Optimal portfolios of blood safety interventions: test, defer or modify?

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# Abstract

**Background** In most health systems, risk of transfusion-transmissible infectious diseases (TTIDs) is managed through a portfolio of blood safety interventions. Shifting epidemiological conditions, emerging infectious diseases, and new technologies necessitate periodic reassessment of blood safety portfolios. However, the number of available blood safety portfolios grows exponentially with the number of available interventions, making it impossible for policy makers to evaluate all feasible portfolios without the assistance of a computer model.

**Methods** We develop a novel optimization model for evaluating blood safety portfolios that enables the systematic comparison of all feasible portfolios of deferral, testing, and modification interventions to identify the portfolio that is preferred from a cost-utility perspective. We present efficient methodologies for solving the optimization, and we apply the model to evaluate U.S. blood safety policies for Zika and West Nile virus.

**Results** xx

**Conclusions** XX.

**Keywords:** Blood safety, public health policy, binary integer programing, cost-effectiveness

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# Introduction

A safe supply of blood for transfusion is a critical component of the healthcare system in high-, middle-, and low-income countries alike (1). In most health systems, risk of transfusion-transmissible infectious diseases (TTIDs) is managed through a portfolio of blood safety interventions. These portfolios consist of three types of interventions. *Donor deferral policies* turn away potential donors who have characteristics associated with increased risk for harboring a TTID. *Disease marker tests* test collected donations for known TTIDs, with donations that test positive being discarded. *Risk-reducing modifications* like pathogen inactivation or leukoreduction reduce the likelihood that a TTID is transmitted to a recipient if it is present in a transfused donation. Because of shifting epidemiological conditions, emerging infectious diseases, and new technologies, blood safety portfolios should be periodically reassessed. However, the number of available blood safety portfolios grows exponentially with the number of available interventions, making it impossible for policy makers to systematically enumerate, much less evaluate, all feasible portfolios without the assistance of a computer model.

In recent years, decision analytic modeling has played a growing role in informing decisions regarding blood safety portfolios. Because the health and economic consequences of a blood safety intervention depend on local epidemiological conditions, the existing blood safety portfolio, and the larger healthcare system, analyses of blood safety interventions are necessarily for a specific jurisdiction at a specific time. Most studies have been cost-utility analyses that incorporate relevant risks, costs, and health consequences. These studies typically consider adding or changing one intervention while keeping others constant. Several such analyses have been conducted to evaluate disease marker tests (2–5), pathogen reduction technologies (a new category of risk-reducing modifications) (6–9), and donor deferral policies (10). Methods have recently been proposed to systematically select a portfolio of disease marker tests for a specific context, assuming donor deferral and risk-reducing treatments interventions are held constant (11–13). These optimization-based frameworks are designed to ensure that risk is sufficiently reduced, with considerations for waste and robustness, but are not designed to evaluate changes in deferral or modification interventions and are not necessarily consistent with finding the optimal policy from a cost-utility perspective.

In this paper, we develop a new framework for evaluating blood safety portfolios that uses a definition of optimality that is consistent with standard cost-utility analysis methods (14). In this framework, all relevant decision factors are expressed as costs or probabilities, and the set of blood safety decisions that minimizes the cost function is considered optimal. Unlike currently available methods, this framework enables the systematic comparison of all feasible portfolios of deferral, testing, and modification interventions to identify the portfolio that is preferred from a cost-utility perspective.

In the following sections, we derive our model by first introducing a simple model and progressively adding complexity. The model is a binary integer program (whether to implement each possible blood safety intervention). We discuss efficiency improvement techniques that reduce the computation time needed to identify the optimal portfolio. We apply the model to analyze U.S. policies for two TTIDs that have been difficult to manage due to geographical and seasonal variations in prevalence and infectiousness, Zika virus and West Nile virus. We conclude with a discussion of implications and potential extensions of our modeling framework.

# Model Specification

In this section we develop our model by developing the components for donor deferral, risk-reducing modification, and disease marker testing. All notation is summarized in Table 1.

## Donor deferral model

We begin with a simplified model for deciding whether to accept a donation in light of the risk of a single TTID. A donation may be infectious for the TTID () or not (), and the decision is to accept () or reject () the donation. If the donation is rejected (also called deferring the donor), a replacement cost is incurred because another donor must be recruited to meet demand. If the donation is accepted, a processing cost is incurred. We assume ; otherwise, the optimal decision would be to always reject donations regardless of blood safety concerns.

If the donation is accepted and is infectious for the TTID () then, in the absence of testing or modification interventions, an infectious donation is released for transfusion. Because many donations are fractionated into components that can be transfused to multiple patients, one infectious donation can expose multiple recipients to infection. We use the variable to represent the expected net monetary cost of releasing an infectious donation. We estimate this cost as , where is the net present expected cost of a breakthrough infectious donation, is the decision maker’s willingness to pay to avert the loss of one quality-adjusted life year (QALY), and is the net present expected QALYs lost. Estimating is a nontrivial exercise; its value depends on the TTID, the donor’s stage of infection, transfusion recipient characteristics, and how recipient exposures are treated.

Using the above notation, we express the cost function as follows:

For TTIDs of concern, we assume (the net monetary cost of releasing an infectious donation exceeds the replacement cost of rejecting a donation), which ensures that optimal decision is to reject a donation if it is known to be infectious. In practice, a blood center does not know whether a donation will be infectious, but the center can usually estimate the risk.

The optimal policy is to choose (accept or reject) such that the expected cost is minimized:

Here represents the probability the donation is infectious (). From this equation, one can see that a decision maker should be indifferent between rejecting and accepting the donation when . When , the optimal decision is to accept the donation (), and when , the optimal decision is to reject the donation ().

Policy makers are typically concerned about multiple TTIDs. We now consider multiple TTIDs indexed by . We define a vector where entry indicates whether the potential donation is infectious for TTID , and a vector where entry () represents the expected cost of releasing a donation that is infectious for TTID . Our new cost function is

Taking the expectation, we obtain

where is a vector for which . The decision maker should reject the donation when , accept when , and be indifferent when .

Finally, we consider the case of deferral with multiple TTIDs and donor segments. Rather than deciding whether to accept the entire donor population, blood centers often use a pre-donation questionnaire to classify potential donors into segments. The center’s decision makers then decide whether to accept or reject donations from each segment. Donor segments may be defined in ways that facilitate temporary deferrals (e.g., “travel to Mexico within the past 60 days”) or according to the level of demand for the donor’s blood (e.g., by blood type).

We assume that the donor population has been divided into segments indexed by , and the decision to accept or reject donations from a specific segment is represented by a vector with elements . We introduce a prevalence matrix whose rows correspond to donor segments and whose columns correspond to TTIDs. Entry represents the risk of infectiousness for TTID in donations from donor segment (). We define where represents the replacement cost of a donation from segment . It is possible that donor segments have different associated processing costs, so we define where represents the cost of processing a donation from segment . Finally, we define where is the estimated number of donors from each segment to present for donation in the period of analysis. Using this notation, the total expected cost of a given deferral policy is

where is a vector of all 1’s, in this case with length .

## Disease marker testing model

We now consider disease marker testing. We start with the case of one test for one TTID. We introduce a binary decision variable , where if the test is used and 0 otherwise. The test has an associated cost , sensitivity , and specificity . The probability of a positive test result is and the probability of a false negative is . We assume the blood center will always dispose of donations that test positive for a TTID, incurring a per donation cost of for a donation that tests positive. The constant should reflect the costs of any confirmatory testing, donor notification and counseling, and the cost of replacing the donation. Expected cost is

Note that not using a test is equivalent to using a test with sensitivity of 0 and specificity of 1. The expression will equal when and when . The expression will equal when and will equal when . Using these, we can rewrite the cost function as

For the case of testing for more than one TTID, we define where is the sensitivity for detecting TTID , where is the specificity for detecting TTID , and is as defined above. The probability that a single test returns a negative result is . The probability that *any* TTID tests positive is one minus the probability that *all* TTIDs test negative and is computed as . Using , the expected cost for one test and multiple TTIDs is

We now consider multiple tests and multiple TTIDs. We assume that tests are independent. We define a matrix where is the sensitivity of test for TTID and a matrix where is the specificity of test for TTID , and a vector where is the cost of test . We use the decision variable where when disease marker test is used.

Assuming that every available test is used, the probability of any positive result is . Replacing and with expressions that evaluate correctly when , we obtain .

To calculate the probability of a false negative test result for each TTID, we can take the element-wise product of and the following vector:

Using and , the expected cost function for multiple tests and multiple TTIDs is

Finally, we develop an expected cost function for the case of multiple tests, TTIDs, and donor segments. We define the decision variable where if test is used on donor segment . To calculate the risk of each TTID in each segment after tests are applied, we take the element-wise product of and the following matrix:

Additionally, we define a vector that represents the probability that a unit is disposed of in each donor segment:g:

Using and , the expected cost function for multiple donor segments, TTIDs, and tests is

## Risk-reducing modification model

Risk-reducing modifications (e.g., pathogen reduction or leukoreduction) can decrease the risk of TTID infection in components derived from blood donations. We first consider one available modification and one TTID. We define as the risk-reduction multiplier for the modification and as the per-donation cost. Often, modifications are applied to only some of the components derived from a donation rather than the whole donation. For example, pathogen inactivation is currently FDA approved for platelet and plasma components but not red blood cells [add reference]. In this case, either can be scaled proportionally to the fraction of components modified or the same TTID in different components can be modeled as different TTIDs (e.g. HIV in platelets vs. HIV in red blood cells). Because not applying a modification is equivalent to applying a modification with a risk multiplier of 1, we use the expression , which equals 1 when and when . Expected cost is

A modification can sometimes reduce the risk of multiple TTIDs. We model this by introducing where is the risk-reduction multiplier for TTID . The expected cost for a single modification with multiple TTIDs is

Often multiple modifications are available, each of which might reduce the risk for multiple TTIDs. To model this, we define the vector where is the cost for modification , and where is the risk-reduction multiplier for modification and TTID . We replace the single decision variable with the vector where if modification is added to the portfolio. The product of risk-reducing multipliers for each modification in use can be calculated as follows:

Using this, the new expected cost is

Lastly, we integrate the model for multiple modifications with the model for multiple donor segments. We define a new decision variable where if modification is used on donor segment . Because each element in must be multiplied by the product of any risk-reduction modifiers that are used in that sub-population, we define the following matrix:

> Using this, the expected cost with multiple donor segments and modifications is as follows:

## Optimal portfolio model

Finally, we can write the expected cost function for a portfolio containing any combination of donor deferral policies, disease marker tests, and risk-reducing modifications:

Identifying the optimal combination of interventions for a pre-specified willingness to pay per QALY gained is equivalent to solving the following optimization problem:

The constraint ensures that no tests or modifications are applied to deferred donor segments.

