



# Epidemiological and Economic Evaluation of Disease Burden in the United States: Data, Models, and Applications

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# EPIDEMIOLOGICAL AND ECONOMIC EVALUATION OF DISEASE BURDEN IN THE UNITED STATES: DATA, MODELS, AND APPLICATIONS

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A Dissertation Submitted to the Faculty of The Harvard T.H. Chan School of Public Health in Partial Fulfilment of the Requirements For the Degree of *Doctor of Science* In the Department of *Global Health and Population* Harvard University Boston, Massachusetts November 2020

## Epidemiological and Economic Evaluation of Disease Burden in the United States: Data, Models, and Applications Abstract

This dissertation is comprised of three studies that evaluate disease burden in the United States, for specific chronic and infectious diseases. These studies use mathematical modelling to synthesize empirical evidence and estimate both epidemiological and economic outcomes. In the first paper, I investigate trends in the prevalence and incidence of diabetes and diabetes diagnosis among adults ages 20 years and older in the United States, over the period 2000-2016. Using an age-stratified Markov model of undiagnosed and diagnosed diabetes, I examine trends in true incidence of diabetes and the diagnosis rates. The model is estimated using repeated cross-sectional survey data on the prevalence of undiagnosed and diagnosed diabetes from the National Health and Examination Survey (NHANES) 1988-1994 and 1999-2016. In the second paper, I develop a novel model to assess the 10year risk of fatal-plus-non-fatal cardiovascular disease (CVD) for patients with type 2 diabetes mellitus in the United States. This model is constructed as a sex-and-cohort stratified Cox proportional-hazards model using pooled data on fatal-plus-non-fatal CVD outcomes from 5 prospective cohorts. The resulting risk prediction equation provides more accurate predictions of total CVD risk compared to current risk scores and can to be used in future comparative effectiveness and cost-effectiveness analyses to simulate outcomes of primary intervention policies targeted toward diabetic populations. In the third paper, I investigate disparities in health and economic outcomes associated with N. gonorrhoeae infection in the US in 2015. With probability tree models, I quantify the lifetime qualityadjusted life-years and costs associated with gonorrhea and its sequelae in the US and examine disparities in burden across race/ethnicity. These three studies report findings of substantive importance within each disease area. They also illustrate the utility of mathematical models for synthesizing data, estimating outcomes that would be difficult or impossible to measure empirically, and answering questions directly relevant to the goals of planning and prioritizing prevention policies.

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#### **Chapter 1. Introduction**

Estimates of the health and economic implications of disease are needed to inform policymaking, evaluate health system performance, and quantify health disparities. Disease burden estimates aim to capture the impact of diseases, injuries and risk factors in a given population.<sup>1</sup> Disease burden is measured using a variety of indicators that can describe the impact of disease from its early stages to the final clinical manifestation and health consequences: sickness, recovery, disability, or death. Epidemiological measures of disease burden include mortality, morbidity, and trends in these indicators over time. To facilitate comparison of the burden of different diseases and to consider both mortality and morbidity in a single measure, several summary health measures have been devised, including quality-adjusted life-years (QALYs)<sup>2</sup> and disability-adjusted life-years (DALYs).<sup>3–5</sup> In addition to measures of the population health impact of disease, assessing the economic consequences of health conditions provides complementary information for policy-making. Economic evaluation focuses on the direct and indirect costs of diseases for individuals, households, healthcare systems, and societies.<sup>6</sup>

Both epidemiological and economic evaluation of disease impact at population-level rely on estimating measures of disease frequency such as prevalence or incidence. In addition, a comprehensive assessment of disease burden requires estimation of prevalence and/or incidence of health consequences and complications secondary to the disease. For comparative analysis across diseases, mapping from occurrence of disease-specific events into generic measures can be accomplished using additional information such as duration of disability, magnitude of health losses associated with different disabilities, and relevant costs.

Information about the prevalence or incidence of disease typically provide the starting point for measuring disease burden. Prevalence and incidence of disease in the United States are commonly estimated from nationally-representative health surveys, surveillance and disease registration systems, administrative databases or prospective epidemiological studies. While direct analysis of these data sources can provide policy makers and researchers an intuitive and timely description of epidemiological patterns of disease, direct estimation from these sources will often lead to biased measures. For example, there have been several studies that used national surveillance data to estimate the prevalence and incidence of diabetes from 1980 to 2017.<sup>7–11</sup> However, overall diabetes prevalence was underestimated by studies based on self-reported diagnosis in the National Health Interview Survey (NHIS) or Behavioral Risk Factor Surveillance (BRFSS), as almost a quarter of diabetes cases remain undiagnosed.<sup>12</sup> The incidence of diagnosed diabetes, estimated using the NHIS or the National Health and Nutrition Examination Surveys (NHANES), will be a biased estimate of the true incidence of diabetes without considering the effects of changes in diabetes diagnosis rates.<sup>13</sup> Several cohort studies have attempted to estimate diabetes incidence, but these studies also have important limitations.<sup>14,15</sup> Estimation of current incidence is challenging in cohort studies that rely on long duration of follow-up and therefore track incidence over an extended period. Incidence estimates from cohort studies using claims data may lack generalizability to the general population, because study participants enrolled in commercial insurance programs will not be representative of the national populations.

Prevalence and incidence of disease complications and sequelae are important components of a comprehensive disease burden evaluation, especially when the disease complications and sequelae are long-term chronic conditions that may have significant health effects and economic costs. For example, cardiovascular disease (CVD) causes 70% of deaths among patients with diabetes in the United States, and contributes substantially to the total health and economic burden of diabetes.<sup>16,17</sup> The prevalence and incidence of CVD among diabetic populations can be directly observed using disease registration data linked with hospital records or vital registration. However, national diabetes registries (NDRs) are only available in limited number of developed countries (Denmark, Sweden, Australia) worldwide. In the absence of such data in the US, one can indirectly estimate CVD risk among diabetics by applying a CVD risk prediction equation to data from the most recent nationally representative datasets such as NHANES. However, current CVD risk prediction equations for diabetic

populations have limitations. CVD risk prediction equations developed in the general population including diabetes as a predictor, such as the 2013 ACC/AHA Pooled Cohort Risk Equation<sup>18</sup>, tend to underestimate CVD risk for diabetic populations, due to differences in CVD incidence between the diabetic and general populations.<sup>19–21</sup> Diabetes-specific prediction models, such as the United Kingdom Prospective Diabetes Study Outcomes Model 2 (UKPDS OM2)<sup>22</sup> and the Risk Equations for Complications Of type 2 Diabetes (RECODe)<sup>23</sup>, were developed and validated in populations of people with diabetes outside of the United States or in clinical trial populations, and may lack generalizability to populations in the United States.

Measuring long-term health and economic burden associated with a defined disease requires an overarching framework to aggregate measures of disease occurrence, measures of downstream health consequences, and summary measures such as QALYs lost and total related costs. QALYs lost and costs of disease and sequelae require estimation of disutilities, durations, and costs associated various health outcomes that are relevant to the natural history of disease, and interventions and policies relating to the disease. In the context of gonorrhea and other sexually transmitted diseases (STDs) in racial and ethnic minorities, disparities have been measured using incidence and prevalence in several previous studies.<sup>24–27</sup> However, incidence and prevalence of gonorrhea only represent disease frequency without assessing downstream complications secondary to infection. Measuring disparities in gonorrhea-associated burden requires assessment of both short- and long-term health outcomes and costs relating to the sequelae of gonococcal infections.

In this dissertation, I report three studies that employ mathematical modeling to evaluate the epidemiological and economic disease burden of specific health conditions in the United States. In each study, I develop models that incorporate observed data and other relevant evidence specifically in the disease area of diabetes and diabetic cardiovascular complications, and in the disease area of gonorrhea. The overall goal is to address some of the challenges in estimation of disease burden described above, and to answer the following three questions:

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- How has the epidemiological burden of diabetes changed over recent decades in the United States?
- II. What is the 10-year risk of cardiovascular disease (CVD) for patients with type 2 diabetes in the United States? What is the epidemiological burden of CVD among diabetic populations in recent years in the United States?
- III. What is the health and economic burden of gonorrhea, and related disparities, in recent years in the United States?

In the second chapter of this dissertation, "Dynamic Modeling of Prevalence and Incidence Trends for Diabetes and Diabetes Diagnosis among Adults Aged 20 Years or Older, United States, 2000-2016", I examine how the epidemiological burden of diabetes in the United States has changed over recent decades. To do so, I develop a dynamic mathematical model that simulates progression of individuals from no diabetes, to undiagnosed diabetes, to diagnosed diabetes. This model allows the estimation of incidence and diagnosis rates from cross-sectional data. I fit this model using repeated crosssectional survey data on the prevalence of undiagnosed and diagnosed diabetes from the National Health and Examination Survey (NHANES) 1988-1994 and 1999-2016. Using the fitted model, I estimate trends in the incidence of diabetes and diagnosis rates, both of which determine trends in incidence of diagnosed diabetes. Overall, I estimate a 17-year period of decreasing prevalence of undiagnosed diabetes and increasing prevalence of diagnosed and total diabetes, and decreasing incidence of diabetes, decreasing rates of diabetes diagnosis, and decreasing incidence of diagnosed diabetes over the same period.

In the third chapter, "Risk score to predict cardiovascular disease (CVD) risk for patients with type 2 diabetes mellitus (T2DM) in the United States: a pooled analysis of prospective cohorts", I develop a novel CVD risk prediction model specifically for populations with T2DM in the US, and compare the performance of this model to published CVD risk scores that can be applied to diabetic patients. The model is constructed as a multivariable risk factor model estimated using pooled data on fatal-plus-

non-fatal CVD outcomes from 5 prospective cohorts. I find that this model predicts an accurate 10year fatal-plus-non-fatal CVD risk for patients with T2DM in the US, with good discrimination and calibration performance. This performance is superior to the 2013 ACC/AHA Pooled Cohort Risk Equation, which underestimates 10-year atherosclerotic CVD risk in diabetic populations. The model developed in this study can be used to quantify total diabetes-specific CVD burden in the US over the next decade, and to simulate health outcomes for future studies that evaluate the effectiveness and cost-effectiveness of primary prevention options for diabetic patients.

In the fourth chapter, "*Disparities in health and economic outcomes associated with N. gonorrhoeae infection in the United States: costs and quality-adjusted life-years lost in 2015*", I evaluate the health and economic burden of gonorrhea and assess disparities in this burden across race/ethnicity. To implement this analysis, I develop probability tree models that capture clinical outcomes of gonorrhea and sequelae. These models allow quantification of both short- and long-term consequences and costs of gonococcal infection and sequelae, and synthesize information on gonorrhea and sequelae from different sources into a consistent framework that allows an integrated analysis of disparities in gonorrhea disease burden. I use these models to estimate attributable disease burden in terms of the discounted lifetime costs and quality-adjusted life-years (QALYs) lost due to incident infections acquired during 2015. I report population-level disease burden, disaggregated by sex, age, race/ethnicity, and for men who have sex with men (MSM). This analysis shows the highest absolute burden of both QALYs and costs to be in Non-Hispanic Black women, and the highest per-capita burden to be in MSM and American Indian/Alaska Native women. In the final chapter of this dissertation I provide a synthesis of key themes across the three studies.

In summary, this dissertation uses mathematical models to evaluate the epidemiological and economic burden of three different diseases in the United States. These results illustrate the use of mathematical modelling to synthesize observed data to infer epidemiological trends that are not always directly observable, to quantify the short-term and long-term health outcomes associated with disease and complications, and to measure disparities in the health and economic burden of disease across population subgroups.

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# Chapter 2. Prevalence and incidence trends for diabetes and diabetes diagnosis among adults ages 20 years and older, United States, 2000-2016: results of a mathematical model

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#### Abstract

#### Background

Although the prevalence and incidence of diagnosed diabetes are thought to have decreased in the United States after 2008, there is a lack of population-based estimates describing national trends in the prevalence of undiagnosed and all diabetes, and trends in the incidence of diabetes and rates of diabetes diagnosis.

#### Methods

We developed an age-stratified Markov model of undiagnosed and diagnosed diabetes in the US adult population. In this model, smooth functions were used to represent year- and age-specific incidence of diabetes and rates of diabetes diagnosis. Using Bayesian methods, we calibrated this model separately for men and women, using nationally representative data on the prevalence of undiagnosed and diagnosed diabetes from the National Health and Nutrition Examination Survey (NHANES III and Continuous NHANES 1999-2016). We estimated the prevalence of all, undiagnosed, and diagnosed diabetes, as well as the incidence of diabetes and diagnosed diabetes over the period 2000-2016. Prevalence and incidence trends were summarized as the annual percentage change (APC).

#### Results

Overall, the age-standardized prevalence of all diabetes per 100 adults was estimated to increase from 10.4 (95% uncertainty interval, 8.9 to 12.0) in 2000 to 12.0 (10.3 to 14.1) in 2016. Over the same period, the age-standardized prevalence of diagnosed diabetes per 100 adults increased from 6.8 (5.7 to 8.0) to 8.9 (7.5 to 10.5), and the age-standardized prevalence of undiagnosed diabetes per 100 adults decreased from 3.6 (2.7 to 4.7) to 3.2 (2.0 to 4.7). For diabetes-free adults, the age-standardized incidence of diabetes per 1,000 person-years decreased from 7.5 (6.6 to 8.5) in 2000 to 6.9 (4.3 to 10.7) in 2016. For adults with undiagnosed diabetes, the age-standardized rate of diabetes diagnosis per 1,000 person-years decreased from 168 (142 to 201) to 144 (98 to 208) during 2000-2016. Among

adults without diagnosed diabetes, the age-standardized incidence of diagnosed diabetes per 1,000 person-years decreased from 6.2 (5.5 to 6.9) to 5.7 (4.4 to 7.4) during 2000-2016. Trends within individual age categories were generally similar to these age-standardized results. However, the prevalence of undiagnosed diabetes and incidence of diabetes among men and women ages 20-49 years increased over 2000-2016. The age-standardized incidence of diagnosed diabetes in men ages 65 years and older increased with an APC of 1.5% (-2.2% to 5.2%) during 2000-2016.

#### Conclusions

During 2000-2016, incidence of diabetes, rates of diabetes diagnosis, and incidence of diagnosed diabetes decreased in the US adult population. Continuing diabetes prevention efforts, monitoring and screening are needed to further reduce diabetes incidence and diabetes complications.

#### Background

Diabetes is a leading cause of disease burden in the United States.<sup>1,2</sup> Between 1990 and 2016, diabetes rose from the sixth leading cause of disability-adjusted life-years (DALYs) to the fourth, with an estimated 66 thousand deaths, 2.5 million years lived with disability (YLDs) and 3.8 million DALYs attributable to diabetes in the U.S. in 2016.<sup>3</sup> Estimated economic costs due to diabetes increased by 26% from 2012 to 2017,<sup>4</sup> reaching \$327 billion, including \$237 billion in direct medical costs and \$90 billion in reduced productivity.<sup>4,5</sup> Systematic analyses of patterns and trends in diabetes are needed by policymakers to assess population health needs and to plan and evaluate different intervention strategies.

There have been several studies that used national surveillance data to describe the prevalence and incidence of diabetes from 1980 to 2017.<sup>6–11</sup> Some studies have reported a 20-year increase in prevalence of diagnosed diabetes nationally between the 1990s and the mid-2000s, followed by a plateau through 2017.<sup>6,8</sup> However, studies based on self-reported diagnosis in the National Health Interview Survey (NHIS)<sup>6,8</sup> or Behavioral Risk Factor Surveillance (BRFSS)<sup>12</sup> will underestimate overall diabetes prevalence, as undiagnosed diabetes accounted for an estimated 24% of all diabetes in 2017.<sup>13</sup> Prevalence of laboratory-confirmed diabetes, including undiagnosed cases, has been measured in the National Health and Nutrition Examination Surveys (NHANES).<sup>7,11</sup> In addition to prevalence, studies have also examined trends in the incidence of diagnosed diabetes, <sup>6,8</sup> which is determined by both trends in true incidence and trends in diagnosis rates.<sup>10,14</sup> Disentangling these two drivers of trends in incident diagnosed diabetes is challenging without directly measured, laboratory-confirmed diagnosed and undiagnosed diabetes.

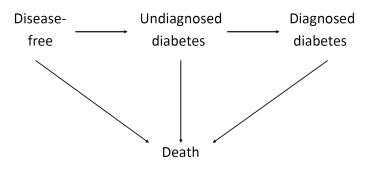
To overcome these limitations and provide contemporary, unbiased estimates of the epidemiological trends of diabetes incidence and diagnosis, we constructed a dynamic model that incorporated both undiagnosed and diagnosed diabetes. We estimated this model using nationally representative cross-sectional data, including information not only on self-reported diabetes diagnoses but also on

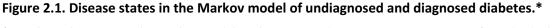
laboratory-measured glucose levels. Using the fitted model, we examined trends in rates of prevalence of all, undiagnosed and diagnosed diabetes, and in rates of incidence of diabetes, diagnosed diabetes, and diabetes diagnosis over the period 2000-2016.

#### Methods

#### **Analytic overview**

We developed a Markov model of undiagnosed and diagnosed diabetes in the U.S. population ages 20 years and older (Figure 2.1). Hazard rates for mortality among people without diabetes were estimated from the general all-cause mortality data reported in United States life tables, with adjustment for diabetes-related mortality using the Second National Health and Nutrition Examination Survey Mortality Study (SNHANES-MS).<sup>15,16</sup> Annual, age-specific transition rates from disease free to undiagnosed and from undiagnosed to diagnosed diabetes were specified using B-spline surfaces, which are flexible continuous functions in two dimensions (age and time), and separate functions were estimated for men and women. We calibrated this model to nationally representative NHANES III and Continuous NHANES data describing the prevalence of undiagnosed and diagnosed diabetes. A Bayesian approach was used to estimate model parameters, operationalized using incremental mixture importance sampling (IMIS).<sup>17</sup> We examined model fits using both visual inspection and posterior prediction interval checks.<sup>18</sup> Prevalence and incidence trends were summarized as the annual percentage change (APC) between 2000 and 2016. Analyses were undertaken in R (R-3.5.2).





\*Details on the states in the Markov model, with corresponding states transition matrix for individuals at single year of age (i) and single calendar year (t) are reported in Supplementary Material Figure S2.1.

#### **Data sources**

We extracted nationally-representative cross-sectional data from the NHANES III (1988-1994) and Continuous NHANES (1999-2016), describing the prevalence of diagnosed and undiagnosed diabetes among the U.S. population ages 20 years and older. Conducted by the National Center for Health Statistics, NHANES is a national health and nutrition survey that uses a stratified, multistage cluster sample design to be representative of the U.S. civilian, noninstitutionalized population.<sup>19,20</sup> NHANES is unique in that it combines personal interviews with standardized physical examinations and laboratory tests.<sup>19,20</sup> For NHANES III, the overall responses rate was 86% in the interviewed sample and 78% in the examined sample. For Continuous NHANES 2015-2016 this decreased to 65% in the interviewed sample and 62% in the examined sample. Nonresponse bias analyses have suggested that the declining response rates did not produce substantial bias in the final survey estimates.<sup>21,22</sup>

We used data from the interview questionnaire and laboratory examination to provide a full accounting of diagnosed, undiagnosed, and all diabetes. The interview questionnaire was standardized to collect information on age, sex, pregnancy, and fasting status. Women who were pregnant were excluded from our analysis because pregnancy affects glucose measurements.<sup>7</sup> We excluded individuals who were randomly selected to participate in an afternoon or evening examination or had a total length of "food fast" hours less than 8 hours or longer than 24 hours.

Further details on the number of participants in the analytic sample can be found in Supplementary Material Table S2.1.

#### **Definition of Diabetes**

Consistent with previous studies, 'diagnosed diabetes' was defined as a self-reported previous diagnosis of diabetes.<sup>6,7,11</sup> Participants were asked "other than during pregnancy for women, have you ever been told that you have diabetes or sugar diabetes" by a "doctor" (NHANES III) or "doctor or other health professionals" (Continuous NHANES). 'Undiagnosed diabetes' was defined as having a Fasting Plasma Glucose (FPG) level of 126mg/dL or higher without a self-reported previous diagnosis of diabetes. 'All diabetes' was defined as having either diagnosed or undiagnosed diabetes. Following the National Center for Health Statistics (NCHS) recommendations, FPG values in NHANES 2005-2016 were adjusted to be comparable to earlier values using a published CDC regression-based adjustment equation.<sup>20,23-28</sup> We did not use Hemoglobin  $A_{1c}$  or 2-hour plasma glucose because they are not available in all NHANES rounds. In addition, previous analyses of NHANES data have indicated that, assuming universal screening of undiagnosed diabetes than the FPG cut point of  $\geq 126 \text{mg/dL}$ .<sup>29</sup> Two-hour plasma glucose is used less frequently in clinical care because it is relatively costly and burdensome for patients. Our definition of diabetes included both type 1 and type 2 diabetes, since NHANES cannot distinguish between the type of diabetes.

#### **Statistical analysis**

We developed a Markov model to represent undiagnosed and diagnosed diabetes in the U.S. population ages 20 years and older between 1990-2016 (Figure 2.1). We stratified by sex, because observed patterns of diabetes incidence differ between men and women.<sup>6,30,31</sup> We assumed that people may only progress from disease-free to undiagnosed diabetes to diagnosed diabetes (with progression to death possible from any of the other three states), as diabetes is generally considered a progressive condition without remission. In addition, we assumed that there is no possibility of

progression from disease-free to diagnosed diabetes directly, as immediate diagnosis upon disease onset is unlikely.<sup>32</sup> The average duration between onset and clinical diagnosis for non-insulin-dependent diabetes in the U.S. has been estimated previously as 4-6 years.<sup>33,34</sup>

We modeled the transition probabilities between disease states by single year of age (i) and single calendar year (t) (Figure S2.1 in Supplementary Material). Yearly age- and sex-specific hazard rates from disease-free to death were estimated by subtracting diabetes-related mortality from all-cause mortality based on prevalence and risk ratios estimates (see Supplementary Material for details). Yearly age- and sex-specific all-cause mortality rates among the general populations were obtained from the annual United States Life Tables published by NCHS.<sup>15</sup> Prevalence of undiagnosed and diagnosed diabetes were estimated directly from NHANES III and Continuous NHANES. Risk ratios for all-cause mortality comparing those with undiagnosed or diagnosed diabetes to those without diabetes were estimated by fitting Cox proportional hazards models by age, sex and survey year to prospective mortality follow-up data from SNHANES-MS.<sup>16</sup> Details on distributions of risk ratios are reported in Supplementary Material Table S2.2.

The incidence of diabetes was represented as the transition rate from disease-free to undiagnosed diabetes. The diagnosis rate of diabetes was represented as the transition rate from undiagnosed to diagnosed diabetes. For each of these transition rates, we constructed individual B-spline surfaces in the dimensions of calendar year and age, allowing rates to change smoothly as a function of age and year. For the age dimension we allowed 5 control points, with three internal knots at the boundaries between age groups 20-34 years, 35-49 years, 50-64 years, and 65 years and older, and two additional boundary knots at ages 20 years and 99 years. For the year dimension we allowed 7 control points, with internal knots located in the middle year of NHANES III, and every two survey years of Continuous NHANES. This resulted in 48 parameters defining each spline surface. We specified weakly-informative priors for these parameters. We used a second-degree difference penalty on the time dimension to avoid overfitting. We conducted seven-fold cross-validation to determine the optimal value of the

penalty.<sup>35,36</sup> To implement the cross-validation, the NHANES data were divided into seven equal-sized folds for men and women separately. For each fold, we predicted the prevalence of undiagnosed and diagnosed diabetes from a model estimated using the data for the other six folds. This procedure was conducted for all seven folds. We selected the penalty value to maximize the log-likelihood of these out-of-sample predictions when compared to the original data.

We estimated the model separately for men and women, using incremental mixture importance sampling (IMIS). IMIS implements a Bayesian approach to estimate the joint posterior distribution of the model parameters, allowing for correlation and multi-modality of this distribution. All analyses were conducted in R.<sup>17</sup>

#### **Outcome measures**

Primary model outcome measures included: the prevalence of undiagnosed, diagnosed, and all diabetes; rates of diabetes incidence and diagnosis (for disease-free and undiagnosed diabetes respectively); and incidence of diagnosed diabetes. These outcomes were estimated for each year during the period 2000-2016, stratified by sex and age group. Model outputs during the first ten-year period (1990-1999) were not reported due to lack of data from NHANES between 1995-1998, and were used to stabilize model conditions by the start of 2000. Results were summarized by age categories 20-34, 35-49, 50-64, and 65 years and older. To standardize results by age, we used the 2000 U.S. population. To quantify trends in each quantity of interest, we calculated APCs over the 17-year period by sex and age group. Uncertainty intervals were calculated as the 2.5th and 97.5th percentiles of the distribution of results for each outcome.

