USING SYSTEM SCIENCE METHODOLOGIES TO EVALUATE THE IMPACT OF THE NEW YORK STATE HIV TESTING LAW

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Systems modeling can be a useful supplement to policy evaluation. A recent New York law requires medical providers to offer HIV tests as part of routine care. We developed a system dynamics simulation model to supplement the health department's policy evaluation. After calibrating the model to New York data, we conducted counterfactual analyses of short- and long-term outcomes under alternate implementation scenarios. As designed, the new law may result in averted HIV infections and a reduction in the fraction of undiagnosed cases, although it will not eliminate the epidemic. Even though new infections will decline, the number of individuals in care will remain relatively constant due to the survival benefits of antiretroviral therapy, highlighting the importance of continued funding for HIV care.

INTRODUCTION

To increase HIV testing among New York State (NYS) residents, and subsequent entry into care and treatment among diagnosed individuals, Chapter 308 of the Laws of 2010 authorized significant changes in HIV testing. Effective September 1, these changes include a requirement that all persons aged 13 to 64 be offered HIV testing as part of routine medical care, a simplified informed consent and pre-test counseling process, and a requirement that providers and facilities offering HIV tests arrange an appointment for medical care for individuals testing positive. An impetus for the NYS legislation was updated HIV testing recommendations from the Centers for Disease Control and Prevention (CDC) in 2006, which encouraged routine HIV testing in all healthcare settings for the general population and annual testing for high-risk populations, and a more streamlined consent process (Centers for Disease Control and Prevention 2006). Prior to the law, a third of newly diagnosed cases in NYS were identified in late stage disease, and progressed to AIDS within a year of diagnosis (New York State Department of Health AIDS Institute 2011). HIV-infected individuals receiving antiretroviral therapy have better survival and reduced viral load, thereby becoming less infectious and reducing their likelihood of transmitting new infections (Barroso, Schechter et al. 2000; Quinn, Wawer et al. 2000; Castilla, del Romero et al. 2005; Walensky, Paltiel et al. 2006; Antiretroviral Therapy Cohort Collaboration 2008; Cohen, Chen et al. 2011). Increased HIV testing is critical to identifying individuals earlier in their infection, thereby linking them to medical care sooner (Branson 2007).

Chapter 308 of the Laws of 2010 additionally includes a statutory requirement that the Commissioner of Health evaluate the number of New Yorkers who receive HIV tests, and of

those testing positive, the number who access HIV care and treatment. A report based on this evaluation was submitted to the governor and state legislature in September 2012. As part of its evaluation, the AIDS Institute of the New York State Department of Health (NYSDOH) collected extensive empirical data to understand various features of the law's implementation and early outcomes. These research studies are based on a broad set of data sources (such as administrative data for outpatient hospital visits, the HIV surveillance registry, and surveys) and address a wide range of stakeholders and areas affected by the law (such as patients, laboratories, providers, and public programs). However, there are limitations to these studies, which are inherent to policy evaluation studies.

First, applied statistical analyses of surveys and secondary data sources may not adequately address complexities in the system of HIV testing and care, which involves multiple public and private payers, government agencies, facilities, providers, and social services (Kates 2004; Institute of Medicine 2005; National Alliance of State and Territorial AIDS Directors 2011). Qualitative research (such as interviews and site visits) can provide a nuanced understanding of these complex issues, and can therefore be a useful supplement to a quantitative analysis (Patton 1999; Corbin and Strauss 2008). However, qualitative research cannot generate quantitative predictions.

Second, the law is being implemented in the context of concurrent policies that may affect testing and linkage to care. Some of these related policies, such as national guidelines on HIV testing frequency (Centers for Disease Control and Prevention 2006) and the Bronx Knows campaign to encourage all residents to be tested (New York City Department of Health and Mental Hygiene 2012), have similar goals to the state law, thereby attenuating its observed effect in empirical data. Other factors such as general fiscal strain within county and state budgets, and

funding cuts from the federal government for supportive services that may improve testing and entry into care, may counteract the law's potential effects. The likely effect of other concurrent policies, such as upcoming financial changes from health reform (Martin and Schackman 2012) and NYS Medicaid redesign (New York State Department of Health AIDS Institute 2011), is unclear. These concurrent policies make it difficult to isolate the marginal effect of the law using empirical data.

Third, the empirical data that the NYSDOH collected for the used for the other studies included in the policy evaluation are limited to a short two-year time horizon. However, the law may take several years to fully implement and its impact may occur over decades. The final regulations implementing the intent of the legislation were only published in February 2012, although the evaluation study was due to the governor's office in September 2012, which limited the law's observed effect. Furthermore, many of the data sources require a lag time of a year or more for data collection and processing.

Finally, policy goals may not be directly measurable with available empirical data. For example, one of the law's goals is to reduce the incidence of new HIV infections, as a result of increased awareness of HIV status (which may lead to behavior changes) and receiving antiretroviral therapy (which may reduce viral load and infectiousness). However, it is impossible to directly measure *new infections*, as surveillance data are limited to *new diagnoses*. The number of new diagnoses is related to both new infections and also the success of HIV testing.

We developed a system dynamics computer simulation model to supplement the policy evaluation prepared for elected officials. After the model was calibrated to NYS data, we modified inputs to conduct counterfactual analyses of short- and long-term outcomes from the

NYS HIV testing law, holding other factors constant. Outcomes include: HIV testing rates, HIV diagnoses, linkage to care among newly diagnosed individuals, proportion of late diagnoses, and future infections.

We ran multiple computer simulations to assess (a) baseline projections of what would happen in the absence of the law, (b) how results would change under three different levels of implementation (low, high, and perfect), (c) how results would change under alternate scenarios on the frequency of repeat testing in the general population (annual repeat testing, five-year repeat testing, and one-time testing), (d) whether findings change under different assumptions about the time it takes until the law is fully implemented in practice, and (e) how findings would change if all individuals engaged in HIV care achieved complete viral suppression, which would render them unable to transmit new infections. The results are presented as percent changes over time and across scenarios, analogous to differences in differences.

System Dynamics Modeling

System dynamics is a branch of computer simulation modeling that is useful for analysis and design of policies to address problems arising in complex social, managerial, economic, or ecological systems (Forrester 1961; Richardson and Pugh III 1981; Richardson 1996; Sterman 2000). Discussions with system experts (such as AIDS Institute staff, program managers at HIV testing facilities, and practitioners) are used to understand the structure of the system, and to develop a conceptual model of the important variables and their relationships. The conceptual model is then transformed into a system of mathematical relationships between variables. System dynamics models aim to understand policy implications, rather than emphasizing point predictions. Models predict dynamic implications of policies to determine whether they will result in a future that will be better or worse than it would have been without the intervention.

Systems modelers seek to understand how internal policies, internal decisions, and external phenomena interact to generate the observed behavior of key variables. An explicit goal of system dynamics is to provide an explanation for *why* and *how* the outcome will change, potential unintended consequences, and areas where implementation may not lead to intended outcomes.

System dynamics differs from other simulation modeling approaches because it takes a holistic view of all organizations and processes involved in the system. It incorporates feedback loops, which represent circular causality, accumulations, and time delays, to capture the dynamic processes observed in the real world. For example, as the size of the HIV-infected population grows in the real world, the number of new people infected will increase because there are more infectious individuals who can interact with uninfected individuals. However, individuals who become newly infected are no longer in the susceptible population and eventually there will be fewer new infections in a time period, even if the transmission rate were constant (Sterman 2000). System dynamics models should be designed to incorporate these real-world feedback processes.

System dynamics models also include nonlinearities in the relationships between variables. Changes caused in one variable by another may not be proportional over a range of inputs. For example, there are nonlinearities in the relationship between physician reputation and waiting times for patients scheduling appointments. A physician with an excellent reputation will have a delay between the time someone calls for an appointment and the time she is given an appointment. As her practice grows, the waiting time will become longer as more people wish to seek care. However, after a certain point patients will be unwilling to wait any longer and will go elsewhere for treatment. Initial increases in waiting time have minimal effect upon the

willingness of patients to seek care, but after a limit, most patients will be unwilling to wait. When there is a relatively short waiting time, physician reputation will have a positive causal relationship with patients' demand for services. As waiting time increases, the magnitude of this causal relationship declines.

System dynamics models take an aggregate perspective to examine population averages for different categories of people in the system. Each stock (represented by a box on a model's stock and flow diagram) represents the number or accumulation of people in each category at any given point in time. The flows (represented by pipes with valves) determine the rate at which individuals move among categories. The model assigns each category an average time delay for flows and average transition probabilities of moving to specific stocks. This contrasts with microsimulation models which track specific simulated individuals in the system.

System dynamics modelers work extensively with key stakeholders and experts to develop the structure of the system and incorporate data from numerous sources. Although all simulation models are imperfect representations of reality, close collaborations with stakeholders throughout the process can increase its accuracy and legitimacy.

