to verify the accuracy of these estimates. I can exploit geographic and demographic variations in HIV/AIDS incidence to conduct my analysis. As depicted in Table 1.1, high HIV/AIDS counties are different from low HIV/AIDS counties. The effects mentioned above could be the result of different trends between counties with different characteristics. I also do not observe actual HIV status or sexual orientation in the mortality data. I have argued that HAART would have significantly larger effects on HIV-positive individuals and gay men but I am unable to observe if these groups are driving the observed results. The 90s are also a period of falling urban violence and crime (Levitt, 2004). Since much of this decline occurred in high HIV/AIDS areas and has larger effects on men aged 25 to 44, relative to other groups, it is possible that the same factors that are driving these changes are affecting my results. Below, I conduct several robustness tests, which provide some evidence that the estimates are driven because of the introduction of HAART.

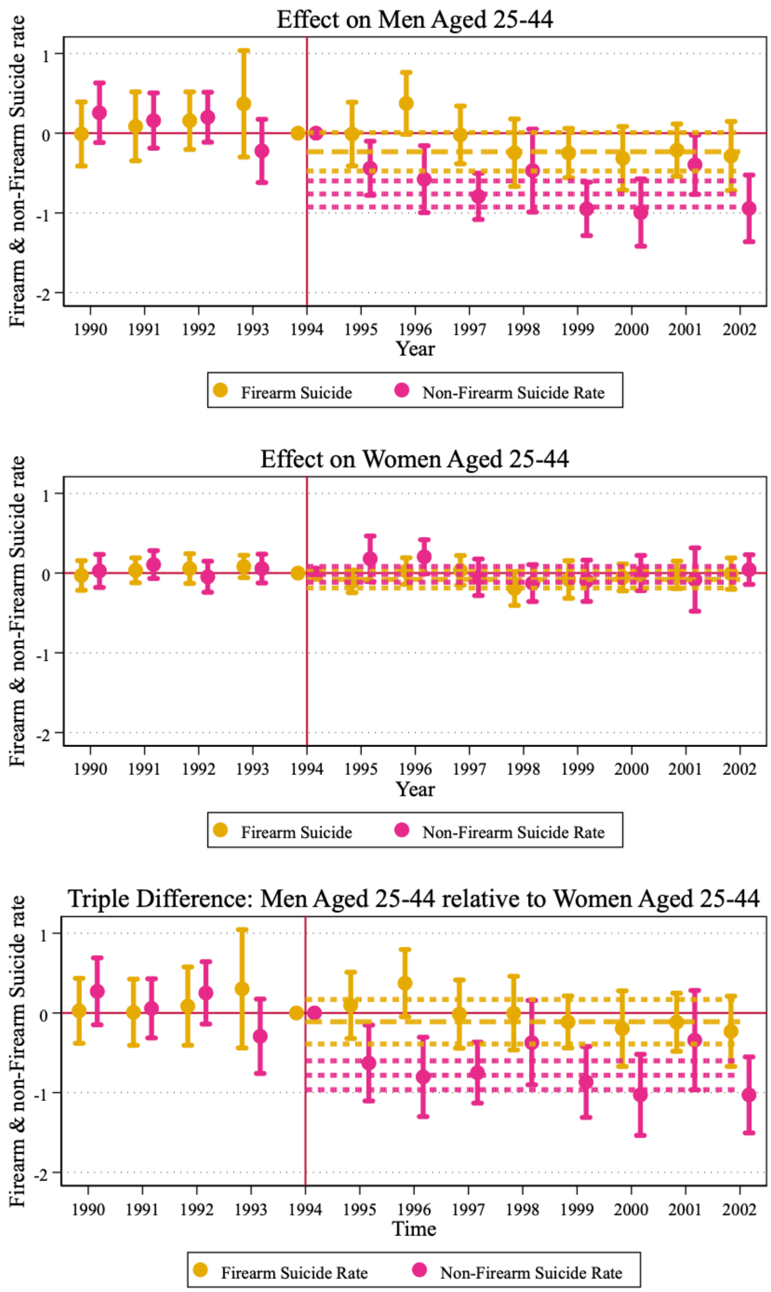
1.6.1 Firearm and Non-firearm Suicides

If my estimates are a result of the introduction of combination drug therapy, I expect my results to be driven by individuals who are more likely to be affected by the treatment. Although I do not observe sexual orientation in the suicide data, I do observe the method of suicide. There are significant differences in the methods of suicide employed by homosexual and heterosexual men. Clark et al. 2020a finds that sexual minority men are significantly less likely to be gun owners compared to heterosexual men. Clark et al. 2020b finds that firearms are half as likely to be used in suicide for homosexual men compared to heterosexual men.

Figure 1.6 depicts that my effects are driven almost entirely by non-firearm suicides. This provides further evidence that my estimates are driven by effects on gay men who are more likely to contract HIV. Since my results are largely driven by non-firearm suicides, this provides some evidence that my estimates are not a result of changes in gun access, which has been found to have a significant effect on suicide rates.[16]

[16] In appendix A.10, I explicitly explore how trends in violence might affect the results by comparing trends in homicides and suicides.

Figure 1. 6: Firearm and Non-firearm Suicides



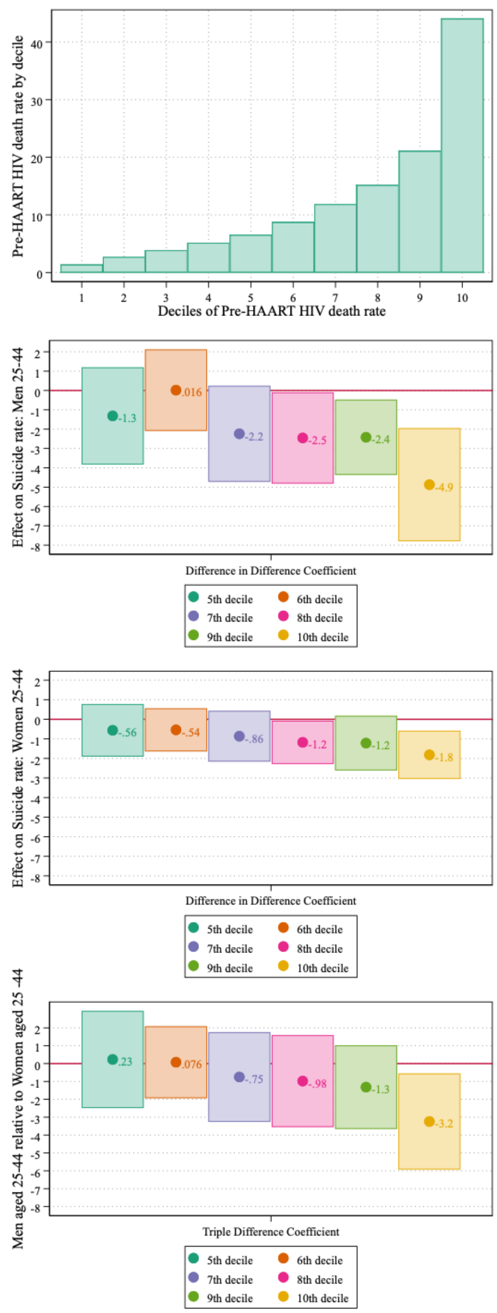
1.6.2 Exploiting Continuous Treatment

In order to verify that my results are driven by changes in pre-HAART HIV incidence, I also exploit the continuous nature of the treatment measure used in this study. Meyer (1995) argues that "differences in the intensity of the treatment across different groups allow one to examine if the changes in outcomes differ across treatment levels in the expected direction." If my results are, in fact, driven by the introduction of HAART treatment, I expect the largest effects in counties with the highest preHAART HIV incidence and smaller effects in counties with lower rates of pre-HAART HIV.

The first panel in Figure 1.7 shows mean pre-HAART HIV/AIDS death rates by deciles of pre-HAART HIV/AIDS death rate in a county. The pre-HAART HIV/AIDS death rate is under 10 per 100,000 population in the first 6 deciles and we expect the treatment to have little effect on these counties. Thereafter, we see exponential increases in HIV/AIDS death rates with larger jumps when we move from the 7th to the 8th, 8th to the 9th decile, and the largest jump, when moving from the 9th to 10th decile.

I modify my treatment variable from Equation 1.3 and Equation 1.4 into a dummy variable which is equal to one when looking at different deciles of pre-HAART HIV incidence and zero when looking at the lowest two deciles. The next two panels of Figure 1.7 represent the difference-in-differences estimates from Equation 1.3 for men and women. I observe larger negative coefficients at higher deciles of pre-HAART HIV/AIDS death rates. This adds credibility to my main findings. In the last panel of Figure 1.7, I present triple-difference estimates from Equation 1.4. Again, I observe larger coefficients at higher deciles of pre-HAART HIV incidence.

Figure 1. 7: Exploiting Continuous Treatment



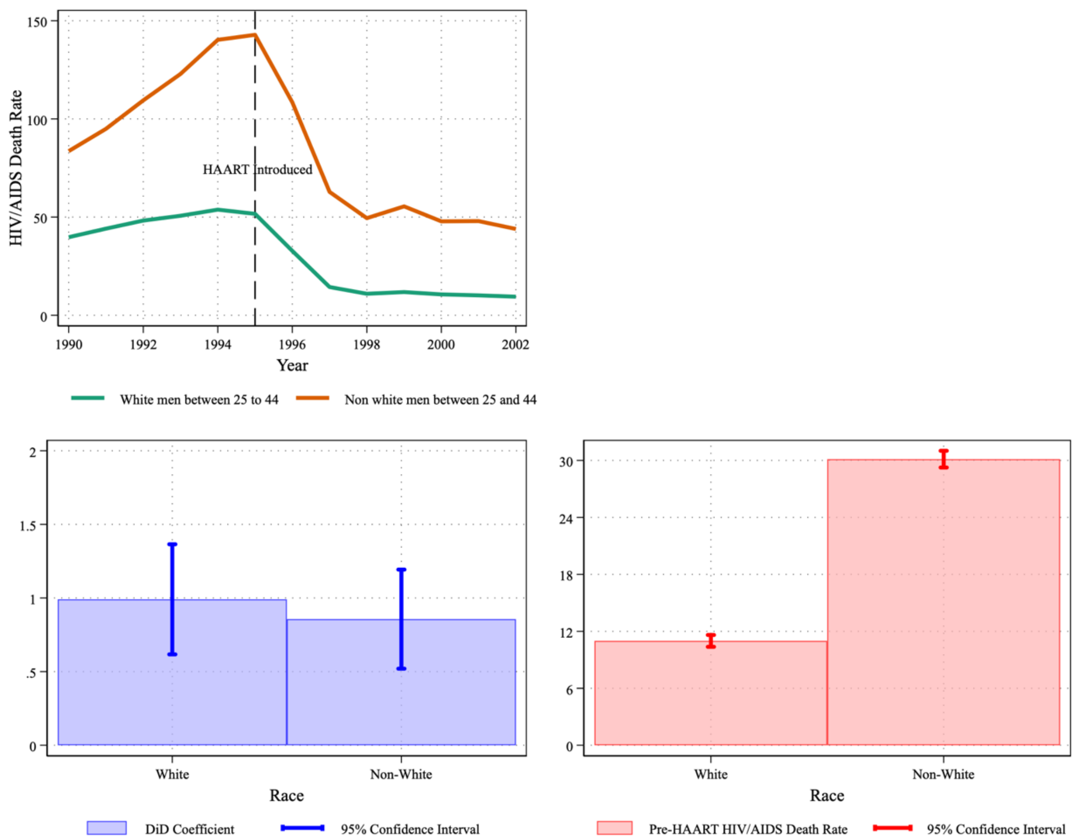
1.7 Effects by Race

There are significant differences in HIV/AIDS incidence and HAART take-up between white and non-white Americans. HIV/AIDS incidence was significantly higher among non-white Americans and some studies have documented how the introduction of HAART widened the Black-White mortality gap Levine et al. (2007). Although the introduction of HAART significantly reduced HIV/AIDS deaths among white men, there remain significant concerns about the rates of HIV/AIDS mortality among non-white men. The first panel of Figure 1.8 depicts trends in HIV/AIDs death rates for white and non-white men aged 25 to 44. We observe higher pre-HAART rates of HIV/AIDS deaths amongst non-White men. Although both groups experience a decline in death rates following the introduction of HAART, there is a starker decrease in HIV/AIDS death rates among white men.

In Figure 1.8, I present coefficients estimates from Equation 1.3 for white and nonwhite men aged 25 to 44 separately. I also present pre-HAART rates of HIV/AIDS death rates by race. I find that the effects for the two groups are similar in size. However, pre-existing rates of HIV/AIDS are greater for non-white men. This implies that effects on HIV-affected white populations are relatively larger than HIV-affected non-white populations.

These effects might be the result of different levels of access to treatment for whites and non-whites. This implies that access to treatment not only had effects on the physical but also the mental health of the affected population. This further emphasizes the importance of programs that seek to expand access to treatment. Several studies estimate the effect of Ryan White funding on the physical health of affected populations, but it may also be important to study the mental health effects of these programs.

Figure 1. 8: Effects by Race



1.8 Welfare Implications

Accurately measuring the welfare implications of HAART through its effects on suicide is challenging due to data limitations. Simply multiplying the measured effect with the statistical value of life would result in an incomplete and potentially misleading estimation of the overall welfare impact. This is because the population contributing to this effect differs from the general population. HIV-positive individuals generally have a lower life expectancy compared to the general population. Consequently, preventing the death of an HIV-positive individual would result in a lower number of years of life saved in comparison to preventing the death of someone from the general population. In addition to HIV status, the number of life years saved is influenced by the age of the individual, the stage of infection, and other underlying health factors. If the men who were previously dying by suicide were in the late stages of their infection, the number of years of life saved by preventing suicide would be small. Since HAART is an intervention that improves both physical and mental health, this would imply that the welfare benefits of HAART in terms of years of life saved of those individuals who are no longer dying by suicide are driven by preventing HIV/AIDS deaths rather than mental health improvements.

To categorize the individuals driving these results, three groups can be considered: individuals who are HIV negative, individuals in the early phase of HIV infection, and individuals in the later phase of HIV (AIDS). I assume the average individual driving my results is 35 years old.[17] Studies find that without treatment, a person who is exposed to HIV has 5 to 10 years before their infection progresses to AIDS, after which the individual has a life expectancy of 2 years (Poorolajal et al., 2016). Therefore, I assume that the number of life years lost due to

[17] This is the average of ages 25, 35, and 45, weighted by coefficients presented in Table 1.9. Men's life expectancy is 1998 is 72 years.

poor mental health for a person in the early phases of an HIV infection is 9.5 years whereas the years of life lost for a person in the late phase of an HIV infection is 2 years. Since HAART improves physical health in addition to mental health, I obtain life expectancies of HIV positive individuals in the years following HAART from Harrison et al. (2010) to determine the total years of life saved by preventing an HIV related suicide. According to Harrison et al. (2010), as of 1998, HIV-positive men had a life expectancy of approximately 15.9 years, while men in the late stages of their infection had a life expectancy of approximately 12.1 years. These findings provide important information for estimating the welfare implications of preventing an HIV-related suicide in terms of years of life saved, categorized by HIV status and progression. Based on these statistics, I present estimates of the average years of life saved for a person in each of these three groups through improvements in mental health and physical health in the table 1.6.[18]

Table 1.6: Years of Life Saved

	Mental Health	Physical Health
Status	years	years
HIV -	37	0
HIV +: early stages	9.5	6.4
HIV +: late stages (AIDS)	2	10.1

It is reasonable to assume that my effects are being driven by some combination of these three groups. As mentioned earlier, HAART may affect the mental health of HIV positive individuals by improving the prognosis of infection but may also improve outcomes for HIV negative individuals through reducing the consequences of contracting HIV, and seeing fewer friends and family members dying from the virus. Although there is a limited literature which

[18] "Mental Health" represents how many additional years a person may have lived had they not died by suicide but there was still no treatment for HIV. "Physical Health" represents the additional number of years a person would live due to the improved life expectancy of an HIV positive individual following HAART

explores HIV/AIDS progression and suicide prior to the introduction of HAART, there is some evidence that suicide risk may be highest directly following the diagnosis of an infection or late stages of the virus when an individual might experience pain and disability (Siegel and Meyer, 1999). More recent literature offers examples of both heightened suicide risk directly following the diagnosis of an HIV infection as well as heightened suicide risk following the progression of the virus (Pelton et al., 2021).[19]

While the stage of the virus is not observed in the dataset, the ages of individuals driving the observed effects on suicide as well as the ages of those dying from HIV/AIDS are available. In the primary analysis, the effects of HAART on suicide rates are measured using a broad age group consisting of men aged 25 to 44. While this grouping offers certain benefits, it may also be beneficial to consider effects by narrower age groups to discern who is driving these results.[20] Therefore, I reestimate Equation 1.3 for men in their 20s, 30s and 40s.[21] Thereafter, I conduct a triple difference analysis where I reetimate Equation 1.4 and measure effects on men in their 20s, 30s and 40s, relative to women in their 20s, 30s, and 40s. Estimates are provided in Table 1.8 and Table 1.9. My estimates are significantly larger for men in their 20s and 30s compared to men in their 40s. In Figure 1.9, I break down pre-HAART HIV/AIDS death rates by age groups. Although the effects in this study are driven by men in their 20s, and 30s, I find higher death rates for older cohorts. Although it is possible that the kinds of people who are dying by suicide are different from those that are dying by HIV/AIDS, this provides some suggestive evidence that there is a non-trivial difference in the age of suicide and the age of HIV/AIDS death and that

[19] For many individuals, the time of diagnosis and the progression of the virus to AIDS may have coincided. For example, from 1994-1999, 41% of new HIV diagnosis represented cases of AIDS.

