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Impact of the COVID-19 pandemic on tuberculosis epidemiology in California, Florida, New York, and Texas

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Abstract

Rationale: The United States (US) experienced a considerable decline in tuberculosis (TB) incidence in 2020 following the COVID-19 pandemic.

Objectives: While TB rates have since returned to near pre-pandemic levels, analyzing the pandemic's impact offers insight into TB epidemiology in the US.

Methods: Focusing on California, Florida, New York, and Texas – the four states with the highest TB incidence – we explored three potential mechanisms of pandemic-related disruption on TB epidemiology: (i) reduced immigration; (ii) reduced *Mtb* transmission (through social distancing and other behavior changes); and (iii) delays in care-seeking. We used data on volume of non-immigrant arrivals and new permanent residents, Google mobility and US transit data, and data on volume of emergency department visits and cancer screenings to inform the magnitude of these effects at the state level, adapting previously developed state-specific transmission models. We then estimated the impact of each mechanism and projected future TB incidence through 2032.

Measurements and Main Results: Disruptions to migration and care-seeking across all four states were considerable but short-lasting, with 70–90% reductions in the first four months of the pandemic that returned to pre-pandemic levels by 2021. In contrast, transmission disruptions were moderate but more prolonged, with mobility still 10–20% lower than pre-pandemic in 2022. No statistical evidence was identified to favor models emphasizing immigration, transmission, versus access to care.

Conclusions: Revised projections for pandemic-related disruptions did not substantially differ from pre-pandemic projections beyond 2024. Future declines in TB incidence in the four states are likely to be small without additional interventions.

Keywords

tuberculosis; tuberculosis in the United States; mathematical modeling of tuberculosis; COVID-19 pandemic

Introduction

The United States (US) observed a 20% decline in TB incidence in between 2019 and 2020, compared with an average 2–3% annual decline between 2010 and 2019 (1). Declines from 2019 to 2020 were universal, observed across almost all states (although there was substantial variability between states), all age-strata, both US-born and non-US-born populations, and across almost all subpopulations disaggregated by race or ethnicity (1–3). In 2022 the incidence rate increased by 5.5% compared with 2021, but remained lower than 2019 levels (4).

Since the beginning of the COVID-19 pandemic in early 2020, the US experienced numerous disruptions. First, the pandemic disrupted international travel, leading to reductions in net immigration between 2020 and 2022 (resulting in a decrease in the population at risk for TB), as well as reductions in travel of non-US-born persons across borders (resulting in less transmission) (5). This migration-driven impact could have resulted in fewer TB cases, as well as a reduction in transmission of TB.

Second, the pandemic also resulted in reduced social mixing, along with adoption of masking, physical distancing, and reduced travel, which all contributed to reduced airborne disease transmission. This transmission-driven impact, which has been observed across many respiratory pathogens (6), may have led to reduced transmission of TB in the short term.

And finally, the pandemic changed health seeking behaviors (7,8) (e.g., reflecting lower rates of seeking care for symptoms resulting in increased delays in TB diagnosis) and healthcare provision (e.g., delays related to healthcare provider staffing and service provision; reduced TB clinic capacity to conduct contact investigations and outbreak response, and the possibility of TB being misdiagnosed as COVID) (9). Such access-driven impacts could have resulted in short-term reductions in TB notification rates initially followed by a rebound in TB rates as reduced services and diagnostic delays resulted in increased transmission (10).

Using an updated version of a previously developed state-level TB transmission model, recent TB treatment initiation data, data on migration across borders, and assumptions on social mixing, we inferred the potential impact of each of the three mechanisms on the projected TB incidence in four states that contribute half of incident TB in the US: California, Florida, New York, and Texas (11).

Methods

State-level TB transmission model

We used a previously developed individual-based model (11) to assess the impact of the COVID-19 pandemic between 2020 and 2022 on TB epidemiology in California, Florida, New York, and Texas, the four states with the highest number of incident TB cases (12). The model incorporated differences in demographic composition, immigration patterns, and natural history and epidemiological complexities of TB across the four states. The model

accounted for immigration from eight different regions (Mexico, Americas, China, India, Asia, Africa, Europe, Rest), with each region having specific sizes of immigrant populations that were uninfected, having latent infection or having active disease at arrival. In the model, individuals could transition through four TB states: “Uninfected”, “LTBI” for latent TB infection, “Active TB” for active TB disease, and “Post-Treatment” once individuals are successfully identified and treated for active disease (see Figure 1).

Further model details can be found in the original paper and its supplementary materials (11), and model parameters are included in the online data supplement of this paper in Table E1. The model was calibrated to reflect the baseline (no-pandemic) trend of age-specific TB incidence among US-born and non-US-born populations between 1993 to 2015 across the four states, California, Florida, New York and Texas.

Hypothesized pathways of the impact of pandemic-related disruptions

We assessed three potential mechanisms of COVID-19 pandemic-related disruptions and their impact on TB epidemiology: (1) Migration-driven impact accounts for the impact of disruptions to migration patterns into the US, resulting from countries around the world closing their borders and considerably reducing entries into the US. We model this as a reduction in the importation of TB and LTBI among newly arriving non-US-born individuals as a result of the reduction in immigration rates. (2) Transmission-driven impact accounts for the impact of TB transmission from disrupted social mixing patterns, as a result of stay-at-home orders and mask wearing, and is modeled as a reduction in rates of new TB infection and reinfection. (3) Access-driven impact accounts for the potential impact of disruptions in care-seeking and TB services provision, as a result of delays in diagnosis and resources being diverted to COVID-19 testing and management. This is modeled as delays in TB diagnosis and treatment initiation. Figure 1 shows where in the model the disruptions are assumed to act, based on which mechanism is disrupted by the pandemic.

Data synthesis to characterize the level of pandemic-related disruptions

We used publicly available data to quantify each mechanism of disruption. For each mechanism of disruption, we split the data over three periods: pre-pandemic period for data up to February 2020; pandemic period for data between March 2020 and March 2021; and post-pandemic period for data after March 2021 (where available). For simplicity, we assumed that each set of data informing the mechanisms of disruption was equally informative and important, therefore we did not apply any weighting to the different sources found.

