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ORIGINAL ARTICLE

Comparative Modeling of Tuberculosis Epidemiology and Policy Outcomes in California

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Abstract

Rationale: Mathematical modeling is used to understand disease dynamics, forecast trends, and inform public health prioritization. We conducted a comparative analysis of tuberculosis (TB) epidemiology and potential intervention effects in California, using three previously developed epidemiologic models of TB.

Objectives: To compare the influence of various modeling methods and assumptions on epidemiologic projections of domestic latent TB infection (LTBI) control interventions in California.

Methods: We compared model results between 2005 and 2050 under a base-case scenario representing current TB services and alternative scenarios including: *1*) sustained interruption of *Mycobacterium tuberculosis* (*Mtb*) transmission, *2*) sustained resolution of LTBI and TB prior to entry of new residents, and *3*) one-time targeted testing and treatment of LTBI among 25% of non–U.S.-born individuals residing in California.

Measurements and Main Results: Model estimates of TB cases and deaths in California were in close agreement over the historical period but diverged for LTBI prevalence and new *Mtb* infections—outcomes for which definitive data are unavailable. Between 2018 and 2050, models projected average annual declines of 0.58–1.42% in TB cases, without additional interventions. A one-time LTBI testing and treatment intervention among non–U.S.-born residents was projected to produce sustained reductions in TB incidence. Models found prevalent *Mtb* infection and migration to be more significant drivers of future TB incidence than local transmission.

Conclusions: All models projected a stagnation in the decline of TB incidence, highlighting the need for additional interventions including greater access to LTBI diagnosis and treatment for non–U.S.-born individuals. Differences in model results reflect gaps in historical data and uncertainty in the trends of key parameters, demonstrating the need for high-quality, up-to-date data on TB determinants and outcomes.

Keywords: latent tuberculosis infection; tuberculosis; immigration; infectious disease modeling; public health

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At a Glance Commentary

Scientific Knowledge on the Subject: Mathematical models of infectious disease epidemiology are increasingly being used to drive public health decision-making, including in tuberculosis. However, the effect of variation and differences between model assumptions as well as uncertainty about critical elements of disease epidemiology is unknown.

What This Study Adds to the Field: We conducted a comparative analysis of tuberculosis (TB) epidemiology and impact of hypothetical scenarios using three epidemiologic models of TB in California. Our results provide consensus evidence on the drivers of TB incidence and prevalence, as well as suggest intervention levers to enhance TB prevention and care efforts.

The United States has made considerable progress in reducing tuberculosis (TB) incidence in the past two decades. In 2018, both the number of reported TB cases (9,029) and the annual incidence rate (2.8 per 100,000 population) were the lowest ever recorded (1). However, the rate of decline has stagnated in recent years (2). During 2014–2017, reported TB incidence has shown an average annual decline of 1.6%, compared with an average annual decline of 4.7% during 2010–2014 (1). The continued threat of tuberculosis in the United States results in approximately 500 deaths annually (3) and U.S. $6–14 billion in costs (4). It is becoming increasingly clear that achieving the U.S. CDC's strategic target of TB elimination (defined as annual incidence below 1 case per million) will require expanded and innovative approaches for TB prevention and control.

Mathematical and computational models of infectious diseases capture epidemiology and transmission dynamics and can play an important role in public health planning and resource allocation. These models can be used to synthesize historical data, shed light on underlying mechanisms that drive observed epidemiological patterns, and provide predictions of future disease trends. For example, several modeling studies have estimated future TB trends in the United States at national (5, 6) and subnational levels (7–9). These models have been used to project the potential impact and cost effectiveness of interventions, providing estimates that can be used for policy prioritization and implementation (6, 10).

However, model results can vary depending on the modeling approach, model structure, data used for parameterize and calibration, and the incorporation of uncertainty (11–13). Variation can also result from existing uncertainty about TB natural history and epidemiology (14–16). In the United States, where the availability of data on trends and distribution of TB burden is better (3), obtaining consistent results from independently developed models can strengthen confidence in their use for decision-making. When results diverge, comparative modeling can provide insight into the mechanisms underlying specific areas of uncertainty and epidemic drivers.

We compared three independently developed models of TB transmission and epidemiology (6, 10, 17). For this study, the three models were parameterized to represent California, the state that accounted for 23% of U.S. TB cases in 2018 (18). Analyses were undertaken through a CDC-funded modeling collaboration (https://www.cdc.gov/nchhstp/neema/index.html). The objective of our comparison was to generate consensus evidence to support potential programmatic interventions and policy priorities that may enhance domestic TB prevention and care efforts by *1*) establishing consensus about trends in California TB epidemiology; *2*) identifying major influences on those epidemiologic trends; and *3*) highlighting important sources of uncertainty around model projections.

Methods

Data Sources

Models used several common data sources. The American Community Survey, a nationally representative survey of 1% of the U.S. population (19), was used to estimate U.S.-born and non–U.S.-born population sizes. Evidence on latent TB infection (LTBI) prevalence for different population groups was estimated using published data from the 2011–2012 National Health and Nutrition Examination Survey (20, 21). Reported TB cases and deaths in California (22, 23) from 2005 to 2017 were used to calibrate models.