[20] Looking at a broader group allows me to estimate effects on mortality rates more precisely. Estimating rates for smaller populations are noisier.

[21] Although I restrict my treatment group to men aged 25 to 44 in my primary specification, men who are slightly younger and slightly older may also experience similar effects since they have similar rates of HIV/AIDS.

a significant portion of the welfare benefits from preventing an HIV related suicide are a result of improvements in mental health.

Estimates from my main specification suggest that HAART saved approximately 500 men aged 25 to 44 from suicide each year. Assuming an average value of statistical life year (VSLY) of $302,000, I present welfare implications of HAART due to a fall in suicides for several reasonable combinations of the previously mentioned groups in Table 1.7[22].

Table 1.7: Value of Statistical Life Years Saved

	Mental Health	Physical Health
Scenario	Value (USD millions)	Value (USD millions)
10% HIV-, 45% HIV+ early, 45% HIV+ late	1,340.1	1,121.2
5% HIV-, 30% HIV+ early, 65% HIV+ late	906.0	1,281.0
5% HIV-, 65% HIV+ early, 30% HIV+ late	1,302.4.7	1,085.7

The estimates suggest that the introduction of HAART resulted in over 2 billion dollars' worth of annual savings in VSLY terms through its effect on suicides.[23] Of the 2 billion dollars saved, a significant portion was driven by improvements in mental health. It is also important to note that suicide is an extreme mental health outcome and the estimates presented in this study are a lower bound of the benefits of HAART through improvements in mental health.[24]

[22] There is significant variation in estimates of the value of a statistical life year (VSLY), a VSLY of $302,000 is obtained from Aldy and Viscusi (2008)

[23] It is important to note that this figure only represents benefits through effects of suicide. There were significantly larger benefits through falling HIV/AIDS death rates.

[24] In appendix A.11, I use data from The Behavioral Risk Factor Surveillance System to explore trends in poor mental health days for the affected population. I find suggestive evidence that HAART improved non-extreme mental health outcomes for at-risk groups.

Figure 1. 9: HIV/AIDS Death Rate by Age

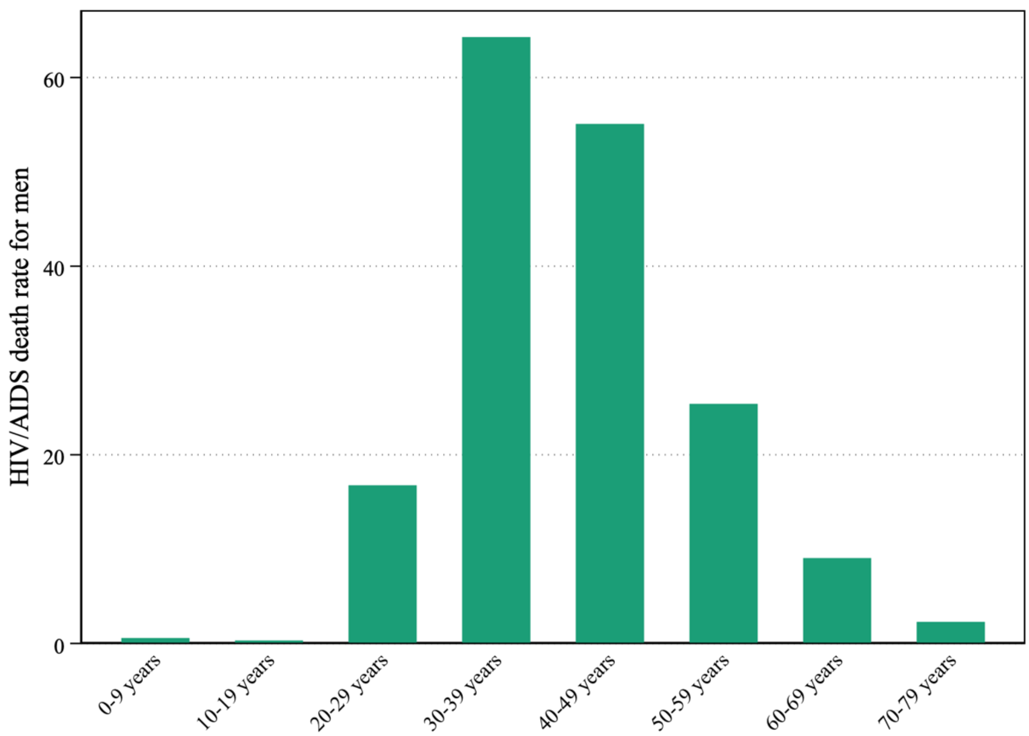


Table 1.8: Difference in Differences: Alternate Age Group

	Men 20-29		Men 30-39		Men 40-49	
	(1)	(2)	(3)	(4)	(5)	(6)
Post=1 × Stdz 1994 HIV death rate	-0.86307***	-0.97666***	-1.03428***	-1.03117***	-0.66340**	-0.63776*
	(0.251)	(0.245)	(0.221)	(0.215)	(0.336)	(0.357)
Population Density	0.00352*	0.00633***	-0.00397**	-0.00231	-0.00768***	-0.00326
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Unemployment Rate	0.08237	0.03616	0.17851	0.05419	0.56474***	-0.20805
	(0.169)	(0.210)	(0.150)	(0.206)	(0.203)	(0.234)
Percentage Pop White	-0.26570	-0.08523	-0.09493	0.00131	0.21995	0.21384
	(0.175)	(0.190)	(0.125)	(0.150)	(0.170)	(0.179)
Proportion Pop Evangelical	14.46651	-11.71189	23.59298	28.02732	3.51019	2.92832
	(17.208)	(18.373)	(20.749)	(23.016)	(19.802)	(22.943)
Proportion Pop Religious	3.57914	5.49290	-1.74026	1.67780	-5.03902	3.14922
	(4.998)	(5.629)	(4.375)	(4.138)	(5.164)	(5.422)
Title 1 Eligible=1	-1.49012**	-1.28525*	-1.36224**	-1.23310*	-0.20163	-0.27977
	(0.700)	(0.717)	(0.582)	(0.691)	(0.667)	(0.714)
Observations	4970	4866	4970	4866	4970	4866
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No	Yes	No
State X Time FE	No	Yes	No	Yes	No	Yes

Table 1.9: Triple Difference (Men Relative to Women): Alternate Age Groups

	Men20-29		Men30-39		Men40-49	
	(1)	(2)	(3)	(4)	(5)	(6)
Post=1 × male=1 × Stdz 1994 HIV death rate	-0.91218***	-0.99127***	-1.07565***	-0.97328***	-0.53483*	-0.36952
	(0.312)	(0.374)	(0.250)	(0.273)	(0.283)	(0.307)
Observations	10112	9930	10140	9958	10140	9958
County FE	No	No	No	No	No	No
Time FE	No	No	No	No	No	No
County X Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Time X Sex FE	Yes	Yes	Yes	Yes	Yes	Yes
Sex X County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time X Sex X State FE	No	Yes	No	Yes	No	Yes

1.9 Conclusion

This study highlights the substantial fall in suicide rates among HIV-affected populations following the introduction of HAART. I find a 0.9-point decrease in suicide rates for men aged 25 to 44 in counties that have a 1 standard deviation higher pre-HAART HIV/AIDS death rate. In the most extreme case, where I compare effects in counties in the highest decile of pre-HAART HIV/AIDS death rate to the bottom 3 deciles, I find that suicide rates for men aged 25 to 44 fall by approximately 20% in high HIV counties relative to low HIV counties. The estimates suggest that the introduction of HAART saved approximately 500 men aged 25 to 44 from suicide each year. I find that suicide rates for other groups such as women aged 25-44, men over 65, and men under 20, are largely unaffected by the introduction of HAART. I also difference out effects on these groups and find that my estimates are robust to triple difference specifications.

I do not observe sexual orientation or HIV status in the suicide data so I conduct several tests to ascertain that my results are driven by the introduction of HAART. Homosexual men are half as likely as hetrosexual men to use firearms as their method of suicide Clark et al. (2020b). After breaking down suicides into firearm and nonfirearm suicides, I find that my results are driven almost entirely by non-firearm suicides. This provides some evidence that my estimates are a result of changing suicide rates among gay men.

This study finds extremely large effects. To argue that these estimates are reasonable, I extrapolate from a similar study in Switzerland and compare estimates. The Swiss study finds large reductions in suicide rates among HIV-positive populations after the introduction of HAART Keiser et al. (2010). Although I do not observe HIV status in my suicide data, I approximate HIV-positive populations using my HIV/AIDS death data. I use these approximations and the estimates in the Swiss study to predict the fall in suicide rates. These predictions are very similar to my estimated effects and lends credibility to my findings. Although I am unable to discern the exact mechanisms driving my result, finding similar estimates to the Swiss stud provides some evidence that results are largely driven by changing patterns of suicide amongst HIV-positive individuals after the introduction of HAART.

When I break down effects by race, I find larger effects on HIV-positive white populations compared to HIV-positive non-white population suggesting that access to treatment may play an integral role in improving the mental health outcomes of HIV-affected communities. This also underscores the importance of conducting more research which explores how access to HIV/AIDS treatment might affect mental health.

This study has important implications for understanding the effects of the HIV/AIDS crisis and the introduction of HAART treatment. By simply measuring HIV/AIDS mortality as deaths that were the direct result of HIV/AIDS progression, we are underestimating the total number of HIV/AIDS deaths. We must account for suicides among populations affected by the virus to get a more accurate figure. It also implies that if we only focus on the direct benefits of HIV treatment, we miss meaningful parts of the benefits of innovations in medical treatments. This has implications for the cost-benefit analyses of HIV treatments but may also affect how we estimate the effects of other treatments for medical conditions. Finally, this study also warns us about the potential threat of chronic health conditions to mental health outcomes. Although HIV/AIDS was a specific type of virus that affected a particularly vulnerable community, poorer mental health outcomes are observed in patients with other chronic health conditions as well. Understanding the physical and mental health challenges of those with chronic illnesses is integral to their care.

Chapter 2: State Responses to Federal Funding for Life Saving Drugs: Evidence from the AIDS Drug Assistance Program

2.1 Introduction

Federalism refers to the sharing of power between national and subnational governments (Gluck and Huberfeld, 2018). Fiscal federalism is a central feature of the United States healthcare system and affects the country's ability to respond to the everchanging healthcare needs of the population. The federal governments often adopts the approach of allocating federal funds to local areas in order to meet the healthcare needs of the population. When federal governments distribute funds to address a certain crisis, an increase in funding does not necessarily lead to an equivalent increase in expenditure. When resources are fungible, sub-national governments can simply alter their own contribution towards tackling that particular problem and the observed change in expenditure would only represent and "income effect" (Inman, 2008). In practice, this is not always the case. The literature finds that often money received for a particular program tends to result in disproportionate increases in spending on those programs. The phenomenon is known as "flypaper effects". Although many studies identify flypaper effects, some recent evidence suggest that these findings are a result of the endogeniety of federal funding. Gordon (2004) and Knight (2002) find no evidence of crowd out effects after accounting for the endogeneity of federal funds. Making use of a 2006 rule change in the AIDS Drug Assistance program (ADAP), this paper exploits a plausibly exogenous shock to federal ADAP funding and finds significant evidence of flypaper effects in this context.

The AIDS Drug Assistance Program (ADAP) provides access to life-saving antiretroviral medications for people living with HIV who are uninsured or underinsured and have low income. The program is part of the Ryan White HIV/AIDS Program, which was created to improve the availability and quality of care for individuals and families affected by HIV/AIDS. ADAP provides medication assistance to eligible individuals who cannot afford to pay for HIV treatment. The program is funded through a combination of federal and state funds and is administered by state health departments or other designated entities. ADAP plays a critical role in ensuring that people living with HIV have access to the medications they need to manage their condition and lead healthy lives. Serving over 300,000 clients in 2020 alone, the ADAP program provides a unique setting to study state responses to federal funding in the context of the provision of life-saving drugs (HRSA, 2020).

The federal government mandates that state ADAPs follow certain guidelines related to the use of their funds but states have a large amount of discretion in affecting their ADAPs. Although the majority of ADAP funding comes from the federal government, states also have the discretion to use their own funds to supplement ADAPs.[25] States also make important decisions which determines who is eligible to receive ADAP funds and the kinds of treatment they may receive. All states aim to provide treatment to low-income uninsured/underinsured HIV positive individuals but states set their own income eligibility requirements. In 2011, ADAP income eligibility requirements ranged from 200% of the Federal Poverty Level (FPL) in ten states to 500% FPL in five states (NASTAD, 2012b). In addition to income eligibility requirements, some states also have medical eligibility requirements. Although ARV treatment is recommended to HIV positive individuals at all stages of infection, in order to contain costs, some states require that the HIV infection have progressed to a certain stage before the individual becomes eligible for treatment through ADAP.[26] These policies affect the proportion of individuals who are eligible for treatment through ADAP. Even among ADAP eligible individuals, there are

[25] In 2011, state contributions made up 16% of the national ADAP budget (NASTAD, 2012b)

[26] Most often this takes the form of a state ADAP requiring that an individual's CD4 cell count be below a certain threshold before the ADAP strarts providing treatment.

important differences in the kinds of services that are provided to them in different states. As a cost containment measure, some states also implement wait lists. This means that ADAP eligible individuals must wait till funds become available to provide these clients with treatment. There are also important differences in the formularies of drugs provided by different state ADAPs. States are required to cover certain ARVs but have discretion to increase the number of ARV drugs in their formularies offering their clients with more options. ADAPs also provide treatments for HIVrelated opportunistic infections (OIs) and there is significant variation in the types of OIs provided by an ADAP.[27]

Prior to the 2006 reauthorization of the Ryan White Care Act, federal ADAP funds were distributed to states based on the number of people living with Acquired Immune Deficiency Syndrome (AIDS). AIDS is the final and most severe stage of HIV and is characterized by a severely weakened immune system, which can lead to life-threatening infections and cancers. Since ARV treatments are recommended for all xstages of HIV infections, in 2006, it was decided that ADAP funds would to distributed via a formula based on each state's proportion of living HIV cases. This resulted in major changes to the amounts of funds received by each state from the federal government. States where a larger portion of HIV positive populations had developed AIDS experienced a fall in federal ADAP funds relative to states where a small portion of HIV positive populations had developed AIDS. Figure 2.2 depicts how this rule change affected federal funds for states above and below the median AIDSto-HIV ratio in 2005 (right before the 2006 reauthorization). The first panel depicts federal ADAP funding per AIDS case overtime. Prior to the 2006 reauthorization, states received similar

[27] HIV positive individuals are at a higher risk of contracting certain infections including Hepatitis A, B, and C. As of 2009, 27 ADAPs covered vaccinations for Hepatitis A and B and treatments for Hepatitis C. NASTAD

amounts of funds per each AIDS case whereas after 2006, states with a lower AIDS-to-HIV ratio experienced a disproportionate rise in the amount of funding per AIDS case. Similarly, the second panel shows that states with a below median AIDS-to-HIV ratio received less funds per HIV positive population before 2006. After 2006, states received similar proportions of federal funds per HIV population. The third panel depicts federal ADAP funds as a percentage of 2005 federal ADAP funds. We observe that the 2006 reauthorization resulted in a 20% increase in federal ADAP funds for states with below median AIDS-to-HIV ratio.

This paper exploits this exogenous shock to evaluate how states respond to changes in federal funding in the the context of providing life saving treatments. Using a Instrumental Variable analysis where I exploit this rule change, I am able to estimate the causal effect of changes in federal ADAP funds on a range of outcomes. I first estimate the effect of changes in federal funding on ADAP expenditure. Since ADAPs are funded through a combination of state and federal sources, we might expect states to divert their funds elsewhere as a response to increases in federal funding. In line with a phenomenon known as the "Fly Paper Effect" which documents that an increase in federal grant revenues tends to stimulate higher expenditures by recipient subnational governments to a much greater extent than an increase in state income, this paper finds that changes in federal funding for ADAPs have a near dollar-todollar effect on expenditures.

The estimates suggest that states do not respond to changes in federal funding by changing their own contribution. Instead, states alter some of their ADAP policies and ultimately change their expenditure as a response to changes in federal contribution. I find that increased funding resulted in a decreased probability of wait lists, less stringent income eligibility requirements, increases in the number of drugs covered and the number of clients served.