We collated data on the volume of arrivals of new non-immigrant persons (non-immigrant visas) between 2009–2021, and registration of new, lawful permanent residents between 2018–2021, in each of the four states (13,14). Since there were no state-level differences in the level of disruption across the four states, we used the same parameter for the pandemic-related disruption on migration for each state (see Figure E1 in the online data supplement for details).

To quantify the pandemic-related disruption on mobility, we analyzed Google mobility data representing the population not staying home (in millions) between 2019–2023 and

US government transit data representing the change in mobility of different categories of movement compared to pre-pandemic levels, across the four states between 2020–2022 (15,16). We did not find state-level differences in the changes to the rates of travel or mobility, so assumed that the pandemic-related disruption parameter would be the same across the four states (see Figure E2 in the online supplement for details).

Finally, we were unable to identify data that described the impact of the pandemic on access to TB services. We therefore quantified the pandemic-related disruption to access by analyzing data on cancer screenings and emergency department (ED) visits, as proxies. Although not TB-specific, these data were still representative of how the pandemic may have affected care-seeking behavior, for both routine (asymptomatic) visits and emergency (symptomatic) visits. We analyzed data pre-, during and post-pandemic (respectively pre-2020, 2020–2021 and post 2021 based on data availability, see Figure E3 in the online supplement for details) (17–20). These data were not available at the state-level, so we assumed similar trends of disruptions to care-seeking across the four states.

For these disruption parameters, we generated a relative trend of pandemic-related disruption (disruption covariate) by averaging the pandemic years' data and dividing it by the pre-pandemic levels (up to the end of 2019), such that a value of “1” represented no disruption, and “0” represented full disruption. We extrapolated the observed trend for the remainder of the time period where data were not available (2022–2024 for migration, 2023–2024 for mobility, and 2021–2024 for access), by making optimistic and pessimistic assumptions about when trends might return to pre-pandemic levels, but assuming they'd all return to pre-pandemic levels by the end of 2024, latest (see Figure 2 and Table E2 in the online supplement for the average value of each covariate). The optimistic and pessimistic estimates were chosen to reflect estimates from simulations that assumed optimistic versus pessimistic values for the end of pandemic-related disruptions.

Inference of the impact of the pandemic on TB

We used a likelihood-based approach along with monthly state-level TB treatment initiation data among US-born and non-US-born individuals between 2020 and 2023 across each of the four states (Figure 3) to infer each of the three hypothesized impacts of pandemic-related disruption: migration-driven, transmission-driven, and access-driven impacts.

We drew 100,000 combinations of the three impact parameters – transmission-driven impact ($\Delta\beta$), migration-driven impact (Δm), and access-driven impact ($\Delta\omega$) – using Latin Hypercube sampling, allowing each of the three impact parameters to vary between [0–1], where a value of “0” for a proposed mechanism indicates the maximum impact on TB via the proposed mechanism of disruption, and “1” indicates no impact. Each impact parameter was exponentiated by their respective time-varying disruption covariate – $cov_{trans}(t)$, $cov_{migr}(t)$, $cov_{care}(t)$, for transmission, migration, and access, respectively – so that we could account for both the magnitude of the disruption, and the way this magnitude of disruption changed through the pre-, during and post-pandemic periods. This was represented in the updated model such that the updated, effective rates were:

$$\beta_{eff}(t) = \beta_0 \cdot \Delta\beta^{(1 - cov_{trans}(t))}$$

$$m_{eff}(t) = m_0 \cdot \Delta m^{(1 - cov_{migr}(t))}$$

$$\omega_{eff}(t) = \omega_0 \cdot \Delta\omega^{(1 - cov_{care}(t))}$$

where $\beta_{eff}(t)$, $m_{eff}(t)$ and, $\omega_{eff}(t)$ represent the effective transmission, migration, and treatment-initiation rates, respectively, and β_0 , m_0 , and ω_0 represents baseline (pre-pandemic) transmission, migration, and treatment-initiation rates, respectively.

For each combination of parameters, we compared monthly TB notification rates and model simulations using a binomial likelihood function. To identify a range of parameter values that best explained reported data, we generated likelihood profiles for each of the three parameters. For each parameter, we constructed a likelihood profile by maximizing the likelihood function over the remaining two parameters while holding the parameter being profiled constant. The 95% uncertainty interval (UI) was estimated for each parameter by finding the range of parameter values whose likelihood estimates were within 1.92 log-likelihood units of the estimated maximum, on the basis of univariate confidence limits using the χ^2 distribution with one degree of freedom (21).

Model projections with and without pandemic-related disruptions

In each of the four states, we simulated the model between 2020 and 2032 under two scenarios, no-pandemic and pandemic. In the no-pandemic scenario, we generated model projections assuming that there was no COVID-19 pandemic. In the pandemic scenario, we generated projections incorporating the three hypothesized mechanisms of impact based on the parameter ranges that were found to be consistent with the data. The projections were based on the epidemiological parameters of the baseline model (11), including the continuation of current immigration trends and the continuing decline in transmission rates as estimated in the baseline model. We conducted five replicated simulations of the model with each of the parameters consistent with the data, and estimated the mean/median and 95% UI from the simulations.

Results

Magnitude and time-scale of pandemic-related disruptions

The trend of lawful non-immigrant entries saw a sharp drop in the first quarter of 2020, followed by a slow trend upwards over the following year, still quite far from pre-pandemic levels. Between April 2020 and July 2021, the volume of arrivals of new immigrants was 75–90% lower compared to the average volume in 2019 (pre-pandemic). New lawful immigrants also saw a decline at the beginning of 2020, with a 15–20% drop in 2020 and 2021, across the four states. These data, however, suggest that trends returned to

pre-pandemic levels in 2022 (Figure 2A). The migration covariate, which was constructed by aggregating the two forms of data found, reached as low as 0.1 (i.e., 90% reduction, 95% uncertainty interval 0.05–0.5) during April–July of 2020, and was assumed to gradually return to 1 by the end of 2023.