The model is calibrated by comparing model output to empirical data, and if discrepancies exist, refining the model and parameter estimates for which adequate data is lacking or does not exist. Once the model has been developed, calibrated, and tested whether it behaves realistically, inputs can be modified to conduct "what if" analyses of how short- and long-term outcomes would change in response to various policy scenarios (Zagonel, Rohrbaugh et al. 2004). In addition, the process of developing the model and running the base case scenario may expose new concepts and previously unknown but significant variables (Richardson 1996). For example, combining numerical data, written data, and the knowledge of experts in

mathematical form may identify inconsistencies about how we think the system is structured and how it behaves over time (Forrester 1975).

System dynamics' holistic view makes it appropriate for examining population-level health care problems such as the dynamics of epidemics, patient flows, allocations of health care resource, and capacity limits (Homer and Hirsch 2006). Policy level modeling of health care systems has covered waiting lists in hospitals (Gonzalez-Busto and Garcia 1999), the epidemiological consequences of HIV/AIDS (Roberts and Dangerfield 1990), the implications of national health reform in the U.S. (Milstein, Homer et al. 2010) and cardiovascular disease interventions (Hirsch, Homer et al. 2010). Models can provide insights into differences in short-term and long-term outcomes. For example, a system dynamics model of poliomyelitis eradication versus disease control predicted that although eradication is more expensive in the short-run, it was the only policy that could adequately control the disease in the long run, and that the total cost of eradication was less than disease control policies (Thompson and Tebbens 2007). This analysis was reported to be "a nail in the coffin for the idea of a cheap and painless way out" by Bruce Aylward of the World Health Organization (Roberts 2006). System dynamics models of HIV have been developed to examine the effects of antiretroviral drugs on the epidemic over time in the UK (Dangerfield, Fang et al. 2001), needle exchange programs for reducing transmission among intravenous drug users (Homer and St Claire 1991), the cost and benefits of antenatal HIV testing (Gibb, Ades et al. 1998) and possible long-term trajectories of the epidemic (Roberts and Dangerfield 1990).

METHODS

Model Overview

The model divides HIV-infected individuals into 16 categories (Figure 1), depending on their diagnosis (i.e. awareness of infection and engagement in care), and disease stage. From left to right, there are four "columns" of stocks that represent disease stages 0, 1, 2, and 3 (also known as acute, early, mid, and late stage). These stages mirror the staging used by the CDC (Centers for Disease Control and Prevention 2008). The four "rows" of stocks represent different levels of engagement in care. Individuals are initially *unaware of their infection* (row 1), and become *aware of their infection but not in care* (row 2) upon diagnosis. They are *engaged in HIV care* (row 3) after being linked to care. A certain fraction of individuals who have been linked to care may transition in and out of care, described here as *entered care but care is now sporadic* (row 4). In this framework, individuals who seek care sporadically (row 4) can later become re-engaged in care (row 3).

New infections (the flow from Uninfected to *S0R1*, where S=stage and R=row) are calculated as the total new HIV infections from disease transmission by individuals in each of the 16 categories of previously infected individuals (*S0-S3*; *R1-R4*). As described in the section on transmission rate calculations below, the categories have different transmission rates because in the real world, transmission varies by viral load (based on disease progression and suppression with antiretroviral therapy), contact rate and frequency of encounters (sexual, injection drug, or other encounters), and behavioral aspects related to encounters (harm reduction strategies such as barrier methods that would reduce the likelihood of transmitting an infection during a given encounter). Within each category, the transmission rate is constant.

During the simulation, the number of individuals in the 16 stocks may change over time reflecting differences in case identification, linkage to care, and retention in care. As the relative

distribution of individuals across the 16 categories changes, the total transmission rate in NYS (all new infections per month, summed across the 16 categories) may change.

HIV testing, the subject of the law, is represented through two mechanisms, background testing and incremental testing. Background testing represents testing that previously occurred and will continue to occur in the absence of the law, such as risk-based testing, offering tests to patients who requested them, and campaigns to encourage testing. In contrast, the incremental testing is the new testing that will occur in routine care settings as a result of the law. The background testing rate is operationalized as a transition probability from unaware (first row of main stock and flow diagram) to being aware but not yet linked to care (second row), and is based on historical diagnosis data. The model assumes that background testing will continue after the law's enactment at a constant rate. For individuals who are infected but not aware, the likelihood of diagnosis through background testing is not influenced by the incremental testing policy.

The testing module (Figures 2 and 3) is an additional layer of the main stock and flow diagram. As shown in Figure 2, it includes the entire *Uninfected* population as well as HIV-infected individuals who are unaware (*R1*). The *Not Recently Tested* and *Recently Tested* stocks correspond to whether individuals have been tested as part of the law (incremental testing). Individuals who have not been recently tested in routine medical care settings can become diagnosed either as part of background testing, or else by receiving a test in a setting covered by the law. Individuals who receive a test in a routine medical care setting with a negative result are moved to the *Recently Tested* stock. Individuals in this category may become infected over time and may be diagnosed via background testing. After a period of time, individuals with a prior negative test result move back into the *Not Recently Tested* pool, where they can be diagnosed

both through background testing and by receiving a test as part of routine medical care. This period of time (or value of the variable *X Months Until Appropriate to Offer Repeat Testing*) is selected to test different scenarios on the frequency of testing in routine medical care. Newly diagnosed cases from both types of testing (background testing and incremental testing) move into the *Diagnosed HIV Cases* stock (corresponding to the second row of the main stock and flow diagram).

Figure 3 shows an additional model view of the testing law structure. In order to receive an incremental test, patients must seek care from a medical professional who is aware of the testing law. Based on expert opinion, medical professionals were not instantly aware of the law and changing their practices in 2010, and there has been an implementation period. To adjust for the time to implementation, the model contains levers to implement the law in a gradual linear fashion (*Testing Law Implementation Ramp*), and modelers can specify the time until providers are aware. In the base case, we assumed the law would be implemented gradually over three years, based on conversations with NYC Department of Health and Mental Hygiene staff who implemented the Bronx Knows initiative to encourage all residents to be tested for HIV. There are an estimated 15,000 providers in NYS who see 126 unique patients per month (Kaiser Family Foundation). The fraction offered a test by providers during the encounter and accepting the test if offered was based on the scenarios (described in more detail below).

All modeling was done using Vensim® DSS software. Full technical documentation is available upon request.

Data Sources Used to Estimate Stocks and Flows at the Start of the Simulation

Table 1 summarizes the NYS data, published literature, and discussions with system experts that were used to derive inputs for model parameters and calibration. These data

elements were used to allocate the number of individuals in the Uninfected and each of the 16 HIV-infected stocks in 2006 (the start of the simulation) and also to specify the average length of time in each category (flows). After 2006, all data in the model are generated endogenously. The model starts in 2006 rather than 1981 (the first documented case in NYS) because ongoing advances in HIV treatment (Walensky, Paltiel et al. 2006) and secular declines in the number of new infections generated by people living with HIV (Holtgrave, Hall et al. 2009) have affected the dynamic properties of the epidemic over time. Addressing these temporal changes would add considerable complexity to the model and were not relevant to the purpose of understanding the dynamic implications of the new testing law.

One set of historical data was used to estimate the number of individuals starting in each stock in 2006. The number of new diagnoses per year, number of people living with diagnosed HIV infection, fraction of individuals linked to care, distribution of disease stage among individuals newly linked to care, background mortality among people living with HIV, and HIV-related mortality were derived from NYS surveillance data. There are no empirical data on the number of new infections or the fraction of people living with HIV infection who are unaware of their infection. The CDC develops historical estimates of new infections per year based on a mathematical algorithm and laboratory data (Centers for Disease Control and Prevention 2008). NYS experts believe that the fraction of individuals who are unaware of their infection is lower than the CDC estimate, and this lower bound was used in the model. The fraction of individuals who have ever been linked to care and are currently engaged in care (operationalized as having at least one visit every six months) was estimated using Medicaid claims data.

Additional data were used to estimate the rate of disease progression, or the flows across the stages from left to right. The length of time spent in each disease stage for individuals living

with HIV who have not been linked to care is based on cohort studies of the natural history of HIV disease and other HIV modeling studies (Paltiel, Weinstein et al. 2005; Paltiel, Walensky et al. 2006; Martin, Paltiel et al. 2010). The average length of time for individuals in care was based on calibration to NYS surveillance data on the number of people living with HIV and AIDS, using the Powell algorithm built into the Vensim® software and giving equal weight to the multiple data series used in the calibration. The specified system parameters were automatically adjusted to minimize the error between the historical data and the specified model variables (Oliva 2003), with a maximum of 1,000 iterations. All of the survival benefit (additional months in each stage) was assumed to accrue to stages 1-3, and not in the acute stage. Because of the difficulty in estimating differences in these times between individuals in regular care versus those in sporadic care, it was assumed that the amount of time spent in each stage by individuals in sporadic care was approximately 75% of the amount of corresponding time among individuals engaged in care.