This implies that changes in federal funding for ADAPs can have a significant impact on who has access to HIV/AIDS treatments and the kinds of treatments they can expect to receive. Despite improvements in the treatment of HIV/AIDS and increased access to public health insurance through the Affordable Care Act (ACA), many Americans continue to rely on ADAP for providing them with access to life saving medical treatments. As of 2019, almost 300,000 Americans were ADAP clients (HRSA, 2019). That's approximately one-third of known HIV cases. Given the large number of Americans who rely on ADAP to gain access to life-saving treatments, changes in ADAP policy and generosity can significantly affect the well being of those living with HIV. Since ARV treatments also decrease viral loads and decrease the probability of spreading HIV, benefits to access to treatment are not only limited to those who are currently HIV positive (Chan et al., 2016).

Despite annual expenditures of over 900 million USD, few studies examine the effects of changes to ADAP funding. Some studies have looked at the effects of ADAP policy changes on health outcomes (McManus et al. 2014; Snider et al. 2016), but these studies do not exploit exogenous changes and do not make causal claims. Estimating the effects of programs targeting HIV positive populations is complicated by the fact that funding is generally a product of need. Since ADAPs receive funding based on their share of HIV positive or AIDS population, it is hard to disentangle causal effects of funding changes. By exploiting an exogenous shock to funding, this study overcomes this problem. Dillender (2021) uses a similar approach where he exploits a rule change which occurred alongside the 1996 Ryan White Reauthorization to estimate the effect of Ryan White Title 1 funding on HIV/AIDS mortality. Exploiting the unique setting of the AIDS Drug Assistance Program (ADAP), I find evidence of flypaper effects.

2.2 Background

The AIDS Drug Assistance program began serving clients in 1987. Initially, ADAPs would provide low-income HIV positive Americans with the only HIV treatment available at the time, Zidovudine or AZT. Although AZT was the first FDA approved drug for the treatment of HIV/AIDS, it only observed moderate levels of success in delaying the progression of the virus and was accompanied with severe side effects. In the absence of an effective treatment, ADAP remained a relatively small program serving only a small number of HIV positive individual. The introduction of Highly Active Antiretroviral Therapy (HAART) in 1995 transformed the role of ADAP from a relatively small and cheap program to one of the most expensive government programs in the U.S. which served a critical role in preventing HIV/AIDS deaths.

ADAP programs are federally funded but state administered, and states have some amount of discretion about how to use their funds. The vast majority of ADAP funds are used for the provision of antiretroviral (ARV) medications which prevent the progression of the virus. In addition to providing ARVs, ADAPs also offer treatments for certain Opportunistic Infections which are common amongst people living with HIV/AIDS. For example, a large number of ADAPs provide treatment and vaccination from Hepatitis C.

The Ryan White HIV/AIDS program has been reauthorized four times in 1996, 2000, 2006, 2009. Some reauthorizations simply extend coverage and are not accompanied with large rule changes (2009) while others amend the funding rules to better cater to the needs of the HIV positive population (1996, 2006). These rule changes provide us with meaningful exogenous variations in levels of funding that can be used to evaluate causal effects of funding changes on several outcomes.

2.3 Data

This paper evaluates the effect of changes in federal ADAP funding. My primary source for observing state ADAP policies and client outcomes was the annual ADAP Monitoring reports from 2003-2011. ADAP monitoring reports contain information about the breakdown of ADAP Budgets, drug expenditures, number of clients served, number of people on the ADAP waitlist, income eligibility requirements, number of drugs and treatments offered by an ADAP as well as some demographic and health characteristics of ADAP clients.

I also incorporate state level data about HIV and AIDS incidence through a combination of Atlas (2001-2011) data and CDC HIV Surveillance Reports from 2003-2012. This provides me with the number of people living with HIV/AIDS infections by state and year. I am unable to obtain rates of HIV infection for all state-year combination because prior to the 2006 reauthorization, ADAP funding was based on the number of AIDS cases and there were differences in the ways states recorded HIV cases. The HIV surveillance report does not report cases for states without confidential name-based reporting systems (CDC, 2006).[28] Due to these limitations, I am only able to include 33 states in my analysis. These 33 states account for approximately 63% of the epidemic in the 50 states and the District of Columbia (CDC, 2006).

2.3.1 Summary Statistics

The direction and magnitude of the change in ADAP funding which accompanied the 2006 reauthorization of the Ryan White Care act was determined by the proportion of HIV positive individuals whose infection had progressed to AIDS. Therefore, I construct a continuous treatment variable "AIDS-to-HIV ratio". This is the total number of AIDS cases in a state

[28] Some states used confidential code-based recording systems as opposed to name-based. Code based reporting systems are susceptible to double counting (Ngugi et al., 2019).

divided by the total number of people living with HIV prior to the 2006 rule change. The first panel in Figure 2.1 shows the AIDS-to-HIV ratio for the 33 states used in this analysis. There is significant geographic variation in the AIDS-to-HIV ratio. There is also little evidence to suggest that high AIDS-to-HIV states are concentrated in any specific region of the US.

Although I use a continuous treatment measure in my main specification, in order to compare characteristics across the distribution of treatment intensity, I group together states that are either above or below the median AIDS-to-HIV ratio.

Table 2.1 presents summary statistics for states that are above and below the median AIDS-to-HIV ratio. There are important differences between these two kinds of states. States with above median AIDS-to-HIV ratios tend to have higher rates of HIV/AIDS incidence and death rates. We do not observe meaningful differences in the demographic composition of states that are above or below the median AIDS-to-HIV ratio. We also do not observe meaningful differences in poverty rates in states that are above and below the median AIDS-to-HIV ratio.

Table 2.2 shows some of the state ADAP policy differences between the two kinds of states prior to the 2006 reauthorization. Federal ADAP contributions per AIDS case are quite similar but states that have above median AIDS-to-HIV ratios receive significantly higher federal funds per person living with HIV. In general, states with below median AIDS-to-HIV ratios are less generous than states with above median AIDS-to-HIV. They have a smaller proportion of people living with HIV as ADAP clients, lower income eligibility requirements, cover few drugs and are more likely to have a wait list. This provides some suggestive evidence that that ADAP programs of states with low AIDS-to-HIV ratios were more income constrained prior to the policy change relative to states with high AIDS-to-HIV ratios.

Figure 2. 1: 2005 AIDS-to-HIV Ratio

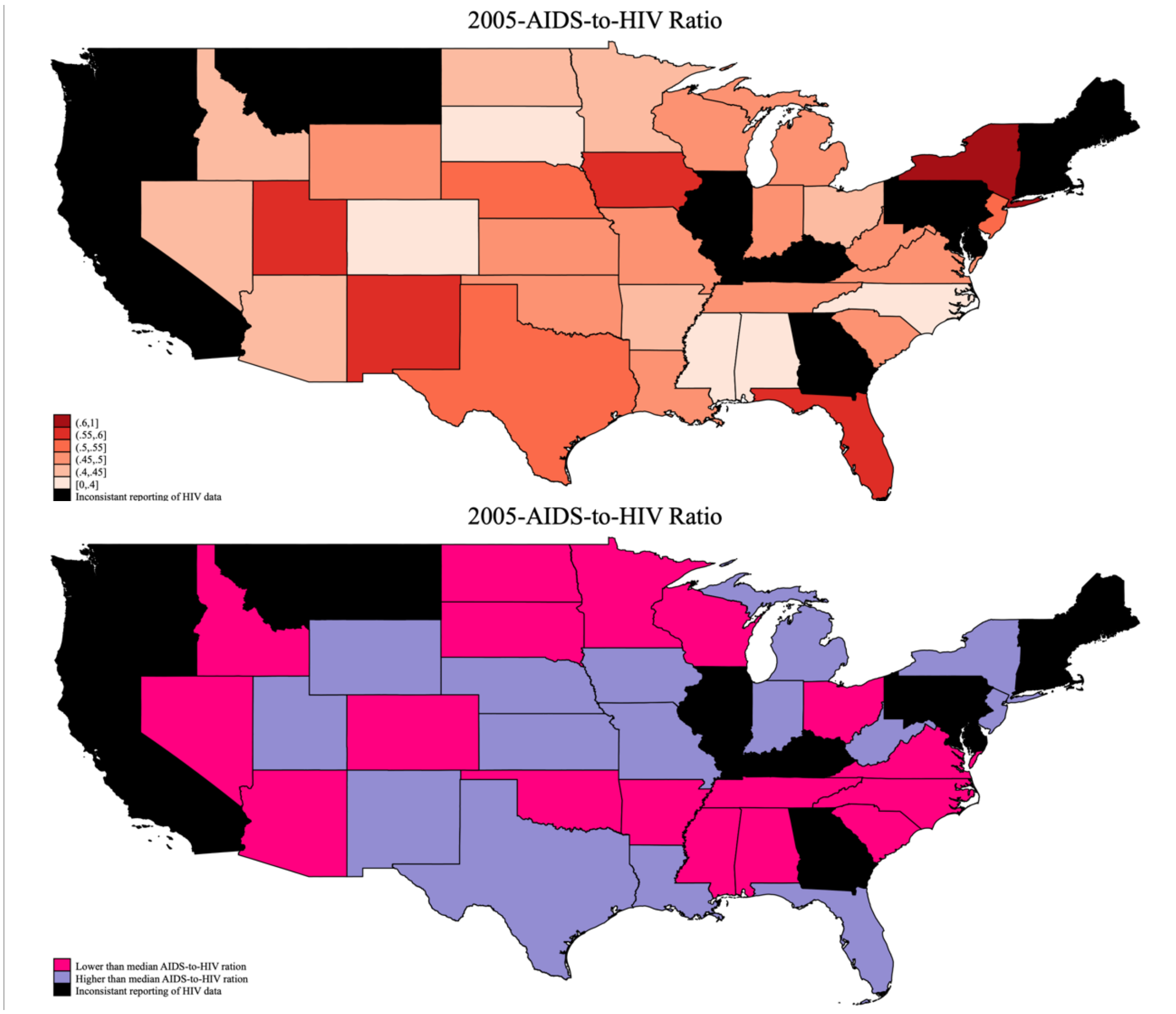


Figure 2. 2: Effect of 2006 Reauthorization on Funding by AIDS-to-HIV Ratio

Table 2.1: 2005 Summary Statistics - Population Characteristics

	Below median AIDS-to-HIV	Above median AIDS-to-HIV
HIV/AIDS death per 100,000 population	3.08	5.46
	(1.63)	(3.38)
HIV prevalence per 100,000 population	169.86	289.43
	(63.26)	(170.28)
AIDS prevalence per 100,000 population	73.11	164.43
	(28.46)	(108.51)
AIDS to HIV ratio	0.43	0.55
	(0.03)	(0.05)
Percentage under poverty	12.38	13.13
	(3.08)	(2.64)
Proportion White	0.81	0.81
	(0.08)	(0.07)
Proportion Female	0.51	0.51
	(0.01)	(0.01)
Proportion Under 25	0.35	0.35
	(0.01)	(0.03)
Observations	17	16

Table 2.2: 2005 Summary Statistics - ADAP Policy

	Below median AIDS-to-HIV	Above median AIDS-to-HIV
Federal ADAP Contribution per AIDS case	1,958.98	1,992.80
	(241.96)	(99.38)
Federal ADAP Contribution per HIV+ population	843.01	1,131.63
	(120.47)	(107.89)
ADAP Budget per HIV+ population	1,279.96	1,781.79
	(237.44)	(465.68)
State ADAP Contribution per HIV+ population	217.77	283.34
	(227.21)	(192.35)
Clients serves per HIV+ population	0.10	0.13
	(0.03)	(0.03)
Income eligibility as a percentage of FPL	297.31	367.75
	(104.38)	(110.10)
Medical Eligibility Requirement	0.16	0.00
	(0.38)	(0.00)
Number of drugs covered	68.41	246.81
	(21.21)	(210.70)
Hepatitis C treatment covered	0.65	0.46
	(0.49)	(0.52)
Waitlist for ADAP	0.24	0.01
	(0.44)	(0.09)
Observations	17	16

2.4 Empirical Strategy & Results

In this paper, I exploit a funding rule change which occurred alongside the 2006 Ryan White Reauthorization Act. I construct a continuous treatment variable which serves as a measure of treatment intensity, AIDS-to-HIV. States with lower AIDS-to-HIV ratio lost funds relative to states with high AIDS to HIV based on the 2006 rule change. I first evaluate the effect of the funding rule change on ADAP expenditure. This serves as a way of testing for flypaper effects. Thereafter, I explore the effect of federal funding rule changes on state ADAP policies.

2.4.1 Fly Paper Effects

Inman (2008) documents the long history of research that finds that federal grants often lead to significantly greater public spending than an equivalent dollar of citizen income. Arthur Okun first coined the term "Fly Paper Effect" to describe this phenomenon because money seems to "stick where it hits" (Hines Jr and Thaler, 1995).

This contrasts with standard theory which predicts that a local government's inclination to spend from both grant and tax revenues should be equivalent, provided that both sources of revenue are entirely interchangeable. Standard theory would predict a "crowd out effect". Local governments would decrease or divert their contributions to a particular program as a response to a federal grant.

Prior research finds evidence of crowd-out with regards to education spending and Medicaid expansion (Gordon 2004; Lutz 2010; Baicker 2001). Other studies find evidence of flypaper effects with regards to education spending, infrastructure spending, and spending on tobacco control programs (Card and Payne 2002; Leduc and Wilson 2017; Singhal 2008). Despite the federal government spending over 2 billion dollars a year on funding for the Ryan White Program, this is the first study to evaluate flypaper effects with regards to Ryan White funding.

In order to determine whether federal ADAP contributions are subject to crowdout effects or Fly paper effects, I estimate the relationship between federal ADAP contributions and ADAP expenses. Since states receive ADAP funds based on a need basis, we cannot treat overall federal ADAP grants as exogenous shocks. To this end, I exploit an Instrumental Variable strategy, where I instrument Federal ADAP contribution with the 2006 rule change. Prior to 2006, federal ADAP contributions were determined by the Total number of AIDS cases in a particular state. After 2006, federal ADAP funds were based on the number of people living with HIV. This meant that states where a small proportion of the HIV positive population had AIDS experience an exogenous increase in funding relative to states where a larger portion of HIV positive population had developed AIDS. Although a state's AIDS-to-HIV ratio may well affect their expenditure even in the absence of changes in funding, there is no reason why the relationship between AIDS-to-HIV and ADAP expenditures would change before and after the 2006 rule change other than through changes in federal funding. This allows me to isolate plausibly "exogenous" shocks to federal funding.

Therefore, the first stage of my Instrumental Variable equation, estimates the effect of the 2006 rule change on federal funding. Formally, the following equation represents my first stage:

$$
\begin{aligned}
&Federal\ ADAP\ Contribution\ per\ HIV_{st} \\
&\qquad = \beta_0 + \beta_1 Post_t \times AIDS - to - HIV_s + \gamma X_{st} + \delta_t + \nu_s + \epsilon_{st}
\end{aligned}
\tag{2.1}
$$

Here, the AIDS-to-HIV$_s$ variable represents the standardized form of the proportion of HIV positive people living in a state that have developed AIDS in 2005. I use the standardized form for ease of interpretation. Post$_t$ is a binary variable that equals to one in years following the 2006 reauthorization. Federal ADAP Contribution per HIV_{st} is the amount of money granted by the federal government to a state ADAP per HIV positive population. $\mathbf{X}_{st}$ is a matrix of time varying state characteristics including the poverty rate, percentage of the population that is white, and the percentage of the population that is under 25. The results for the first stage are presented in Table 2.3. I also control for state and year fixed effects. My standard errors are clustered at the state level, and I weight my estimates by the HIV positive population. As expected, the estimates suggest that an increase in the AIDS-to-HIV ratio is associated with a lower federal ADAP contribution per HIV positive population. A 1 standard deviation increase in pre-reauthorization AIDS-to-HIV ratio is associated with an 8% decrease in federal ADAP contribution after the 2006 reauthorization.

Thereafter, I estimate the following second stage:

$$\begin{aligned}\text{ADAP Expenditure per HIV}_{st}\\ = \beta_0 + \beta_1 \text{Federal ADAP } \widehat{\text{Contribution}} \text{ per HIV} + \gamma X_{st} + \delta_t + \nu_s + \epsilon_s t\end{aligned} \tag{2.2}$$

where Federal ADAP Contribution per HIV depicts the predicted Federal ADAP contribution per HIV positive population obtained from the first stage. Other features of this feature are similar to Equation 2.1.

Estimates from Equation 2.2 are provided in Table 2.4. Estimates reveal that even after using the instrumental variable strategy, a dollar increase in Federal ADAP contributions per HIV positive individual results in a near dollar increase in ADAP expenditures per HIV positive individual. This suggests strong evidence of Fly Paper effects in the setting of the provision of life saving drugs. Changes in federal funding are almost completely translated into changes in state expenditure.

In order to further rule out crowd out effects, I also estimate the effect of ADAP funding on state contributions. Since state contributions tend to be a smaller part of the overall ADAP budget, it's possible that an increase in federal funding is followed by states reducing their contributions but that reduction having a small effect on overall expenditure. To rule out this possibility, I reestimate Equation 2,2 while changing the outcome variable to State Contributions per HIV positive individual. States reducing their ADAP contributions in response to an increase in Federal ADAP contribution would be evidence of crowd out. Estimates are provided in Table 2.5 and reveal that states do not decrease their contributions as a result of increasing federal contribution. In fact, I find that states increase their contribution towards ADAP following an increase in federal ADAP funding.

