Health information and health care use:  
Evidence from HIV testing∗

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Abstract

Information campaigns are a common tool in national preventive screening interventions that rely on individual choice. The ultimate impact of these policies depends on the individuals that select into screening. I explore the relevance of the selection driver in the context of HIV testing and a government information campaign in Chile. I study the impact of the campaign on individuals’ testing and health services use. The campaign was effective in increasing HIV testing. Nevertheless, marginal testers that act on the campaign have similar health care use as people who get tested on their own and as a result, have similar health care use after the test and diagnosis rates. Hence, this provides indirect evidence that the campaign may be just moving forward the HIV testing of individuals that may have gotten tested anyway, even in absence of the campaign. Importantly, it may also be moving forward in time the detection for a few individuals. With a contagious and transmittable disease such as HIV, the timing of detection is key for both managing the disease and to contain its spreading.

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1 Introduction

Information campaigns are a common tool in national preventive screening interventions, but there is little research on their impact (Buchmueller and Goldzahl (2018)). Moreover, their public health consequences are driven by selection of marginal screeners into acting on the campaign. This is an often overlooked challenge (Einav et al. (2019)). Individuals acting on the campaign may not be similar to individuals acting on their own and may not be the most at risk. As a result, campaigns may not encourage the use of health care services in patients who will benefit the most.

Selection determines the ultimate impact of a policy that involve individuals’ choice, such as with the endogenous choice of testing following a screening intervention. Even when a campaign increases testing, it can be deemed as a negative result from a public policy perspective. It is possible that marginal testers exhibit generally positive health behaviors or are frequently screening for diseases. Hence, the campaign may be only moving forward the timing of testing instead of encouraging unscreened or at-risk individuals. Nevertheless, encouraging repeated testers would be a positive result for contagious diseases where the timing of screening is important for early detection and to avoid spread of the disease.

An evident problem is that marginal testers cannot be identified individually, and therefore cannot be distinguished from testers that would have acted even in absence of the campaign. Nevertheless, it is possible to learn about the marginal testers’ characteristics from the variation in the campaign exposure. The underlying assumption is that any change in characteristics between individuals exposed and not exposed to the campaign is driven by the marginal testers or compliers. To this end, it is key to have detailed and high-frequency individual level data on characteristics and health services use.

I explore the relevance of the selection driver in the context of Human Immunodeficiency Virus (HIV) testing and a government information campaign in Chile. I study the impact of the campaign on individuals’ screening and health services use, focusing on how selection drives this impact. The HIV information campaign effectively increases HIV testing. The evidence shows that marginal testers that act on the campaign are similar in their health care use and demographics characteristics to people who self-select into testing regardless of exposure to the campaign. Back of the envelope calculations show that marginal testers are more likely to be young, single, and repeated testers,
which are characteristics associated with higher riskiness. Furthermore, they have similar diagnosis rates. These similarities suggest that the campaign attracts people that is comparable to those who would have gotten an HIV test anyway in the future, or that are more in contact with health care services. In this situation, the campaign may be moving forward in time the HIV testing of some individuals, and hence, it also be moving forward their diagnosis. With a contagious and transmittable disease such as HIV, timing of diagnosis is key for both managing the disease and to contain its spreading, so the results still point to the campaign having a positive impact in terms of public health.

To examine this driver empirically, I use administrative health claims data for all privately insured individuals in Chile between 2012 and 2017. The privately insured are 14% of the Chilean population, a sample that is of higher income than the rest of the population. Private health insurance often provides better, more timely attention than the public one, and the plans offered are generally more expensive. These data includes a rich set of demographics, including, age, gender, marital status, and income, and a detailed account of individuals’ health services use. Importantly, although test results are not included in the service use data, I use data from a registry of self-reported diagnosis for a list of diseases with expensive treatment, where HIV is included. Individuals must voluntarily register with their health insurer to receive benefits related to their diagnosed disease.

The Chilean government promotes preventive health care use mainly through nationwide health information campaigns. These respond to a generally low use of preventive health services. Although HIV infection remains incurable, early detection and treatment reduce the risk of transmission, and hence the government routinely launches HIV information campaigns. Both the content and timing of these campaigns vary, providing an unexpected information shock. Roughly one campaign is launched per year and they usually last two months, consisting of mostly commercials on national TV, radio, out of home advertising (eg. bus shelter posters), internet, and social media.

The analysis is organized into three main parts. First, I begin by studying the impact of the information campaign on HIV testing. I construct a balanced panel of individuals and estimate an event study around the HIV information campaign, controlling for seasonality. I find a large increase in HIV testing after the HIV information campaign is launched. The number of testers increases by 30% with respect to the weeks prior to the campaign. To further support my findings,
I test for unknown structural break dates in the trend of HIV testing. The estimated break date is the campaign launch date or a week before. Raw data do not show any demographic groups distinctively driving the increase in testing.

Second, I study whether testers at the time of the campaign are different in terms of observables from testers at other times when there was no campaign. I find that individuals tested around the campaign are more likely to be young (ages 18 to 24), single, and of high income. Some of these characteristics are associated with risky sexual behaviors. Moreover, there are no differences in the health services use at the time of the HIV test event. Lab work use is similar, with most testers bundling tests for sexually transmitted diseases (STDs) and general check-ups. Testers at the time of the information campaign are also more likely to have used any health service in the year prior and to have taken an HIV test. Taking another approach to compare the testers, I find that the predicted probability of HIV testing is very similar for individuals that got an HIV test regardless of the occurrence of the information campaign, although the predictive power of this exercise is low given that there are very few HIV testers.

Third, I investigate the intended and unintended consequences of getting an HIV test. The campaign pushes individuals to contact health services, presenting an opportunity to also undergo preventive health screening tests. I study the impact on an intended consequence, the diagnosis rates, and on an unintended consequence, the use of health services after taking the HIV test, which indicates usage of treatments and follow-ups of detected health problems. Again, I compare the groups of testers exposed and not exposed to the campaign. Diagnosis rates in the first 12 weeks after the test are statistically indistinguishable between these groups. However, since the number of testers increased as a result of the campaign this translated into 11 more diagnosis with respect to the year without campaign. This roughly constitutes one additional diagnosis per week. Using a difference-in-differences design, I find that health services usage after the HIV test does not show any statistically significant differences.

These results demonstrate that the campaign was effective in increasing testing. Furthermore, marginal testers are very similar to other testers, in terms of demographics, health care utilization before, around, and after testing, as well as in terms of diagnosis rates. This provides indirect evidence that marginal testers may be moving forward their testing and also their detection of HIV infection. Nevertheless, the number of tests does not decline right after the campaign ends and
therefore I do not observe direct evidence of this channel in the short term\(^1\). Testing could alternatively decrease in the longer term. The increase in the number of reported diagnosis, although with a similar rate, is a key element to assess the effectiveness of the campaign in light of selection into testing. This suggests that marginal testers are similarly risky and are moving forward their detection. Therefore, they may initiate treatment earlier and become less likely to further transmit the infection.

This paper relates to three main literatures. First, it relates to a literature on the role of information on health behaviors and preventive screening. Broadly, findings support small impacts from information shocks coming from different sources, such as organized screenings (Buchmueller and Goldzahl (2018)), celebrity promotional campaigns (Cram et al. (2003)), social networks (Deri (2005), Fadlon and Nielsen (2017)), psychological interventions (Haushofer et al. (2019)), diagnosis (Oster (2018b)). Mass media information campaigns, very common tools in national screening interventions, have been studied mostly in the health literature showing small and short-lived impacts (Snyder et al. (2004), Snyder (2007), Wang et al. (2012), Wakefield et al. (2010))\(^2\). The majority of the literature has focused on non-contagious and chronic health problems. I confirm the significant role that campaigns have on screening in the setting of a contagious disease, where higher rates of screening affect not only individual health, but also have public health consequences.