Transmission Rate Calculations

All dynamic infectious disease models require an estimate for the transmission rate, or the number of transmissions per person per unit time. We used general findings from the published literature (such as the extent to which transmission rates are higher among unaware individuals) to estimate the relative contribution of infections from individuals in the 16 categories. The transmission rates for each stock were estimated during the calibration exercise described above. The transmission rate values were subsequently used as fixed parameters in the model.[1]

[1] Historical data indicate that transmission rates are continuing to decline in NYS. From 2006 to 2010, the model includes a calculation in which the category-specific transmission rates are allowed to decline in a linear fashion based on empirical data. The transmission rates are constant starting in 2010 when the law was implemented. This simplifying assumption was used because experts were not confident about how soon the decline will level off. The

Four general findings from the literature were applied to the transmission rate calibration exercise. First, individuals who are unaware of their infection (first row) transmit 3.5 times more infections than individuals who have been diagnosed. This reflects different risk behaviors, as well as viral suppression among those in care (Marks, Crepaz et al. 2005; Metsch, Pereyra et al. 2008; Marks, Gardner et al. 2010).

Second, three-quarters of individuals who are engaged in care in NYS have a transmission rate of zero and the remaining individuals have a similar transmission rate to individuals who are diagnosed but not in care, and in sporadic care. The NYS Quality of Care report, based on a chart review of HIV-infected NYS residents in regular care, reports that 72.4% of individuals in regular care have viral suppression (New York State Department of Health AIDS Institute 2011). Studies indicate that individuals with viral suppression have minimal transmission (Pedraza, del Romero et al. 1999; Quinn, Wawer et al. 2000; Castilla, del Romero et al. 2005; Attia, Egger et al. 2009; del Romero, Castilla et al. 2010; Donnell, Baeten et al. 2010; Cohen, Chen et al. 2011).

Third, one-quarter of new infections are attributable to individuals in the acute stage. This reflects different risk behaviors and high viral load. Although numerous studies have confirmed this finding, the estimated fraction of new infections attributable to this group differ across studies due to variation in how the acute phase is defined (Pedraza, del Romero et al. 1999; Quinn, Wawer et al. 2000; Pilcher, Chuan Tien et al. 2004; Xiridou, Geskus et al. 2004; Pao, FIsher et al. 2005; Wawer, Gray et al. 2005; Brenner, Roger et al. 2007; Pinkerton 2007; Boily, Baggaley et al. 2009; Prabhu, Hutchinson et al. 2009; Powers, Miller et al. 2011). Some studies estimate this number to be as high as 50%, although in practice it may not be reasonable to

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constant transmission rate assumption may overestimate the number of new infections overall, but the direction of the bias is consistent across all scenarios.

assume that half of new infections are generated by individuals who remain in this stage for two months.

Fourth, individuals in stages 1, 2, and 3 have the same transmission rate. In reality, individuals in stage 3 have a higher infectivity per contact due to increased viral load. However, there is some evidence for behavior changes among individuals in late stage, which would decrease the number of unprotected encounters (de Vincenzi 1994) and therefore offset increased infectivity.

Another approach to modeling infectious disease epidemics mathematically is to calculate new infections (incidence) as a product of the number of uninfected and infected persons, contact rate, infectivity (likelihood of transmission per encounter), and the fraction of contacts in which individuals use a barrier method such as condoms (thereby reducing infectivity) (Anderson and May 1991). In practice these estimates are difficult to obtain, and published estimates may not be directly relevant to NYS. Cohort studies have been used to derive estimates for HIV infectivity through heterosexual contacts, although studies acknowledge the difficulty of accurately measuring these per-act transmission probabilities (Downs and De Vincenzi 1996; Padian, Shiboski et al. 1997; Gray, Wawer et al. 2001; Boily, Baggaley et al. 2009; Powers, Miller et al. 2011). NYS has a mixed epidemic comprised of men who have sex with men (MSM), heterosexual, and injection drug users (IDUs) (New York State Department of Health AIDS Institute 2011). Each behavior has a different infectivity (Centers for Disease Control and Prevention 2012), there are gender-specific differences in transmission (Padian, Shiboski et al. 1997; Pinkerton, Abramson et al. 2000; Fideli, Allen et al. 2001), and the frequency of contacts may differ by behavior. Consequently, existing infectivity estimates may not be appropriate for the entire NYS population. Some estimates are virtually impossible to

obtain from empirical data; for example, it is challenging to conduct cohort studies of IDUs because they are such a marginalized and hard-to-reach population. Some HIV modelers address uncertainty in these estimates by using "best guess" assumptions, or else considering IDUs in sensitivity analyses only (Sanders, Bayoumi et al. 2005; Long, Brandeau et al. 2006; Alistar, Owens et al. 2011). Additional computational challenges to modeling new infections are that individuals' risk behaviors may change over time, they may be engaged in multiple high risk behaviors, and the presence of biological factors such as sex during menses or coinfection with another STD may increase infectivity (Downs and De Vincenzi 1996; del Romero, Castilla et al. 2010). Finally, awareness of HIV status may lead to less risky sexual behaviors (Marks, Crepaz et al. 2005), which needs to be considered.

Model Verification and Validation

Although a model can never be proven to be "valid," there are multiple checks during model development to assess *suitability* (whether the model is appropriate for its intended purpose) and *consistency* (whether the model is consistent with reality). These include boundary adequacy (ensuring the model contains all relevant variables without being so large that it becomes difficult to apply appropriate empirical data and explain model behavior), having the model structure consistent with experts' descriptions of the system, dimensional consistency among variables and equations, using appropriate numerical data and verbal descriptions for fixed parameters, subjecting the model to extreme conditions, and evaluating whether the model can replicate historical data from the real system (Richardson and Pugh III 1989; Sterman 2000).

Ongoing discussions with NYSDOH experts with knowledge of different data systems and program operations allowed the model to meet face validity criteria. The Vensim software allowed modelers to perform some model validation checks directly, such as dimensional

consistency, extreme condition tests (such as setting the transmission rate to zero), and running sensitivity analyses on parameters (such as the assumption that individuals in sporadic care have 75% the life expectancy of individuals who are engaged in care). In addition, as the model simulation starts in 2006, the simulated data from 2006-2009 was compared to empirical data in that time period to verify that the model is capable of matching empirical data. The technical appendix includes graphs that compare historical and simulated data for newly diagnosed HIV cases, new infections, people living with diagnosed HIV infection, living diagnosed ADIS cases, deaths among diagnosed HIV cases, fraction of diagnosed HIV cases ever linked to care, fraction of HIV cases who are undiagnosed, and fraction of newly diagnosed cases with AIDS.

Description of Policy Scenarios

Table 2 summarizes the policy scenarios considered in the evaluation. In addition to the no law scenario (also referred to as the baseline projection), there are nine scenarios that vary according to the level of implementation (perfect, high, and low, which differed by the fraction of patients seeking care who were offered and accepted tests) and whether individuals are able to receive repeat offers of testing as part of routine care (annual, five year, and no repeat offer of testing). The three implementation scenarios were combined with the three frequency of testing scenarios to generate nine unique policy scenarios in addition to the baseline projection.

All of the scenarios evaluate the incremental effect of the HIV testing law, in addition to the background testing that occurs as a result of risk-based testing and other outreach programs. The baseline projection assumes that unaware HIV-infected individuals continue to be diagnosed at the same rate, which could be attributable to current practice of risk-based testing in routine care settings (i.e., for patients who discuss a high-risk behavior with a physician), testing at traditional outreach sites such as STD clinics, syringe exchange programs, and mobile testing

vans, and other broad campaigns to encourage testing. The policy scenarios therefore should be interpreted as incremental changes from testing in routine care settings, in addition to existing testing efforts.

A separate set of scenarios varied the implementation time, from 18 months to five years. The earlier time frame represents a best case scenario, whereas the longer time frame captures the delayed regulations.

Two additional scenarios changed the transmission rate for all individuals who are engaged in care to zero. This could reflect a combination of complete viral suppression and behavioral interventions to reduce risky behaviors in this group. The first complete viral suppression scenario considered a zero transmission rate for all individuals engaged in care, combined with the no law scenario. The second complete viral suppression scenario considered a zero transmission rate for all individuals engaged in care, combined with the perfect implementation and annual repeat testing scenario. That would represent the maximum benefit that could be achieved if both policies were implemented perfectly.

Outcome Variables

Ten model output variables were used to assess the projected success of the policy, and are presented here. They are: (1) new infections, newly diagnosed (2) HIV and (3) AIDS cases, (4) fraction of newly diagnosed cases with AIDS, (5) diagnosed HIV cases newly linked to care, (6) diagnosed HIV cases ever linked to care, (7) diagnosed HIV cases currently engaged in care, (8) people living with diagnosed HIV infection, (9) people living with HIV infection (diagnosed and undiagnosed), and (10) fraction of HIV cases who are undiagnosed. Table 3 provides a description of these variables.