The above formulation allows each non-deferred donor segment to receive a tailored portfolio of tests and modifications. Health systems often use the same set of tests and modifications for all accepted donations regardless of donor segment. Such policies may produce less benefit at a fixed willingness-to-pay than tailored policies but are easier to implement and might be perceived as fairer. To consider only universal testing and modification policies, two additional constraints can be introduced:

If tailored test and modify policies for each donor segment are allowed, there will be feasible policies. If only universal test and modify policies are considered, the feasible state space will be which is smaller by a factor of approximately .

When evaluating policies, the expected cost by itself does not convey much meaning. As shown in Table 2, a variety of performance measures can be derived from the cost function. These performance measures can also be used to impose additional constrants on the optimization problem. For instance, one could limit the number of donors deferred (, where is the limit) or the total budget for tests and modifications (, where is the limit).

# Efficient Solutions

The optimal portfolio model is a binary integer program, and the exact solution can be found using exhaustive search. Because the state space increases exponentially in the number of available interventions, exhaustive search is not feasible for larger problems. Here we describe methods for more efficient identification of the optimal policy.

## Eliminate infeasible tests or modifications

Eliminating some tests or modifications from consideration in advance can considerably reduce the time needed to compute a solution for both the tailored and universal versions of the optimal portfolio problem. We can do so by leveraging the following theorum:

**Theorem 1:** *If use of a single test or modification is not preferred over using no interventions in any donor group it cannot be part of an optimal portfolio.*

To see why this theorum holds, consider the following. Tests and modifications reduce the cost function by reducing the multipliers on the expected cost of releasing an infectious donation (i.e., making the term smaller by decreasing one or more entries in and [tests] or [modifications]). Addition of a test or modification will generate the greatest reduction in expected cost when the term is largest, i.e. when no interventions are in use. Therefore, any test or modification that is part of an optimal portfolio will be preferred over a ‘no intervention’ scenario in at least one donor group.

## Tailored policies

When policies can be tailored to individual donor groups, the objective function is linearly separable, and we can solve a single, smaller optimization problem for each donor group. In this case we can identify the optimal portfolio by evaluating policies, rather than the evaluated by exhaustive search.

# Case study: West Nile virus and Zika

Both West Nile virus (WNV) and Zika virus are most often transmitted by mosquitos but can also be transmitted by blood transfusion [ADD REFERENCE]. For both diseases, more than 70% of infected individuals show no symptoms [ADD REFERENCE], creating a high risk of collecting a donation from an infectious, unaware donor. Additionally, incidence of both viruses varies geographically, seasonally, and annually, largely due to differences in mosquito population. This necessitates regular reassessment of blood safety interventions. Available interventions include nucleic acid testing (NAT), pathogen inactivation, and donor deferral. Currently, the United States mandates year-round mini-pooled NAT testing for both Zika and WNV in all areas and requires that regions temporarily escalate to individual donation NAT for WNV following the detection of confirmed positive [ADD REFERENCE].

## Case study method

We applied our model to identify the optimal combinations of blood safety interventions for preventing transfusion-transmitted Zika and WNV in blood products derived from whole blood donations in the United States. We considered four screening tests and one risk-reducing modification. We considered 104 donor groups, based on geographic area and season. We developed separate policies for 2017, 2018, and 2019. Parameter values, shown in Table 3, were derived from the academic literature, Centers for Disease Controll and Prevention (CDC) reports, and personal communications with blood safety experts. The optimization model was programmed in R. To estimate the harms of releasing a Zika- or WNV-infectious donation into the blood supply we developed microsimulation models of transfusion recipients in Python. All data and code will be uploaded to a public repository upon publication acceptance.

### Tests and modifications

Nucleic Acid Testing (NAT) is used for routine screening for both Zika and WNV. Tests can either be run on individual donations (ID-NAT) or in a minipooled testing procedure (MP-NAT) where the test is run on a pooled sample of 6-16 donations, with subsequent individual donation testing for any minipool that is initially reactive. MP-NAT can reduce the number of tests run per sample and therefore has a lower per-donation cost, but the test has a lower sensitivity. However, because the minipooled testing procedure requires both a reactive minipool and a subsequent reactive ID-NAT test, the risk of a false positive is greatly diminished. We considered four tests: Zika ID-NAT and MP-NAT as well as WNV ID-NAT and MP-NAT.

Pathogen inactivation (PI) is an effective modification that reduces the transmission risk for many types of viruses and bacteria, including enveloped retroviruses like Zika and WNV [CITATION NEEDED]. PI is currently only avaailable for treating plasma or platelets components, not whole blood donations or red cell components, in the United States. Because platelet PI is typically done for apheresis rather than whole blood-derived platelets, We only included PI of whole blood-derived plasma as a possible blood safety intervention. We assumed that PI decreases risk of transmission by plamsa exposure by 99% for both Zika and WNV. Based on our calculations using the 2015 National Blood Collection and Utilization Survey (15), plamsa exposure accounts for 36% of the transfusion-transmission risk of an infectious donation, yeilding a per-donation risk reduction multiplier around 65%.

### Donor groups

We included donors from 52 geographic areas (50 states, Puerto Rico, and the District of Columbia [DC]). We segmented donors based on geographic area and season. We estimated the total number of donations in a year from the 2015 NBCUS (15) for the 50 states and D.C. and from Russell et al. for Puerto Rico (2). We assumed that the number of donors in each geographic area was proportional to the area’s population for a given year per U.S. Census Bureau estimates (16). The probability of an infectious blood donation in the U.S. was based on CDC data on viremic blood donations interdicted by testing each year, and the risk assigned to an individual geographic area was assumed to be proportional to the number of CDC-reported symptomatic cases for that area (17,18). An analysis of CDC case reports by symptom onset date revealed that from 1999-2018, 99.1% of WNV cases occurred in the 6-month period from June to November (17). We assumed that half the donations were collected during this ‘high mosquito season’ and the other donations were during ‘low mosquito season’ and assigned risk proportionally. Zika risk by season was proportional to that found in an earlier analysis of 2016-2017 data [#Russell2019]. Most Zika cases in the continental U.S. were travel-acquired, from either the northern or southern hemisphere, and do not exhibit the same seasonal trends as an outbreak driven by a local mosquito population. We therefore assumed that Zika risk in the continental United States did not change between the high and low mosquito seasons.

### Costs and QALYs

A 2014 analysis in the Netherlands estimated that the cost of a donation visit resulting in deferral cost the donor €16 in lost time and transportation and cost the blood center €2.65 – €31.82 depending on whether the donor was a routine donor or a first-time donor who needed to be recruited. The cost of recruiting, inviting, and evaluating a replacement donor cost €2.58 – €31.25, depending on whether the donor was a first-time or routine donor, giving a totl deferral cost of €21.23 for routine donors and €79.07 for routine donors. Donors who are deferred are less likely to present to donate in the future than those who donate successfully (19), an additional cost not captured in the 2014 analysis. No data were available for the United States, so we assumed that the replacement cost for a deferred donor in the United States was $90. We also assumed a donation processing cost of $20 and a donation disposal cost of $60, which reflects confirmatory testing and donor notification costs.

To estimate the societal costs (medical expenses and productivity losses due to illness and death) and quality-adjusted life years (QALYs) lost that result from transfusion-transmission, we developed separate microsimulations for each diseases (Zika and WNV). We adapted the model structure from a prior publication (2). Both models simulated individual transfusion recipients whose age, sex, and number of red blood cell, platelet and plasma components transfused followed a similar distribution to transfusion recipients in the United States. The expected post-transfusion survival for each recipient was calculated as a function of age and the number and type of blood components transfused (2). For the Zika model, we adapted parameters including probabilities, costs, and QALY multipliers for Zika fever and more severe sequelae are all adapted from the prior publication (2) and updated to 2019 US dollars using the personal healthcare component of the National Health Expenditure Data provided by the Centers for Medicare and Medicaid Services (20). The Zika model also captures costs and QALY losses due to secondary sexual or congenital transmission of Zika to a transfusion recipient’s sexual partner or offspring. In the WNV model, recipients could experience no acute disease, acute WNV fever, or one of three neurological diseases (meningitis, encephalitis, or acute flaccid paralysis). No secondary transmission was modeled. Transfusion recipients experiencing acute disease were also at risk for long-term disability. The WNV model was developed using parameter values from a recent cost-effectiveness analysis of a WNV vaccine (21) as well as a study of the costs of WNV infection (22) with costs updated to 2019 US dollars. All costs and QALYs lost were discounted to net present using an annual discount rate of 3%. The decision tree structures for the two models are shown in Supplemental Figure S1. Parameter values are shown in Supplemental Tables S1 and S2.

To estimate the health outcomes for patients experiencing transfusion-transmission based on the blood component type from the Zika and WNV microsimulation output, awe calculated a weighted average of the outcomes by component type:

where outcome is cost or QALYs lost due to disease , is the blood component type, indexes individual transfusion recipients, and is the number units of component transfused to recipient . To estimate the expected net health costs of releasing an infectious donation, the average number components transfused per whole blood donation collected was estimated from the 2015 National Blood Collection and Utilization Survey (NBCUS) (15) and the component-specific probability of transfusion-transmission for both WNV and Zika were estimated from literature (2,23). The expected value of the outcomes (cost and QALY loss) per donation were then calculated as follows:

where is the probability of that disease is transmitted to a recipient exposed to an enfectious component of type , and is the average number of units of component tye produced per whole blood donation. This procedure was used to estimate both cost and QALYs lost, which were then used to calculate net health cost was calculated assuming a willingness-to-pay threshold of $1 million per QALY [ADD REFERENCE].