Second, it relates on a more recent literature studying the role of selection in the context of health-related choices. The importance of selection stems from its impact on the effectiveness of policies such as screening interventions or recommendations. Einav et al. (2019) uses an oncology model to show that selection into screening overestimates the benefits of recommending early screening, compared to the case where responders were representative of covered individuals. Oster (2018a) shows that selection makes difficult learning about causal effects of recommendations. I provide empirical evidence on the selection driver in the context of HIV testing by characterizing marginal testers using a rich set of individuals’ characteristics. This allows me to better assess the effectiveness of the campaign. The role of selection has also been documented in other health settings, such as health insurance choice (Bundorf et al. (2019)). Moreover, Myerson et al. (2018)

\(^1\)Due to data limitations, I can only observe a short period after the campaign was launched and hence cannot explore if testing decreases in the longer term.

\(^2\)Short-lived impacts of information campaigns are also observed in other settings relevant for public policy, such as social security systems (Finseraas et al. (2017)).
discuss that economists have paid scant attention to these complexities and their implications for evaluating screening programs. Screening interventions in general may produce different outcomes depending on the reasons why patients went unscreened in the first place, which can also impact treatment take-up.

Third, it relates to a broader literature on the incentives and benefits of preventive screening for a potential disease. There is a vast literature documenting the benefits of preventive screening (CDC (2009), Maciosek et al. (2010), McMorrow et al. (2014)). More particularly, a rich set of papers studies the case of HIV testing (Baggaley et al. (2017), Montoy et al. (2016), Montoy et al. (2018), Nichols and Meyer-Rath (2017), Nakagawa et al. (2012), Reitsema et al. (2019), Zah and Toumi (2016)). They document that early detection of HIV reduces morbidity, mortality, the probability of onward transmission, and their associated costs. Moreover, they find that screening for HIV in primary care is cost-effective, despite the cost of earlier initiation of antiretroviral treatment. I present indirect evidence of a policy that moves forward HIV detection and highlight the role of selection in its assessment.

The remainder of this paper is organized as follows. Section 2 describes the background information for the information campaign and the data sources used. Section 3 shows evidence of the direct impact of the campaign on HIV testing. Section 4 investigates the role of selection as a driver of the increase in testing. Section 5 studies whether the increase in testing had impacts in outcomes after the HIV test took place. Section 6 concludes.

2 Background and Data

2.1 HIV information campaign in Chile

In Chile, HIV infection has been a relentless public health challenge. The HIV epidemic has been characterized by a rapid increase in the estimated new infections since the early 2000s, despite having the highest access to ART among Latin American countries. Sexual transmission accounts for 99% of the infections. The Chilean government estimates that 65,000 individuals live with HIV by 2016 and 5,212 infections were diagnosed in 2017.

The medical advances in the last decades have transformed HIV infection into a chronic disease. Preventive screening is a standard and powerful policy to deal with chronic diseases. Since HIV
remains incurable, early detection and treatment have an important role in reducing the risk of developing Acquired Immune Deficiency Syndrome (AIDS) and of transmission. Moreover, preventive health services use in Chile is generally low (Rotarou and Sakellariou (2018)), therefore the government promotes preventive health care use mainly through nationwide health information campaigns. The Chilean government routinely launches HIV information campaigns to foster preventive screening of HIV infection. Both the content and timing of these campaigns varies, providing an unexpected information shock to the whole Chilean population. Roughly one campaign is launched per year and they usually last two months, consisting mostly of commercials on national TV, radio, out of home advertising (eg. bus shelter posters), internet and social media.

In early August of 2017, the government launched an HIV information campaign was launched under the slogan “The more we ignore it, the stronger it becomes. Use a condom and take the test”. Hence, it explicitly promoted HIV testing and condom use. Table 1 shows the timeline of events surrounding the campaign. The launch of the campaign occurred just two weeks after a report from the Joint United Nations Programme on HIV/AIDS (UNAIDS) was released, describing Chile as the Latinamerican country with the highest increase in new HIV infections between 2010 and 2016. The findings of this report had wide newspaper coverage in Chile.

<table>
<thead>
<tr>
<th>Date</th>
<th>Event</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>July 20th</td>
<td>UNAIDS report</td>
<td>“Ending Aids 2017” shows Chile is the Latin American country with largest increase of new cases between 2010 and 2016</td>
</tr>
<tr>
<td>(week 29)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>July 28th</td>
<td>Announcement of campaign</td>
<td>Ministry of health announces HIV campaign will be released the following week</td>
</tr>
<tr>
<td>(week 30)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>August 3rd</td>
<td>Launch of campaign</td>
<td>Slogan: The more we ignore it, the stronger it becomes. Use a condom and take the test. Media: TV, Radio, Internet, Social media</td>
</tr>
<tr>
<td>(week 31)</td>
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</tr>
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Google searches surrounding the campaign launch suggest awareness among the Chilean population of the HIV information campaign. Figure 1 shows the trends of Google searches for two terms related to sexually transmitted diseases (STDs). I observe a large spike for the search term “HIV” around the 2017 campaign but not for “syphilis”, suggesting that the spike may be prompted by the information campaign. The increase in “HIV” searches slowly begins two weeks prior to the campaign, corresponding to the time at which the UNAIDS report was released. The observed
trends for the combined search of each STD and terms related to testing also show a spike for HIV, but not for syphilis, although the trends are much noisier.

**Figure 1: Google trends**

(a) STDs searches

(b) STDs testing searches

Notes: The figure shows the Google trend searches for selected terms. The black dashed vertical line corresponds to the campaign launch and the gray dashed vertical lines correspond to the release of the UNAIDS report and the campaign announcement, respectively. Panel (a) corresponds to searches of the terms “HIV/AIDS”, and “syphilis”. Panel (b) corresponds to the same searches as above combined with testing related terms; for HIV/AIDS I consider “test” and “ELISA”, while for syphilis I consider “test” and “VDRL”.

In Chile, HIV testing is widely entangled with doctor visits. The clinical practice guidelines for HIV detection follow the most widely used approach for diagnosis of this infection and instruct using the Enzyme Linked Immunosorbtent Assay (ELISA) test that requires sophisticated equipment and skilled technicians. This test is labor intensive and time consuming, since it requires the collection of a blood sample at a laboratory, which then is sent to the National Laboratory that performs the ELISA test. Recently, resource-limited countries have introduced the rapid diagnostic tests (RDTs), which has the benefit of allowing counseling and results during a single encounter, although some studies find slightly worse diagnostic performance. The Chilean government has not followed this trend. Only on December 2017 the Ministry of Health launched a short-lived program to make available the RDTs for HIV for individuals enrolled in a few public primary care clinics in the country. The program has not been scaled since.

2.2 Health claims data from Chilean private health insurers

I use administrative data for all privately insured individuals between 2012 and 2017. Figure 2 shows the trends for all enrollees and the health services use for a balanced panel of enrollees, showing
an increase of 15% over the full period. The privately insured are 14% of the Chilean population, a sample that is higher income than the rest of the Chilean population. Private health insurance often provides better, more timely attention than the public one. For instance, wait times in the public sector are 6 times larger than those in the private sector and are concentrated in specialist doctor visits and surgeries. The in-network providers for the private health insurance are not capacity constrained for general doctor visits. Also, the private plans offered are generally more expensive. Plan choice is not associated with the employer, as individuals can switch insurer at any time.

