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² Susceptible host dynamics explain pathogen resilience
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⁵ **Abstract**

⁶ Major priority for epidemiological research in the time of anthropogenic change is
⁷ understanding how infectious disease dynamics respond to perturbations. Interven-
⁸ tions to slow the spread of COVID-19 significantly disrupted the transmission of other
⁹ human pathogens, providing unique opportunities to learn about pathogen charac-
¹⁰ teristics from spatiotemporal variation in re-emergence patterns. As interventions
¹¹ lifted, a key question of whether and when respiratory pathogens would eventually
¹² return to their pre-pandemic dynamics remains to be answered. To address this
¹³ gap, we develop a framework for estimating pathogen resilience based on how fast
¹⁴ epidemic patterns return to their pre-pandemic, endemic cycles. Our analysis re-
¹⁵ veals a possibility that some pathogens may have settled to endemic cycles that are
¹⁶ different from their pre-pandemic patterns. Finally, we show that heterogeneity in
¹⁷ pathogen resilience can be understood in terms of how fast a susceptible host popula-
¹⁸ tion becomes replenished. Our framework offers a novel perspective to characterizing
¹⁹ epidemic dynamics of endemic pathogens and measuring epidemic time scales.

Understanding how ecological systems respond to perturbations is a fundamental challenge in predicting species persistence and extinction [1, 2, 3]. These responses can be characterized in terms of resilience, which often measures how fast a system returns to its stable, reference state following a perturbation [4, 5, 6, 7]. Both theoretical and empirical efforts to quantify resilience of ecological systems have provided key insights for understanding the dynamics of complex systems and linking these findings to actionable strategies for species conservation [8]. However, despite rich literature on ecological resilience, there have been limited applications to measuring the resilience of host-pathogen systems, especially for human pathogens.

Non-pharmaceutical interventions (NPIs) to slow the spread of COVID-19 disrupted the transmission of other human pathogens, providing large-scale natural experiments for understanding how various host-pathogen systems respond to perturbations [9, 10, 11, 12]. In particular, as interventions lifted, large heterogeneities in outbreak dynamics were observed across different pathogens in different countries (Figure 1), likely reflecting differences in NPI patterns, pathogen characteristics, immigration/importation from other countries, and pre-pandemic pathogen dynamics [13]. Even though more than four years have already passed since the emergence of COVID-19, current circulation patterns for many respiratory pathogens appear to be different from their pre-pandemic, seasonal patterns, especially in Hong Kong and Korea: some pathogens, such as human metapneumovirus and bocavirus in Korea, are circulating at lower levels, whereas other pathogens, such as RSV in Korea, seem to exhibit different seasonality (Figure 1). These observations pose two fundamental questions for current and future infectious disease dynamics: (1) can we learn about underlying pathogen characteristics, such as their transmissibility or duration of immunity, from re-emergence patterns? and (2) can we predict whether and when other respiratory pathogens will eventually return to their pre-pandemic dynamics?

To address this question, we propose a framework for characterizing the resilience of a host-pathogen system based on how fast the system recovers from perturbation. We begin by laying out a few representative scenarios that capture the potential impact of COVID-19 interventions on endemic pathogen dynamics and illustrating how resilience can be measured by comparing the pre- and post-pandemic dynamics of susceptible and infected hosts. In practice, information on susceptible hosts are often unavailable, and traditional methods for reconstructing the dynamics of susceptible hosts require long-term endemic time series [14, 15], which cannot be applied due to disruptions in epidemic patterns caused by COVID-19 interventions. Instead, we utilize Takens' embedding theorem to reconstruct empirical attractors from data and further measure the distance from this empirical attractor [16]. This reconstruction allows us to characterize the rate at which this distance decreases over time, which correspond to pathogen resilience. We apply this framework to analyzing pathogen surveillance data for a wide array of respiratory and non-respiratory pathogens from Canada, Hong Kong, Korea, and US. Finally, we show that susceptible host dynamics are a key determinants of pathogen resilience. Our study offers unique insights into understanding pathogen re-emergence patterns following COVID-19 interventions.