RESULTS

Scenarios That Varied Level of Implementation and Frequency of Testing

Table 4 displays the baseline projections of the outcome variables in the absence of the testing law. For each variable, the simulated value from 2010 is compared to the simulated values in 2015 and 2020. (Note that 2010 values are also simulated, as the most recent empirical data are from 2009.) These differences are represented as percent changes from 2010. For example, the percent change in new infections in 2015 is calculated as $[(\text{new infections})_{2015} - (\text{new infections})_{2010}] / (\text{new infections})_{2010} * 100$. The baseline projections show that even in the short-term, substantial changes would be expected in the absence of the law. There will be a continuing decline in the number of new infections per year (simulated value is 62.8% lower in 2020, compared to the simulated value in 2010), number of newly diagnosed HIV and AIDS cases (59.7% and 60.3% lower, respectively), diagnosed cases newly linked to care (54.1% lower), and fraction of HIV cases who are undiagnosed (57.8% lower). There will be a slight increase in the number of people living with diagnosed HIV infection (simulated value is 2.2% higher in 2020, compared to the simulated value in 2010) and diagnosed cases currently and ever linked to care (6.1% and 7.4% higher, respectively). Although the absolute number of newly diagnosed HIV and AIDS cases per year will decline, the fraction of newly diagnosed cases with concurrent AIDS will remain constant.

Tables 5 and 6 summarize the differential changes in these outcomes comparing the law and no law scenarios, in the case of annual repeat testing (Table 5) and one-time testing (Table 6). This is analogous to “differences in differences” regression models. The no law scenario is identical to the base case in Table 4. For each variable, the simulated value for the law scenario in 2015 or 2020 is compared to the simulated value for the no law scenario. The three sets of

columns correspond to the three levels of implementation (low, high, and perfect). For example, the percent change in new infections in 2015 comparing the low implementation scenario to the no implementation scenario is calculated as [(new infections)$_{2015\ Low\ Impl}$ − (new infections)$_{2015\ No\ Law}$] / (new infections)$_{2015\ No\ Law}$ * 100.

Compared to the no law scenario, there will be a relative decrease in new infections that will persist throughout the 10-year period. The number of newly diagnosed HIV cases will initially increase, and then decline. In the annual repeat testing scenario with low implementation, there will be a 9.1% decrease in newly diagnosed HIV cases in 2015 (compared to the no law scenario), and a 21.1% decrease in newly diagnosed cases in 2020. The corresponding values for the perfect implementation scenario are a 40.3% decrease in 2015 and 36.0% decrease in 2020.[2] The number of newly diagnosed AIDS cases and the fraction of undiagnosed HIV cases is expected to decline under all law scenarios. Compared to the baseline projection, there will be minimal differences in the number of people living with HIV infection and the number of people currently and ever in care. The fraction of newly diagnosed cases with concurrent AIDS will be lower with the law, although the percent difference in later years is less pronounced in the one-time testing scenario. The number of diagnosed cases newly linked to care will be initially higher under the law, but will then be lower than the baseline projection. To illustrate, in the annual repeat testing scenario with perfect implementation, there will be a 2.9% decrease in cases newly linked to care in 2015 (compared to the no law scenario), and a 28.0% decrease in 2020. This trend is not consistent across scenarios; the corresponding values for the

[2] The percent increase by 2015 is lower in the perfect implementation scenario, compared to the low implementation scenario. The number is somewhat misleading. Graphs that display this information visually show that the initial surge in the perfect implementation scenario has higher values than the low implementation scenario. However, the surge occurs prior to 2015. The technical appendix contains the graphs.

low implementation and annual testing scenario are 4.0% increase in 2015 and 1.8% increase in 2020.

Differences in scenarios for the three levels of implementation (low, high, and perfect) can be assessed by comparing the three sets of columns in Tables 5 and 6. Under higher levels of implementation, the number of new infections, fraction of HIV cases who are undiagnosed, newly diagnosed AIDS cases will decrease. The number of newly diagnosed HIV cases and cases newly linked to care will initially increase as implementation is improved, but then be lower than the low implementation scenarios. As implementation improves, there will be virtually no differences in the number of cases ever linked to care, cases currently engaged in care, and people living with HIV infection.

The scenarios for repeat annual testing and one-time testing can be compared by examining Tables 5 and 6. Overall there are minimal differences in new infections, newly diagnosed HIV and AIDS cases, diagnosed cases newly linked to care, cases currently in care, people living with HIV infection, and fraction of cases who are undiagnosed.

To further illustrate these findings, Figures 4 through 7 display results graphically for new infections, newly diagnosed HIV cases, newly diagnosed AIDS cases, and people living with diagnosed HIV infection under the annual repeat testing scenario. The technical appendix contains graphs for other outcomes and the one-time testing scenarios, which had very similar graphs to the annual repeat testing scenarios.

Scenarios That Varied Implementation Time

Varying the implementation time from 1.5 to 5 years has little effect on all outcomes, particularly the number of new infections or people living with diagnosed HIV infection. Under perfect implementation, reducing the implementation time would lead to an immediate increase

in the number of newly diagnosed HIV cases. A longer implementation time would result in a similar number of people being identified, but at a later date.

Scenarios of Perfect Viral Suppression

Scenarios of perfect viral suppression among individuals in care, and perfect viral suppression in addition to perfect implementation of the law (additive), were compared to the baseline projection and the scenario of perfect implementation of the law. Compared to baseline projection, complete viral suppression among individuals engaged in care will lead to small increases in the number of people living with diagnosed HIV infection and small decreases in the fraction of HIV cases who are undiagnosed. The overall trends for other variables will be similar to the baseline projections, although values will be lower. There will be fewer diagnosed HIV and AIDS cases, and HIV cases newly linked to care. The decline in new infections will be similar to that expected under perfect implementation of the HIV testing law. The simultaneous implementation of complete viral suppression among individuals engaged in care and perfect implementation of the HIV testing law will yield additional improvements to new infections and newly diagnosed HIV cases, although other outcomes did not show large additive effects from incorporating both policies.

DISCUSSION

Even in the absence of the law, New York can expect a continuing decline in the annual number of new HIV infections, HIV diagnoses, and fraction of undiagnosed cases over the 10-year time horizon. However, in the near term the number of individuals living with HIV infection and the number of cases currently in care will increase slightly. This somewhat

counterintuitive finding is because individuals remain in the system for a long time, as a result of large survival benefits from antiretroviral therapy.

If the law is fully implemented as designed (under any of the repeat testing scenarios), it has the potential to reduce the number of new infections and the fraction of undiagnosed cases. The state could expect an initial surge in the number of newly diagnosed HIV cases per year in the first five years. This will be followed by a decline, and a steadily declining number of newly diagnosed AIDS cases. The initial surge in newly diagnosed HIV cases reflects the rapid identification of individuals who are unaware of their infection. The anticipated decline in the number of newly diagnosed AIDS cases is due to individuals being diagnosed earlier in their infection and brought into care before they progress to late stage disease.

There will be a *relative* increase in the number of individuals newly linked to care per year, compared to the baseline projection without the law. However, the *absolute* number of individuals newly linked to care annually will not rise except in the short-run in the extreme condition of perfect implementation. This is due to other ongoing trends such as declines in new infections. There will be virtually no change in the number of people living with HIV infection or the number of cases in care because individuals in these groups live a long time (thereby staying in these stocks).

Even if the law is implemented perfectly, the number of new infections and the fraction of undiagnosed cases do not approach zero. By itself, the law will not eliminate the HIV epidemic.

There are minimal differences in outcomes between the annual repeat testing and one-time testing scenarios. In contrast, increasing the level of implementation can lead to improvements in outcomes such as the number of new infections, newly diagnosed cases, the

fraction of newly diagnosed cases with concurrent AIDS, and the fraction of cases that are undiagnosed. Varying the time to implementation did not change results significantly. Although a shorter implementation time will lead to higher increases of newly diagnosed cases and individuals newly linked to care in the short-run, long term results are virtually identical.

An alternative scenario of complete viral suppression among individuals engaged in care will yield a decline in new infections that is similar to that expected under perfect implementation of the law. There is an additive effect of the law and viral suppression, and the largest improvement to new infections will happen if both the law is implemented perfectly and all individuals in care have complete viral suppression.

How Model Findings Supplemented the Broader HIV Testing Law Evaluation

The system dynamics model provided several key policy insights. First, results highlighted the importance of continued investment of resources in programs that provide medical care to HIV patients, improve their retention in care, and encourage reductions in risky behaviors. This is based on the projected increase in the number of HIV cases in care, even under baseline projections without the law. Even as transmission rates decline, there is an overall increase in the number of people living with HIV infection. The scenario on viral suppression highlights the potential gains from reducing infections arising from individuals who are in care, which could occur through a combination of high adherence to medications and reductions in risky behaviors. Continued funding for programs that support individuals in care will continue to be important.

The temporary increase in new diagnoses under the law will be offset by the anticipated decrease in new infections and new diagnoses under the baseline projections. Consequently, although demand for services among newly diagnosed individuals will be greater in the law

scenarios compared to the baseline projection, there will not be a large absolute increase in the demand for services. The NYSDOH will not experience an increase in the number of clients being linked to care annually except in the extreme scenario of perfect implementation.

Third, the NYSDOH might maximize its return on investment by promoting a policy to test all patients once as part of routine care (in addition to continuing risk-based testing efforts at facilities such as STD clinics and mobile outreach vans), rather than devoting additional resources to working with hospitals and physicians to test patients more frequently. As written, the law did not directly address the frequency of test offers in routine care settings. Outcomes such as new infections, new diagnoses, and the fraction of HIV cases who are undiagnosed did not vary significantly between the annual repeat testing and one-time testing scenarios. In contrast, there are large differences in these outcomes under more complete implementation of the law. This finding is consistent with CDC recommendations that everyone in the general population should be tested once, with annual repeat testing among high risk populations (Centers for Disease Control and Prevention 2006).