**Figure 2: Raw data**

Notes: The enrollees correspond to 2,575,393 families and 4,399,932 individuals, of which 54.31% are men. The median number of months enrolled is 58 and 40% of the individuals are enrolled the full period. The trend on health services correspond to a balanced panel of individuals. It includes 187,568,004 observations, 1,039,812 families, and 1,774,224 individuals of which 43.92% are men.

The dataset I use is composed by three main pieces; beneficiaries characteristics, health service claims, and the registry of a subset specific diagnosis. I use each of the three data sources in turn to construct individual level characteristics, health service use variables, and HIV diagnosis reports, respectively.

First, I determine enrollment status and construct individual level characteristics from the list of beneficiaries with demographics information that I observe each month. I observe whether individuals are enrolled or not each month and determine enrollment spells, which allows me to accurately identify when there are no health services use. For each individual, I observe their gender, date of birth and death, and municipality of residence, as well as an indicator for being

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378% of the population has public health insurance, 3% have military health insurance and the rest are not covered.
the main insured in the health insurance plan and their relationship with the main insured (self, spouse, child, parent, other). For the main insured only, I observe marital status and taxable income. Marital status is a relevant characteristic when studying risky sexual behavior, therefore I infer it as best as possible in certain cases. I assign marital status of married to spouses, and single to children. Further, I assign marital status to some of those with a relationship labeled as other who are in a group plan with a family structure given the age differences or because of the presence of children. For the rest of the sample I assign marital status as unknown.

Second, I construct a comprehensive list of types of health care services which capture a broad range of health services use from the health claims data. These data are high frequency, including daily dates, health service codes, co-payment, and plan and provider characteristics. The large majority of the health service codes are defined by the Chilean government, which I use to construct eight types of services. For each type I construct an indicator for any service use and a count for the number of a particular type of services.

I consider the following types of services: doctor visits with a general physician; specialist visits, such as urology, traumatology and orthopedic, ophthalmology, cardiology, or in some cases no specialization is provided; preventive care services, from service codes included in a national list of services such as fasting blood glucose (diabetes), syphilis blood test, smoking questionnaire, measurement of weight and height and waist circumference (obesity), blood pressure measurement (hypertension); diagnosis and therapy services, such as ECG, physical therapy, vitreoretinal exam, endoscopy; surgeries, such as circumcision, appendectomy, meniscectomy, tonsillectomy, nose surgery, corneal surgery; hospitalizations coded as any day of hospitalization; lab tests, such as blood test (CBC, lipid profile, biochemical profile), or urine test (complete urinalysis, urine sediment); and mental health services, such as visits to the psychologist or psychiatrist.

Third, I use the reports of diagnosis for a list of health problems, where HIV infection and AIDS are included, to construct an indicator for HIV diagnosis. The reports are freely given by individuals to the health insurer and allow them to gain access to benefits related to their health problem. In the case of HIV, individuals will have access to examinations and lab tests, to the antiretroviral therapy treatment, and to monthly follow-up examinations and lab tests, at a reduced co-payment that varies between zero and 20 percent of the price determined by the Ministry of Health. Although the prices have slightly increased over time, the battery of benefits has been the
3 Impact on HIV testing

A first question is whether the information campaign increased HIV testing. I construct a balanced panel of individuals and estimate an event study at the weekly level for the number of HIV tests around the information campaign. I find a large increase in testing in the weeks following the campaign launch. To further support my findings, I test for unknown structural break dates in the trend of HIV tests. The estimated break date is statistically significative and coincides with the campaign launch date or a week before. No single demographic group appears to distinctively drive the testing increase.

3.1 Event study design

I use a balanced sample of individuals enrolled with any health insurer between the years 2012 and 2017. I focus on individuals that voluntarily take the test; therefore I exclude women likely to be pregnant since they have mandatory HIV testing. Each HIV test observed for the sample of individuals has a daily date, which I aggregate at the weekly level to construct the outcome of interest, $y_t$, the weekly number of HIV tests. The raw trends of this measure are shown in figure 3. I observe a large spike in the number of HIV tests around the launch of the 2017 campaign, that stays at a higher level than the prior trend, although with plenty of noise. The number of tests increased by 39% in the first 15 weeks after the campaign is launched with respect to the prior 15 weeks\(^4\). A similar pattern is observed for the trends by gender, as shown in figure A.1.

I quantify the effects of the unexpected launch of the information campaign using an event study design, relying on a time trend analysis. For non-emergency related health services use, seasonality is an important factor that can bias the results. For instance, health services use is lower around holidays, but more use may be observed during winter. I use a balanced panel of individuals enrolled during the full period of 2012 to 2017, which allows me to include calendar time trends to control for the seasonality concern. Also, using a balanced panel fixates the individuals considered in the

\(^4\)This also represents a 50% increase in the first 15 weeks after the campaign is launched with respect to the average since 2016.
The figure shows the raw weekly trend for the number of HIV tests. The sample includes 132,340 individuals, ages 18 to 50, 57% of which are men. The black dashed vertical line corresponds to the campaign launch and the gray dashed vertical lines correspond to the release of the UNAIDS report and the campaign announcement, respectively. The shaded gray area corresponds to the period used in the event study design.

Analysis, ensuring that testing trends do not change because the universe of enrolled individuals changes.

$$y_t = \alpha + \gamma(t - t_0) + \sum_{\tau = -15}^{15} \beta_\tau \mathbb{1}(t - t_{2017} = \tau) + \theta_w(t) + \theta_a(t) + \varepsilon_t$$ (1)

Equation 1 shows the event study model. I estimate the campaign’s impact from dummies for each week around the campaign launch, represented by $t_{2017}$, and where $\tau$ is the relative time with respect to $t_{2017}$ in an event window of 15 periods. $\hat{\beta}_\tau$ is the estimated additional number of tests in week $\tau$. The model implicitly restricts the coefficients $\hat{\beta}_\tau$ to be zero for the weeks outside of the event window. I include a time trend, $\gamma$, where $t_0$ corresponds to week 1 of 2012. To deal with seasonality, I control for a set of calendar week and year fixed effects, $\theta_w(t)$ and $\theta_a(t)$, respectively, where $w(t)$ and $a(t)$ yield calendar week and year from weekly date $t$. I estimate the model using an OLS regression.

Figure 4 shows the estimated coefficients $\hat{\beta}_\tau$. I observe a large increase in the weeks following the campaign launch, suggesting that the campaign increased the number of tests, after controlling
by seasonal trends. Note that the estimated coefficients of the two weeks just before the campaign launch are positive, although not statistically different from zero. These weeks coincide with the timing of the release of the UNAIDS report and the campaign announcement, shown as shown gray dashed lines in figure 4. In all the weeks prior to the campaign, the estimated coefficients are not statistically different from zero, indicating that there was no pre-trend and that they do not differ from the coefficients outside the event window. Figure A.2 in the Appendix shows similar estimated trends for separate regressions by gender. Table B.1 in the Appendix shows the coefficients of the estimation of equation 1. Results are similar when excluding the time trend or year fixed effects.

**Figure 4: Event study, HIV tests**

Notes: The figure shows the $\hat{\beta}_t$ coefficients of equation 1 estimated using data from 2012 to 2017. The coefficients represent the number of additional HIV tests in the weeks around the 2017 campaign launch, pictured as a black dashed vertical line. The gray dashed vertical lines correspond to the release of the UNAIDS report and the campaign announcement, respectively. The model is estimated using OLS and includes a time trend and a set of calendar week and year fixed effects. The average number of tests during the weeks prior to the campaign launch is 759.