Standardized Scenarios for Model Comparison

All models estimated historical TB epidemiology in California between 2005 and 2015. Models were parameterized to reproduce current coverage and effect of treatment services for TB and LTBI in California, including contact investigation. In addition, we developed four hypothetical scenarios for projections:

1. *Scenario 1. Continuation of current TB trends without additional interventions (base case).* Models assumed continuation of current TB health service coverage and TB prevention and care activities. We also assumed that all major epidemiological drivers follow existing trends conceptualized separately within each model.
2. *Scenario 2. Halting future TB transmission.* In addition to continuation of existing TB prevention and care activities, this scenario assumed an immediate halt to all *Mycobacterium tuberculosis* (*Mtb)* transmission within California from 2018 onwards.
3. *Scenario 3. Halting future importation of Mtb.* In addition to continuation of existing TB prevention and care activities, this scenario assumed that all persons entering California from 2018 onward were free of *Mtb* infection (i.e., all new residents were either cured of TB and LTBI prior to entry, or had no prior *Mtb* infection), with total numbers of projected entrants unchanged from the base case.
4. *Scenario 4. Targeted testing and treatment for LTBI among non–U.S.-born.* In addition to continuation of existing TB prevention and care efforts, this scenario assumed one-time testing of 25% of the non–U.S.-born population, conducted in 2018. We assumed realistic values for the LTBI care cascade, with diagnostic performance based on interferon-gamma release assay sensitivity and specificity, and 72% of those diagnosed positive initiated on LTBI treatment (24). The majority (75%) of treated individuals were assumed to receive

a 12-week isoniazid plus rifapentine regimen (3HP) (25), whereas the remainder received 9 months of isoniazid (9H). Treatment completion was assumed to be 82% and 66% for 3HP and 9H regimens, respectively (26), and treatment efficacy was assumed to be 93% for those completing the regimen (27, 28).

Scenario 1 examined the continuation of current policy and practice. Scenarios 2 and 3 tested theoretical changes in key epidemiological drivers to examine their relative contribution to projected TB incidence. Scenario 4 tested the impact of expanding LTBI testing and treatment policy within California (29, 30). All four scenarios were projected from 2018 to 2030. In addition, we undertook an extended projection of scenario 1, with outcomes projected to 2050, to examine the long-term trajectory of TB epidemiology and possible progress toward TB elimination goals.

Mathematical Models

The three models of TB epidemiology and transmission have been published by Harvard University, Johns Hopkins University School of Public Health (JHSPH), and the University of California San Francisco (UCSF), in partnership with CDC as part of a National Epidemiologic and Economic Modeling Agreement (6, 10, 31). Key structural features of each TB model used in this comparison are summarized in Table 1. Additional model details are described in the online supplement. The three models differed in approach and structure, as well as interpretation of evidence on epidemiological outcomes such as number of *Mtb* infections, for which empirical data are not directly available. Each model was calibrated to TB incidence and mortality in California from 2005 to 2017. Key differences included the approach used to estimate LTBI prevalence in non–U.S.-born persons, immigration and emigration projections, the current state of practice for LTBI testing and treatment, risks of progression to TB disease for persons with LTBI, and prevalence of medical risk factors for TB disease. In these instances, there are no definitive sources of data for estimation, and each team made their own estimates based on a combination of data sources, literature review, and expert opinion (*see* online supplement).

Outcomes Used to Summarize Epidemiological Projections

The following outcomes were reported by each model:

1. *TB incidence.* Diagnosed cases of active TB disease (total number per year and per 100,000 per year).
2. *TB deaths.* Deaths due to any cause among individuals with active TB disease (total number per year and per 100,000 per year).
3. *LTBI prevalence.* Individuals with latent *Mtb* infection (total number per year and percent of population).
4. *Transmissions.* The number of new *Mtb* infections per year acquired from persons with infectious TB disease within California (total number).
5. *Prevalent Mtb infection among new residents entering California.* Number of persons entering California per year with prevalent *Mtb* infection (total number).

We estimated absolute numbers for each outcome from 2018 to the end of the time horizon. For scenarios 2–4 we also calculated percentage differences compared with the base-case scenario. Outcomes were stratified by age group and nativity (U.S.-born vs. non–U.S.-born).

Table 1. Major Structural Features of Participating Models

	Harvard Model	JHSPH Model	UCSF Model
Modeling approach	Deterministic state-transition model	Stochastic individual-based model	Stochastic individual-based model
Age structure	All ages, stratified into 11 age bands	All ages, by single year of age	Adults (15+), by single year of age
Stratification of non–U.S.-born residents	Recent vs. long-term residents based on years in the United States	Eight countries/regions of origin	11 countries/regions of origin, years in the United States
Risk strata for TB exposure or progression	HIV/ART, homelessness, age	HIV, diabetes, incarceration, homelessness	Homeless shelter, correctional facility, or long-term care facility residence, race, HIV, diabetes, smoking, ESRD, organ transplant, TNF-α inhibitor use, age
Other population stratification	TB drug resistance, prior LTBI/TB treatment	Prior LTBI/TB treatment	Prior LTBI/TB treatment
Uncertainty analysis*	Second-order Monte Carlo simulation	First-order Monte Carlo simulation	First-order Monte Carlo simulation

Definition of abbreviations: ART = antiretroviral therapy; ESRD = end-stage renal disease; JHSPH = Johns Hopkins University School of Public Health; LTBI = latent TB infection; TB = tuberculosis; TNF = tumor necrosis factor; UCSF = University of California San Francisco.
*First-order Monte Carlo simulation allows for stochastic uncertainty in the realization of individual-level events (e.g., tuberculosis infection, death). Second-order Monte Carlo simulation allows for uncertainty in the parameters describing population-level characteristics and mechanisms (37).

