NBER WORKING PAPER SERIES

THE IMPACT OF INSURANCE AND HIV TREATMENT TECHNOLOGY ON HIV TESTING

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Working Paper 19397
http://www.nber.org/papers/w19397

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2013

We thanks seminar participants at the Harris School, University of Chicago for helpful comments. Sood acknowledges funding from R01 grant # HD054877 from NICHD. Sood and Wu have no relevant material or financial relationships that bear on this research. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 19397
September 2013
JEL No. I12,I13

ABSTRACT

This paper investigates the effects of health insurance and new antiviral treatments on HIV testing rates among the U.S. general population using nationally representative data from the Behavioral Risk Factor Surveillance Survey (BRFSS) for the years 1993 to 2002. We estimate recursive bivariate probit models with insurance coverage and HIV testing as the dependent variables. We use changes in Medicaid eligibility and distribution of firm size over time within a state as instruments for insurance coverage. The results suggest that (a) insurance coverage increases HIV testing rates, (b) insurance coverage increases HIV testing rates more among the high risk population, and (c) the advent of Highly Active Antiretroviral Therapy (HAART) increases the effects of insurance coverage on HIV testing for high risk populations.

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1. Introduction

The number of uninsured Americans has risen steadily during the last decade. In 1999, about 40 million Americans lacked health insurance, and in 2009 more than 50 million were uninsured. The recent economic downturn has exacerbated the problem with the number of uninsured rising even more rapidly compared to historical trends with 6 million more uninsured since 2007. Health care reform in the U.S. seeks to reverse this trend by providing subsidies for insurance coverage to low income persons and by creating insurance exchanges to promote competition among health insurers. This naturally raises the question: How will changes in uninsurance affect the health of Americans now and in the future? It is well understood that lack of health insurance can affect health status by reducing access to treatment, especially new and expensive treatments (Bhattacharya, Goldman and Sood 2003; Card, Dobkin and Maestas 2008; Card, Dobkin and Maestas 2009). However, it is less clear how uninsurance affects health related behaviors which might affect long term population health. In this paper, we seek to investigate this issue in the context of HIV/AIDS—a disease that has claimed more than half a million lives in the U.S. and about 25 million lives worldwide. CDC estimates that approximately 50,000 people are newly infected with HIV each year in the United States.

There are several reasons that make HIV/AIDS an interesting case study for examining the effects of health insurance on population health and health related behaviors. First, insurance coverage might have competing effects on health and health related behaviors in the context of HIV. On one hand, insurance coverage saves lives by improving access to expensive but efficacious HIV treatments (Bhattacharya, Goldman and Sood 2003). On the other hand, insurance coverage might increase the spread of HIV by increasing risky sexual behavior among the HIV positive (Lakdawalla, Sood and Goldman 2006). However, prior work does not address how insurance coverage might affect HIV testing rates, a question we address in the current paper. Second, new but expensive treatments for HIV – Highly Active Antiretroviral Therapy (HAART) - were introduced in the mid-1990s. The introduction of HAART allows us to understand how the effects of insurance coverage on health related behavior are influenced by health care innovation. In particular, we study how the effects of insurance coverage on HIV testing differed in the pre- and post-HAART era. Finally, changes in HIV testing rates induced by changes in health insurance might have significant externalities in terms of changing the dynamics of the HIV epidemic. Thus, the results of the analysis are relevant for understanding the welfare implications of government-financed health insurance expansions in the U.S. as well as in several African countries ravaged by HIV.

We estimate recursive bivariate probit models with insurance coverage and HIV testing as the dependent variables. We use changes in Medicaid eligibility and distribution of firm size over time within a state as instruments for insurance coverage. The validity of these instrumental variables is discussed in detail in section 4 and section 5. The results suggest that insurance coverage increases HIV testing among both the high risk and low risk populations. The results also suggest that the advent of HAART increases the effects of insurance coverage on HIV testing for high risk populations but lowers the effects of insurance coverage on HIV testing for low risk populations.

Overall these results suggest that insurance coverage has the potential to have significant effects on health related behaviors. The paper also contributes to literature on the economic epidemiology of HIV. Past work has shown that increased insurance coverage save lives and improves welfare of the infected by improving access to HIV treatment. The results from this paper show that insurance coverage might also have long term effects on welfare of the current uninfected by altering HIV testing rates and hence the dynamics of the epidemic. The results of this paper also add to our understanding of the motivations for HIV testing. For example, a recent paper in this field uses data from a randomized experiment to show that small financial incentives or subsidies for HIV testing can have significant effects on HIV testing rates in poor countries (Thornton 2008). Our results suggest that HIV testing rates can not only be improved by subsidizing HIV testing but also by improving access to treatment.

The rest of the paper proceeds as follows: Section 2 presents the conceptual framework; Section 3 describes the data used in the estimation of the empirical model; Section 4 presents the empirical results and section 5 concludes.