The increase in testing can be better appreciated by comparing the testing trend with the predicted trend of tests excluding the dummies around the event study, $\hat{\beta}_t$. I show this in figure 5, in green and blue lines, respectively. I plot the period 2016 to 2017, although the estimation used data between 2012 and 2017. The predicted pre-period trend closely follows the actual trend, showing the relevance of seasonality modeled through the calendar week fixed effects. After the campaign launch, the predicted trend does not increase, showing a large gap between the actual
and predicted trends. Two weeks after the campaigns show a plunge in the number of tests. They corresponds to weeks in which there was a national holiday and therefore had fewer business days.

**Figure 5: Predicted tests and raw data**

![Graph showing predicted and raw tests](image)

Notes: The green line shows the actual testing trend. The blue line shows the predicted testing trend using the model in equation 1 and the data from 2012 to 2017, but excluding the dummies $\hat{\beta}$ in the event window, which is shown as the shaded gray area. The coefficients represent the number of additional HIV tests in the weeks around the 2017 campaign launch, pictured as a black dashed vertical line. The gray dashed vertical lines correspond to the release of the UNAIDS report and the campaign announcement, respectively.

### 3.2 Test for unknown structural breaks

A well-known limitation of event studies is that it is difficult to identify the exact date of a specific event. In the context of the information campaign I study, the timeline of events is well known (see table 1). Furthermore, I can take advantage of the high-frequency of the data to test for a structural break date without imposing a known break date. Intuitively, this approach provides an objective measure to investigate whether the raw data shows evidence of the impact of the campaign by comparing the maximum sample test with what could be expected under the null hypothesis of no break.

I begin this analysis by deseasonalizing the trend of the number of HIV tests using the balanced sample of individuals for the full period between 2012 and 2017 aggregated at the weekly level. Then, I take the deseasonalized subset between 2016 and 2017 and estimate a simple time trend
regression, $y_t = a + b(t - t_0) + \varepsilon_t$, where I test for unknown structural break dates on the coefficients. I perform this test for the intercept and the slope simultaneously, as well as separately for each coefficient. The null hypothesis in the test is that there is no structural break date on the coefficient of interest.

For each possible break date, figure 6 plots the Wald statistic of the test. The red vertical dashed line shows the estimated break date and the black vertical dashed line shows the actual campaign launch date. Both lines coincide at the campaign launch date, and I find evidence of statistically significative structural break in the intercept and slope at that exact date. When I test for unknown structural breaks in a subsample excluding the weeks after the campaign launch, I do not find any statistically significative structural break. Figure A.3 in the Appendix shows similar results when testing for unknown structural break date in the slope and intercept separately. The estimated break date is two weeks before the campaign launch and corresponds to the date of the release of the UNAIDS report. In each case I find evidence of a statistically significative structural break.

Figure 6: Structural break test for slope and intercept

Notes: The figure plots the Wald statistics for a structural break test at each possible break date. The red vertical dashed line shows the estimated break date, displayed in the top-left box along with the p-value for the test under the null hypothesis of no break date. The black vertical dashed line shows the actual campaign launch date.
3.3 Testing and demographics groups

Having shown that the information campaign increased HIV testing, the public health consequences of this result would be different if the increases were concentrated in low versus high-risk groups. According to general trends of sexual and preventive behaviors by demographic groups, higher-risk groups would be more exposed to HIV infection. Therefore increasing testing among such groups would hinder the spread of HIV. Usually, individuals that are younger, single, and lower income, are regarded as higher-risk towards HIV infection.

From the raw data, I do not observe a sharp change in the pattern of testers by demographic groups around the time of the campaign. Figure A.4 in the Appendix shows that the number of testers increased thoroughly around the campaign for every demographic group, although the share of single and young individuals slightly increased. This evidence proves to be suggestive at best, but further analysis needs to be done to draw any conclusion.

I investigate whether the campaign is encouraging people to get their first HIV test or if they are recurring testers. I use two different categorizations. First, I define an initiation status for either being a first-time tester or a recurring testers. Second, I define the recent testers as individuals that got an HIV tests in he year prior. Figure A.5 plots the trends showing no marked change around the campaign. About 40% of testers have had a prior HIV test and 20% of testers had the prior test within a year.
4 Selection into testing

Screening choices are inherently an endogenous choice, even when individuals are exposed to an exogenous and unexpected encouragement to get screened. Researchers studying such an intervention will identify its impact from individuals who comply with the encouragement. Nevertheless, it is not possible to individually identify the compliers. Observed testers after the encouragement can do so motivated by the encouragement or would have done so regardless of it. In this context, an increase in testing can be considered more or less effective from a public health perspective depending on who are the people that act on the encouragement. In this section, I take a deep dive to characterize the test takers and understand the role of selection into responding to the HIV information campaign.

I study the selection driver by drawing a parallel between characterizing the compliers in an instrumental variables’ framework and characterizing the test takers that act encouraged by the campaign. The underlying assumption is that any change in characteristics between individuals exposed and not exposed to the campaign is driven by marginal testers or compliers. I investigate the marginal testers’ distribution of characteristics from the variation in the campaign exposure by comparing two groups of testers. I compare testers periods with and without an information campaign. Marginal testers that act on the information campaign do not differ greatly in the health care use from other testers and, as a result, do not have different health care use after the test and have similar diagnosis rates. The information campaign may be moving forward in time the HIV testing of individuals that may be more in contact with health care services or may have gotten tested anyway.

4.1 Study groups and health services use event

I take advantage of the detailed and high-frequency individual level data to construct two groups of testers, differentiated by their exposure to the campaign when taking an HIV test. The group of testers exposed to the campaign, which I refer to as the treatment group, consists of individuals observed taking an HIV test at the time of the information campaign, between weeks 29 and 36 of 2017. This group comprises 11,452 testers, of which 46% are men. The control group consists of individuals who took an HIV test in a period without an information campaign, between weeks 29
and 36 of 2016. This group consists of 7,935 testers, of which 50% are men. I use data for the same weeks in each years as a way to consider the seasonality concern (discussed in section 3) between the two groups of testers.

Comparing individuals according to their exposure to the campaign does not guarantee that testers in the treatment group are compliers or marginal testers in the sense that they chose to screen solely motivated by the encouragement of the campaign. The study of selection in this context is challenging since it is not possible to differentiate between always takers and compliers to the campaign. This situation is analogous to describing the distribution of compliers' characteristics in an instrumental variables’ framework, where the effects are identified from those who comply with the encouragement. Nevertheless, I can compare the average of the two groups under the assumption that differences in these averages will be driven by the campaign.

HIV tests are performed following a doctors’ prescription order. As such, it requires a visit to a doctor and introduces the possibility of getting it along with other tests. For instance, individuals may be taking only an HIV test, or may be bundling it with only STDs tests, or with a more general health check up. I define a health services event as the set of health services that occurs within an interval of 10 days or less. Note that this means that the event may last longer than 10 days. For instance, health services on October 3rd, 10th and 18th will be considered part of the same event spanning 15 days. Figure 7 shows that most events occur within just a few days. This allows me to identify any bundling of health services presumably originating from the same testing event and to separately study the health services use surrounding the HIV test event and in the period following the HIV test (in section 5).

4.2 Marginal testers’ distribution of characteristics

Marginal testers may differ from other testers in terms of demographic characteristics or their health services use. I compare the average characteristics of testers in both groups under the assumption that differences in these averages will be driven by the campaign. I use a proportion test to test whether the share of individuals with each characteristic varies between treatment and control. Figure 8 shows bar graphs for each characteristic, along with the p-values in the square brackets.