Statistical Analysis

For any given scenario, each model produced a large number of simulated projections representing estimation uncertainty (Table 1). The mean or median of these projections was used to create point estimates. The distribution of these projections was used to characterize the uncertainty in modeled estimates, with each model estimating a 95% uncertainty interval based on the 2.5th and 97.5th percentiles of the distribution of a particular outcome and year. Further details are provided in the online supplement. We calculated the percentage reductions in outcomes within each simulation and reported point estimates and intervals based on the distribution of that metric across simulations.

Results

TB Cases and TB Deaths, 2005–2015

Between 2005 and 2015, TB cases reported in California declined from 2,900 in 2005 to 2,131 in 2015, at an average annual rate of 3.0%. All three models projected similar declines during this period: Harvard model projected a decline from 3,064 in 2005 to 2,095 in 2015 at an average annual rate of 3.7%; JHSPH model projected a decline from 2,794 to 2,234 at 2.2%; and UCSF projected a decline from 2,600 to 2,121 at 2.1% (Figure 1A). Deaths with TB (not shown in the figure) followed a similar declining trend, with the ratio of TB deaths to TB cases relatively constant over the 2005–2015 period (10.2%, 10.1%, and 9.9% for Harvard, JHSPH, and UCSF models, respectively). Figure 1B shows modeled and observed TB incidence rates in 2015 as a function of age and nativity (U.S.-born, non–U.S.-born)—all models estimated higher incidence rates in older age groups and among non–U.S.-born individuals, as observed in the data.

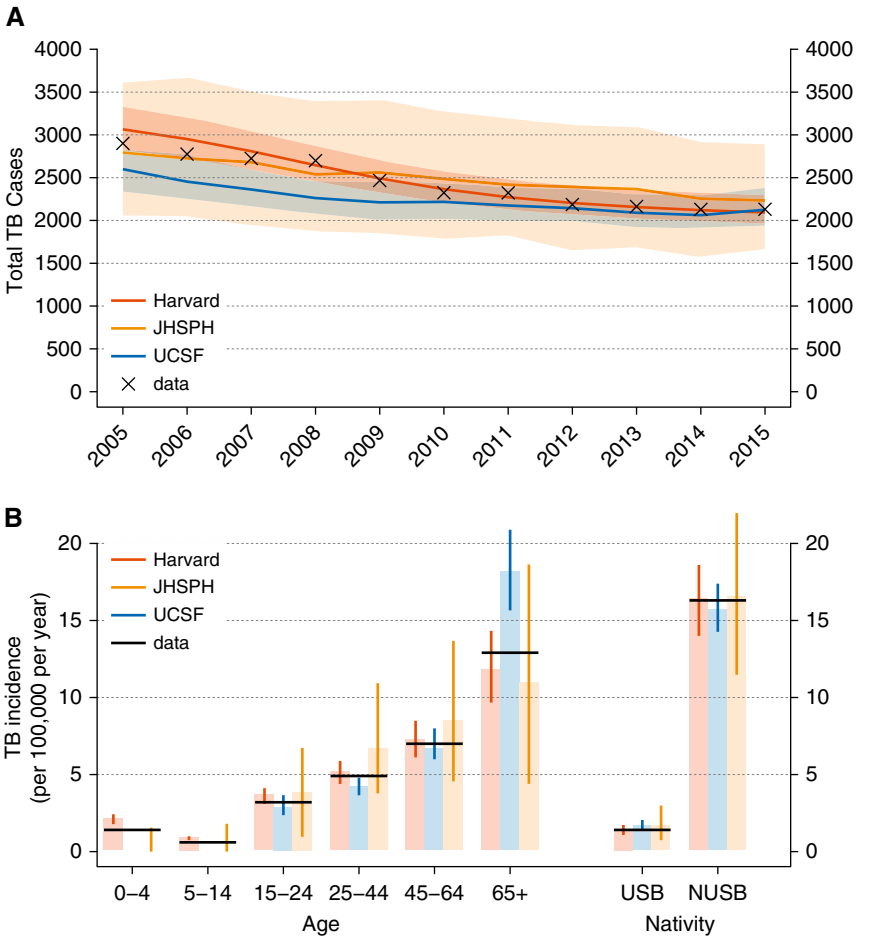

Figure 1. Model estimates of tuberculosis (TB) cases compared with reported data, 2005–2015. (*A*) Model estimates of TB cases from all three models and reported number of TB cases (indicated by "x") for California between 2005 and 2015. For model estimates, solid lines represent point estimates, and shaded areas represent 95% uncertainty intervals for each model. (*B*) Model estimates for TB incidence in 2015 (per 100,000 per year) stratified by age and nativity, with reported data shown in horizontal black lines. University of California San Francisco model represents population 15+ years old. JHSPH = Johns Hopkins University School of Public Health. NUSB = non–U.S.-born; UCSF = University of California San Francisco; USB = U.S.-born.

