Supplemental Information

HYPOTHETICAL POPULATION

The hypothetical population included all children ages 0 to 17 years in California in 2014. Children were assigned realistic demographic, socioeconomic, and spatial characteristics. The base population was built from estimates of population by age and race and ethnicity for Census block groups in 2014 from ESRI Business Analyst (2015 version). ESRI Business Analyst provided population counts by the 6 racial categories recognized by the US Census (White, Black or African American, American Indian and/or Alaskan native, Asian, Native Hawaiian and/or Pacific Islander), which does not include a distinct category for Hispanic and Latino. To separate counts of Hispanic and Latino children, we used population counts by Hispanic and Latino ethnicity from the 2010 Census at the block group level.

We assigned children household income, maternal level of education, and maternal employment status on the basis of 2014 Census block group-level data from ESRI Business Analyst and the 2014 ACS. We aggregated children into families using predicted sibship size and sibling age gaps by race and ethnicity, maternal level of education, and geographic location (3-digit zip code) as informed by data from the 2000 California Birth Statistical Master File. We assigned children point-level geographic locations using block-level population density data from the 2010 Census.

School-aged children (5–17 years) could be enrolled in 1 of 4 school types: public, charter, private, or home-based. Charter schools are public but operate without traditional residential restrictions on enrollment and often provide alternative methods of instruction. Retaining school type was important because private and charter schools had both higher rates of students with PBEs and larger increases in PMEs after the elimination of PBEs than public schools.[19,51,52]

Younger children (ages 2–4 years) could be assigned to attend a licensed child care center. Licensed child care centers included public and private day care centers and Head Start programs. Head Start is a federal program that provides early childhood education to low-income families. To be eligible for Head Start, families generally must have incomes at or below the federal poverty line. Again, it is important to retain distinctions among child care type because children enrolled in Head Start programs were significantly less likely to have PBEs.[53]

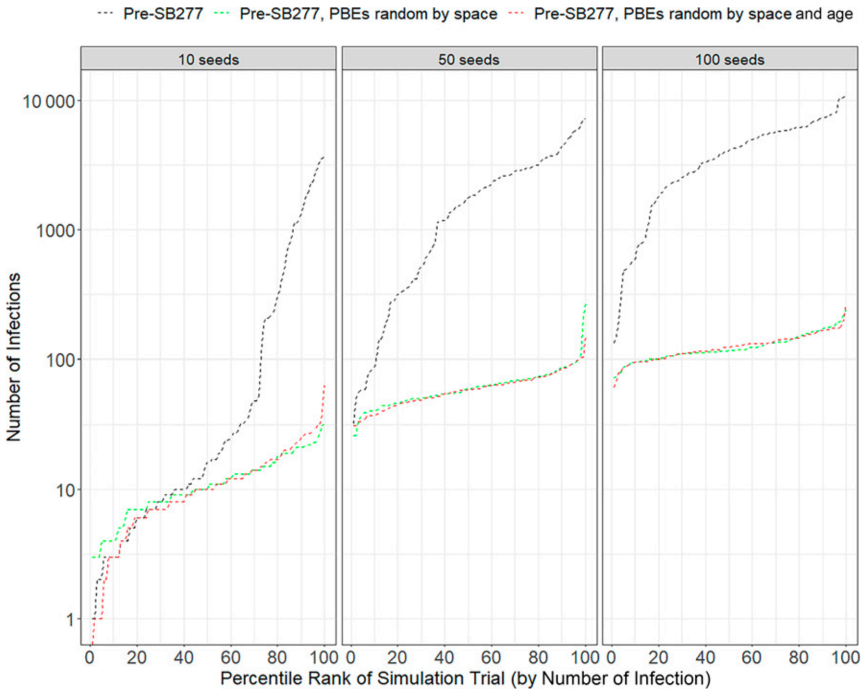
We predicted the type of school or whether a child would be enrolled in a licensed child care center (and, if so, what type of center) using data from the National Household Education Surveys Program. This program provides information on the socioeconomic and demographic characteristics of enrolled children by types of child care and kindergarten through 12th grade education in the United States. We predicted the probabilities of attending a school type or child care center by race and ethnicity, maternal education level, maternal employment status, and household income in our hypothetical population using data from the 2012 National Household Education Surveys (the most recent year of data available in 2014).