5 Analogous to the previous section, I use a balanced sample for the period between 2015 to 2017. I restrict individuals to ages 18 to 50 on December 31st on 2017, both male and non-pregnant female.
Figure 7: Number of days within health event

(a) All health services

(b) Health services around HIV test

Notes: The figures show the distribution of the health events’ length in days. Panel (a) show the distribution for all health services, while panel (b) shows the distribution of a subset of health events where an HIV test occurred.

for the test of equality of proportions. The null hypothesis is that the two populations have equal proportion of the characteristic.

The bar graphs on the left side of figure 8 show the results for a set of demographic variables. I find that testers exposed to the campaign are slightly more likely to be young, single, and of high income than testers in the year without a campaign. These differences are statistically significant but very small in magnitude. The bar graphs on the right side of figure 8 show the results for a set of health service use variables. The health services use at the HIV health event does not differ by groups. Marginal testers are slightly more likely to have used any health service in the previous year and less likely to be first time testers, as shown in figures 8d and 8f. Taken together, the results suggest that marginal testers are more likely to be part of higher risk groups and that they may be more in contact with health care services.

I take a deeper dive at two higher risk groups, single and young individuals ages 18 to 24. The results are shown in figure 9. I observe that among young individuals, the group exposed to the campaign is slightly less likely to undertake comprehensive health check-ups and STDs tests, both at the time of the HIV test event and in the previous year. Similarly to the results for the full sample, marginal testers are more likely to have used any health service in the previous year and to be repeated testers. This evidence indicates that the campaign brings marginal testers that are in contact with health care services and that have taken HIV tests before, suggesting that some of
these testers may be moving forward in time their testing decision encouraged by the information campaign.

All things considered, the evidence shows that most people are getting tested for HIV when they also test for general check-ups and for other STDs. From the results in the previous section, I quantified an increase in the number of testers of 30% that is statistically significative. This points to a situation in which some individuals go to the doctor anyway and decide to get an HIV test, while the increase of 30% of individuals act on the campaign and end up going to the doctor when they would not have gone otherwise. The latter group is what I call marginal testers and, under the assumption that changes are driven by the campaign, fully accounts for the 30% increase in testers exposed to the campaign.

I use a back of the envelope calculation to compare the characteristics of marginal testers and regular testers exposed to the campaign. I consider two assumptions. First, marginal testers fully account for the 30% increase in testers exposed to the campaign, which corresponds to a 23% of the testers in 2017. Second, regular testers’ characteristics are equivalent to those of testers not exposed to the campaign. With these assumptions in hand and since I observe the total share of testers exposed to the campaign for each characteristics, I back out the shares for the marginal testers. Figure 10 shows bar graphs that compare the average characteristics of these groups.

Let’s consider figure 10a. From the previous results we know that the share of young individuals, ages 18 to 24, from 18% to 22% and that marginal testers comprise 23% of all testers exposed to the campaign. Testers exposed to the campaign comprise regular and marginal testers. I assume that the share of young individuals among the regular testers is the same as among those not exposed to the campaign, 18%, and back out the share of young individuals among the marginal testers as 35%, such that the total share is the observed value of 22%. Using this approach, I observe that marginal testers are 16% more likely to be young. They are also 18% more likely to be single and 10% less likely to be first time testers.

---

6This implies that if is there are 130 testers, 100 belong to the regular testers’ group and 30 belong to the marginal testers’ group. Therefore, 30 over 130 yields constitutes 23% of marginal testers.
Figure 8: Test of equality of proportions

Demographics
(a) Age groups

Health services use
(b) At the HIV test event

(c) Marital status
(d) In the previous year

(e) Income groups (above 0, below max TI)
(f) HIV tests

Notes: The figures show bar graphs for the distribution of characteristics for testers exposed (Treatment, 2017) and not exposed to (Control, 2016) the campaign. I use a proportion test to compare the share of individuals with each characteristic between treatment and control, under the assumption that differences in these shares will be driven by the campaign. p-values for the test of equality of proportion are shown in square brackets below each characteristic. The null hypothesis is that the two population have equal proportion of the characteristic.
Figure 9: Health services use, higher-risk groups

(a) At the HIV test event, single
(b) At the HIV test event, young
(c) In the previous year, single
(d) In the previous year, young
(e) HIV tests, single
(f) HIV tests, young

Notes: The figures show bar graphs for the distribution of characteristics for testers exposed (Treatment, 2017) and not exposed to (Control, 2016) the campaign. I use a proportion test to compare the share of individuals with each characteristic between treatment and control, under the assumption that differences in these shares will be driven by the campaign. p-values for the test of equality of proportion are shown in square brackets below each characteristic. The null hypothesis is that the two population have equal proportion of the characteristic.
Figure 10: Marginal and regular testers

Demographics

(a) Age groups

(b) Health services use

(b) At the HIV test event

Notes: The figures show a back of the envelope calculation to compare the groups of characteristics of regular and marginal testers, among testers exposed to the campaign. I use two assumptions. First, marginal testers fully account for the 30% increase in testers exposed to the campaign. Second, regular testers’ characteristics are as if they would behave as the testers not exposed to the campaign. With these assumptions I back out the share of marginal testers needed for to get the total share of the exposed testers.
4.3 Probability of HIV testing

Previous results show that marginal testers have statistically different characteristics with respect to other testers, but that these differences are quite small in magnitude. Therefore, individuals that select into testing after exposure to the campaign are similar to those that select into testing in absence of the campaign. In this section, I use a complementary approach to further contrast the testers exposed and not exposed to the campaign with the goal of comparing the predicted likelihood of getting an HIV test between them.

I construct a model to predict the likelihood of getting an HIV test using a rich set of observables without the nudge of the information campaign. To this end, I estimate the model using a sample of every individual around weeks 29 to 36 in 2016, when there was no campaign. I pool all individuals in the mentioned period in a cross-section format. This sample includes the testers in the control group defined above as well as every non-tester during that period. Note that very few take the test (about 0.86 %) as shown in table 2.

<table>
<thead>
<tr>
<th>Table 2: Sample sizes</th>
</tr>
</thead>
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<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>2016</td>
</tr>
<tr>
<td>(no campaign)</td>
</tr>
<tr>
<td>Not tester</td>
</tr>
<tr>
<td>Tester</td>
</tr>
<tr>
<td>Total</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

I estimate a logit regression where the left hand size variable is an indicator for getting an HIV test at any moment during weeks 29 to 36 in 2016. The right hand size variables include observables about demographic characteristics and past health service use. Table 3 shows the estimated coefficients. Most of the observables are statistically significant, nevertheless the pseudo-$R^2$ is very low signaling that the predictive power of the model is not strong. This may be due to the fact that only a very small share of individuals in the full sample take an HIV test.