### Uncertainty analysis

We performed probabilistic sensitivity analysis by randomly sampling 10,000 sets of input parameters from the probability distributions listed in Table 3 and Supplemental Tables S1 and S2 and then re-running the recipient microsimulations for Zika and WNV as well as the optimal portfolio model for each set. We calculated performance metrics for each iteration as well as the percentage of time each safety measure was part of the optimal portfolio across each of the 10,000 iterations.

## Results of case study (not completed)

In a given calendar year, 8.422669310^{157} tailored portfolios are possible, but by exploiting linear separability and finding the optimal portfolio for each donor group separately we could identify the optimal portfolio by evaluating just 3328 policies. In the basecase, the net monetary cost of releasing a infectious donation for transfusion was $9,739 for Zika and $37,992 for WNV, which carries a higher risk for severe disease.

# Discussion (rough outline)

The framework itself has limitations that could probably be addressed by extensions.

* We made assumptions about fold reduction of modification technologies.
* Assuming tests are independent. Usually fair assumption for comparing tests for different TTIDs or serologic vs. nucleic acid tests, but probably does not hold when considering multiple tests for same TTID that are both serologic or DNA/RNA-based.
* Hard to estimate and . Donor replacement costs were considered constants, but in fact they can vary with time and might increase if aggressive deferral and testing policies reduce the available supply.
* Assume donation discarded if tests positive on any test, but some might want to consider protocols where an initially reactive donation is released into supply if it tests negative in confirmatory testing.

One key limitation, however, is the level of effort involved in developing a thorough model, given how many parameters need to be assigned for every TTID, test, modification, and donor segment. It’s like developing a CEA for every available blood safety intervention at once. However, we think that the insights would be worth the effort. For a health system to use the model, considerable work is required to fully parameterize the model for their setting. However, once a model is developed, newly available interventions can be added and evaluated with relative ease. A health system may wish to fully develop the model only once every ~2-5 years but evaluate potential changes to their portfolio as needed.

The U.S. analysis also has limitations. [will list]

Possible extensions:

* optimal definition of donor segments.
* Robust optimization, stochastic optimization.

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##### 

Table 1. Summary of notation

* : single variable
* with elements : vector
* with elements : matrix
* : indicator variable
* : vector for which every entry is 1
* : probability equals
* : Hadamard (element-wise) product of same-dimensioned vectors or matrices

###### Indices

* : transfusion-transmissible infectious diseases (TTIDs)
* : segments of the donor population
* : available disease marker tests
* : available risk-reducing modifications

###### Decision variables

* where : 1 if donations from donor segment are accepted
* where : 1 if modification is used in donations from donors in segment
* where : 1 if disease marker test is used for donations from donors in segment

###### Parameters related to transfusion-transmissible infectious diseases (TTIDs)

* where : 1 if a donor is infectious with TTID
* where : probability that a donor is infectious with TTID
* where : net health cost of releasing a donation infectious for TTID

###### Parameters related to donor segments

* where : probability a donation from donor segment will be infectious for TTID
* where : cost of replacing a deferred donation from a deferred donor from segment
* where : cost of processing a donation for a donor from segment
* where : number of donors in subgroup

###### Parameters related to disease marker tests

* where : per-donation cost of disease marker test
* where : sensitivity of test for TTID
* where : specificity of test for TTID
* : disposal cost for collected donations that test positive

###### Parameters related to modification interventions

* where : per-donation cost of modification intervention
* where : percent reduction in risk of TTID from modification intervention

##### 

Table 2. Key policy measures

|  |  |
| --- | --- |
| **Measure** | **Formula** |
| Risk reduction for TTID in segment by testing () |  |
| Risk reduction for TTID in segment by modifications () |  |
| Residual risk for TTID in segment (returns ) |  |
| Donation yield |  |
| Residual risk of infection for TTID () |  |
| Number of infectious donations released for TTID () |  |
| Total modification cost |  |
| Total cost of initial tests |  |
| Total donor replacement cost |  |
| Total processing cost |  |
| Total cost due to released infectious donations |  |
| Total cost due to removed donations testing positive |  |
| Number of donations testing positive |  |

##### 

Table 3. Parameters for optimization model

| Parameter | Value (range) | Distribution |
| --- | --- | --- |
| Net monitary cost of releasing ZIKV-infectious donation | $9,739 |  |
| Net monitary cost of releasing WNV-infectious donation | $37,992 |  |
| Donation replacement cost | $90 (45—135) | Tri |
| Donation processing cost | $20 (10—30) | Tri |
| Donation disposal cost (exc. replacement) | $60 (30—90) | Tri |
| ZIKV ID-NAT cost per donation | $10 (5—15) | Tri |
| ZIKV MP-NAT cost per donation | $6 (3—9) | Tri |
| WNV ID-NAT cost per donation | $10 (5—15) | Tri |
| WNV MP-NAT cost per donation | $6 (3—9) | Tri |
| Sensitivity of ZIKV ID-NAT for ZIKV | 0.999 (0.998—1) | Tri |
| Sensitivity of ZIKV MP-NAT for ZIKV | 0.98 (0.961—0.999) | Tri |
| Sensitivity of WNV ID-NAT for WNV | 0.99 (0.98—1) | Tri |
| Sensitivity of WNV MP-NAT for WNV | 0.95 (0.91—0.99) | Tri |
| Specificity of ZIKV ID-NAT for ZIKV | 0.9997 (0.9994—1) | Tri |
| Specificity of ZIKV MP-NAT for ZIKV | 0.999999999 (0.999999998—1) | Tri |
| Specificity of WNV ID-NAT for WNV | 0.9997 (0.9994—1) | Tri |
| Specificity of WNV MP-NAT for WNV | 0.999999999 (0.999999998—1) | Tri |
| Cost of FFP PRT | $81 (40.64—121.92) | Tri |
| Risk reducing multiplier of FFP PRT on ZIKV | 0.645664139 (0.5165313112—0.7747969668) | Tri |
| Risk reducing multiplier of FFP PRT on WNV | 0.64287943 (0.514303544—0.771455316) | Tri |
| Red blood cell units transfused per donation | 0.944 (0.908—0.98) | Tri |
| Platelet units transfused per donation | 0.015 (0.012—0.018) | Tri |
| Plasma units transfused per donation | 0.541 (0.4328—0.6492) | Tri |
| Transmissibility of ZIKV in RBC components | 0.5 (0.3—0.7) | Tri |
| Transmissibility of ZIKV in PLT components | 0.5 (0.3—0.7) | Tri |
| Transmissibility of ZIKV in FFP components | 0.9 (0.8—1) | Tri |

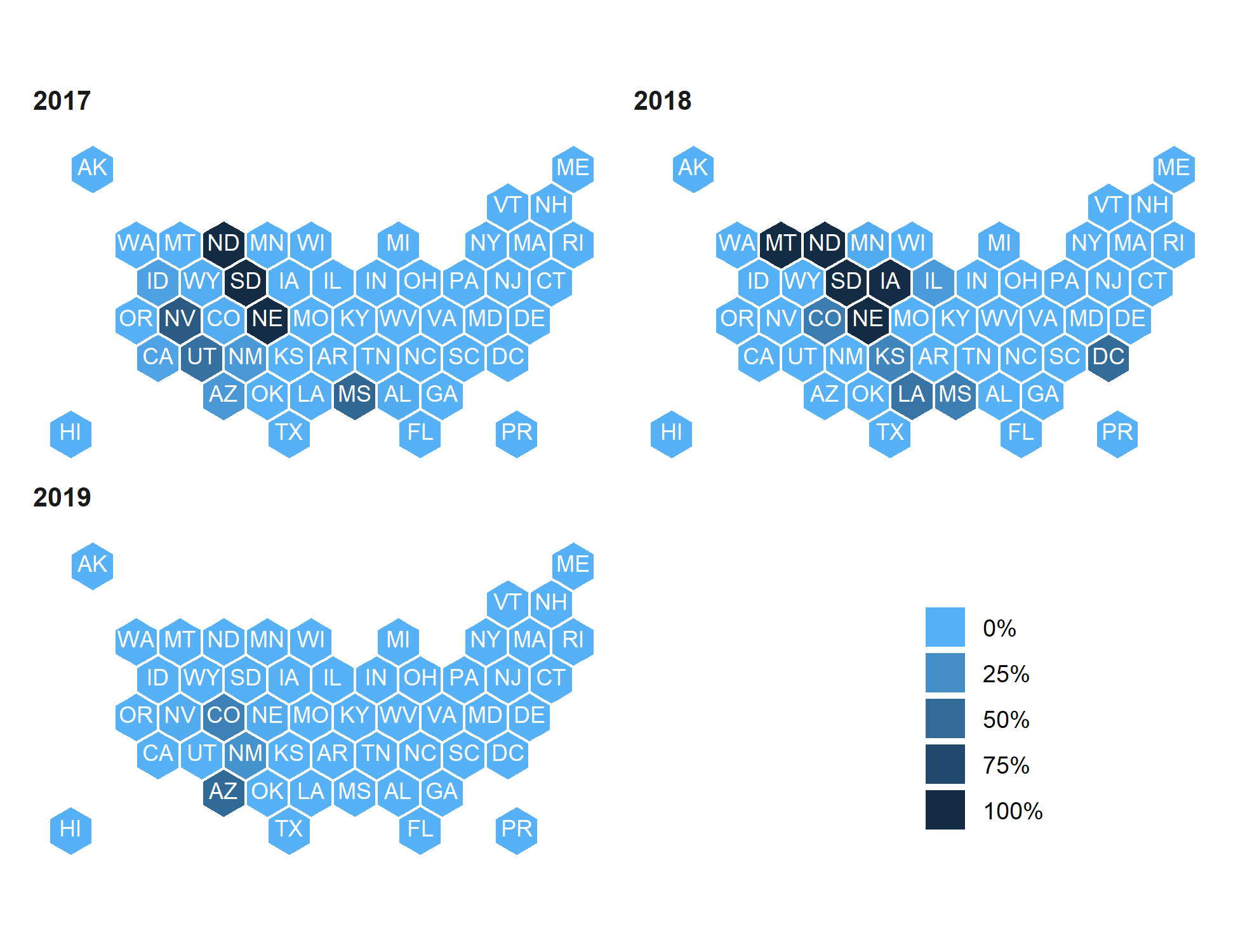
##### 

Table 4. Performance of optimal policy compared to universal testing and not testing

| Policy metric | 2017 | 2018 | 2019 |
| --- | --- | --- | --- |
| Objective function value | $216,351,846 ($134—397 million) | $217,995,136 ($143—398 million) | $210,348,296 ($140—398 million) |
| Donation yield | 10,327,006 (10.3—10.3) | 10,349,081 (10.3—10.3) | 10,327,046 (10.3—10.3) |
| Test cost | $899,004 ($0—$150,025,224) | $731,450 ($0—$150,025,224) | $0 ($0—$150,025,224) |
| Net monitary cost of released infectious donations | $8,905,954 ($92.—4.8 million) | $10,264,630 ($343—18. million) | $3,807,376 ($251—13. million) |
| Zika residual risk | 3.10e-06 (4.11e-10—4.84e-08) | 2.90e-07 (2.47e-09—2.91e-07) | 4.84e-08 (2.63e-08—3.10e-06) |
| WNV residual risk | 2.19e-05 (—) | 2.60e-05 (—) | 9.69e-06 (—) |

##### 

Figure 1.Hexbin map showing percent of PSA iterations for which WNV testing during high mosquito season was optimal by geographic area in 2017, 2018, and 2019



##### 

Optimal portfolios of blood safety interventions: test, defer or modify?