Fourth, it is important that New York continue to rely on a broader policy approach that includes a wide range of HIV prevention policies and interventions, in addition to the law. Model results demonstrate that if the law is implemented as designed, many of the outcomes considered will improve. Yet even under perfect implementation and annual repeat testing, the law alone will not curb the HIV epidemic and there will continue to be new infections.

Finally, results suggest that the number of newly diagnosed HIV cases and newly diagnosed AIDS will be the best indicators to monitor the law's success in the future because there were noticeable numerical differences across scenarios, their visual patterns over time were straightforward to interpret, and NYSDOH can easily generate these statistics with existing

empirical data. The simulation runs demonstrated that under different levels of implementation, there should be an initial surge in newly diagnosed HIV cases followed by a sharp decline. In addition, the decline in newly diagnosed AIDS cases will be lower than the historical trend. None of the outcomes based on cross-sectional counts (such as people living with HIV and people engaged in care) changed noticeably across scenarios. The fraction of newly diagnosed cases with concurrent AIDS is relatively easy to generate by surveillance staff using existing data, but will not be a useful indicator because the changing denominator makes it difficult to interpret trends. The number of new infections and the fraction of cases who are undiagnosed are impossible to measure directly in the real world and the historical estimates have wide confidence intervals. Although these measures are important and expected to change over time under different scenarios, they are not good indicators to track progress over time due to measurement difficulties.

Overall, the model supplemented the other evaluation studies in several ways. Other empirical studies were retrospective, or else used early data. The final regulations were not adopted until approximately six months prior to the evaluation report was scheduled to be delivered, and hospitals and other medical facilities may have waited until their adoption before changing their own policies and procedures to adhere to requirements. Consequently, findings from other evaluation studies likely underestimate the law's potential effect. The system dynamics model provided NYSDOH with a projection of the future HIV testing and care system in NYS, and how and why outcomes could change under alternative assumptions about the level of implementation. In addition, the model results and modeling process more generally provided a broader context for understanding the system of HIV testing and care, relevant data sources, and how to monitor the law's future success.

Using System Dynamics Models for Policy Analysis in Other Domains

This case demonstrates that system dynamics modeling can be a useful supplement to a policy evaluation, particularly when data time lags make it difficult to do pre-post comparisons and key outcome variables are hard to measure empirically. These models can generate forecasts of both short- and long-term outcomes, thereby generating insights into early effects and whether they may change over time. In addition to providing evidence about whether a policy works and how, models can also be used to test alternate scenarios about what would happen under different implementation scenarios. This could provide feedback on how to improve implementation.

Several factors improved the model's development and success. First, it was a collaborative enterprise between academic researchers and the NYSDOH. The NYSDOH steering committee had broad expertise in local data and system operations, provided access to unpublished data, and gave modelers ongoing feedback about the model's design, how to operationalize scenarios, and the interpretation of results. Multiple datasets were used to calibrate the model. The model's ability to replicate historical data increased confidence in the model to the policy audience, thereby making the key findings and model insights more credible. Finally, modelers devoted extensive time to talking to experts in the field about the system of HIV testing in care and the law's possible effects. This provided a deeper context to understand the main findings, and describe how and why the law would change the outcomes.

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Figure 1. Stock and Flow Diagram of the System of HIV Testing and Care