2. Conceptual Framework

To examine the potential implications of insurance on HIV testing, one needs to understand the potential benefits and costs for HIV testing or not testing. Prior work suggests two benefits from testing (Tomas J. Philipson and Posner 1995). First, HIV testing is a way to signal quality or HIV negative status to potential partners in the market for mutually beneficial sexual trades. Signaling HIV negative status might enable a person to attract a greater number of sexual partners. Second, HIV testing is motivated by the desire to seek early treatment – if a person knows that he is infected then he can start treatment early. Finally, sometimes HIV testing is required for purposes of employment or for health related purposes such as donating blood.

Insurance coverage can affect HIV testing rates through several pathways. First, for individuals seeking to test because of a desire to start HIV treatment, testing is more valuable when treatment costs are lower. Since insured consumers face lower treatment costs than uninsured consumers they enjoy greater benefit from testing. That is, for individuals seeking to test because of a desire to start HIV treatment, testing is more valuable when treatment costs say $2,000 rather than $15,000. Second, insurance might encourage testing by reducing the monetary costs of testing as insurance plans might offer free or subsidized testing services to their beneficiaries. Third, insurance likely increases contacts with the health care system and therefore increases the chance that a doctor or nurse recommends HIV testing.

The effects of insurance on HIV testing likely depend on the risk status of persons getting tested. High risk individuals are more likely to test positive compared to low risk individuals. Those who test positive primarily benefit from testing due to initiation of treatment. Since insurance reduces HIV treatment costs it might increase the value of testing more for high risk individuals since they are more likely to test positive and thus more likely to enjoy the benefits of lower treatment costs. High risk individuals are also more likely to increase sexual activity in response to a negative test result. The reasoning is that the signaling value of a negative HIV test is higher for high risk individuals compared to low risk individuals. In other words, high risk individuals are more likely to be surprised by a negative test result and therefore more likely to alter sexual behavior in response to a negative test result (Boozer and Philipson 2000). Low risk individuals expect to be HIV negative and thus a negative test result is unlikely to change behavior. The consequent increase in sexual activity among high risk might increase the risk of future HIV infection and thus increase expected HIV treatment costs. Since insurance subsidizes treatment costs it might again affect incentives for testing more for high risk individuals. Finally, increased contact with doctors and nurses due to insurance is more likely to affect high risk individuals. High risk individuals might be more likely to use health care and doctors or nurses are more likely to recommend HIV testing to high risk individuals.

New treatments that are effective but expensive might mediate the effects of insurance coverage on incentives for HIV testing in complex ways. New expensive treatments increase the value of subsidized treatments available through insurance. That is an insurance policy that covers 80% of treatment costs is more valuable if treatment costs $15,000 rather than $5,000. This implies that the effect of insurance on HIV testing would increase with the advent of new expensive treatments such as

HAART. However, new treatments also reduce the signaling value of a negative test as potential partners are less worried about getting infected. This implies a smaller increase in the risk of infection and decreased expected burden of future infections. Thus, if the reduction in signaling value dominates then new treatments might reduce the effect of insurance on HIV testing. Again the effects might be heterogeneous and depend on the risk of infection or the probability of testing positive.

Our empirical model is motivated by the theoretical framework above. In particular, we estimate the effects of insurance coverage on HIV testing rates and allow the effects of insurance on HIV testing to differ by risk status. We also examine the extent to which the introduction of HAART affects the link between insurance and HIV testing. Finally, we allow the effects of HAART to vary by risk status. In summary, we aim to answer the following questions:

(1) How does health insurance affect HIV testing? And how does the effect of insurance on HIV testing differ for high risk and low risk individuals?
(2) How does the introduction of HAART affect the impact of insurance on HIV testing? And how is this effect of HAART different for high risk people and low risk individuals?

3. Empirical Strategy

We observe two discrete outcomes: having health insurance and undergoing HIV testing, which take the form of (T_i, HI_i) . In a bivariate probit model these outcomes are modeled using a latent variable approach where we only observe whether the latent variable is above or below zero.

We use a Recursive Bivariate Probit model to estimate the causal effect of health insurance coverage on the probability of testing for HIV. The recursive structure builds on a first equation for the potentially endogenous dummy–insurance status and a second equation determining the outcome of interest-decision to undergo an HIV test. We estimate separate models from each risk group $k = \{HighRisk, LowRisk\}$. We discuss the empirical definitions of the risk group in the data section of the paper.