#### Results

#### Model checking

We used posterior predictive checks to evaluate model fit to the NHANES data.<sup>18</sup> Supplementary Material Figures S2.2 and S2.3 provide a comparison of modelled estimates to the empirical values. These comparisons show that the model predicted the prevalence of diabetes well: the 95% prediction intervals cover 96.8% and 98.4% of NHANES mean prevalence estimates for men and women separately. Full results of these posterior predictive checks (comparing modelled and empirical estimates for the prevalence of undiagnosed, diagnosed, and all diabetes) are reported in Supplementary Material Figure S2.5.

#### Prevalence of undiagnosed, diagnosed, and all diabetes in 2016

In the overall population in 2016, the crude prevalence per 100 persons was 12.6 (95% Uncertainty Interval, 11.8 to 13.5) for all diabetes, 3.5 (2.9 to 4.1) for undiagnosed diabetes, and 9.1 (8.4 to 9.8) for diagnosed diabetes. The crude and age-standardized prevalence of all diabetes and diagnosed diabetes differed by sex and age groups (Table 2.1). The crude prevalence of all diabetes in 2016 was higher in men (14.0 per 100 persons [12.9 to 15.4]) than in women (11.2 per 100 persons [10.3 to 12.4]); age-standardized prevalence was also higher among men. The prevalence of diagnosed diabetes and all diabetes were highest among those ages 65 years and older, followed by ages 50-64 years, ages 35-49 years, and ages 20-34 years for both men and women.

Population	Undiagnosed Diabetes		Diagnosed Diabetes		All Diabetes	
	Prevalence Per 100 persons (95% UI)	APC % (95% UI)	Prevalence Per 100 persons (95% UI)	APC % (95% UI)	Prevalence Per 100 persons (95% UI)	APC % (95% UI)
Total						
Crude	3.5	-0.4	9.1	2.4	12.6	1.5
	(2.9, 4.1)	(-1.8, 1.0)	(8.4 <i>,</i> 9.8)	(1.7, 3.1)	(11.8, 13.5)	(0.9, 2.1)
Age- standardized* Men	3.2 (2.0, 4.7)	-0.8 (-2.3, 0.6)	8.9 (7.5, 10.5)	1.7 (1.1, 2.4)	12.0 (10.3, 14.1)	0.9 (0.3, 1.5)
Crude	3.9	-0.9	10.1	3.2	14.0	1.8
	(3.1, 4.8)	(-2.9, 1.4)	(8,2, 11.4)	(2.2, 4.3)	(12.9, 15.4)	(0.9, 2.7)
Age- standardized* Women	3.6 (2.2, 5.2)	-1.0 (-3.0, 1.4)	9.4 (8.0, 11.1)	2.3 (1.4, 3.3)	13.0 (11.1, 15.2)	1.2 (0.3, 2.1)
Crude	3.2	0.1	8.1	1.6	11.2	1.1
	(2.5, 4.0)	(-1.8, 2.0)	(7.3, 9.0)	(0.7, 2.6)	(10.3, 12.4)	(0.3, 1.9)
Age-	2.8	-0.7	8.3	1.1	11.1	0.6
standardized*	(1.8, 4.1)	(-2.7, 1.3)	(7.1, 9.8)	(0.3, 2.0)	(9.5, 13.1)	(-0.1, 1.4)
Men, Age group						
20-34	2.3	2.8	1.2	-0.8	3.5	1.3
	(1.4, 3.9)	(-1.4, 7.0)	(0.6, 1.9)	(-5.8 <i>,</i> 3.6)	(2.2, 5.2)	(-2.6, 4.6)
35-49	3.9	1.2	5.6	1.5	9.4	1.4
	(2.5, 5.7)	(-2.6, 5.5)	(4.4, 7.0)	(-1.0, 3.9)	(7.6, 11.6)	(-0.9, 3.3)
50-64	4.2	-3.0	15.4	2.3	19.6	0.7
	(2.6, 5.7)	(-6.3, -3.2)	(13.2, 18.0)	(0.9, 3.7)	(17.0, 22.5)	(-0.5, 2.0)
65+	4.7	-4.0	26.7	3.2	31.5	1.6
	(3.0, 6.4)	(-6.0 <i>,</i> -1.3)	(24.0, 29.6)	(2.1, 4.1)	(29.0, 34.0)	(0.7, 2.3)
Women, Age group						
20-34	1.7	1.5	1.3	-0.1	3.0	0.8
	(0.9, 2.8)	(-3.0, 5.9)	(0.8, 2.0)	(-4.2, 4.3)	(2.0, 4.3)	(-2.3, 3.8)
35-49	2.5	0.06	5.7	1.7	8.2	1.1
	(1.5, 3.8)	(-3.7, 3.9)	(4.6, 7.1)	(-2.8, 4.0)	(6.6, 9.8)	(-0.5, 3.0)
50-64	3.3	-1.3	11.6	0.9	14.9	0.4
	(2.1, 4.7)	(-4.5, 1.7)	(10.1, 13.7)	(-0.7, 2.4)	(13.0, 17.4)	(-0.8, 1.7)
65+	4.4	-1.8	19.0	1.0	23.3	0.4
	(3.1, 6.1)	(-4.3, 1.1)	(16.9, 21.1)	(-0.1, 2.2)	(20.9, 26.1)	(-0.5, 1.3)

Table 2.1. Prevalence per 100 persons of undiagnosed, diagnosed, and all diabetes in the U.S. general population ages 20 years and older in 2016, and annual percentage changes of the prevalence of undiagnosed, diagnosed, and all diabetes over 2000-2016, by age group and sex.

Abbreviation: APC = Annual percentage change.

\*Age-standardized to the U.S. 2000 population based on age groups 20-34 years, 35-49 years, 50-64 years, and 65 years and older.

#### Incidence of diabetes, diagnosed diabetes, and rates of diabetes diagnosis in 2016

Among adults without diagnosed diabetes, the crude incidence of diagnosed diabetes per 1,000 person-years was 6.2 (95% UI, 4.7 to 8.0) in 2016. For diabetes-free adults, the crude incidence of diabetes per 1,000 person-years was 7.1 (4.4 to 11.0) in 2016. For adults with undiagnosed diabetes, the crude rate of diabetes diagnosis per 1,000 person-years was 148 (101 to 213) in 2016. The crude incidence of diabetes and diagnosed diabetes were higher among men than women (Table 2.2). Among adults ages 50 years and older, the incidence of diabetes per 1,000 person-years was similar among men (7.7 [3.7 to 15.8] for ages 65 years and older) and women (7.7 [3.8 to 15.0] for ages 65 years and older). With a similar incidence of diabetes, the rate of diabetes diagnosis was higher for men than women ages 50 years and older, leading to a higher incidence of diagnosed diabetes for men than women.

Population	Diabetes		Diabetes Diagnosis <sup>†</sup>		Diagnosed Diabetes <sup>‡</sup>	
	Incidence Per 1,000 person-years (95% UI)	APC % (95% UI)	Rates Per 1,000 person-years (95% UI)	APC % (95% UI)	Incidence Per 1,000 person-years (95% UI)	APC % (95% UI)
Total						
Crude	7.1	-0.7	148	-0.5	6.2	-0.1
	(4.4, 11.0)	(-2.8, 1.6)	(101, 213)	(-2.7, 1.9)	(4.7, 8.0)	(-2.0, 1.9)
Age-	6.9	-0.8	144	-0.6	5.7	-0.6
standardized*	(4.3 <i>,</i> 10.7)	(-2.9 <i>,</i> 1.4)	(98, 208)	(-2.9, 1.8)	(4.4, 7.4)	(-2.5, 1.3)
Men	7.2	-1.2	160	0.5	7.8	0.9
Crude	(4.8, 11.3)	(-3.6, 1.9)	(107, 233)	(-2.5, 3.8)	(5.2, 11.0)	(-2.0, 3.6)
Age-	7.1	-1.3	152	0.2	7.1	0.3
standardized*	(4.7, 11.0)	(-3.8, 1.9)	(104, 223)	(-3.1, 3.5)	(4.8, 9.8)	(-2.5, 2.8)
Women	6.3	-0.2	146	-1.4	4.6	-1.6
Crude	(4.0, 9.7)	(-3.5, 3.1)	(93, 226)	(-4.7, 1.9)	(3.1, 6.9)	(-4.2, 1.2)
Age-	6.2	-0.4	148	-1.3	4.5	-1.9
standardized*	(4.0, 9.3)	(-3.6, 2.7)	(94, 231)	(-4.6, 2.0)	(3.0, 6.6)	(-4.5, 1.1)
Men, Age group						
20-34	6.0	3.3	135	-0.9	2.6	0.5
	(3.2, 10.0)	(-1.5, 8.2)	(66, 257)	(-6.3, 5.2)	(1.2, 4.8)	(-5.0, 5.7)
35-49	7.6	-0.3	126	-1.6	5.5	-0.3
	(3.8, 13.4)	(-4.3 <i>,</i> 4.5)	(62, 226)	(-6.1, 3.4)	(3.0 <i>,</i> 9.8)	(-4.6, 4.3)
50-64	7.9	-4.9	208	1.8	12.0	-0.3
	(3.9, 15.9)	(-9.2, -0.09)	(115, 347)	(-2.2, 6.4)	(7.2, 19.7)	(-4.1, 3.5)
65+	7.7	-2.3	172	3.7	13.3	1.5
	(3.7, 15.8)	(-6.6, 2.2)	(90, 275)	(-0.3 <i>,</i> 8.4)	(8.1, 19.3)	(-2.2, 5.2)
Women, Age group						
20-34	4.8	2.0	172	-1.1	2.5	-0.3
	(2.6, 7.9)	(-2.5, 6.7)	(88, 313)	(-6.3, 4.1)	(1.2, 4.7)	(-5.4, 5.7)
35-49	5.8	-0.09	160	-1.8	3.9	-2.4
	(2.8, 10.2)	(-5.0, 4.3)	(75, 317)	(-7.7, 3.5)	(2.0, 7.1)	(-7.1, 1.9)
50-64	7.2	-1.4	148	-1.4	5.5	-2.9
	(3.4, 13.5)	(-6.2, 3.4)	(71, 263)	(-6.6, 3.2)	(2.8 <i>,</i> 9.5)	(-6.6, 1.4)
65+	7.7	-1.6	98	-0.9	7.1	-1.5
	(3.8, 15.0)	(-6.1, 4.4)	(54, 158)	(-4.9, 3.2)	(4.0, 11.4)	(-5.7, 2.3)

Table 2.2. Incidence per 1,000 person-years of diabetes, rates of diabetes diagnosis, and incidence of diagnosed diabetes for ages 20 years and older in the U.S. general population in 2016 and annual percentage changes of incidence of diabetes, rates of diabetes diagnosis, and incidence of diagnosed diabetes over 2000-2016, by age group and sex.

<sup>†</sup>Diabetes Diagnosis was defined as detection and diagnosis of diabetes for adults with undiagnosed diabetes who having a Fasting Plasma Glucose (FPG) level of 126mg/dL or higher without a self-reported previous diagnosis of diabetes.

<sup>‡</sup>Diagnosed Diabetes was defined as a self-reported previous diagnosis of diabetes.

Abbreviation: APC = Annual percentage change.

\*Age-standardized to the U.S. 2000 population based on age groups 20-34 years, 35-49 years, 50-64 years, and 65 years and older.

#### Trends in the prevalence of undiagnosed, diagnosed, and all diabetes over 2000-2016

During 2000-2016, the age-standardized prevalence of all diabetes and diagnosed diabetes increased. Estimates of APC were 0.9% (0.3% to 1.5%) for all diabetes and 1.7% (1.1% to 2.4%) for diagnosed diabetes in the overall population (Figure 2.2 and Table 2.1). Over the same period, the APC for the age-standardized prevalence of undiagnosed diabetes was -0.8% (-2.3% to 0.6%).

Similar results of an increasing trend in the prevalence of all and diagnosed diabetes and a decreasing trend in the prevalence of undiagnosed diabetes were estimated in many age groups in men and women (Figure 2.3 and Figure 2.4). However, the prevalence of undiagnosed diabetes among ages 20-34 years and ages 35-49 years men and women continued to increase during 2000-2016. For example, the prevalence of undiagnosed diabetes per 100 persons was 1.5 (0.9 to 2.1) in 2000 and 2.3 (1.4 to 3.9) in 2016 for men ages 20-34 years, with an estimated APC of 2.8% (-1.4% to 7.0%). The prevalence of undiagnosed diabetes per 100 persons for women ages 20-34 years increased from 1.3 (0.8 to 1.9) in 2000 to 1.7 (0.9 to 2.8) in 2016, with an APC of 1.5% (-3.0% to 5.9%).

The estimated increases in diagnosed and all diabetes prevalence and decrease in undiagnosed diabetes prevalence were driven primarily by the 50-64 years and 65 years and older populations, and among men in particular. For example, the prevalence of diagnosed diabetes per 100 men ages 65 years and older was estimated to increase substantially from 16.3 (14.5 to 18.1) in 2000 to 26.7 (24.0 to 29.6) in 2016, with an APC of 3.2% (2.1% to 4.1%). The APC of the prevalence of all diabetes for men ages 65 years and older was estimated to be 1.6% (0.7% to 2.3%) during 2000-2016.

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# Trends in incidence of diabetes, diagnosed diabetes, and rates of diabetes diagnosis 2000-

#### 2016

In the overall population, the age-standardized incidence of diagnosed diabetes per 1,000 personyears was similar in 2000 (6.2 [5.5 to 6.9]) and 2016 (5.7 [4.4 to 7.4]), corresponding to an estimated APC of -0.6% (-2.5% to 1.3%) (Figure 2.2 and Table 2.2). Decreasing trends were also estimated in the overall incidence of diabetes (APC -0.8% [-2.9% to 1.4%]) and rates of diabetes diagnosis (APC -0.6% [-2.9% to 1.8%]) during the study period.

Whereas the trend in incidence of diabetes was relatively flat among women (APC of -0.36% [-3.6% to 2.7%]), incidence has decreased among men, with an estimated APC of -1.3% (-3.8% to 1.9%). Rates of diabetes diagnosis were estimated to have a minor increase in men and a substantial decrease in women with an APC of 0.2% (-3.1% to 3.5%) versus an APC of -1.3% (-4.6% to 2.0%) during the study period, but these changes were not statistically significant. Changes in the incidence of diagnosed diabetes were driven by both trends in incidence of diabetes and rates of diabetes diagnosis, leading to an increase in men but a decrease in women during 2000-2016.

Inspection of age-stratified trends in diabetes incidence suggested differential changes among younger vs. older adults. For example, the incidence of diabetes was estimated to increase in the age group 20-34 years for both men (APC 3.3% [-1.5% to 8.2%]) and women (APC 2.0% [-2.5% to 6.7%], but decrease in the age group 65 and older years for men (APC -2.3% [-6.6% to 2.2%]) and women (APC -1.6% [-6.1% to 4.4%]). Rates of diabetes diagnosis were estimated to decline in all age groups for women and in ages below 50 years in men, but increased in men ages 50 years and older. Incidence of diagnosed diabetes were estimated to decrease in most age groups in men and women, except for men ages younger than 35 years or older than 65 years. The increase in diagnosed diabetes was mostly driven by the increasing trend in incidence of diabetes for men ages younger than 35 years, and by improving rates of diabetes diagnosis for men ages 65 years and older.

Figure 2.2. Trends in age-standardized prevalence of undiagnosed, diagnosed, and all diabetes, incidence of diabetes and diagnosed diabetes, and rates of diabetes diagnosis in the overall population, men and women ages 20 years and older, 2000-2016.

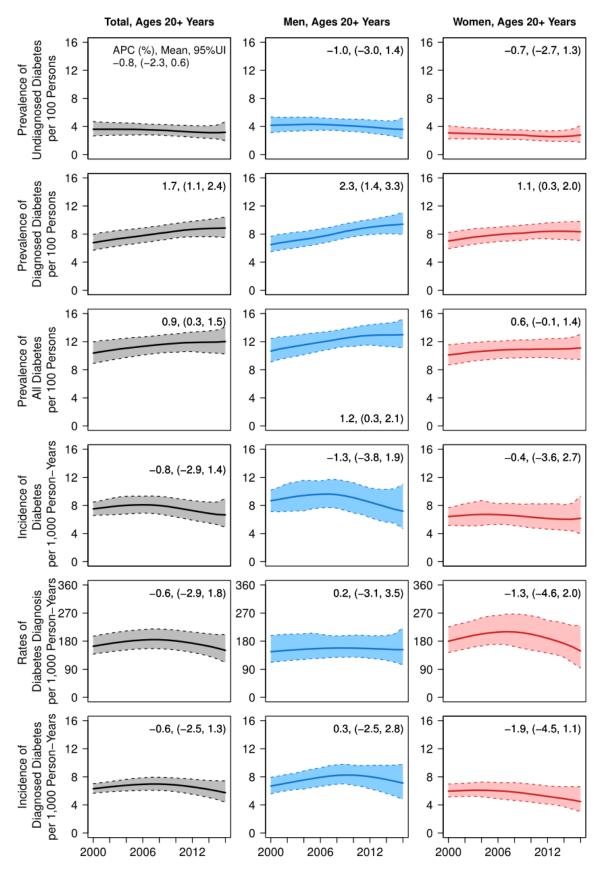


Figure 2.3. Trends in prevalence of undiagnosed, diagnosed, and all diabetes, incidence of diabetes and diagnosed diabetes, and rates of diabetes diagnosis in men ages 20 years and older, by four age groups, 2000-2016.

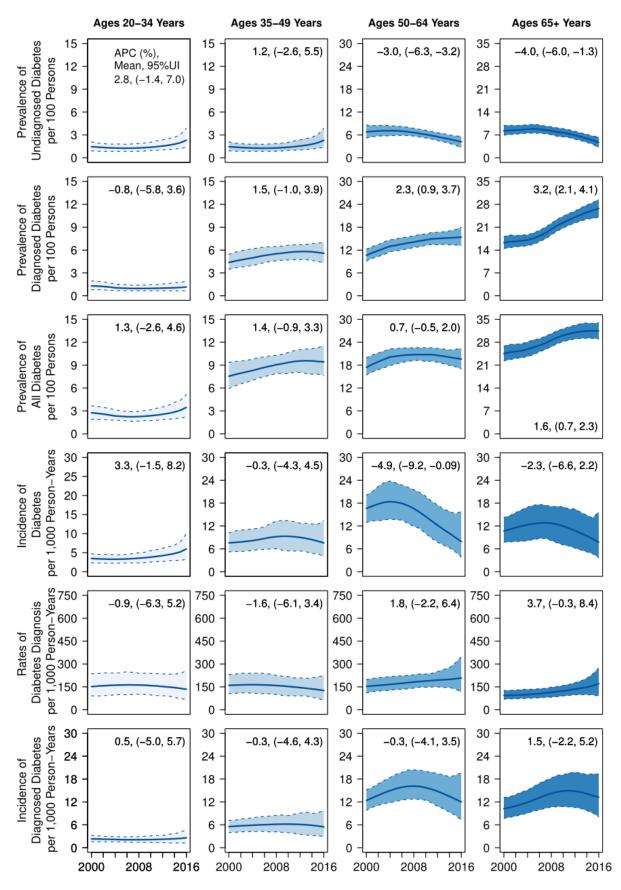
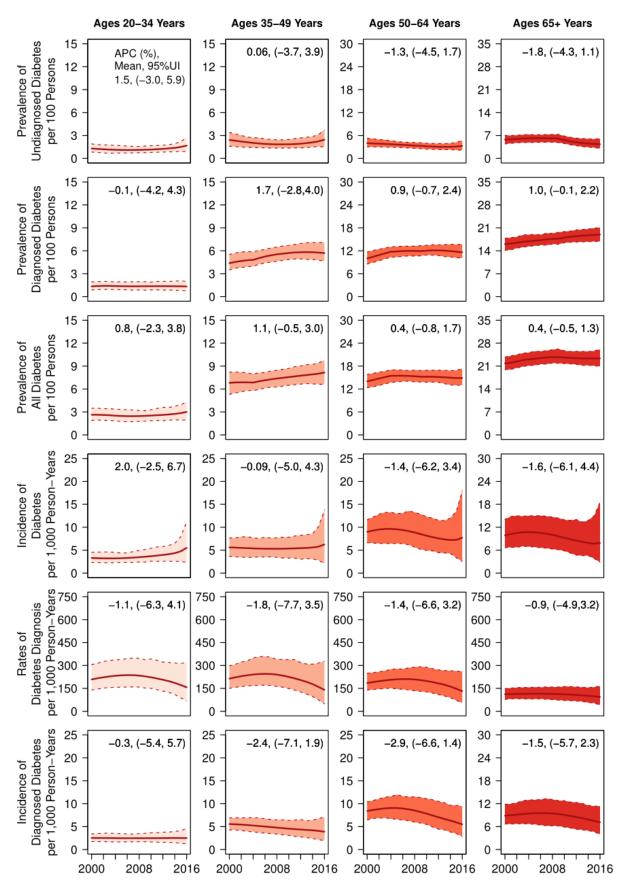


Figure 2.4. Trends in prevalence of undiagnosed, diagnosed, and all diabetes, incidence of diabetes and diagnosed diabetes, and rates of diabetes diagnosis in women ages 20 years and older, by four age groups, 2000-2016.



# Discussion

Overall, our analysis estimated a 17-year period of decreasing prevalence of undiagnosed diabetes and increasing prevalence of diagnosed and all diabetes during 2000-2016. The incidence of diabetes, rates of diabetes diagnosis, and incidence of diagnosed diabetes all decreased in the overall US population. In many age strata, trends in the prevalence and incidence of diabetes were similar to overall trends. However, the prevalence of undiagnosed diabetes and incidence of diabetes among young adults ages 20-34 years increased during 2000-2016. Incidence of diagnosed diabetes increased in men ages 65 years and older, driven by an improvement in rates of diabetes diagnosis.

Most previous studies using data from national surveys among U.S. adults (NHANES, NHIS, BRFSS) have focused on the prevalence and incidence of diagnosed diabetes.<sup>2,6–8,37,38</sup> Our estimated trends in the prevalence of undiagnosed, diagnosed and all diabetes, and trends in the incidence of diagnosed diabetes were comparable to these of previous studies.<sup>8,37</sup> However, little is known about the trends in the incidence of diabetes directly from nationally representative surveys. The Surveillance, Prevention, and Management of Diabetes Mellitus (SUPREME-DM) study, using electronic health records of inpatient care, laboratory and pharmacy data to identify diabetes in a diverse open cohort of 7 million insured adults in US, reported stabilization in incidence of overall diabetes over 2006-2010.<sup>39</sup> Another analysis based on claims data from all 50 US states suggested the annual rate of diagnosed diabetes declined substantially over 2007-2012, from 11.0 to 6.5 per 1,000 person-years.<sup>40</sup> Similar stable or decreasing trends in incidence of total or type 2 diabetes were reported by several studies for populations from Europe and Canada since 2006.<sup>14</sup>

Trends in the incidence of diabetes reported here are consistent with period changes in the four most important determinants of diabetes risk: age, overweight or obesity, smoking, and prediabetes. In our study, all outcome measures were age standardized, meaning that changes in age structure cannot explain the reported results. Regarding trends in prevalence of obesity, there were no significant changes during 2003-2010 among men and women adults, an increasing but not significant trend during 2010-2016 among men adults, and a significant increasing trend during 2010-2016 among women adults in US.<sup>41,42</sup> Smoking prevalence was reported having significant declines after 2010 compared with 2003-2005, except for low socio-economic status (annual incomes of less than \$10,000).<sup>43</sup> Prediabetes, defined as FPG values of 100 to 126 mg/dL or Hemoglobin A<sub>1c</sub> values of 5.7% to 6.4%, was reported having stable prevalence among US adults during 2005-2016.<sup>37</sup> Trends in sugared beverage purchases, total food calories intake, and physical inactivity either plateaued or decreased since mid-2000s.<sup>44–47</sup> Taken together, current evidence on diabetes risk factors is consistent with the plateauing and slowing in diabetes incidence.

Trends in the incidence of diagnosed diabetes were not only related to trends in diabetes incidence but also to trends in the diagnosis rate, which has been affected by changes in diabetes diagnostic criteria and changes in testing and screening practices. In 1997 the American Diabetes Association (ADA) lowered the threshold for a diagnosis of diabetes from an FPG of 140 mg/dL to 126 mg/dL.<sup>48</sup> A subsequent increase in the diabetes diagnosis rates from 2000 to late-2000s was estimated in the overall and most population subgroups in our study. In 2010 the ADA added a Hemoglobin  $A_{1c}$  of 6.5% or higher to the diagnostic criteria for diabetes.<sup>48</sup> Rates of diabetes diagnosis could increase if this change leads to increased awareness and detection of diabetes, as suggested by the SUPREME-DM study.<sup>39</sup> Alternatively, this change could lead to a lower rate of diabetes diagnosis because Hemoglobin A<sub>1c</sub> threshold is a less sensitive indicator than the FPG threshold.<sup>29,49</sup> In addition, it has been reported that Hemoglobin A<sub>1c</sub> is still used less frequently than glucose for screening during the first five years of this added recommendation in US.<sup>50</sup> As such, the balance of whether Hemoglobin A<sub>1c</sub> contributed to an increase or decrease in diabetes diagnosis rates remains uncertain. As suggested by our model results, estimated increases in the rates of diabetes diagnosis for men ages 65 years and older or decreases for women were not statistically significant. Practices around screening, testing, and diagnosis of diabetes were not monitored well by national surveillance systems, leaving limited information on diabetes screening changes associated with health reforms in the past few years.