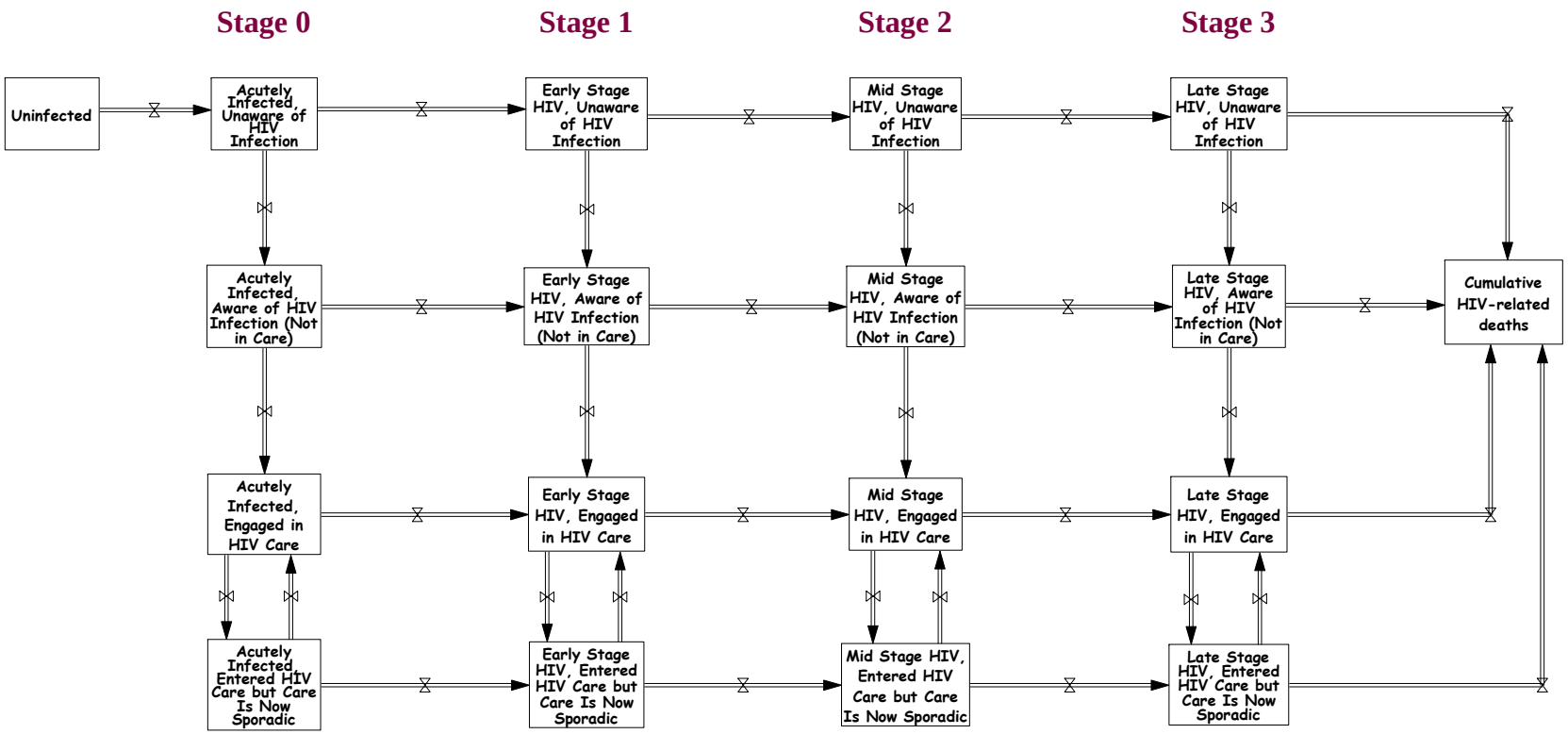


Figure 2. Stock and Flow Diagram for HIV Testing Structure

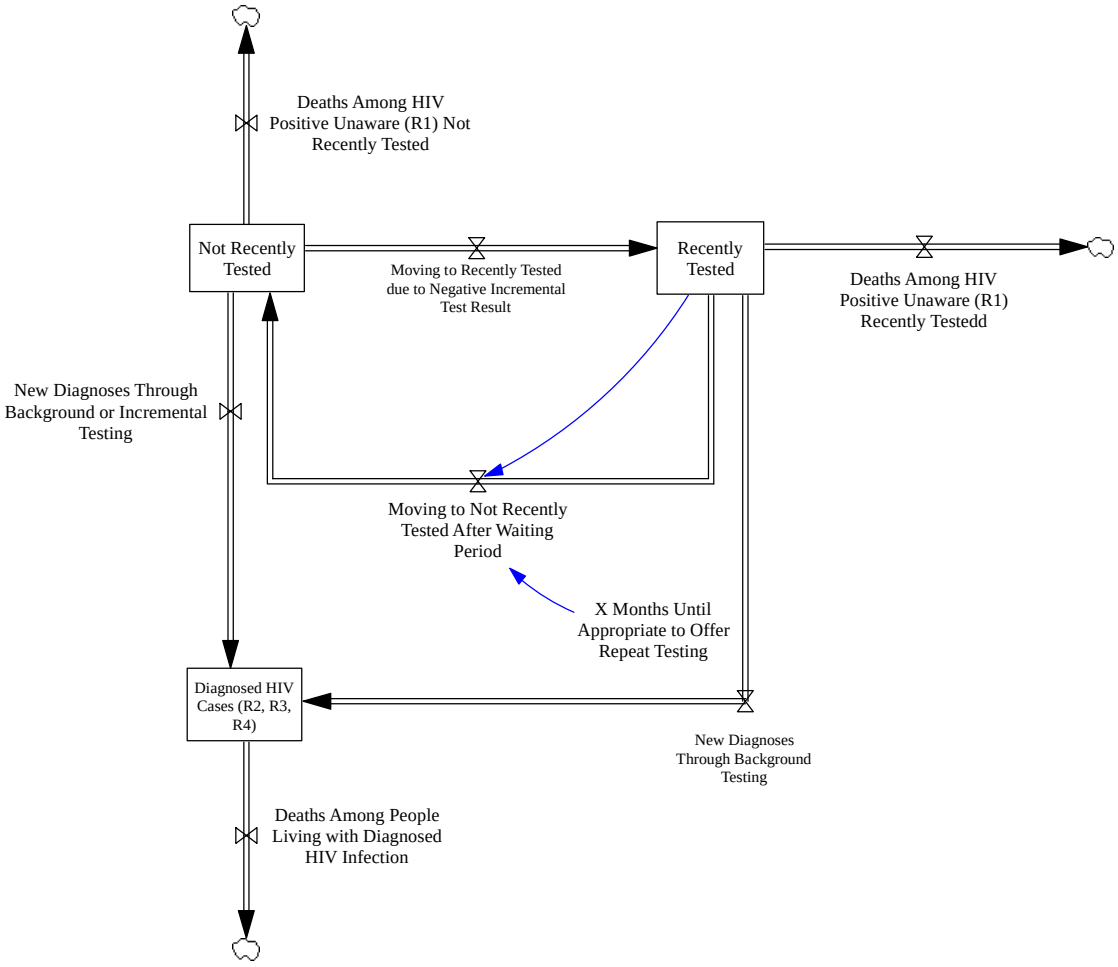


Figure 3. Additional Model View of Testing Law Structure

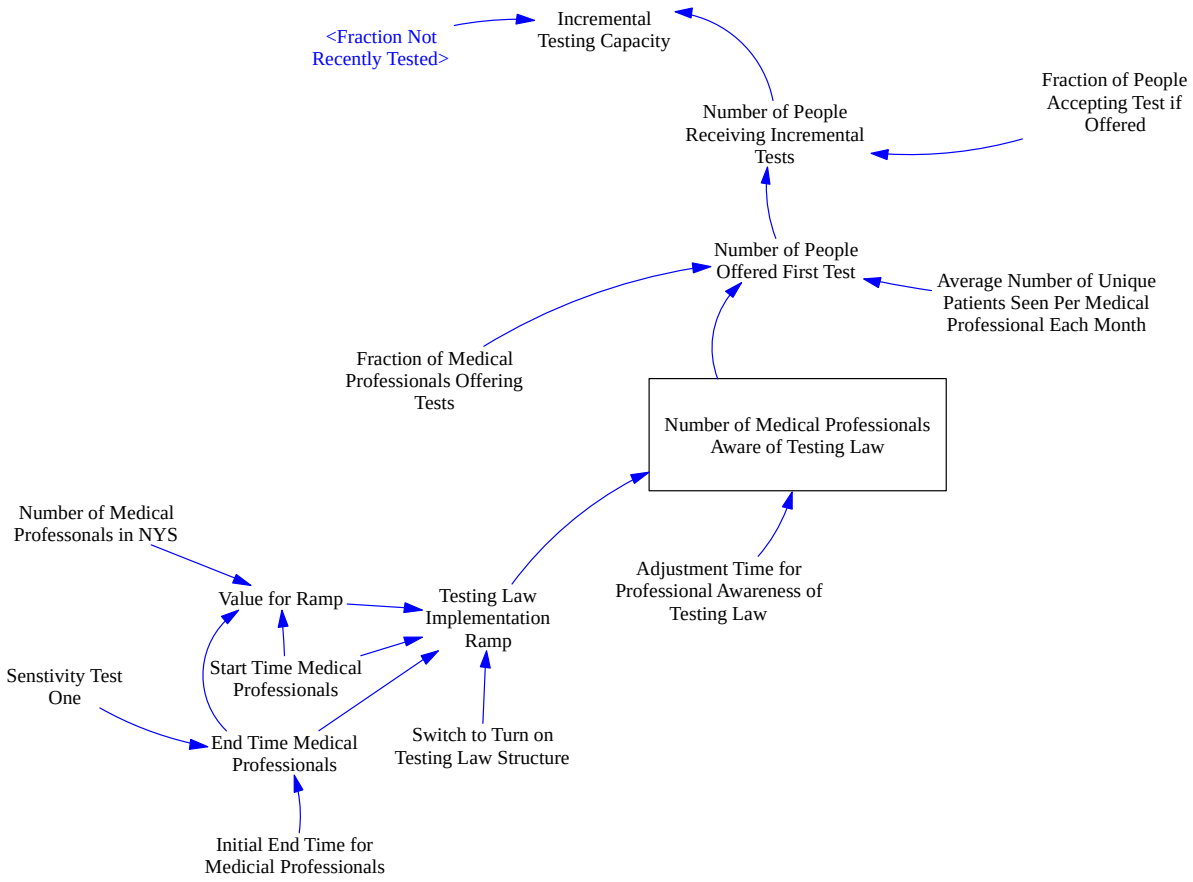


Table 1. Inputs and Historical Data for Simulation Model of HIV Testing and Care in New York

Variable	Sources
New infections per year	CDC estimate, 2006-2009 (time series)
People living with diagnosed HIV infection	NYS surveillance data, 2006-2009 (time series)
Living diagnosed AIDS cases	NYS surveillance data, 2006-2009 (time series)
Newly diagnosed HIV cases[2]	NYS surveillance data, 2006-2009 (time series)
Fraction of diagnosed HIV cases ever linked to care	NYS surveillance data, 2006-2008 (average)
Among diagnosed HIV cases linked to care, fraction in each disease stage	NYS surveillance data, 2006-2008 (average)
Fraction of people living with HIV who are unaware of their infection	Range based on expert opinion and CDC estimate (Centers for Disease Control and Prevention 2008)
Length of time spent in each stage for people living with HIV who are unaware or diagnosed but not in care	Literature (Paltiel, Weinstein et al. 2005; Paltiel, Walensky et al. 2006; Martin, Paltiel et al. 2010)
Length of time spent in each stage for people living with HIV and engaged in care	Calibration to NYS surveillance data
Length of time spent in each stage for people living with HIV who are in sporadic care	Calibration to NYS surveillance data; assumption that time spent in each stage is 75% of time for those engaged in care
Fraction of individuals who have ever been linked to care who are currently engaged in care	NYS Medicaid data (2010), and also consistent with NYC analysis of surveillance data (Torian and Wiewel 2011)
Deaths among diagnosed AIDS cases per year (includes HIV-related deaths and background mortality)	NYS surveillance data, 2006-2009 (time series)
Deaths among HIV non-AIDS cases per year (background mortality for diagnosed HIV cases in stages 0-2)	NYS surveillance data, 2006-2009 (time series)
Transmission rate for acute unaware	Optimization after model calibration (see text)
Transmission rate for acute aware, not engaged in care	Optimization after model calibration (see text)
Transmission rate for non-acute unaware (stages 1-3)	Optimization after model calibration (see text)
Transmission rate for non-acute aware (stages 1-3), not engaged in care	Optimization after model calibration (see text)
Transmission rate for individuals engaged in care	Optimization after model calibration (see text) and fraction of individuals in care who have viral suppression (New York State Department of Health AIDS Institute 2011)

Table 2. Policy Scenarios Considered in the Evaluation of the New York HIV Testing Law

Scenario	Description	Data Sources
No law	Baseline projection of outcomes in the absence of the law	Data sources listed in Table 1; identical to final calibration run
Perfect implementation	100% of patients who seek care are offered a test by a provider, and 100% accept a test if they are offered.	These conditions will not be observed in the real world, but the scenario can provide insight into the maximum benefit that could be accrued from the law
High implementation	75% of patients who seek care are offered a test, and 60% of patients accept a test if offered	New York module of Behavioral Risk Factor Surveillance Survey (questions on offering and accepting tests, and seeking care at medical settings); represents upper bound for what experts expect to happen
Low implementation	25% of patients who seek care are offered a test, and 60% of patients accept a test if offered	New York module of Behavioral Risk Factor Surveillance Survey (questions on offering and accepting tests, and seeking care at medical settings); represents lower bound for what experts expect to happen
Annual eligibility for repeat testing in routine care settings	All New Yorkers are eligible to receive an initial test, with a one year delay until being able to receive a subsequent test offer in a routine medical care setting.	Assumption; law does not specify frequency of test offers as part of routine medical care.
Five-year eligibility for repeat testing in routine care settings	All New Yorkers are eligible to receive an initial test, with a five year delay until being able to receive a subsequent test offer in a routine medical care setting.	Assumption; law does not specify frequency of test offers as part of routine medical care.
One-time testing in routine care settings	All New Yorkers are eligible to receive an initial test, and those who are tested are unable to receive a subsequent test offer in a routine medical care setting.	Assumption; law does not specify frequency of test offers as part of routine medical care.
Sensitivity analysis on implementation time	Base case assumes three years until full implementation; varied from 18 months to five years.	Discussions with NYC officials who implemented the Bronx Knows campaign to encourage all residents to get tested
Sensitivity analysis on complete viral suppression	Assumption that 100% of individuals engaged in care have a transmission rate of 0 starting in 2010	Assumption

Notes: The three implementation scenarios (perfect, high, and low) were considered in conjunction with the three frequency of testing scenarios (annual, five-year, and one-time), yielding a total of nine policy scenarios in addition to the baseline projection and sensitivity analyses.