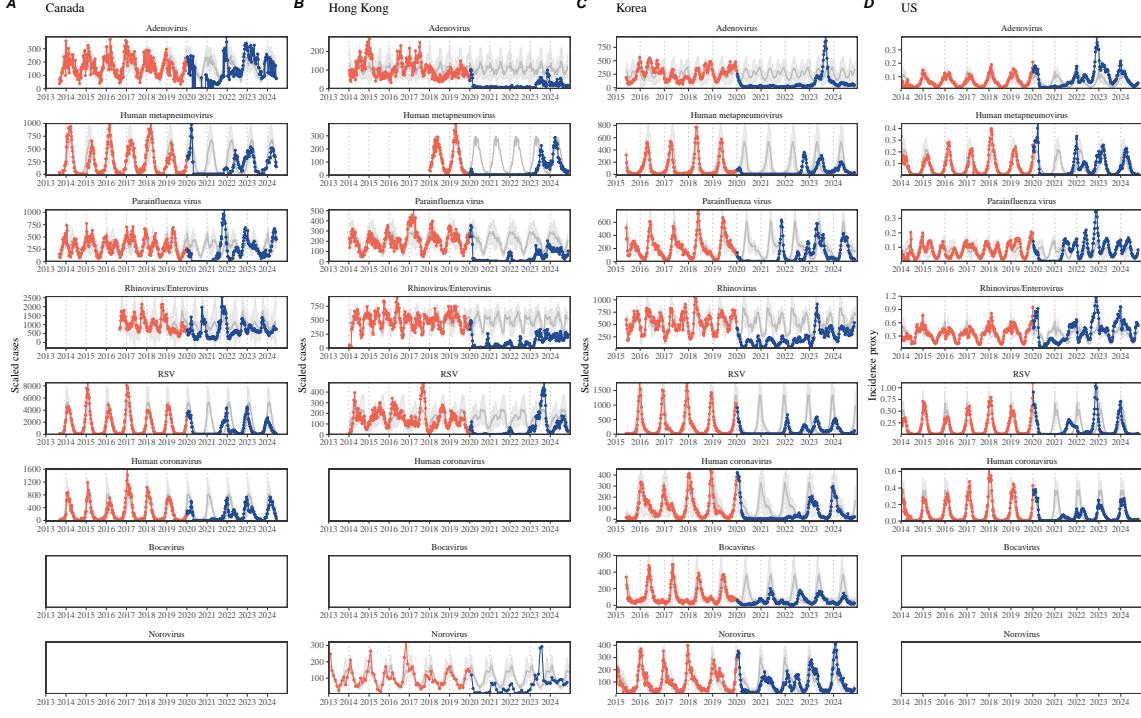


Figure 1: **Observed heterogeneity in responses to COVID-19 pandemic across respiratory pathogens and norovirus in (A) Canada, (B) Hong Kong, (C) Korea, and (D) US.** Red points and lines represent data before 2020. Blue points and lines represent data since 2020. Gray lines and shaded regions represent the mean seasonal patterns and corresponding 95% confidence intervals based on the observed outbreak patterns before 2020.

63 Conceptual introduction to pathogen resilience

64 In classical ecological literature, resilience of an ecological system is measured by
 65 the rate at which the system returns to its reference state following a perturbation
 66 [4, 5, 6, 7]. This rate corresponds to the largest real part of the eigenvalues of the
 67 linearized system near equilibrium—here, we refer to this value as the *intrinsic* re-
 68 silience of the system, which represents the expected rate of return from perturbated
 69 states. However, respiratory pathogens often exhibit seasonal variation in transmis-
 70 sion, meaning that the intrinsic resilience of a host-pathogen system varies across
 71 season. Nonetheless, we can still measure the *empirical* resilience of a host-pathogen
 72 system by looking at how fast the system returns to the pre-pandemic, endemic
 73 dynamics after interventions are lifted.