The overall modest decrease in diabetes incidence and increase in diabetes prevalence in this study are consistent with substantial reductions in all-cause and cardiovascular disease specific mortality among individuals with diagnosed diabetes over the last three decades.<sup>51</sup> Extended life expectancies of individuals with diabetes after diagnosis would increase the number of people with diagnosed diabetes, leading to increased prevalence of diagnosed and all diabetes. Our results do not support the hypothesis of saturation of diagnosed diabetes, which postulates that recent declines in the incidence of diagnosed diabetes are due to depletion of the susceptible population through increased screening and diagnostic practices.<sup>52</sup> In our results, the prevalence of undiagnosed diabetes increased for adults ages 20-34 and 35-49 years, indicating that saturation has not been reached. The substantial decrease in undiagnosed diabetes prevalence for men aged 50 years and older was driven by both a decrease in diabetes incidence and an increase in diagnosis rates during 2000-2016.

To our knowledge, this study provides the first estimates of the incidence of diabetes, and rates of diabetes diagnosis among the US adult population from nationally representative surveys. Previous studies using national survey data only estimated the incidence of diagnosed diabetes from self-reports and were not verified by medical records, which underestimate disease incidence. However, there are several limitations. First, there were a substantial number of model parameters governing spline surfaces that described the annual age-specific incidence of diabetes and rates of diabetes diagnosis. Computational complexity would have increased substantially if we had further stratified by race/ethnicity, levels of income and education, or other social economic factors, so we did not extend the analysis to this level of detail. Second, the overall response rates for the Continuous NHANES has decreased over recent survey years. Although not introducing bias in the final survey estimates, the declining response rates do increase sampling error, especially in populations with relatively low prevalence such as young adults ages 20-34 years. Third, our analysis combined type 1 and type 2 diabetes because national surveys NHANES, NHIS, BRFSS do not distinguish the subtypes of diabetes. Prevalence of diagnosed type 1 diabetes was approximately estimated using data from NHANES by defining type 1 diabetes with self-report age of diabetes diagnosis and self-report

treatment with insulin.<sup>53</sup> Prevalence of undiagnosed type 1 diabetes cannot be estimated from NHANES due to lack of laboratory confirmation on cases of type 1 diabetes. Since type 2 diabetes is understood to account for around 95% of all diabetes for adults, the results from our estimates are most likely to be representative of trends in type 2 diabetes.

We estimated an overall decrease in diabetes incidence and an increase in diabetes prevalence for US adults ages 20 years and older during 2000-2016. Rates of diabetes diagnosis did not increase over the same interval. The findings in our study have important implications for monitoring the diabetes epidemic and guiding prevention efforts in the future. Although the incidence of diabetes decreased, declining mortality among diagnosed diabetic populations, and high and increasing prevalence of all diabetes have resulted in continued high total burden of diabetes. Diabetes prevention efforts, and improved screening and diagnosis, are needed to reduce the burden of both diabetes and diabetes complications.

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# **Supplementary Material**

## 1. Analytic sample

Table S2.1 shows numbers of participants and participant characteristics in the analytic samples for the interview and laboratory examination, by survey cycle years for NHANES III (1988-1994) and Continuous NHANES (1999-2016).

	NHAN	NES III				Conti	nuous NH	IANES			
Survey	1988-	1992-	1999-	2001-	2003-	2005-	2007-	2009-	2011-	2013-	2015-
years	1991	1994	2000	2002	2004	2006	2008	2010	2012	2014	2016
	Mean	Mean	Mean	Mean	Mean						
	(95%	(95%	(95%	(95%	(95%	(95%	(95%	(95%	(95%	(95%	(95%
	CI)	CI)	CI)	CI)	CI)						
Interview	9488	9337	2168	2479	2299	2191	2901	3118	2781	2897	2814
sample (n)											
Laboratory	3227	3399	2168	2479	2299	2191	2901	3118	2781	2897	2814
sample (n)											
Women	52.4	53.8	50.6	51.4	51.3	50.8	51.3	51.2	51.7	51.3	51.3
(%)	(50.1,	(50.8,	(48.1,	(49.9,	(49.6,	(48.5 <i>,</i>	(48.9 <i>,</i>	(49.2,	(49.0,	(49.2,	(49.7,
	54.7)	55.3)	53.2)	53.0)	53.1)	53.1)	53.7)	53.1)	54.3)	53.4)	52.9)
Age	44.6	44.9	45.6	45.7	46.5	47.0	46.9	47.2	47.6	47.6	47.9
(mean,	(43.8 <i>,</i>	(43.7 <i>,</i>	(44.3 <i>,</i>	(44.0 <i>,</i>	(45.2 <i>,</i>	(45.4 <i>,</i>	(45.8 <i>,</i>	(46.1,	(46.3 <i>,</i>	(46.4 <i>,</i>	(46.7,
years)	45.4)	46.1)	46.9)	47.4)	47.7)	48.7)	48.0)	48.3)	48.9)	48.9)	49.1)
Ages 20-34	35.6	33.7	29.7	28.7	27.9	26.3	27.0	27.8	26.1	27.2	27.2
(%)	(33.5,	(31.0,	(26.1,	(24.2,	(25.0,	(23.1,	(23.8,	(24.9,	(22.4,	(24.5,	(23.8,
	37.8)	36.5)	33.7)	33.7)	31.1)	29.9)	30.5)	30.9)	30.3)	30.1)	30.8)
Ages 35-49	29.2	31.3	33.1	33.2	32.0	32.5	30.7	28.7	28.7	27.2	26.3
(%)	(27.2,	(29.0 <i>,</i>	(29.1,	(29.6,	(28.6,	(27.6,	(26.7,	(26.8,	(25.4,	(23.8,	(23.3,
	31.4)	33.6)	37.2)	37.0)	35.7)	37.8)	35.1)	30.1)	32.2)	30.9)	29.7)
Ages 50-64	18.3	17.9	21.3	23.2	23.6	23.8	25.4	25.5	27.8	26.8	25.9
(%)	(17.6,	(16.2,	(19.0,	(19.4,	(20.3,	(20.8,	(22.3,	(22.6,	(24.7,	(24.2,	(23.1,
	19.1)	19.8)	23.8)	27.6)	27.2)	27.1)	28.8)	28.7)	31.1)	29.7)	28.8)
Ages ≥ 65	16.8	17.1	15.9	14.8	16.5	17.4	16.8	18.3	17.4	18.7	20.6
(%)	(15.1,	(14.7,	(14.0,	(13.0,	(14.2,	(14.0,	(14.9,	(16.8,	(15.8,	(16.3,	(18.1,
	18.7)	19.7)	18.0)	16.8)	19.1)	21.3)	19.0)	19.8)	19.1)	21.4)	23.4)

Table S2.1. Description of participants in the analytic sample of interview questionnaire and laboratory examination for NHANES III (1988-1994) and Continuous NHANES (1999-2016).

#### 2. Markov model

We developed a Markov model to represent undiagnosed and diagnosed diabetes in the U.S. population ages 20 year and older between 2000-2016. Four disease states were distinguished: disease-free (state 0), undiagnosed diabetes (state1), diagnosed diabetes (state 2), and death (state 3) (Figure S2.1 Panel A).

We modeled the transition probabilities between the four states by single year of age (i) and single calendar year (t) with the transition matrix presented in Figure S2.1 Panel B. The transition probabilities include mortality rates (noted as  $\mu$ ) and incidence rates (noted as  $\lambda$ ). We estimated mortality rates by from national life tables.<sup>1</sup> We estimated incidence rates by constructing individual B-spline surfaces with weakly-informative priors for parameters of the surfaces (see main manuscript).

Age- and sex-specific yearly mortality rates for each of the three diabetes states ( $\mu_{df}$ ,  $\mu_{ud}$ ,  $\mu_{dd}$ ) were estimated using 1) all-cause mortality rates (M) among the general population, 2) prevalence of undiagnosed and diagnosed diabetes ( $pr_{ud}$ ,  $pr_{dd}$ ), 3) and risk ratios ( $rr_{ud}$ ,  $rr_{dd}$ ) of all-cause mortality for undiagnosed and diagnosed diabetes compared to those without diabetes.

The mortality rates for disease-free ( $\mu_{df}$ ) were estimated based on subtracting diabetes-related mortality from all-cause mortality based on prevalence and risk ratios estimates, using equation (1).

$$\mu_{df} = M/(1 + (rr_{ud} - 1)*pr_{ud} + (rr_{dd} - 1)*pr_{dd})$$
(1)

#### where

M is the all-cause mortality rates among the general population, which was obtained from the annual United States Life Tables by NCHS.<sup>1</sup>

 $rr_{ud}$  is the risk ratio of all-cause mortality of undiagnosed diabetes to all-cause mortality of disease free, which was estimated from the SNHANES-MS<sup>2</sup> and reported in Table S2.2.

pr<sub>ud</sub> is the prevalence of undiagnosed diabetes, which was estimated from the NHANES III and Continuous NHANES.

 $rr_{dd}$  is the risk ratio of all-cause mortality of diagnosed diabetes to all-cause mortality of disease free, which was estimated from the SNHANES-MS<sup>2</sup> and reported in Table S2.2.

 $pr_{dd}$  is the prevalence of diagnosed diabetes, which was estimated from the NHANES III and Continuous NHANES.

Mortality rates for undiagnosed diabetes ( $\mu_{ud}$ ) and diagnosed diabetes ( $\mu_{dd}$ ) were estimated based on the mortality rates for disease-free ( $\mu_{df}$ ) and corresponding risk ratios ( $rr_{ud}$ ,  $rr_{dd}$ ), using equation (2) and equation (3).

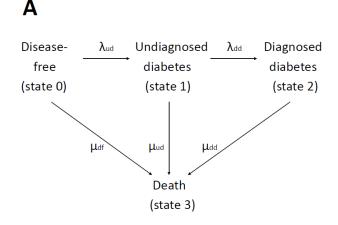
$$\mu_{ud} = rr_{ud}^* \mu_{df} \tag{2}$$

$$\mu_{dd} = rr_{dd}^* \mu_{df} \tag{3}$$

The total number of parameters in our model was 324. In each sex, there were 48 parameters defining the B-spline surface for incidence of diabetes ( $\lambda_{ud}$ ), 48 parameters defining the B-spline surface for diagnosis rate of diabetes ( $\lambda_{dd}$ ), 33 parameters for the risk ratios of undiagnosed diabetes to diseasefree (rr<sub>ud</sub>), 33 parameters for the risk ratios of diagnosed diabetes to disease-free (rr<sub>dd</sub>).

To avoid overfitting and computational complexity, it is usually not necessary to place a knot at every interval (calendar year) in a spline function. A penalized spline that uses a reduced set of equidistant knots based on the B-spline basis is suggested as a general class of spline regression to approximate smoothing.<sup>3-5</sup> Penalty level, denoted as  $\theta$ , controls the trade-off between smoothness and model fit.  $\theta=0$  implies that a smoothing spline interpolates the data, while  $\theta=\infty$  implies a linear function.<sup>3</sup> Figure S2.2. shows the B-splines basis when applying different levels of penalty:  $\theta = 0$ ,  $\theta = 1$ ,  $\theta = 55$  to the B-spline surface of incidence of diabetes at year dimension.

Each B-spline surface had 5 knots with 2 degrees of freedom in the age dimension and 7 knots with 2 degrees of freedom in the calendar year dimension, resulting in a total of (5+2-1)\*(7+2-1)=48 number of parameters. For the risk ratios  $(rr_{ud})$ , each had 33 parameters as independent means of the estimated risk ratios for 11 survey cycle years (2 for NHANES III and 9 for Continuous NHANES) by 3 age groups (20-49, 50-64, and  $\geq$ 65 years). We specified weakly informative priors for 96 parameters of B-spline surfaces. We specified log-normal distributions for the risk ratios, with priors of means estimated by fitting Cox proportional hazards models on data from the Second National Health and Nutrition Examination Survey Mortality Study (SNHANES-MS)<sup>2</sup> and reported in Table S2.2. The most recent available data of SNHANES-MS was survey cycle year of 2009-2010. We set the means of risk ratios after 2010 equal to the estimates in 2009-2010 and allowed broad standard deviations.



# В

	Disease free	Undiagnosed diabetes	Diagnosed diabetes	Death
	0	1	2	3
0	$(1-\lambda_{\text{ud}(i,t)}-\mu_{\text{df}(i,t)}$	$\lambda_{ud(i,t)}$	0	$\mu_{df(i,t)}$
1	0	$1\text{-}\lambda_{\text{dd}(i,t)}-\mu_{\text{ud}(i,t)}$	$\lambda_{dd(i,t)}$	$\mu_{ud(i,t)}$
2	0	0	$1\text{-}\mu_{dd(i,t)}$	$\mu_{dd(i,t)}$
3	0	0	0	1 )

# Figure S2.1. A four-state Markov model of undiagnosed and diagnosed diabetes (Panel A) and states transition matrix for individuals at single year of age (i) and single calendar year (t).

df=disease free; ud=undiagnosed diabetes; dd=diabetes diagnosis.

 $\lambda_{ud}$ : diabetes incidence rate, representing the transition rate from disease-free to undiagnosed diabetes.  $\lambda_{dd}$ : diagnosis rate of diabetes, representing the transition rate from undiagnosed to diagnosed diabetes.  $\mu_{df}$ : all-cause mortality rate for disease-free individuals.

 $\mu_{ud}$ : all-cause mortality rate for undiagnosed diabetic individuals, representing the transition rate from undiagnosed diabetes to death,  $\mu_{ud} = rr_{ud}^* \mu_{df}$ .

 $\mu_{dd}$ : all-cause mortality rate for diagnosed diabetic individuals, representing the transition rate from diagnosed diabetes to death,  $\mu_{dd} = rr_{dd}^* \mu_{df}$ .

rr<sub>ud</sub>: Risk ratio of all-cause mortality of undiagnosed diabetes to all-cause mortality of disease-free. rr<sub>dd</sub>: Risk ratio of all-cause mortality of diagnosed diabetes to all-cause mortality of disease-free.

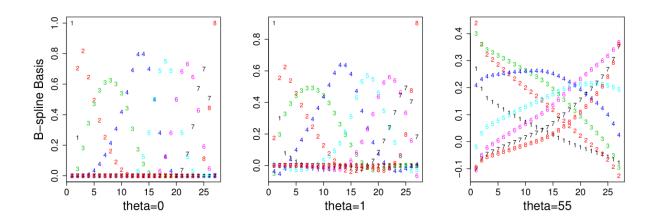


Figure S2.2. Example of B-spline basis with three different levels of penalty  $\theta$  = 0,  $\theta$  = 1,  $\theta$  = 55.

NHANES III				Continuous NHANES					
Sex and	1988-	1991-	1999-	2001-	2003-	2005-	2007-	2009-	
age group	1990	1994	2000	2002	2004	2006	2008	2010	
Risk ratios for all-cause mortality comparing undiagnosed diabetes to those without diabetes (rr <sub>ud</sub> )									
Men									
Ages 20- 49	5.06	4.65	3.98	5.60	4.50	6.35	6.55	3.91	
Ages 50- 64	1.19	1.16	1.12	1.32	1.21	1.49	1.54	1.15	
Ages ≥65	1.09	1.05	1.06	1.20	1.08	1.37	1.41	1.07	
Women									
Ages 20- 49	3.73	3.19	3.13	2.16	2.53	2.57	2.60	3.32	
Ages 50- 64	2.19	1.87	1.84	1.27	1.48	1.51	1.53	2.29	
Ages ≥65	1.66	1.42	1.39	1.02	1.12	1.14	1.16	1.25	
Risk rati	os for all-ca	ause mortali	ty comparin	g diagnosed	diabetes to	those witho	out diabetes	(rrd <sub>d</sub> )	
Men									
Age 20-49	7.59	7.21	6.42	8.34	8.42	8.13	6.39	7.09	
Age 50-64	2.70	2.57	2.29	2.97	3.00	2.90	2.28	2.53	
Age ≥65	1.37	1.30	1.16	1.50	1.52	1.47	1.15	1.28	
Women									
Age 20-49	4.38	5.09	4.28	3.36	4.11	4.27	4.68	3.28	
Age 50-64	3.15	3.66	3.08	2.41	2.95	3.07	3.36	2.35	
Age ≥65	1.99	2.31	1.94	1.52	1.86	1.93	2.12	1.49	

Table S2.2. The risk ratios for all-cause mortality of undiagnosed and diagnosed diabetes compared to the general population without diabetes, by age groups and sex.

#### 3. Evaluation of model fits with posterior predictive checks

We used posterior predictive checks to evaluate the model fits to prevalence trends implied by NHANES data.<sup>6</sup> Visual comparison of modelled estimates (mean and 95% predictive intervals [95% PI]) to empirical values (mean and confidence intervals) for prevalence of undiagnosed, diagnosed, and all diabetes are presented in Figure S2.3 and Figure S2.4, by sex and age groups.

Model fits with posterior predictive checks were evaluated based on the proportion of empirical values observed from NHANES data being covered by the percentage of predictive intervals of modelled estimates. The proportion of observed NHANES data covered by the percentage of PI of modelled estimates for undiagnosed, diagnosed, and all diabetes, from 0% PI to 100% PI by 0.05 increment of the sequence, were plotted in Figure S2.5 for men and women separately. In details, in each panel of Figure S2.5, the x-axis represented the percentage from 0% to 100% PI of modelled estimates for each of the prevalence quantity by 5% increment of the sequence. The y-axis represented the proportion of observed data for each of the prevalence quantity from NHANES covered by the PI of modelled estimates. For example, the 95% PI covered 96.8% of observed prevalence of diagnosed diabetes for men and 98.4% of diagnosed diabetes for women, respectively. Most of the points were slightly higher or close to the 45-degree line, indicating that nearly all of the model estimated PIs covered slightly more or equal to the corresponding proportion of empirical values from the observed data. In summary, the posterior predictive checks showed that our model predicted the prevalence of diabetes well.

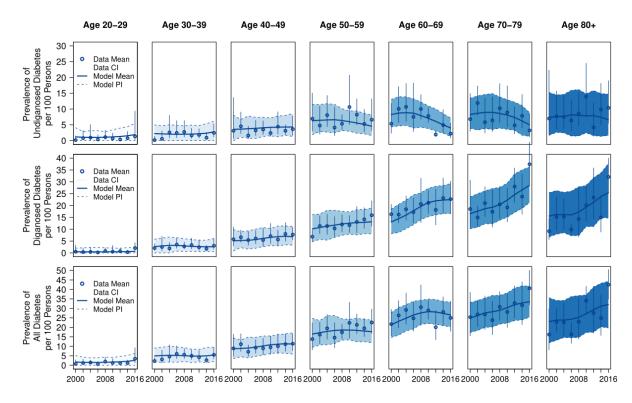


Figure S2.3. Model fits of observed NHANES estimates (mean and confidence intervals) versus model predictions (mean and predictive intervals) of prevalence of undiagnosed, diagnosed and all diabetes, by age group in men during 2000-2016.

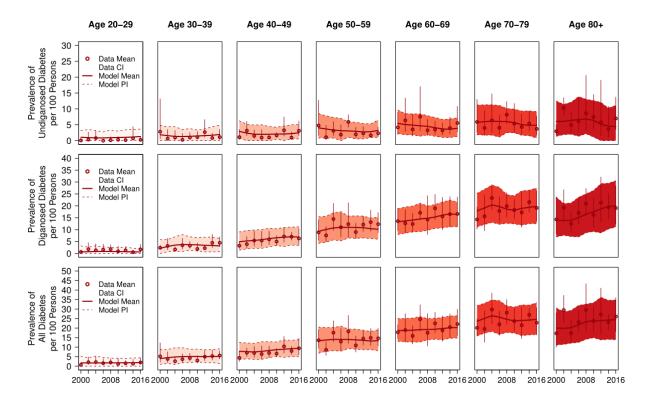


Figure S2.4. Model fits of observed NHANES estimates (mean and confidence intervals) versus model predictions (mean and predictive intervals) of prevalence of undiagnosed, diagnosed and all diabetes, by age group in women during 2000-2016.

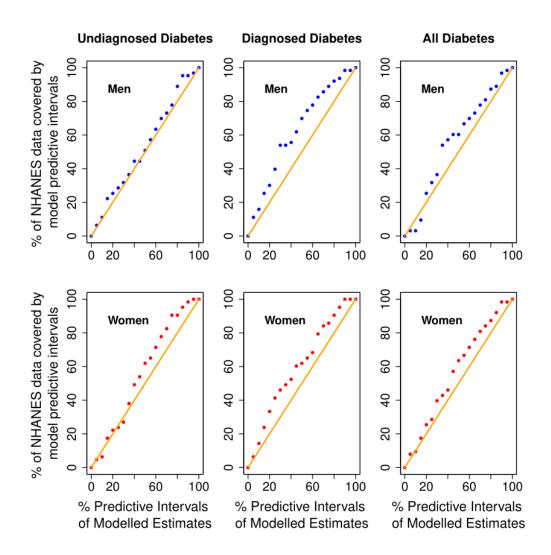


Figure S2.5. Model fits evaluation: proportion of observed NHANES data covered by percentage of model posterior predictive intervals by outcomes and sex.

## 4. Wide uncertainty intervals (UIs) of incidence estimates

In these analyses, the uncertainty intervals (UIs) were wider for estimates of incidence than estimates of prevalence (Figure 2.3 and Figure 2.4). This is due to our model being calibrated to prevalence of undiagnosed, diagnosed, and all diabetes using data from NHANES. NHANES doesn't have measures for incidence of diabetes, and incidence of diabetes diagnosis among undiagnosed adults. In addition, our analysis did not consider claims data or other cohort studies with measures of incidence of diabetes. Therefore, our model was not fit to to incidence estimates but only prevalence estimates from empirical data, leading to wider UIs of model estimated incidence than model estimated prevalence, across all age groups. Second, when only examining UIs of incidence, absolute width of UIs was not larger among old age groups than young age groups. For example, absolute width of UIs of incidence of diabetes diagnosis for women adults ages 50-64 years, and ages 65 years and older were smaller than that for women ages 20-49 years. Moreover, the relative width of UIs was also not larger among old age group than young age groups. For example, the UIs of incidence of diabetes were similar twice of the mean estimates for women ages 20-34 years and women ages 50-64 years.

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Chapter 3. Risk score to predict cardiovascular disease risk for patients with type 2 diabetes mellitus in the United States: a pooled analysis of prospective cohorts

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## Abstract

#### Background

Previous research has shown that most cardiovascular disease (CVD) prediction models developed for the general population tend to underestimate CVD risk for diabetic patients. Current prediction equations specifically designed for patients with type 2 diabetes mellitus (T2DM) were developed using data from randomized clinical trials, and may lack generalizability to diabetic populations without intensive treatment and routine management. We developed a model to predict CVD risk (defined as fatal-plus-non-fatal coronary heart disease and stroke) among diabetic patients in the United States.

#### Methods

We used data from diabetic patients with no history of CVD enrolled in five prospective cohort studies in the United States. With these data, we estimated the coefficients of a risk equation for fatal-plusnon-fatal CVD, using a sex-and-cohort stratified Cox proportional-hazards model. The risk prediction equation included age, body mass index (BMI), current smoking, systolic blood pressure (SBP), total cholesterol (TC), high-density lipoproteins cholesterol (HDL-C), fasting plasma glucose (FPG), treatment with hypertension medications, and treatment with diabetes medications. We conducted internal validation and out-of-sample cross-validation to evaluate model discrimination and calibration.

#### Findings

We included data from 3,723 participants with diabetes. The mean age at baseline was 60 years (standard deviation 9.6), and 48.6% of eligible participants were women. During 15 years of follow-up, 659 (34.5%) men and 451 (24.9%) women developed a first CVD event. The risk score demonstrated good discrimination (Harrell's C statistic, 70% [95% confidence interval, 68% to 72%]) and calibration (regression slope, 0.99 [0.98 to 1.00]). In the cross-validation, the median C statistic was 70%, with a

range of 68% to 71%. The median slope of the calibration regression was 0.99, with a range of 0.96 to 1.05.

# Conclusions

We developed a novel CVD risk prediction model specifically for populations with T2DM in the United States. Our risk equation demonstrated improved performance relative to current models, which underestimate the total CVD risk among diabetic patients.