LTBI Prevalence and New *Mtb* Infections, 2005–2015

From 2005 to 2015, all models estimated a declining trend in LTBI prevalence (Figure 2A)—3.3%, 1.9%, and 2.5% average annual decline for Harvard, JHSPH, and UCSF models, respectively—with more rapid declines estimated for the U.S.-born population (3.0–4.7% across models) compared with the non–U.S.-born population (1.4–2.9% across models). By 2015, overall LTBI prevalence was estimated at 5.1%, 7.1%, and 6.3% by Harvard, JHSPH, and UCSF models, respectively. Because no comprehensive LTBI prevalence survey has been conducted in California recently, there are no data to directly compare with these model estimates. However, model estimates were generally consistent with the California Department of Public Health's estimate of 6% prevalence, based on race and nativity distribution of California applied to 2011–2012 National Health and Nutrition Examination Survey data (32). All three models estimated higher LTBI prevalence among older age categories and non–U.S.-born individuals (Figure 2B). As a consequence, the population with LTBI is estimated to be largely non–U.S.-born—of the 2.0–2.8 million California residents estimated by the models to have LTBI in 2015, 81–86% were estimated to be non–U.S.-born, despite these individuals representing 27% of the California population.

Model estimates for the annual number of new *Mtb* infections in the California population due to *1*) transmission (Figure 2C) and *2*) in-migration of individuals with prevalent *Mtb* infection (Figure 2D) quantitatively differed between the models, particularly for the second of these outcomes. However, all models suggested a declining trend for