74 As an example, consider an intervention that reduce transmission by 50% for 6
 75 months starting in 2020, which causes epidemic patterns to deviate from its original
 76 stable annual cycle for a short period of time and eventually come back (Figure 2A).
 77 To measure the empirical resilience of this system, we first need to be able to measure

78 the distance from its pre-pandemic attractor. There are many different ways we can
79 measure the distance from attractor, but for illustrative purposes, we choose one of
80 the most parsimonious approach: that is, we look at how the susceptible (S) and
81 infected (I) populations change over time and measure the distance on the SI phase
82 plane (Figure 2B). In this simple case, the locally estimated scatterplot smoothing
83 (LOESS) fit indicates that the distance from attractor decreases linearly on average
84 (Figure 2C). Furthermore, the overall rate of return matches the intrinsic resilience
85 of the seasonally unforced system (Figure 2C).

86 Alternatively, NPIs can permanently change our behavior and have persisting
87 impact on the pathogen dynamics; as an example, we consider a scenario in which a
88 10% reduction in transmission persists even after the NPIs are lifted (Figure 2D–F).
89 In such cases, we cannot know whether the pathogen will return to its original cycle
90 or a different cycle until many years have passed after the NPIs are lifted, meaning
91 that we cannot measure the distance against the new attractor that the system will
92 eventually approach. Nonetheless, we can still measure the distance against the orig-
93 inal, pre-pandemic attractor and ask how the distance changes over time (Figure 2E).
94 The LOESS fit suggests that the distance from the attractor will initially decrease
95 exponentially on average (equivalently, linearly on a log scale) and eventually plateau
96 (Figure 2F). Here, a permanent 10% reduction in transmission rate slows down the
97 system, which causes the distance from the attractor to decrease at a slower rate
98 (Figure 2F) than it would have otherwise in the absence of permanent transmission
99 reduction (Figure 2C). This example shows that resilience is not necessarily an in-
100 trinsic property of a specific pathogen. Instead, pathogen resilience is a property of
101 a specific attractor that a host-pathogen system approaches, which depends on both
102 pathogen and host characteristics.

103 Finally, transient phenomena can also complicate the picture (Figure 2G–I). For
104 example, a stage-structured model for RSV initially exhibits a stable annual cycle,
105 but perturbations from NPIs cause the epidemic to exhibit biennial cycles (Figure
106 2G). Despite this biennial cycle, we see that the system eventually approaches the
107 original pre-pandemic attractor (Figure 2H), suggesting that this biennial cycle is a
108 transient phenomenon. The LOESS fit indicates that the distance from the attractor
109 will initially decrease exponentially at a rate that is consistent with the intrinsic
110 resilience of the seasonally unforced system, but the rate of decrease slows down
111 as the epidemic exhibits a biennial cycle (Figure 2I). In classical ecological theory,
112 this behavior is also referred to as a ghost attractor, which causes long transient
113 dynamics and slow transitions [17]. As we show in Supplementary Figure S1, strong
114 seasonal forcing in transmission can also lead to transient phenomena for a simple
115 SIRS model, causing a slowing down of the system.

116 In Supplementary Materials, we also explore measuring the resilience of a two-
117 strain host-pathogen system: when the dynamics two strains (or two pathogens) are
118 coupled through cross immunity, we would expect the entire system to be character-
119 ized by a single resilience value (rather than having two separate resilience for each
120 strain). Simulations from a simple two-strain system illustrate that separate anal-