# Background

Patients with type 2 diabetes mellitus (T2DM) have a two-to-three-fold increased risk of cardiovascular disease (CVD) and death compared to people without diabetes.<sup>1–6</sup> T2DM patients also have substantially greater health resource use and economic costs from CVD than people without T2DM.<sup>7,8</sup> Multifactorial interventions through the management of high blood pressure, hypercholesterolaemia and hyperglycaemia have been effective in reducing the risk of fatal-plus-nonfatal CVD among diabetic populations.<sup>9–12</sup> Most guidelines for CVD prevention considered diabetes as a "coronary risk equivalent" that assigns patients with T2DM without prior myocardial infarction (MI) a high risk of coronary heart disease (CHD) similar to non-diabetic individuals who have had a MI.<sup>13–19</sup> The potential benefits of such treatment is often estimated using models obtained from the general population including diabetes as a predictor.<sup>1,2,4,20-23</sup> These risk prediction models usually do not perform well in diabetic populations, with moderate to poor discrimination or calibration.<sup>24,25</sup> Previous research showed that most CVD prediction models developed in the general population tend to underestimate CVD risk for diabetic populations, due to differences in CVD incidence between the diabetic and general populations.<sup>25–29</sup> Several studies in recent years have suggested that this problem could be overcome by developing diabetes-specific prediction models using data from exclusively diabetic populations.<sup>25,28</sup>

However, current diabetes-specific CVD prediction models have their own limitations. First, most data for model formation and validation have been derived from a limited set of populations, mostly from developed countries or Caucasian diabetic populations outside of the US.<sup>30–36</sup> There is growing evidence that the risk equations developed in one population cannot be applicable to other populations or between subgroups of population within a country.<sup>37,38,38,39</sup> This is because the mean risk factor levels and other determinants of CVD and death, such as genetics, societal factors, health care system for diagnostic, treatment, and follow-up among diabetic populations are different, resulting in differences in the risk of CVD and death between different diabetic populations and over

time. Second, current available diabetes-specific models developed among US populations predict only an individual CVD component such as CHD, rather than the combination of major CVD events, which is of interest to patients and care providers.<sup>40,41</sup> Recently, two diabetes-specific models have been developed based on multi-center data of clinical trials from multiple countries.<sup>39,42,43</sup> These models were developed and validated in clinical trial populations, and may lack generalizability to diabetic populations without intensive treatment regimens. Compared to other CVD risk equations,<sup>1,36</sup> these models used data with fewer years of follow-up<sup>39,42</sup> or had inferior internal validation.<sup>43</sup>

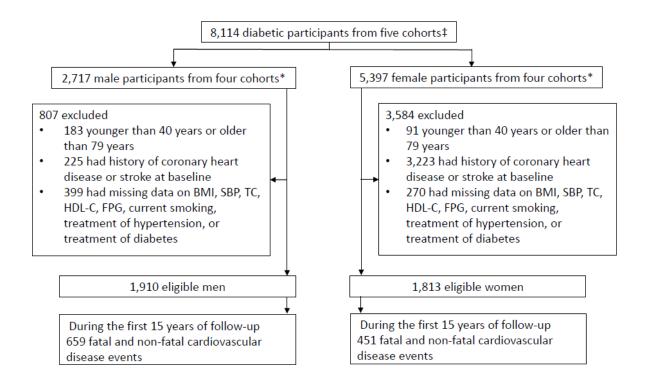
Therefore, we developed a novel CVD risk prediction model specifically for populations with T2DM in the US. Our model can be used to quantify the CVD disease burden over the next decade, simulate treatment guidelines and evaluate effectiveness and cost-effectiveness of interventions strategies, and guide primary care prevention policies for US diabetic populations. Although there are only a few countries with diabetes registries that have CVD and death rates among diabetic populations at this moment, our approach allows for recalibration of the model for use in different countries when the data become available.

# Methods

#### **Data sources**

We collated individual-level data from 10 prospective cohorts: the Atherosclerosis Risk in Communities (ARIC), the Cardiovascular Health Study (CHS), the Framingham Heart Study original cohort (FHS-original), the Framingham Heart Study offspring cohort (FHS-offspring), the Honolulu Heart Program (HHP), the Puerto Rico Heart Health Program (PRHHP), the Jackson Heart Study (JHS), the Multi-Ethnic Study of Atherosclerosis (MESA), the Multiple Risk Factor Intervention Trial (MRFIT), and the Women's Health Initiative Clinical Trial and Observational Study (WHICTOS). We excluded the FHS-original and FHS-offspring cohorts because the total number of individuals with diabetes was low (less than 200 in each cohort). HHP, PRHHP and JHS were excluded due having to few CVD events (less than 50 in each cohort) among eligible participants with diabetes who met our study inclusion criteria. We pooled individual-level data from the remaining 5 cohorts (ARIC, CHS, MESA, MRFIT, and WHICTOS). Pooling data from multiple cohorts enhanced statistical prediction power, which in turn allowed inclusion of interaction terms between age or sex and risk factors. Pooling data from multiple cohorts also reduced the effect of between-cohort variation on the coefficients.

Participants with diabetes were defined as individuals who had any one of (i) self-reported diabetes, (ii) medication with insulin or oral hypoglycaemic agents, (iii) fasting plasma glucose ≥126 mg/dL or 7mmol/L, (iv) random plasma glucose  $\geq$  200 mg/dL or 11.1 mmol/L, or (v) postprandial plasma glucose ≥225 mg/dL or 12.5 mmol/L at baseline, depending on the available data in each cohort. Our definition of diabetes did not distinguish between type 1 and type 2 diabetes, as most of the cohort studies did not distinguish the subtypes of diabetes. Since T2DM is generally considered as accounting for almost 95% of all diabetes for adults, risk prediction equation developed in this study will be more applicable to patients with T2DM. We included participants who were aged older than 40 years and younger than 80 years at baseline, due to the small number of events in younger participants and the heterogeneity and complexity of age-covariate interactions in the elderly population.<sup>1,44</sup> Participants were included if they did not have a history of CHD or stroke. The number of female participants with a history of CHD or stroke at baseline was 3,223, which was much larger than the number in male participants (225). This can be explained by that the substantial sex/gender differences in the prevalence and burden of CVDs among diabetic populations.<sup>45</sup> This was also consistent with findings from the previous Globorisk study that the association of CVD risk and diabetes was stronger in women than in men.<sup>2</sup> In addition, this can be explained by the inclusion of male participants from the MRFIT cohorts. Male participants from MRFIT were aged between 40-57 years at baseline, compared with female participants from the four perspectives were aged from 45-79 years. Female participants accounted for a larger proportion of the elderly population in which the prevalence of baseline CVD is greatest.<sup>46</sup> A total of 669 participants were excluded if they had missing data for the risk factors used in the risk prediction equation. After exclusion, 3,723 participants with diabetes (mean age, 60 years; 1,813 women) were included in the analysis (Figure 3.1).



## Figure 3.1. Flowchart of inclusion and exclusion of cohort participants.

 $\pm$ Diabetic participants were defined as individuals who had any one of (i) self-reported diabetes, (ii) medication with insulin or oral hypoglycaemic agents, (iii) fasting plasma glucose ≥126 mg/dL or 7mmol/L, (iv) random plasma glucose ≥200 mg/dL or 11.1 mmol/L, or (v) postprandial plasma glucose ≥225 mg/dL or 12.5 mmol/L at baseline, depending on the available data in each cohort.

\*The Multiple Risk Factor Intervention Trial include only men, and the Women's Health Initiative Clinical Trial includes only women.

Abbreviations: BMI = body mass index, SBP = systolic blood pressure, TC = total cholesterol, HDL-C = high density lipoprotein-cholesterol, FPG = fasting plasma glucose

## **Statistical analysis**

Cox proportional hazards regression was used to estimate the coefficients of the risk equation to

predict 10-year risk of a first CVD event for patients with T2DM in the United States.<sup>47</sup> Similar to

previous cohort pooling studies, the baseline CVD hazard was allowed to vary by sex and cohort.

Importantly, this formulation of the risk prediction equation also facilitates recalibration of the risk

equation in other countries where CVD incidence and mortality data among diabetic populations

becomes available, e.g. through linked data from diabetes registries.

The primary outcome for our model was fatal-plus-non-fatal CVD, which was defined any one of nonfatal myocardial infarction (MI, ICD10 codes I21-I22) or stroke (ICD10 codes I60-I69), death from ischaemic heart disease (IHD), sudden cardiac death (ICD10 codes I20-I25), or death from stroke. Outcomes were assessed over a 10-year period. Events data defined by ICD10 codes were not in use during the follow-up period for most these cohorts. We defined model outcome events using ICD10 codes and mapped them to clinical endpoints defined by each cohort's event ascertainment and adjudication committee. Heart failure was not included in the outcome events because the adjudication of heart failure varied substantially between study cohorts. We truncated participants with follow-up longer than 15 years, because baseline risk factors might have little value in the prediction of CVD events after a long period of time.

Covariates included in our model were age, current smoking, body mass index (BMI), systolic blood pressure (SBP), total cholesterol (TC), high-density lipoproteins cholesterol (HDL-C), fasting plasma glucose (FPG), treatment with hypertension medications, and treatment with diabetes medications. These covariates were chosen according to their causal effects on CVD and relevance to diabetes history or intensity.<sup>48–58</sup> We considered but did not select other variables such as low-density lipoprotein cholesterol, hemoglobin A1c, duration of diabetes or age at onset of diabetes because they were not measured in the baseline examination cycle of one or more of the cohorts. Baseline participant characteristics included in the risk prediction model are summarized in Table 3.1. We tested and confirmed that the assumption of proportionality of hazards of included covariates was met (Table S3.1 in the Supplementary Material). We included interaction terms between sex and SBP, and age and SBP, due to significant sex differences in CVD risk and gradient of CVD risk associated with increasing SBP.<sup>59,60</sup> We included an interaction term between sex and age because evidence suggests the existence of sex differences in the proportional changes in CVD risk with age.<sup>61–63</sup> We included an interaction term between sex and age because evidence suggests the existence of sex differences in the proportional changes in CVD risk with age.<sup>61–63</sup> We included an interaction term between sex and age because evidence suggests the existence of sex differences in the proportional changes in CVD risk with age.<sup>61–63</sup> We included an interaction term between sex and age because evidence suggests the existence of sex differences in the proportional changes in CVD risk with age.<sup>61–63</sup> We included an interaction term between sex and age because shown that the CVD hazard ratio of BMI often decreases with age.<sup>52</sup>

Cohort	ARIC	СНЅ	MESA	MRFIT	WHICTOS	Pooled
Baseline date	1986-1990	1989-1993	2001	1973-1976	1993	1986-2001
Median follow-up years	14.9	8.8	8.4	6.8	8.0	8.3
Number of participants	1242	662	830	647	342	3723
Percent female	58.6	51.9	47.8	0	100	48.6
Age range at baseline	45-66	65-79	45-79	40-57	50-79	40-79
Mean (SD) age at baseline	55.9 (5.7)	71.4 (3.9)	63.9 (8.8)	49.0 (4.7)	63.7 (6.7)	59.9 (9.6)
Number of fatal-plus- non-fatal CVD	423	315	112	206	54	1110
Percent current smoker	22.9	11.2	13.7	53.6	8.2	22.7
Mean (SD) systolic blood pressure (mm Hg)	129.8 (20.6)	140.3 (21.3)	132.7 (21.8)	141.7 (15.9)	134.4 (17.7)	134.8 (20.6)
Mean (SD) body mass index	31.0 (5.8)	28.7 (4.2)	30.7 (5.8)	28.7 (3.5)	32.1 (6.2)	30.2 (5.4)
Mean (SD) total cholesterol (mmol/L)	5.7 (1.2)	5.4 (1.1)	4.9 (1.0)	6.0 (1.1)	5.8 (1.1)	5.5 (1.2)
Mean (SD) high-density lipoproteins cholesterol (mmol/L)	1.2 (0.4)	1.2 (0.3)	1.2 (0.3)	1.0 (0.3)	1.3 (0.3)	1.2 (0.4)
Mean (SD) fasting plasma glucose (mmol/L)	9.7 (3.9)	9.4 (3.4)	8.3 (3.1)	7.2 (2.0)	9.2 (3.2)	8.8 (3.4)
Percent treated with hypertension medications*	51.0	62.4	62.7	58.4	48.2	56.7
Percent treated with diabetes medications	40.8	53.0	81.0	20.9	55.8	49.9

Table 3.1. Information about cohorts used in estimating the coefficients of the risk score.

\*Treatment with hypertension medication was a binary covariate. The reference group included individuals who had blood pressure levels not being diagnosed as hypertension, and/or who had hypertension but were not taking hypotension lowering medications at baseline.

‡Abbreviation: ARIC = atherosclerosis risk in communities; CHS = cardiovascular health study; MESA = multiethnic study of atherosclerosis; MRFIT = multiple risk factor intervention trial; WHICTOS = women's health initiative clinical trial and observational study. Detailed information on these cohorts are provided elsewhere. SD = standard deviation.

We fitted several alternative models and evaluated if they have improvement in model fit. We fitted a sex-specific multivariable risk factor algorithm by adding interaction terms between sex and risk factors due to the findings of prospective studies that said sex differences in CVD risk with risk factors.<sup>64–66</sup> We included a covariate indicating firstly, whether a diabetic patient was under treatment with hypertension medications, and secondly, whether his/her SBP level match the target set by the recent Guideline for the Prevention, Detection, Evaluation and Management of High Blood Pressure in Adults.<sup>67,68</sup> This covariate was defined in two ways with different SBP cutoff points: elevated blood pressure with SBP  $\geq$ 120 mm Hg; or hypertension with SBP  $\geq$ 140 mm Hg. For example, the covariate with a cutoff point of 140 mm Hg of SBP was defined as a four-level categorical variable: "hypertension (SBP  $\geq$ 140 mm Hg) without antihypertensive drugs", "hypertension (SBP  $\geq$ 140 mm Hg) with antihypertensive drugs", "SBP controlled (<140 mm Hg) with antihypertensive drugs", using "SBP controlled (<140 mm Hg) without antihypertensive drugs" as the reference group. According to the work from the Prospective Study Collaboration that TC/HDL-C ratio is more informative than HDL or TC in predicting cardiovascular risk, we fitted another alternative model by replacing HDL-C and TC as separate covariates to TC/HDL-C ratio as one covariate.<sup>64</sup> We used improvement in model fit, which was defined as a relative discrimination improvement on Harrell's C statistic of 2% or more, as the criteria for model selection.

We conducted internal validation to examine the discrimination and calibration of the fitted model. Discrimination, which compares the predicted survival time between cases and non-cases and examines whether the cases have shorter survival time, was evaluated using Harrell's C statistic.<sup>69–71</sup> Calibration, which measures the ability of the risk equation to correctly quantify the absolute 10-year CVD risk, was evaluated by comparing the predicted number of events during 10 years of follow-up with the observed number of events (corrected for censoring with the Kaplan-Meier estimator), stratified by sex and decile of risk.

We also examined out-of-sample predictive performance via cross-validation, as a more rigorous test of model fit. To do so, we first randomly split the data into five folds. We then iteratively withheld each two of the five folds as a testing set and used the other three folds to estimate the risk factor

coefficients; we then recalibrated the model to the testing set by replacing the mean risk factor levels and the baseline hazard and estimated discrimination and calibration statistics for each comparison.

We compared out fitted model to other recent risk models developed in the general population in the US, the atherosclerotic cardiovascular disease (ASCVD) risk equations published in the 2013 ACC/AHA Guidelines,<sup>1</sup> with a validation analysis in our study population. To examine whether CVD risk prediction models developed in the general population underestimate the real CVD risk in patients with T2DM, we compared the actual observed 10-year risk with the predicted 10-year risk of ASCVD by the 2013 ACC/AHA Pooled Cohort Risk Equation in our study population.

All analyses were performed with R (R-3.5.2). The study protocol was approved by the institutional review board at the Harvard T.H. Chan School of Public Health (Boston, MA, USA).

# Results

We included 3,723 participants with T2DM in the estimation of the proportional hazards model (Figure 3.1, Table 3.1). The mean age at baseline was 60 years (standard deviation 9.6) and 48.6% of eligible participants were women. During 15 years of follow-up, 659 (34.5%) men and 451 (24.9%) women had a first CVD event. Without controlling for differences in covariates, women had a lower risk of fatal-plus-non-fatal CVD (the 10-year risk was 21.3% in women versus 38.4% in men, p<0.0001).

The coefficients and hazard ratios (HRs) of the multivariable-adjusted regression for prediction of the 10-year risk of a first CVD event are presented in Table 2. Current smoking (HR: 1.36 [95% Cl, 1.17 to 1.58]), increased TC (HR: 1.14 [1.08 to 1.21]), increased FPG with diabetes medications (HR: 1.04 [1.02 to 1.05]) had positive and statistically significant associations with CVD risk (p<0.0001). Increased HDL-C was associated with decreased fatal-plus-non-fatal CVD risk (HR: 0.60 [0.49 to 0.73]). HRs of risk factors that were not statistically significant at the 5% level ranged from 1.00 to 1.17. The magnitude of the association of SBP with an increased CVD risk was stronger in women than in men (HR: 1.07 [1.00 to 1.31]) (Table 3.2).

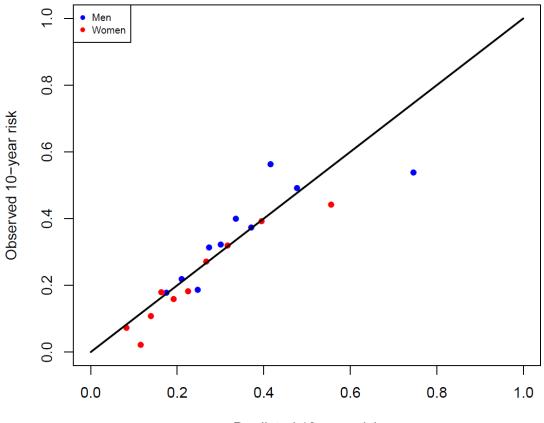
The Harrell's C statistic for the final model was 70% (68% to 72%) in the total study population, 66% (62% to 69%) in men and 75% (95% CI, 72% to 78%) in women (Table 3.3). The calibration regression slopes were 0.99 (95% CI, 0.98 to 1.00) in the total study population, 0.98 (95% CI, 0.95 to 1.01) in men, and 1.00 (95% CI, 0.99 to 1.02) in women (Figure 3.2). In the cross-validation, the median C statistic was 70%, with a range of 68% to 71% and the median slope of calibration regression was 0.99, with a range of 0.96 to 1.05 (Table 3.3).

Risk Factors	Coefficient (95% CI)	Hazard Ratio (95% CI)
Age (year)	0.0249	1.03 (0.92 to 1.14)
	(-0.0788 to 0.1286)	
Age squared	0.0003	1.00 (0.99 to 1.01)
	(-0.0004 to 0.0011)	
Current smoking	0.3065	1.36 (1.17 to 1.58)
	(0.1557 to 0.4572)	
Body mass index (per 1 unit)	0.0194	1.02 (0.94 to 1.11)
	(-0.0637 to 0.1025)	
Systolic blood pressure (per 10 mm Hg)	0.1602	1.17 (0.97 to 1.43)
<b>T</b> · · · · · · · · · · · · · · · · · · ·	(0.0356 to 0.3561)	1 1 1 (1 00 + 1 01)
Total cholesterol (per 1mmol/L)	0.1334	1.14 (1.08 to 1.21)
Lieb density linearetains abeleatenel (non	(0.0801 to 0.1868) -0.5180	0.00(0.40+0.72)
High-density lipoproteins cholesterol (per 1mmol/L)	-0.5180 (-0.7221 to -0.3139)	0.60 (0.49 to 0.73)
Fasting plasma glucose (per 1mmol/L)	0.0034	1.00 (0.98 to 1.03)
rasting plasma glucose (per minor/L)	(-0.0183 to 0.0251)	1.00 (0.98 (0 1.03)
Treatment with hypertension medications*	0.0686	1.07 (0.94 to 1.22)
reachent with hypertension meanations	(-0.0580 to 0.1951)	1.07 (0.34 to 1.22)
Treatment with diabetes medications and fasting	0.0348	1.04 (1.02 to 1.05)
plasma glucose (per 1mmol/L)	(0.0213 to 0.0483)	,
Age and female	0.0028	1.00 (0.98 to 1.03)
-	(-0.0207 to 0.0264)	
Systolic blood pressure (per 10 mm Hg) and	0.0633	1.07 (1.00 to 1.13)
female	(0.0047 to 0.1220)	
Age and systolic blood pressure (per 10 mm Hg)	-0.0017	1.00 (0.99 to 1.00)
	(-0.0048 to 0.0013)	
Age and body mass index (per 1 unit)	-0.0004	1.00 (0.99 to 1.00)
	(-0.0018 to 0.0010)	

 Table 3.2. Coefficients and hazard ratios from the Cox proportional hazard model used to predict the 10-year risk of fatal-plus-non-fatal CVD for patients with T2DM.

\*Treatment with hypertension medication was a binary covariate. The reference group included individuals who had blood pressure being diagnosed as not having hypertension, and/or who had hypertension but were not taking hypotension lowering medication at baseline.

Abbreviation: CVD = cardiovascular disease; FPG = fasting plasma glucose; T2DM = type 2 diabetes mellitus.



Predicted 10-year risk

Figure 3.2. Observed and predicted 10-year risk of a cardiovascular disease event in risk score internal validation, by deciles of risk and sex.

CVD Risk Model		Discrimination	Calibration regression slope
	Cohort name	Harrell's C statistic (95% CI)	Mean (95% CI)
Internal validation	Total	70 (68 to 72)	0.99 (0.98 to 1.00)
	Men	66 (62 to 69)	0.98 (0.95 to 1.01)
	Women	75 (72 to 78)	1.00 (0.99 to 1.02)
Cross-validation in each	1 <sup>st</sup> testing set	69 (66 to 73)	0.99 (0.95 to 1.03)
of the ten sets of	2 <sup>nd</sup> testing set	68 (65 to 72)	1.03 (0.99 to 1.07)
testing data*	3 <sup>rd</sup> testing set	70 (66 to 73)	1.01 (0.99 to 1.03)
	4 <sup>th</sup> testing set	70 (66 to 73)	0.96 (0.92 to 0.99)
	5 <sup>th</sup> testing set	68 (64 to 72)	1.05 (1.01 to 1.08)
	6 <sup>th</sup> testing set	71 (68 to 74)	0.97 (0.93 to 1.01)
	7 <sup>th</sup> testing set	70 (67 to 73)	0.96 (0.92 to 1.00)
	8 <sup>th</sup> testing set	71 (68 to 74)	1.01 (0.99 to 1.04)
	9 <sup>th</sup> testing set	70 (67 to 73)	0.96 (0.93 to 0.98)
	10 <sup>th</sup> testing set	70 (67 to 74)	0.98 (0.95 to 1.01)

Table 3.3. Validation results of the CVD risk model for patients with T2DM.

\*The pooled cohorts were randomly split into five folds. We iteratively withheld every two of the five folds as the testing set from the Cox model and used the other three folds to estimate the coefficients; we then validated the obtained model against the withheld testing set data. Abbreviation: CVD = cardiovascular disease; T2DM = type 2 diabetes mellitus.

#### Alternative model specifications

Fitting separate models for each sex produced a similar C statistics (69% [67% to 71%]) to the main model but lower calibration regression slopes (0.90 [0.89 to 0.91]). In addition, all the sex and risk factors interaction variables (except for SBP and female) were not statistically significant (p>0.05; Supplementary Material Table S3.2). Model with the covariate replacing the binary hypertension treatment variable with a four-level categorical variable defined as SBP levels ( $\geq$ 140 mm Hg or not) and hypertension treatment (with antihypertensive drugs or not) performed worse than the selected final model, with a C statistic of 68% (66% to 70%) and calibration regression slope of 0.96 (0.95 to 0.97) (Supplementary Material Table S3.3). Model with the covariate replacing the binary hypertension treatment variable with a four-level categorical variable defined as SBP levels ( $\geq$ 120 mm Hg or not) and hypertension treatment (with antihypertensive drugs or not) had even worse validation, with a C statistic of 66% (64% to 68%) and calibration regression slope of 1.05 (1.04 to 1.06) (Supplementary Material Table S3.4). Model with the covariate replacing TC and HDL-C with the TC/HDL-C ratio as one covariate had good discrimination with a C statistic of 70% (68% to 72%) but worse calibration with a regression slope of 0.94 (0.93 to 0.95) (Supplementary Material Table S3.5).

#### **Comparison to other risk equations**

We evaluated the performance of the 2013 ACC/AHA Pooled Cohort Risk Equation<sup>1</sup> in our study population. The predicted 10-year risk of ASCVD by the 2013 ACC/AHA Pooled Cohort Risk Equation underestimated the observed risk for all race-sex groups of participants with T2DM, with the percentage point differences ranging from 4.5% in White men to 11.7% in White women (Supplementary Material Table S3.6). Since ASCVD events accounted for 94.7% of CVD events in our study population, these results demonstrate consistent underestimation when applying the 2013 ACC/AHA Pooled Cohort Risk Equation in populations with T2DM. *Both* the 2013 ACC/AHA Pooled

Cohort Risk Equation and our risk prediction models were developed based on (partial) available prospective cohorts with pre-date baseline recruitment years from the National Heart, Lung, and Blood Institute (NHLBI). The difference between these two models is that the 2013 ACC/AHA Pooled Cohort Risk Equation used both diabetics and non-diabetics versus in our model we restricted the population to diabetes patients. Therefore, the comparison with model performance of their risk equations with ours by applying their risk equation in our study population is reasonable. When applying the two sets of risk models to current US diabetic population, it is necessary to recalibrate the baseline CVD incidence and mortality to current rates.