We then assigned children to specific schools on the basis of geographic distance to match the 2014 school-level enrollment records from the California Department of Education.[54] We used age to assign grade level across all school types. California Department of Education data included enrollment proportions by race and ethnicity for public but not private schools. For public (including charter) schools, we maintained the race and ethnicity distributions for school enrollments. We used data from the 2012 Private School Universe Survey to determine race and ethnicity proportions in private schools. The Private School Universe Survey provides descriptive statistics for private school enrollments across the United States and is available from the National Center for Education Statistics.

We assigned children to attend licensed child care centers by the same method using data from the California Department of Social Services. Consistent with the 2014–2015 CDPH Child care Immunization Assessment report, approximately one-third (32.2%) of children ages 2 to 4 years in the hypothetical population were assigned to licensed child care centers.[27] A higher proportion of the children assigned to child care centers were ages 3 to 4 years; this is consistent with data from the 2014 ACS reporting that 47.8% of 3- to 4-year-olds in California were enrolled in school.[82] In the hypothetical population, 44.6% of children ages 3 to 4 years were enrolled in a child care center. The California Department of Social Services also licenses infant centers that serve children ages 0 to 2 years. We did not include infant centers in the hypothetical population because they tended to be smaller, with 59.7% less capacity than child care centers, on average, and were less numerous (there was a 5:1 ratio of child care to infant care centers). For these reasons, infant care centers would be unlikely to substantially affect measles outbreak potential in the population.

We then assigned children neighborhood and community focal points to represent the interaction that occurs in local areas outside the home. We defined neighborhoods as the 2010 Census block group in which the child resided. Use of block groups as neighborhoods is consistent with previous health research examining walkability[55] and adolescents' access to local resources.[56] Census tracts are also often used to define neighborhoods in health research,[57] but we chose to use block groups as children are not likely to traverse as large of a daily "neighborhood" as adults. Neighborhood interaction could represent contact with neighbors, family members who live close by, or visits to other nearby locations, such as parks.

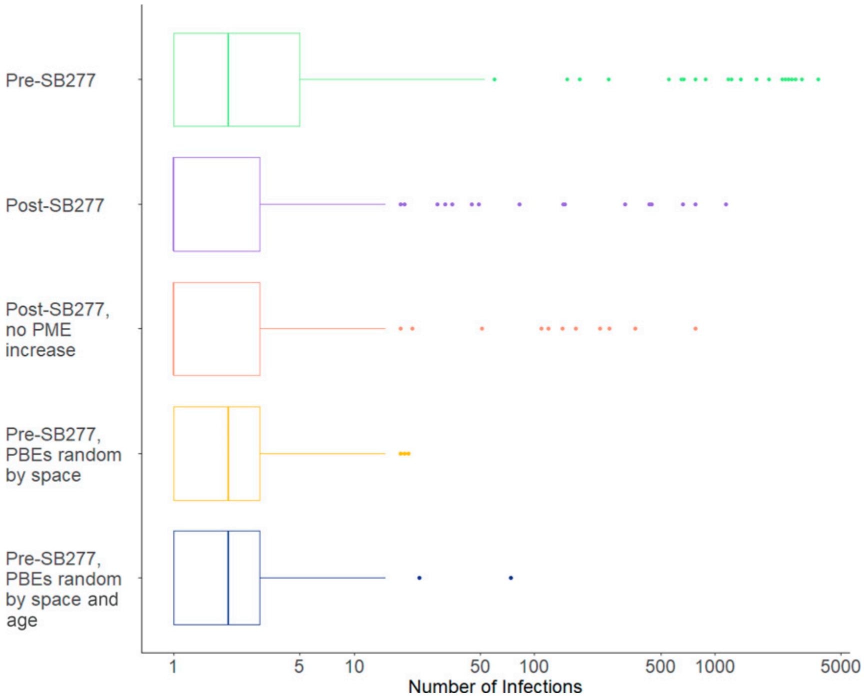
Community interaction occurred in 2 locations: physician offices and shopping malls. We included physician offices because of their noted role as exposure and transmission settings in epidemiological studies of measles infections.[6,34,58,59] We obtained data on physician specialties (eg, pediatricians, internal medicine, general practice) and office locations from the American Medical Association's 2012 Directory of Physicians. We restricted physician assignment to pediatricians, family medicine, and general practitioners because these would be the physician specialties most likely to treat children and adolescents. We assigned children to a local physician using standardized inverse weighted distance to the physician's office. Physician offices have not been routinely included in previous simulation studies of measles transmission. As a robustness check, we ran a supplementary set of models that did not include contact in these locations. The distribution of outbreak sizes was almost indistinguishable from the results presented in the main text that included contact in physician offices (Supplemental Fig 6).