$$\mathrm{HI}^{*k}_{i} = \alpha_0^k + \alpha_1^k X_i^k + \alpha_2^k z_i^k + \upsilon_i^k, \tag{1}$$

$$\mathrm{HI}_i^k = 1(\mathrm{HI}^{*k}_{i} > 0). \tag{2}$$

$$\mathrm{T}^{*k}_{i} = \beta_0^k + \beta_1^k \mathrm{HI}_i^k + \beta_2^k \mathrm{Post}_i^k + \beta_3^k \mathrm{Post}_i^k * \mathrm{HI}_i^k + \beta_4^k X_i^k + \varepsilon_i^k, \tag{3}$$

$$\mathrm{T}_i^k = 1(\mathrm{T}^{*k}_{i} > 0), \tag{4}$$

In (1)-(4), T^{*k}_{i} is the latent variable for HIV testing, HI^{*k}_{i} is the latent variable for health insurance, $Post_i$ is a dummy variable for post HAART years (i.e. following introduction of HAART in1996), $X_i^k = \{Demog_i^k, State_i^k, Year_i^k\}$ where $Demog_i$ are demographic variables including age, gender, education, race, and income level. We add state fixed-effects ($State_i$) to control for time invariant unobserved heterogeneity across states and year fixed-effects ($Year_i$) to control for secular time trends. In particular, We assume that $(\varepsilon_i^k, \upsilon_i^k)$ is independent of z_i^k and distributed as bivariate normal with mean zero, each has unit variance, and $\rho^k = \mathrm{corr}(\varepsilon_i^k, \upsilon_i^k)$. Standard errors are clustered at the state level.

In this model, insurance status and HIV testing are linked for two reasons. First, insurance status enters as a regressor in the HIV testing equation – that is, insurance is causally linked to HIV testing. Second, unobserved determinants of HIV testing and insurance status (the error terms in each equation) are correlated. For example, individuals engaged in risky behaviors might be more likely to undergo an HIV test but less likely to have insurance.

Our model belongs to the general class of simultaneous equation models with both continuous and discrete endogenous variables introduced by Heckman (1978). In this general context, Heckman (1978) argues that only the full rank of the regressor matrix is needed to identify the parameters. However, Maddala (1983) asserts that the parameters of the second equation are not identified if there are no exclusion restrictions on the exogenous variables. However, Wilde (2000) shows that this assertion is not true and exclusion restrictions are not necessary for identification as long as each equation contains at least one exogenous regressor, i.e., theoretical identification does not require exclusion restrictions if there is sufficient variation in the data.

Although the model is identified by its non-linear functional form even in the absence of exclusion restrictions, identification by functional form relies heavily on the assumption of bivariate normality. Under distributional misspecification, exclusion restrictions might help to make the estimation results more robust. In a Monte Carlo simulation study, Chiara Monfardini and Radice (2008) show that, even under correct distributional assumptions, the lack of availability of a valid instrument will make exogeneity tests unreliable.

It is therefore a common practice to impose exclusion restrictions to improve identification. These exclusion restrictions (instruments), z_i^k, should be causally linked to insurance status and should affect HIV testing only through their effect on insurance status. We use expansion in Medicaid coverage and changes in the distribution of firm size within states overtime as instruments for insurance coverage. They are discussed in greater detail in the data section.

The key parameters of interest are the parameters related to the causal effect of health insurance coverage on HIV testing. In particular, β_1^k, specifies the causal effect of health insurance on HIV testing for risk group $k = \{HighRisk, LowRisk\}$ in the pre-HAART era. Similarly, $\beta_1^k + \beta_3^k$, specifies the causal effect of health insurance on HIV testing in the post HAART era. Since the bivariate probit model is non-linear these parameters cannot be directly interpreted as marginal effects. However, it is straightforward to derive marginal effects based on these parameter values and the cumulative distribution function of the normal distribution. We denote the corresponding marginal effects by δ_j^k. We next describe the data used for estimating the bivariate probit model.

4. Data

4.1 Behavioral Risk Factor Surveillance System (BRFSS)

BRFSS is a population-based, random-digit-dialed telephone survey administered yearly to a representative sample of non-institutionalized U.S. adults aged 18 years and older that inquires about various health behaviors associated with premature morbidity and mortality. The survey has been approved by institutional review boards in each state, and participants provide oral consent to be interviewed. Interviewers record answers using computer software. We used data from 1993 to 2002 surveys. Below we describe the variables from BRFSS that we used in our analysis.

HIV Testing of Adults Under 65

We measured HIV testing as the self-report of an HIV test within 12 months before the interview. The HIV/AIDS section of the current BRFSS core questionnaire collects the following information: whether the respondent was ever tested for HIV and, if so, the month and year of the last test and the facility where last tested. Respondents were coded as having tested (tested = 1) if they reported that they tested for HIV sometime in the year preceding their interview date; we assigned a value of 0 otherwise. Respondents who had never been tested for HIV were coded as 0 because they had not been tested in the preceding 1 year.

HIV-Risk Group: Self-perceived HIV Risk

Subject's self-perception of HIV risk was based on their response to the core BRFSS question that asked: "What are your chances of getting infected with HIV, the virus that causes AIDS?" Responses were categorized as *High, Medium, Low, None, Not applicable* or *Refused*. We defined those who reported having a high or medium risk of HIV infection as the *high risk group* and those who evaluated themselves as having low or no risk as the *low risk group*.