Prior research has found evidence of crowding-in as response to changes in federal infrastructural funding (Leduc and Wilson, 2017). Since state contributions are not the only form of non-federal ADAP funding and my overall effect on expenditures are still below a dollar for dollar, I cannot conclude that I observe crowding-in effects.[29] However, since I observe an almost dollar for dollar change in state ADAP expenditures as a response to changes in federal funding as well as no evidence of states decreasing their ADAP contributions in response to increased federal funding, I can rule out the possibility of crowd out effects in favor of flypaper effects.

[29] Apart from Federal and State contributions, some states also receive significant funding in the form of Drug Rebates. Whether or not a state receives a drug rebate is dependant on a states drug purchasing mechanism.

Table 2.3: Flypaper Effects - First Stage

	(1)	(2)
	Log(Federal ADAP Cont)	Federal ADAP Cont
post=1 × Standardized values of aids-to-HIV	-0.080***	-75.787***
	(0.017)	(12.377)
Percentage under poverty	-0.002	-1.707
	(0.005)	(4.336)
Proportion White	-0.351	553.793
	(3.486)	(2902.662)
Proportion Under 25	-8.000	-6833.356
	(6.743)	(5142.618)
Observations	297	297
State FE	Y	Y
Year FE	Y	Y

Table 2.4: Flypaper Effects- Second Stage

	OLS		IV	
	(1)	(2)	(3)	(4)
	Log(Total Expenditures)	Total Expenditures	Log(Total Expenditures)	Total Expenditures
Log(Federal ADAP Cont)	0.985**		0.950*	
	(0.423)		(0.526)	
Federal ADAP Cont		1.091**		0.947*
		(0.448)		(0.488)
Percentage under poverty	-0.031	-42.382	-0.031	-41.614
	(0.030)	(37.475)	(0.029)	(36.125)
Proportion White	21.925	6873.160	21.971	7250.624
	(27.905)	(26987.070)	(26.711)	(25829.839)
Proportion Under 25	15.226	-10594.926	14.416	-13423.088
	(46.753)	(38741.321)	(48.031)	(39955.661)
Observations	264	264	264	264
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
First-stage F-Statistic			18.699	30.006

Table 2.5: Flypaper Effects- State Contributions

	OLS	IV
	(1)	(2)
	State Cont	State Cont
Federal ADAP Cont	0.275***	0.281**
	(0.095)	(0.141)
Percentage under poverty	-3.386	-3.403
	(7.964)	(7.727)
Proportion White	8514.715***	8483.306***
	(2722.304)	(2733.285)
Proportion Under 25	15908.029*	15943.473*
	(9155.619)	(8645.039)
Observations	296	296
State FE	Y	Y
Year FE	Y	Y
First-stage F-Statistic		33.425

2.4.2 *Effects on State ADAP policies*

In addition to estimating effects on expenditure overall, I also make use of my instrumental variable strategy to estimate the effect of changes in federal funding on State ADAP policies. Formally, I estimate the following equation:

$$Y = \beta_0 + \beta_1 \text{Federal ADAP } \widehat{\text{Contribution}} \text{ per HIV} + \gamma X_{st} + \delta_t + \nu_s + \epsilon_s t \quad (2.3)$$

where Y_{st} represents the outcome variable in consideration.

Estimates for Equation 2.3 are provided in Table 2.6. I present effects of Federal ADAP contributions per HIV in terms of thousands of dollars. I observe that greater Federal ADAP contribution results in a greater number of clients being served, state ADAPs offering a less stringent income eligibility requirement, a lower probability of state having a waitlist and a more generous number of drugs covered in the ADAP formulary. I find no evidence that increased funding resulted in the provision of Hepatitus C treatments or a decreased probability that a state has a Medical Eligibility requirement in addition to the income eligibility requirement.

Some back of the envelope calculations reveal that in order to provide ADAP services to another client, federal contributions to ADAP should increase by approximately 11,000\$s.[30] This is particularly interesting given average annual cost of treatment per ADAP client ranges from 10,824\$s to 12,768\$s in this period (NASTAD, 2012a). This implies that all contributions from the federal government translate into the provision of services to new clients.

[30] Table 2.6 suggests that a 1\$ increase in Federal ADAP contributions per HIV increases the the number of Clients per HIV by 0.00009. In order to increase provision of ADAP serves by 1, an ADAP must provide a additional 11,111 \$s ($_0\frac{1}{00009}$).

Table 2.6 ADAP Outcomes

	Clients per HIV		Income Elig Req(%FPL)		Wait List		Drugs Covered		Hep C Treatment		Medical Elig Req	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Federal ADAP Cont (1000s of dollars)	0.07537***	0.08679***	196.80382**	330.79227***	-0.21360	-0.78018*	64.49243**	131.47306***	-0.44998	-0.16321	-0.11614	-0.09067
	(0.02426)	(0.03321)	(80.67762)	(79.80915)	(0.14679)	(0.40216)	(30.53347)	(33.23777)	(0.41323)	(0.58213)	(0.31095)	(0.48852)
Percentage under poverty	0.00072	0.00067	2.00090	1.46997	-0.00280	-0.00126	3.44389	3.03510	0.03245*	0.03167*	0.02759**	0.02753**
	(0.00189)	(0.00185)	(3.86788)	(3.84879)	(0.01787)	(0.01784)	(2.04894)	(2.00544)	(0.01861)	(0.01906)	(0.01349)	(0.01287)
Proportion White	2.26094**	2.19913**	1371.92580	647.01607	-7.11025	-4.06951	830.25269	338.59013	4.02387	2.48486	-11.20009	-11.33677
	(0.91666)	(0.85588)	(1549.86778)	(1455.07147)	(5.57012)	(5.56948)	(789.49213)	(898.39905)	(17.24774)	(16.85846)	(10.17559)	(10.15151)
Proportion Under 25	2.01586	2.08119	2108.41921	2859.62092	-11.24098	-14.59996	2238.30715*	2611.27188**	26.31051	28.01061	-13.01482	-12.86384
	(1.64215)	(1.61589)	(4903.71463)	(4084.31930)	(8.46767)	(9.58258)	(1174.31084)	(1061.98707)	(34.71439)	(32.73802)	(18.06800)	(17.28438)
Observations	292	292	294	294	297	297	230	230	297	297	297	297
State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

2.4.3 Effects on Health-Related Outcomes

I extend my study to look at health outcomes of ADAP clients. The ADAP monitoring reports provide information about the CD4 count of ADAP Clients. CD4 cells are a type of white blood cell and CD4 counts are used to check the health of the immune system. CD4 counts are considered low if they fall below 500 and a CD4 count below 200 represents AIDS. In general, lower CD4 counts indicates the progression of the virus and indicate poorer health. Regularly taking ARV treatment prevents the depletion of CD4 cells and can increase CD4 counts. I reestimate Equation 2.3 and change the outcome variable to represent average CD4 level, proportion of clients with CD4 levels below 200 and proportion of clients with CD4 levels below 500. I find that states with increased funding may be experience a lowering of average CD4 counts. I am unable to determine whether this change is a result of changes in treatments as a result of changes in funding, or a result of changes in composition. For example, an increase the average CD4 level could be the result of some Clients with lower CD4 clients dying, new healthier clients being enrolled, or improvements in the CD4 levels of existing clients.

Table 2.7: ADAP Client Health Outcomes

	Avg CD4		CD4 below 200		CD4 below 500	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Federal ADAP Cont (1000s of dollars)	-71.89306***	-108.24879***	0.18304**	0.12247	-0.05289	-0.22409***
	(12.82248)	(16.00857)	(0.06790)	(0.09445)	(0.06887)	(0.08380)
Percentage under poverty	-0.76279	-0.72290	-0.01625**	-0.01619**	-0.01400*	-0.01381**
	(1.45649)	(1.31259)	(0.00769)	(0.00732)	(0.00712)	(0.00658)
Proportion White	2036.50497***	2255.80111***	1.03684	1.40222	6.84425*	7.87689***
	(562.36388)	(498.04483)	(2.48500)	(2.27753)	(3.40489)	(3.01716)
Proportion Under 25	518.18945	332.60140	6.66766**	6.35845**	7.01683**	6.14291*
	(612.58920)	(844.63262)	(3.06547)	(2.96070)	(2.84578)	(3.55946)
Observations	192	193	192	193	192	193
State FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

2.5 Sensitivity to Dropping Each State

Given the small sample size in this study, and the variation in weights (states with higher rates of HIV/AIDS are given larger weights), it is important to establish that effects are not the result of individual states with large weights. To this end, I reestimate Equation 3 while dropping each state one at a time. Estimates are provided in Table 2.8.

Table 2.8 reveals that although my estimates are sensitive to the inclusion of certain high HIV states, I find evidence of flypaper effects no matter which states are dropped. For example, dropping New York significantly increases my estimated coefficient but does not affect the direction of effects measured. This indicates that the findings presented in this paper are not the result of differential trends in specific states but rather, reflect broader patterns across all states and provide further evidence of flypaper effects.

Table 2.8: Flypaper Effects: Dropping Each State

	OLS		IV	
Excluded state	Total Expenditures	SE	Total Expenditures	SE
Alabama	1.221*	(2.65)	1.190*	(2.31)
Alaska	1.090*	(2.43)	0.949	(1.94)
Arizona	1.096*	(2.43)	0.948	(1.95)
Arkansas	1.099*	(2.40)	0.978	(1.92)
Colorado	1.316*	(2.43)	1.105	(1.85)
Florida	0.926	(2.01)	0.826*	(2.07)
Idaho	1.075*	(2.43)	0.925	(1.92)
Indiana	1.096*	(2.44)	0.947	(1.94)
Iowa	1.092*	(2.42)	0.952	(1.94)
Kansas	1.083*	(2.44)	0.857	(1.80)
Louisiana	1.111*	(2.45)	0.968*	(1.99)
Michigan	1.166*	(2.60)	0.972	(1.94)
Minnesota	1.208*	(2.45)	1.065*	(2.09)
Mississippi	1.100*	(2.38)	1.013*	(2.03)
Missouri	1.042*	(2.31)	0.936	(1.91)
Nebraska	1.093*	(2.44)	0.945	(1.94)
Nevada	1.103*	(2.14)	0.961	(1.50)
New Jersey	1.029*	(2.15)	0.665	(1.33)
New Mexico	0.941*	(2.14)	0.830	(1.77)
New York	1.302*	(2.63)	1.525*	(2.37)
North Carolina	1.161*	(2.58)	0.971*	(1.98)
North Dakota	1.091*	(2.44)	0.944	(1.94)
Ohio	1.187*	(2.50)	0.978	(1.88)
Oklahoma	1.083*	(2.41)	0.929	(1.88)
South Carolina	0.838*	(2.25)	0.833	(1.61)
South Dakota	1.086*	(2.42)	0.936	(1.92)
Tennessee	0.963*	(2.31)	0.714	(1.72)
Texas	0.964*	(2.24)	0.952*	(2.13)
Utah	1.111*	(2.42)	0.958	(1.90)
Virginia	1.161*	(2.41)	0.966	(1.73)
West Virginia	1.101*	(2.44)	0.949	(1.95)
Wisconsin	1.040*	(2.36)	0.899	(1.85)
Wyoming	1.090*	(2.43)	0.947	(1.94)

2.6 Conclusion

This study finds evidence of flypapper effects in the context of the provision of life saving treatments. I find that federal ADAP funding plays an important role in providing low-income people living with HIV access to life-saving treatments. Making use of an exogenous shock to funding which occurred alongside the 2006 reauthorization of Ryan White, this paper find significant evidence of flypaper effects with regards to federal ADAP funding. Changes in federal contributions are matched with dollar-to-dollar changes in state ADAP expenditure.

I also find evidence that greater contributions from the federal government result in states being more generous with the kinds of clients they treat and the kinds of treatments that are offered. I find that increases in federal contributions increase the number of clients served. Although this finding is in line with other studies that find that more generous state ADAP policies result in increases in the number of clients served (Snider et al., 2016), this is the first study of its kind that exploits an exogenous shock to estimate the causal effect of changes in federal ADAP funding on state ADAPs. These findings underscore the importance of federal support.

Appendix A. Additional Robustness Tests for Chapter 1

A.1 ICD Code

Table A.1: ICD Codes

Cause of Death	ICD 9 Code (1990 - 1998)	ICD 10 Code (1999 - 2002)
Suicide	E950-E959	U03, X60-X84, Y87.0
HIV/AIDS death	042	B20-B24
Firearm Suicide	E955	X72, X73, X74
Non Firearm Suicide	E950-E954, E956-E959	U03, X60-X71, X76-X84, Y87.0
Motor Vehicle Accident	E810-E825	V89.0, V89.2, V89.9

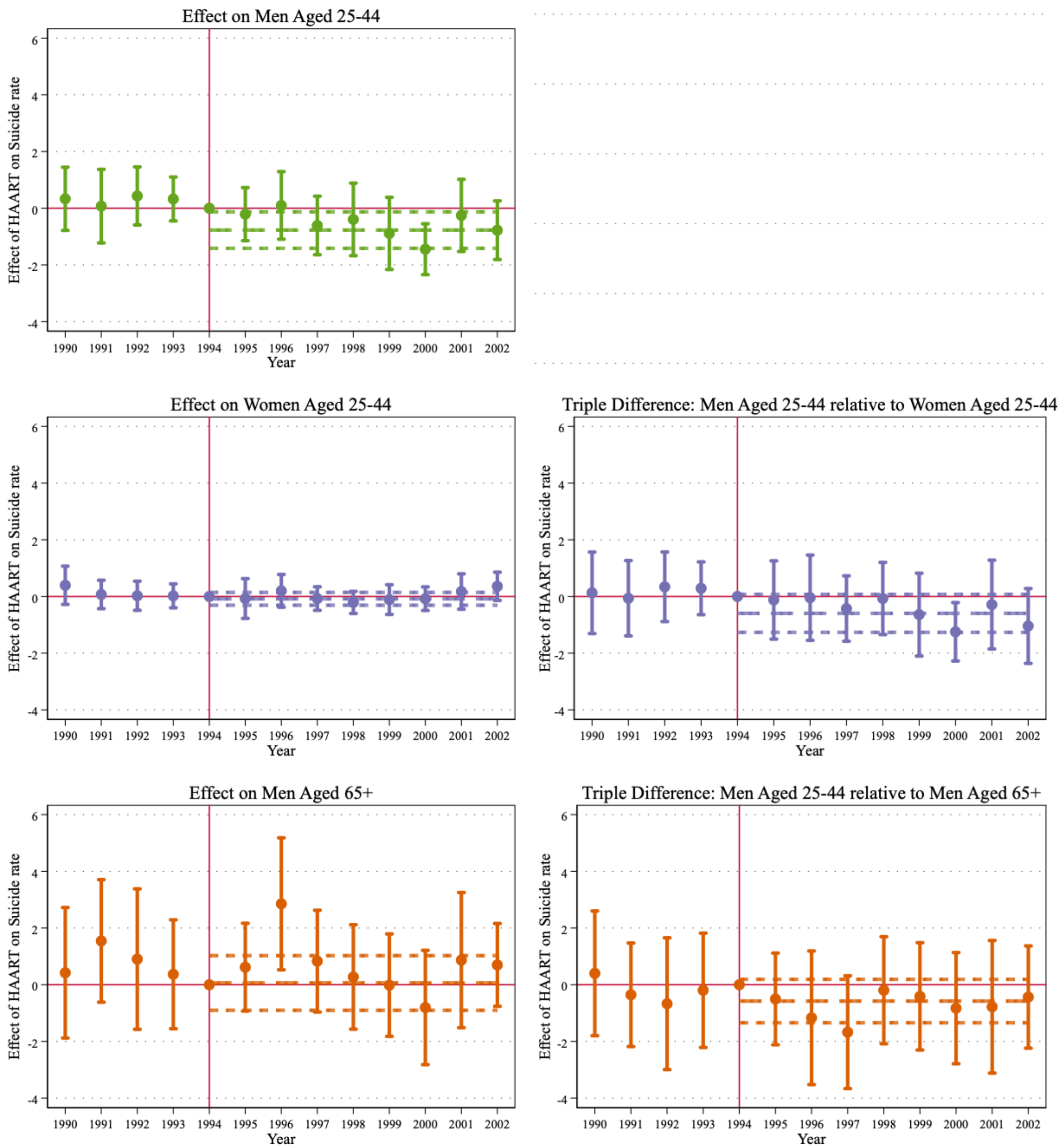
A.2 AIDS Data

I obtain total annual city counts of AIDS cases from the AIDS Public Information Data set from the Department of Health and Human Services CDC (1990-2002a). The AIDS Public Information data set contains data through 2002 for each city that has a population of at least 500,000 people as per the 2000 census. We may be concerned that it has similar effects on suicide rates, and therefore I control for Title 1 eligibility. Using the AIDS case data, I impute Title 1 eligibility. I verify that my estimates match those provided by Dillender (2021). Due to a large number of counties with missing AIDS case data, I do not use AIDS case rates as a measure for HIV/AIDS incidence in my main analysis. However, to verify my findings, I repeat my analysis by changing the HIV incidence measure to AIDS cases instead of HIV/AIDS deaths and find similar effects. I repeat I repeat the analysis using AIDS case rate data as the treatment variable. As mentioned earlier, the AIDS Public Information Dataset only includes data from cities with populations over 500,000.