Table 3. Outcome Variables Considered in Scenario Analysis to Evaluate the Effect of the New York HIV Testing Law

Variable	Description
New infections	Individuals who were previously uninfected and become newly infected. Impossible to measure directly in the real world.
Newly diagnosed HIV cases	Individuals who are newly diagnosed with HIV at any disease stage.
Newly diagnosed AIDS cases	Individuals who are newly diagnosed with HIV at disease stage 3 (also known as "concurrent HIV/AIDS diagnoses"), plus individuals previously diagnosed with HIV whose HIV disease has reached stage 3.
Fraction of newly diagnosed cases with concurrent AIDS	Among all individuals who are newly diagnosed with HIV, the fraction who are diagnosed in stage 3 (also known as "concurrent HIV/AIDS").
Diagnosed HIV cases newly linked to care	Individuals who have been previously diagnosed and are linked to care for the first time.
Diagnosed HIV cases ever linked to care	Individuals who have been diagnosed and initially linked to care. Includes individuals currently engaged in care and in sporadic care. Includes all disease stages.
Diagnosed HIV cases currently engaged in care	Individuals who have been diagnosed and initially linked to care, and are currently engaged in care. Includes all disease stages.
People living with diagnosed HIV infection	Individuals who are currently living with HIV at any disease stage, and have been diagnosed.
People living with HIV infection (diagnosed and undiagnosed)	Individuals who are currently living with HIV at any disease stage, including both those who have been diagnosed and those who are undiagnosed. Impossible to measure directly in the real world.
Fraction of HIV cases who are undiagnosed	Among all individuals currently living with HIV, the fraction that has been diagnosed. Impossible to measure directly in the real world.

Table 4. Baseline Projections of Outcome Variables in the Absence of the New York HIV Testing Law

Outcome	% Change 2010 to 2015	% Change 2010 to 2020
Annual New Infections	-38.0	-62.8
Annual Newly Diagnosed HIV Cases	-43.2	-59.7
Annual Newly Diagnosed AIDS Cases	-34.2	-60.3
Fraction of Newly Diagnosed Cases with Concurrent AIDS	4.0	-1.5
Annual Diagnosed HIV Cases Newly Linked to Care	-29.7	-54.1
Diagnosed HIV Cases Ever Linked to Care	7.1	7.4
Diagnosed HIV Cases Currently Engaged in Care	5.9	6.1
People Living with Diagnosed HIV Infection	3.9	2.2
People Living with HIV Infection Diagnosed and Undiagnosed	-0.7	-3.7
Fraction of HIV Cases Who Are Undiagnosed	-44.4	-57.8

Notes: All calculations are based on the "no law" scenario. For each variable, the value from 2010 is compared to the projected values in 2015 and 2020. These differences are represented as percent changes. As an example, the percent change in new infections in 2015 is calculated as $[(\text{new infections})_{2015} - (\text{new infections})_{2010}] / (\text{new infections})_{2010} * 100$.

Table 5. Projected Changes to Outcome Variables with the New York HIV Testing Law under Annual Repeat Testing in Routine Medical Care

Variable	% Change from No Law in 2015			% Change from No Law in 2020		
	Low Impl	*High Impl*	*Perfect Impl*	*Low Impl*	*High Impl*	*Perfect Impl*
Annual New Infections	-17.2	-27.5	-33.2	-19.0	-27.5	-31.3
Annual Newly Diagnosed HIV Cases	-9.1	-28.0	-40.3	-21.1	-31.8	-36.0
Annual Newly Diagnosed AIDS Cases	-46.3	-74.8	-86.7	-58.8	-80.2	-87.6
Fraction of Newly Diagnosed Cases with Concurrent AIDS	-41.5	-65.5	-78.0	-47.9	-71.1	-80.8
Annual Diagnosed HIV Cases Newly Linked to Care	4.0	1.8	-2.9	-13.3	-23.4	-28.0
Diagnosed HIV Cases Ever Linked to Care	0.7	1.2	1.5	0.3	0.2	-0.1
Diagnosed HIV Cases Currently Engaged in Care	0.8	1.3	1.6	0.1	-0.3	-0.3
People Living with Diagnosed HIV Infection	1.4	2.1	2.2	0.2	-0.1	-0.5
People Living with HIV Infection Diagnosed and Undiagnosed	-0.6	-1.2	-1.6	-1.6	-2.8	-3.4
Fraction of HIV Cases Who Are Undiagnosed	-40.7	-66.1	-77.2	-47.3	-67.3	-75.4

Notes: Numbers represent differential change in outcomes comparing the law and no law scenarios, for the annual repeat testing scenario. The annual repeat testing occurs as part of incremental testing in routine medical care settings by the law, holding background testing constant. For each variable, the projected value for the law scenario in 2015 or 2020 is compared to the projected value for the no law scenario. The three sets of columns (Low Impl, High Impl, and Perfect Impl) correspond to the three levels of implementation (low, high, and perfect). For example, the percent change in new infections in 2015 comparing the low implementation scenario to the no law scenario is calculated as $[(\text{new infections})_{2015\ \text{Low Impl}} - (\text{new infections})_{2015\ \text{No Law}}] / (\text{new infections})_{2015\ \text{No Law}} * 100$.

Table 6. Projected Changes to Outcome Variables with the New York HIV Testing Law under One-Time Testing in Routine Medical Care

Outcome	% Change from No Law in 2015			% Change from No Law in 2020		
	Low Impl	*High Impl*	*Perfect Impl*	*Low Impl*	*High Impl*	*Perfect Impl*
Annual New Infections	-13.8	-17.8	-16.9	-9.5	-7.5	-6.5
Annual Newly Diagnosed HIV Cases	-14.8	-35.9	-41.6	-19.0	-19.1	-16.0
Annual Newly Diagnosed AIDS Cases	-38.3	-50.5	-49.0	-30.7	-23.7	-19.7
Fraction of Newly Diagnosed Cases with Concurrent AIDS	-27.6	-22.8	-12.6	-14.4	-5.7	-4.3
Annual Diagnosed HIV Cases Newly Linked to Care	1.8	-3.6	-9.4	-12.9	-18.1	-18.2
Diagnosed HIV Cases Ever Linked to Care	0.6	0.9	0.9	0.0	-0.4	-0.6
Diagnosed HIV Cases Currently Engaged in Care	0.6	0.9	0.9	-0.2	-0.5	-0.2
People Living with Diagnosed HIV Infection	1.1	1.2	0.8	-0.3	-0.9	-1.2
People Living with HIV Infection Diagnosed and Undiagnosed	-0.5	-0.9	-1.2	-1.2	-1.6	-1.7
Fraction of HIV Cases Who Are Undiagnosed	-32.5	-41.3	-38.2	-22.5	-15.9	-12.8

Notes: Numbers represent differential changes in outcomes comparing the law and no law scenarios, for the one-time testing scenario. The one-time testing occurs as part of incremental testing in routine medical care settings by the law, holding background testing constant. For each variable, the projected value for the law scenario in 2015 or 2020 is compared to the projected value for the no law scenario. The three sets of columns (Low Impl, High Impl, and Perfect Impl) correspond to the three levels of implementation (low, high, and perfect). For example, the percent change in new infections in 2015 comparing the low implementation scenario to the no law scenario is calculated as $[(\text{new infections})_{2015\ \text{Low Impl}} - (\text{new infections})_{2015\ \text{No Law}}] / (\text{new infections})_{2015\ \text{No Law}} * 100$.