Supplement

#### W. Alton Russell, Brian Custer, Margaret L. Brandeau

## Estimating the potential value of a novel test or modification

It is possible to develop insight into the potential utility of a new test or modification for blood banking before the technology has been developed. By making pessimistic assumptions about the risk of disease in the donor populations and optimistic simplifications about the efficacy and costs of an interventions, we have developed simple criteria that can remove infeasible interventions from consideration. For a given test (with index ) or a given modification (with index ) that influences risk for only one disease (with index ), the following must hold for the intervention to be part of an optimal portfolio:

The quantity is the value of the intervention assuming it eliminates all risk of infection for disease in the donor group with the highest risk, without incurring any additional costs (e.g., replacing donations testing positive). If the per-donation cost of a test () or modification () are not below that quantity, the intervention can be removed from consideration.

For interventions that reduce the risk for multiple disease we can use a generalization requiring for the inequality to hold for all donor groups (unless the analyst identifies one donor group which has the highest risk for all diseases influenced by the intervention). The conditions for interventions influencing risk for multiple disease are:

Where indicates the diseases a given test can detect and indicates the disease for which the modification reduces risk.

While these conditions were derived for eliminating interventions from consideration with the optimal portfolio model, they can be applied more generally to eliminate tests and modifications from consideration.

##### 

Table S1. Number of donors and prevalence of Zika and WNV by donor group

| Geographic area | Year | Season | Donors, N | Zika prevalence | WNV prevalence |
| --- | --- | --- | --- | --- | --- |
| Alabama (AL) | 2019 | High | 76549 | 0 | 7.1e-06 |
| Alaska (AK) | 2019 | High | 11421 | 0 | 9.5e-06 |
| Arizona (AZ) | 2019 | High | 113636 | 0 | 0.00017 |
| Arkansas (AR) | 2019 | High | 47114 | 0 | 2.1e-05 |
| California (CA) | 2019 | High | 616868 | 2e-08 | 3.7e-05 |
| Colorado (CO) | 2019 | High | 89906 | 0 | 0.00015 |
| Connecticut (CT) | 2019 | High | 55662 | 0 | 1.9e-06 |
| Delaware (DE) | 2019 | High | 15202 | 0 | 0 |
| District of Columbia (DC) | 2019 | High | 11018 | 0 | 6.9e-05 |
| Florida (FL) | 2019 | High | 335312 | 0 | 6.4e-07 |
| Georgia (GA) | 2019 | High | 165760 | 3.8e-08 | 9.1e-06 |
| Hawaii (HI) | 2019 | High | 22105 | 0 | 0 |
| Idaho (ID) | 2019 | High | 27900 | 1.1e-07 | 4.3e-05 |
| Illinois (IL) | 2019 | High | 197833 | 0 | 1.3e-05 |
| Indiana (IN) | 2019 | High | 105104 | 0 | 4.1e-06 |
| Iowa (IA) | 2019 | High | 49257 | 0 | 1.1e-05 |
| Kansas (KS) | 2019 | High | 45483 | 0 | 1.4e-05 |
| Kentucky (KY) | 2019 | High | 69750 | 0 | 1.5e-06 |
| Louisiana (LA) | 2019 | High | 72577 | 0 | 3e-05 |
| Maine (ME) | 2019 | High | 20986 | 0 | 0 |
| Maryland (MD) | 2019 | High | 94386 | 0 | 3.4e-06 |
| Massachusetts (MA) | 2019 | High | 107606 | 0 | 5e-06 |
| Michigan (MI) | 2019 | High | 155916 | 0 | 8.3e-06 |
| Minnesota (MN) | 2019 | High | 88046 | 0 | 3.7e-06 |
| Mississippi (MS) | 2019 | High | 46464 | 0 | 3.5e-05 |
| Missouri (MO) | 2019 | High | 95818 | 0 | 3.4e-06 |
| Montana (MT) | 2019 | High | 16686 | 0 | 1.9e-05 |
| Nebraska (NE) | 2019 | High | 30200 | 1e-07 | 0.0001 |
| Nevada (NV) | 2019 | High | 48088 | 6.5e-08 | 9.9e-05 |
| New Hampshire (NH) | 2019 | High | 21228 | 0 | 0 |
| New Jersey (NJ) | 2019 | High | 138669 | 6.8e-08 | 6.2e-06 |
| New Mexico (NM) | 2019 | High | 32736 | 0 | 0.00013 |
| New York (NY) | 2019 | High | 303710 | 3.1e-08 | 5.7e-06 |
| North Carolina (NC) | 2019 | High | 163741 | 0 | 6.6e-07 |
| North Dakota (ND) | 2019 | High | 11897 | 0 | 8.2e-05 |
| Ohio (OH) | 2019 | High | 182491 | 0 | 1.8e-06 |
| Oklahoma (OK) | 2019 | High | 61777 | 0 | 1.2e-05 |
| Oregon (OR) | 2019 | High | 65848 | 4.7e-08 | 1.5e-05 |
| Pennsylvania (PA) | 2019 | High | 199866 | 0 | 3.8e-06 |
| Rhode Island (RI) | 2019 | High | 16539 | 0 | 0 |
| South Carolina (SC) | 2019 | High | 80382 | 0 | 1.3e-06 |
| South Dakota (SD) | 2019 | High | 13811 | 0 | 8.6e-05 |
| Tennessee (TN) | 2019 | High | 106618 | 0 | 3e-06 |
| Texas (TX) | 2019 | High | 452686 | 1.4e-08 | 7.2e-06 |
| Utah (UT) | 2019 | High | 50052 | 6.2e-08 | 4.5e-05 |
| Vermont (VT) | 2019 | High | 9742 | 0 | 0 |
| Virginia (VA) | 2019 | High | 133257 | 2.3e-08 | 4.9e-06 |
| Washington (WA) | 2019 | High | 118884 | 0 | 4.5e-06 |
| West Virginia (WV) | 2019 | High | 27979 | 0 | 0 |
| Wisconsin (WI) | 2019 | High | 90900 | 0 | 2.4e-06 |
| Wyoming (WY) | 2019 | High | 9036 | 0 | 3.6e-05 |
| Puerto Rico (PR) | 2019 | High | 39023 | 8.7e-06 | 0 |
| Alabama (AL) | 2019 | Low | 76549 | 0 | 6.1e-08 |
| Alaska (AK) | 2019 | Low | 11421 | 0 | 8.2e-08 |
| Arizona (AZ) | 2019 | Low | 113636 | 0 | 1.4e-06 |
| Arkansas (AR) | 2019 | Low | 47114 | 0 | 1.8e-07 |
| California (CA) | 2019 | Low | 616868 | 2e-08 | 3.2e-07 |
| Colorado (CO) | 2019 | Low | 89906 | 0 | 1.3e-06 |
| Connecticut (CT) | 2019 | Low | 55662 | 0 | 1.7e-08 |
| Delaware (DE) | 2019 | Low | 15202 | 0 | 0 |
| District of Columbia (DC) | 2019 | Low | 11018 | 0 | 6e-07 |
| Florida (FL) | 2019 | Low | 335312 | 0 | 5.6e-09 |
| Georgia (GA) | 2019 | Low | 165760 | 3.8e-08 | 7.9e-08 |
| Hawaii (HI) | 2019 | Low | 22105 | 0 | 0 |
| Idaho (ID) | 2019 | Low | 27900 | 1.1e-07 | 3.7e-07 |
| Illinois (IL) | 2019 | Low | 197833 | 0 | 1.1e-07 |
| Indiana (IN) | 2019 | Low | 105104 | 0 | 3.6e-08 |
| Iowa (IA) | 2019 | Low | 49257 | 0 | 9.5e-08 |
| Kansas (KS) | 2019 | Low | 45483 | 0 | 1.2e-07 |
| Kentucky (KY) | 2019 | Low | 69750 | 0 | 1.3e-08 |
| Louisiana (LA) | 2019 | Low | 72577 | 0 | 2.6e-07 |
| Maine (ME) | 2019 | Low | 20986 | 0 | 0 |
| Maryland (MD) | 2019 | Low | 94386 | 0 | 3e-08 |
| Massachusetts (MA) | 2019 | Low | 107606 | 0 | 4.4e-08 |
| Michigan (MI) | 2019 | Low | 155916 | 0 | 7.2e-08 |
| Minnesota (MN) | 2019 | Low | 88046 | 0 | 3.2e-08 |
| Mississippi (MS) | 2019 | Low | 46464 | 0 | 3e-07 |
| Missouri (MO) | 2019 | Low | 95818 | 0 | 2.9e-08 |
| Montana (MT) | 2019 | Low | 16686 | 0 | 1.7e-07 |
| Nebraska (NE) | 2019 | Low | 30200 | 1e-07 | 8.7e-07 |
| Nevada (NV) | 2019 | Low | 48088 | 6.5e-08 | 8.6e-07 |
| New Hampshire (NH) | 2019 | Low | 21228 | 0 | 0 |
| New Jersey (NJ) | 2019 | Low | 138669 | 6.8e-08 | 5.4e-08 |