# Discussion

We developed a CVD risk prediction model for patients with T2DM in the United States, using pooled individual-level data from five prospective cohort studies. The risk prediction equation demonstrated good discrimination and calibration in internal validation, with Harrell's C statistics generally 70% or more and calibration regression slopes close to 1.

The discrimination for the risk prediction equation in men was not as good as it was in women. A potential cause of this was the use of data from the MRFIT cohort, which enrolled participants over an earlier period than the other cohorts with male participants. The risk factor characteristics were substantially different among men from the MRFIT and men from other prospective cohorts in our sample (Table 3.1). For example, the participants from MRFIT had a much lower level of FPG with a smaller proportion treated with diabetes medications than men from other cohorts (mean FPG: 7.2 mmol/L versus 9.1 mmol/L, p<0.0001; percent receiving diabetes medications: 20.9% versus 62.6%, p<0.0001). When excluding participants from MRFIT, the discrimination of risk prediction in men was substantially improved to 70% (95% CI, 67% to 73%) (Supplementary Material Table S3.7). We did not select the model excluding MRFIT as the main model, because the number of male participants would be smaller than current, resulting in poor model performance in cross-validation.

We compared our risk prediction equation with the 2013 ACC/AHA Pooled Cohort Risk Equation,<sup>1</sup> the United Kingdom Prospective Diabetes Study Outcomes Model 2 (UKPDS OM2),<sup>36</sup> and the Risk Equations for Complications Of type 2 Diabetes (RECODe).<sup>43</sup> The ACC/AHA risk model underestimated 10-year ASCVD risk for all race-sex groups in participants with T2DM. With calibration regression slopes all close to 1, our model predicted an accurate 10-year fatal-plus-non-fatal CVD risk that was highly comparable to the observed 10-year total CVD risk for participants with T2DM. We were unable to quantitatively compared our risk prediction equation with the UKPDS OM2 and the RECODe in our study population, because many parameters (e.g. age at diagnosis of diabetes, HbA1c, estimated glomerular filtration rate, albuminuria) of UKPDS OM2 equations and RECODe equations were not measured in the baseline examination of most of our study cohorts. UKPDS OM2 is one of the most commonly used risk equations presently for evaluating microvascular and cardiovascular risk among individuals with T2DM in many policy simulation studies.<sup>72–76</sup> UKPDS OM2 was developed in patients with T2DM from both clinical trials and observational data. UKPDS OM2 covariates included not only time invariant factors (e.g. sex, ethnicity, age at diagnosis of diabetes) but also time varying clinical risk factors (e.g. SBP, HDL-C, LDL-C) and time varying comorbidities (e.g. history of stroke, history of amputation). UKPDS OM2 can be used to assess the risk of individual components of cardiovascular events (e.g. IHD, MI, stroke) and death. By considering a wide range of covariates and health outcomes, the UKPDS OM2 is able to provide evidence for personalized treatment strategies during clinical practice and risk distributions by patient subgroups. UKPDS OM2 can also be appropriately applied to secondary prevention for diabetic patients with clinical manifest CVD. Our model does not include covariates of time varying risk factors or comorbidities, due to absence of relevant data or lack of inclusion in the appropriate examination cycle of one or more of the study cohorts. Our risk prediction equation predicts a general risk of a first fatal-or-non-fatal CVD. The application of our risk prediction equation is targeted to the adult diabetic population without clinical signs or symptoms of CVD, who merit evaluation for the primary prevention of CVD. UKPDS OM2 has fixed baseline CVD hazards that cannot be recalibrated when applied to diabetic populations in other countries. When applied to the

US diabetic populations, UKPDS OM2 may not have good discrimination with limited calibration.<sup>43</sup> For example, one previous study evaluated that the mortality predicted by the UKPDS OM was comparable to the observed mortality in US adults with T2DM using the National Health and Nutrition Examination Surveys (NHANES) 1988-1994.<sup>77</sup> However, their results were limited to a small sample size of 156 adults with diabetes who had characteristics similar to the UKPDS cohorts of newly-diagnosed diabetes. The RECODe equations were developed and validated in patients with T2DM in clinical trials, limiting their generalizability to diabetic populations without intensive treatment regimens. The RECODe equations also had inferior interval validation for CVD compared with the ACC/AHA risk equations and our model.<sup>1,43</sup>

Our study pooled multiple high-quality prospective cohorts, demonstrated good performance in both internal validation and cross-validation. The inclusion of multiethnic community-based cohorts (ARIC and MESA) offers a racially and geographically diverse population with T2DM in our model.<sup>78,79</sup> We conducted harmonization of data regarding to the different measures of glucose and risk factors across cohorts. The definition and adjudication of outcome events also varied across cohorts. We used the ICD10 codes to define the model outcome, which were mapped to clinical endpoints ascertained and adjudicated by each cohort. We developed the model stratified by sex and cohort and calibrated the sex- and cohort-specific baseline hazards during validation, allowing the sex-specific CVD incidence and mortality to vary across cohorts. Our study also has some limitations. First, although pooling data from multiple cohorts provides enhanced statistical power compared with using a single cohort, our cohorts were all from United States and territories. Validity of the risk prediction equation needs to be assessed for other diabetic populations, which may have different cardiovascular complications profiles.<sup>80,81</sup> Second, we developed a single general CVD risk score for any initial fatal-or-non-fatal CVD events as opposed to modeling CHD and stroke separately. Stratified by cohort and sex, the number of outcomes events defined as CHD and stroke separately was smaller than the number of outcomes events defined as total CVD, resulting in a poorer model performance. Lastly, the number of participants, duration of follow-up years, and candidate covariates were much smaller in this study

than used for other studies such as UKPDS OM2, which limited our ability to develop an enhanced model including additional risk factors.

In summary, we developed a novel CVD risk prediction model specifically for populations with T2DM in the US. Our risk equation can be utilized to simulate outcomes of intervention policies targeted on patients with T2DM in comparative effectiveness and cost-effectiveness research. As a more accurate risk assessment tool than the ACC/AHA risk equations, our model allows recalibration of baseline CVD incidence and mortality to target diabetic populations. With our risk model, the estimated effectiveness for high-risk diabetic patients would be even larger from intervention strategies such as "benefit-based tailored treatment", medication adherence and lifestyle interventions, or adding pharmacists to health care management, compared with benefits quantified by other risk equations.<sup>73,74,76</sup> This novel risk equation may be useful for future studies that evaluate the effectiveness and cost-effectiveness of primary prevention options for diabetic patients.

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## **Supplementary Material**

Table S3.1. Test of proportional-hazards assumptions for risk factors in CVD risk model for patients with T2DM.

Covariates	Slope	Chi2	df	Prob>chi2
Age (year)	-0.02	0.30	1	0.58
Age squared	-0.01	0.09	1	0.76
Current smoking	0.03	1.27	1	0.26
Body mass index (per 1 unit)	-0.04	1.68	1	0.20
Systolic blood pressure (per 10 mm Hg)	-0.01	0.07	1	0.78
Total cholesterol (per 1 mmol/L)	-0.04	1.98	1	0.16
High-density lipoproteins cholesterol (per 1mmol/L)	0.01	0.12	1	0.73
Fasting plasma glucose (per 1 mmol/L)	0.01	0.05	1	0.82
Treatment with hypertension medications*	0.04	1.93	1	0.17
Treatment with diabetes medications and fasting plasma glucose (per 1 mmol/L)	-0.03	1.08	1	0.30
Age and female	-0.04	1.41	1	0.58
Systolic blood pressure (per 10 mm Hg) and female	-0.02	0.30	1	0.24
Age and systolic blood pressure (per 10 mm Hg)	0.02	0.00	1	0.96
Age and body mass index (per 1 unit)	0.04	1.98	1	0.16
Global test		10.87	15	0.91

\* Treatment with hypertension medication was a binary covariate. The reference group included individuals who had blood pressure being diagnosed as not having hypertension, and/or who had hypertension but were not taking hypotension lowering medications at baseline.

Abbreviation: T2DM = type 2 diabetes mellitus.

	Harrell's C statistic	Calibration slope
	(95% CI)	(95% CI)
	69% (67% to 71%)	0.90 (0.89 to 0.91)
Risk Factors	Coefficient (95% CI)	Hazard Ratio (95% CI)
Age (year)	0.0103	1.01 (0.91 to 1.12)
	(-0.0939 to 0.1146)	
Age squared	0.0004	1.00 (0.99 to 1.00)
	(-0.0004 to 0.0011)	
Current smoking	0.2474	1.28 (1.06 to 1.54)
	(0.0609 to 0.4339)	
Body mass index (per 1 unit)	0.0156	1.02 (0.94 to 1.10)
	(-0.0672 to 0.0985)	
Systolic blood pressure (per 10 mm Hg)	0.1594	1.17 (0.96 to 1.43)
Tatal shalastanal (non 1 mm al /l)	(-0.0372 to 0.3559)	1 12 (1 04 + 1 20)
Total cholesterol (per 1 mmol/L)	0.1103 (0.03751 to 0.1831)	1.12 (1.04 to 1.20)
High-density lipoproteins cholesterol (per 1	-0.6269	0.53 (0.40 to 0.71)
mmol/L)	(-0.9167 to -0.3372)	0.55 (0.40 to 0.71)
Fasting plasma glucose (per 1 mmol/L)	0.0127	1.01 (0.98 to 1.04)
	(-0.0177 to 0.0430)	1.01 (0.00 to 1.0 l)
Treatment with hypertension medications*	0.0155	1.02 (0.86 to 1.20)
	(-0.1482 to 0.1793)	. , , , ,
Treatment with diabetes medications and fasting	0.0356	1.04 (1.02 to 1.06)
plasma glucose (per 1mmol/L)	(0.0173 to 0.0540)	
Age and female	-0.0014	1.00 (0.97 to 1.02)
	(-0.0254 to 0.0226)	
Current smoking and female	0.1694	1.18 (0.86 to 1.62)
	(-0.1459 to 0.4846)	
Body mass index (per 1 unit) and female	-0.0192	0.98 (0.96 to 1.01)
	(-0.0456 to 0.0073)	
Systolic blood pressure (per 10 mm Hg) and	0.0628	1.06 (1.00 to 1.13)
female Total cholesterol (per 1 mmol/L) and female	(0.0026 to 0.1230) 0.0522	1.05 (0.95 to 1.17)
Total cholesterol (per 1 mmol/L) and female	(-0.0548 to 0.1592)	1.05 (0.93 (0 1.17)
High-density lipoprotein cholesterol (per 1	0.2566	1.29 (0.86 to 1.95)
mmol/L) and female	(-0.1528 to 0.6660)	1.25 (0.00 to 1.55)
Fasting plasma glucose (per 1 mmol/L) and	-0.0176	0.98 (0.94 to 1.03)
female	(-0.0613 to 0.0261)	
Treatment with hypertension medications* and	0.1327	1.14 (0.88 to 1.48)
female	(-0.1254 to 0.3909)	
Fasting plasma glucose (per 1 mmol/L) and	-0.0002	1.00 (0.97 to 1.03)
treatment with diabetes medications and female	(-0.0273 to 0.0270)	
Age and systolic blood pressure (per 10 mm Hg)	-0.0017	1.00 (0.99 to 1.00)
	(-0.0048 to 0.0013)	
Age and body mass index (per 1 unit)	-0.0001	1.00 (0.99 to 1.00)
	(-0.0015 to 0.0012)	

Table S3.2. Coefficients and hazard ratios from the Cox proportional hazard model used to predict the 10-year risk of CVD for our study populations, with all sex and risk factors interactions.

\*Treatment with hypertension medication was a binary covariate. The reference group included individuals who had blood pressure being diagnosed as not having hypertension, and/or who had hypertension but were not taking hypotension lowering medication at baseline.

Table S3.3. Coefficients and hazard ratios from the Cox proportional hazard model used to predict the 10-year risk of CVD for our study populations, when hypertension and treatment with hypertension medications were included as a four categorical variable.

	Harrell's C statistic (95% Cl) 68% (66% to 70%)	Calibration slope (95% Cl) 0.96 (0.95 to 0.97)
Risk Factors	Coefficient (95% CI)	Hazard Ratio (95% CI)
Age (year)	0.0250 (-0.0791 to 0.1290)	1.03 (0.92 to 1.14)
Age squared	0.0003 (-0.0004 to 0.0011)	1.00 (0.99 to 1.00)
Current smoking	0.3066 (0.1559 to 0.4574)	1.36 (1.17 to 1.58)
Body mass index (per 1 unit)	0.0168 (-0.0665 to 0.1002)	1.02 (0.94 to 1.11)
Systolic blood pressure (per 10 mm Hg)	0.1822 (-0.0207 to 0.3851)	1.20 (0.98 to 1.47)
Total cholesterol (per 1mmol/L)	0.1335 (0.0799 to 0.1867)	1.14 (1.08 to 1.21)
High-density lipoproteins cholesterol (per 1mmol/L)	-0.5185 (-0.7226 to -0.3143)	0.60 (0.49 to 0.73)
Fasting plasma glucose (per 1mmol/L)	0.0031 (-0.0186 to 0.0248)	1.00 (0.98 to 1.03)
Systolic blood pressure controlled with treatment ‡	-0.0225 (-0.2582 to 0.2132)	0.98 (0.77 to 1.24)
Hypertension without treatment*	0.0844 (-0.0750 to 0.2437)	1.09 (0.93 to 1.28)
Hypertension with treatment <del>I</del>	-0.0653 (-0.3176 to 0.1869)	0.94 (0.73 to 1.21)
Treatment with diabetes medications and fasting plasma glucose (per 1mmol/L)	0.0350 (0.0214 to 0.0485)	1.04 (1.02 to 1.05)
Age and female	0.0028 (-0.0208 to 0.0263)	1.00 (0.98 to 1.03)
Systolic blood pressure (per 10 mm Hg) and female	0.0623 (0.0038 to 0.1207)	1.06 (1.00 to 1.13)
Age and systolic blood pressure (per 10 mm Hg)	-0.0018 (-0.0049 to 0.0013)	1.00 (0.99 to 1.00)
Age and body mass index (per 1 unit)	-0.0003 (-0.0017 to 0.0010)	1.00 (0.99 to 1.00)

\* Hypertension without treatment were diabetic individuals who had SBP ≥140 mm Hg and were not taking any hypertension medications at baseline. The reference group was individuals who had SBP <140 mm Hg and were not taking any hypertension medications at baseline.

Hypertension with treatment were diabetic individuals who had SBP ≥140 mm Hg and were taking any hypertension medications at baseline. The reference group was individuals who had SBP <140 mm Hg and were not taking any hypertension medications at baseline.

<sup>‡</sup> Systolic blood pressure controlled with treatment were diabetic individuals who had SBP <140 mm Hg and were taking any hypertension medications at baseline. The reference group was individuals who had SBP <140 mm Hg and were not taking any hypertension medications at baseline.

Table S3.4. Coefficients and hazard ratios from the Cox proportional hazard model used to predict the 10-year risk of CVD for our study populations, when elevated systolic blood pressure and treatment with hypertension medications were included as a four categorical variable.

	Harrell's C statistic (95% Cl) 66% (64% to 68%)	Calibration slope (95% Cl) 1.05 (1.04 to 1.06)
Risk Factors	Coefficient (95% CI)	Hazard Ratio (95% CI)
Age (year)	0.0190 (-0.0852 to 0.1232)	1.02 (0.92 to 1.13)
Age squared	0.0003 (-0.0004 to 0.0011)	1.00 (0.99 to 1.01)
Current smoking	0.3074 (0.1566 to 0.4583)	1.36 (1.17 to 1.58)
Body mass index (per 1 unit)	0.0202 (-0.0630 to 0.1035)	1.02 (0.94 to 1.11)
Systolic blood pressure (per 10 mm Hg)	0.1077 (-0.0985 to 0.3139)	1.11 (0.91 to 1.37)
Total cholesterol (per 1mmol/L)	0.1335 (0.0802 to 0.1868)	1.14 (1.08 to 1.21)
High-density lipoproteins cholesterol (per 1mmol/L)	-0.5182 (-0.7220 to -0.3143)	0.60 (0.49 to 0.73)
Fasting plasma glucose (per 1mmol/L)	0.0030 (-0.0187 to 0.0248)	1.00 (0.98 to 1.03)
Systolic blood pressure controlled with treatment ‡	0.3054 (0.0530 to 0.5579)	1.36 (1.05 to 1.75)
Elevated systolic blood pressure without treatment*	0.1131 (-0.1725 to 0.3986)	1.12 (0.84 to 1.49)
Elevated systolic blood pressure with treatment <del>l</del>	0.2472 (0.0002 to 0.4941)	1.28 (1.00 to 1.64)
Treatment with diabetes medications and fasting plasma glucose (per 1mmol/L)	0.0350 (0.0215 to 0.0486)	1.04 (1.02 to 1.05)
Age and female	0.0017 (-0.0219 to 0.0252)	1.00 (0.98 to 1.03)
Systolic blood pressure (per 10 mm Hg) and female	0.0674 (0.0069 to 0.1279)	1.07 (1.01 to 1.14)
Age and systolic blood pressure (per 10 mm Hg)	-0.0013 (-0.0045 to 0.0018)	1.00 (0.99 to 1.00)
Age and body mass index (per 1 unit)	-0.0004 (-0.0018 to 0.0010)	1.00 (0.99 to 1.00)

\*Elevated systolic blood pressure without treatment were diabetic individuals who had SBP ≥120 mm Hg and were not taking any hypertension medications at baseline. The reference group was individuals who had SBP <120 mm Hg and were not taking any hypertension medications at baseline.

+ Elevated systolic blood pressure with treatment were diabetic individuals who had SBP ≥120 mm Hg and were taking any hypertension medications at baseline. The reference group was individuals who had SBP <120 mm Hg and were not taking any hypertension medications at baseline.

‡ Systolic blood pressure controlled with treatment were diabetic individuals who had SBP <120 mm Hg and were taking any hypertension medications at baseline. The reference group was individuals who had SBP <120 mm Hg and were not taking any hypertension medications at baseline.
Abbreviation: CVD = cardiovaccular disease

	Harrell's C statistic (95% Cl)	Calibration slope (95% Cl)
	70% (68% to 72%)	0.94 (0.93 to 0.95)
Risk Factors	Coefficient (95% CI)	Hazard Ratio (95% CI)
Age (year)	0.0347	1.04 (0.93 to 1.15)
	(-0.0689 to 0.1383)	
Age squared	0.0003	1.00 (0.99 to 1.00)
	(-0.0005 to 0.0010)	
Current smoking	0.2912	1.34 (1.16 to 1.56)
	(0.1409 to 0.4416)	
Body mass index (per 1 unit)	0.0179	1.02 (0.94 to 1.11)
	(-0.0648 to 0.1007)	
Systolic blood pressure (per 10 mm Hg)	0.1768	1.19 (0.98 to 1.45)
	(-0.0196 to 0.3731)	
Total cholesterol/high-density lipoproteins	0.1157	1.12 (1.09 to 1.16)
cholesterol	(0.0939 to 0.1475)	
Fasting plasma glucose (per 1 mmol/L)	0.0015	1.00 (0.98 to 1.02)
	(-0.0202 to 0.0232)	
Treatment with hypertension medications*	0.0630	1.07 (0.84 to 1.21)
	(-0.0636 to 0.1895)	
Treatment with diabetes medications and fasting	0.0352	1.04 (1.02 to 1.05)
plasma glucose (per 1mmol/L)	(0.0217 to 0.0486)	
Age and female	0.0032	1.00 (0.98 to 1.03)
	(-0.0204 to 0.0268)	
Systolic blood pressure (per 10 mm Hg) and	0.0634	1.07 (1.00 to 1.13)
female	(0.0049 to 0.1220)	
Age and systolic blood pressure (per 10 mm Hg)	-0.0020	1.00 (0.99 to 1.00)
	(-0.0050 to 0.0011)	
Age and body mass index (per 1 unit)	-0.0003	1.00 (0.99 to 1.00)
	(-0.0017 to 0.0010)	

Table S3.5. Coefficients and hazard ratios from the Cox proportional hazard model used to predict the 10-year risk of CVD for our study populations, with TC/HDL-C ratio covariate.

\*Treatment with hypertension medication was a binary covariate. The reference group included individuals who had blood pressure being diagnosed as not having hypertension, and/or who had hypertension but were not taking hypotension lowering medication at baseline.

Table S3.6. Comparison of 10-year CVD observed risk with 10-year ASCVD predicted risk by the 2013 ACC/AHA Pooled Cohort Risk Equation1 in our study population from the five prospective cohorts, by race and sex.

Diabetic Populations	10-Year risk of ASCVD predicted by ACC/AHA model (%)	10-Year risk of CVD† observed	Underestimates (percentage point difference)
Women African American	13.92	18.97	5.05
Women White	11.58	23.23	11.65
Men African American	23.10	30.93	7.83
Men White	33.47	37.99	4.52
Total	25.11	29.13	4.02

Abbreviations: CVD = cardiovascular disease; ASCVD = atherosclerotic cardiovascular disease; ACC/AHA model = American College of Cardiology/American Heart Association.

+94.7% of CVD events were ASCVD event in our study population.

## Table S3.7. Validation results of the 10-year CVD risk model for participants with T2DM in the pooled four prospective cohorts (MRFIT excluded).

CVD Risk Model (MRFIT excluded)		Discrimination	Calibration regression slope
	Study Population	Harrell's C statistic (%) (95% CI)	Mean (95% CI)
Internal validation	Total	73 (71-75)	1.01 (1.00-1.03)
	Men	70 (67-73)	1.01 (0.98-1.04)
	Women	75 (72-77)	1.00 (0.98-1.02)

Abbreviation: CVD = cardiovascular disease; MRFIT: multiple risk factor intervention trial; T2DM = type 2 diabetes mellitus.

# Chapter 4. Disparities in health and economic outcomes associated with *N. gonorrhoeae* infection in the United States: costs and quality-adjusted life-

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#### Abstract

#### Background

Disparities in the health and economic burden of gonorrhea have not been systematically quantified. We estimated population-level health losses and costs associated with gonococcal infection and sequelae in the United States.

#### Methods

We used probability tree models to capture gonorrhea sequelae and to estimate attributable disease burden in terms of the discounted lifetime costs and quality-adjusted life-years (QALYs) lost due to incident infections acquired during 2015. Numbers of infections in 2015 were estimated using a gonorrhea transmission model. We evaluated population-level disease burden, disaggregated by sex, age, race/ethnicity, and for men who have sex with men (MSM). We conducted a multivariate sensitivity analysis for key parameters.

#### Findings

Discounted lifetime QALYs lost per incident gonococcal infection were estimated as 0.093 (95% uncertainty interval [UI] 0.022-0.22) for women, 0.0020 (95% UI 0.0015-0.0024) for heterosexual men, and 0.0017 (95% UI 0.0013-0.0022) for MSM. Discounted lifetime costs per incident infection were USD 254 (95% UI 109-460), 306 (95% UI 157-479), and 281 (95% UI 145-443), respectively. Total discounted lifetime QALYs lost due to infections acquired during 2015 were 53,293 (95% UI 12,326-125,366) for women, 623 (95% UI 431-876) for heterosexual men, and 1,286 (632-2,074) for MSM. Total discounted lifetime costs were USD 145 million (63 to 266 million), 97 million (46-168 million), and 206 million (82-410 million), respectively. The highest absolute burden of both QALYs and costs was observed in Non-Hispanic Black women, and highest relative burden was identified in MSM and American Indian/Alaska Native women.

## Interpretation

Gonorrhea causes significant health losses and costs in the United States. The results can inform planning and prioritizing prevention policies.

### Funding

Centers for Disease Control and Prevention, Charles A. King Trust

#### Background

In the United States, there were 583,405 gonorrhea diagnoses reported in 2018, making *Neisseria gonorrhoeae* the second most common notifiable infection.<sup>1</sup> Along with chlamydia, gonorrhea is an important cause of pelvic inflammatory disease (PID), chronic pelvic pain (CPP), ectopic pregnancy (EP), and tubal infertility (TI) in women and epididymitis in men.<sup>2–4</sup> Gonococcal infection may also increase the risk of human immunodeficiency virus (HIV) acquisition and transmission.<sup>5,6</sup>

In the United States, reported gonorrhea rates have increased since 2009,<sup>1,7–9</sup> with a pronounced increase among men who have sex with men (MSM).<sup>1,10–12</sup> Although disparities in gonorrhea and other STIs are often measured using diagnosis rates,<sup>2,7,8,10</sup> diagnosed infections represent only a subset of all infections. Moreover, a comprehensive assessment of gonorrhea-associated burden requires evaluation of downstream health consequences secondary to infection.

To date, the population-level disparities in costs and sequelae associated with gonococcal infection have not been systematically quantified, reflecting a knowledge gap in our understanding of gonorrhea burden in the United States. This study estimated lifetime quality-adjusted life-years (QALYs) lost and costs associated with gonococcal infections acquired in 2015 by age, sex, race/ethnicity, and for MSM in the United States. We developed probability tree models to quantify long-term health and economic consequences associated with gonorrhea. We combined these estimates with estimates of gonococcal infection incidence derived from a gonorrhea transmission model.<sup>13</sup> The aim of this study was to present a comprehensive analysis of gonorrhea burden and disparities in the context of current prevention efforts.