The mobility data showed moderate drops at the beginning of the pandemic, as a result of stay-at-home orders, reduced travel and movement. The data showed a 25–50% drop in volume in 2020 compared to 2019. Both forms of data showed mobility slowly returning to pre-pandemic levels in 2021. However, the volume of mobility remained far from pre-pandemic levels through 2022 and into 2023 (Figure 2B and Figure E2 in the online supplement for details). The aggregated covariate for mobility declined to the lowest level of 0.6 at the end of 2020, and was projected to return to pre-pandemic levels by mid-2024.

Finally, the data on access to care-seeking trends suggests that a modest decline occurred at the beginning of the pandemic. Data on various cancer screening showed a 10% reduction through 2020 in the proportion of individuals recently screened for breast or cervical cancer, compared to 2019; while the number of mammograms performed dropped by 100% in April–May of 2020 compared to 2019, and returned to pre-pandemic levels by the Fall of 2020. Data from EDs showed a 50% decrease in volume in April 2020 compared to 2019, then started trending upwards towards pre-pandemic levels by the end of 2020. Most forms of data saw a quick return to pre-pandemic levels by the end of 2020 (Figure 2C and Figure E3 in the Online Supplement for details). The aggregated covariate declined to 0.3 in April 2020, then was projected to return to pre-pandemic levels by 2021.

Trends in TB treatment initiation

Figure 3 shows that TB treatment initiation trends, used as a proxy for TB notifications, were in a stable decline between 2009–2019, prior to the COVID-19 pandemic. In April 2020, as a result of the pandemic-related disruptions, notifications dropped by 30% in California, (from an average between the end of 2019 and March 2020 of 155 to 108 in April 2020), 20% in Florida (from an average of 38 to 30), by 55% in New York (from an average of 57 to 26), and 30% in Texas (from an average of 84 to 59). The linear trends in TB treatment initiations during the pandemic months (March 2020–March 2021) were all below the pre-pandemic levels in the four keys states: 25% in California, 30% in Florida, 20% in New York, and 30% in Texas. During the post-pandemic period, after March 2021, the linear trend of treatment initiations returned to pre-pandemic levels.

Inferred impact of pandemic-relation disruptions on TB

The likelihood profiles in Figure 4 allowed us to assess the strength of the evidence used to inform each mechanism disrupted by the COVID-19 pandemic. The results from the model inference suggested that the impact of all the disruptions could range from strong to no impact (the 95% confidence intervals (CI) for the likelihoods range from one, no impact, to smaller values (less than one), representing a reduction from baseline). The profiles for migration and mobility show a very homogenous distribution of the likelihood, across all values of disruption. For both of these, the 95% uncertainty intervals are [0.005–1] and therefore include both extreme values of the impact. Because of this, we were unable

to statistically attribute the changes to TB notifications from the National Tuberculosis Surveillance System (NTSS) data to one specific mechanism. For the care-seeking profile, we saw a stronger signal in favor of values in the uncertainty interval [0.38–1]. However, because this interval also included values of “1”, it was still not possible to statistically attribute changes to the TB notifications to this mechanism. These results were consistent for both the aggregated profiles and the state-specific profiles, shown in Figure E5 in the online supplement.

Figure 5 shows that our model was able to capture the small dip in monthly notifications reported by the NTSS data through 2020, but both the data and the model simulations seemed to return to pre-pandemic levels in 2021.

State-level projections

The final part of the analyses included comparing TB projections over the next 10 years, up to 2032, with and without disruptions from the COVID-19 pandemic. Our revised model projections, which considered a range of potential impacts of the pandemic that were consistent with the monthly treatment initiation data (i.e., the impact parameters values that were within the estimated 95% UI including values of “1”, indicating no pandemic impact), were similar to our projections from the no-pandemic model. The difference in the average number of annual cases between the revised model and the no-pandemic model ranged between –70 to 70 (Figure 6).

Under the pandemic scenario, between 2020 and 2032, the TB incidence of the overall population was projected to decrease from 5.5 per 100,000 to 4.4 in California; from 3.0 per 100,000 to 2.0 in Florida; from 4.0 per 100,000 to 3.2 in New York; and from 3.0 per 100,000 to 2.5 in Texas.

Conclusions

In this analysis, we aimed to assess the impact of the COVID-19 pandemic on the incidence of TB in the four states in the US with the highest burden of disease, California, Florida, New York, and Texas. We hypothesized three mechanistic pathways via which the pandemic-related disruptions may impact local TB epidemiology: migration, mobility, and access to care. We reviewed the literature and synthesized publicly available data to assess the trends in the three mechanisms of disruptions. Finally, we incorporated these mechanisms of disruptions in a previously developed state-level TB transmission models and inferred the potential impact of these disruptions on local TB epidemiology by confronting the models with local TB treatment initiation data between 2020 to 2023.

Based on the synthesis of data and literature, we found that the pandemic-related disruptions in access to care were substantial but relatively short-lasting. Although the rate of access to care declined by about 70% in the early months after the start of the pandemic compared to the pre-pandemic levels, it returned to 80% of the pre-pandemic levels within 5 months. Similarly, the rate of migration for lawful non-immigrant admissions saw 90% decline in the early months after the start of the pandemic, but new lawful permanent residents showed a quick return to pre-pandemic levels over the next 12 months. In contrast, the disruption in

mobility, taken as a proxy for transmission, was likely less drastic but has also taken the longest to return to the pre-pandemic levels.