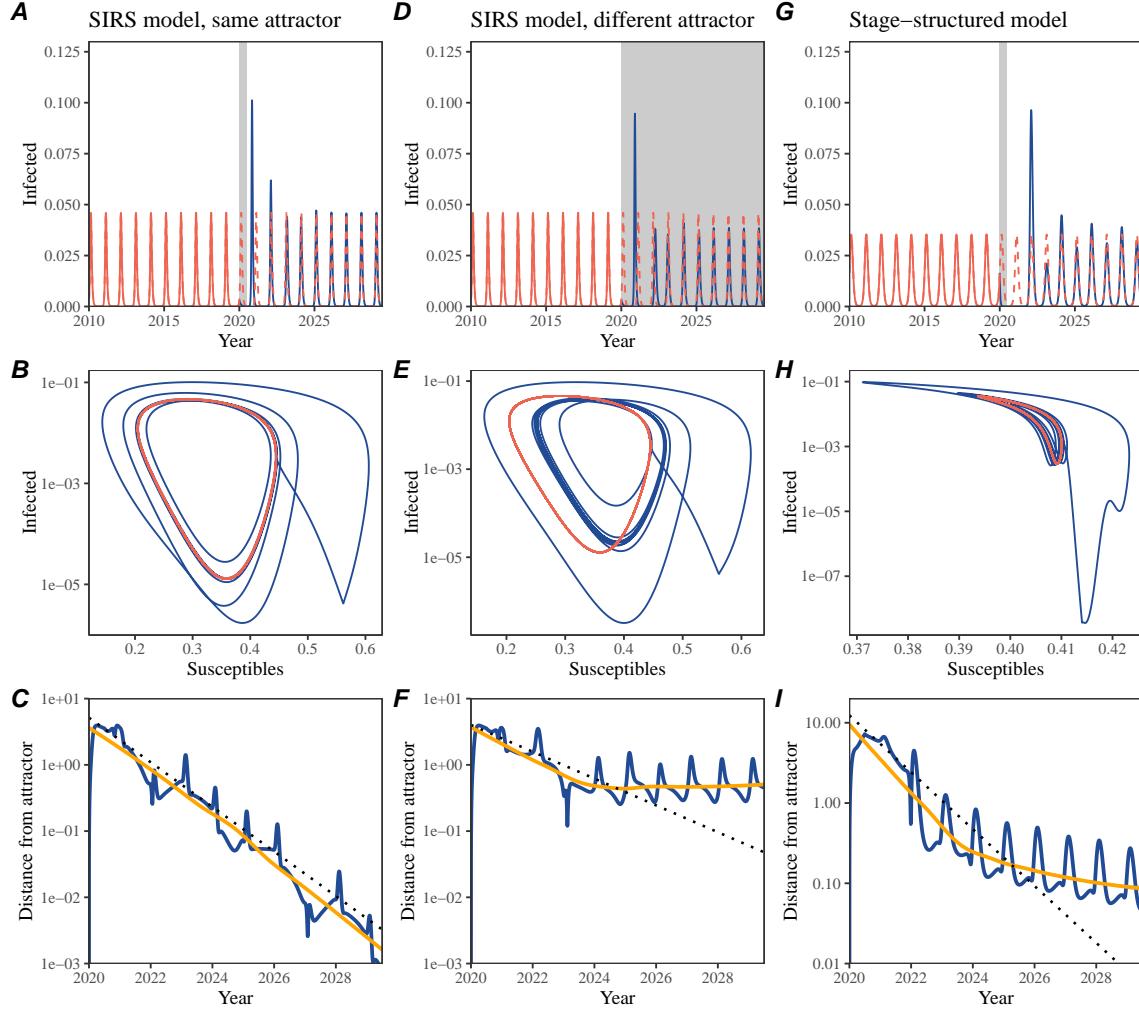


Figure 2: Conceptual framework for measuring pathogen resilience following NPIs across different scenarios. (A, D, G) Simulated epidemic trajectories across various models. Red and blue solid lines represent epidemic dynamics before and after interventions are introduced, respectively. Red dashed lines represent counterfactual epidemic dynamics in the absence of interventions. Gray regions indicate the duration of interventions. (B, E, H) Phase plane representation of the corresponding model. Red and blue solid lines represent epidemic trajectories on an SI phase plane before and after interventions are introduced, respectively. (C, F, I) Changes in logged distance from attractor over time. Blue lines represent the logged distance from attractor. Orange lines represent the locally estimated scatterplot smoothing (LOESS) fits to the logged distance from attractor. Dotted lines are superimposed as a comparison to have the same slope as the intrinsic resilience of the seasonally unforced system.

yses of individual strain dynamics (e.g., RSV A vs B) and a joint analysis of total

122 infections (e.g., total RSV infections) yield identical resilience estimates, confirming
123 our expectation (Supplementary Figure S2, 3). Analogous to a single system, strong
124 seasonal forcing in transmission can cause the system to slow down through transient
125 phenomena (Supplementary Figure S4).