| New Mexico (NM) | 2019 | Low | 32736 | 0 | 1.2e-06 |
| New York (NY) | 2019 | Low | 303710 | 3.1e-08 | 4.9e-08 |
| North Carolina (NC) | 2019 | Low | 163741 | 0 | 5.7e-09 |
| North Dakota (ND) | 2019 | Low | 11897 | 0 | 7.1e-07 |
| Ohio (OH) | 2019 | Low | 182491 | 0 | 1.5e-08 |
| Oklahoma (OK) | 2019 | Low | 61777 | 0 | 1.1e-07 |
| Oregon (OR) | 2019 | Low | 65848 | 4.7e-08 | 1.3e-07 |
| Pennsylvania (PA) | 2019 | Low | 199866 | 0 | 3.3e-08 |
| Rhode Island (RI) | 2019 | Low | 16539 | 0 | 0 |
| South Carolina (SC) | 2019 | Low | 80382 | 0 | 1.2e-08 |
| South Dakota (SD) | 2019 | Low | 13811 | 0 | 7.5e-07 |
| Tennessee (TN) | 2019 | Low | 106618 | 0 | 2.6e-08 |
| Texas (TX) | 2019 | Low | 452686 | 1.4e-08 | 6.2e-08 |
| Utah (UT) | 2019 | Low | 50052 | 6.2e-08 | 3.9e-07 |
| Vermont (VT) | 2019 | Low | 9742 | 0 | 0 |
| Virginia (VA) | 2019 | Low | 133257 | 2.3e-08 | 4.2e-08 |
| Washington (WA) | 2019 | Low | 118884 | 0 | 3.9e-08 |
| West Virginia (WV) | 2019 | Low | 27979 | 0 | 0 |
| Wisconsin (WI) | 2019 | Low | 90900 | 0 | 2.1e-08 |
| Wyoming (WY) | 2019 | Low | 9036 | 0 | 3.1e-07 |
| Puerto Rico (PR) | 2019 | Low | 39023 | 8.6e-07 | 0 |
| Alabama (AL) | 2018 | High | 76669 | 1.8e-07 | 5.1e-05 |
| Alaska (AK) | 2018 | High | 11532 | 0 | 1.2e-05 |
| Arizona (AZ) | 2018 | High | 112283 | 1.2e-07 | 3.2e-05 |
| Arkansas (AR) | 2018 | High | 47211 | 0 | 2.4e-05 |
| California (CA) | 2018 | High | 619004 | 2.8e-07 | 4.9e-05 |
| Colorado (CO) | 2018 | High | 89275 | 0 | 0.00015 |
| Connecticut (CT) | 2018 | High | 56024 | 0 | 5.7e-05 |
| Delaware (DE) | 2018 | High | 15145 | 0 | 9.2e-05 |
| District of Columbia (DC) | 2018 | High | 11005 | 0 | 0.00016 |
| Florida (FL) | 2018 | High | 333244 | 2.9e-07 | 1.5e-05 |
| Georgia (GA) | 2018 | High | 164880 | 0 | 3e-05 |
| Hawaii (HI) | 2018 | High | 22284 | 0 | 0 |
| Idaho (ID) | 2018 | High | 27459 | 0 | 8.1e-05 |
| Illinois (IL) | 2018 | High | 199577 | 1e-07 | 0.00012 |
| Indiana (IN) | 2018 | High | 105027 | 0 | 4.6e-05 |
| Iowa (IA) | 2018 | High | 49390 | 0 | 0.00029 |
| Kansas (KS) | 2018 | High | 45668 | 0 | 0.00014 |
| Kentucky (KY) | 2018 | High | 69979 | 0 | 2.4e-05 |
| Louisiana (LA) | 2018 | High | 73093 | 0 | 0.00016 |
| Maine (ME) | 2018 | High | 21005 | 0 | 1.3e-05 |
| Maryland (MD) | 2018 | High | 94679 | 1.4e-07 | 6.6e-05 |
| Massachusetts (MA) | 2018 | High | 107963 | 6.3e-08 | 6.3e-05 |
| Michigan (MI) | 2018 | High | 156613 | 0 | 9.1e-05 |
| Minnesota (MN) | 2018 | High | 87941 | 7.8e-08 | 1e-04 |
| Mississippi (MS) | 2018 | High | 46761 | 0 | 0.00015 |
| Missouri (MO) | 2018 | High | 96025 | 0 | 3.3e-05 |
| Montana (MT) | 2018 | High | 16638 | 0 | 0.00039 |
| Nebraska (NE) | 2018 | High | 30206 | 0 | 0.0012 |
| Nevada (NV) | 2018 | High | 47488 | 0 | 2.6e-05 |
| New Hampshire (NH) | 2018 | High | 21231 | 0 | 0 |
| New Jersey (NJ) | 2018 | High | 139388 | 2.4e-07 | 6.1e-05 |
| New Mexico (NM) | 2018 | High | 32827 | 0 | 3e-05 |
| New York (NY) | 2018 | High | 306358 | 1.8e-07 | 4.5e-05 |
| North Carolina (NC) | 2018 | High | 162849 | 1.3e-07 | 8.6e-06 |
| North Dakota (ND) | 2018 | High | 11891 | 0 | 0.0024 |
| Ohio (OH) | 2018 | High | 183158 | 0 | 4.9e-05 |
| Oklahoma (OK) | 2018 | High | 61807 | 0 | 4.1e-05 |
| Oregon (OR) | 2018 | High | 65598 | 1e-07 | 4.2e-06 |
| Pennsylvania (PA) | 2018 | High | 200798 | 0 | 9e-05 |
| Rhode Island (RI) | 2018 | High | 16601 | 0 | 8.4e-06 |
| South Carolina (SC) | 2018 | High | 79751 | 0 | 2.6e-05 |
| South Dakota (SD) | 2018 | High | 13783 | 0 | 0.0017 |
| Tennessee (TN) | 2018 | High | 106221 | 0 | 1.6e-05 |
| Texas (TX) | 2018 | High | 449076 | 6.1e-08 | 4.5e-05 |
| Utah (UT) | 2018 | High | 49467 | 2.8e-07 | 3.1e-05 |
| Vermont (VT) | 2018 | High | 9794 | 0 | 1.4e-05 |
| Virginia (VA) | 2018 | High | 133353 | 5.1e-08 | 5e-05 |
| Washington (WA) | 2018 | High | 118021 | 0 | 3.5e-06 |
| West Virginia (WV) | 2018 | High | 28303 | 0 | 9.8e-06 |
| Wisconsin (WI) | 2018 | High | 91096 | 0 | 5e-05 |
| Wyoming (WY) | 2018 | High | 9060 | 0 | 6.2e-05 |
| Puerto Rico (PR) | 2018 | High | 39023 | 4.6e-05 | 0 |
| Alabama (AL) | 2018 | Low | 76669 | 1.8e-07 | 4.4e-07 |
| Alaska (AK) | 2018 | Low | 11532 | 0 | 1e-07 |
| Arizona (AZ) | 2018 | Low | 112283 | 1.2e-07 | 2.8e-07 |
| Arkansas (AR) | 2018 | Low | 47211 | 0 | 2e-07 |
| California (CA) | 2018 | Low | 619004 | 2.8e-07 | 4.2e-07 |
| Colorado (CO) | 2018 | Low | 89275 | 0 | 1.3e-06 |
| Connecticut (CT) | 2018 | Low | 56024 | 0 | 5e-07 |
| Delaware (DE) | 2018 | Low | 15145 | 0 | 8e-07 |
| District of Columbia (DC) | 2018 | Low | 11005 | 0 | 1.4e-06 |
| Florida (FL) | 2018 | Low | 333244 | 2.9e-07 | 1.3e-07 |
| Georgia (GA) | 2018 | Low | 164880 | 0 | 2.6e-07 |
| Hawaii (HI) | 2018 | Low | 22284 | 0 | 0 |
| Idaho (ID) | 2018 | Low | 27459 | 0 | 7e-07 |
| Illinois (IL) | 2018 | Low | 199577 | 1e-07 | 1.1e-06 |
| Indiana (IN) | 2018 | Low | 105027 | 0 | 4e-07 |
| Iowa (IA) | 2018 | Low | 49390 | 0 | 2.5e-06 |
| Kansas (KS) | 2018 | Low | 45668 | 0 | 1.2e-06 |
| Kentucky (KY) | 2018 | Low | 69979 | 0 | 2.1e-07 |
| Louisiana (LA) | 2018 | Low | 73093 | 0 | 1.4e-06 |
| Maine (ME) | 2018 | Low | 21005 | 0 | 1.2e-07 |
| Maryland (MD) | 2018 | Low | 94679 | 1.4e-07 | 5.7e-07 |
| Massachusetts (MA) | 2018 | Low | 107963 | 6.3e-08 | 5.5e-07 |
| Michigan (MI) | 2018 | Low | 156613 | 0 | 7.9e-07 |
| Minnesota (MN) | 2018 | Low | 87941 | 7.8e-08 | 8.7e-07 |
| Mississippi (MS) | 2018 | Low | 46761 | 0 | 1.3e-06 |
| Missouri (MO) | 2018 | Low | 96025 | 0 | 2.9e-07 |
| Montana (MT) | 2018 | Low | 16638 | 0 | 3.4e-06 |
| Nebraska (NE) | 2018 | Low | 30206 | 0 | 1e-05 |
| Nevada (NV) | 2018 | Low | 47488 | 0 | 2.3e-07 |
| New Hampshire (NH) | 2018 | Low | 21231 | 0 | 0 |
| New Jersey (NJ) | 2018 | Low | 139388 | 2.4e-07 | 5.3e-07 |
| New Mexico (NM) | 2018 | Low | 32827 | 0 | 2.6e-07 |
| New York (NY) | 2018 | Low | 306358 | 1.8e-07 | 3.9e-07 |
| North Carolina (NC) | 2018 | Low | 162849 | 1.3e-07 | 7.4e-08 |
| North Dakota (ND) | 2018 | Low | 11891 | 0 | 2.1e-05 |
| Ohio (OH) | 2018 | Low | 183158 | 0 | 4.3e-07 |
| Oklahoma (OK) | 2018 | Low | 61807 | 0 | 3.5e-07 |
| Oregon (OR) | 2018 | Low | 65598 | 1e-07 | 3.7e-08 |
| Pennsylvania (PA) | 2018 | Low | 200798 | 0 | 7.8e-07 |
| Rhode Island (RI) | 2018 | Low | 16601 | 0 | 7.3e-08 |
| South Carolina (SC) | 2018 | Low | 79751 | 0 | 2.3e-07 |
| South Dakota (SD) | 2018 | Low | 13783 | 0 | 1.5e-05 |
| Tennessee (TN) | 2018 | Low | 106221 | 0 | 1.4e-07 |
| Texas (TX) | 2018 | Low | 449076 | 6.1e-08 | 3.9e-07 |