Demographics and Health Insurance Status

Demographic characteristics in the BRFSS include gender, age, education (*Less than a high school degree, High school degree, Some college* or *AA degree*), marital status, ethnicity (*Non-white* or *Hispanic*). The BRFSS also includes information on whether the respondent is employed and their income level (*Less than 200% of federal poverty line* (FPL) or *More than 200% of FPL*). Finally, BRFSS asks respondents "Do you have any kind of health care coverage, including health insurance, prepaid plans such as HMOs, or government plans such as Medicare?" Respondents that answered yes to this question are coded as insured.

4.2 Instruments

We used the two sets of instruments for insurance choice – Medicaid expansion and firm size distribution. These instruments are similar to those used by Bhattacharya, Goldman and Sood (2003) who estimate the causal effect of insurance on HIV related mortality.

The first instrument captures availability of public insurance through the Medicaid program. There has been a significant expansion of Medicaid eligibility with significant variation across states in the pace at which these expansions have occurred. Prior research documents a strong association between Medicaid expansions and insurance coverage despite evidence that public insurance crowds-out private insurance coverage (Jonathan Gruber and Simon 2008). However, other research finds no evidence of a crowding out effect of Medicaid expansion (John

C. Ham, Ozbeklik and Shore-Sheppard 2011; Lara Shore-Sheppard, Buchmueller and Jensen 2000). Medicaid is also an important source of coverage for HIV+ individuals with about half of the HIV insured receiving coverage from Medicaid (Bhattacharya, Goldman and Sood 2003). Medicaid eligibility criteria vary from state to state and change over time, but the eligibility criteria are mandated by a Federal statute as the federal government pays about half of Medicaid expenditures. We measure changes in Medicaid eligibility within a state by estimating the percentage of Medicaid 1115 waiver beneficiaries over the total Medicaid beneficiaries in every state and year. These data were obtained from Centers for Medicaid and Medicare Service. These data are available online at https://www.cms.gov/MedicaidDataSourcesGenInfo/MSIS/list.asp accessed August 20, 2012.

The reason we choose the fraction of 1115 beneficiaries as an instrument is that section 1115 demonstration authority is one of the ways that States can expand eligibility for the Medicaid program beyond what is authorized under federal law (J. Jordan, Adamo and Ehrmann 2000). Waivers allow states to provide coverage and deliver services to the low-income population by using federal Medicaid funds in ways that do not conform to existing federal standards and options. Medicaid section 1115 waivers have recently been promoted as a way to expand coverage without committing new federal resources. About 13 states have utilized section 1115 demonstrations to increase Medicaid enrollment by expanding eligibility for state-sponsored health insurance (Teresa A. Coughlin and Zuckerman 2008). To date, ten states have also applied for Section 1115 waivers to expand Medicaid coverage to people living with HIV who are not legally considered disabled and three HIV 1115 waivers have been approved in the District of Columbia, Maine, and Massachusetts (ASPE 2009).

The second set of instruments capture availability of private insurance. These data are obtained from the Statistics of U.S. Businesses (SUSB) available online at http://www.sba.gov/advo/research/data.html accessed August 20, 2012.

In particular, we use data on the distribution of firm size in every state and year to construct two instruments at the state-year level (Bhattacharya, et al. 2009): (1) the percentage of workers employed in firms with 100 to 499 employees, and (2) the percentage of workers employed in firms with 500 or more employees. These instruments are strong predictors of insurance coverage as large firms are much more likely to offer insurance coverage. For example, data from the 2008 Current Population Survey show that 32% of workers in firms with less than 25 employees are uninsured and only 13% of workers in private firms with more than 500 employees are uninsured. For our analysis we interact these instruments with poverty status as prior research suggests that the effects of availability of insurance on take-up of insurance might vary with income (Ham et al. 2011)

The proposed instruments are valid under two conditions. First, they should be strong predictors of insurance coverage. Second, they should affect HIV testing only through their effect on insurance choice. In the next section, we show that the instruments are strong predictors of insurance coverage. The second assumption cannot be directly tested. However, it seems unlikely that changes in firm size distribution within a state or timing of adoption of 1115 waivers (our models have state fixed effects) would be related to HIV testing, except through insurance coverage. However, one concern is that variation in our instruments might be correlated with state economic conditions or other characteristics correlated with HIV testing. To address this concern, Table 1 compares five important state characteristics (unemployment rate, disposable income, poverty rate, percent White and age distribution of population) between 19 states with an increasing proportion of 1115 waiver beneficiaries over total Medicaid beneficiaries from 1993 to 2003 with 31 states without 1115 waiver or with a decreasing proportion of 1115 waiver beneficiaries over the total Medicaid beneficiaries in the same period. We find that not only are the levels of these characteristics similar across these two types of states but trends in these characteristics over the sample period are also similar. This allays concerns about systematic differences in characteristics of states with high versus low values of our instrumental variable for public insurance coverage. Table 2 compares the same state characteristics between 41 states with rising proportion of employment in medium and large firms from 1993 to 2003 to 9 states with falling proportion of employment in medium and large firms from 1993 to 2003. Again, the data show little difference in levels or trends in state characteristics across states with high versus low values of our instrumental variable for private insurance coverage. In another similar test of validity of our instrumental variables, we estimate alternate models which include these state-year level variables as covariates. We find that our results are robust to the inclusion of these state-year level variables as covariates. The results section provides more details on this specification test.