126 These observations indicate three possibilities. First, we can directly estimate
127 the empirical resilience of a host-pathogen system by looking at how fast the system
128 approaches a pre-pandemic attractor, provided that we can measure the distance
129 from attractor. The empirical approach to estimating pathogen resilience is partic-
130 ularly convenient because it does not require us to know the true underlying model.
131 As we show in Supplementary Figure S5, estimating the intrinsic resilience from fit-
132 ting standard compartmental models can lead to biased estimates, especially under
133 model misspecification. Second, resilience estimates allow us to make phenomenolog-
134 ical predictions about the dynamics of a host-pathogen system following a perturba-
135 tion: assuming that the distance from the attractor will decrease exponentially over
136 time, we can obtain a ballpark estimate for when the system will reach an attractor.
137 Finally, deviation from an exponential decrease in the distance from attractor can
138 provide information about whether the system has reached an alternative attractor,
139 or a ghost attractor, that is different from the original, pre-pandemic attractor. These
140 alternative attractors may reflect continued perturbations from permanent changes
141 in transmission patterns as well as changes in immune landscapes.

142 Inferring pathogen resilience from real data

143 Based on these observations, we now set out to infer pathogen resilience from real
144 data. Here, we briefly lay out our approach to estimating pathogen resilience from
145 real data (Figure 3). We then test this approach against simulations and apply it to
146 real data.

147 So far, we focused on simple examples that assume a constant transmission re-
148 duction. However, in practice, the impact of NPIs on pathogen transmission is
149 likely more complex (Figure 3A), reflecting introduction and relaxation of various
150 intervention strategies. These complexities can lead to longer delays between the
151 introduction of NPIs and pathogen re-emergence as well as temporal variation in
152 outbreak sizes (Figure 3B): in this example, continued transmission reduction from
153 NPIs limits the size of the first outbreak in 2021 following the emergence, allowing
154 for a larger outbreak in 2022 when NPIs are further relaxed.

155 Previously, we relied on the dynamics of susceptible and infected hosts to compute
156 the distance from attractor (Figure 2), but information on susceptible hosts are
157 often not available in practice. In addition, uncertainties in case counts due to
158 observation error as well as the possibility of complex, multiannual attractor adds
159 challenges to measuring the distance from attractor. To address these challenges, we
160 first reconstruct an empirical attractor by utilizing Takens' theorem, which states
161 that an attractor of a nonlinear multidimensional system can be mapped onto a

162 delayed embedding [16]. Here, we use delayed copies of logged values of pre-pandemic
 163 cases $C(t)$ (Figure 3C) to reconstruct the attractor:

$$\langle \log(C(t) + 1), \log(C(t - \tau) + 1), \dots, \log(C(t - (M - 1)\tau) + 1) \rangle, \quad (1)$$

164 where the delay τ and embedding dimension M are determined based on autocorrelations
 165 and false nearest neighbors, respectively [18, 19]. We then apply the same delay
 166 and embedding dimensions to the entire time series to determine the position on a
 167 multi-dimensional state space (Figure 3D), which allows us to measure the nearest
 168 neighbor distance between the current state of the system and the empirical attractor
 169 (Figure 3E). In principle, we can quantify how fast this distance decreases by fitting
 170 a linear regression on a log scale, where the slope of the linear regression corresponds
 171 to pathogen resilience. As we show in Supplementary Figure S6, overall temporal
 172 variations in the distance from attractor, especially the observed rate of decrease,
 173 appear robust to choices about embedding delays and dimensions; we note that using
 174 longer delays and higher dimensions tend to smooth out temporal variations in the
 175 distance from attractor.