Table A.2: Summary Statistics for AIDS Data

	4th Quartile	3rd Quartile	2nd Quartile	1st Quartile
Male Suicide Rate	16.13	18.09	16.41	19.18
	(6.26)	(7.71)	(7.19)	(7.66)
Female Suicide Rate	4.32	4.56	3.98	4.43
	(2.32)	(2.48)	(2.35)	(2.88)
1994 AIDS Case Rate	58.89	30.88	18.32	11.22
	(29.13)	(4.63)	(2.22)	(2.76)
Male HIV Death Rate	30.01	17.32	13.22	9.24
	(48.68)	(22.05)	(21.07)	(14.16)
Female HIV Death Rate	5.39	2.82	2.08	0.96
	(11.30)	(4.35)	(3.61)	(1.64)
1994 HIV Death Rate	28.72	17.19	13.28	8.37
	(26.14)	(8.33)	(10.24)	(5.39)
Male Fire Arm Suicide Rate	9.08	10.36	9.46	11.28
	(4.34)	(5.75)	(5.71)	(5.08)
Female Fire Arm Suicide Rate	1.46	1.54	1.28	1.42
	(1.31)	(1.50)	(1.40)	(1.46)
Male Non Fire Arm Suicide Rate	7.05	7.73	6.95	7.90
	(4.04)	(4.01)	(3.81)	(4.61)
Female Non Fire Arm Suicide Rate	2.86	3.02	2.70	3.01
	(1.68)	(1.76)	(1.76)	(2.15)
Eligible for Title 1 funding by 1996	0.98	0.71	0.56	0.26
	(0.14)	(0.45)	(0.50)	(0.44)
Unemployment Rate	5.58	5.30	5.12	5.45
	(1.97)	(1.75)	(2.25)	(2.86)
Population Density	2,695.05	1,646.44	1,886.24	1,210.94
	(3,037.16)	(1,744.34)	(1,911.38)	(1,128.67)
Percentage Pop Male	48.95	49.04	48.55	48.48
	(0.99)	(1.09)	(0.86)	(1.00)
Percentage Pop White	73.73	79.95	81.77	86.16
	(13.37)	(10.87)	(11.69)	(9.05)
Percentage Pop aged b/w 0 and 24	35.38	35.51	35.03	36.13
	(3.53)	(3.64)	(2.28)	(3.98)
Percentage Pop aged b/w 25 and 44	33.75	32.53	32.46	31.01
	(2.84)	(2.76)	(2.12)	(2.27)
Observations	3120	3016	2704	3276

Figure A. 1: Effects Using AIDS Rate Data

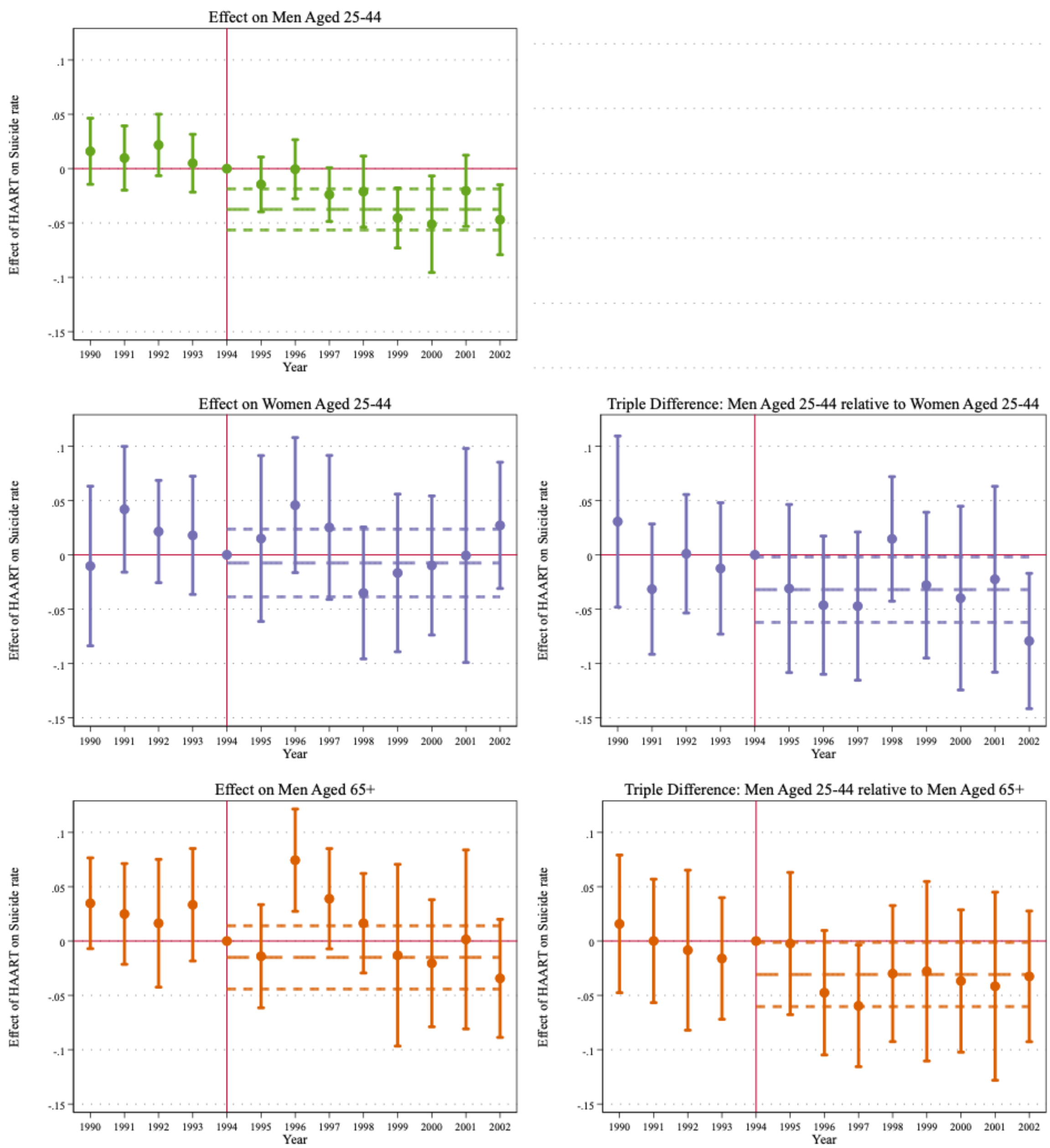


A.3. Inverse Hyperbolic Sine Transformation of Suicide Rates

The main analysis for this paper uses level suicide rates. Some researchers may argue that percentage changes are more relevant than level changes especially when comparing suicide rates across different groups (for example, women have lower rates of suicide compared to men). Similarly, there may also be important geographical differences in pre-treatment suicide rate. For example, a high HIV/AIDS county may also have higher rates of suicide and it is problematic to compare changes in the rate of suicide if there is significant variation in the baseline mean. A 1 unit increase in a county with very high rates of suicide may not be as meaningful as a 1 unit increase in suicide rates for a county with very low rates of suicide. In order to account for this, I re-estimate Equation 1.1 and Equation 1.2 while applying the inverse hyperbolic sine transformation to my dependent variable. I do not use the natural logarithm because that does not retain zero valued observations. Applied researchers often employ the inverse hyperbolic sine transformation to convert right-skewed variables, which may contain zero values. Since my dataset consists of many county-year combinations with zero suicides, I find this transformation appropriate in my setting.

My results are depicted in Figure A.2. I find larger standard errors when measuring effects on the inverse hyperbolic sin of suicide rates for several groups. Suicides by subgroup at the county level tend to be zero for many year-county-group combinations. Therefore, a unit change in the number of suicides performed would have a large effect on the percentage change of suicide rate. This explains the large standard deviations on the inverse hyperbolic sine transformation. Nevertheless, the estimates are qualitatively similar to my main findings and lends credence to my estimates.

Figure A. 2: Inverse Hyperbolic Sin Transformation

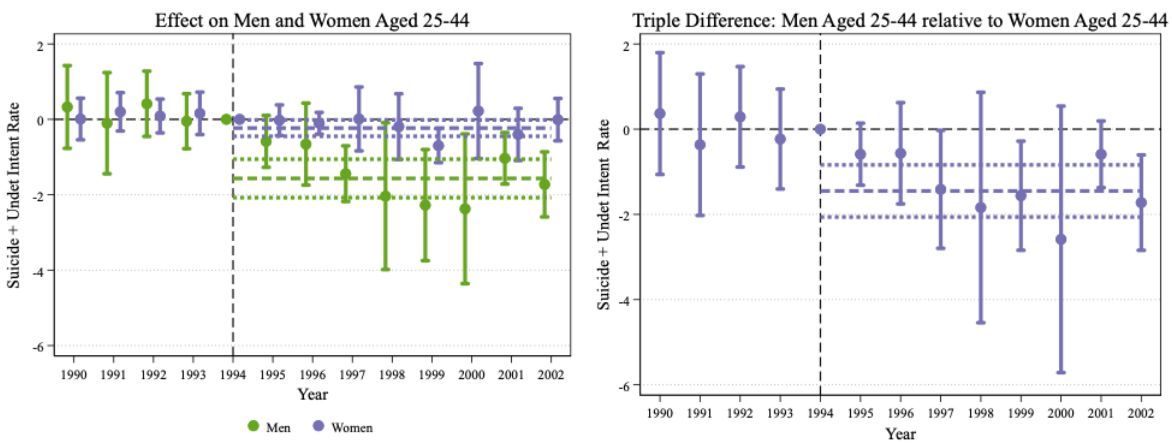


A.4 Accounting for Problems With Data

A.4.1 Accounting for Suicide Misclassification

Some studies argue that a large portion of deaths classified as undetermined intent are in fact suicides Bj¨orkenstam et al. (2014). If there are geographic and gender differences in the proportion of suicides being classified as undetermined intent, this may affect our result. In order to account for this possibility, I include all deaths with undermined intent as suicides. Event study estimates are provided in Figure A.3.

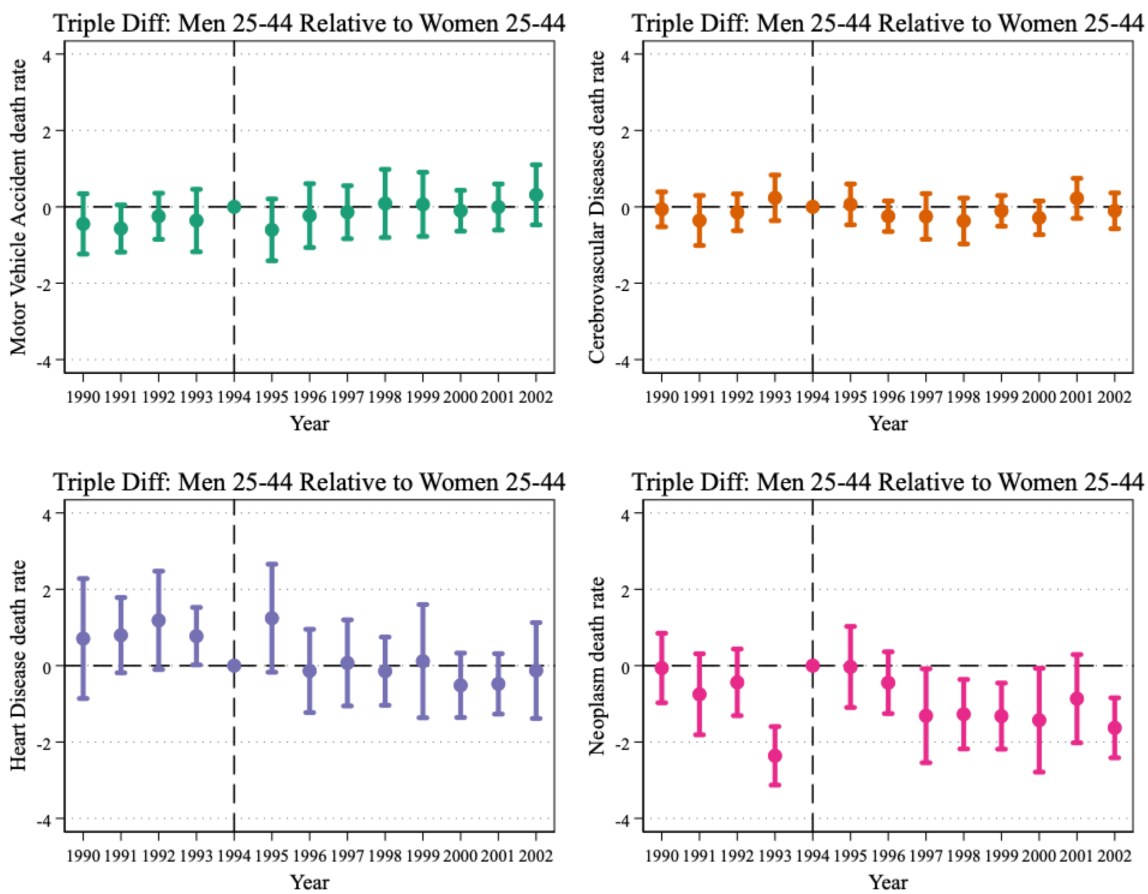
Figure A. 3: Misclassifies Suicide Data



A.4.2 Falsification Test

In order to ensure that my results are not being driven by problems in the way deaths are recorded in the Multiple Cause of Death data file, I conduct several falsification tests. My main analysis is based upon comparing suicide rates over time between counties and demographics with different rates of HIV/AIDS incidence. I provide triple difference estimates from Equation 1.2 while changing my dependent variable to measure death rates from motor vehicle accidents, cerebrovascular diseases, heart diseases, and neoplasm. The Event Studies for this analysis are presented in Figure A.4. HAART appears to have little consequence on these causes of death.

Figure A. 4: Falsification Tests



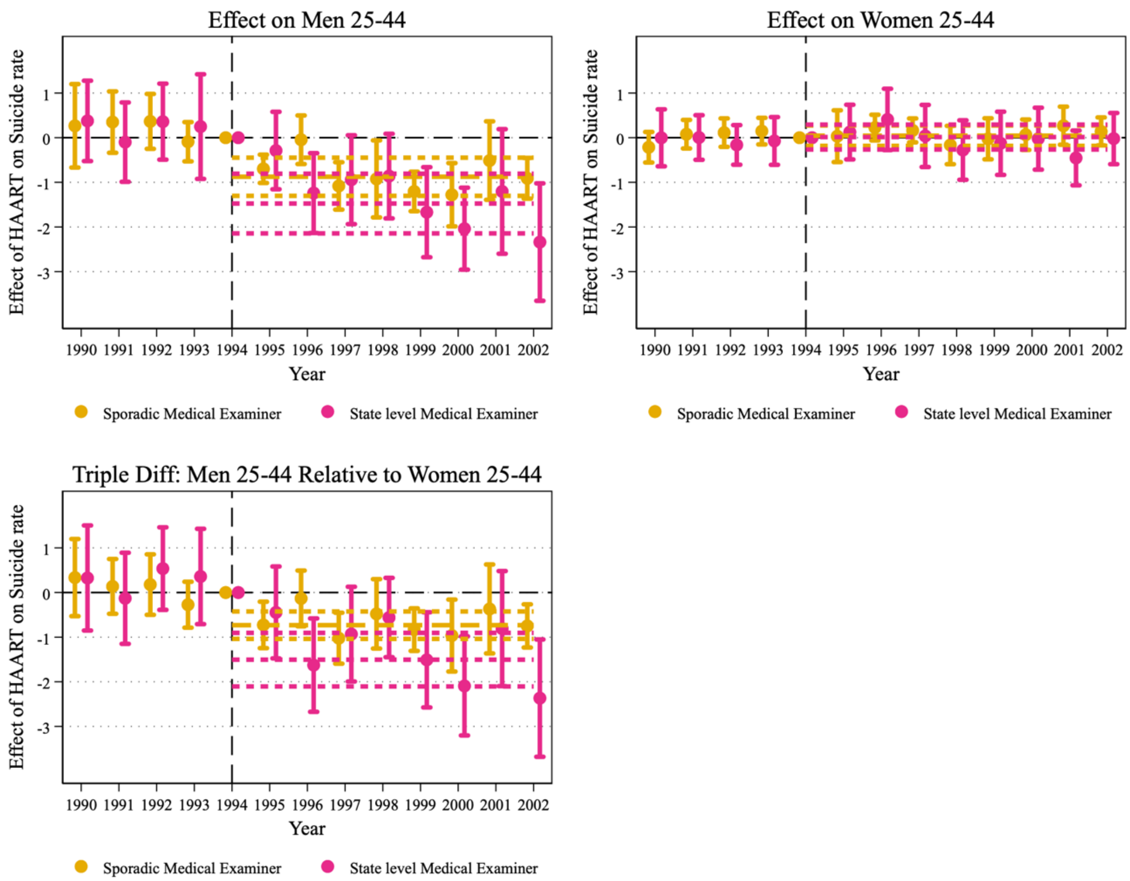
A.4.3 Coroners and Medical Examiners

Recent evidence suggests that geographic differences in Medicolegal Systems can affect suicide rates calculated using data abstracted from death certificates (Fern´andez et al.2019 ; Klugman et al. 2013). There is spatial and temporal variation in who records the underlying cause of death on the death certificates. Medical examiners and coroners determine and report the cause of death when the death is sudden, violent, or untimely. In this section, I adjust my estimation equation and reestimate my results to rule out the possibility that effects are being driven by changes in Medicolegal system policies.