I use the estimated model from table 3 to compute the predicted probability of the testers in each group and compare their distributions. As expected, the probabilities are mostly close to zero, due the low predictive power of the model. The results suggest, similarly to the previous section, that marginal testers are similar in terms of observables to testers taking an HIV test without exposure to the campaign. The two-sample Kolmogorov-Smirnov test for equality of distribution
### Table 3: Prediction of HIV test taking

<table>
<thead>
<tr>
<th>Probability of taking HIV test</th>
<th>Coef.</th>
<th>Std. Err.</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Last year - Any specialist visit</td>
<td>0.416</td>
<td>0.036</td>
<td>0.000</td>
</tr>
<tr>
<td>Last year - Any panel tests</td>
<td>-0.267</td>
<td>0.024</td>
<td>0.000</td>
</tr>
<tr>
<td>Last year - Any gyn or proc visit</td>
<td>0.216</td>
<td>0.031</td>
<td>0.000</td>
</tr>
<tr>
<td>Last year - Any doctor visit</td>
<td>0.483</td>
<td>0.023</td>
<td>0.000</td>
</tr>
<tr>
<td>Last year - Any psychologist visit</td>
<td>0.277</td>
<td>0.027</td>
<td>0.000</td>
</tr>
<tr>
<td>Last year - Any service</td>
<td>0.103</td>
<td>0.120</td>
<td>0.388</td>
</tr>
<tr>
<td>Last year - Any surgery</td>
<td>0.169</td>
<td>0.042</td>
<td>0.000</td>
</tr>
<tr>
<td>Last year - Any preventive screening</td>
<td>0.448</td>
<td>0.052</td>
<td>0.000</td>
</tr>
<tr>
<td>Last year - Any STDs tests</td>
<td>0.650</td>
<td>0.035</td>
<td>0.000</td>
</tr>
<tr>
<td>Last year - Any HIV tests</td>
<td>0.758</td>
<td>0.039</td>
<td>0.000</td>
</tr>
<tr>
<td>Last year - Any hospitalization</td>
<td>-0.136</td>
<td>0.049</td>
<td>0.006</td>
</tr>
<tr>
<td>Marital status - Married</td>
<td>-0.296</td>
<td>0.030</td>
<td>0.000</td>
</tr>
<tr>
<td>Marital status - Unknown</td>
<td>0.073</td>
<td>0.029</td>
<td>0.011</td>
</tr>
<tr>
<td>TI - Below median</td>
<td>-0.161</td>
<td>0.039</td>
<td>0.000</td>
</tr>
<tr>
<td>TI - Above median</td>
<td>-0.138</td>
<td>0.038</td>
<td>0.000</td>
</tr>
<tr>
<td>TI - Max and above</td>
<td>-0.165</td>
<td>0.038</td>
<td>0.000</td>
</tr>
<tr>
<td>Age - 25_30</td>
<td>0.215</td>
<td>0.035</td>
<td>0.000</td>
</tr>
<tr>
<td>Age - 31_40</td>
<td>0.130</td>
<td>0.035</td>
<td>0.000</td>
</tr>
<tr>
<td>Age - 41_50</td>
<td>-0.300</td>
<td>0.039</td>
<td>0.000</td>
</tr>
<tr>
<td>Female</td>
<td>-0.079</td>
<td>0.025</td>
<td>0.002</td>
</tr>
<tr>
<td>Constant</td>
<td>-5.528</td>
<td>0.137</td>
<td>0.000</td>
</tr>
</tbody>
</table>

*Notes:* The table shows the estimated coefficients of demographic and health service use variable of the logit model that predicts the likelihood of getting an HIV test. I use data for weeks 29 to 36 of 2016, when there was no campaign. Region dummies coefficients are ommitted from the table. Number of observations: 1,058,596. Pseudo R2: 0.038.
**Figure 11:** Distributions of testers’ estimated probability of HIV testing

Notes: The figure shows an histogram of the estimated probabilities of getting an HIV test for the groups of testers in 2016 and 2017. The estimations come from the logit model.

**Figure 12:** Quantile-quantile plot of testers’ estimated probability of HIV testing

Notes: The figure shows a quantile-quantile plot that compares distribution of the estimated probabilities of getting an HIV test between the testers in 2016 and the testers in 2017. The estimations come from the logit model. Note that 99 percent of the estimated probabilities fall below 5%, for both groups of testers.
5 Impact after the HIV test

The HIV information campaign fosters contact with health care services that is less likely to be driven by individuals’ health status or by preference toward health screening. This push to contact health services presents an opportunity for testers to not only screen for HIV infection, but to undergo other preventive health screening tests. This can have intended and unintended consequences on health outcomes and health services use. An intentional result would be to find an increase in HIV detection, depending on whether marginal testers are more or less at risk with respect to other testers. An unintentional result would be the early detection of other health problems unrelated to HIV. In the data I cannot observe test results, nevertheless I observe the use of health services which can shed light on the follow-up and treatment of health problems. I find an increase in the number of reported HIV diagnosis. Although individuals bundle their HIV screening with other check-up services, I find no differences in the use of other health services such as specialist visits or hospitalizations. The latter suggests that marginal testers are not more likely to undergo diagnosis of other health problems.

5.1 Self-reported diagnosis

Two issues difficult the assessment of the campaign impact on outcomes after the testing event. First, the health services data does not include test results. Nevertheless, I observe the full universe of self-reported diagnosis for the private insured population, where insurees can self-report it with the health insurers to receive health care benefits, such as reduced-price treatment. The self-reporting nature of these records poses two main concerns; individuals may be changing their reporting behavior and they may take too long to report it. Reassuringly for the former concern, during the period under study there was no change in the benefits program that may have directly affected the incentives to registering. For the latter, I identify the HIV test that is closest to the date of the diagnosis report. About 60% of all diagnosed individuals in the period 2012 to 2017 (2,460 over 4,034) take an HIV test at most 60 days prior to registering their diagnosis, suggesting that reporting is spread over time but that a large share of them occur soon after receiving the result.

Second, the information campaign occurs by the end of the period of time under study, which
factually restricts the timespan to detect any potential impact. To make a congruent comparison of diagnosis reports, and given the self-reporting nature of the data, I take advantage of the high-frequency data and use only diagnosis reports occurring within 12 weeks of the observed HIV test.

I compare the share and number of diagnosis reports between testers in the treatment and control groups. Diagnosis rates are very small in magnitude, 0.48% for the control and 0.43% for the treatment, and they are not statistically different; the test of proportions yields a p-value of 0.60. Figure 13 shows the number of reported diagnosis by weeks relative to the HIV test. In 2016, 38 diagnosis were reported in the first 12 weeks out of 7,892 testers, while in 2017 there were 49 reported diagnosis out of 11,411 testers. This yields an increase of 11 diagnosis in the first 12 weeks after the HIV test.

**Figure 13: Interval between HIV test and diagnosis report, weeks**

![Interval between HIV test and diagnosis report, weeks](image)

Notes: The figure above shows the overlapped distribution of the weekly number of reported diagnosis for testers in the treatment and control groups. I include reported diagnosis occurring only within the first twelve weeks after the HIV test took place (week zero). For most of the weeks, the number of reported diagnosis of testers exposed to the campaign (green bars) is higher than those of testers not exposed to the campaign (purple bars).

The increase in reported diagnosis, from 38 to 49, implies an increase of 30% and yields roughly one additional reported diagnosis per week after the campaign. This can be very valuable in the context of a contagious disease such as HIV. The evidence suggests that marginal testers are similar to regular testers, and hence the increase in testing may be pushing forward the diagnosis for a
few marginal testers. Although small in magnitude, this increase is large in proportion. Hence, it
has a potential great impact, since in the health literature, delays in diagnosis pose the greatest
risk of excess mortality for people with HIV. Nakagawa et al. (2012) perform a series of simulations
varying the rate of diagnosis. Decreasing the diagnosis rate mechanically increases the number
of late diagnosis, this means diagnosis at later stages of the HIV infection. They show that late
diagnoses not only reduce the life expectancy of the HIV-positive person but also impact the
probability of onward transmission because treatment, which reduces infectivity, is also delayed.
Therefore, the campaign may be moving forward in time the diagnosis and can result in decreased
risk of death by 10 years from infection and decreasing transmission.