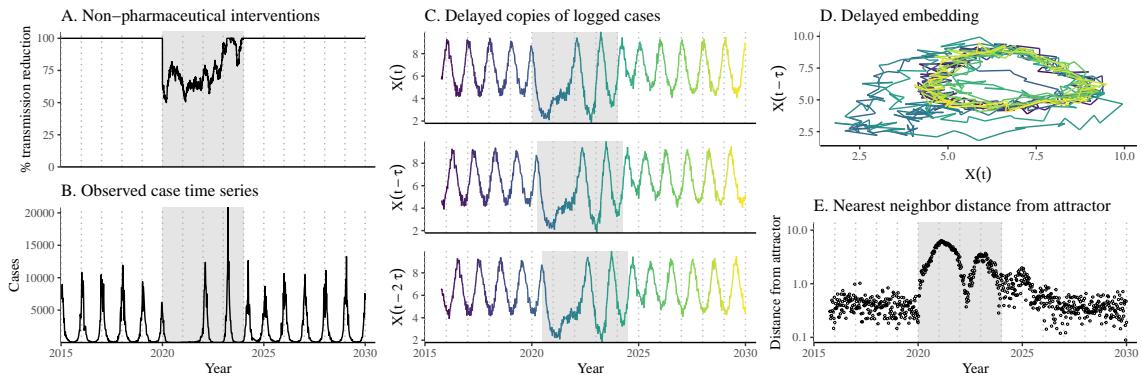


Figure 3: A schematic diagram explaining how pathogen resilience can be inferred from real data. (A) A realistic example of a synthetic NPI, represented by a relative reduction in transmission. (B) The impact of the synthetic NPI on epidemic dynamics simulated using a stochastic SIRS model. (C) Generating delayed copies of the logged time series allows us to obtain an embedding. (D) Two dimensional representation of an embedding. (E) Delayed embedding allows us to calculate the nearest neighbor distance from the empirical attractor, which is determined based on the pre-pandemic time series. This distance time series can be used to infer pathogen resilience by fitting a linear regression after choosing an appropriate window for regression.

176 Complex changes in the distance from attractor suggest that estimating pathogen
 177 resilience from linear regression will likely be sensitive to our choice of fitting windows
 178 for the regression. In Supplementary Materials, we explore an automated window
 179 selection criteria for linear regression and test it against randomized, stochastic sim-
 180 ulations across a wide range of realistic NPI shapes. We find that resilience estimates

181 based on the automated window selection criteria are moderately correlated (0.54)
182 with the intrinsic resilience of the post-NPI attractor (Supplementary Figure S7). In
183 contrast, a naive approach that uses the entire time series, starting from the peak
184 distance, only gives a correlation of 0.21 and consistently underestimates the intrinsic
185 resilience (Supplementary Figure S7).

186 Now, we apply this approach to pathogen surveillance data presented in Figure
187 1. For each time series, we apply Takens' theorem independently to reconstruct the
188 empirical attractor and obtain the corresponding time series of distance from at-
189 tractors (Supplementary Figure S8 for the distance time series and linear regression
190 fits). Then, we use the automated window selection criteria to fit a linear regression
191 and estimate the empirical resilience for each pathogen in each country. For most
192 respiratory pathogens, resilience estimates fall between 0.5/year and 2/year (Figure
193 4A), with the exception of Rhinovirus in the US (0.066/year; 95% CI: 0.018/year–
194 0.113/year) and Bocavirus in Korea (0.087/year; 95% CI: 0.023/year–0.151/year).
195 Excluding these exceptions, the mean resilience of common respiratory pathogens is
196 0.974/year (95% CI: 0.784/year–1.16/year). As a reference, this is \approx 7 times higher
197 than the intrinsic resilience of pre-vaccination measles dynamics (\approx 0.13/year). Fi-
198 nally, resilience estimates for norovirus appears to be comparable to the intrinsic
199 resilience of measles: 0.119/year (95%CI: 0.004/year–0.233/year) for Korea and
200 0.385/year (95% CI: 0.167/year–0.603/year). A simple ANOVA shows that there
201 are significant differences in resilience estimates across countries ($p < 0.036$) and
202 pathogens ($p < 0.030$).