SUPPLEMENTAL FIGURE 5

Measles outbreak distributions with 10, 50, and 100 randomly seeded infections, pre-SB277 (2014). Note: $N = 100$ simulation trials in each scenario. The y-axis (number of infections) is shown on $\log_{10}$ scale to increase figure legibility. The lower risk of smaller outbreaks offered by spatial clustering of PBEs remain with 10 seeded infections. In the first third of the outbreak distribution (first to 30th percentiles), there are a higher number of infections when PBEs are distributed randomly by space (green line) than when assigned as observed in schools and child care centers (black line). As the number of seeded infections increases, the distribution of outbreak sizes in the scenario in which PBEs are assigned as observed moves farther away from those generated by randomly distributed of PBEs. This is what we should expect; as the number of initial infections introduced into the population increases, the virus has increased opportunities to quickly reach clusters of exempted children.

Shopping malls represented general community locations in which many children from different schools and neighborhoods may have contact. We did not include shopping malls as singular settings in which kids would interact but rather to represent a general class of community contact points. This could include visits with friends or family from outside the local neighborhood and contact in other community settings, such as places of worship, recreation centers (eg, community swimming pool, dance studio), or other types of marketplaces. We used the Directory of Major Malls to collect information on the locations of shopping malls across California. Unlike neighborhoods and physicians, which can be expected to remain the same for the simulation period (36 weeks), families visit many different locations in the larger community in relatively short periods of time. Thus, for each child, we calculated the standardized inverse weighted distance to the nearest 3 malls. The probability of visiting each of the 3 possible malls was weighted on the basis of this distance. During each time step (ie, day) in the model, children were randomly assigned to "visit" 1 of the 3 nearest malls on the basis of these weights. If the 3



SUPPLEMENTAL FIGURE 6

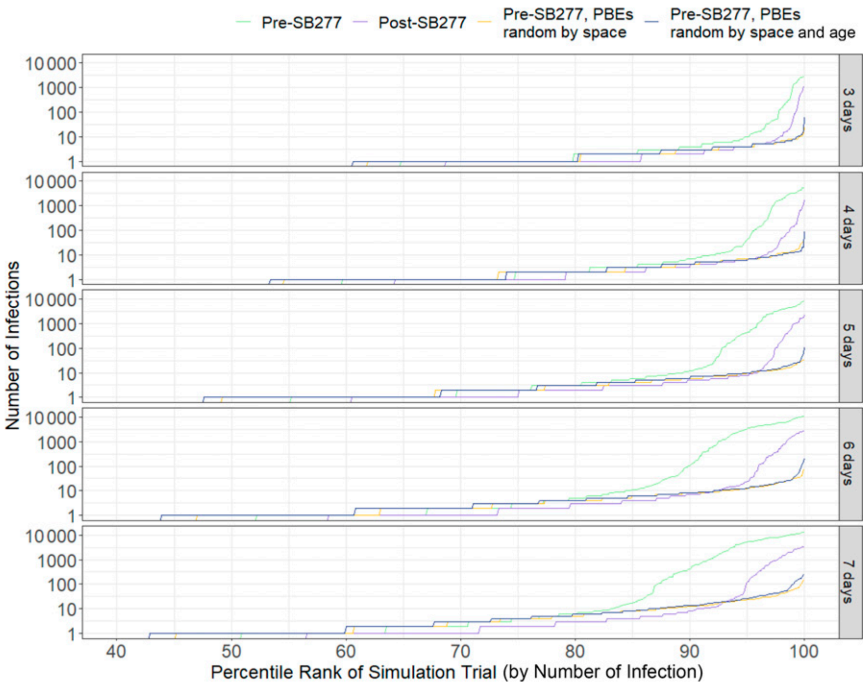
Distributions of outbreak size without contact in physician offices, by exemption scenario. Note: $N =$ 1000 simulation trials in each scenario; lower bound of box shows the 25th percentile (same as minimum for all exemption scenarios), middle line in box shows the 50th percentile (median), upper bound of box shows the 75th percentile, upper whisker shows 1.5 times interquartile range, points show outbreak sizes above this range. The x-axis (number of infections) shown on $\log_{10}$ scale to increase figure legibility. For the 2 post-SB277 scenarios, the values for the 25th and 50th percentiles were the same (1 infection), which is reflected in the seemingly "empty" boxes.

nearest malls were located at similar distances from the child's home, the probabilities of visiting them were roughly equal. The weighting primarily influenced mall selection when there were substantial differences in the distances to the 3 nearest malls. We included daily interaction in malls (both weekdays and weekends) in the simulation to reinforce that this interaction represents multiple types of contact in the larger community (ie, children would not be expected to visit the mall every day but may have daily interactions that represent contact with other children (known or unknown) outside those in the same home, school, or neighborhood). In Supplemental Table 3 we provide descriptive statistics for the focal points (ie, interaction settings) in the population.