5 Results

Table 3 shows the descriptive statistics for the analytic sample. The average age of respondents is 40 years and slightly more than half the respondents are females. About 60% have some college education, more than a third have incomes below 200% of the federal poverty line and 85% have health insurance. Overall, about 16% of the respondents report testing for HIV in the previous year and not surprisingly, the testing rate among high risk individuals is 10 percentage points higher than the rate among low risk individuals. High risk individuals also are less likely to be white, female, and single. High risk individuals have similar insurance coverage and education.

Table 4 reports results from the recursive bivariate probit model of HIV testing and health insurance coverage. We estimate separate regressions for the low and high risk groups. Key marginal effects and their standard errors are reported in Table 5. We use 5,000 bootstrap replications clustered at the state-year level to estimate standard errors.

The results suggest that health insurance coverage significantly increases the probability of testing for HIV in both the pre and post HAART period. For example, among the low risk population insurance coverage increases the probability of HIV testing by 2.6 percentage points in the pre-HAART period. Similarly, among the high risk population insurance coverage increases the probability of HIV testing by 2.7 percentage points in the pre-HAART period. Second, the results suggest that the effects of insurance coverage on HIV testing are larger for the high risk group in both the pre-HAART and HAART period. For example, in the post-HAART period insurance increases the probability of HIV testing for the high risk group by 4.8 percentage points. In contrast, in the post-HAART period insurance increases the probability of HIV testing for the low risk group by 1.8 percentage points. Third, the results suggest that HAART increases the effects of insurance on HIV testing for the high risk group. Specifically, the marginal effect of insurance on HIV testing for the high risk group increases from 2.9 percentage points in the pre-HAART period to 4.8 percentage points in the post-HAART period. We do not observe a similar increase in the marginal effect of insurance for the low risk group. In fact, the evidence suggests a modest decrease in the effect of insurance on HIV testing for the low risk group.

Instrument Validity

The results in Table 4 suggest that our instrumental variables are statistically significantly related to insurance coverage. Firm size distribution is a strong predictor of insurance coverage for the low risk population and Medicaid eligibility expansion is a strong predictor of insurance coverage for high risk population. We also find that availability of both public and private employer provided insurance has a stronger effect on insurance coverage for poor rather than rich households. In both the high risk and low risk models the instruments are jointly significant with a Chi-2 statistic of 18 (p-value = 0.0062) and 42.84 (pvalue = 0.0000) respectively.

Since our instruments vary at the state year level, one concern is that they might be correlated with other state year level determinants of HIV testing. To address this concern, Tables 6 and 7 reports results from models that include additional state-year level covariates. The additional covariates are poverty rate, unemployment rate, per capita income and population age structure. The results are robust to the inclusion of these state controls. As before, we find that health insurance increases the likelihood of testing for HIV and that the effects of insurance coverage on HIV testing are larger for the high risk group. Finally, we also find that the advent of HAART increases the effects of insurance coverage on HIV testing for the high risk population but not for the low risk population.

Finally, in a second indirect test of instrument validity, we checked the robustness of our results to the inclusion or exclusion of certain sets of instruments. This test is in the spirit of the Hausman over-identification test and is based on the principle that if all our instruments are valid then the estimates obtained by using only a subset of instruments should differ only as a result of sampling error (Hausman 1978). Thus, for this test we estimated two different sets of models. The first set of models only used the instruments related to availability of private insurance and the second set of models only used the instruments related to availability of public insurance. The results from both these sets of models were virtually identical to the model that used both sets of instruments. Thus, these results also suggest that our instruments are valid.

6. Conclusions

In this paper we analyzed the effects of insurance coverage on HIV testing behavior and how this link between testing and insurance coverage changed with HIV treatment innovations. The results suggest that (a) insurance coverage increases HIV testing among both the high risk and low risk populations (b) insurance has larger effects on HIV testing for the high risk population, and (c) the advent of effective HIV treatment increased the effects of insurance coverage on HIV testing for high risk group.

Overall these results suggest that providing insurance or subsidized treatment can be an effective strategy for increasing HIV testing rates. These results have important implication for developing economies which are considering subsidizing treatment and for developed economies like the U.S. where budget pressures might force several states to reduce the generosity of public insurance coverage for HIV.