203 Using resilience estimates, we now predict when each pathogen will return to
204 their original pre-pandemic cycles. Specifically, we extend our linear regression fits
205 to distance-from-attractor time series and ask when the predicted regression line
206 will cross a threshold value, which we set to a mean of pre-pandemic distances. We
207 predict that a return to pre-pandemic cycles would be imminent for most pathogens
208 (Figure 4B; see Supplementary Figure S9 for a zoomed out version). In addition, we
209 also predict that many pathogens should have already returned to their pre-pandemic
210 dynamics by the end of 2024; but these predictions contradict some of the observed
211 pathogen dynaics. For example, we predict that both human metapneumovirus and
212 RSV in Korea should have returned to their attractors by now, but the magnitude
213 and timing of recent epidemics are different from pre-pandemic patterns (Figure 1).
214 These observations suggest the possibility that some common respiratory pathogens
215 may have converged to different attractors.

216 In Supplementary Materials, we also consider using a lower threshold for the false
217 nearest neighbor approach when determining the embedding dimension; this gives
218 a higher embedding dimension. As explained earlier (Supplementary Figure S6),
219 this gives a smoother distance-from-attractor time series (compare Supplementary
220 Figure S10 with S8); this also requires us to use longer time series, which prevents
221 us from estimating resilience for some pathogens. Overall, resulting estimates of
222 pathogen resilience with higher embedding dimensions still fall between 0.5/year
223 and 2/year for the most part (Supplementary Figure S11). A direct comparison

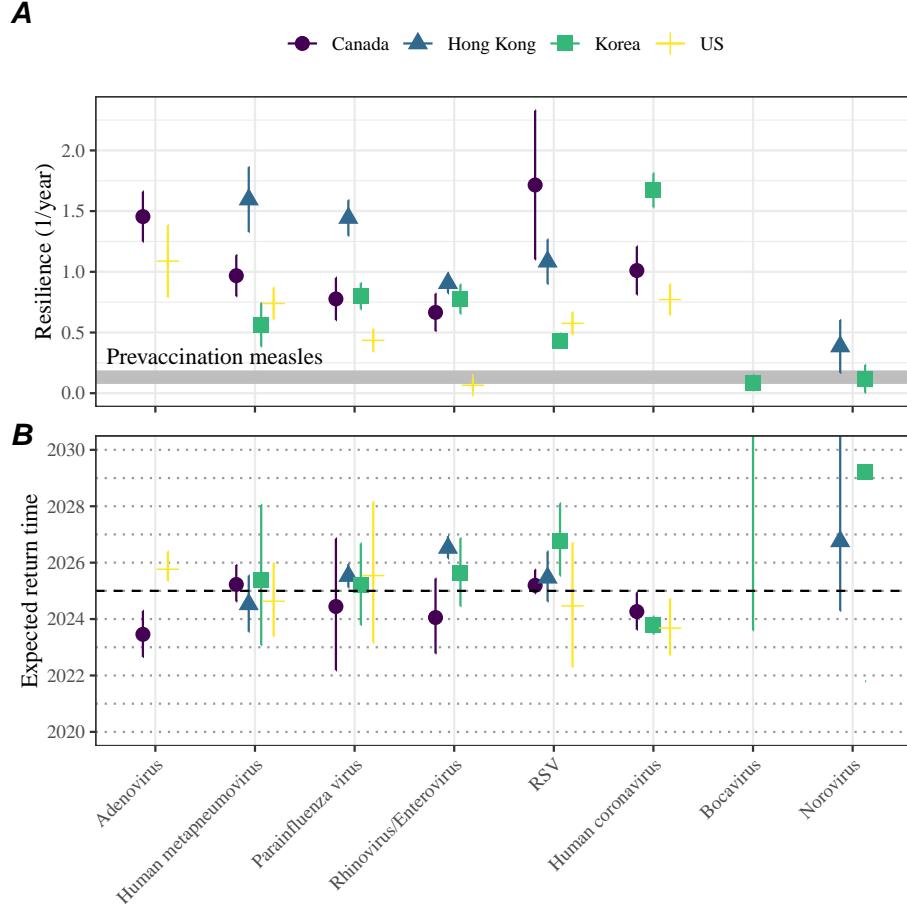


Figure 4: **Summary of resilience estimates.** (A) Estimated pathogen resilience. The gray horizontal line represents the intrinsic resilience of pre-vaccination measles dynamics. (B) Predicted timing of when each pathogen will return to their pre-pandemic cycles. The dashed line in panel B indicates the end of 2024 (current observation time). Error bars represent 95% confidence intervals.