Vaccine Exemptions

In California, proof of immunization is required when entering child care, kindergarten, or the seventh grade. School-level counts of vaccine exemptions, including both PBEs and PMEs, for child care, kindergarten, and seventh grade enrollment are released annually by CDPH. Data are only released for schools and child care centers with enrollments of >10 students for privacy reasons. Additionally, the data do not include any information on the vaccination status of exempted children. Children with exemptions may be entirely unimmunized or may only be missing 1 or 2 required vaccines. Here, we make no assumptions about partial vaccination and all children with exemptions are treated as susceptible. Treating these children as unvaccinated is consistent with previous research on vaccination coverage and the association between children with nonmedical exemptions and disease risk.[6,9,10,60–64] Audits of vaccination records for children with PBEs in California in 2009 showed low MMR coverage, particularly in schools with high PBE rates, indicating a positive correlation between exemptions and lack of vaccination against measles.[45]

We assigned exemptions on the basis of annual CDPH data for the 2000–2001 to 2018–2019 school years. To examine the effect of the elimination of PBEs in 2016 by SB277, we recreated the prevalence and distribution of exemptions in 2 school years: 1 before (2014–2015) and 1 after (2018–2019) the policy change. We refer to these school years by their fall semesters, 2014 and 2018, respectively. For child care centers, kindergartens, and the seventh grade, we assigned exemptions based directly on the school-level counts reported in 2014 and 2018. The remaining grades were assigned exemption rates consistent with those reported in the same school in the year that they would have entered kindergarten or the seventh grade: kindergarten rates were used for elementary grades (typically first through fifth) and seventh grade rates were used for middle school grades (typically sixth through eighth). Usually, vaccine requirements are not checked when students enroll in high school grades (typically ninth through 12th); however, in the 2011–2012 school year, the CDPH collected information on exemptions for all students in the seventh through 12th grades. We used these data to assign exemption rates in high schools in the hypothetical population.

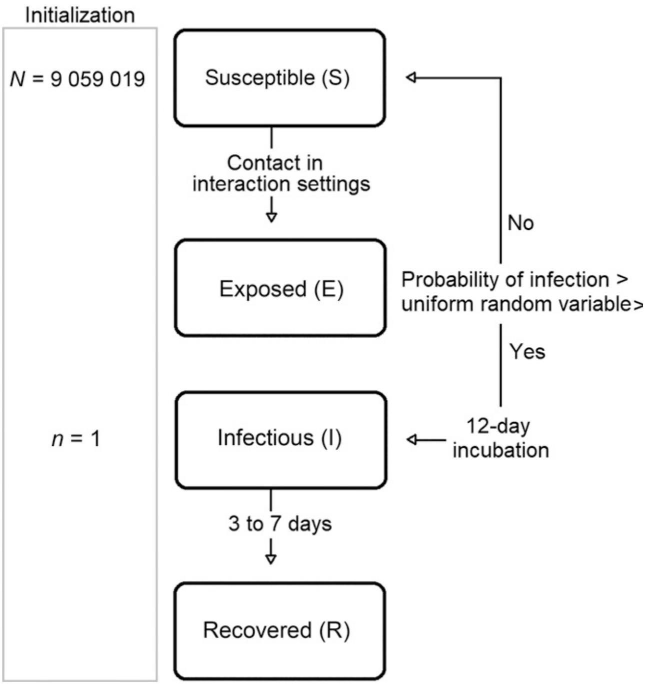


SUPPLEMENTAL FIGURE 7

Distribution of outbreak sizes by number of days infections and exemption scenario Note: $N =$ 1000 simulation trials in each scenario. There were no secondary infections in the first through 40th percentile of trials. The y-axis (number of infections) is shown on $\log_{10}$ scale to increase figure legibility.

Some schools and child care centers, including those with enrollments of 10 or fewer students, were missing exemption data. We assigned exemptions for these schools on the basis of the average exemption rates by grade level within the same school type (public, private, charter) in the same school district. We assigned child care centers with missing data exemptions on the basis of average rates for the same center type (day care or Head Start) within the same county. After completing the exemption assignments, including to schools and child care centers with missing data, we verified that the overall exemption rates by grade level were consistent with those released in annual CDPH immunization reports for the corresponding year.