5.2 Health services use results

Section 4 showed evidence that many testers bundle their HIV test with other health check-up
tests. Therefore, an unintentional result of the campaign would be the early detection of other
health problems. Individuals undergoing a battery of lab work would increase the knowledge of
their health status, which would allow them to receive appropriate health care treatment. This can
be investigated through the use of health care services after the HIV test. I consider health services
such as doctor visit, specialist visit, preventive care, diagnosis/therapy, surgery, hospitalization, lab
test, and mental health services, which are measured as indicators for any service use and as the
count of a type of services, as detailed in section 2.2.

I use a difference-in-differences methodology to investigate whether testers encouraged by the
campaign use more health services after the HIV test event. I define an event window of 24 weeks
before and 12 weeks after the test. I pool all the lags and leads outside of the event window into
two dummies: farther lags and farther leads. The main event date corresponds to the date of the
individual’s HIV test, provided that it occurred between weeks 29 to 36. This takes into account
that the encouragement to get an HIV test slowly began when the UNAIDS report was released.
Moreover, the event window considers that the campaign occurs very close to the end of the sample
period. The model is shown in equation 2.

\[
y_{it} = \alpha + \gamma \text{Treat}_i + \sum_{\tau = T_{pre}}^{T_{post}} \delta_\tau D_{it}^\tau + \sum_{\tau = T_{pre}}^{T_{post}} \beta_\tau D_{it}^\tau \text{Treat}_i + \beta X_i + \mu_G + \mu_h(t) + \varepsilon_{it}
\]  

(2)
$D_{it}$ is an indicator for the relative time with respect to the date of the test. $T_{pre}$ and $T_{post}$ corresponds to the bounds of the interval between 24 weeks prior and 12 weeks a posteriori. $\mu_{h(t)}$ corresponds to calendar time fixed effects. $\mu_{G}$ corresponds to geographic area indicators. The model includes controls for individual level characteristics, $X_i$, such as age group, civil status, region, income. I also include controls for health services use in the previous year such as any HIV or STD test, and doctor visits, among others.

Presumably, marginal testers end up going to the doctor when they would not have gone otherwise. Figure 14 shows that testers at the time of the campaign use similar types or levels of health services after the HIV testing with respect to testers not exposed to the campaign. This supports the finding that marginal testers have fairly similar characteristics to regular testers, hence they also have similar use of health services after the campaign. Note that this comparison implies that the contact with health services has no impact for marginal testers relative to the control group. When studying the treated testers under an event study design, results show an increase in certain types of services such as hospitalizations and surgeries after the HIV test. Therefore, these increases also occur in the control group, either by seasonality of health services use or because the two groups share similar characteristics or risks.
Notes: The figures above show the $\hat{\beta}_\tau$ coefficients of equation 2 estimated separately for outcomes of types of health services. $\tau$ is the relative time with respect to the date of the test for each individual, considering an interval between 24 weeks prior and 12 weeks a posteriori. The model is estimated using OLS and includes calendar time fixed effects, geographic area indicators, and controls for individual level characteristics.
6 Conclusion

The campaign is effective in its intended goal of increasing HIV testing. Nevertheless, selection has implications for policy-making and to assessing the overall effectiveness of the campaign. The characterization of marginal testers shows that they are quite similar to other testers. Marginal testers who select into testing after being exposed to the campaign have statistically significative differences in terms of demographics and health services use before, at the time of testing, and after the test with respect to other testers. Although the differences are very small in magnitude, they point out to marginal testers belonging to groups usually related with riskier sexual behaviors. Marginal testers are slightly more likely to be repeated testers and to have used any health care in the year before the test. Hence, they may be just moving forward their testing and may benefit from early detection of HIV infection. The latter is important in the context of contagious and transmittable diseases such as HIV, where timing of detection is key for both managing the disease and to contain its spreading.
References


CDC. The power of prevention: Chronic disease... the public health challenge of the 21st century. Atlanta, GA: National Center for Chronic Disease Prevention and Health Promotion, Centers for Disease Control and Prevention, 2009.


Appendix

A Figures

**Figure A.1:** Weekly trends, balanced

(a) Men  
(b) Women

Notes: The figures show the raw weekly trends for the number of HIV tests, by gender. The full sample includes 132,340 individuals, ages 18 to 50, 57% of which are men. The black dashed vertical line corresponds to the campaign launch and the gray dashed vertical lines correspond to the release of the UNAIDS report and the campaign announcement, respectively. The shaded gray area corresponds to the period used in the event study design.

**Figure A.2:** Event study, HIV tests

(a) Men  
(b) Women

Notes: The figures show an event study for the number of HIV tests, picturing the $\hat{\beta}_t$ coefficients of equation 1. Each panel correspond to a separate regression by gender. The coefficients represent the number of additional HIV tests in the weeks around the 2017 campaign launch, pictured as a black dashed vertical line. The gray dashed vertical lines correspond to the release of the UNAIDS report and the campaign announcement. The model is estimated using OLS and includes a time trend and a set of calendar week and year fixed effects.
Figure A.3: Structural break test

(a) Test for intercept only

(b) Test for slope only

Notes: The figure plots the Wald statistics for a structural break test at each possible break date. The red vertical dashed line shows the estimated break date, displayed in the top-left box along with the p-value for the test under the null hypothesis of no break date. The black vertical dashed line shows the actual campaign launch date.
Figure A.4: Trends by demographics: level and share

(a) Marital status, level

(b) Marital status, share

(c) Income, level

(d) Income, share

(e) Age groups, level

(f) Age groups, share

Notes: The figures show the raw weekly trends for the number of HIV tests, by testing behavior. The black dashed vertical line corresponds to the campaign launch and the gray dashed vertical lines correspond to the release of the UNAIDS report and the campaign announcement, respectively. I use a balanced sample of individuals for the period 2015 to 2017. Figures on the left show the trends in levels and those on the right show the trend in shares over the full sample. Panels (a) and (b) break down the trend by marital status, single or married, and a third category is unknown. Panels (c) and (d) break down the sample by income of the head of household. Panels (e) and (f) break down the sample by age groups.
Figure A.5: Trends by testing: level and share

(a) Recent test, level
(b) Recent test, share
(c) Initiation, level
(d) Initiation, share

Notes: The figures show the raw weekly trends for the number of HIV tests, by testing behavior. The black dashed vertical line corresponds to the campaign launch and the gray dashed vertical lines correspond to the release of the UNAIDS report and the campaign announcement, respectively. I use a balanced sample of individuals for the period 2015 to 2017. Figures on the left show the trends in levels and those on the right show the trend in shares over the full sample. Panels (a) and (b) break down the sample according to whether the individuals had a recent HIV test, that is to say within one year or more. Panels (c) and (d) break down the sample according to whether the individuals had any prior HIV test, namely by recurring testers and first time testers (initiation status).
### Table B.1: Event study of HIV tests