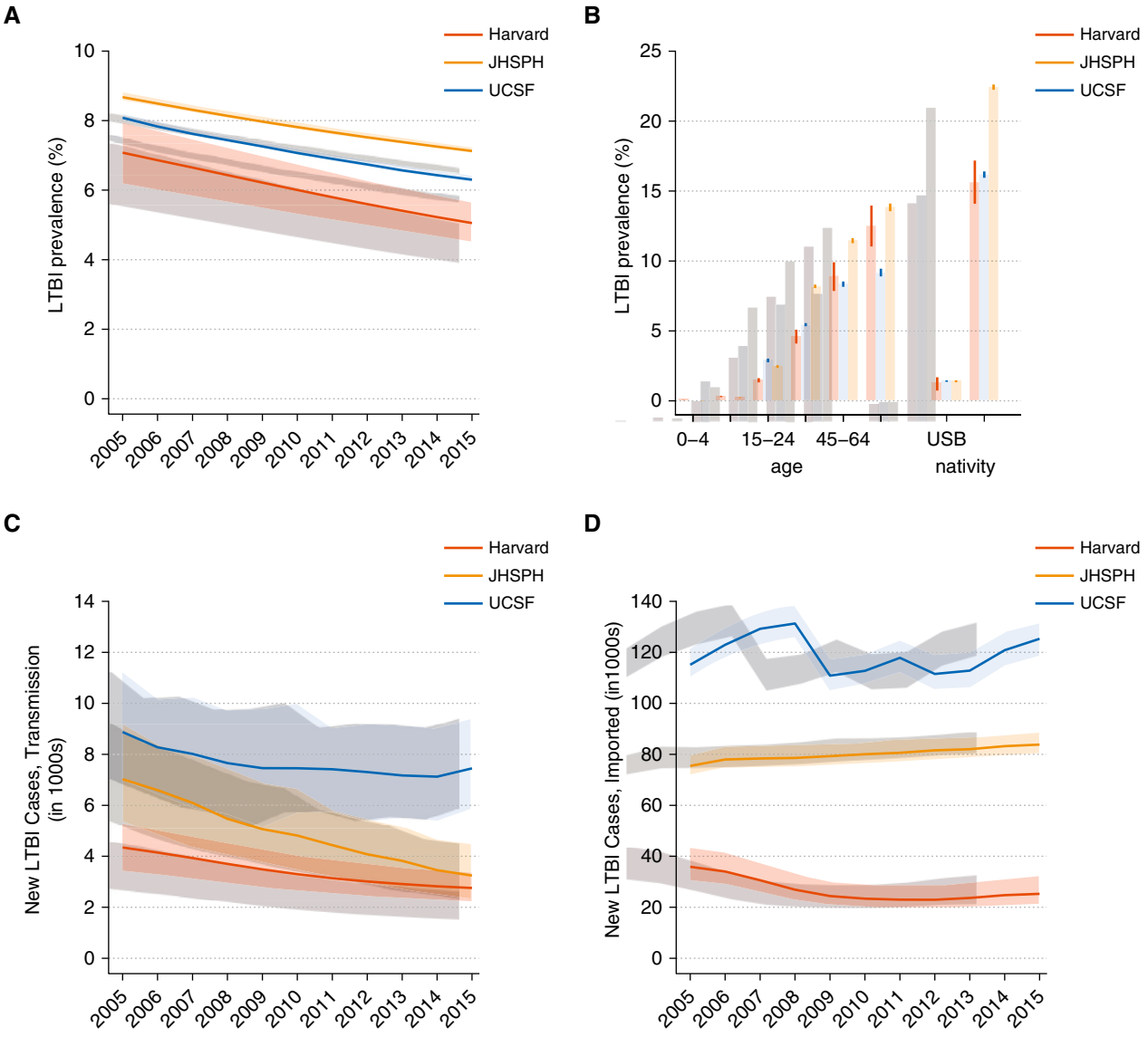

Figure 2. Model-based estimates of latent tuberculosis infection (LTBI) and new *Mycobacterium tuberculosis* (*Mtb*) infections, 2005–2015. (*A*) Model-based estimates of LTBI prevalence in California between 2005 and 2015 (colored lines show point estimates, and shaded areas show uncertainty ranges). (*B*) Colored histograms represent point estimates of LTBI prevalence stratified by age and nativity. (*C*) New *Mtb* infections due to transmission. (*D*) New *Mtb* infections due to immigration of individuals with prevalent *Mtb* infection. JHSPH = Johns Hopkins University School of Public Health; UCSF = University of California San Francisco; USB = U.S.-born.

transmission (1.9–7.4% average annual decline across models), but stagnant trends for entry of individuals with prevalent *Mtb* infection, with models estimating a 0.9–2.2% average annual increase in the count of prevalent infections between 2010 and 2015. In addition, all models suggested that local transmission is a relatively minor contributor to total new *Mtb* infections, with 5.8–11.3% of all *Mtb* infections estimated to result from transmission within the state boundaries of California.

Projections of Future TB Outcomes under the Base-Case Scenario

Figure 3 shows model projections of TB cases (Figure 3A), deaths with TB (Figure 3B), and LTBI prevalence (Figure 3C) in California between 2015 and 2050 under the base-case scenario. All three models projected slower declines in total TB cases than have been observed historically. Between 2018 and 2050, models projected average annual declines of 0.6–1.4% for TB cases, for an 18–39% cumulative decline over the period. Higher annual rates of decline were estimated for U.S.-born populations (0.8–7.1%) compared with non–U.S.-born populations (0.5–0.8%). Because all models projected population growth, projected declines in incidence rates were greater than in total TB cases. Across models, average annual declines in TB incidence rates were 1.5–2.1%, 1.7–7.7%, and 1.3–2.2% for total, U.S.-born, and non–U.S.-born populations, respectively. By 2050, U.S.-born populations were projected in all models to have an incidence rate below the

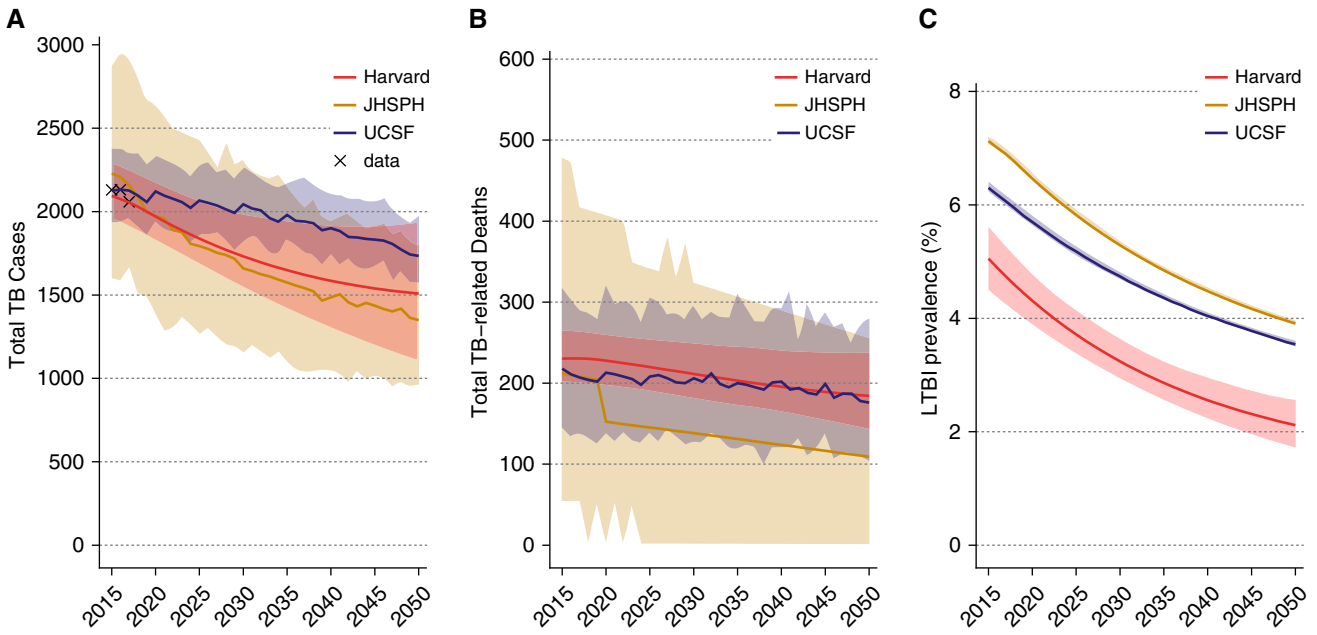

Figure 3. Model-based projections of tuberculosis (TB) cases, TB deaths, and latent TB infection prevalence, 2015–2050. (*A–C*) Model-based projections of TB cases (*A*), TB deaths (*B*), and latent TB infection prevalence (*C*) in California between 2015 and 2050, under scenario 1 (base case, assuming current trends in the absence of new interventions or implementation strategies). Color-coded lines represent point estimates, and shaded areas with matching colors represent uncertainty ranges for each of the three models. JHSPH = Johns Hopkins University School of Public Health; LTBI = latent TB infection; UCSF = University of California San Francisco.

preelimination threshold of 1 per 100,000, with incidence estimated to be 0.10–0.89 per 100,000. Incidence rates for the total population (2.7–3.8 per 100,000) and non–U.S.-born populations (7.5–9.9 per 100,000) were not projected to cross the preelimination threshold before 2050. Trends in projected TB deaths and LTBI were similar across the models, with models projecting 109–184 deaths with TB in 2050 and 43–58% declines in LTBI prevalence over the projection period.