Figure 4. Projected New Infections per Year, for Annual Repeat Testing in Routine Medical Care and Three Levels of Implementation

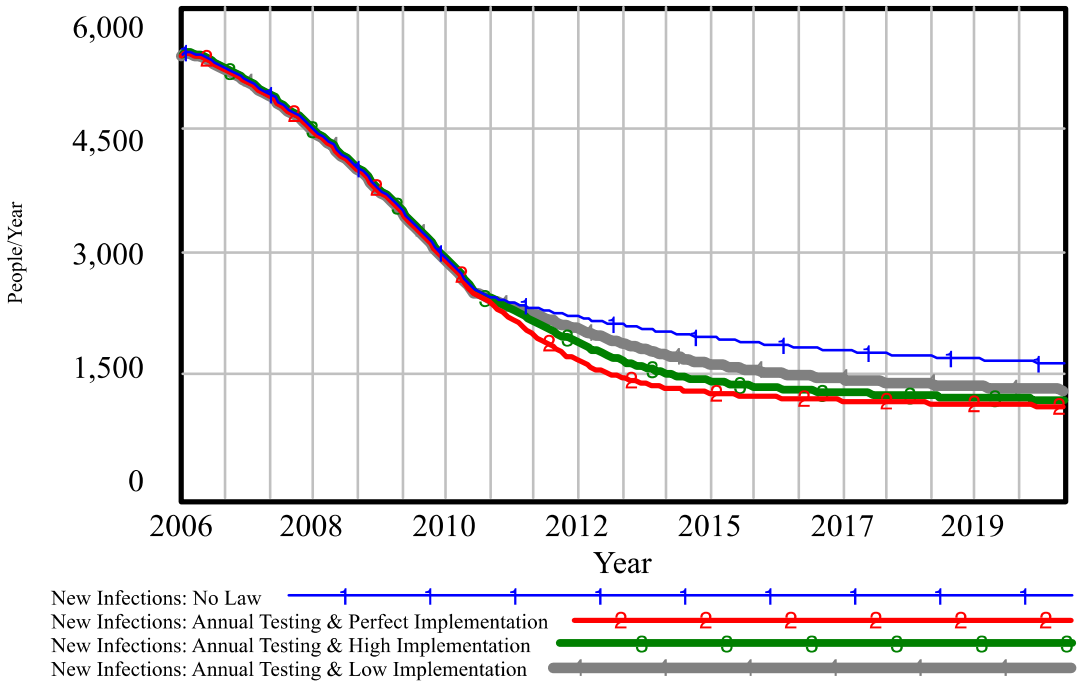


Figure 5. Projected Newly Diagnosed HIV Cases per Year, for Annual Repeat Testing in Routine Medical Care and Three Levels of Implementation

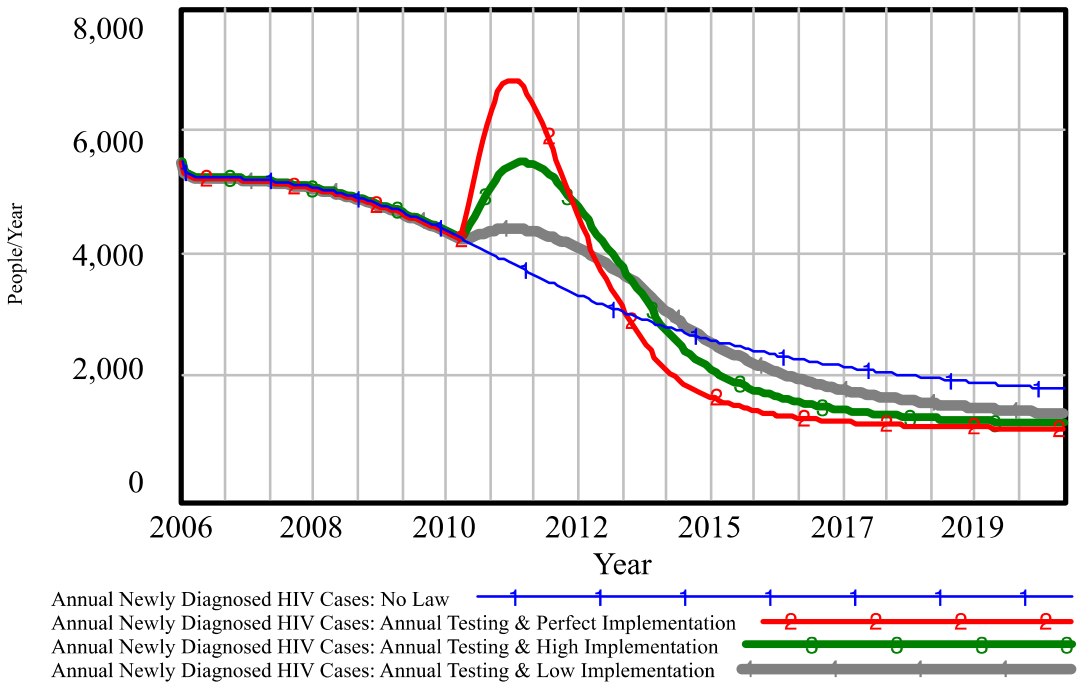


Figure 6. Projected Newly Diagnosed AIDS Cases per Year, for Annual Repeat Testing in Routine Medical Care and Three Levels of Implementation

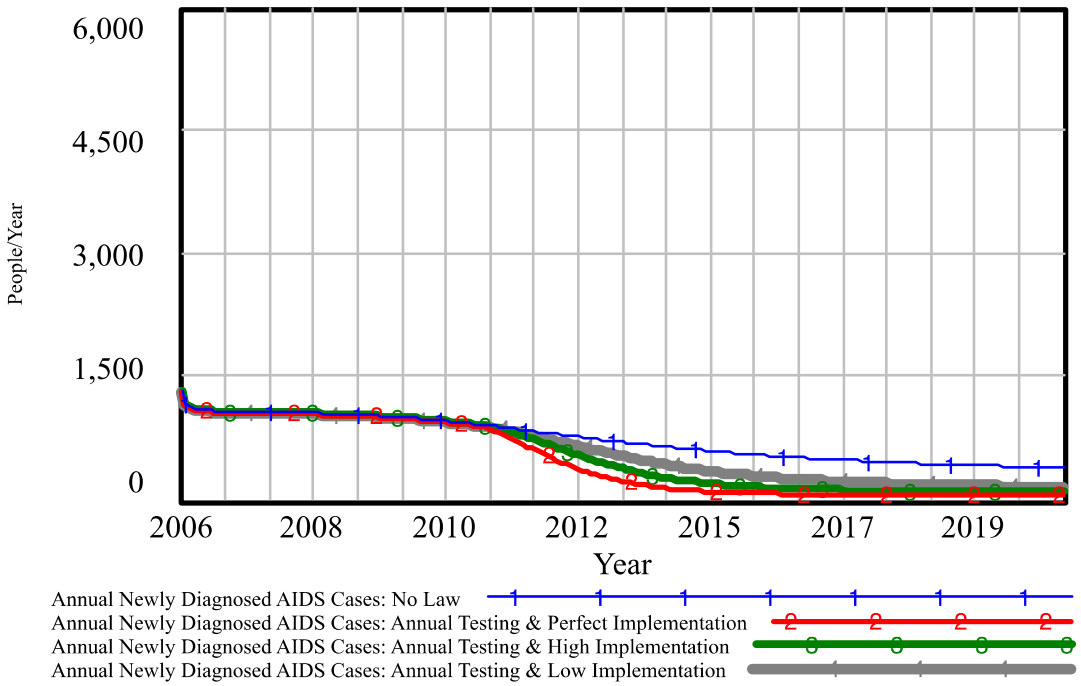
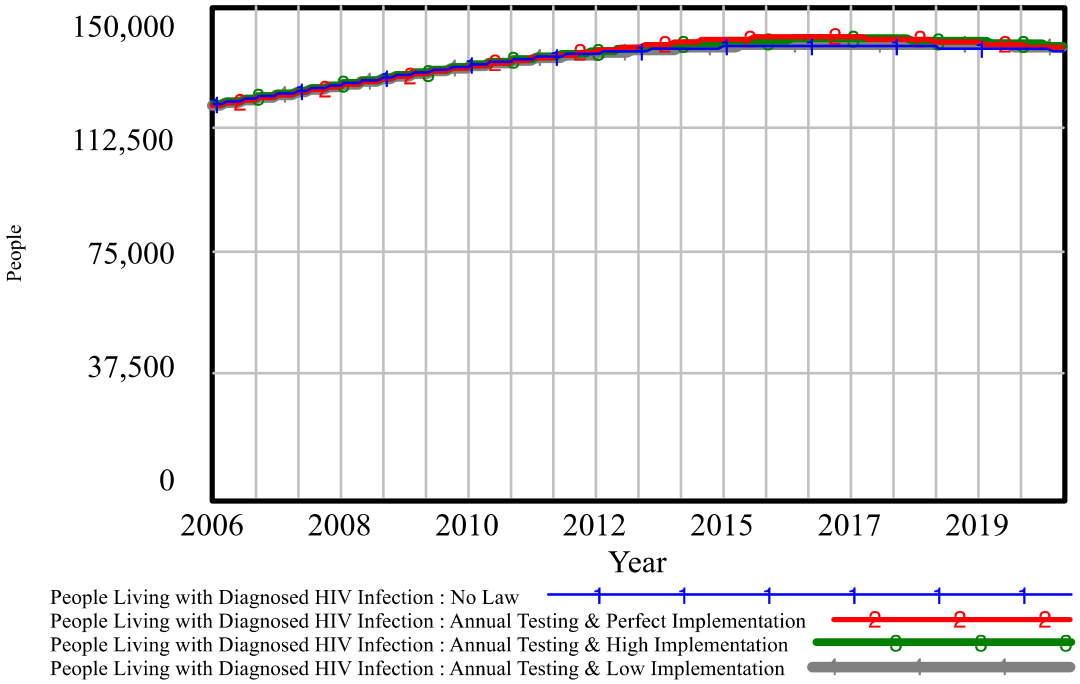


Figure 7. Projected People Living with Diagnosed HIV Infection, for Annual Repeat Testing in Routine Medical Care and Three Levels of Implementation



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