<table>
<thead>
<tr>
<th></th>
<th>(1) All Coeff.</th>
<th>p-value</th>
<th>(2) Men Coeff.</th>
<th>p-value</th>
<th>(3) Women Coeff.</th>
<th>p-value</th>
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</thead>
<tbody>
<tr>
<td>Constant</td>
<td>329.19</td>
<td>(0.000)</td>
<td>207.72</td>
<td>(0.000)</td>
<td>120.43</td>
<td>(0.000)</td>
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<td>Trend</td>
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<td>0.90</td>
<td>(0.000)</td>
<td>0.90</td>
<td>(0.000)</td>
</tr>
<tr>
<td>$\beta_{-15}$: 2017w16</td>
<td>-101.54</td>
<td>(0.135)</td>
<td>-44.00</td>
<td>(0.311)</td>
<td>-65.50</td>
<td>(0.069)</td>
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<td>$\beta_{-14}$: 2017w17</td>
<td>-47.94</td>
<td>(0.480)</td>
<td>-40.80</td>
<td>(0.348)</td>
<td>-18.90</td>
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<td>$\beta_{-13}$: 2017w18</td>
<td>-88.34</td>
<td>(0.194)</td>
<td>-43.00</td>
<td>(0.322)</td>
<td>-51.10</td>
<td>(0.156)</td>
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<tr>
<td>$\beta_{-12}$: 2017w19</td>
<td>-35.54</td>
<td>(0.600)</td>
<td>5.80</td>
<td>(0.894)</td>
<td>-28.90</td>
<td>(0.422)</td>
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<tr>
<td>$\beta_{-11}$: 2017w20</td>
<td>-50.94</td>
<td>(0.453)</td>
<td>-4.00</td>
<td>(0.927)</td>
<td>-67.10</td>
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<tr>
<td>$\beta_{-10}$: 2017w21</td>
<td>4.46</td>
<td>(0.948)</td>
<td>14.60</td>
<td>(0.737)</td>
<td>13.10</td>
<td>(0.716)</td>
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<td>$\beta_{-9}$: 2017w22</td>
<td>-29.54</td>
<td>(0.663)</td>
<td>-8.20</td>
<td>(0.850)</td>
<td>-10.30</td>
<td>(0.774)</td>
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<tr>
<td>$\beta_{-8}$: 2017w23</td>
<td>-74.74</td>
<td>(0.271)</td>
<td>-2.80</td>
<td>(0.949)</td>
<td>-66.10</td>
<td>(0.067)</td>
</tr>
<tr>
<td>$\beta_{-7}$: 2017w24</td>
<td>-78.34</td>
<td>(0.249)</td>
<td>-48.40</td>
<td>(0.265)</td>
<td>-20.30</td>
<td>(0.572)</td>
</tr>
<tr>
<td>$\beta_{-6}$: 2017w25</td>
<td>-78.14</td>
<td>(0.250)</td>
<td>-38.20</td>
<td>(0.379)</td>
<td>-49.10</td>
<td>(0.173)</td>
</tr>
<tr>
<td>$\beta_{-5}$: 2017w26</td>
<td>-67.74</td>
<td>(0.319)</td>
<td>-38.80</td>
<td>(0.372)</td>
<td>-28.50</td>
<td>(0.428)</td>
</tr>
<tr>
<td>$\beta_{-4}$: 2017w27</td>
<td>-30.34</td>
<td>(0.655)</td>
<td>-1.40</td>
<td>(0.974)</td>
<td>-41.30</td>
<td>(0.251)</td>
</tr>
<tr>
<td>$\beta_{-3}$: 2017w28</td>
<td>-45.94</td>
<td>(0.499)</td>
<td>-2.40</td>
<td>(0.956)</td>
<td>-55.30</td>
<td>(0.125)</td>
</tr>
<tr>
<td>$\beta_{-2}$: 2017w29</td>
<td>94.26</td>
<td>(0.166)</td>
<td>80.80</td>
<td>(0.064)</td>
<td>33.70</td>
<td>(0.349)</td>
</tr>
<tr>
<td>$\beta_{-1}$: 2017w30</td>
<td>76.86</td>
<td>(0.258)</td>
<td>43.80</td>
<td>(0.313)</td>
<td>38.30</td>
<td>(0.287)</td>
</tr>
<tr>
<td>$\beta_{0}$: 2017w31</td>
<td>179.46</td>
<td>(0.009)</td>
<td>124.80</td>
<td>(0.004)</td>
<td>60.90</td>
<td>(0.091)</td>
</tr>
<tr>
<td>$\beta_{1}$: 2017w32</td>
<td>276.46</td>
<td>(0.000)</td>
<td>178.00</td>
<td>(0.000)</td>
<td>138.50</td>
<td>(0.000)</td>
</tr>
<tr>
<td>$\beta_{2}$: 2017w33</td>
<td>337.86</td>
<td>(0.000)</td>
<td>217.20</td>
<td>(0.000)</td>
<td>128.90</td>
<td>(0.000)</td>
</tr>
<tr>
<td>$\beta_{3}$: 2017w34</td>
<td>386.46</td>
<td>(0.000)</td>
<td>188.60</td>
<td>(0.000)</td>
<td>229.70</td>
<td>(0.000)</td>
</tr>
<tr>
<td>$\beta_{4}$: 2017w35</td>
<td>365.46</td>
<td>(0.000)</td>
<td>203.20</td>
<td>(0.000)</td>
<td>207.10</td>
<td>(0.000)</td>
</tr>
<tr>
<td>$\beta_{5}$: 2017w36</td>
<td>251.06</td>
<td>(0.000)</td>
<td>117.00</td>
<td>(0.007)</td>
<td>168.90</td>
<td>(0.000)</td>
</tr>
<tr>
<td>$\beta_{6}$: 2017w37</td>
<td>188.06</td>
<td>(0.006)</td>
<td>46.40</td>
<td>(0.286)</td>
<td>141.70</td>
<td>(0.000)</td>
</tr>
<tr>
<td>$\beta_{7}$: 2017w38</td>
<td>164.06</td>
<td>(0.016)</td>
<td>84.40</td>
<td>(0.053)</td>
<td>67.70</td>
<td>(0.061)</td>
</tr>
<tr>
<td>$\beta_{8}$: 2017w39</td>
<td>226.46</td>
<td>(0.001)</td>
<td>107.60</td>
<td>(0.014)</td>
<td>146.50</td>
<td>(0.000)</td>
</tr>
<tr>
<td>$\beta_{9}$: 2017w40</td>
<td>236.26</td>
<td>(0.001)</td>
<td>114.60</td>
<td>(0.009)</td>
<td>139.50</td>
<td>(0.000)</td>
</tr>
<tr>
<td>$\beta_{10}$: 2017w41</td>
<td>50.46</td>
<td>(0.457)</td>
<td>3.00</td>
<td>(0.945)</td>
<td>67.10</td>
<td>(0.063)</td>
</tr>
<tr>
<td>$\beta_{11}$: 2017w42</td>
<td>225.26</td>
<td>(0.001)</td>
<td>115.60</td>
<td>(0.008)</td>
<td>128.70</td>
<td>(0.000)</td>
</tr>
<tr>
<td>$\beta_{12}$: 2017w43</td>
<td>-69.34</td>
<td>(0.307)</td>
<td>-71.60</td>
<td>(0.100)</td>
<td>4.90</td>
<td>(0.892)</td>
</tr>
<tr>
<td>$\beta_{13}$: 2017w44</td>
<td>259.26</td>
<td>(0.000)</td>
<td>131.00</td>
<td>(0.003)</td>
<td>152.10</td>
<td>(0.000)</td>
</tr>
<tr>
<td>$\beta_{14}$: 2017w45</td>
<td>210.86</td>
<td>(0.002)</td>
<td>124.60</td>
<td>(0.004)</td>
<td>121.10</td>
<td>(0.001)</td>
</tr>
<tr>
<td>$\beta_{15}$: 2017w46</td>
<td>127.66</td>
<td>(0.061)</td>
<td>27.40</td>
<td>(0.528)</td>
<td>120.10</td>
<td>(0.001)</td>
</tr>
</tbody>
</table>

Notes: The table shows selected coefficients of equation 1. The $\hat{\beta}_\tau$ coefficients represent the number of additional HIV tests in the weeks around the 2017 campaign launch ($\beta_0$). The model is estimated using OLS and includes a time trend and a set of calendar week and year fixed effects.