Projections of Future Outcomes under Scenarios Representing Different Epidemiological Mechanisms

Under scenario 2, in which all future TB transmission in California was halted from 2018 onwards (Figure 4A), the UCSF model projected larger reductions in TB cases than the other two models: 1,418 projected cases in 2030 (6,824 TB cases averted, or 25.5% reduction in cumulative TB cases between 2018 and 2030 compared with the base case) compared with 1,530 (2,305 cases averted, or 9.5% reduction) for the Harvard model and 1,612 (1,949 cases averted, or 8.1% reduction) for the JHSPH model. Under scenario 3, in which all new residents were assumed to enter California without *Mtb* infection starting in 2018 (Figure 4B), the projected number of TB cases in 2030 was 837 (9,259 cases averted, or 38.1% reduction in cumulative TB cases between 2018 and 2030 compared with the base case) for the Harvard model, compared with 1,129 (7,471 cases averted, or 31.1% reduction) for the UCSF model and 1,016 (5,846 cases averted, or 21.9% reduction) for the JHPSH model.

Future Projections for Targeted Testing and Treatment of LTBI

Figure 5 shows projections of future TB cases for scenario 4 (targeted testing and treatment for LTBI among 25% of previously untested non–U.S.-born individuals in 2018), over the period 2018 to 2030. In this scenario, the JHSPH model projected 1,476 TB cases in 2030 (3,229 cases averted, or 13.4% reduction in cumulative TB cases between 2018 and 2030 compared with the base case) compared with 1,668 (1,115 cases averted, or 4.6% reduction) for the Harvard model and 1,922 (1,745 cases averted, or 6.5% reduction) for the UCSF model. Although the intervention examined in this scenario was only implemented for a single calendar year, intervention effects were sustained over the full analysis period, with annual percent reductions in TB cases (compared with the base case) in 2030 similar to those estimated for the years immediately after implementation (2019–2020).

Discussion

The combined analyses undertaken in this study suggest that without major scale-up of TB interventions or changes in major TB determinants, TB incidence and deaths in California will continue to decline slowly but will remain well above the preelimination threshold of 1 case per 100,000 through 2050. Projections of average annual declines in TB cases ranged between 0.6% and 1.4% for the 2018 and 2050 period, which is consistent with recent national TB data (1, 2), but much slower than historical trends.

The results of these analyses shed light on the current successes of TB policy and service provision and suggest potential directions to further strengthen TB control efforts. Model results consistently found a minor role for TB transmission as a source of incident *Mtb* infections, confirming the