| Utah (UT) | 2018 | Low | 49467 | 2.8e-07 | 2.7e-07 |
| Vermont (VT) | 2018 | Low | 9794 | 0 | 1.2e-07 |
| Virginia (VA) | 2018 | Low | 133353 | 5.1e-08 | 4.3e-07 |
| Washington (WA) | 2018 | Low | 118021 | 0 | 3.1e-08 |
| West Virginia (WV) | 2018 | Low | 28303 | 0 | 8.5e-08 |
| Wisconsin (WI) | 2018 | Low | 91096 | 0 | 4.4e-07 |
| Wyoming (WY) | 2018 | Low | 9060 | 0 | 5.3e-07 |
| Puerto Rico (PR) | 2018 | Low | 39023 | 4.6e-06 | 0 |
| Alabama (AL) | 2017 | High | 76863 | 5.8e-07 | 9.8e-05 |
| Alaska (AK) | 2017 | High | 11664 | 2.6e-06 | 0 |
| Arizona (AZ) | 2017 | High | 111073 | 4e-07 | 0.00013 |
| Arkansas (AR) | 2017 | High | 47326 | 0 | 4.8e-05 |
| California (CA) | 2017 | High | 620620 | 1.2e-06 | 0.00011 |
| Colorado (CO) | 2017 | High | 88490 | 1e-06 | 9.7e-05 |
| Connecticut (CT) | 2017 | High | 56345 | 2.1e-06 | 6.7e-06 |
| Delaware (DE) | 2017 | High | 15088 | 0 | 8.3e-06 |
| District of Columbia (DC) | 2017 | High | 10958 | 4.1e-06 | 4.6e-05 |
| Florida (FL) | 2017 | High | 330563 | 5e-06 | 1.9e-06 |
| Georgia (GA) | 2017 | High | 164154 | 1.8e-07 | 3.7e-05 |
| Hawaii (HI) | 2017 | High | 22460 | 4e-06 | 0 |
| Idaho (ID) | 2017 | High | 27086 | 0 | 0.00012 |
| Illinois (IL) | 2017 | High | 201502 | 5.2e-07 | 5.6e-05 |
| Indiana (IN) | 2017 | High | 104987 | 4.3e-07 | 3.1e-05 |
| Iowa (IA) | 2017 | High | 49537 | 3e-07 | 3e-05 |
| Kansas (KS) | 2017 | High | 45866 | 6.5e-07 | 7.4e-05 |
| Kentucky (KY) | 2017 | High | 70205 | 4.3e-07 | 1.8e-05 |
| Louisiana (LA) | 2017 | High | 73647 | 2e-07 | 9.1e-05 |
| Maine (ME) | 2017 | High | 21045 | 7.1e-07 | 0 |
| Maryland (MD) | 2017 | High | 94987 | 1.7e-06 | 7.9e-06 |
| Massachusetts (MA) | 2017 | High | 108168 | 1.7e-06 | 7e-06 |
| Michigan (MI) | 2017 | High | 157260 | 6.6e-07 | 3.2e-05 |
| Minnesota (MN) | 2017 | High | 87771 | 1.4e-06 | 4.3e-05 |
| Mississippi (MS) | 2017 | High | 47124 | 6.3e-07 | 0.00017 |
| Missouri (MO) | 2017 | High | 96292 | 3.1e-07 | 2.5e-05 |
| Montana (MT) | 2017 | High | 16596 | 0 | 8.3e-05 |
| Nebraska (NE) | 2017 | High | 30211 | 9.9e-07 | 0.00028 |
| Nevada (NV) | 2017 | High | 46831 | 3.2e-07 | 0.00018 |
| New Hampshire (NH) | 2017 | High | 21268 | 0 | 5.9e-06 |
| New Jersey (NJ) | 2017 | High | 140110 | 1.3e-06 | 7.2e-06 |
| New Mexico (NM) | 2017 | High | 32984 | 0 | 0.00013 |
| New York (NY) | 2017 | High | 308896 | 3.1e-06 | 2.1e-05 |
| North Carolina (NC) | 2017 | High | 161914 | 7.4e-07 | 6.2e-06 |
| North Dakota (ND) | 2017 | High | 11904 | 0 | 0.00065 |
| Ohio (OH) | 2017 | High | 183854 | 2.4e-07 | 2.3e-05 |
| Oklahoma (OK) | 2017 | High | 61991 | 2.4e-07 | 8.5e-05 |
| Oregon (OR) | 2017 | High | 65338 | 1.1e-06 | 1.2e-05 |
| Pennsylvania (PA) | 2017 | High | 201641 | 5.2e-07 | 1.2e-05 |
| Rhode Island (RI) | 2017 | High | 16646 | 2.7e-06 | 1.5e-05 |
| South Carolina (SC) | 2017 | High | 79177 | 3.8e-07 | 2.9e-05 |
| South Dakota (SD) | 2017 | High | 13764 | 0 | 0.00067 |
| Tennessee (TN) | 2017 | High | 105787 | 2.8e-07 | 3.6e-05 |
| Texas (TX) | 2017 | High | 446171 | 1.8e-06 | 3.8e-05 |
| Utah (UT) | 2017 | High | 48898 | 1.2e-06 | 0.00016 |
| Vermont (VT) | 2017 | High | 9845 | 6.1e-06 | 3.8e-05 |
| Virginia (VA) | 2017 | High | 133457 | 7.8e-07 | 1.2e-05 |
| Washington (WA) | 2017 | High | 117054 | 1.9e-06 | 1.4e-05 |
| West Virginia (WV) | 2017 | High | 28651 | 5.2e-07 | 4.4e-06 |
| Wisconsin (WI) | 2017 | High | 91302 | 6.5e-07 | 7e-05 |
| Wyoming (WY) | 2017 | High | 9129 | 3.3e-06 | 9.6e-05 |
| Puerto Rico (PR) | 2017 | High | 39023 | 0.00043 | 0 |
| Alabama (AL) | 2017 | Low | 76863 | 5.8e-07 | 8.5e-07 |
| Alaska (AK) | 2017 | Low | 11664 | 2.6e-06 | 0 |
| Arizona (AZ) | 2017 | Low | 111073 | 4e-07 | 1.1e-06 |
| Arkansas (AR) | 2017 | Low | 47326 | 0 | 4.1e-07 |
| California (CA) | 2017 | Low | 620620 | 1.2e-06 | 9.7e-07 |
| Colorado (CO) | 2017 | Low | 88490 | 1e-06 | 8.4e-07 |
| Connecticut (CT) | 2017 | Low | 56345 | 2.1e-06 | 5.8e-08 |
| Delaware (DE) | 2017 | Low | 15088 | 0 | 7.2e-08 |
| District of Columbia (DC) | 2017 | Low | 10958 | 4.1e-06 | 4e-07 |
| Florida (FL) | 2017 | Low | 330563 | 5e-06 | 1.6e-08 |
| Georgia (GA) | 2017 | Low | 164154 | 1.8e-07 | 3.2e-07 |
| Hawaii (HI) | 2017 | Low | 22460 | 4e-06 | 0 |
| Idaho (ID) | 2017 | Low | 27086 | 0 | 1e-06 |
| Illinois (IL) | 2017 | Low | 201502 | 5.2e-07 | 4.9e-07 |
| Indiana (IN) | 2017 | Low | 104987 | 4.3e-07 | 2.7e-07 |
| Iowa (IA) | 2017 | Low | 49537 | 3e-07 | 2.6e-07 |
| Kansas (KS) | 2017 | Low | 45866 | 6.5e-07 | 6.4e-07 |
| Kentucky (KY) | 2017 | Low | 70205 | 4.3e-07 | 1.6e-07 |
| Louisiana (LA) | 2017 | Low | 73647 | 2e-07 | 7.8e-07 |
| Maine (ME) | 2017 | Low | 21045 | 7.1e-07 | 0 |
| Maryland (MD) | 2017 | Low | 94987 | 1.7e-06 | 6.9e-08 |
| Massachusetts (MA) | 2017 | Low | 108168 | 1.7e-06 | 6e-08 |
| Michigan (MI) | 2017 | Low | 157260 | 6.6e-07 | 2.8e-07 |
| Minnesota (MN) | 2017 | Low | 87771 | 1.4e-06 | 3.7e-07 |
| Mississippi (MS) | 2017 | Low | 47124 | 6.3e-07 | 1.5e-06 |
| Missouri (MO) | 2017 | Low | 96292 | 3.1e-07 | 2.2e-07 |
| Montana (MT) | 2017 | Low | 16596 | 0 | 7.2e-07 |
| Nebraska (NE) | 2017 | Low | 30211 | 9.9e-07 | 2.5e-06 |
| Nevada (NV) | 2017 | Low | 46831 | 3.2e-07 | 1.6e-06 |
| New Hampshire (NH) | 2017 | Low | 21268 | 0 | 5.1e-08 |
| New Jersey (NJ) | 2017 | Low | 140110 | 1.3e-06 | 6.2e-08 |
| New Mexico (NM) | 2017 | Low | 32984 | 0 | 1.1e-06 |
| New York (NY) | 2017 | Low | 308896 | 3.1e-06 | 1.8e-07 |
| North Carolina (NC) | 2017 | Low | 161914 | 7.4e-07 | 5.4e-08 |
| North Dakota (ND) | 2017 | Low | 11904 | 0 | 5.7e-06 |
| Ohio (OH) | 2017 | Low | 183854 | 2.4e-07 | 2e-07 |
| Oklahoma (OK) | 2017 | Low | 61991 | 2.4e-07 | 7.4e-07 |
| Oregon (OR) | 2017 | Low | 65338 | 1.1e-06 | 1e-07 |
| Pennsylvania (PA) | 2017 | Low | 201641 | 5.2e-07 | 1.1e-07 |
| Rhode Island (RI) | 2017 | Low | 16646 | 2.7e-06 | 1.3e-07 |
| South Carolina (SC) | 2017 | Low | 79177 | 3.8e-07 | 2.5e-07 |
| South Dakota (SD) | 2017 | Low | 13764 | 0 | 5.8e-06 |
| Tennessee (TN) | 2017 | Low | 105787 | 2.8e-07 | 3.1e-07 |
| Texas (TX) | 2017 | Low | 446171 | 1.8e-06 | 3.3e-07 |
| Utah (UT) | 2017 | Low | 48898 | 1.2e-06 | 1.4e-06 |
| Vermont (VT) | 2017 | Low | 9845 | 6.1e-06 | 3.3e-07 |
| Virginia (VA) | 2017 | Low | 133457 | 7.8e-07 | 1.1e-07 |
| Washington (WA) | 2017 | Low | 117054 | 1.9e-06 | 1.2e-07 |
| West Virginia (WV) | 2017 | Low | 28651 | 5.2e-07 | 3.8e-08 |
| Wisconsin (WI) | 2017 | Low | 91302 | 6.5e-07 | 6.1e-07 |
| Wyoming (WY) | 2017 | Low | 9129 | 3.3e-06 | 8.4e-07 |
| Puerto Rico (PR) | 2017 | Low | 39023 | 4.2e-05 | 0 |