However, the specific impact of these disruptions on the local TB epidemiology remained unclear even after our analysis. We could not unequivocally attribute the short-term changes in TB initiation rates to a specific pathway of disruption based on our model-based inference, as suggested by the observation that “1” (i.e., no impact) is included in our estimated 95% UI for each mechanism of impact. However, in the same vein, since the estimated 95% UI for each of the mechanisms of impact also includes values <1 , we also cannot rule out the potential impact of each of the hypothesized mechanisms of disruption. Consequently, our revised projections of TB incidence in the four states are relatively similar to the projections of the models without the pandemic.

There may be several potential reasons for our inability to attribute the declines to specific pathways of the pandemic-related disruptions. First, disruption in some of the mechanisms may not be as consequential for shorter-term TB incidence. This may be particularly relevant for inferring the transmission impact since only 10–15% of TB incidence is thought to result from recent transmission (22). Second, disruptions in the proposed mechanisms might not have been sustained long enough to make their impact substantial and statistically differentiable from alternative sources of the disruption and inherent stochasticity. The disruption in both migration and access to care, as shown in Figure 2, was drastic only for a few months before it started returning to pre-pandemic levels. Finally, the impact of these disruptions may take several years to manifest, and we may need to incorporate more data to conclusively estimate the impact of the pandemic-related disruptions. Similar findings from work by Swartwood et al. suggest that pandemic-related effects are likely to continue to impact TB incidence and mortality in the future (23).

The analyses presented here carry several limitations. First, we were only able to use three years of notification data from NTSS (2020–2022) to infer the impact of pandemic-related disruptions. Although 2023 data have been collected, they were not yet available in the finalized form for us to include at the time of the analysis. Second, we were not able to find state-level data for care-seeking behavior trends, therefore informing disruptions to this mechanism was only possible by making the assumption that the four states saw similar levels of disruption. Incorporation of state-specific data on the disruptions may improve our inference of the impact. Furthermore, we were unable to include data on changes to healthcare provisions. As such, we were not able to comprehensively capture state-level differences in the disruptions, and their impact on TB. Third, both the pandemic-related disruptions and their impact may vary considerably by race, age, and other demographic factors that we did not include in this analysis. Other studies have indicated that the pandemic has impacted minority racial and ethnic groups significantly more (24–26), and this may have important and diverse implications across the four states, which have heterogeneous racial and ethnic compositions. Fourth, we were also unable to explore the impact of the pandemic on TB mortality, and several studies have linked co-infection to increased risk of death (27,28), nor were we able to assess future uncertainties around changes to migration patterns, health behavior and coverage. All these factors certainly will impact TB notifications in the future. Our models use American Community Survey data

to estimate the non-US-born population in different states before the pandemic and track non-immigrant arrivals and lawful permanent resident registrations to capture post-pandemic immigration trends. However, these projections are limited by the data's ability to fully capture immigration patterns, including undocumented migrants. Fifth, while we evaluated three different mechanisms of disruption separately, it is likely that all three mechanisms operated simultaneously to some extent during the pandemic. As such, interactions between these three causal mechanisms may also play an important role in TB epidemiology. While we were not able to identify strong correlations between the mechanisms in our data (see Figure E6 in the online supplement), this may reflect the short period of time over which measurable reductions in migration and care-seeking may have occurred. Finally, the future projections also did not account for potentially longer-lasting changes in future migration trends, past what we were able to observe through data up to 2023, and potential changes in local TB control efforts as a result of the pandemic.

In conclusion, the data we synthesized to characterize the disruption resulting from the COVID-19 pandemic in migration, mobility, and access to care was either mild and/or relatively short-lasting (even if drastic). There were modest short-term declines in TB treatment initiation rates across all four states, California, Florida, New York, and Texas, however, we were unable to attribute these changes to a specific pandemic-related disruption. The revised projections across these four states, which account for a range of potential impacts of the pandemic, indicate that, as was the case before the pandemic, TB incidence is likely to decline at a relatively lower rate in the next decade, compared to the declines observed in the last decade, unless additional measures are adopted.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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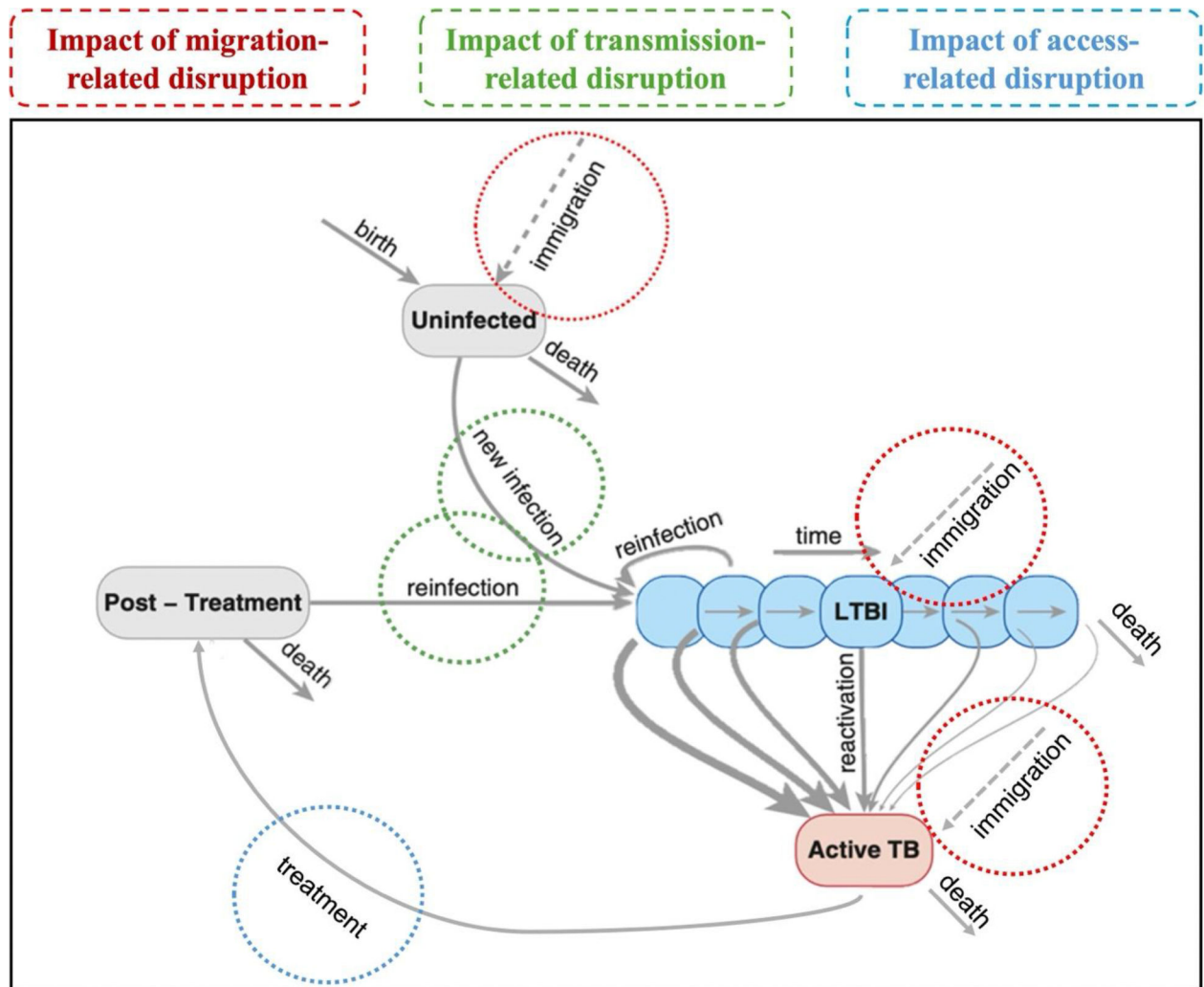