We then needed to assign exemptions to children who were not enrolled in schools or child care centers, including those in home-based schools. Home-based schools included traditional homeschooling programs as well as online or other alternative programs that students participated in virtually. We assigned exemptions to children in home-based schools consistent with rates reported in charter schools located in the same county. Vaccine refusals tend to be particularly high among homeschooled children,[65] and enrollment in home-based study increased after the implementation of SB277.[18] If children in home-based programs are more likely to be missing some or all vaccines than children enrolled in schools, this may overestimate vaccination rates among these children. We assigned exemptions to children ages 1 to 4 years not enrolled in licensed child care consistent with exemption rates observed in child care centers in the same county. Infants <1 year of age were considered to be unvaccinated because the Centers for Disease Control and Prevention does not typically recommend the



SUPPLEMENTAL FIGURE 8

Stages of the SEIR model.

SUPPLEMENTAL TABLE 1 Odds Ratios for Proportion of Trials with 0 Secondary (Nonseeded) Infections

				95% CI Bounds	
	Odds Ratio	SE	*P*	Lower	Upper
Pre-SB277 (observed PBEs and PMEs)	(Reference)	(Reference)	(Reference)	(Reference)	(Reference)
Post-SB277 (observed PBEs and PMEs)	1.195	0.112	.056	0.995	1.435
Post-SB277, no PME increase	1.267	0.119	.012	1.054	1.523
Pre-SB277, PBEs random by space	0.850	0.078	.075	0.710	1.017
Pre-SB277, PBEs random by space and age	0.816	0.074	.026	0.682	0.976
Constant	1.632	0.106	.000	1.436	1.854

Note: $N = 5000$ trials. Odds ratios were estimated in logistic regression with outcome as binary indicator of 0 nonseeded infections ($1 = 0$ infections). The constant represents the baseline odds for 0 secondary infections pre-SB277 (the reference scenario). The odds ratios for the remaining scenarios are the effects of the changes in exemption distributions as compared with pre-SB277 PBE and PME distributions. CI, confidence interval.

first dose of the MMR vaccine until ages 12 to 15 months.[28]

Siblings were given similar PBE status to reflect the tendency of vaccine-hesitant parents to make selective vaccination decisions for all of their children.[66] Children had a higher likelihood of receiving a PBE if another child in their household had already been assigned a PBE; however, the total number of PBEs in any grade level within a school could not exceed the maximum number of available PBEs that had been observed (or assigned) for that particular school-grade level, resulting in a small proportion of siblings who did not share vaccination status. PMEs observed pre-SB277 in 2014 were assigned without preference for shared vaccination status among siblings. Because of the ease of access to PBEs before the policy change,[29] PMEs would not be expected to have been sought by vaccine-hesitant parents. Post-SB277 in 2018, sibling preference for the same vaccination status was incorporated into the assignment of both PBEs and PMEs. Increases in PMEs after the elimination of PBEs by SB277 in 2016 suggested a replacement effect,[18] indicating that parents who previously sought PBEs may be more likely to now seek PMEs. For this reason, shared preference for vaccination status among siblings was considered when assigning PMEs post-SB277, and younger siblings of children with PBEs obtained before 2016 were given a higher likelihood of obtaining a PME. Again, only the maximum number of available exemptions, PBEs or PMEs, could be assigned in each school-grade, resulting in some siblings not sharing the same vaccination status. The assignment of PBEs and PMEs for these 2 school years (2014 and 2018) created our first 2 exemption scenarios. The first, 2014, represented observed exemption prevalence pre-SB277. The second, 2018, represented observed exemption prevalence post-SB277. Supplemental Table 4 shows the prevalence of PBEs and PMEs across child care center and school types pre- and post-SB277. We created 3 additional hypothetical (unobserved) scenarios of exemption prevalence to examine measles transmission under counterfactual conditions in the hypothetical population.

The third scenario helped isolate the effects of increases in PMEs post-SB277. To do this, we created a hybrid condition by retaining post-SB277 PBE assignments (2018) but assigning PMEs consistent with

SUPPLEMENTAL TABLE 2 Descriptive Statistics for Outbreak Distributions, by Scenario