The results suggest that providing subsidized treatment not only improves the health of the infected but also has important effects on the dynamics of the HIV epidemic. Prior research suggests that knowing one's HIV status can reduce risky sexual activity. For example, a meta-analytic review of published research from1985 to 1997 found that after testing and counseling, HIV positive participants reduced unprotected intercourse and increased condom use. A more recent review (Gary Marks, et al. 2005) found that the prevalence of high-risk sexual behavior is reduced substantially after people become aware they are HIV+. Following these findings, Marks et al. (2006) estimate the proportion of sexual transmission of HIV attributable to HIV-positive aware and unaware persons in the USA. They found that the transmission rate from the unaware group was 3.5 times that of the aware group. Similarly, Thornton (2008) found in an experiment in rural Malawi that sexually active HIV-positive individuals who learned their results are three times more likely to purchase condoms two months later than sexually active HIV-positive individuals who did not learn their results. These prior studies indicate increased HIV testing can potentially have a large impact on HIV transmission. Juxtaposing these results from the prior literature with the results from this study suggest that insurance coverage might reduce risky sexual behavior and reduce the spread of HIV.

The results of this study also improve our understanding of the motivation for HIV testing and how changes in treatment technology can influence HIV testing behavior. The results are consistent with the notion that high risk individuals are motivated to test primarily due to the desire to seek early treatment. Therefore, improvements in treatment technology increase the incentives for HIV+ persons to test.

Overall, the lessons learnt from this research might have wider applicability. They suggest that public policy and health care innovation can have important and complex effects on health related behaviors. Policymakers should be cognizant of such effects as they design policies to improve health.

Role of Funding Source: This research was supported by a grant from EUNICE KENNEDY SHRIVER NATIONAL INSTITUTE OF CHILD HEALTH AND HUMAN DEVELOPMENT (GRANT #: R01HD054877). The funding source had no role in the design or conduct of this study.

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Table 1: State Characteristics by Levels of Instruments[a]

	Public Insurance Instrument	
	States with an increasing proportion of 1115 waiver beneficiaries (19 states[b])	**States with no change or decreasing proportion of 1115 waiver beneficiaries (31 states)**
	State characteristics in 1993	
Unemployment rate	6.49%	6.17%
Disposable income	$18,714	$18,109
Poverty rate	13.20%	15.03%
Age less than 20	29.16%	28.93%
Age 20-64	58.63%	58.09%
Percent White(2000)	80.12%	83.52%
	State characteristics in 2003	
Unemployment rate	5.50%	5.66%
Disposable income	$28,748	$28,064
Poverty rate	11.39%	12.13%
Age less than 20	27.84%	27.70%
Age 20-64	59.80%	59.65%
Percent White	79.70%	83.09%
	Change in state characteristics in 1993 to 2003	
Unemployment rate	-0.99%	-0.52%
Disposable income	54.04%	55.12%
Poverty rate	-1.82%	-2.90 %
Age less than 20	-1.32%	-1.24%
Age 20-64	1.17%	1.56%
Percent White	-0.42%	-0.43%

Notes:
[a] Data on poverty rate, percent of white and population age structure are from census bureau. Data on unemployment rate is from the bureau of labor statistics. Data on disposable income is from the bureau of economic analysis.

[b] The 19 states that passed section 1115 waivers or had increasing proportion of 1115 waiver beneficiaries as a share of total Medicaid population include Alabama, Arizona, California, Delaware, Hawaii, Illinois, Maine, Maryland, New Jersey, New Mexico, New York, Rhode Island, South Carolina, Utah, Vermont, Virginia, Washington, Wisconsin, Wyoming.

Table 2: State Characteristics by Changes in Firm Size[a]

	Private Insurance Instrument	
	States with increasing proportion of employment in medium and large firms (41 states)	**States with decreasing proportion of employment in medium and large firms (9 states[b])**
State characteristics in 1993		
Unemployment rate	6.19%	6.74%
Disposable income	$18,260	$18,682
Poverty rate	14.25%	14.82%
Age less than 20	29.03%	28.93%
Age 20-64	58.20%	58.72%
Percent White(2000)	82.52%	81.00%
State characteristics in 2003		
Unemployment rate	5.57%	5.71%
Disposable income	28,164	$29,040
Poverty rate	11.80%	12.12%
Age less than 20	27.73%	27.84%
Age 20-64	59.67%	59.86%
Percent White	82.11%	80.51%
Change in state characteristics in 1993 to 2003		
Unemployment rate	-0.62%	-1.03%
Disposable income	54.57%	55.39%
Poverty rate	-2.45%	-2.70%
Age less than 20	-1.30%	-1.09%
Age 20-64	1.47%	1.14%
Percent White	-0.41%	-0.49%

Notes:

[a] Data on poverty rate, percent of white and population age structure are from census bureau. Data on unemployment rate is from the bureau of labor statistics. Data on disposable income is from the bureau of economic analysis.

[b] The 9 states that have decreasing proportion of employment in medium and large size firms include Alaska, Colorado, Florida, Georgia, Massachusetts, Minnesota, North Carolina, New Jersey and Utah.