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#### Methods

#### Analytic overview

We used probability tree models to represent clinical outcomes following gonococcal infection among women, men who have sex with women (MSW), and MSM. Next, we estimated costs and health losses associated with the clinical endpoints of each distinct path along the probability tree and aggregated these into the total numbers of expected discounted lifetime QALYs lost and expected total discounted lifetime costs per each incident gonococcal infection. We combined these estimates with the total numbers of estimated incident infections acquired in 2015 by age, sex and race/ethnicity to estimate overall population-level health and economic disease burden and disparities. Model inputs and parameter values were derived from a variety of sources, including: (1) estimates of gonorrhea incidence, and probabilities of symptomatic infection, testing and treatment from a gonorrhea transmission modeling study<sup>13</sup>; and (2) probabilities of gonorrhea sequelae, durations, disutilities and costs from synthesis of published literature. Analyses were undertaken in R (R-3.5.2).

#### Model structure and probabilities of key clinical outcomes

We developed probability trees to model clinical outcomes following gonococcal infection, adapted from prior decision analysis studies.<sup>14–16</sup> Separate trees were specified for women, MSW and MSM (Figure 4.1, Figure 4.2).

For women, gonococcal infections were categorized as symptomatic or asymptomatic with different durations of infections, leading to distinct probabilities of developing PID and subsequent complications (Figure 4.1).<sup>14</sup> Although treatment for gonorrhea is not explicitly distinguished as a separate branch in Figure 4.1, the estimated durations of infections accounted for the fraction of cases treated. The possible complications following PID were CPP, EP, and TI (Figure 4.1B). Although we included disseminated gonococcal infection (DGI) as a sequela for men (see below), we excluded this sequela for women in the interest of parsimony, given that it occurs with lower probability than the

other included sequelae. The probability of symptomatic infection and durations of either symptomatic or asymptomatic infection were derived from a prior transmission modelling study. Duration of asymptomatic infection differed across age groups due to differences in screening rates.<sup>13</sup> For the probability of developing PID, we synthesized data from previously published studies<sup>17–22</sup> on rates of developing PID secondary to chlamydial infection,<sup>23</sup> and translated the rated into associated probabilities of PID given durations of symptomatic or asymptomatic gonococcal infection. The conditional probabilities of CPP, EP, and TI given PID were derived by pooling estimates from previous longitudinal studies on sequelae among women infected with chlamydia.<sup>24–30</sup>

For MSW, infections were categorized as symptomatic or asymptomatic urethral gonococcal infections (Figure 4.2A), followed by possible sequelae of epididymitis and DGI (Figure 4.2C). We assumed that all symptomatic infections are diagnosed and successfully treated, and that treatment prevents any further complications in men; this simplifying assumption implies that epididymitis and DGI occur only among untreated asymptomatic cases. There is sparse evidence on the relationship between duration of infection and sequelae development for men, and epididymitis and DGI were modeled as probabilities that were independent of duration. We assumed that urethritis was present in all symptomatic infections.<sup>31</sup> The probabilities of symptomatic and asymptomatic infections were obtained from the gonorrhea transmission model.<sup>13</sup> We estimated the probability of epididymitis and sequelae among men infected with chlamydia.<sup>32,33</sup> The probability of DGI was derived from a previous Institute of Medicine (IOM) study.<sup>16</sup>

For MSM, the model treated urethral infections as described for MSW (Figure 4.2B and Figure 4.2C). In addition, rectal and pharyngeal infections, which are typically asymptomatic, were assumed to incur no direct health utility losses, consistent with assumptions made in a study on rectal chlamydia.<sup>34</sup> This was a simplifying assumption that also implied that only urethral infections lead to epididymitis and

DGI. The probability of symptomatic urethral infection for both MSW and MSM was obtained from the gonorrhea transmission model.<sup>13</sup> We estimated the probability of asymptomatic urethral infection among MSM by assuming that the odds of symptoms given urethral infection were the same for MSM as for MSW. Further details can be found in Supplementary Material.

Diverging from the approach taken in prior related studies using probability trees, we have explicitly modeled both independent sequelae and combinations of sequelae following PID for women and following urethral infections for MSW and MSM, whereas prior studies have assumed that all complications were independent and additive.<sup>13,15,16</sup> Further details on the values, ranges, distributions, and sources of probabilities for key clinical outcomes can be found in Table 4.1 and in Supplementary Material. In addition to the pathways of clinical outcomes shown in Figure 4.1 and Figure 4.2, we further stratified some health states by treatment status for the purpose of computing costs and utility losses. For gonococcal infections, we distinguished treated and untreated infections; for sequelae following infection, we assumed that all cases are treated and distinguished inpatient from outpatient treatment for PID, EP, epididymitis and DGI. Yearly probabilities of testing and treatment for gonococcal infections for women, MSW and MSM were obtained from the gonorrhea transmission model,<sup>13</sup> and were stratified by age and race/ethnicity (Table S4.5-(a) and Table S4.5-(b) in Supplementary Material). We estimated the probabilities of inpatient (vs. outpatient) treatment for PID, EP, epididymitis and DG2, respectively.<sup>16,35-37</sup>

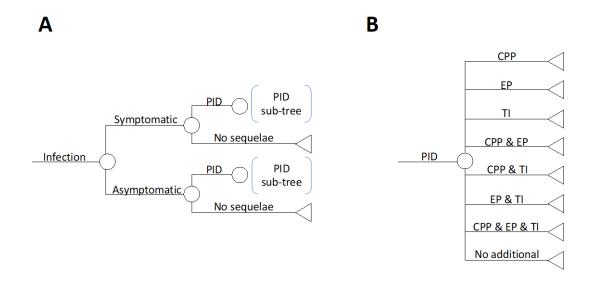


Figure 4.1. Probability tree for sequelae following gonococcal infection among women. Abbreviations: PID = pelvic inflammatory disease, CPP = chronic pelvic pain, EP = ectopic pregnancy, TI = tubal infertility.

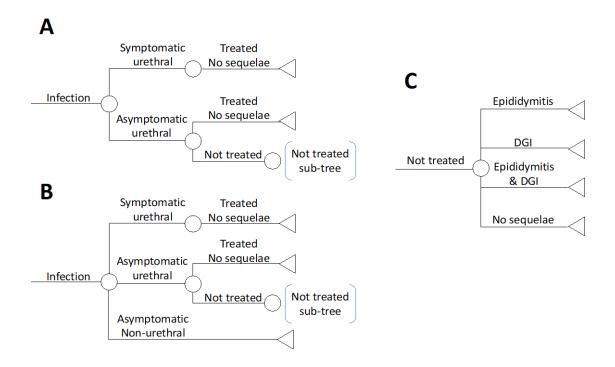


Figure 4.2. Probability tree for sequelae following gonococcal infection among MSW (Panel A) and MSM (Panel B), with complications of untreated urethral infections shown in Panel C. Abbreviations: DGI = disseminated gonococcal infection.

#### Lifetime QALYs lost and costs per incident infection

Utilities and durations for clinical outcomes related to gonorrhea and sequelae were derived from the prior IOM study, which used an expert panel to estimate durations of sequelae and health-state weights measured via the Health Utilities Index (HUI).<sup>16</sup> The utility weights for gonorrhea and sequelae were multiplied by background utilities reflecting chronic comorbidities by age, based on nationally representative EQ-5D index scores.<sup>38</sup> CPP and TI were treated as chronic sequelae, and durations were estimated using a life table approach. Age-specific mortality rates for women were derived from National Center for Health Statistics (NCHS) data.<sup>39</sup> Costs were estimated from the healthcare perspective and included all direct medical costs regardless of payer. All costs were inflated to 2018 U.S. dollars using the medical care component of the consumer price index.<sup>40</sup> Costs and QALYs incurred in years after the incidence of infection were discounted to the year of infection, using a discount rate of 3% per year.<sup>41</sup> Further details can be found in Table 4.1 and Supplementary Material.

Based on the probability tree models in Figure 4.1 and Figure 4.2, discounted lifetime QALYs lost per incident infection were estimated by summing the expected losses for each unique sequela or sequelae combination (the product of the probability, duration, and disutility). Lifetime costs per incident infection were estimated analogously for diagnosis and treatment of symptomatic cases and asymptomatic cases. For symptomatic infection, all cases were assumed to be diagnosed and treated. For asymptomatic infection, the proportion of diagnosis and treatment can be found in Table 4.1 and Supplementary Material Table S4.5. Details on the discounted costs of diagnosis and treatment for gonorrhea and sequelae can be found in Table 4.1.

#### Disease burden and disparities at population level

Estimates for the incidence of gonococcal infection were obtained from a transmission modelling study.<sup>13</sup> The study used a model that was calibrated using a Bayesian approach to synthesize information from several large national datasets over the period 2000-2015, including reported gonorrhea diagnoses, prevalence estimates from the National Health and Nutrition Examination

Survey, and other sources.<sup>13</sup> This national-level gonorrhea meta-population model described a population aged 15-24 and 25-39 years, with the heterosexual population of men and women stratified into the following race/ethnicity groups: Non-Hispanic Black, Hispanic, and "White and Other." The population of MSM was stratified by age, but not by race/ethnicity due to limited data available at the national level.

In our model, the population was stratified by age and sex, and men were further stratified into MSW and MSM. Among the heterosexual population (women and MSW), the population in the present study was additionally divided into five race/ethnicity categories following the classification of the NCHS bridged-race categories: Non-Hispanic Black (NHB), Hispanic, American Indian or Alaska Native (AI/AN), Asian, Native Hawaiian or Other Pacific Islander (A/NH/OPI), and Non-Hispanic White (NHW).<sup>42,43</sup> To compute incidence of gonococcal infection among heterosexual AI/AN, A/NH/OPI and NHW as sub-populations of incidence estimated among "White and Other," we assumed that incidence rates for the three subgroups followed the same relative rates as those observed in reported case rates in these subgroups, which were obtained from the NCHHSTP AtlasPlus data.<sup>44</sup>

To estimate the population size in the United States by sex, age, and race/ethnicity, we used Bridged-Race Population Estimates from CDC WONDER.<sup>45</sup>

#### **Outcome measures**

The health and economic burden of disease associated with gonorrhea was measured as the numbers of discounted lifetime QALYs lost and costs due to gonococcal infections that occurred in 2015, by age and race/ethnicity for women, MSW, and MSM. These aggregate costs and QALYs were computed as the product of population size, incidence rates per population, and QALYs lost and costs per incident infection. Results are summarized in terms of aggregate population-level counts, as well as measures per 1,000 person-years.

#### Multivariate sensitivity analysis

We performed multivariate sensitivity analyses including uncertainty in (i) incidence of gonorrhea in each sub-population, (ii) proportion of each sub-population tested for gonorrhea yearly, (iii) proportion of infected persons within each sub-population receiving treatment; (iv) sequelae probabilities, and (v) utilities, durations and costs. 1,000 samples were used in the sensitivity analyses. The five groups of input parameters were drawn from the posterior distributions estimated by the previously published calibrated transmission model<sup>13</sup> (for input categories i-iii above) or from specified distributions describing uncertainty in sequelae probabilities (Table 4.1). We report all outcomes using the mean and 95% uncertainty intervals (95% UI).

The reporting in this study follows Consolidated Health Economic Evaluation Reporting Standards (CHEERS)<sup>46</sup> and Guidelines for Accurate and Transparent Health Estimates Reporting (GATHER)<sup>47</sup> as applicable.

Parameter	Mean estimate	Uncertainty interval*	References
Testing and treatment probabilities			
Probability of diagnosis and treatment	Table S4.5 (a)	and (b)	13
Probability of adverse reactions to			
ceftriaxone and azithromycin			
Mild to moderate	0.15	0.076 to 0.25	48–51
Severe	0.0016	0.00017 to 0.0047	48–51
Probability of inpatient treatment for PID	0.10	0.098 to 0.11	35
Probability of inpatient treatment for EP	0.15	0.13 to 0.18	35
Probability of inpatient treatment for	0.0054	0.0028 to 0.0092	36
epididymitis			37
Probability of inpatient treatment for DGI	0.29	0.17 to 0.43	57
Outcome probabilities (women)			
	0.37	0.27 to 0.47	13
Proportion of infections that are symptomatic	0.37	0.27 10 0.47	
Probability of PID given symptomatic	0.0025	0.00092 to 0.0055	13,17–23
infection			

Table 4.1. Model input parameters describing gonorrhea and sequelae probabilities, proportions of testing and treatment for gonorrhea in women, MSW and MSM.

testing and treatment for gonorrhea in wome	en, wisw and w	(Continued)	
Probability of PID given asymptomatic infection (age 15-24y)	0.075	0.031 to 0.13	13,17–23
Probability of PID given asymptomatic infection (age 25-39y)	0.091	0.037 to 0.16	13,17–23
Probability of CPP given PID	0.26	0.23 to 0.29	24,25
Probability of EP given PID	0.071	0.049 to 0.098	25–27,29
Probability of TI given PID	0.17	0.12 to 0.23	25,26,28–30
,			
Outcome probabilities (men)			
Probability of symptomatic urethral infection (MSW)	0.72	0.60 to 0.84	13
Probability of symptomatic urethral	0.62	0.43 to 0.76	13
infection (MSM)	0.02	0.45 10 0.70	
Probability of asymptomatic urethral	0.22	0.12 to 0.34	Supplementary
infection (MSM)	0.22	0.112 00 0.01	Material
Probability of urethral infection (MSW)	1	Fixed	
Probability of symptoms given urethral	0.72	0.60 to 0.84	13
infection (MSW)			
Probability of urethral infection (MSM)	0.83	0.62 to 0.96	Supplementary
			Material
Probability of symptoms given urethral	0.74	0.61 to 0.85	13,
infection (MSM)			Supplementary
			Material
Probability of epididymitis given untreated urethral infection	0.042	0.0012 to 0.14	32,33
Probability of DGI given untreated urethral	0.010	0.0075 to 0.013	16,52
infection	0.010	0.0075 (0 0.015	
meeten			
Durations (years)			
Gonococcal infection (women,	0.017	0.0099 to 0.031	10
symptomatic) <del>l</del>			
Gonococcal infection (women,	0.53	0.39 to 0.66	10
asymptomatic, ages 15-24y) <del>l</del>			
Gonococcal infection (women,	0.65	0.47 to 0.83	10
asymptomatic, ages 25-39y) <del>l</del>			
PID (inpatient treatment)	0.036	0.019 to 0.054	16
PID (outpatient treatment)	0.027	0.014 to 0.041	16
СРР	+	5 to lifetime	16,39,53
EP (inpatient treatment)	0.085	0.044 to 0.13	16
EP (outpatient treatment)	0.076	0.040 to 0.11	16
TI	+	5 to lifetime	16,39,53
Urethritis	0.019	0.0010 to 0.028	16
Epididymitis (inpatient treatment)	0.0082	0.0043 to 0.012	16
Epididymitis (outpatient treatment)	0.019	0.0010 to 0.028	16
DGI (inpatient treatment)	0.030	0.016 to 0.044	16
DGI (outpatient treatment)	0.022	0.011 to 0.032	16

Table 4.1. Model input parameters describing gonorrhea and sequelae probabilities, proportions of testing and treatment for gonorrhea in women, MSW and MSM (Continued)

	•	. ,	
State-specific utilities			
Symptomatic gonococcal infection (women)	0.85	0.78 to 0.92	16
PID (inpatient treatment)‡	0.76	0.64 to 0.87	16
PID (outpatient treatment)‡	0.63	0.45 to 0.81	16
CPP	0.60	0.41 to 0.79	16
EP (inpatient treatment)‡	0.62	0.44 to 0.80	16
EP (outpatient treatment)‡	0.58	0.38 to 0.78	16
TI ,	0.82	0.73 to 0.91	16
Urethritis	0.84	0.76 to 0.92	16
Epididymitis (inpatient treatment)	0.30	0.012 to 0.59	16
Epididymitis (outpatient treatment)	0.46	0.20 to 0.72	16
DGI (inpatient treatment)‡	0.68	0.53 to 0.84	16
DGI (outpatient treatment)‡	0.60	0.41 to 0.79	16
Costs (in 2018 US\$)			
Testing costs			
Urine nucleic acid amplification and	60	31 to 89	15,16,54–56
diagnosis procedure			
Treatment of gonorrhea			
Azithromycin 1 g	28	15 to 41	15,48,55,57
Ceftriaxone 250 mg	22	11 to 32	48,55,56
Short clinic visit	37	19 to 54	15,55,56
Side effect			
Adverse reactions to ceftriaxone and azithromycin			
Mild to moderate	77	40 to 115	16,48
Severe	8,007	4,174 to 11,898	48,58–61
Treatment of sequelae	-,	, ,	
PID (inpatient treatment)	10,637	5,544 to 15,805	15,16,35,48,57,6
	- ,	-,	-65
PID (outpatient treatment)	582	303 to 864	15,16,35,48,57,6 65
СРР	1,191	622 to 1,769	16,35,48
EP (inpatient treatment)	1,191	6,243 to 17,798	16,35,48
EP (outpatient treatment)	3,229	1,683 to 4,798	16,35,48
TI	6,245	3,255 to 9,280	16,35,48,57,63-
	0,245	3,233 (0 9,280	65
Urethritis	235	123 to 349	16,48,62–65
Epididymitis (inpatient treatment)	7,364	3,838 to 10,942	16,36,48,57,62-
	,,	0,000 10 10,042	64
Epididymitis (outpatient treatment)	422	220 to 627	16,36,48,57,62-
		220 10 027	64
DGI (inpatient treatment)	6,849	3,570 to 10,176	16
DGI (outpatient treatment)	563	293 to 836	16

Table 4.1. Model input parameters describing gonorrhea and sequelae probabilities, proportions of testing and treatment for gonorrhea in women, MSW and MSM (Continued)

\*Uncertainty intervals given as 95% uncertainty intervals for probabilities and durations of gonococcal infections based on results from the previous transmission model,<sup>13</sup> for probabilities of sequelae based on beta

distributions, and for all other parameters based on uniform distributions (see Supplementary Material for details).

+ The previous transmission model was used to estimate duration of asymptomatic infection, which varies in relation to the fraction of infections that are diagnosed. Differences over years and between different race/ethnicity groups were relatively small, while differences between age groups were larger. For parsimony, we therefore allowed durations to vary by age but not by year and race/ethnicity group. Symptomatic infection was assumed to be 100% diagnosed and treated, with a much shorter duration of infection.

<sup>†</sup>Mean duration taken from uniform distribution between 5 years and lifetime duration. While expert opinion suggests lifetime duration of these conditions,<sup>16</sup> previous analyses have assumed much shorter durations based on unspecified evidence.<sup>53</sup> Details on life table calculations used to compute discounted QALY losses for lifetime duration are provided in Supplementary Material.

<sup>‡</sup>The utility values were higher for inpatient treatment than outpatient treatment for sequelae of PID and EP for women and DGI for men. The utility values shown for inpatient and outpatient treatment reflect the average values over the duration of the condition, which is longer for inpatient treatment than outpatient treatment for most outcomes.<sup>16</sup> Inpatient treatment is associated with a greater total utility loss than outpatient treatment for most outcomes. For example, for PID, the 0.63 utility value for outpatient treatment is applied for 10 days. For inpatient treatment, the 0.76 value is applied for an average of about 13.3 days and reflects a utility value of about 0.55 applied for 3.3 days of inpatient care plus a utility value of about 0.82 applied for 10 days of follow-up outpatient care after the inpatient visit. Details of calculations are described in Supplementary Material table S4.3.

PID = pelvic inflammatory disease; CPP = chronic pelvic pain; EP = ectopic pregnancy; TI = tubal infertility; DGI = disseminated gonococcal infection; MSM = men who have sex with men; MSW= men who have sex with women.

#### Results

#### Lifetime QALYs lost and costs per gonococcal Infection

The discounted lifetime QALYs lost per incident gonococcal infection in 2015 were estimated as 0.093 (95% UI 0.022-0.22) for women, 0.0020 (0.0015-0.0024) for MSW, and 0.0017 (0.0013-0.0022) for MSM in (Table 4.2). The QALYs lost per incident infection were highest for women aged 25-39 years and were higher for women than for MSW and MSM. QALYs lost from gonococcal infection in women were predominantly from chronic sequelae such as CPP and TI, both of which are long-term complications with duration from years to lifetime. QALYs lost in men were from short-term complications with durations of several days to weeks. QALYs lost per incident gonococcal infection were higher in MSW than in MSM, since the estimates only measured the QALYs lost per incident urethral gonococcal infection, and we assumed all infections in MSW were urethral.

Sex and age-group	QALYs lost per infection	95% uncertainty interval (UI)
Women	· · ·	, , , ,
Ages 15-24 years	0.089	(0.021 to 0.21)
Ages 25-39 years	0.11	(0.026 to 0.25)
Ages 15-39 years	0.093	(0.022 to 0.22)
MSW		
Ages 15-24 years	0.0020	(0.0015 to 0.0024)
Ages 25-39 years	0.0019	(0.0015 to 0.0024)
Ages 15-39 years	0.0020	(0.0015 to 0.0024)
MSM		
Ages 15-24 years	0.0018	(0.0013 to 0.0023)
Ages 25-39 years	0.0017	(0.0012 to 0.0022)
Ages 15-39 years	0.0017	(0.0013 to 0.0022)

Table 4.2. Estimated number of discounted lifetime QALYs lost associated with gonorrhea, per incident gonococcal infection in 2015, by sex and age-group.

Estimated discounted lifetime costs per incident infection in 2015 were \$254 (95% UI 109-460) for women, \$306 (157-479) for MSW, and \$281 (145-443) for MSM (Table 4.3). The costs per incident infection in the 15-24 year population were lower than for the 25-39 year population, for women, which can be attribute to a lower probability of PID and sequelae given asymptomatic infection among young than old age groups. Costs of treatment per incident infection by race/ethnicity groups are reported in Supplementary Material Table S4.6.

 Table 4.3. Estimated discounted lifetime costs associated with gonorrhea, per incident gonococcal infection in 2015 (in 2018 US dollars), by sex and age-group.

Sex and age-group	Costs (2018 US dollars)	95% uncertainty interval (UI)
Women		
Ages 15-24 years	248	(108 to 446)
Ages 25-39 years	278	(115 to 511)
Ages 15-39 years	254	(109 to 460)
MSW		
Ages 15-24 years	307	(157 to 480)
Ages 25-39 years	306	(157 to 479)
Ages 15-39 years	306	(157 to 479)
MSM		
Ages 15-24 years	282	(145 to 444)
Ages 25-39 years	281	(144 to 444)
Ages 15-39 years	281	(145 to 443)

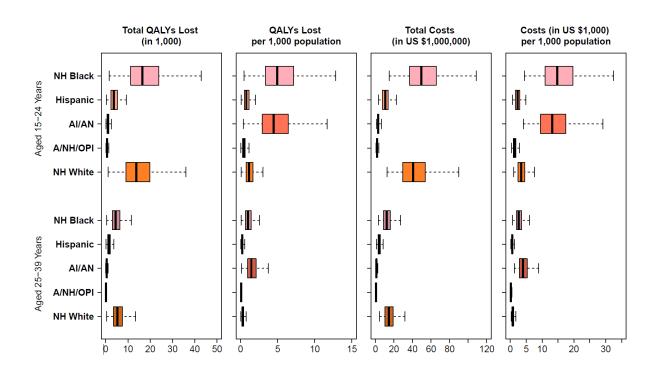
#### Population-level QALYs lost and costs due to gonococcal infections

The population-level discounted lifetime QALYs lost associated with gonococcal infections in 2015 were 53,293 (95% UI 12,326-125,366) for women, 623 (431-876) for MSW, and 1,286 (632-2,074) for MSM (Table S4.7). The total population-level discounted lifetime costs associated with gonococcal infections in 2015 were \$145 million (63-266 million) for women, \$97 million (46-168 million) for MSW, and \$206 million (82-410 million) for MSM (Table S4.8). The total QALYs lost were highest for women aged 15-24 years and were higher for women than for MSW and MSM, which can be attributed to a higher number of QALYs lost per gonococcal infection for women than for men (Table 4.2, Figure 4.3, Figure 4.4, Figure 4.5). The total QALYs lost were higher for MSM than MSW, as a result of higher gonorrhea incidence among MSM than MSW (0.34, 95%UI 0.21-0.50 versus 0.0060, 0.0045-0.0080) in 2015.<sup>13</sup> With similar costs per gonococcal infection (Table 4.3), the total costs were highest for MSM than for women and MSW (Figure 4.3, Figure 4.4, Figure 4.5), primarily due to a much higher incidence for MSM (0.34, 95% UI 0.21-0.50) than women (0.011, 0.0087-0.013) and MSW (0.0060, 0.0045-0.0080) in 2015.<sup>13</sup>

Disparities in the total lifetime QALYs lost and costs reflect variation in the incidence of gonococcal infection across different populations, as well as different population sizes across groups. The total QALYs lost in 2015 were highest among NHB and NHW, followed by Hispanic, AI/AN, and A/NH/OPI, for both women and heterosexual men. For example, the total QALYs lost in 2015 were 18,694 (95% UI 4,437-44,119) for NHB, 15,583 (3,447-37,711) for NHW, 4,074 (962-9,504) for Hispanic, 1,090 (241-2,638) for AI/AN, and 632 (140-1,529) for A/NH/OPI among women aged 15-24 (Figure 4.3, Table S4.7). The total costs in 2015 were highest among NHB and NHW for women. For men, the highest total costs were among MSM, NHW, and NHB (Figure 4.4, Figure 4.5 and Table S4.8).