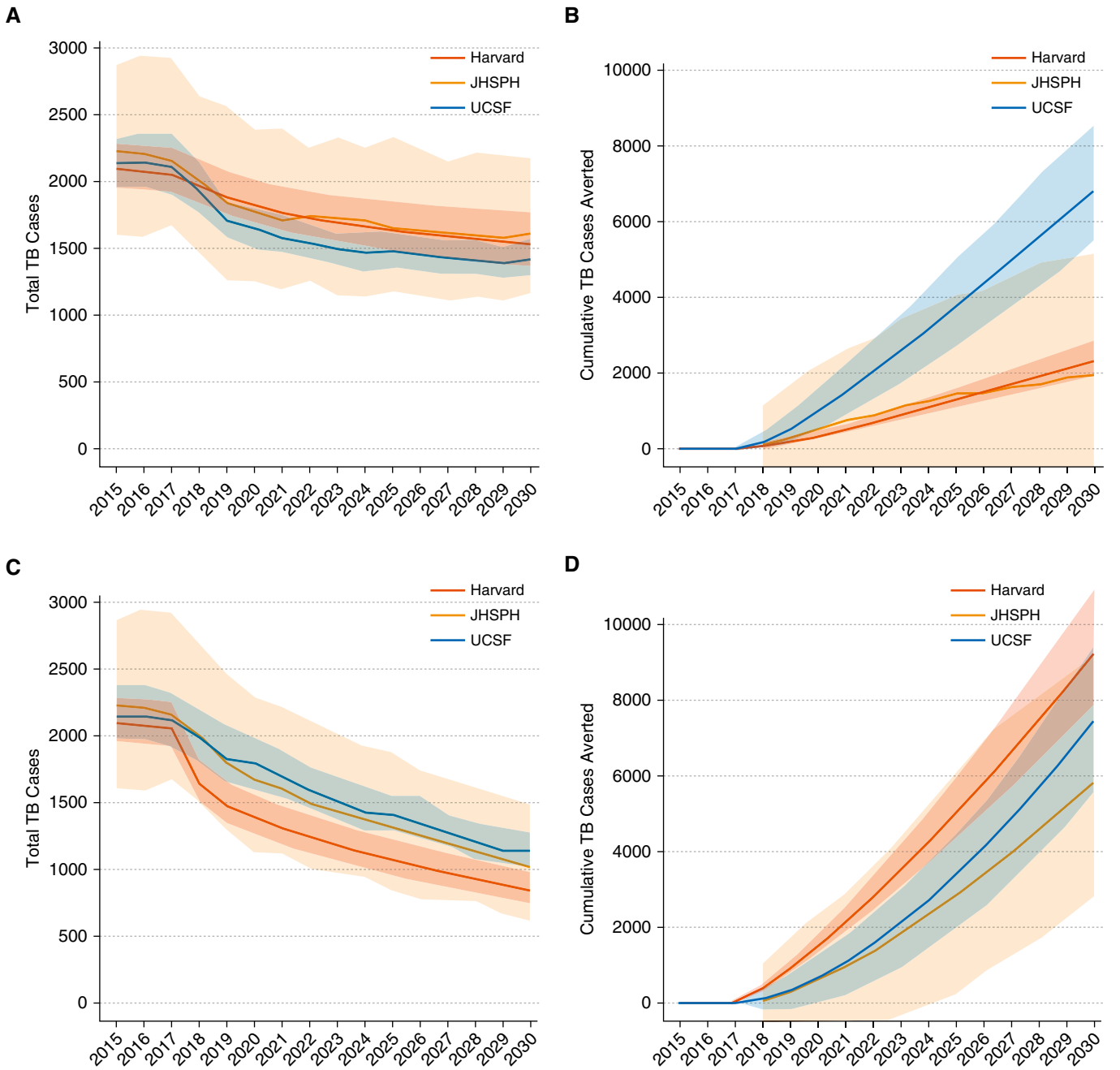

Figure 4. Model projections of tuberculosis (TB) cases under scenarios representing different epidemiological mechanisms. (*A*) Model-based projections of TB cases in California between 2015 and 2030, under scenario 2 (halting *Mycobacterium tuberculosis* transmission). (*B*) Cumulative cases averted under scenario 2 as compared with the base case. (*C*) Model-based projections of TB cases in California between 2015 and 2030, under scenario 3 (halting future importation of *Mycobacterium tuberculosis*). (*D*) Cumulative cases averted under scenario 3 as compared with the base case. JHSPH = Johns Hopkins University School of Public Health; UCSF = University of California San Francisco.

findings of earlier empirical studies (33, 34). The low proportion of cases estimated to result from transmission within California (5.8–11.3% during 2005–2015) reflects the current successes of local clinicians, laboratories, and public health departments in ensuring early and accurate TB diagnosis and initiation and support for curative treatment. There are two important policy implications of this finding. First, additional interventions to interrupt transmission may have minimal impact on the overall trajectory of TB epidemiology in California, despite being critical to preventing disease outbreaks. Second, as the primary driver of future TB in California is prevalent *Mtb* infection, additional policies addressing the community burden of LTBI will be required to achieve public health priorities.