			No. Secondary Infections (Outbreak Sizes)							
Scenario	Exemption Distribution	% Vaccinated	Mean	Min	5th Percentile	25th Percentile	Median	75th Percentile	95th Percentile	Max
1	Pre-SB277 (observed)	92.15	52.03	0.00	0.00	0.00	0.00	1.00	16.00	4350.00
2	Post-SB277 (observed)	92.97	7.00	0.00	0.00	0.00	0.00	1.00	6.00	1269.00
3	Post-SB277, no PME increase	93.26	3.24	0.00	0.00	0.00	0.00	1.00	5.00	861.00
4	Pre-SB277, PBEs random by space	92.15	1.17	0.00	0.00	0.00	0.00	1.00	5.00	19.00
5	Pre-SB277, PBEs random by space and age	92.15	1.19	0.00	0.00	0.00	0.00	1.00	6.00	26.00
		85.00	745.42	0.00	0.00	0.00	7.00	1066.50	3492.00	7266.00
		86.00	261.23	0.00	0.00	0.00	3.00	333.50	1332.00	4043.00
4	Pre-SB277, PBEs random by space	87.00	80.20	0.00	0.00	0.00	2.00	54.50	463.00	1925.00
		88.00	23.25	0.00	0.00	0.00	1.00	12.00	151.00	421.00
		89.00	18.17	0.00	0.00	0.00	1.00	9.00	105.50	818.00
		90.00	6.53	0.00	0.00	0.00	1.00	4.00	31.00	169.00
		91.00	2.78	0.00	0.00	0.00	1.00	3.00	14.00	47.00
		92.00	1.42	0.00	0.00	0.00	0.00	2.00	6.00	22.00

SUPPLEMENTAL TABLE 3 Descriptive Statistics for Focal Points (ie, Interact Settings) in Hypothetical Population

			Focal Point Size		
Foci	Type	*n*	Mean	SD	% Enrolled
Families	Siblings	5 895 518	1.54	0.79	100.00
Child care	Day care	9451	43.56	27.68	4.54
	Head start	1583	47.99	32.00	0.84
School: type	Public	8746	607.69	497.73	58.67
	Private	3177	153.74	205.60	5.39
	Charter	1048	424.09	403.52	4.91
School: grades	Elementary	48 376	60.36	42.37	32.23
	Middle	16 105	88.99	122.16	15.82
	High	13 706	138.25	195.28	20.92
Neighborhood	Block groups	23 112	391.96	311.81	100.00
Community	Physicians	19 247	470.67	299.86	100.00
	Malls	801	12 078.69	7868.75	100.00

school and child care center data in 2014 before the implementation of SB277. This scenario represented a counterfactual population in which access to PBEs was eliminated in 2016 without a subsequent increase in PMEs.

The fourth and fifth scenarios were counterfactual conditions of PBE assignment pre-SB277. These scenarios disentangled the role of the spatial clustering of PBEs within schools and child care centers from the tendency of these exemptions to increase over time. In these hypothetical scenarios, we started from the observed exemption distribution pre-SB277 in 2014 (the first scenario) and varied only the assignment of PBEs. We retained PME assignments as observed in schools. In the fourth scenario, we retained the same number of PBEs observed for each grade level (or age for children ages 1–4 years) but distributed them randomly across space. Here, we retained the temporal trend of increasing PBEs over time (ie, younger children still had higher PBE rates than older children) but eliminated their tendency to cluster within schools or households. In the fifth scenario, we retained the same overall number of PBEs in the population but distributed them randomly across both grade and age cohorts and space. In this scenario, any child in the population ages 1 year or older without a PME was eligible to receive a PBE. We then had 3 pre-SB277 scenarios: PBEs and PMEs assigned as observed in schools and child care (first scenario), PMEs assigned as observed but PBEs distributed randomly across space within age cohorts (fourth scenario), and PMEs assigned as observed but PBEs distributed randomly across both space and age cohorts (fifth scenario). This allowed us to separate the effects of (1) the overall number of PBEs and PMEs, (2) higher PBE rates in younger children, and (3) the spatial clustering of nonmedical PBEs on measles outbreak potential. Figure 1 in the main text shows the prevalence, spatial clustering, and age distributions of exemptions across the 5 exemption scenarios.

SUPPLEMENTAL TABLE 4 Prevalence of Vaccine Exemptions in the Hypothetical Population Pre- and Post-SB277

		Pre-SB277 (2014)		Post-SB277 (2018)	
	% Children	% PBE	% PME	% PBE	% PME
Ages <1 y	5.47	0.00	0.00	0.00	0.00
Ages 1–4 y (not in child care)	16.84	2.54	0.53	0.00	1.40
Child care					
Day care centers	4.54	2.71	0.62	0.18	1.02
Head Start programs	0.84	0.52	0.15	0.03	0.30
Schools					
Public	58.67	1.55	0.15	0.94	0.26
Private	5.39	3.46	0.27	2.30	0.71
Charter	4.91	3.79	0.17	2.65	0.66
Home-based programs	3.33	8.94	0.22	6.48	0.61
Total	99.99	2.14	0.24	1.03	0.53

Note: All children ages <1 y are assumed to be unvaccinated (and ineligible for exemptions) because the first MMR dose is recommended at 12–15 mo.