Figure 1. Schematic diagram of the underlying state-level tuberculosis transmission model and the three hypothesized pathways of the impact of COVID-19 pandemic-related disruptions. The previously developed underlying TB transmission model (11) was adapted in order to account for disruptions brought on by the pandemic to various model transitions. Red circles represent the hypothesized impact of the pandemic-related disruptions to migration, migration-driven impact (e.g., as a result of the US closing their borders); green circles represent the hypothesized impact of the pandemic-related disruptions to TB transmission (transmission-driven impact) as a result of reductions to mixing within the community and stay-at-home orders; and the blue circle represents the hypothesized impact of the pandemic-related disruption to care-seeking (access-driven impact), as a result of delays in care-seeking and TB diagnosis and reductions to TB control efforts during the pandemic.

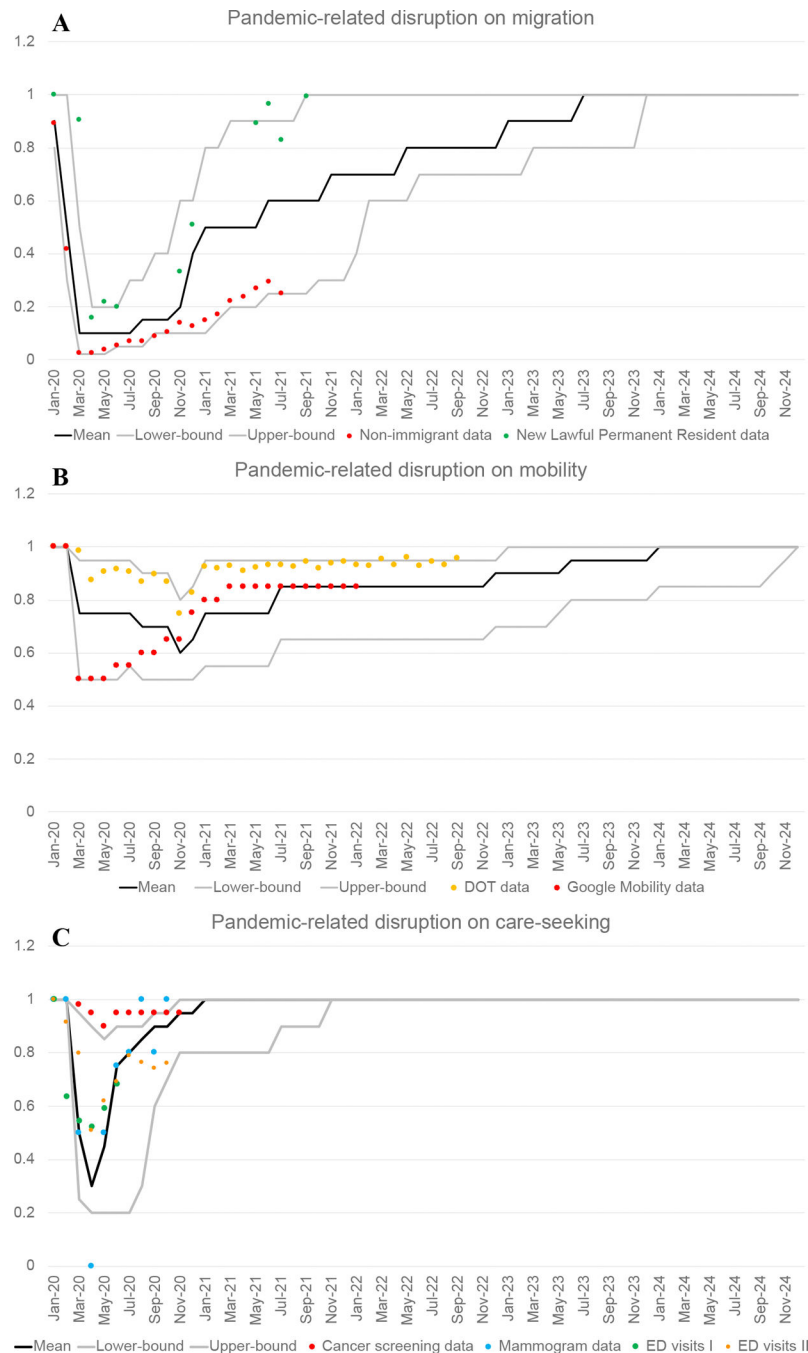


Figure 2. COVID-19 pandemic-related disruptions on migration (A), mobility (B), and access to care-seeking (C) in the United States.