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Table S2. Parameters values and sources for the microsimilation of transfusion-transmitted Zika outcomes

| Probability | Age, low | Value (range) | | Distribution | |
| --- | --- | --- | --- | --- | --- |
| Zika fever |  | 0.1836 (0.0959—0.2711) | | Beta | |
| Guillain-Barré |  | 0.000257 | | Beta (42, 1.634e+05) | |
| Death from Guillain-Barré |  | 0.0258 | | Beta (128, 4954) | |
| Permanent disability from Guillain-Barré | 0 | 0 | |  | |
|  | 15 | 0.0484 (0.0416—0.0548) | | Beta | |
|  | 20 | 0.121 (0.104—0.137) | | Beta | |
|  | 35 | 0.22 (0.208—0.232) | | Beta | |
|  | 65 | 0.488 (0.471—0.505) | | Beta | |
| Penetrative sex | 0 | 0 | |  | |
|  | 10 | 0.016 (0.00972—0.02732) | | Beta | |
|  | 15 | 0.21352 (0.14814—0.30974) | | Beta | |
|  | 20 | 0.5324 (0.4605—0.6208) | | Beta | |
|  | 25 | 0.7646 (0.7222—0.8303) | | Beta | |
|  | 30 | 0.7272 (0.6817—0.7853) | | Beta | |
|  | 40 | 0.6244 (0.5826—0.6814) | | Beta | |
|  | 50 | 0.4476 (0.402—0.5032) | | Beta | |
|  | 60 | 0.3974 (0.3442—0.4653) | | Beta | |
|  | 70 | 0.282 (0.221—0.3595) | | Beta | |
| Transmission from penetrative sex |  | 0.1 (0.01—0.2) | | Tri | |
| Congenital Zika syndrome |  | 0.0343 (0.0095—0.195) | | Beta | |
| Stillbirth after congenital transmissoin |  | 0.07 (0.054—0.084) | | Tri | |
| Recipient pregnant | 0 | 0 | |  | |
|  | 15 | 0.023357573 | |  | |
|  | 20 | 0.05734304 | |  | |
|  | 25 | 0.062300081 | |  | |
|  | 30 | 0.054130878 | |  | |
|  | 35 | 0.030337086 | |  | |
|  | 40 | 0.007693326 | |  | |
|  | 45 | 0 | |  | |
| Pregnancy multiplier for PSA |  | 1 (0.2—1.8) | | Tri | |
| Partner pregnant | 0 | 0 | |  | |
|  | 15 | 0.044175 | |  | |
|  | 20 | 0.10845 | |  | |
|  | 25 | 0.117825 | |  | |
|  | 30 | 0.102375 | |  | |
|  | 35 | 0.057375 | |  | |
|  | 40 | 0.01455 | |  | |
|  | 45 | 0 | |  | |
| Health state utility | Age, low | Value (range) | | | Distribution |
| Baseline |  | 0.9 (0.8—1) | | | Tri |
| Zika fever, female recipient | 0 | 0.57 (0.4—0.75) | | | Beta |
|  | 20 | 0.58 (0.44—0.72) | | | Beta |
|  | 35 | 0.63 (0.52—0.75) | | | Beta |
|  | 50 | 0.61 (0.48—0.74) | | | Beta |
|  | 65 | 0.59 (0.37—0.81) | | | Beta |
| Zika fever, male recipient | 0 | 0.5 (0.3—0.7) | | | Beta |
|  | 20 | 0.59 (0.4—0.77) | | | Beta |
|  | 35 | 0.58 (0.44—0.71) | | | Beta |
|  | 50 | 0.55 (0.41—0.68) | | | Beta |
|  | 65 | 0.54 (0.37—0.71) | | | Beta |
| Guillain-Barré , year 1 |  | 0.76 (0.3493738—0.9867666) | | | Beta (3.818, 1.206) |
| Guillain-Barré , year 2 |  | 0.87 (0.2425902—1) | | | Beta (1.423, 0.2126) |
| Guillain-Barré , years 3-6 |  | 0.99 | | |  |
| Zika fever, partner |  | 0.57 (0.54—0.6) | | | Beta |
| Congenital Zika syndrome |  | 0 | | |  |
| Duration (years) | Age, low | Value (range) | | | Distribution |
| Zika fever, recipient |  | 21 (1.4—66.2) | | | Gamma (1.456, 14.42) |
| Zika fever, partner |  | 7 (2.3—14.2) | | | Gamma (5.201, 1.346) |
| Congenital Zika syndrome |  | 79.8 | | |  |
| Cost | Age, low | Value (range) | Distribution | | |
| Productivity | 0 | $32,268 |  | | |
|  | 25 | $74,082 |  | | |
|  | 35 | $96,581 |  | | |
|  | 45 | $109,366 |  | | |
|  | 55 | $88,342 |  | | |
|  | 65 | $60,735 |  | | |
|  | 75 | $38,786 |  | | |
| Consumption | 0 | $32,039 |  | | |
|  | 25 | $56,457 |  | | |
|  | 35 | $71,198 |  | | |
|  | 45 | $75,387 |  | | |
|  | 55 | $66,212 |  | | |
|  | 65 | $56,268 |  | | |
|  | 75 | $43,181 |  | | |
| True positive test result |  | $92 (75.6—108) | Tri | | |
| False positive test result |  | $92 (75.6—108) | Tri | | |
| Zika fever in recipient (hospitalized) |  | $1,358 (238.9392—2476.6992) | Gamma | | |
| Zika fever in partner (non-hospitalized) |  | $109 (55.6416—164.6892) | Gamma | | |
| Guillain-Barré |  | $61,676 (51000.84—72351.36) | Gamma | | |
| Permanent disability from Guillain-Barré |  | $38,580 (30863.66112—46295.49168) | Tri | | |
| Death from Guillain-Barré |  | $72,476 (57980.448—86970.672) | Tri | | |
| Normal delivery |  | $25,386 (18803—28205.6) | Tri | | |
| Infant testing |  | $243 (194.4—291.6) | Tri | | |
| Mother testing |  | $505 (403.812—606.312) | Tri | | |
| Stillbirth |  | $6,645 (5315.76—7972.56) | Tri | | |
| delivery with congenital Zika syndrome |  | $26,132 (20905.452—31358.124) | Tri | | |
| Lifetime medical costs with congenital Zika syndrome |  | $4,358,764 (3487011.2064—5230516.8096) | Tri | | |

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Table S3. Parameter values and sources for the microsimulation of transfusion-transmitted WNV outcomes