In general, there has been rise in medical examiner system overtime in the US. Many state and county coroner systems have converted to medical examiner systems. Since my analysis is at the county level and I control for state-year fixed effects, I am not concerned about changes in state level policies in Medicolegal systems. I am more concerned about states with sporadic county medical examiner systems. Therefore, I obtain the year at which counties switched from coroner systems to medical examiner systems for states with sporadic county medical examiner systems from Hanzlick 2007.[31] Thereafter, I reestimate Equation 1.1 and Equation 1.2 for states with sporadic county medical examiner systems while including a control variable which equals 1 when a county has transitioned into a medical examiner system. I also provide estimates of Equation 1.1 and Equation 1.2 while dropping all states with sporadic medical examiner systems. Estimates for this specification are provided in Figure A.5. My estimates are similar to that of my main specification although my effects appear larger for states with state-level medical examiner policies.

[31] These states include Alabama, California, Colorado, Georgia, Hawaii, Illinois, Minnesota, Missouri, New York, Ohio, Pennsylvania, Texas, Washington and Wisconsin

Figure A. 5: Coroners and Medical Examiners



A.5 Removing Control Variables & Removing Additional Fixed Effects

Recent developments in the Difference-in-Difference literature argue that assuming parallel trends conditional on the inclusion of covariates might cause problems with the suggested estimation procedure Sant'Anna and Zhao (2020). Additionally, since I include state-time fixed effects in my difference in difference model and state-time-sex fixed effects in my triple difference equation, I am exploiting within state variation to conduct my analysis. Although this method accounts for changes in state policy which may be important, we might expect that our estimates are different when we consider across state variation. Therefore, I make the following changes:

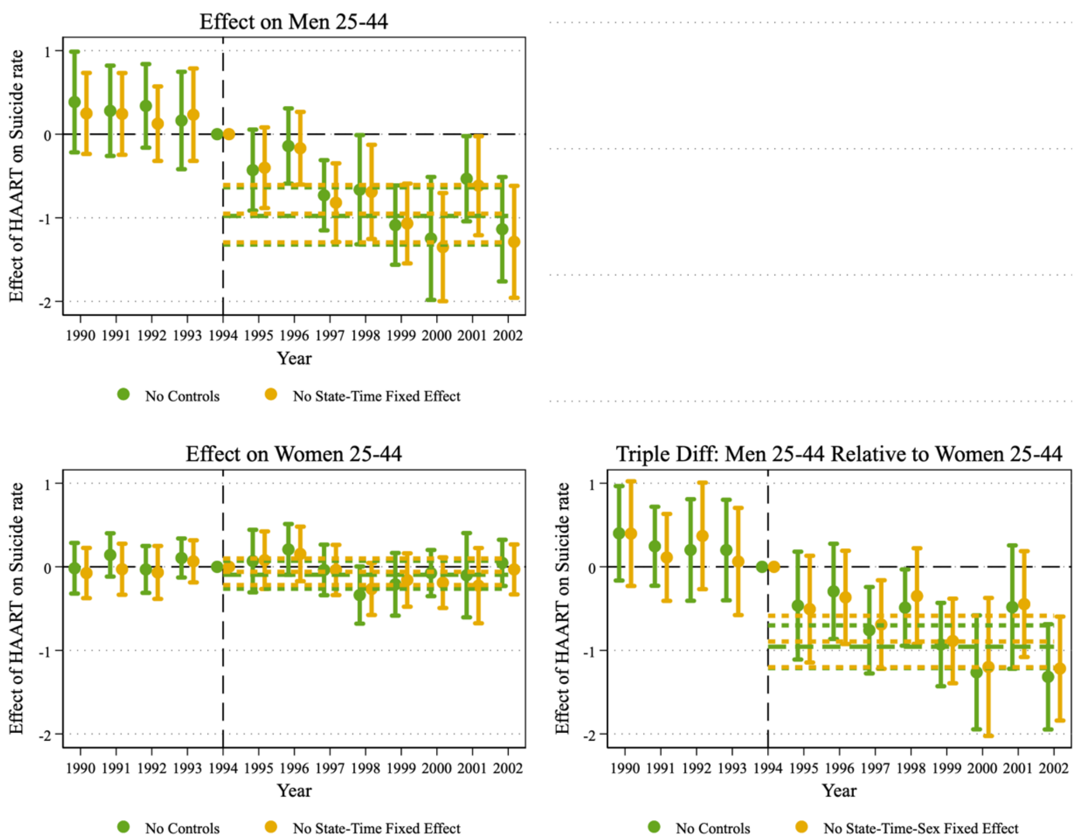
1. I reestimate Equation 1.1 without any control variables for men and women aged 25-44.

2. I reeestimate Equation 1.1 with the state-time fixed effect for men and women aged 25-44. Now, I only control for county and year fixed effects.

3. Since the fixed effects in Equation 1.2 already account for any covariated which I control for, I present the these estimates for men and women aged 25-44 once again.
4. I reestimate Equation 1.2 while removing state-year-sex fixed effects for men and women aged 25-44. Now, I only control for county-year, county-sex, and sex sex-year fixed effects.

Figure A.6 shows that these changes don't have large effects on my estimates.

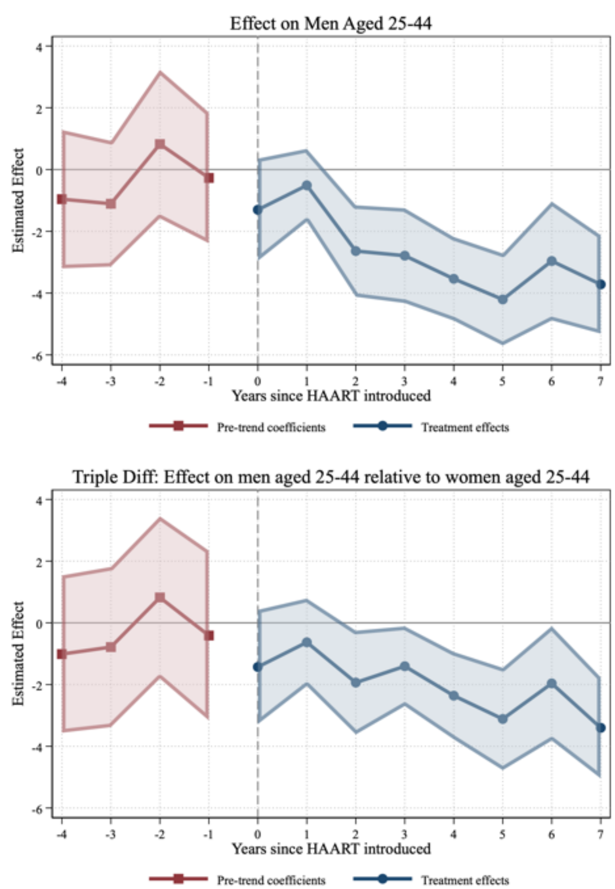
Figure A. 6: Removing Control Variables



A.6 Alternative Estimator

Although my estimation strategy does not rely on the staggered timing of treatment, recent studies show that heterogeneous treatment effects can bias even non-staggered treatments (De Chaisemartin and d'Haultfoeuille 2022a; Borusyak et al. 2021). In order to account for these developments, I use the imputation estimator developed by Borusyak et al. 2021 and reestimate Equation 1.1 & Equation 1.2. Estimates are provided in Figure A.7. Note that I use a binary treatment variable and considering counties in the top 10 percentile of pre-HAART HIV/AIDS death rates as treated states instead of the continuous treatment used in my main specification.[32]

Figure A. 7: Alternative Estimator



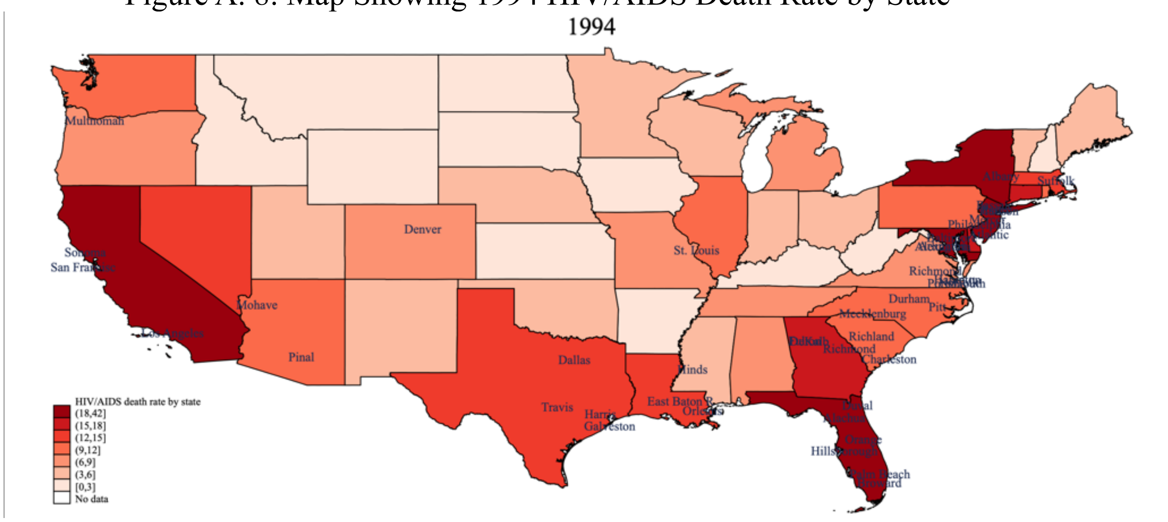
[32] Current heterogeneity robust estimators with dynamic effects do not allow for continious and non-staggard treatment (De Chaisemartin and d'Haultfoeuille, 2022b).

A.7 State Level Analysis

The analysis conducted in this paper exploits county level variation in pre-HAART HIV/AIDS death rates. Conducting county-level analysis rather than state-level analysis has the benefit of exploiting a greater breadth of variation in pre-HAART HIV/AIDS death rates. However, due to confidentiality rules, I only observe county codes for counties with populations exceeding 100,000. I observe state codes for all years. In order to ensure that my analysis is not affected by this selection process, I conduct my analysis at the state-level using all the data I have at hand.

First, I present a map of the US prior to the introduction of HAART. I also list counties in the top 10 percentile of HIV/AIDS death rates.

Figure A. 8: Map Showing 1994 HIV/AIDS Death Rate by State



In order to conduct state-level analysis, I estimate the following equation:

$$Suicide\ Rate_{st} = \alpha + \sum_{\substack{m \neq 1994 \\ m=1990}}^{2002} \beta_m (Pre - HIV/AIDS\ deathrate_t \times 1[t\ =\ m]) + a_t + \mu_s + \epsilon_{st} \qquad \text{(A.1)}$$

Now, Suicide Rate$_{st}$ now measures the number of suicides per 100,000 population in state s at year t for men aged 25 to 44. Pre-HIV/AIDS deathrate$_s$ is the number of HIV/AIDS deaths per 100,000 population in 1994 in state s. a_t and μ_s represent state and year fixed effects. I also estimate this equation for women aged 25-44.

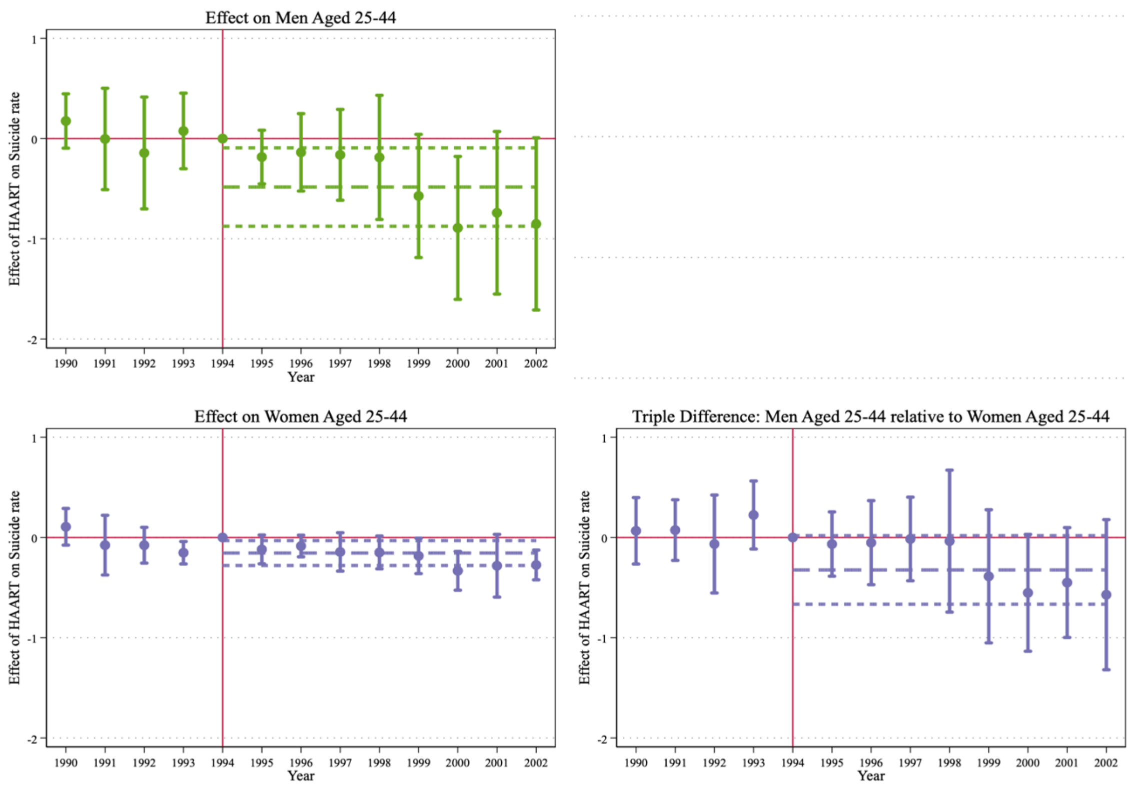
Thereafter, I estimate the following triple difference equation:

$$Suicide\ Rate_{jst} = \alpha + \sum_{\substack{m \neq 1994 \\ m=1990}}^{2002} \beta_m (Pre - HIV/AIDS\ deathrate_t \times 1[t\ =\ m] + Men\ 25 - 44_j) + \theta_{st} + \iota_{js} + \delta_{jt} + \epsilon_{ctj} \tag{A.2}$$

where *Suicide Rate$_{jst}$* measures state-level group-specific suicide rates Men 25-44$_j$ is a dummy variable which measures whether the observation represents Suicide rates for men aged 25 to 44. In my triple difference analysis, I compare effects on men aged to 25 to 44 to women aged 25 to 44.

The estimates presented in Figure A.9 show that the introduction of HAART lead to statistically significant reductions in suicide rates for men aged 25 to 44 but not for women. Triple difference estimates suggests that state level analysis yields muted results. This highlights the importance of using disaggregated data. Since the treatment variable in the main analysis is the standardized form of county-level pre-HAART HIV/AIDS death rates and the treatment variable for the state-level analysis is the standardized form of state-level pre-HAART HIV/AIDS death rate, we cannot compare coefficients. 1 standard deviation in pre-HAART HIV/AIDS death rates at the state level is smaller than 1 standard deviation in pre-HAART HIV/AIDS death rates at the county level.

Figure A. 9: State Level Analysis



A.8 Deaths of Despair

Economists have documented the rise in alcohol, drug, and suicide deaths among Americans without a college degree between 1999 and 2013 Case and Deaton (2021). These deaths are often lumped together as "deaths of despair" and could all be the result of poor mental health. Since this study documents such large decreases in suicide rates, I also examine the effect of HAART on other deaths of despair. I reestimate Equation 1.1 and Equation 1.2, changing the outcome variable from suicide rates to alcohol-related deaths and drug-related deaths. The relevant ICD codes are provided in subsection A.1. The first panel of Figure A.10 shows trends in each death of despair over time.

Estimating the effect on drug-related deaths proves difficult because drug-related deaths are less common, especially in the early years of our analysis. During our period of study, drug-related deaths are increasing rapidly. This results in my estimates being noisy and having large standard errors. Therefore, in my analysis, I only focus on suicide and alcohol related deaths[33]. I provide estimates for Equation 1.1 for men aged 25 to 44 and women aged 25 to 44 for suicide rates and alcohol-related death rates in the second and third panels of Figure A.10. I find that men experience a large decline in alcohol-related deaths and women experience a small decline.

Although this estimate provides additional evidence of improved mental health outcomes in high-HIV counties assuming that alcohol-related deaths are a result of poor mental health, understanding the effect of HAART on alcohol consumption and death requires further analysis. There is also a body of literature exploring the interaction of HAART treatments and alcohol consumption Kumar et al. (2012). Further research is required to better understand the effect of HAART on alcohol consumption and alcohol-related deaths.