Shown in each panel is the magnitude of disruptions on the y-axis (with 1 indicating no disruption compared to the pre-pandemic level, and 0 indicating maximum disruption) between 2020 to 2024 (x-axis). (A) Disruptions in migration show relative changes in the volume of non-lawful immigrant entries to the United States (red dots) and trends in the number of new lawful permanent residents (green dots) (13,14). The solid black line represents the mean, and the grey lines represent the range of the disruption modeled, with the upper and lower bounds representing the optimistic and pessimistic scenarios,

respectively. (B) Disruptions to mobility are used as a proxy to disruptions to transmission; the data shows the relative changes in the volume of movement from the Department of Transportation Data (DOT, in yellow) and from Google mobility data (in red) (15,16). (C) Disruptions to access to care-seeking show the relative change in the volume of cancer screening (in red), mammograms performed (in blue) and Emergency Department (ED) visits from two data sets (from the National Syndromic Surveillance Program in green and from the Clinical Emergency Department Registry in orange) (17–20). See Figures E1–3 in the supplementary materials for further details on the data found.

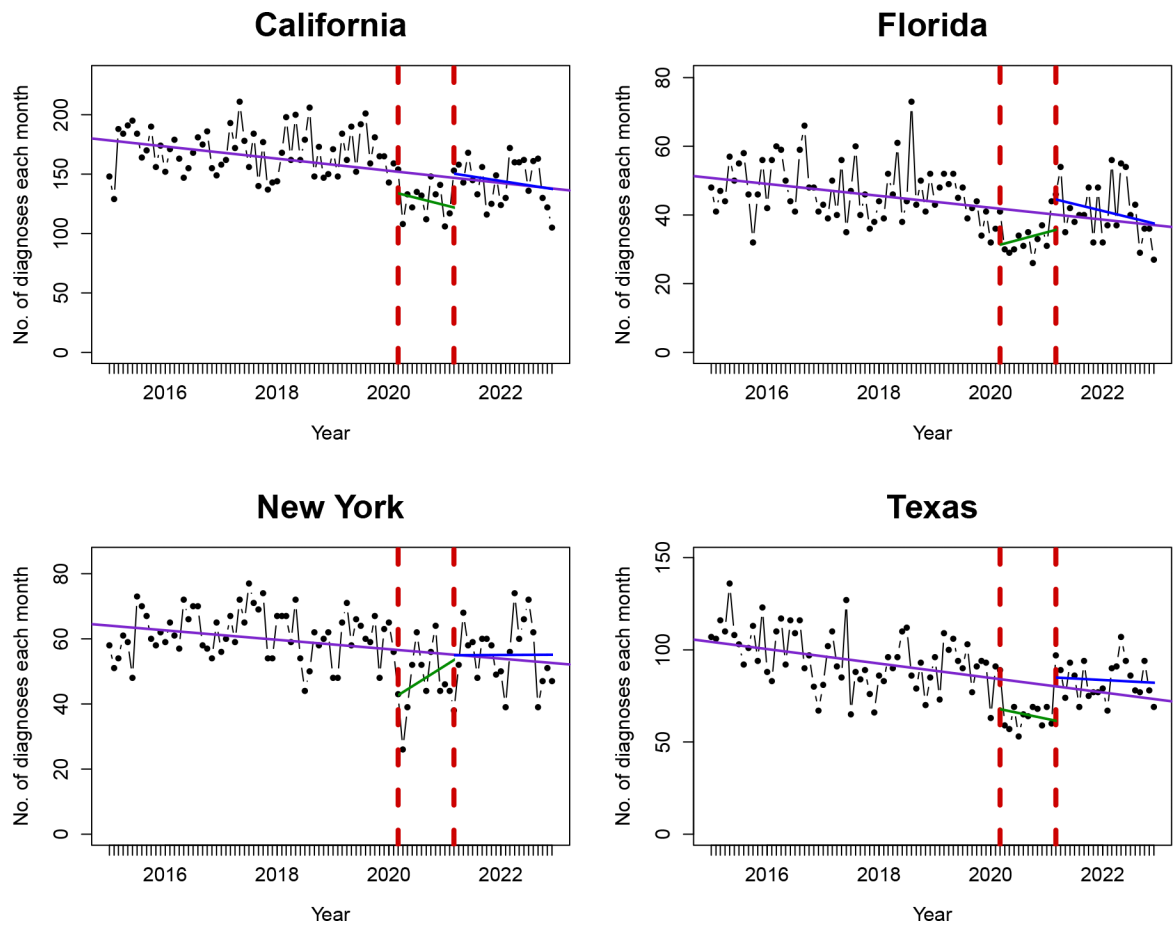


Figure 3. Monthly tuberculosis notifications during 2009 – 2022 in California, Florida, New York, and Texas.

In each panel, we show monthly aggregated TB treatment initiations from the National Tuberculosis Surveillance System (NTSS). The red dashed vertical lines represent the assumed COVID-19 disruption period, from March 2020 to March 2021, when the United States saw the most disruption to services. The purple line shows the linear trend in monthly TB treatment initiations between January, 2009 and February 2020 (i.e., pre-pandemic period); the green line shows the linear trend between March, 2020 and March 2021 (i.e., during the pandemic); and the blue line shows the linear trend between March, 2021 and the end of 2022 (i.e., post-pandemic period).