| Probability | Age, low | Value (range) | | Distribution |
| --- | --- | --- | --- | --- |
| Immunocompromise in platelet recipient |  | 0.5 (0.4—0.6) | | Tri |
| Immunocompromise in other recipient |  | 0.25 (0.2—0.3) | | Tri |
| Relative risk of disease, immunocompromised |  | 2 (1.6—2.4) | | Tri |
| Clinical disease given WNV transmission |  | 0.25 (0.2—0.3) | | Tri |
| Disability from WNV fever, age 50+ |  | 0.11 (0.088—0.132) | | Tri |
| Disability from WNV fever, age under 50 |  | 0.00015 (0.00012—0.00018) | | Tri |
| Disability from meningitis |  | 0.22 (0.176—0.264) | | Tri |
| Disability from encephalitis |  | 0.45 (0.36—0.54) | | Tri |
| Disability from AFP |  | 0.22 (0.176—0.264) | | Tri |
| Symptomatic patient has WNV fever | 0 | 0.98 (0.784—1.176) | | Tri |
|  | 60 | 0.97 (0.776—1.164) | | Tri |
|  | 70 | 0.86 (0.688—1.032) | | Tri |
| Symptomatic patient has encephalitis | 0 | 0.00804 (0.006432—0.009648) | | Tri |
|  | 20 | 0.00682 (0.005456—0.008184) | | Tri |
|  | 30 | 0.0068 (0.00544—0.00816) | | Tri |
|  | 40 | 0.00858 (0.006864—0.010296) | | Tri |
|  | 50 | 0.01048 (0.008384—0.012576) | | Tri |
|  | 60 | 0.01953 (0.015624—0.023436) | | Tri |
|  | 70 | 0.10514 (0.084112—0.126168) | | Tri |
|  | 80 | 0.11088 (0.088704—0.133056) | | Tri |
| Symptomatic patient has meningitis | 0 | 0.01142 (0.009136—0.013704) | | Tri |
|  | 20 | 0.01242 (0.009936—0.014904) | | Tri |
|  | 30 | 0.01188 (0.009504—0.014256) | | Tri |
|  | 40 | 0.01014 (0.008112—0.012168) | | Tri |
|  | 50 | 0.00798 (0.006384—0.009576) | | Tri |
|  | 60 | 0.00819 (0.006552—0.009828) | | Tri |
|  | 70 | 0.0273 (0.02184—0.03276) | | Tri |
|  | 80 | 0.02184 (0.017472—0.026208) | | Tri |
| Symptomatic patient has AFP | 0 | 0.00054 (0.000432—0.000648) | | Tri |
|  | 20 | 0.00076 (0.000608—0.000912) | | Tri |
|  | 30 | 0.00132 (0.001056—0.001584) | | Tri |
|  | 40 | 0.00128 (0.001024—0.001536) | | Tri |
|  | 50 | 0.00154 (0.001232—0.001848) | | Tri |
|  | 60 | 0.00228 (0.001824—0.002736) | | Tri |
|  | 70 | 0.00756 (0.006048—0.009072) | | Tri |
|  | 80 | 0.00728 (0.005824—0.008736) | | Tri |
| Death from WNV fever | 0 | 0 | |  |
|  | 30 | 6e-04 (0.00048—0.00072) | | Tri |
|  | 40 | 4e-04 (0.00032—0.00048) | | Tri |
|  | 50 | 3e-04 (0.00024—0.00036) | | Tri |
|  | 60 | 0.005 (0.004—0.006) | | Tri |
|  | 70 | 0.016 (0.0128—0.0192) | | Tri |
|  | 80 | 0.082 (0.0656—0.0984) | | Tri |
| Death from encephalitis | 0 | 0.015 (0.012—0.018) | | Tri |
|  | 20 | 0.011 (0.0088—0.0132) | | Tri |
|  | 30 | 0.014 (0.0112—0.0168) | | Tri |
|  | 40 | 0.041 (0.0328—0.0492) | | Tri |
|  | 50 | 0.058 (0.0464—0.0696) | | Tri |
|  | 60 | 0.108 (0.0864—0.1296) | | Tri |
|  | 70 | 0.182 (0.1456—0.2184) | | Tri |
|  | 80 | 0.336 (0.2688—0.4032) | | Tri |
| Death from meningitis | 0 | 0.005 (0.004—0.006) | | Tri |
|  | 20 | 0.003 (0.0024—0.0036) | | Tri |
|  | 30 | 0.004 (0.0032—0.0048) | | Tri |
|  | 40 | 0.005 (0.004—0.006) | | Tri |
|  | 50 | 0.006 (0.0048—0.0072) | | Tri |
|  | 60 | 0.008 (0.0064—0.0096) | | Tri |
|  | 70 | 0.045 (0.036—0.054) | | Tri |
|  | 80 | 0.157 (0.1256—0.1884) | | Tri |
| Death from AFP | 0 | 0 | |  |
|  | 30 | 0.036 (0.0288—0.0432) | | Tri |
|  | 40 | 0.061 (0.0488—0.0732) | | Tri |
|  | 50 | 0.086 (0.0688—0.1032) | | Tri |
|  | 60 | 0.091 (0.0728—0.1092) | | Tri |
|  | 70 | 0.194 (0.1552—0.2328) | | Tri |
|  | 80 | 0.3 (0.24—0.36) | | Tri |
| Health state utility | Age, low | Value (range) | | Distribution |
| Baseline in transfusion survivors |  | 0.9 (0.8—1) | | Tri |
| Multiplier for WNV fever |  | 0.52 (0.472—0.568) | | Tri |
| Multiplier for meningitis |  | 0.39 (0.35—0.43) | | Tri |
| Multiplier for encephalitis |  | 0.19 (0.17—0.21) | | Tri |
| Multiplier for AFP |  | 0.15 (0.135—0.165) | | Tri |
| Multiplier for disability caused by WNV fever |  | 0.92 (0.904—0.936) | | Tri |
| Multiplier for disability caused by meningitis |  | 0.88 (0.856—0.904) | | Tri |
| Multiplier for disability caused by encephalitis |  | 0.78 (0.736—0.824) | | Tri |
| Multiplier for disability caused by AFP |  | 0.68 (0.616—0.744) | | Tri |
| Duration (years) | Age, low | Value (range) | | Distribution |
| Duration of WNV fever |  | 0.01775 (0.0027—0.0328) | | Tri |
| Duration of meningitis |  | 0.0123 (0.0055—0.0191) | | Tri |
| Duration of encephalitis |  | 0.07945 (0.0055—0.1534) | | Tri |
| Duration of AFP |  | 0.0959 (0.0055—0.1863) | | Tri |
| Duration of disability |  | 5.5 (4.4—6.6) | | Tri |
| Cost | Age, low | Value (range) | Distribution | |
| Initial cost, WNV fever |  | $9,426 | Gamma (1.795, 3335.8) | |
| Initial cost, meningitis |  | $9,434 | Weibull (3.039, 7791.2) | |
| Initial cost, encephalitis |  | $36,621 | Pearson5 (2.161, 20129.3) | |
| Initial cost, AFP |  | $95,125 | Invgauss (5.593e+04, 22231.8) | |
| Five year cost, WNV fever |  | $2,082 | Expo (0.001271) | |
| Five year cost, meningitis |  | $652 | Expo (0.003184) | |
| Five year cost, encephalitis |  | $10,302 | Expo (0.0001316) | |
| Five year cost, AFP |  | $66,632 | Weibull (1.263, 6182) | |
| Annual productivity | 0 | $32,268 |  | |
|  | 25 | $74,082 |  | |
|  | 35 | $96,581 |  | |
|  | 45 | $109,366 |  | |
|  | 55 | $88,342 |  | |
|  | 65 | $60,735 |  | |
|  | 75 | $38,786 |  | |
| Annual consumption | 0 | $32,039 |  | |
|  | 25 | $56,457 |  | |
|  | 35 | $71,198 |  | |
|  | 45 | $75,387 |  | |
|  | 55 | $66,212 |  | |
|  | 65 | $56,268 |  | |
|  | 75 | $43,181 |  | |

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Table S3. Percent of time intervention part of optimal portfolio across 10,000 probabilistic sensitivity analysis iterations

| **STUSPS** | **2017** | **2018** | **2019** |
| --- | --- | --- | --- |
| AL | WNV ID-NAT, 0.02% WNV MP-NAT, 3.43% |  |  |
| AZ | WNV ID-NAT, 0.35% WNV MP-NAT, 16.41% |  | WNV ID-NAT, 2.38% WNV MP-NAT, 48.07% |
| CA | WNV ID-NAT, 0.1% WNV MP-NAT, 8.55% |  |  |
| CO | WNV ID-NAT, 0.02% WNV MP-NAT, 3.06% | WNV ID-NAT, 1.43% WNV MP-NAT, 34.69% | WNV ID-NAT, 1.23% WNV MP-NAT, 31.77% |
| DC |  | WNV ID-NAT, 2.25% WNV MP-NAT, 47.01% | WNV MP-NAT, 0.09% |
| DE |  | WNV ID-NAT, 0.02% WNV MP-NAT, 2.03% |  |
| IA |  | WNV ID-NAT, 7.13% WNV MP-NAT, 91.75% |  |
| ID | WNV ID-NAT, 0.14% WNV MP-NAT, 10.62% | WNV MP-NAT, 0.62% |  |
| IL |  | WNV ID-NAT, 0.29% WNV MP-NAT, 14.63% |  |
| KS | WNV MP-NAT, 0.22% | WNV ID-NAT, 1.12% WNV MP-NAT, 29.54% |  |
| LA | WNV MP-NAT, 1.76% | WNV ID-NAT, 1.83% WNV MP-NAT, 41.67% |  |
| MA |  | WNV MP-NAT, 0.07% |  |
| MD |  | WNV MP-NAT, 0.08% |  |
| MI |  | WNV MP-NAT, 1.79% |  |
| MN |  | WNV ID-NAT, 0.02% WNV MP-NAT, 3.85% |  |
| MS | WNV ID-NAT, 2.49% WNV MP-NAT, 50% | WNV ID-NAT, 1.42% WNV MP-NAT, 33.94% |  |
| MT | WNV MP-NAT, 0.81% | WNV ID-NAT, 8.23% WNV MP-NAT, 91.75% |  |
| ND | WNV ID-NAT, 11.39% WNV MP-NAT, 88.61% | WNV ID-NAT, 44.56% WNV MP-NAT, 55.44% | WNV MP-NAT, 0.69% |
| NE | WNV ID-NAT, 6.94% WNV MP-NAT, 91.47% | WNV ID-NAT, 18.99% WNV MP-NAT, 81.01% | WNV ID-NAT, 0.02% WNV MP-NAT, 3.92% |
| NJ |  | WNV MP-NAT, 0.05% |  |
| NM | WNV ID-NAT, 0.36% WNV MP-NAT, 16.48% |  | WNV ID-NAT, 0.6% WNV MP-NAT, 21.01% |
| NV | WNV ID-NAT, 3.23% WNV MP-NAT, 59.05% |  | WNV ID-NAT, 0.02% WNV MP-NAT, 3.59% |
| OK | WNV MP-NAT, 1.01% |  |  |
| PA |  | WNV MP-NAT, 1.72% |  |
| PR | Zika ID-NAT, 0.94% Zika MP-NAT, 19.62% | Zika MP-NAT, 0.01% |  |
| SD | WNV ID-NAT, 11.54% WNV MP-NAT, 88.46% | WNV ID-NAT, 29.71% WNV MP-NAT, 70.29% | WNV MP-NAT, 1.08% |
| UT | WNV ID-NAT, 1.93% WNV MP-NAT, 42.71% |  |  |
| WI | WNV MP-NAT, 0.15% |  |  |
| WY | WNV ID-NAT, 0.02% WNV MP-NAT, 2.96% | WNV MP-NAT, 0.06% |  |

##### 

# Author contributions

# Disclosures

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# Previous/planned presentations

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