Across the scenarios we investigated, the largest declines in TB cases were

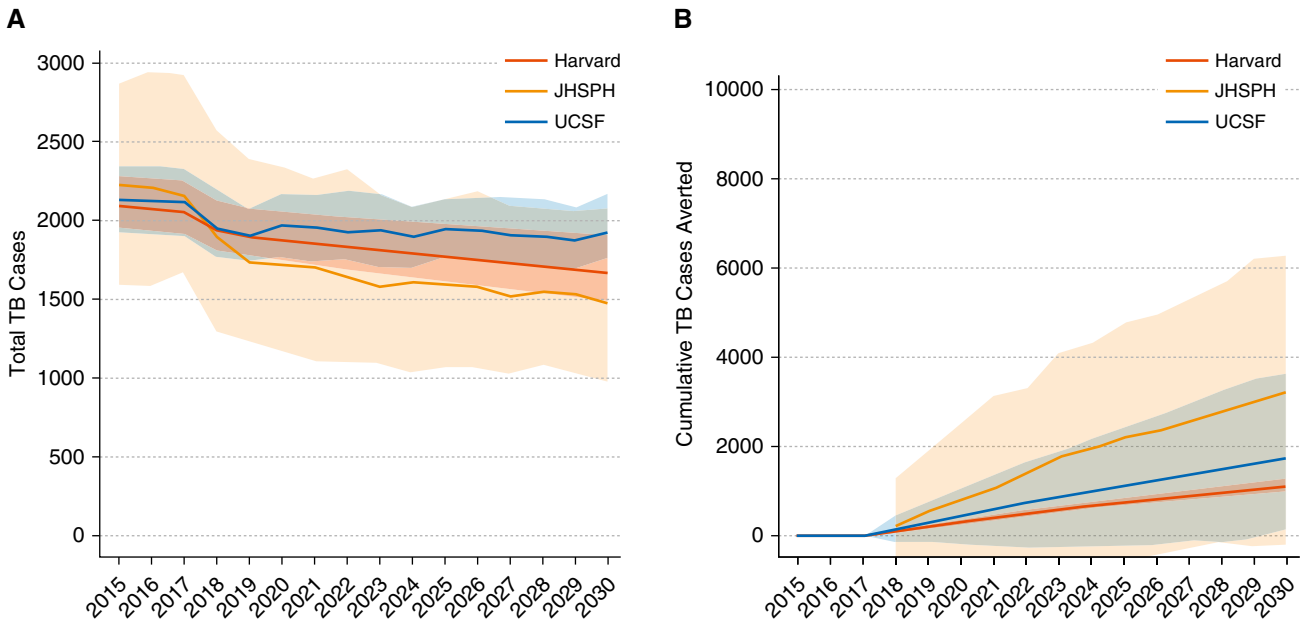

Figure 5. Modeled projections of future tuberculosis (TB) cases, for the total population following a hypothetical intervention to diagnose and treat latent TB infection in the non–U.S.-born. (*A*) Model-based projections of TB cases in California between 2015 and 2030, under scenario 4 (targeted testing and treatment for latent TB infection among non–U.S.-born). (*B*) Cumulative cases averted under scenario 4 as compared with the base case. JHSPH = Johns Hopkins University School of Public Health; UCSF = University of California San Francisco.

estimated for the scenario with complete resolution of active TB disease and LTBI among migrants entering California, highlighting the policy and programmatic priority to provide LTBI and active TB services to this group. This finding validates existing policies targeted to this group, such as immigrant prearrival testing and treatment for active TB (35). It also raises the question of whether additional services—such as immigrant prearrival LTBI testing and treatment, or enhanced strategies that overcome health disparities that affect this group's access to care—may be beneficial.

For the scenario examining LTBI testing and treatment for 25% of all non–U.S.-born individuals in 2018, models predicted population-level incidence reductions of 5–13%, demonstrating the potential impact of greater access to LTBI testing and treatment for this population. The reductions in TB cases produced by this intervention (as compared with the base-case scenario) were relatively stable across the evaluation period, demonstrating that even short-term interventions targeting the reservoir of latent TB infection will generate ongoing benefits in terms of reductions in TB cases and deaths.

This analysis provides the first direct comparison of multiple TB models targeting the same setting and scenarios in the United States. Each of the three models included in this comparison represents the major drivers of TB epidemiology and uses the same primary data sources. However, these models were initially developed for different purposes—one to project long-term national-level outcomes (6), one to investigate differences between four major states (31), and another to project costs and impact of policy options in California (10). Each model operationalizes epidemiologic mechanisms differently, interprets the available evidence differently, and describes the population (e.g., age strata and risk groups) differently. Despite this, we found consistency across models when estimating current TB epidemiology and projecting future trends. Model agreement was strongest when there were rigorous empirical data available to parameterize and calibrate models, such as TB case notifications and deaths. When the model results differed, they tended to do so where definitive local data were not available, such as for *Mtb* infection incidence and prevalence. The UCSF model predicted the largest numbers of both transmissions and prevalent LTBI, and the Harvard model the fewest, with the JHSPH model intermediate between these two. These differences were observed despite the models producing very similar estimates of TB incidence, reflecting the fact that each model has developed a different conceptualization of TB epidemiology that still matched observed data.

Although the models provided relatively consistent TB projections under current policy and services, these results also came with wide uncertainty intervals. For all scenarios, future projections required strong assumptions about trends in immigration, LTBI prevalence among migrants, health services availability, and other time-varying drivers. In the past, major and sometimes rapid changes have been observed for these drivers, and such variability will continue in the future, limiting the possibility of producing precise TB projections. Lack of definitive evidence around some aspects of LTBI natural history contributed additional uncertainty to model projections. For example, although national LTBI prevalence estimates are available for multiple time points (20), these estimates are not designed to be representative at the state level, and sampling uncertainty limits their utility for estimating results for individual population groups and time trends. Additional uncertainty in LTBI epidemiology is introduced by the imperfect sensitivity and specificity of LTBI diagnostics and our limited data on reactivation rates over time

for those who harbor infection (15, 36). Finally, uncertainty around uptake and completion of TB prevention and care activities, particularly for individuals without medical risk factors, may cause the actual impacts of targeted testing and treatment interventions to differ from those estimated in this analysis. These uncertainties highlight the need for stronger empirical evidence to support our understanding of TB epidemiology, through improved and more specific LTBI diagnostic tests, enhanced estimates of LTBI reactivation risks, and more real-world estimates of intervention implementation. These findings were made possible by a comparison of multiple independently developed models. This revealed the different approaches that can be used to model complicated epidemiological processes and how the assumptions of these approaches can influence results. This model comparison provides a more robust examination of uncertainty than could be gained from conventional sensitivity analyses using a single model (37).

California is actively pursuing an intensified strategy for TB prevention in the state through partnerships between public health agencies, private providers, community organizations, and the public to increase LTBI testing and treatment (38). As providers increase testing and treatment to prevent TB, cases of TB disease will decrease, allowing patients and their families and communities to avoid the devastating consequences of TB. Even testing and treating one-quarter of non–U.S.-born persons residing in California could achieve TB disease reductions of meaningful magnitude. The sensitivity of model projections to TB burden among individuals entering California highlights the importance of TB prevention and care policies more broadly and the fact that efforts to identify and treat LTBI in other states and countries will have benefits beyond those individual jurisdictions. The need for LTBI testing and treatment of persons at highest risk is great. ■

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