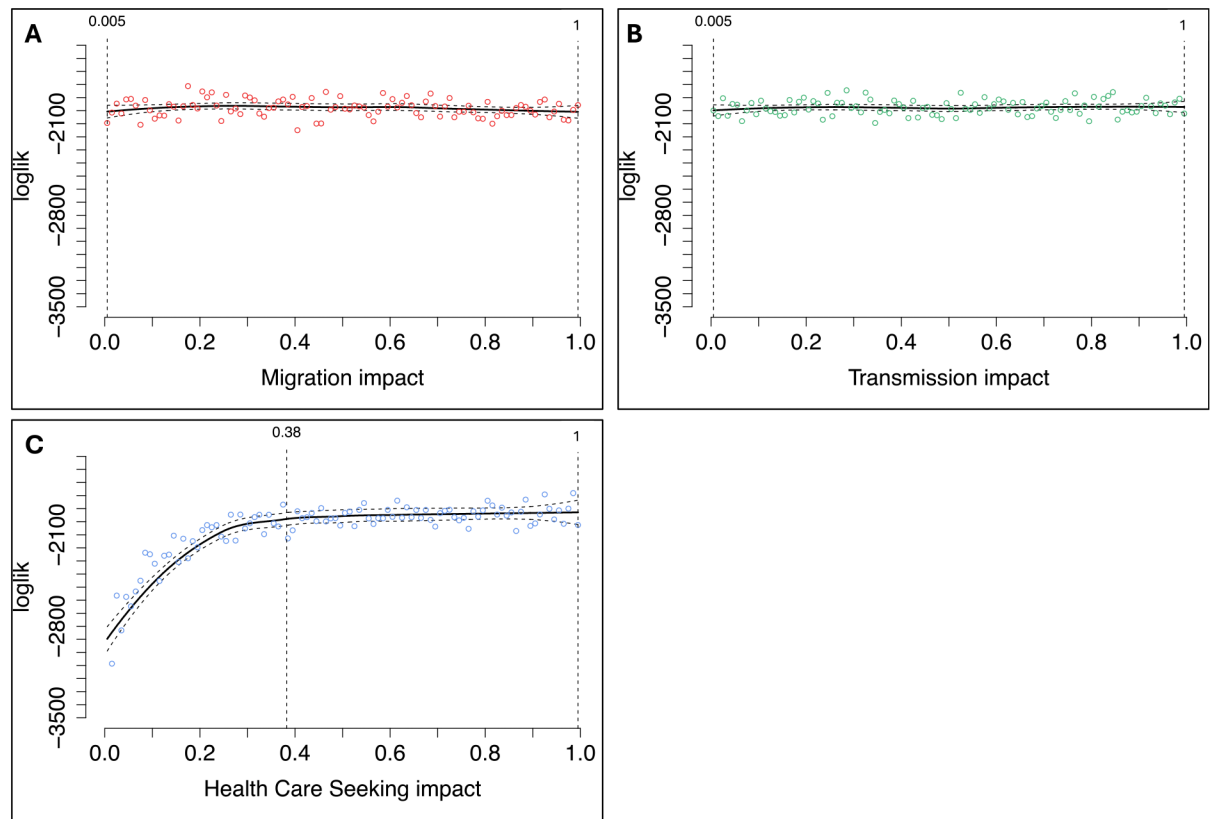


Figure 4. Likelihood profiles for the impact of three hypothesized pandemic-related disruptions, combined across the four states.

Migration-driven impact (A), transmission-driven impact (B), and access-driven impact (C). For each profile, the x-axis represents the values of the disrupted mechanism being profiled (in the interval [0–1]), the two dashed vertical lines show the 95% confidence intervals, while the colored dots represent the value of the maximum log-likelihood from the model simulations, at that value of the profiled disruption mechanism. The horizontal black solid and dashed lines represent the mean and uncertainty intervals of the likelihood profiles of each mechanism. The likelihood profiles for the individual states can be found in the online supplement, Figure E4.