[33] Estimates for drug-related deaths are provided in the appendix.

Figure A. 10: Deaths of Despair

A.9 Altering the Functional Form

There are systematic differences between high and low HIV counties as depicted in Table 1.1. High HIV counties tend to be more urban and have higher population densities. To ensure that my effects are not driven solely by differing trends in sex-specific suicide rates for densely and sparsely populated counties, I alter the functional form in an attempt to disentangle these effects. I also allow for non-linear relationships between Pre-HAART HIV/AIDS incidence and population densities by including squared terms. More formally, I estimate the following equation:

$$\begin{aligned} Suicide\ Rate_{ct} = {} & \alpha + \beta_0 Pre-HIV/AIDS\ deathrate_c \times Post_t + \beta_1 PopDense_c \times Post_t \\ & + \beta_2 PopDense_c \times Pre-HIV/AIDS\ deathrate_c \times Post_t + \beta_4 PopDense_c^2 \times Post_t + \gamma X_{ct} \\ & + a_c + \eta_t + \mu_{st} + \epsilon_{ct} \end{aligned} \tag{A.3}$$

Here, $PopDense_c$ represents the 1994 population density. I include the interaction of $PopDense_c$ and $Post_t$, the interaction of the square of $PopDense_c$ and $Post_t$, the interaction of $PopDense_c$, Pre-HAART HIV incidence, and $Post_t$ as well as the interaction of the square of Pre-HAART HIV incidence and $Post_t$. All other features of this equation reflect Equation 1.3. These additional terms allow us to assess whether the effects are driven by differential trends in more densely populated areas or whether effects are driven by underlying HIV/AIDS incidence.

The results for Equation A.3 are provided in Table A11. Even after accounting for differential effects in more densely populated counties, I find that higher HIV counties experience a disproportionate fall in suicide rates for men aged 25 to 44. I also find no effects on women.

Although the only significant interaction term in my results table is the coefficient for Pre-HIV/AIDS $deathrate_c \times Post_t$, the partial effect of an increase in pre-HAART HIV before and after the introduction of HAART on suicide rates also depends on other terms. I estimate this partial effect using the following equation:

$$\frac{\partial \bigtriangleup \text{Suicide Rate}_{ct}}{\partial \text{Pre-HIV/AIDS deathrate}_c \bigtriangleup Post_t} = \beta_0 + \beta_2 \text{PopDense}_c + 2\beta_3 \text{Pre-HIV/AIDS deathrate}_c \tag{A.4}$$

Equation A.4 measures the partial effect of HIV incidence before and after the introduction of HAART on suicide rates. I insert coefficients from my results table and values from my dataset to estimate partial effects across the distribution of pre-HAART HIV/AIDS deaths and population densities. I present these effects across percentiles of pre-HAART HIV/AIDS deaths and population densities in Figure A.11. I insert pre-HAART HIV/AIDS death rate values from several points in the pre-HAART HIV /AIDS death rate distribution and estimate Equation A.4 across the distribution of population densities. Here, I find some evidence that the effect of a 1 standard deviation increase in pre-HAART HIV/AIDS death rate is slightly smaller for counties with higher pre-HAART HIV/AIDS death rates.[34]

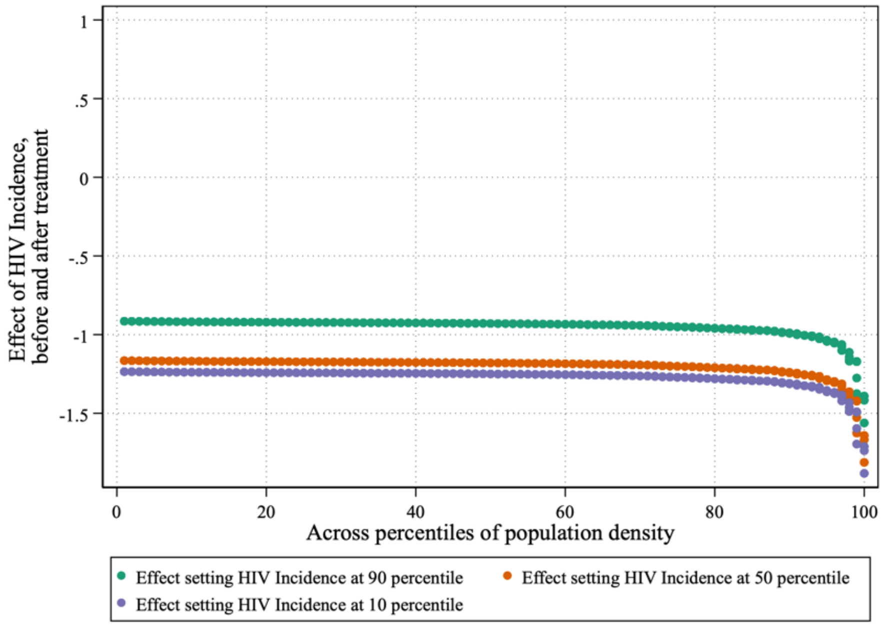
According to the figure, there is approximately a 1 per 100,000 person decrease in suicides in counties with a 1 standard deviation higher pre-HAART HIV/AIDS death rate for most of the distribution of pre-HAART HIV/AIDS incidence and population densities. This estimate is similar to our main specification providing some evidence that these effects are not being driven by differential trends in more densely populated counties.

[34] Note, the effect of a standard deviation increase in pre-HAART HIV/AIDS death rate implied in Figure A11 is different from the overall effects depicted in Figure 1.7.

Table A.3: Alternative Functional Form

	Male	Female
	(1)	(2)
Post=1 × 1994 Population Density	-0.0002372894	-0.0000762272
	(0.00028035)	(0.00015862)
Post=1 × Standardized 1994 HIV death rate	-1.0984083416***	-0.2695155861
	(0.34938719)	(0.19306975)
Post=1 × 1994 Population Density × Standardized 1994 HIV death rate	-0.0000417030	0.0000613873
	(0.00007358)	(0.00004575)
Post=1 × 1994 Population Density Squared	0.0000000086	-0.0000000076
	(0.00000003)	(0.00000002)
Post=1 × Standardized 1994 HIV death rate Squared	0.1013751044	-0.0263399285
	(0.09800664)	(0.06070058)
1994 Population Density	0.0010606808	-0.0006765447
	(0.00151360)	(0.00061887)
Unemployment Rate	-0.0408651843	0.0524218027
	(0.15431379)	(0.08017326)
Percentage Pop White	0.0786624214	0.0684928191
	(0.13311908)	(0.05551084)
Ryan White Title 1 eligible=1	-0.8889187543*	-0.2016953969
	(0.52419174)	(0.24437133)
Observations	4914	4914
County FE	Yes	Yes
Time FE	Yes	Yes
State X Time FE	Yes	Yes

Figure A. 11: Altering Functional Form



A.10 Homicides

As mentioned earlier, the 90s was a period of falling urban violence and crime. Given the disproportionate impact of violence on young men in densely populated areas which tend to also be high HIV/AIDS areas, the results in this paper may be influenced by factors linked to trends in violence, independent of HAART. In this section, I compare trends and effects on homicides and suicides in order to convince the reader that the effects outlined in this paper are not driven by broader trends in violence.

The first panel in Figure A.12 depicts trends in homicide and suicide rates for men aged 25 to 44 living in the highest decile of 1994 HIV/AIDS death rate. Although we observe a fall in both suicide and homicide rates for this group, the fall in suicides occurs after the introduction of HAART in 1995 whereas homicides have been on a downwards trend since the early 90s. In the next panel of Figure A.12, I present trends in homicide rates for men aged 25-44 living in counties that are in the top decile of 1994 HIV/AIDS death rates and bottom 3 deciles. Similarly, the third panel of Figure A.12 depicts trends for women aged 25-44. Since the 90s fall in homicide rate is driven by areas of high HIV/AIDS, it is important to ensure that the effects highlighted in this paper are driven by the introduction of HAART and not broader trends in violence.

The first panel of Figure A.13 presents estimates from Equation 1.2 while changing the outcome variable to homicide rates. Given that the fall in homicides is driven by changes in high HIV/AIDS counties it is unsurprising that we observe negative effects. Unlike the estimates for suicide rate, there are very strong pre-trends and there does not appear to be a discontinuity around the time of HAART introduction. This highlights the importance of using event study models which allow us to observe pre-existing trends. These effects are likely a result of falling homicide rates in more densely populated areas.

In order to account for this possibility, I reestimate the following equation:

$$\begin{aligned} Homicide\ Rate_{jct} = \alpha \\ &+ \sum_{\substack{m \neq 1994 \\ m=1990}}^{2002} \beta_m \big(Pre - HIV/AIDS\ deathrate_c \times 1[t\ =\ m] \times\ Men\ 25 - 44_j\big) \\ &+ \sum_{\substack{m \neq 1994 \\ m=1990}}^{2002} \beta_m \big(PopDence_c \times 1[t\ =\ m] \times\ Men\ 25 - 44_j\big) + \theta_{ct} + \iota_{jc} + \delta_{sjt} + \epsilon_{ctj} \end{aligned}$$

(A.5)

Equation A.5 is similar to Equation 1.2 except it includes a term where I interact 1994 population density (PopDence$_c$) with the treatment variables. This should account for changing trends in homicides in more densely populated counties. Estimates for β_m are presented in the second panel of Figure A13. We no longer observe pretrends and effects are much smaller and statistically not different from zero.

Since both men and women experience a fall in homicide rates in high HIV/AIDS counties relative to low HIV/AIDS counties and men have significantly higher rates of homicide, I consider percentage changes in addition to rates. I re-estimate Equation 1.2 while changing my outcome variable to now represent the inverse hyperbolic sine transformation of homicide rates. Estimates are presented in the third panel of Figure A13. The estimates are now flipped. In percentage terms, effects of women's homicide rates outweigh effects of men's homicide rate. This is in contrast to my findings in Appendix A.3 where I change the outcome variable to the inverse hyperbolic sine of the suicide rate.

Taken together, we find that although homicides have been falling throughout my period of analysis, there does not appear to be a discontinuous change at the time HAART treatment was introduced. After accounting for changing trends by population density, effects appear statistically not different from zero. When I change the outcome variable to represent percentage changes rather than rates, it appears that trends in homicide over this period are larger for women compared to men. This implies that trends in homicide rates do not match the effects on suicide highlighted in this study.

Although there is no way to rule out the possibility that my effects are contaminated by broader trends in violence, it is unlikely since we do not see similar effects on homicides. Given the evidence provided in this section, I conclude that differential trends in violence for high HIV and low HIV counties are unlikely to affect the conclusions found in this paper. Although we do observe changes in homicide rates during this period, they do not follow the same trends as suicide rates.

Figure A. 12: Trends in Homicide Rates

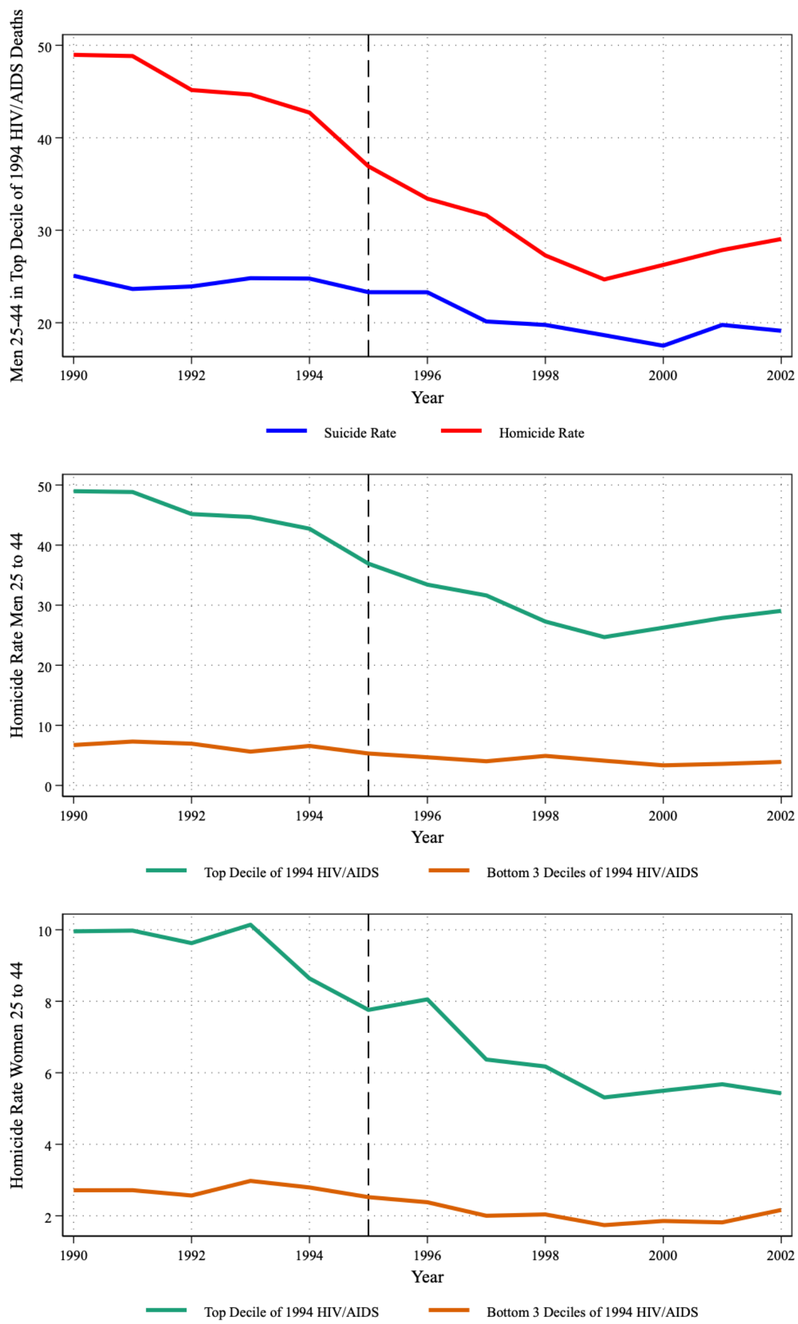
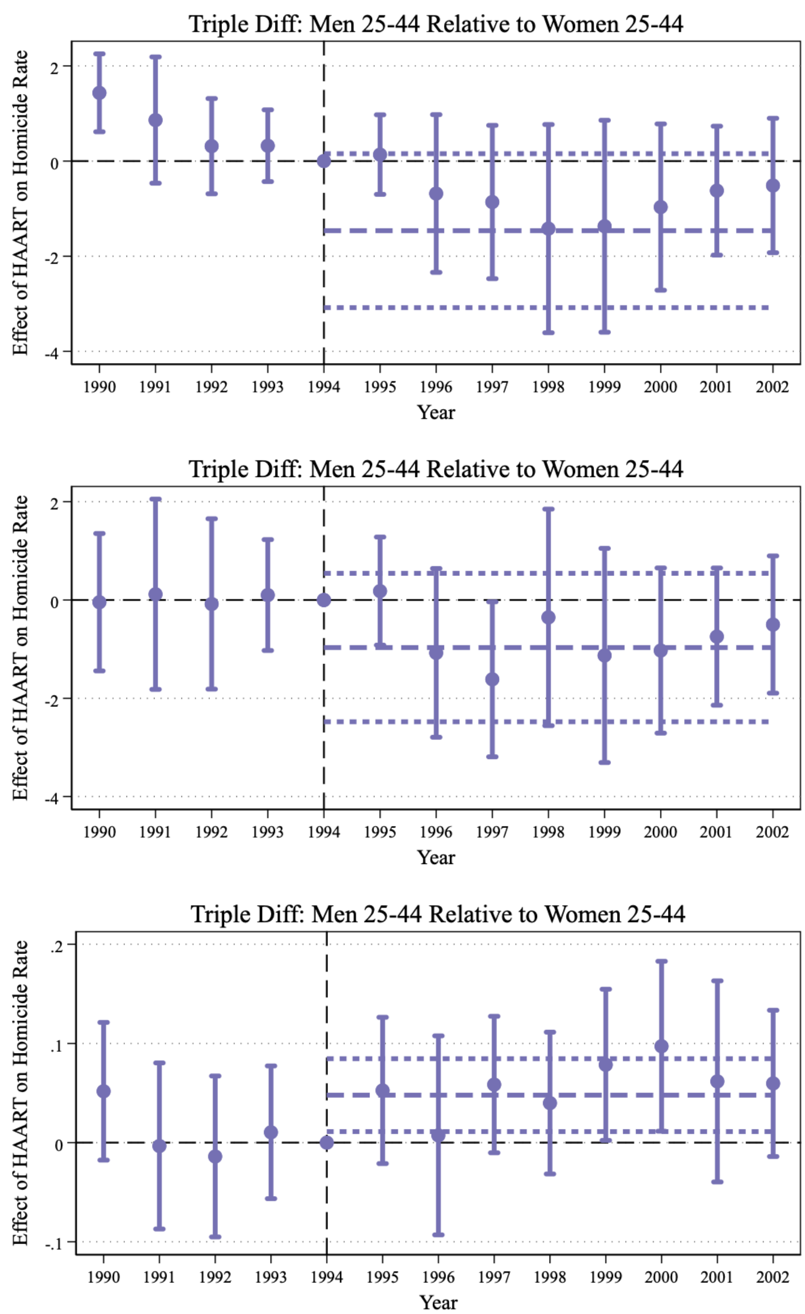


Figure A. 13: Effects on Homicides



A.11 Poor Mental Health Days

Thus far, this paper focuses on the effect of HAART on suicide rates. Suicides represent an extreme outcome resulting from poor mental health; however, poor mental health is often accompanied by several nonextreme outcomes. Mental health also plays an integral role in overall well-being, therefore we may also be concerned about mental health in and of itself. Due to the dearth of mental health data, this study is unable to estimate the causal effects of HAART on non-suicide mental health outcomes. Instead, I use data from the Behavioral Risk Factor Surveillance System (BRFSS) and provide suggestive evidence that the introduction of HAART reduced the average number of poor mental health days for certain at-risk groups.