Contact Probabilities

Children could interact in the 6 focal points described above: households, child care centers, schools, neighborhoods, physician offices, and shopping malls. We adapted contact parameters for interaction in families, child care, schools, neighborhoods, and malls from empirically calibrated influenza simulations.[67,68] Contact networks developed for influenza transmission have been adapted in previous measles simulations.[69] We predicted the expected number daily of contacts in each setting as a Poisson random variable. For all interaction settings besides the home, we scaled the number of contacts by the logged population size of the focal point (see Supplemental Table 3 for average population sizes in focal points). This helped account for the fact that children in more populous contact settings (eg, larger child care centers, schools, neighborhoods) have opportunities for an increased number of contacts[69] but that this association would not be expected to be linear across the full distribution of focal point population sizes (the distributions of population sizes within focal points were right-skewed). We used age-structured contact rates in neighborhood and community interaction settings (block groups, malls, and physician offices) because of the increased tendency of children to interact with others of their own age.[70–72] Not accounting for this tendency can lead to underestimation of effective reproduction numbers[73] and less well-performing models of measles transmission.[74]

These contact parameters reflected (1) the tendency of children to interact with others of similar age (assortative mixing), (2) differences in the number of potential contacts due to the size of the focal points (ie, the number of other children assigned to the same focal point) in this population, and (3) the frequency and intensity of interaction. For example, students are more likely to have adequate contact for disease transmission with other children sharing the same classrooms than in the overall school population.[75] For this reason, school contact in the model occurred at 2 levels: within grade and within the larger school population. Previous research has shown that within-grade contact is estimated to be 5 times greater than that of overall school contact.[70] Contact in schools was of particular interest as we used school-level exemption data and school vaccination coverage can significantly influence opportunities for measles outbreaks in local areas.[73]

We calibrated probability of contact in physician offices from epidemiological reports of measles exposure[6] and adjusted it to reflect the higher probability of contact with other children in pediatrician compared with family or general practitioner offices. The distributions of contacts across settings were similar to those used in previous simulations of measles transmission.[30] Robustness checks confirmed that these contact probabilities, together with the empirical transmission parameters described below, successfully reproduced the expected basic reproduction number for measles ($R_0 = 12–18$)[21,22] in a completely susceptible population. In Supplemental Table 5 we provide descriptive statistics for the average number of contacts and contact probabilities in each interaction setting.

SUPPLEMENTAL TABLE 5 Daily Contact Distributions and Probabilities in Interaction Settings

Focal Point	Ages, y	No. Contacts Mean	SD	Min.	Max.	Contact Probability, Mean
Households	0–17	1.55	0.81	0	10	0.800031
Child care centers	2–4	3.96	0.78	0	20	0.081631
Schools, within grade	5–17	3.00	0.74	0	19	0.026821
Schools, full population	5–17	0.79	0.25	0	10	0.001375
Neighborhood (block group)	0–4	0.26	0.11	0	6	0.000596
	5–17	0.77	0.21	0	11	0.001835
Community (ie, mall)	0–4	0.21	0.10	0	6	0.000017
	5–17	0.64	0.18	0	9	0.000051
Physician's office	0–4	0.53	0.42	0	8	0.001033
	5–17	1.06	0.60	0	10	0.002072

Note: Contact distributions and probabilities are shown for daily interaction. Children are permitted to interact in households, neighborhoods, and the larger community on both weekdays and weekends. Interaction in child care centers and schools occurs only on weekdays. Contact in physician offices occurs only on the final day a child is infectious.

Measles Transmission Parameters

We adapted measles transmission parameters from epidemiological reports. We used probabilities of transmission in the prevaccine era[76] to represent the probability of infection given exposure among unvaccinated children. We used estimates from the prevaccine era because transmission probabilities recorded after the introduction of the vaccine are confounded by both the prevalence of vaccination and probability of contact between children with different vaccination histories. These probabilities were age-dependent to reflect the protection afforded by maternal immunity for the first 6 to 12 months of life.[77] The transmission probabilities are shown in Supplemental Table 6. We also considered using data on force of infection, but these estimates incorporate both infectiousness and age-dependent contact, and we needed to isolate the probability of transmission in our model.