Table 3: Descriptive Statistics by Risk Group

	Low Risk N = 662,283 (93%)	High Risk N=49,267 (7%)	All
Covariates			
Age	39.86	36.55	39.63
Non-White or Hispanic	18.57%	28.25%	19.24%
Female	57.04%	53.10%	56.7%
Married	41.70%	58.12%	42.84%
Income below 200% FPL	37.62%	43.98%	38.06%
Education level			
Less than HS degree	2.20%	3.78%	2.31%
High school degree	38.02%	38.77%	38.07%
Some college or AA degree	29.42%	31.84%	29.59%
College degree	30.36%	25.61%	30.03%
Have health plan	85.72%	81.45%	85.42%
Instruments			
1115 Waiver	1.57%	1.49%	1.56%
Employment at medium size	14.57%	14.56%	14.57%
Employment at large size firms	46.32%	46.60%	46.34%
Dependent Variable			
Tested for HIV in past 12 months	15.64%	25.92%	16.35%

Notes:

Data on covariates, risk status and HIV testing is from the Behavioral Risk Factor Surveillance Survey 1993 to 2003. Data on 1115 waiver is from Centers for Medicaid and Medicare Services (CMS): Medicaid Beneficiaries by Maintenance Assistance Status, available online at https://www.cms.gov/MedicaidDataSourcesGenInfo/MSIS/list.asp. Data on firm size is obtained from the Statistics of U.S. Businesses (SUSB) available online at http://www.sba.gov/advo/research/data.html.

Table 4: Recursive Bivariate Probit Regression Without State Controls

	Self evaluated high risk		Self evaluated low risk	
	Tested for HIV in Past 12 Months	Health Plan	Tested for HIV in Past 12 Months	Health Plan
Age	-0.00441 (0.0040332)	0.0028512 (0.0042165)	-0.01759*** (0.00203)	-0.0015 (0.001526)
Age^2	-0.0001176** (0.0000535)	0.0001047* (0.0000548)	-1.2E-05 (2.38E-05)	0.000105*** (1.87E-05)
Non-White or Hispanic	0.1206372*** (0.0278905)	-0.0745605*** (0.0263186)	0.27511*** (0.026768)	-0.06353*** (0.017478)
Female	-0.0902754*** (0.0166471)	0.1771266*** (0.0180991)	-0.11405*** (0.009364)	0.134873*** (0.012042)
Married	0.1554186*** (0.0332024)	-0.3823977*** (0.0254022)	0.156786*** (0.011776)	-0.38122*** (0.012401)
Income below 200% FPL	0.0719764** (0.0328822)	-1.864541*** (0.3771449)	0.099087*** (0.017174)	-1.32331*** (0.245194)
High School Degree	0.07992* (0.0433959)	0.400258*** (0.0515101)	0.012429 (0.028286)	0.282589*** (0.03575)
Some college or tech school	0.1949218*** (0.051416)	0.6668733*** (0.0480076)	0.059199** (0.028023)	0.486135*** (0.036946)
College graduate or higher	0.2223715*** (0.0570605)	0.8535916*** (0.0515084)	0.04968* (0.02881)	0.702641*** (0.037507)
Health plan coverage	0.3903225* (0.2199806)		0.179839** (0.090972)	
Post97* Health plan	0.0672901** (0.0354586)		-0.03383*** (0.010926)	
Instruments				
1115 Waiver		0.2965837** (0.1616104)		0.083016 (0.111885)
Employment at medium size firm		-3.576105 (2.538708)		3.377685** (1.777654)
Employment at large size firm		0.0907749 (1.425739)		1.208295* (0.720941)
1115 Waiver*Poor		0.1897171 (0.3399313)		0.446019** (0.197146)
Employment at medium size firm* Poor		5.938942*** (1.873143)		3.110923*** (1.189398)
Employment at large size firm * Poor		0.823227** (0.3393542)		0.323573 (0.236484)
Constant	-1.112364*** (0.1903717)	1.031995 (0.9604056)	-0.72135*** (0.111287)	-0.09589 (0.552774)
State controls	**No**		**No**	
Year dummies	**Yes**		**Yes**	
Log likelihood	-47617.85		-505986.3	
rho	-0.1618973**		-.0318648	
Chi-2 Test for joint significance of instruments	18.01*** (p value: 0.0062)		42.84*** (p value: 0.0000)	
Number of obs	49,267		662,283	

***p<0.1,   **p<0.05,   ***p<0.01**

Table 5: Marginal Effects From Recursive Bivariate Probit Model Without State Controls

Marginal Effects	Mean	Bootstrap Std Error
High risk (N=49,267)		
Health insurance-Pre-HAART[(a)]	0.027***	0.010
Health insurance-Post-HAART[(b)]	0.048***	0.008
Change in Marginal Effect Post HAART[(c)]	0.021*	0.012
Low risk (N=662,283)		
Health insurance-Pre-HAART	0.026***	0.002
Health insurance-Post-HAART	0.018***	0.002
Change in Marginal Effect Post HAART	-0.008**	0.003

***p<0.1, **p<0.05, ***p<0.01**

Notes:
We calculate the marginal effects of health insurance on HIV testing in both pre-HAART era and post-HAART era using the following formula.