The BRFSS is a national telephone survey that collects data from U.S. residents regarding their health-related risk behaviors, chronic health conditions, and use of preventive services. The BRFSS is considered to be representative at the state level but, since this paper exploits county-level variations in pre-HAART HIV/AIDS death rates, I conduct analysis at the county level and caution that this should only be considered suggestive evidence. The BRFSS only provides county codes for counties with over 50 respondents. Due to the smaller sample size, I only consider a discrete variable indicating HIV/AIDS intensity instead of the continuous variable used in my main analysis. Counties that are in the top 10 percentile of pre-HAART HIV/AIDS death rates as per the mortality data are classified as high HIV counties whereas all other counties are classified as low HIV counties.

Similar to my main sample, the BRFSS does not provide information about sexual orientation or the HIV status of respondents surveyed. I follow Carpenter et al.2021 and exploit a key feature of the BRFSS to obtain a sample of the population that has a higher proportion of gay respondents. The BRFSS asks the respondent to report the number of adult males and adult females in the household. By creating a sample that includes only households consisting of exactly two adult males, Carpenter et al.2021 argues that we can construct a sample with a greater proportion of gay respondents. Since 2014, some states have added questions about sexual orientation to their survey. Carpenter uses this data and shows that when we restrict the sample to respondents who are over 25 and reside in households consisting of exactly two adult males, the sample consists of 26.1% respondents who identify as gay relative to only 1.8% of respondents who identify as gay overall.

The BRFSS also provides information about self-reported mental health from 1993 onwards. The BRFSS asks the following question: “Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?” To study the effect of HAART on self-reported mental health, I look at responses to this questions among respondents aged 25 to 44 living in households comprised of exactly two same-sex adult males in high HIV/AIDS counties (top 10 percentile). I expect this group to be at a higher risk of contracting HIV, and therefore more likely to be affected by the introduction of HAART. I compare trends for this group to trends of other groups. For some of the years in my sample, the BRFSS also provides information about the self-assessed risk of contracting HIV. Below, I provide information about the proportion of respondents reporting medium or high risk of contracting HIV by the group in question. Same-sex male households residing in high HIV counties report a higher self-assessed risk of contracting HIV. This gives further support to my assertion that this group is more affected by the introduction of HAART.

Table A.4: Self-Reported HIV Risk by Group

Group	High or Medium Risk of contracting HIV
Same-Sex Male HH in high HIV county	0.215
Same-Sex Male HH in low HIV county	0.148
Single Men in high HIV county	0.129
Single Men in low HIV county	0.106
Diff Sex HH Male in high HIV county	0.0850
Diff Sex HH Male in low HIV county	0.057
Diff Sex HH Women in high HIV county	0.074
Diff Sex HH Women in low HIV county	0.058

When I split my sample between the groups mentioned above and the years of the survey, the sample sizes become very small. To ensure that each group-year combination contains at least 50 respondents, I lump responses from every other year together.

I depict trends in the average number of poor mental health days for several groups in Figure A.14. I find that men aged 25 to 44 residing in households consisting of exactly two male adults in high HIV counties experience a steady decline in the average number of poor mental health days following the introduction of HAART. This is the only group that experiences such a reduction. No other group appears to experience a fall in the average number of days with poor mental health. This provides further evidence that these effects are a result of the introduction of HAART. Since frequent mental distress is an indicator of health-related quality of life and is characterized by 14 or more days of self-reported poor mental health in the past month, I construct an indicator variable that is equal to one when the reported number of days with poor mental health is equal to or greater than 14. Trends of this variable by group follow a similar pattern with respondents with over 14 days of poor mental health only decreasing for respondents living in exactly two male adult households in high HIV counties.

Although using BRFSS data for this kind of analysis can be problematic because of the small sample size, the trends provide some suggestive evidence that apart from the introduction of HAART reducing suicide rates, HAART also improved non-extreme mental health outcomes for at-risk groups.

Figure A. 14: Poor Mental Health Days in the Last 30 Days

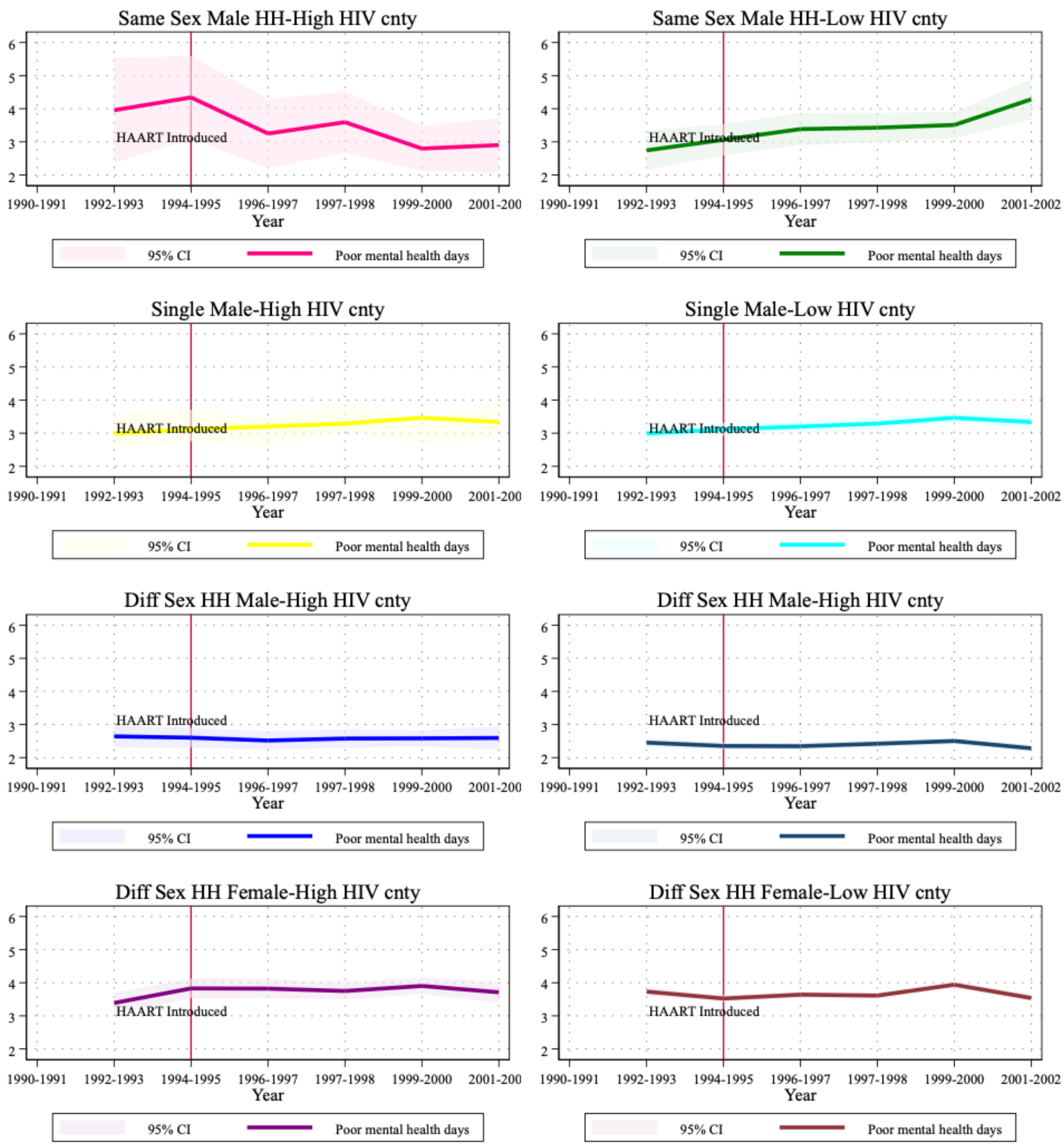
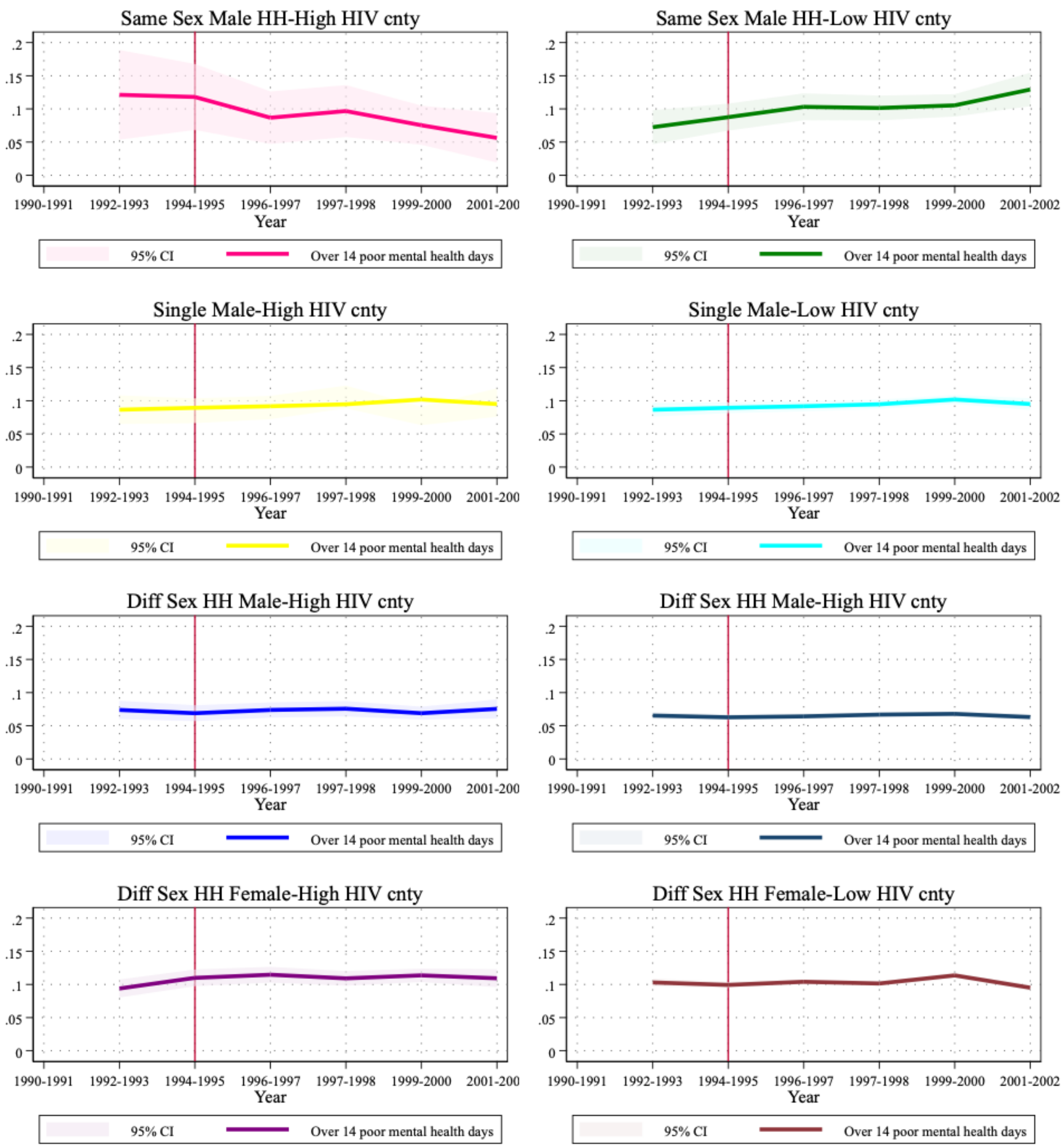


Figure A. 15: Fourteen of More Poor Mental Health Days



Appendix B. Additional Robustness Tests for Chapter 2

B.1. HIV/AIDS Death Rate

My estimates suggest that increasing federal funding increases state ADAP drug expenditure and client enrollment. If these factors are large enough, they might affect overall health outcomes among the general population. Therefore, I evaluate the effect federal ADAP funding on HIV/AIDs death rates.

My period of analysis observes rapid improvements in health outcomes for HIV positive individuals. Figure B1.1 depicts HIV/AIDS death rates in states with above and below median AIDS-to-HIV ratios. Although there are rapid improvements in HIV/AIDS death rates in both kinds of states, above median AIDS-to-HIV states have significantly higher death rates and are experiencing a faster decline in HIV/AIDS deaths over this period.

I reestimate Equation 2.3 while changing the outcome variable to represent HIV/AIDS deaths per 100,000 HIV positive population. I provide estimates in Table B.1. To account for changing trends in HIV/AIDS death rates overtime, I also provide estimates while including state specific linear time trends.

My estimates suggest that states which gain funding experience higher HIV/AIDS death rates. However, the effect is statistically insignificant after the inclusion of in-unit linear time trends. We also do not observe which stage the virus the HIV/AIDS population were prior to the funding rule change and should interpret this result with caution.

Figure B. 1: HIV/AIDS Death Rates by 2005 AIDS-to-HIV Ratio

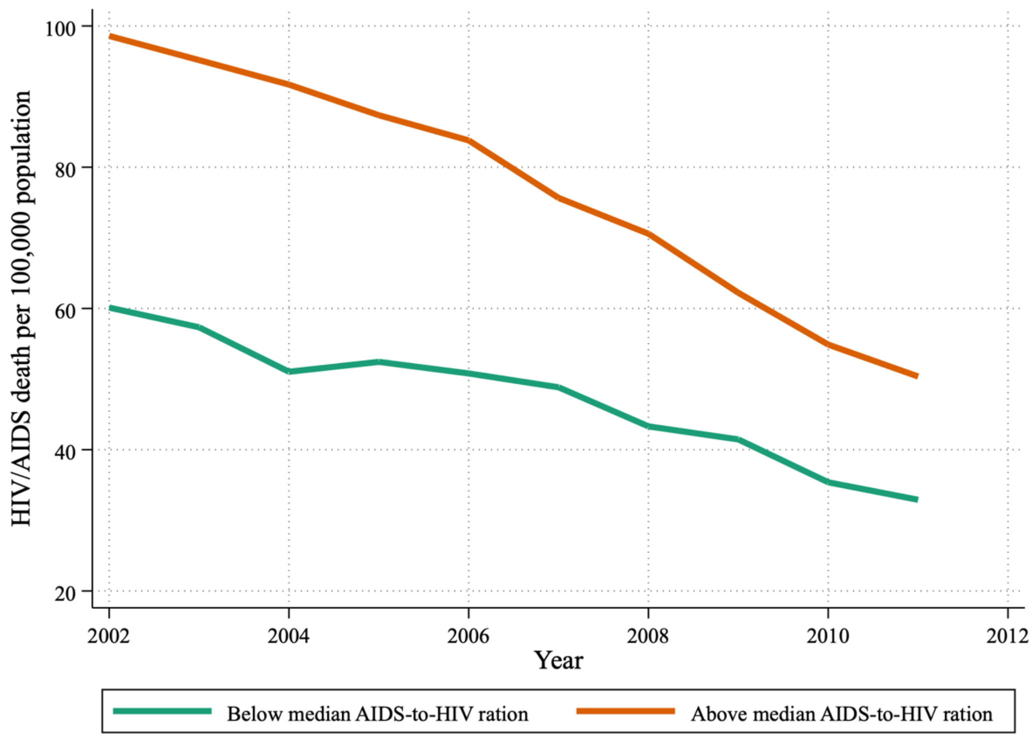


Table B.1: Effects on HIV/AIDS Death Rates

	HIV/AIDS deaths per HIV+ pop			
	(1) OLS	(2) OLS	(3) IV	(4) IV
Federal ADAP Contribtion per HIV+ population	0.712***	0.575*	0.758***	1.279
	(0.234)	(0.287)	(0.282)	(1.476)
Percentage under poverty	-1.358	-5.368	5.137	-2.137
	(10.721)	(8.729)	(11.009)	(8.219)
Proportion White	-12783.945*	-7638.148	-12115.759**	-11260.748
	(7030.168)	(14572.481)	(6004.290)	(13201.663)
Proportion Under 25	-19532.209	7983.481	-23665.920*	6674.036
	(13784.576)	(23142.233)	(12585.229)	(33992.458)
Observations	330	330	330	330
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
In-unit Linear Time Trends		Y		Y

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