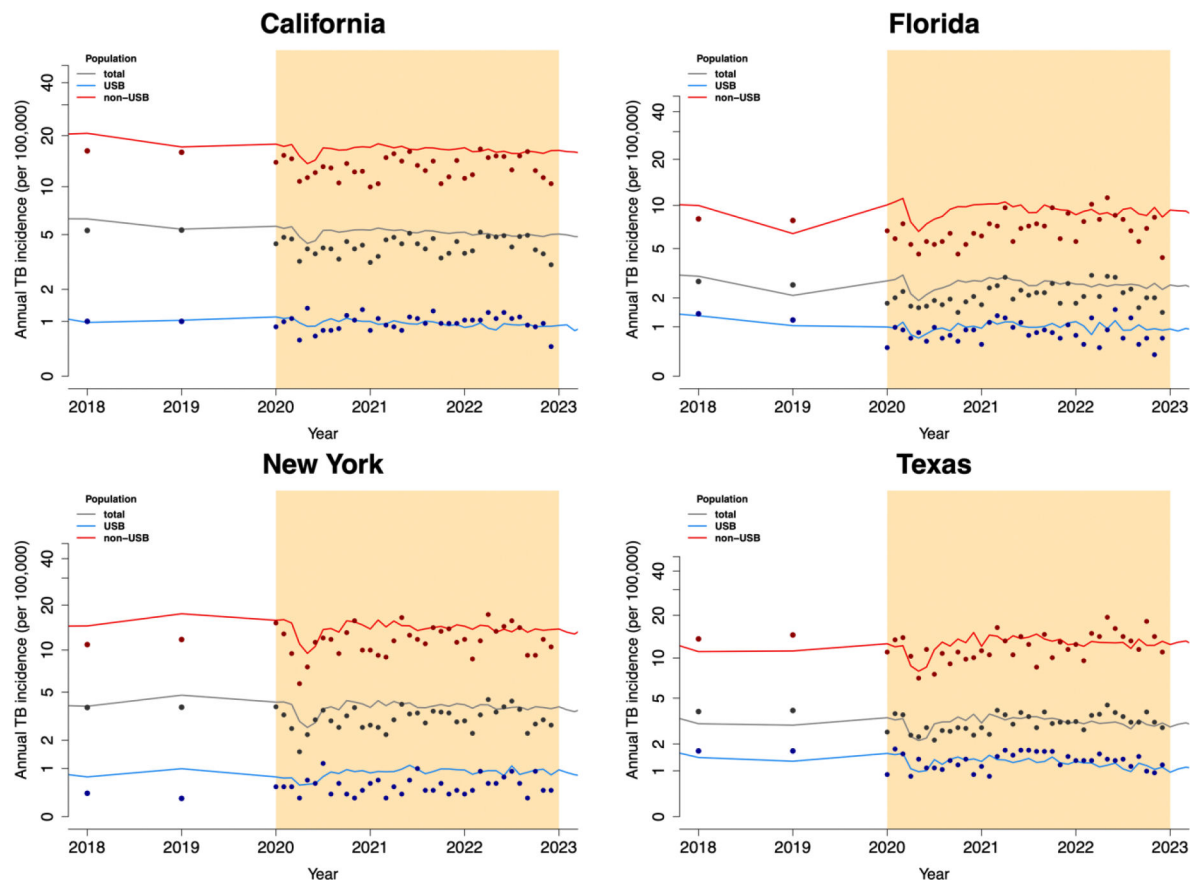


Figure 5. State-level notifications between 2020–2023 projected by the model and compared to the NTSS data.

The dots represent the NTSS data, stratified by origin (red for non-US-born and blue for US-born) and the lines represent the average of model simulations that were consistent with the data, similarly stratified by origin (95% uncertainty intervals omitted for clarity). The shaded orange area represents the time period (2020–2023) for which we had monthly NTSS data on treatment initiation, which was used to infer the hypothesized impact of the pandemic-related disruptions.

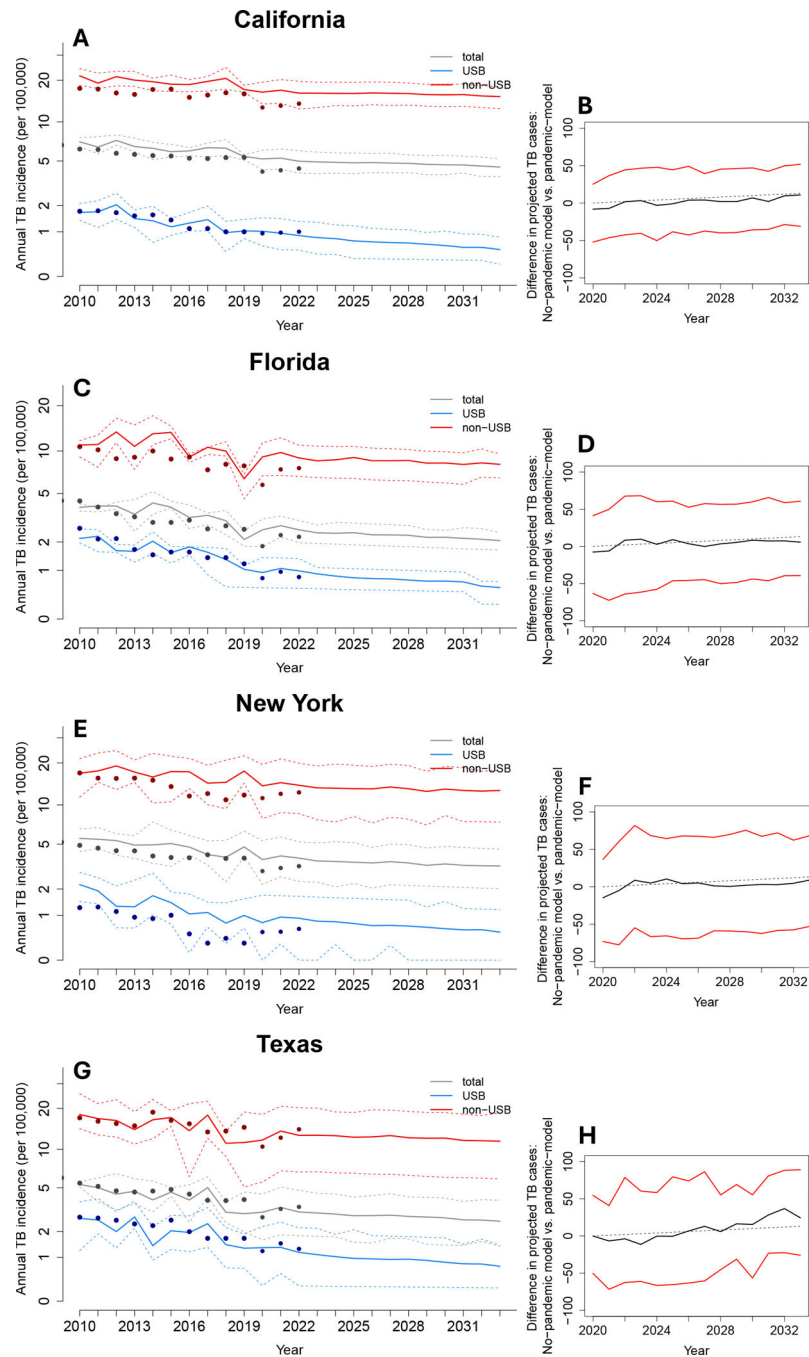


Figure 6. Updated projections of TB incidence in California (A), Florida (C), New York (E), and Texas (G).

The dots represent notification data for each state, stratified by origin (red for non-US-born, blue for US-born). The data is provided on a yearly scale up until 2019, then from 2020 onwards we averaged the monthly NTSS data (A, C, E and G). The solid lines represent the medians of the model simulations, and the dashed lines represent 95% uncertainty interval across simulations. Figures B, D, F and H show the difference in the annual number of projected cases from 2020 to 2032, comparing the projections from the no-pandemic model

and the pandemic model, therefore values under the dashed black line indicate that the model projected more cases in the pandemic scenario than the no-pandemic scenario, while values over the dashed line indicate that the model projected more cases in the no-pandemic scenario compared to the pandemic scenario. The solid black line represents the mean difference in the projections between the two models, and red lines represent 95% range. The model projections for the pandemic period shown at the monthly level and compared to the monthly NTSS data are Figure 5.