Disparities in lifetime QALYs lost and costs per 1,000 person-years reflect variation in incidence across different populations. QALYs lost per 1,000 person-years were highest among AI/AN and NHB, followed by NHW, Hispanic and A/NH/OPI among women. For men, the highest QALYs lost per 1,000

person-years were among MSM and NHB (Figure 4.4, Figure 4.5 and Table S4.7). Costs per 1,000 person-years in 2015 were higher among MSM, at \$96,352 (95% UI 38,412 -191,179) than MSW, at \$1,836 (879-3,182) (Table S4.8).



# Figure 4.3. Population-level numbers of QALYs lost, QALYs lost per 1,000 population, total costs (US\$), total costs per 1,000 population, for women, by age and race/ethnicity, in 2015.

\*NH White (Non-Hispanic White), A/NH/OPI (Asian or Native Hawaiian or Other Pacific Islander), AI/AN (American Indian or Alaska Native), NH Black (Non-Hispanic Black). Note that x-axis differs between the plots

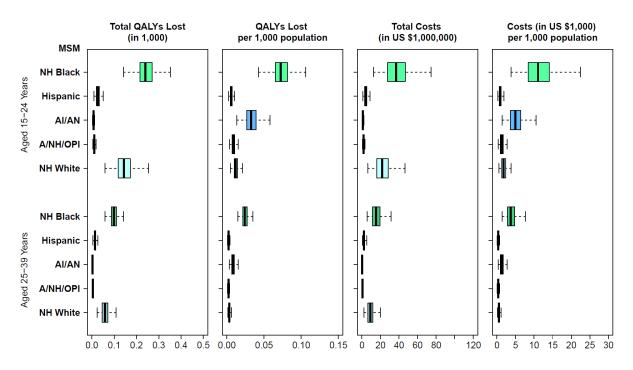
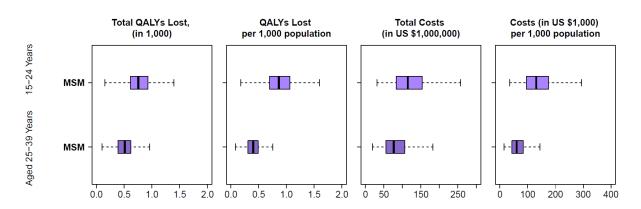
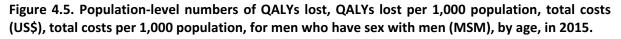


Figure 4.4. Population-level numbers of QALYs lost, QALYs lost per 1,000 population, total costs (US\$), total costs per 1,000 population, for heterosexual men, by age and race/ethnicity, in 2015.

\* NH White (Non-Hispanic White), A/NH/OPI (Asian or Native Hawaiian or Other Pacific Islander), AI/AN (American Indian or Alaska Native), NH Black (Non-Hispanic Black). Note that x-axis differs between the plots.



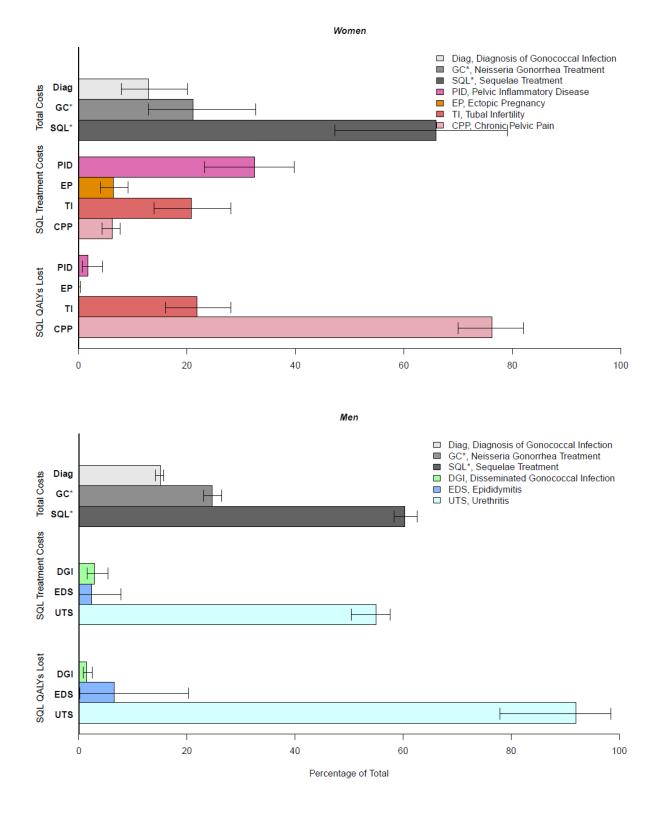


\*Note that x-axis differs between the plots.

#### **Composition of lifetime QALYs lost and costs**

QALYs lost were higher in women than in MSW for all race/ethnicity groups. The duration of chronic sequelae in women was estimated to be longer than the duration of sequelae in men. Among women, the composition of total QALYs lost was estimated to be 76% (95% UI 70%-82%) due to CPP and 22%

(16%-28%) from TI (Figure 4.6), with negligible contributions from other outcomes. Although chronic complications of CPP and TI were the main source of total QALYs lost in women with gonococcal infection due to their long and lifetime durations, the direct costs from these two complications were smaller. TI was estimated to contribute 20% (13%-28%) of the total direct medical costs among women, with a further contribution of 6% (4%-8%) from CPP. The major contributor to the total costs were treatment of PID (32%, 95% UI 22%-39%) and treatment of gonorrhea (23%, 14%-35%). Among men, the major contributor to the total QALYs lost was urethritis (92%, 78%-98%). Urethritis also was the largest component of costs for treating complications (53%, 48%-57%). The cost of test and diagnosis for gonorrhea was the smallest component, contributing 13% (8%-19%) of the total costs for women, and 15% (13%-15%) for men. The main costs were from treatment for gonorrhea sequelae, which contributed 64% (46%-78%) of the total costs for women, and 58% (55%-62%) for men.



# Figure 4.6. Decomposition of total lifetime QALYs lost and costs, by main complications and by broad cost categories.

\*Note GC represented the costs of treatment for gonococcal infections, not including the costs of treatment for gonorrhea sequelae. Sql represented the costs of treatment gonorrhea sequelae.

#### Discussion

In this study we quantified the burden of gonococcal infection in the United States using discounted lifetime QALYs lost and costs, and examined disparities in the population. Women were estimated to have higher QALYs lost and costs per incident gonococcal infection than men, and NHB women had the largest burden of disease of all subpopulations examined. QALYs lost and costs per 1,000 personyears were the highest among MSM and NHB women, reflecting the significant burden of gonococcal infection in these populations. QALYs lost per 1,000 person-years for NHB women were over 4 times those of NHW women, and for AI/AN over 3 times as high as for NHW women. QALYs lost per 1,000 person-years for MSM were over 80 times those of NHW MSW.

Gonococcal infection has relatively short duration, but its longer-term consequences are captured in our estimates of QALYs lost. These estimates point to unmet sexual and reproductive health needs and wider inequities within the population, which place people at differential risk of infection acquisition and sequelae. NHB and MSM have been noted as key populations for gonorrhea prevention also by analyses of surveillance data.<sup>2,8</sup> The high relative burden of gonorrhea among AI/AN has received less attention. Reports of a multi-state syphilis outbreak,<sup>66</sup> and high burden of chlamydia among young AI/AN,<sup>67</sup> signal that there are systemic disparities that need to be addressed. Discrimination, socio-economic status, segregation, institutional racism, and access to and utilization of health care are among the factors contributing to racial/ethnic disparities.<sup>68–70</sup>

We estimated the discounted lifetime costs per incident infection to be \$254 (95% UI 109-460) for women infected in 2015. This is lower than a previous estimate of 354 (95% UI 177-531) per incident infection in women.<sup>56</sup> The difference compared to estimate used in previous study<sup>71</sup> is primarily attributed to a lower probability of PID used in our model, which was estimated based on the duration of gonococcal infection from the previous transmission modeling study<sup>13</sup> and an estimated yearly probability of PID for chlamydial infections synthesized from previous studies.<sup>17–23</sup> It is also attributed to a lower rate of inpatient care of PID and sequelae used in our model, which was estimated from

claims data<sup>35</sup> on the costs of treatment for PID, compared estimates reported in previous studies.<sup>16,48,57,62,63,65</sup> Evidence of a lower rate of inpatient treatment for complications of urethral infection among men from recent studies<sup>36,37</sup> was also applied in our model.

Our study has a number of limitations. First, as with previous studies,<sup>56,62,72</sup> we have assumed that chlamydia and gonorrhea are associated with similar probabilities of developing sequelae. However, gonococcal infection may result in more severe PID than chlamydia.<sup>4</sup> In that case, the assumption that sequelae probabilities are transferrable from studies of outcomes secondary to chlamydial infections may underestimate the QALYs lost due to gonorrhea. Second, costs in our study reflect average costs. There are undoubtedly variations between states, and some costs may have changed over time. Third, as an economic analysis of national disease burden, it would be more consistent with standard methodological recommendations to use community-based rather than expert-based utility measures; however, we were not able to identify any existing studies that report community-based utilities for the range of outcomes associated with gonococcal infection among men. Finally, we did not include the potential increase for HIV acquisition or transmission in people with gonococcal infection. If bacterial STIs increase HIV acquisition and transmission, 10.2% of HIV infections could be attributable to gonorrhea and chlamydia among MSM.<sup>73</sup> This would result in larger total burden associated with gonococcal infection than our current model estimates.

The findings in our study have important implications for resource prioritization and planning, and for informing control policies. They underscore the longer-term burden of a short-term infection, and the continued disparities by race/ethnicity and for MSM within the United States. The QALYs lost and costs associated with gonococcal infection are likely to increase in the future with rising antibiotic resistance. Decreasing disparities by reducing the risk of gonorrhea within disproportionately affected populations would improve the overall health of the population. Measuring both short- and long-term consequences and costs of gonococcal infection provides a comprehensive framework for measuring and evaluating gonorrhea associated health outcomes.

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# **Previous presentation**

Poster at the 2018 National STD Prevention Conference in Washington DC, August 27-30, 2018.

# **Conflict of interest**

The authors declare no conflicts of interest.

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# **Supplementary Material**

#### **Supplementary Methods**

#### 1. Sequelae probabilities

The probability of symptomatic urethral infection (given a gonococcal infection) for both heterosexual men (MSW) and men who have sex with men (MSM) was obtained from a gonorrhea transmission modeling study.<sup>1</sup> The model did not stratify gonococcal infection by site of infection, and it estimated the overall probability of symptomatic infection in MSM and in MSW. The probability of asymptomatic urethral infection among MSM was estimated by assuming that the odds of symptoms given urethral infection were the same for MSM as for MSW (equation 1):

For MSW, we used equation 2, assuming they only have urethral infections (see also Figure 4.2A in main manuscript):

$$Prob^{MSW}(SympUreth) + Prob^{MSW}(AsympUreth) = 1$$
(2)

We used equation 3 for MSM to allow for some infections not being urethral (see also Figure 4.2B in main manuscript):

$$Prob^{MSM}(SympUreth) + Prob^{MSM}(AsympUreth) + Prob^{MSM}(Othersites) = 1$$
(3)

Combining equations 1-3, we have equation 4:

$$Prob^{MSM}(SympUreth) / Prob^{MSW}(SympUreth) + Prob^{MSM}(Othersites) = 1$$
(4)

where:

Prob<sup>MSW</sup>(SympUreth) is the probability of symptomatic urethral infection given gonococcal infection among MSW;

Prob<sup>MSW</sup>(AsympUreth) is the probability of asymptomatic urethral infection given gonococcal infection among MSW;

Prob<sup>MSM</sup>(SympUreth) is the probability of symptomatic urethral infection given gonococcal infection among MSM;

Prob<sup>MSM</sup>(AsympUreth) is the probability of asymptomatic urethral infection given gonococcal infection among MSM;

Prob<sup>MSM</sup>(Othersites) is the probability of other site infections given gonococcal infection among MSM.

Equation 4 implies a restriction that the ratio of the probability of symptomatic urethral infection among MSM to the probability of symptomatic urethral infection among MSW should be greater than 0 but equal to or less than 1. A beta distribution (mean 0.87, 95% UI 0.50-0.99, alpha=4.77, and beta=0.75) was fitted to this ratio estimated in the previous modeling study.<sup>1</sup> Then we calibrated the probability of symptomatic urethral infection among MSM with the fitted beta distribution.

Finally, rearranging equation 1, the probability of asymptomatic urethral infection among MSM was estimated as:

Prob<sup>MSM</sup>(AsympUreth) = Prob<sup>MSM</sup>(SympUreth) \* Prob<sup>MSW</sup>(AsympUreth) / Prob<sup>MSW</sup>(SympUreth)

The probabilities of developing pelvic inflammatory disease (PID), chronic pelvic pain (CPP), ectopic pregnancy (EP), tubal factor infertility (TI), and epididymitis were estimated by synthesizing evidence from primary studies identified through scoping literature reviews. Most relevant studies on these outcomes identified sequelae due to chlamydia, with a lack of direct evidence on sequelae secondary to gonococcal infection. Therefore, as in previous modeling analyses,<sup>2–8</sup> we assumed that probabilities of developing sequelae after gonococcal infection were the same as probabilities after chlamydial infection.

For PID, we used an evidence synthesis model, described elsewhere,<sup>8</sup> to estimate the annual probability that a *Chlamydia trachomatis* infection leads to PID, using information from prospective or retrospective population or clinic-based cohorts, or from RCTs of chlamydia screening. Four trials and one case cohort were included in the analysis.<sup>2–7</sup> Eligible studies ascertained the exposure (infection status) with a range of laboratory investigations (cultures, NAAT assays) and the outcome (PID) with clinical criteria.

We synthesized information using a continuous-time Markov model with four health states: "chlamydia positive symptomatic", "chlamydia positive asymptomatic", "chlamydia negative", and "PID". In each cohort, we modeled the number of patients with PID at the end of follow-up based on the vector of probabilities of being in each health state at the end of the follow-up (i.e., the Markov trace) and the initial conditions (the trace at time 0, known from the design of each cohort). In turn, the time-constant hazard rates for the transitions between states were implicit functions of the trace of the Markov process. The hazard rates for all transitions were allowed to vary by cohort, with the exception of the causal hazard rate for PID attributed to a chlamydial infection, which was assumed to be the same across all cohorts. The causal rate of PID secondary to chlamydial infection was not identifiable using only the available data, namely, from the number of patients in each state at baseline and the number of patients with PID at the end of follow-up. We specified informative priors for the clearance rate of chlamydia with and without treatment. We used external data to inform the clearance rates of chlamydia under treatment. We estimated the clearance rate of chlamydia without treatment assuming that the prevalence of chlamydial infections at baseline for a large populationbased RCT corresponded to the stationary distribution (long-term equilibrium) of the Markov model, and solving for it. Estimation was done using Markov Chain Monte Carlo (MCMC), implemented in the JAGS modeling language. We used the multi-state modeling module in JAGS to obtain solutions to the implicit functions between the Markov trace and the hazard rates. Further details on the methodology are available in a technical report.<sup>8</sup>

There were relatively few studies on the probabilities of CPP, EP, TI, epididymitis, and DGI, which led to a simpler modeling framework for each of these outcomes. We modeled probabilities of CPP, EP and TI conditional on having PID, based on pooled studies on each sequela,<sup>11–17</sup> and using log-link functions. The probabilities of epididymitis were estimated among those with nongonococcal urethritis<sup>18</sup> or *Chlamydia trachomatis* infection.<sup>19</sup> We adopted a previous estimate of the probability of DGI among men with symptomatic *Neisseria gonorrhea*, developed in an Institute of Medicine study (IOM).<sup>9</sup> That study did not report uncertainty around the estimate, so we defined a beta distribution with mean equal to the estimated probability of DGI among men from the IOM study, with the upper limit of the 95% UI equal to the estimate reported in the most recent study.<sup>10</sup>

Table S4.1 summarizes the estimated probabilities resulting from our review and synthesis of the evidence. In our probability trees, we allowed for all possible combinations of sequelae based on a simplifying assumption that the probabilities are independent, which leads to a multiplicative formulation for the joint probabilities.

Sequelae	Mean	Standard deviation	Uncertainty Interval	Distribution for uncertainty analysis
Chronic pelvic pain	0.261	0.0156	(0.231, 0.292)	Beta (alpha=203.608, beta=577.096)
Ectopic pregnancy	0.0708	0.0124	(0.0488, 0.0979)	Beta (alpha=29.048, beta=381.277)
Tubal infertility	0.169	0.0286	(0.117, 0.230)	Beta (alpha=28.186, beta=138.95)
Epididymitis	0.0422	0.0381	(0.00116, 0.137)	Beta (alpha=1.087, beta=24.614)
Disseminated gonococcal infection	0.0100	0.0014	(0.0075, 0.013)	Beta (alpha=48.08, beta=4,759)

Table S4.1. Estimated probabilities of sequelae.

2. Utilities

We used estimates of health state utilities (weights) derived from prior studies among experts, since we did not identify any estimates from the societal or patient perspective for men. Our method follows the same approach used in earlier studies, for example Tuite *et al.* (2012)<sup>20</sup> and Hu *et al.* (2004).<sup>21</sup>

Table S4.2 presents the utility estimates for women aged 15-24 years from expert and patient perspectives identified in the literature review. Estimates from the patient perspective result in higher utility values than those based on expert perspective.

Health state	Utility (expert perspective) <sup>9</sup>	Utility (patient perspective) <sup>22</sup>	Duration (years) <sup>9,23–25</sup>
PID (inpatient treatment)	0.76	0.78	13 days (0.036)
PID (outpatient treatment)	0.63	0.82	10 days (0.027)
Chronic pelvic pain	0.60	0.76	5 years, to remaining lifetime (23.55)
Ectopic pregnancy (inpatient)	0.62	0.82	31 days (0.085)
Ectopic pregnancy (outpatient)	0.58	0.82	28 days (0.076)
Tubal infertility	0.82	0.84	5 years, to remaining lifetime (23.55)

Table S4.2. Quality weight and duration of PID and its sequelae

\*Duration of remaining lifetime was estimated based on lifetable for females aged 15-24 years in 2015.<sup>25</sup>

#### 3. Weighted utilities and durations of sequelae inpatient and outpatient care

There are multiple scenarios for inpatient and outpatient treatment for gonorrhea sequelae of PID, EP and DGI in women and men, according to the IOM framework. For example, there were PID (salpingitis, perihepatitis) outpatient only, PID (salpingitis, perihepatitis) inpatient no surgery, PID (salpingitis, perihepatitis) inpatient with surgery, PID (salpingitis, perihepatitis) outpatient after inpatient, PID (bilateral salpingo-oophorectomy) inpatient, and PID (bilateral salpingo-oophorectomy) outpatient after inpatient. For simplification and matching evidence from other studies, we included inpatient treatment and outpatient treatment in our probability tree as weighted combination of the inpatient and outpatient care scenarios. We illustrate the calculations for the example of inpatient treatment of PID in women, with information in Table S4.3. Table S4.3 column 1, 2, 3, and 4 are derived from the Table A17-2 disease scenarios for gonorrhea infection in women and men in the IOM framework.<sup>9</sup>

Scenarios	% cases among all scenarios <sup>9</sup>	Utilities <sup>9</sup>	Durations (years) <sup>9</sup>	% cases among PID inpatient only (weights)	Weighted durations	Weighted QALYs lost
PID (salpingitis, perihepatitis) inpatient no surgery	0.075	0.57	0.011	0.69	0.0076	0.0033
PID (salpingitis, perihepatitis) inpatient with surgery	0.025	0.46	0.0054	0.23	0.0012	0.00067
PID (salpingitis, perihepatitis) outpatient after inpatient	0.100	0.83	0.027	0.92	0.025	0.0042
PID (bilateral salpingo- oophorectomy) inpatient	0.008	0.40	0.0027	0.074	0.00020	0.00012
PID (bilateral salpingo- oophorectomy) outpatient after inpatient	0.008	0.76	0.027	0.074	0.0020	0.00048
Total	0.1008			1.00	0.036	0.0088

Table S4.3. Weighted utilities and durations of inpatient treatment for PID.

We first calculated the proportion of cases under each scenario among PID inpatient treatment only and reported in the fifth column in Table S4.3, as the second column represented the proportion of cases among all scenarios of gonorrhea and sequelae in the original IOM study. For example, proportion of PID (salpingitis, perihepatitis) inpatient no surgery = 0.075 / (0.075 + 0.025 + 0.008) =0.69. The total duration of PID inpatient care was calculated as a weighted duration of all these scenarios (column 6). That is, 0.011\*0.69 + 0.0054\*0.23 + 0.027\*0.92 + 0.0027\*0.074 + 0.027\*0.074= 0.036 (See also Table 4.1). Then weighted QALYs lost from each scenario were calculated in column 7, leading to a total QALYs lost from inpatient PID as 0.0088. The weighted utility of total inpatient PID treatment is 1 - 0.0088 / 0.036 = 0.76 (also reported in Table 4.1).

#### 4. Durations and discounting for long-term sequelae

Following conventions in an earlier study commissioned by the Institute of Medicine,<sup>9</sup> and in other similar studies, such as Regnier *et al.* (2014),<sup>26</sup> we applied time discounting to the durations of the two long-term sequelae (CPP and TI). Estimated durations for these two sequelae varied widely in the published literature. We therefore assumed a wide uncertainty range, between 5 years and remaining lifetime.<sup>9,23</sup> We also assumed that there was a five-year lag between infection and the occurrence of these sequelae.<sup>9</sup> When duration of CPP and TI were assumed to be remaining lifetime, we used a life table approach with age-specific mortalities to estimate discounted life expectancy for females in 2015, using a 3% annual discount rate. In a preliminary analysis, we compared results across race/ethnicity groups and over time, but given that differences in discounted life expectancy were relatively small in these comparisons, for parsimony we pooled across all race/ethnicity groups and used data from 2015 to apply to all years.<sup>25</sup>

In Table S4.4 we illustrate the calculations for the example of an infection among a woman aged 20 years in 2015. For each five-year age interval (beginning after the five-year lag from incidence), we computed the present value of the loss of quality-adjusted life-years during that interval. We first obtained the age-group-specific conditional probability of all-cause mortality (and its complement, survival) for women in 2015 from the National Center for Health Statistics.<sup>25</sup> We assumed that deaths occurred at the midpoint of each age interval up to 95-99 years and older. For the final, open interval (ages 100 years and more), we used estimated life expectancy at 100 years to define the average years lived in that open interval (2.284 years for females in 2015). The undiscounted total years lived by those who were alive at the start of an interval was calculated using the standard life table approach, accounting for years lived by those surviving the entire interval and years lived by those who died during the interval. For example, the undiscounted total years lived by those who survived and those who died between age 20-24 years was computed as (0.00232\*2.5+(1-0.00232)\*5)\*1=4.994 years. The undiscounted total years lived by those who survived or died between age 25-29 years was

computed as (0.00304\*2.5+(1-0.00304)\*5)\*0.998=4.981 years, and so on. We accounted for both condition-specific QALY adjustments as well as age-specific QALY adjustments (reflecting comorbidities) using a multiplicative model.

Table S4.4. Discounted life years lived and QALYs lost due to CPP with lifetime duration, for a woman who acquires gonorrhea age at 20 years in 2015 and experiences CPP beginning at age 25 years.

Age (x) at start of interval (years)	Conditional probability of dying between ages x and x+n	Probability of surviving from age 20 to exact age x	Years lived within each interval by each person alive at age 20	Discounted years lived within each interval by each person alive at age 20	Back- ground health- state weight <sup>27</sup>	Health state weight for CPP	Discounted QALYs lost due to CPP between ages x and x+n
20	0.00232	1.000	4.994	4.704	0.922	NA	NA
25	0.00304	0.998	4.981	4.030	0.922	0.600	1.486
30	0.00417	0.995	4.963	3.451	0.901	0.600	1.244
35	0.00549	0.990	4.939	2.954	0.901	0.600	1.065
40	0.00791	0.985	4.906	2.525	0.871	0.600	0.880
45	0.0120	0.977	4.857	2.155	0.871	0.600	0.751
50	0.0189	0.965	4.782	1.832	0.842	0.600	0.617
55	0.0275	0.947	4.671	1.549	0.842	0.600	0.522
60	0.0385	0.921	4.517	1.303	0.823	0.600	0.429
65	0.0566	0.886	4.304	1.085	0.823	0.600	0.357
70	0.0904	0.836	3.989	0.886	0.790	0.600	0.280
75	0.145	0.760	3.525	0.698	0.790	0.600	0.221
80	0.240	0.650	2.859	0.514	0.736	0.600	0.151
85	0.392	0.494	1.985	0.331	0.736	0.600	0.0976
90	0.590	0.300	1.059	0.169	0.736	0.600	0.0497
95	0.777	0.123	0.377	0.0587	0.736	0.600	0.0173
100	1.000	0.027	0.0628	0.0097	0.736	0.600	0.00286
Total	NA	NA	56.776	23.551	NA	NA	8.169

#### 5. Probabilities of diagnosis and treatment

We derived year-, race/ethnicity-, and age-specific probabilities of diagnosis and treatment for asymptomatic gonococcal infections from a calibrated gonorrhea metapopulation-model.<sup>1</sup> In the study, heterosexual women and men were categorized as Non-Hispanic black, Hispanic, or "white and other," whereas MSM were not stratified by race/ethnicity. Each population was stratified as two age groups (15-24 years and 25-39 years). As in the previous modeling study,<sup>1</sup> all symptomatic gonococcal

infections were assumed to be reported and have received treatment. That is, the probabilities of

treatment for symptomatic gonococcal infections were assumed to be 100%.