Based on previous research, we set the overall vaccine efficacy at 96.9%.[23] We modeled vaccine failure (ie, a child was vaccinated but still became infected) as an exponentially decreasing function across the number of exposures. If an individual has been vaccinated but has not developed measles seropositivity, the failure would be expected to occur within the initial exposure(s). In other words, the probability of vaccine failure is not uniform across exposures. Using a function in which the risk of failure exponentially decreases with number of exposures resulted in an overall vaccine efficacy rate more consistent with empirical reports than when vaccine failure was set uniformly at 96.9%.

Previous research has shown that the average time from exposure to first symptoms for measles is 14 days and that individuals are most infectious 2 days before and after the appearance of symptoms, such as a rash.[77] In the model, children who were infected incubated the virus for 12 days before becoming

SUPPLEMENTAL TABLE 6 Age-Dependent Probabilities of Measles Transmission (Given Exposure)

Age, y	Transmission Probability
0	0.5000
1–4	0.7295
5–9	0.8788
10–14	0.7083
15–19	0.5294

infectious on the 13th day after exposure. Children then remained infectious for up to 8 days: during a 2-day latent period (before the appearance of symptoms) and up to 6 days after the appearance of symptoms. Children could only transmit the virus to other children during the infectious period. We assumed most children visited a physician, received a measles diagnosis, and were isolated from contact with others on the first (47.5%) or second (47.5%) day of symptom onset. The remaining 5% of children replicated this pattern on either the third (2%), fourth (1%), fifth (1%), or sixth (1%) day after the appearance of symptoms. This variable range of infectious days is consistent with previous simulations of measles transmission.[30,32] Still, we acknowledge that this was a simplifying assumption. Empirically, failure to diagnose measles on the initial health care visit can increase population exposure and opportunities for transmission.[33] This is often particularly an issue at the beginning of an epidemic,[6] and delays in reporting and intervention in measles transmission can result in larger potential outbreaks.[30] Alternative choices for number of days infectious did not substantially alter the findings presented in the main text (Supplemental Fig 7).

Simulation Model

We used a stochastic, agent-based SEIR model to simulate measles transmission. SEIR models are appropriate for the modeling of measles transmission because of the extended latent period between exposure (E) and appearance of symptoms (I) and immunity from reinfection after a case has recovered (R).[78–81] The SEIR model was run with a daily time step over 36 weeks, the typical length of a school year in the United States. The model did not account for holidays or school breaks because contact patterns would be expected to differ in these periods. Holidays would likely decrease measles transmission because school closure can be an effective intervention strategy for reducing contact for disease spread.[68]

We ran 1000 simulation trials for each of the 5 exemption scenarios. We randomly selected 1 child to serve as the initial infection. These initial, seeded infections represented the external introduction point of the disease into the population. After the incubation and infectious periods, children recovered and were considered to be immune from reinfection. Measles immunity is typically considered to be lifelong, although reinfections have been reported later in life on rare occaisions.[81] We made the (reasonable) assumption that recovered children remained immune for the remainder of the 36-week period.

Daily contact in interaction settings was separated by weekdays and weekends. Each weekday, children could have contact in households, child care centers, schools, neighborhoods, and the larger community (represented as malls in the population). On weekends, contact could only occur in households, neighborhoods, and the larger community. Because of the length of the incubation period, weekend contact was relatively less important in early generations of cases. For this reason, we permitted children to have contact in households, neighborhoods, and the larger community (locations where weekend contact would be likely to occur) daily in the simulation. On the final day a child was infectious, they visited their assigned physician office and could expose a small number of other children assigned to the same physician that were randomly selected to visit the office that day.

Infections occurred probabilistically after exposure. We modeled the number of exposures in each focal point as a binomial random variable generated as a function of the number of infectious children in the same focal point and probability of contact. For unvaccinated children, the probability of infection, p_u, was:

$$p_u = 1 - (1 - \beta_a)^{\tau},$$

where β_a was the age-dependent rate of transmission and τ was the number of exposures to infectious children in that focal point. For vaccinated children, the probability of infection, p_v, was:

$$p_v = 1 - (1 - (\beta_a * \gamma))^{\tau},$$

where β_a was the age-dependent rate of transmission, γ was the vaccine efficacy (ie, probability that the vaccine did not fail), and τ was the number of exposures to infectious children in that focal point. Vaccine efficacy was calculated as:

$$\gamma = \pi_0/2,$$

where π_0 was the overall probability of vaccine failure and T was the total number of exposures up to and including that location. Children became infected after exposure if their probability of infection .was greater than a uniform random variable (range: 0–1). A diagram of the SEIR model and how children move through the 4 compartments is shown in Supplemental Fig 8.

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