$$(\mathrm{a}): \frac{\Delta \mathrm{T}}{\Delta \mathrm{HI}}\Big|_{\mathrm{Pre-HAART}} = \Pr(\mathrm{T}=1|\mathrm{HI}=1, \mathrm{Post}=0) - \Pr(\mathrm{T}=1|\mathrm{HI}=0, \mathrm{Post}=0)$$

$$(\mathrm{b}): \frac{\Delta \mathrm{T}}{\Delta \mathrm{HI}}\Big|_{\mathrm{Post-HAART}} = \Pr(\mathrm{T}=1|\mathrm{HI}=1, \mathrm{Post}=1) - \Pr(\mathrm{T}=1|\mathrm{HI}=0, \mathrm{Post}=1)$$

$$(\mathrm{c}): \frac{\Delta \mathrm{T}}{\Delta \mathrm{HI}\Delta \mathrm{Post}} = (\mathrm{b}) - (\mathrm{a})$$

Table 6: Recursive Bivariate Probit Regression with State Controls

	Self evaluated high risk		Self evaluated low risk	
	Tested for HIV in Past 12 Months	Health Plan	Tested for HIV in Past 12 Months	Health Plan
Age	-0.00439 (0.004046)	0.002877 (0.004224)	-0.01758*** (0.002031)	-0.00153 (0.001525)
Age^2	-0.00012** (5.37E-05)	0.000104** (0.000055)	-1.2E-05 (2.38E-05)	0.000106*** (1.88E-05)
Non-White or Hispanic	0.120571*** (0.027911)	-0.07481*** (0.026261)	0.275224*** (0.026785)	-0.06364*** (0.017447)
Female	-0.09029*** (0.016695)	0.177123*** (0.018078)	-0.11414*** (0.009369)	0.134758*** (0.012016)
Married	0.155219*** (0.033247)	-0.38207*** (0.025428)	0.157134*** (0.01166)	-0.38135*** (0.012414)
Income below 200% FPL	0.071533** (0.033455)	-1.86339*** (0.376387)	0.099705*** (0.016848)	-1.33768*** (0.242714)
High School Degree	0.079695* (0.043674)	0.4007*** (0.051954)	0.011215 (0.028147)	0.283337*** (0.035796)
Some college or tech school	0.194768*** (0.051756)	0.667502*** (0.048572)	0.057859** (0.02791)	0.486705*** (0.037006)
College graduate or higher	0.221955*** (0.057823)	0.854054*** (0.051983)	0.04819* (0.02865)	0.703368*** (0.037522)
Health plan coverage	0.389482* (0.220517)		0.183024** (0.08887)	
Post97* Health plan	0.067967** (0.035237)		-0.03275*** (0.010427)	
Instruments				
1115 Waiver		0.240392 (0.18773)		0.029446 (0.10847)
Employment at medium size firm		-3.50809 (2.681891)		3.879333*** (1.530893)
Employment at large size firm		0.259895 (1.587199)		1.651469*** (0.659517)
1115 Waiver*Poor		0.208704 (0.339713)		0.470232** (0.202217)
Employment at medium size firm* Poor		5.927808*** (1.87447)		3.135998*** (1.179203)
Employment at large size firm * Poor		0.823269*** (0.338207)		0.345312 (0.234563)
Constant	-2.87796 (3.154479)	-0.67556 (4.324606)	-1.80055 (2.159406)	-0.91881 (1.504703)
State controls	**Yes**		**Yes**	
Year dummies	**Yes**		**Yes**	
Log likelihood	-47612.285		-505904.01	
rho	-.1632921**		-.0338877	
Chi-2 Test for joint significance of instruments	16.47** (p value: 0.0114)		62.17*** (p value: 0.0000)	
Number of obs	49267		662283	

***p<.01, **p<.05, ***p<.0**

Table 7: Marginal Effects From Recursive Bivariate Probit Model with State Controls

Marginal Effects	Mean	Bootstrap Std Error
High risk (N=49,267)		
Health insurance-Pre-HAART[a]	0.027***	0.010
Health insurance-Post-HAART[b]	0.048***	0.008
Change in Marginal Effect Post HAART[c]	0.022*	0.012
Low risk (N=662,283)		
Health insurance-Pre-HAART	0.026***	0.002
Health insurance-Post-HAART	0.019***	0.002
Change in Marginal Effect Post HAART	-0.008**	0.003

***p<0.1, **p<0.05, ***p<0.01**

Notes:
We calculate the marginal effects of health insurance on HIV testing in both pre-HAART era and post-HAART era using the following formula.

(a): $\frac{\Delta T}{\Delta HI}|_{\text{Pre-HAART}} = \Pr(T=1|HI=1, \text{Post}=0) - \Pr(T=1|HI=0, \text{Post}=0)$

(b): $\frac{\Delta T}{\Delta HI}|_{\text{Post-HAART}} = \Pr(T=1|HI=1, \text{Post}=1) - \Pr(T=1|HI=0, \text{Post}=1)$

(c): $\frac{\Delta T}{\Delta HI \Delta \text{Post}} = (b) - (a)$