Table S4.5 report model-estimated probabilities of diagnosis and treatment for asymptomatic gonococcal infections along the same strata.

Table S4.5-(a). Estimated probabilities of diagnosis and treatment for asymptomatic gonococcal
infections for heterosexual women by age and race/ethnicity over 2000-2015.

Year	Non	-Hispanic Black		Hispanic	Wh	ite and Other
	Mean	UI	Mean	UI	Mean	UI
Age 15-24 y	/ears					
2000	0.178	0.108, 0.260	0.166	0.084, 0.296	0.187	0.115, 0.278
2001	0.178	0.108, 0.260	0.166	0.084, 0.296	0.187	0.115, 0.278
2002	0.191	0.122, 0.276	0.180	0.098, 0.302	0.202	0.138, 0.290
2003	0.202	0.132, 0.286	0.190	0.109, 0.311	0.214	0.152, 0.302
2004	0.212	0.141, 0.297	0.198	0.116, 0.316	0.222	0.162, 0.308
2005	0.221	0.150, 0.305	0.204	0.120, 0.320	0.229	0.166, 0.313
2006	0.229	0.157, 0.314	0.208	0.121, 0.325	0.233	0.169, 0.318
2007	0.236	0.163, 0.319	0.211	0.123, 0.329	0.236	0.170, 0.323
2008	0.242	0.169, 0.328	0.212	0.124, 0.332	0.238	0.171, 0.325
2009	0.247	0.173, 0.337	0.213	0.125, 0.333	0.239	0.171, 0.325
2010	0.251	0.177, 0.343	0.213	0.125, 0.334	0.239	0.171, 0.325
2011	0.254	0.179, 0.345	0.213	0.125, 0.333	0.238	0.171, 0.325
2012	0.256	0.180, 0.349	0.212	0.124, 0.331	0.237	0.170, 0.324
2013	0.257	0.181, 0.351	0.211	0.124, 0.330	0.237	0.170, 0.321
2014	0.258	0.182, 0.351	0.210	0.123, 0.329	0.236	0.169, 0.320
2015	0.257	0.181, 0.349	0.210	0.123, 0.328	0.235	0.169, 0.319
Age 25-39 y	/ears					
2000	0.161	0.083, 0.278	0.123	0.056, 0.229	0.142	0.080, 0.225
2001	0.161	0.083, 0.278	0.123	0.056, 0.229	0.142	0.080, 0.225
2002	0.166	0.094, 0.276	0.146	0.069, 0.258	0.168	0.103, 0.247
2003	0.171	0.098, 0.278	0.163	0.080, 0.282	0.187	0.113, 0.269
2004	0.174	0.104, 0.279	0.175	0.087, 0.307	0.202	0.121, 0.291
2005	0.177	0.106, 0.279	0.185	0.091, 0.326	0.212	0.127, 0.307
2006	0.179	0.104, 0.281	0.191	0.094, 0.340	0.219	0.129, 0.321
2007	0.181	0.102, 0.286	0.196	0.096, 0.348	0.224	0.130, 0.327
2008	0.182	0.102, 0.289	0.198	0.097, 0.353	0.227	0.131, 0.330
2009	0.183	0.100, 0.293	0.199	0.097, 0.353	0.228	0.131, 0.333
2010	0.183	0.099, 0.294	0.199	0.097, 0.353	0.228	0.131, 0.334
2011	0.183	0.096, 0.293	0.199	0.097, 0.351	0.227	0.130, 0.333
2012	0.183	0.091, 0.292	0.197	0.097, 0.349	0.226	0.129, 0.331
2013	0.183	0.088, 0.292	0.196	0.097, 0.347	0.225	0.129, 0.330
2014	0.182	0.087, 0.291	0.195	0.096, 0.345	0.224	0.128, 0.329
2015	0.182	0.087, 0.290	0.195	0.096, 0.345	0.223	0.128, 0.329

Year	Non-H	lispanic Black	Hispanic		Whit	e and Other		MSM
	Mean	UI	Mean	UI	Mean	UI	Mean	UI
Age 15-24	years							
2000	0.015	0.004, 0.032	0.039	0.016, 0.078	0.038	0.015, 0.076	0.138	0.070, 0.229
2001	0.015	0.004, 0.032	0.039	0.016, 0.078	0.038	0.015, 0.076	0.138	0.070, 0.229
2002	0.015	0.001, 0.034	0.045	0.021, 0.086	0.043	0.022, 0.079	0.136	0.067, 0.227
2003	0.017	0.001, 0.037	0.049	0.022, 0.100	0.047	0.023, 0.085	0.139	0.069, 0.230
2004	0.020	0.004, 0.042	0.052	0.021, 0.114	0.050	0.023, 0.091	0.145	0.072, 0.233
2005	0.024	0.008, 0.046	0.055	0.020, 0.122	0.052	0.022, 0.097	0.152	0.082, 0.239
2006	0.029	0.010, 0.052	0.057	0.019, 0.129	0.054	0.022, 0.103	0.162	0.093, 0.247
2007	0.034	0.013, 0.060	0.058	0.019, 0.133	0.055	0.022, 0.105	0.172	0.102, 0.262
2008	0.040	0.015, 0.070	0.058	0.019, 0.135	0.056	0.022, 0.106	0.182	0.110, 0.275
2009	0.046	0.017, 0.080	0.059	0.018, 0.136	0.056	0.022, 0.107	0.193	0.119, 0.289
2010	0.051	0.019, 0.090	0.058	0.018, 0.137	0.056	0.021, 0.106	0.202	0.123, 0.303
2011	0.056	0.021, 0.100	0.058	0.018, 0.136	0.056	0.021, 0.105	0.211	0.127, 0.314
2012	0.060	0.022, 0.108	0.058	0.018, 0.134	0.055	0.021, 0.104	0.218	0.131, 0.324
2013	0.062	0.022, 0.113	0.058	0.018, 0.133	0.055	0.021, 0.103	0.224	0.133, 0.333
2014	0.064	0.023, 0.116	0.057	0.018, 0.131	0.055	0.021, 0.101	0.228	0.134, 0.340
2015	0.064	0.023, 0.115	0.057	0.018, 0.131	0.055	0.021, 0.101	0.229	0.134, 0.342
Age 25-39	years							
2000	0.048	0.018, 0.121	0.055	0.016, 0.119	0.052	0.019, 0.101	0.222	0.121, 0.326
2001	0.048	0.018, 0.121	0.055	0.016, 0.119	0.052	0.019, 0.101	0.222	0.121, 0.326
2002	0.048	0.019, 0.115	0.054	0.017, 0.117	0.051	0.020, 0.095	0.220	0.122, 0.321
2003	0.048	0.020, 0.111	0.053	0.017, 0.113	0.051	0.020, 0.093	0.219	0.122, 0.326
2004	0.048	0.021, 0.104	0.053	0.018, 0.108	0.050	0.020, 0.090	0.218	0.117, 0.337
2005	0.047	0.021, 0.100	0.052	0.018, 0.101	0.049	0.020, 0.088	0.217	0.114, 0.342
2006	0.047	0.021, 0.099	0.051	0.018, 0.098	0.049	0.020, 0.083	0.216	0.110, 0.345
2007	0.047	0.020, 0.095	0.050	0.018, 0.094	0.048	0.020, 0.083	0.215	0.106, 0.351
2008	0.047	0.020, 0.095	0.049	0.018, 0.092	0.047	0.020, 0.086	0.214	0.105, 0.352
2009	0.046	0.018, 0.094	0.048	0.017, 0.091	0.047	0.020, 0.089	0.213	0.104, 0.352
2010	0.046	0.017, 0.095	0.048	0.017, 0.093	0.046	0.020, 0.095	0.213	0.104, 0.352
2011	0.046	0.017, 0.095	0.047	0.016, 0.095	0.045	0.020, 0.101	0.213	0.102, 0.351
2012	0.046	0.016, 0.094	0.047	0.016, 0.098	0.045	0.019, 0.105	0.212	0.102, 0.350
2013	0.045	0.016, 0.094	0.046	0.015, 0.099	0.045	0.018, 0.107	0.212	0.103, 0.348
2014	0.045	0.016, 0.094	0.046	0.015, 0.099	0.044	0.018, 0.108	0.212	0.104, 0.347
2015	0.045	0.015, 0.094	0.046	0.015, 0.099	0.044	0.018, 0.109	0.212	0.105, 0.347

Table S4.5-(b). Estimated probabilities of diagnosis and treatment for asymptomatic gonococcal infections for heterosexual men by age and race/ethnicity, and for MSM by age, over 2000-2015.

# 6. Defining probabilities and costs of side effects from gonorrhea treatment

There are mild to moderate events and severe events as adverse reactions to gonorrhea treatment using Azithromycin (1g) and Ceftriaxone (250mg). Mild to moderate reactions usually include one or more of the following events: vomiting, reduction in hearing, dizziness or unsteadiness, skin rash, injection pain, diarrhea and abdominal pain, fatigue, etc. Severe reactions usually include anaphylaxis, cholestatic jaundice, and interstitial nephritis. In our model, the probabilities of side effects were generated from beta distributions fitted in probabilities observed or estimated from a cost-effectiveness analysis and several meta-analyses of randomized controlled trials.<sup>28–31</sup>The costs of side effects were also driven from these studies,<sup>28–31</sup> with mean as average of costs estimated by each study, and 95% UI as symmetrically to the mean.

#### **Supplementary Results**

#### 1. Lifetime QALYs, costs per incident gonococcal infection by race/ethnicity

Table S4.6. Estimated number of discounted lifetime QALYs lost and costs associated with gonorrhea, per incident infection in 2015 by race/ethnicity groups.

	NHB	Hispanic	AI/AN	A/NH/OPI	NHW	MSM
A. QALYs per	incident infectior	n in 2015. wome	n			
Mean	0.0921	0.0933	0.0935	0.0928	0.0931	NA
95% UI	(0.0221 to	(0.0225 to	(0.0226 to	(0.0224 to	(0.0224 to	NA
	0.217)	0.221)	0.222)	0.220)	0.221)	
B. QALYs per	incident infectior	n in 2015, MSW (	and MSM			
Mean	0.00200	0.00200	0.00200	0.00200	0.00200	0.00175
95% UI	(0.00153 to	(0.00153 to	(0.00153 to	(0.00153 to	(0.00153 to	(0.00125 to
	0.00239)	0.00239)	0.00240)	0.00240)	0.00240)	0.00224)
C. Costs per in	ncident infection	in 2015 (in 2018	USD), women			
Mean	254	252	255	254	255	NA
95% UI	(109 to 459)	(109 to 460)	(109 to 462)	(109 to 459)	(109 to 460)	NA
D. Costs per il	ncident infection	in 2015 (in 2018	B USD), MSW an	d MSM		
Mean	307	306	306	306	306	281
95% UI	(157 to 480)	(157 to 480)	(157 to 479)	(157 to 479)	(157 to 479)	(145 to 443)

\*NH White (Non-Hispanic White), A/NH/OPI (Asian or Native Hawaiian or Other Pacific Islander), AI/AN (American Indian or Alaska Native), NH Black (Non-Hispanic Black)

# 2. Population-level QALYs lost due to gonococcal infections

# Table S4.7. Total number of discounted lifetime QALYs lost, and discounted lifetime QALYs lost per 1,000 person-years associated with gonococcal infections that occurred in 2015, by sex, age-groups and race/ethnicity.

Sex and age-group	Total number of QALYs lost	95% uncertainty interval	QALYs lost per 1000 person- years	95% uncertainty interval
Women				
Ages 15-24 y, all	40,073	(9,425 to 94,124)	1.87	(0.44 to 4.40)
Ages 25-39 y, all	13,221	(3,118 to 31,971)	0.41	(0.097 to 1.00)
Ages 15-39 y, all	53,293	(12,326 to 125,366)	1.00	(0.23 to 2.35)
Ages 15-24 y, NHB	18,694	(4,437 to 44,119)	5.59	(1.33 to 13.20)
Ages 15-24 y, Hispanic	4,074	(962 to 9,504)	0.88	(0.21 to 2.06)
Ages 15-24 y, AI/AN	1,090	(241 to 2,638)	5.05	(1.12 to 12.22)
Ages 15-24 y, A/NH/OPI	632	(140 to 1,529)	0.50	(0.11 to 1.20)
Ages 15-24 y, NHW	15,583	(3,447 to 37,711)	1.31	(0.29 to 3.16)
Ages 25-39 y, NHB	5,073	(1,185 to 12,009)	1.12	(0.26 to 2.64)
Ages 25-39 y, Hispanic	1,625	(387 to 3,890)	0.26	(0.061 to 0.61)
Ages 25-39 y, AI/AN	456	(103 to 1,120)	1.63	(0.37 to 4.01)
Ages 25-39 y, A/NH/OPI	215	(49 to 527)	0.086	(0.019 to 0.21)
Ages 25-39 y, NHW	5,852	(1,323 to 14,367)	0.32	(0.072 to 0.78)
MSW				
Ages 15-24 y, all	440	(302 to 623)	0.020	(0.014 to 0.029)
Ages 25-39 y, all	183	(124 to 261)	0.0059	(0.0040 to 0.0084)
Ages 15-39 y, all	623	(431 to 876)	0.012	(0.0082 to 0.017)
Ages 15-24 y, NHB	245	(173 to 343)	0.071	(0.050 to 0.099)
Ages 15-24 y, Hispanic	27.48	(14.86 to 45.24)	0.0056	(0.0030 to 0.0092)
Ages 15-24 y, AI/AN	7.26	(4.11 to 11.98)	0.032	(0.018 to 0.054)
Ages 15-24 y, A/NH/OPI	11.11	(6.29 to 18.34)	0.0085	(0.0048 to 0.014)
Ages 15-24 y, NHW	149	(84.41 to 246)	0.012	(0.0067 to 0.020)
Ages 25-39 y, NHB	100	(71.52 to 139)	0.024	(0.017 to 0.033)
Ages 25-39 y, Hispanic	15.29	(8.61 to 25.13)	0.0022	(0.0012 to 0.0036)
Ages 25-39 y, AI/AN	2.27	(1.20 to 3.76)	0.0082	(0.0043 to 0.014)
Ages 25-39 y, A/NH/OPI	4.65	(2.45 to 7.70)	0.0020	(0.0011 to 0.0034)
Ages 25-39 y, NHW	60.36	(31.84 to 99.99)	0.0032	(0.0017 to 0.0053)
MSM				
Ages 15-24 y, all	772	(363 to 1,286)	0.88	(0.41 to 1.47)
Ages 25-39 y, all	514	(224 to 860)	0.41	(0.18 to 0.68)
Ages 15-39 y, all	1,286	(632 to 2,074)	0.60	(0.29 to 0.97)

\*NH White (Non-Hispanic White), A/NH/OPI (Asian or Native Hawaiian or Other Pacific Islander), AI/AN (American Indian or Alaska Native), NH Black (Non-Hispanic Black), all is the total population of these five race/ethnicity groups.

# 3. Population-level costs due to gonococcal infections

Table S4.8. Total discounted lifetime costs, and lifetime costs per 1,000 person-years associated with gonococcal infections that occurred in 2015 (in 2018 US dollars), by sex, age-groups and race/ethnicity.

Sex and age-group	Total costs (2018 US dollars, millions)	95% uncertainty interval	Costs per 1000 person- years (2018 US dollars,	95% uncertainty interval
Momon			thousands)	
Women Ages 15-24 y	111.31	(48.44 to 202.84)	5.21	(2.27 to 9.49)
	34.04	(48.44 to 202.84) (13.90 to 64.65)	1.06	(0.43 to 2.02)
Ages 25-39 y		(13.90 to 64.63) (62.79 to 265.92)		. ,
Ages 15-39 y	145.34		2.72	(1.18 to 4.98)
Ages 15-24 y, NHB	52.31	(22.18 to 97.46)	15.65	(6.64 to 29.16)
Ages 15-24 y, Hispanic	11.16	(4.69 to 20.86)	2.42	(1.02 to 4.52)
Ages 15-24 y, AI/AN	3.01	(1.28 to 5.63)	13.96	(5.94 to 26.07)
Ages 15-24 y, A/NH/OPI	1.75	(0.74 to 3.26)	1.37	(0.58 to 2.56)
Ages 15-24 y, NHW	43.08	(18.32 to 80.47)	3.61	(1.54 to 6.74)
Ages 25-39 y, NHB	12.94	(5.34 to 25.42)	2.85	(1.18 to 5.60)
Ages 25-39 y, Hispanic	4.17	(1.67 to 8.21)	0.66	(0.26 to 1.30)
Ages 25-39 y, AI/AN	1.18	(0.48 to 2.31)	4.24	(1.71 to 8.26)
Ages 25-39 y, A/NH/OPI	0.56	(0.22 to 1.09)	0.22	(0.090 to 0.43)
Ages 25-39 y, NHW	15.19	(6.12 to 29.60)	0.83	(0.33 to 1.61)
MSW				
Ages 15-24 y	68.06	(32.76 to 118.43)	3.15	(1.52 to 5.49)
Ages 25-39 y	28.89	(13.58 to 50.61)	0.93	(0.44 to 1.62)
Ages 15-39 y	96.94	(46.39 to 167.97)	1.84	(0.88 to 3.18)
Ages 15-24 y, NHB	38.02	(18.06 to 66.41)	11.04	(5.24 to 19.27)
Ages 15-24 y, Hispanic	4.24	(1.73 to 8.51)	0.86	(0.35 to 1.73)
Ages 15-24 y, AI/AN	1.12	(0.47 to 2.11)	5.00	(2.10 to 9.43)
Ages 15-24 y, A/NH/OPI	1.71	(0.72 to 3.23)	1.31	(0.55 to 2.47)
Ages 15-24 y, NHW	22.96	(9.65 to 43.29)	1.83	(0.77 to 3.44)
Ages 25-39 y, NHB	15.87	(7.61 to 26.98)	3.74	(1.79 to 6.36)
Ages 25-39 y, Hispanic	2.41	(0.97 to 4.81)	0.35	(0.14 to 0.70)
Ages 25-39 y, AI/AN	0.36	(0.14 to 0.71)	1.29	(0.50 to 2.56)
Ages 25-39 y, A/NH/OPI	0.73	(0.28 to 1.45)	0.32	(0.12 to 0.64)
Ages 25-39 y, NHW	9.51	(3.64 to 18.86)	0.51	(0.19 to 1.00)
MSM		,		
Ages 15-24 y	122.98	(48.85 to 244.58)	140.37	(55.75 to 279.14)
Ages 25-39 y	83.46	(31.68 to 167.38)	65.90	(25.02 to 132.17)
Ages 15-39 y	206.44	(82.30 to 409.62)	95.35	(38.41 to 191.18)

\*NH White (Non-Hispanic White), A/NH/OPI (Asian or Native Hawaiian or Other Pacific Islander), AI/AN (American Indian or Alaska Native), NH Black (Non-Hispanic Black), all is the total population of these five race/ethnicity groups.

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# **Chapter 5. Conclusion**

#### Summary of dissertation papers

This dissertation uses mathematical modelling to synthesize empirical evidence and evaluate the epidemiological and economic burden of specific chronic and infectious diseases in the United States. In the second chapter of this dissertation, "Dynamic Modeling of Prevalence and Incidence Trends for Diabetes and Diabetes Diagnosis among Adults Aged 20 Years or Older, United States, 2000-2016", I develop an age-stratified Markov model of undiagnosed and diagnosed diabetes and examine how the epidemiological burden of diabetes in the United States has changed over recent decades. The model estimates a 17-year period of decreasing prevalence of undiagnosed diabetes, rates of diabetes diagnosis, and incidence of diagnosed diabetes in the US adult population. This work provides the first estimates of the incidence of diabetes, and rates of diabetes diagnosis among the US adult population from nationally representative surveys.

In the third chapter, "*Risk score to predict cardiovascular disease (CVD) risk for patients with type 2 diabetes mellitus (T2DM) in the United States: a pooled analysis of prospective cohorts*", I develop a novel CVD risk prediction model specifically for populations with T2DM in the United States. The model is constructed as a multivariable risk factor model estimated using pooled data on fatal-plus-non-fatal CVD outcomes from 5 prospective cohorts. The model predicts a 10-year fatal-plus-non-fatal CVD risk for patients with T2DM in the US, with good discrimination and calibration performance. This performance is superior to the 2013 ACC/AHA Pooled Cohort Risk Equation, which underestimates 10-year atherosclerotic CVD risk in diabetic populations.

In the fourth chapter, "Disparities in health and economic outcomes associated with N. gonorrhoeae infection in the United States: costs and quality-adjusted life-years lost in 2015", I develop probability tree models that capture clinical outcomes of gonorrhea and sequelae, and use these models to

evaluate the health and economic burden of gonorrhea and disparities across race/ethnicity groups. I report population-level disease burden in terms of the discounted lifetime costs and quality-adjusted life-years (QALYs) lost due to incident infections acquired during 2015, disaggregated by sex, age, race/ethnicity, and for men who have sex with men (MSM). The findings suggest that the highest absolute burden of both QALYs and costs occurs in Non-Hispanic Black women, and the highest percapita burden occurs in MSM and American Indian/Alaska Native women.

#### Policy implications and future research

The results of this dissertation illustrate the use of mathematical modelling to synthesize observed data to infer epidemiological trends that are not always directly observable, to quantify the shortterm and long-term health outcomes associated with disease and complications, and to measure disparities of health and economic burden of disease across population subgroups. The findings from our estimation of incidence trends for diabetes and diabetes diagnosis in the US adult population highlight the importance of continuing surveillance of trends in diabetes screening and testing and interventions to reduce diabetes incidence. Although the incidence of diabetes decreased, declining mortality among diagnosed diabetic populations, and high and increasing prevalence of all diabetes have resulted in continued high total number of diabetic individuals in the United States. In addition, according to our diabetes-specific CVD risk model, the estimated cardiovascular disease incidence and death rates among patients with type 2 diabetes in the United States may be higher than the estimates predicted and reported in the 2013 ACC/AHA Guideline on the Assessment of Cardiovascular Risk. With decreasing all-cause and CVD-specific mortality but increasing long-term morbidity, the overall burden of diabetes and cardiovascular complications in the United States will remain high at least over the next decade. For these reasons, continued efforts to implement effective primary and secondary prevention for diabetes remain important public health priorities.

The third paper in this dissertation, while focusing on a different clinical condition, shares several key methodological themes with the first two papers. Our analysis of the health consequences and

economic costs related to gonococcal infection synthesizes evidence from various sources to answer broad questions on resource prioritization and planning, relevant to public health policies. Across all three studies, the findings have identified or can be used to identify subpopulations with high or increasing disease and complications that may have been under-appreciated in previous research. more specifically, findings from the first paper indicate an increasing trend in prevalence of undiagnosed diabetes in adults ages 20-49 years, with continuing increases likely. Patients with high CVD incidence and mortality over the next decade can be quantified when applying the CVD risk prediction model in the second paper to risk factor profiles of diabetic populations in the United States. Results from the third paper not only quantify the large total disease burden associated with gonorrhea among non-Hispanic Black populations and among men who have sex with men, but also highlight the substantial relative burden among American Indian/Alaska Native populations. Identifying subpopulations with disproportionately large disease burden can provide evidence to enable decision making to target groups with the highest need.

In addition to informing decision-making and health policy, the mathematical models developed in this dissertation highlight gaps in information availability, such as limited surveillance data on changes in diabetes detection and screening, CVD incidence and mortality for high-risk diabetic populations, and disparities in gonorrhea and sequelae diagnosis and treatment. By illuminating these limitations, modeling results can indicate directions for collecting new data to enable disease burden assessment. By presenting a comprehensive analysis framework of disease burden associated with gonococcal infection in the third study, we also provide guidance on how to collect and synthesize information that is most relevant to population disease burden and disparities evaluation.

In summary, this dissertation describes three evaluations of disease burden in the United States, in the areas of chronic and infectious disease, and considering both economic and epidemiological outcomes. In each study, modelling is used to synthesize a range of empirical data, describe the

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relationship between these data and subsequent outcomes, and report results directly relevant to policy or clinical decision-making.