²²⁴ between two approaches (i.e., original estimate vs using higher dimensions) shows a
²²⁵ strong consistency in resilience estimates (Supplementary Figure S12).

²²⁶ Susceptible host dynamics explain variation in pathogen ²²⁷ resilience

²²⁸ So far, we focused on quantifying pathogen resilience from the observed patterns of
²²⁹ pathogen re-emergence following COVID-19 interventions. But what factors deter-
²³⁰ mine how resilient a host-pathogen system is? Here, we use a standard Susceptible-
²³¹ Infected-Recovered-Susceptible (SIRS) model to show that susceptible host dynamics

232 are the key determinants of pathogen resilience. To do so, we vary the basic reproduction
 233 number \mathcal{R}_0 , which represents the average number of secondary infections caused
 234 by a newly infected individual in a fully susceptible population, and the duration of
 235 immunity and compute intrinsic resilience for each parameter.

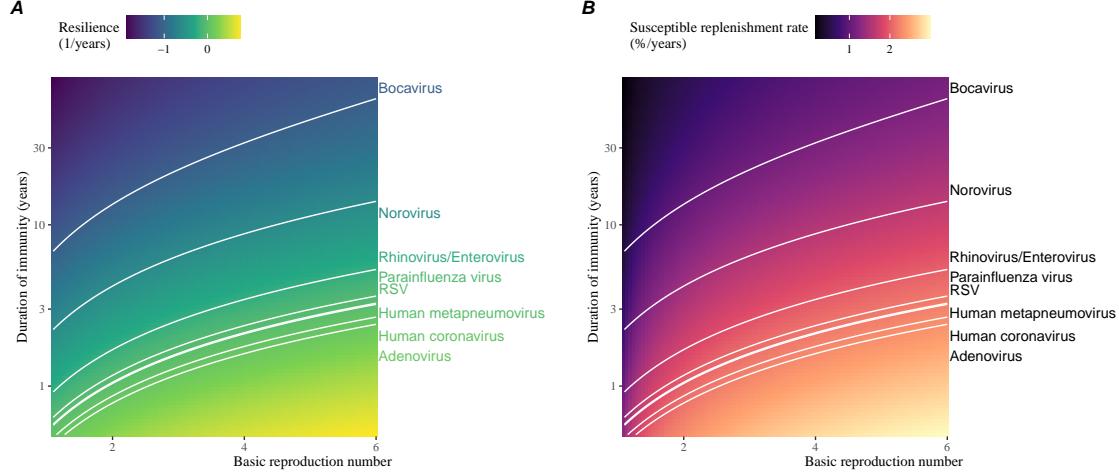


Figure 5: **Linking pathogen resilience to epidemiological parameters and susceptible host dynamics.** (A) The heat map represents intrinsic resilience as a function of the basic reproduction number \mathcal{R}_0 and the duration of immunity. (B) The heat map represents per-capita susceptible replenishment rate as a function of the basic reproduction number \mathcal{R}_0 and the duration of immunity. The standard SIRS model is used to compute intrinsic resilience and per-capita susceptible replenishment rate. Lines correspond to a set of parameters that are consistent with mean resilience estimates for each pathogen. Pathogens are ranked based on their mean resilience estimates, averaged across different countries.

236 We find an increase in \mathcal{R}_0 and a decrease in duration of immunity correspond
 237 to an increase in pathogen resilience (Figure 5A). These variations can be under-
 238 stood in terms of the susceptible host dynamics, where faster per-capita susceptible
 239 replenishment rate causes the system to be more resilient (Figure 5B). This rate can
 240 be expressed as a ratio between absolute rate at which new susceptibles enter the
 241 population and the equilibrium number of susceptible individuals in the population,
 242 \bar{S} . Therefore, both higher \mathcal{R}_0 and shorter duration of immunity can drive faster
 243 per-capita susceptible replenishment rate (Figure 5B), especially because higher \mathcal{R}_0
 244 leads to lower \bar{S} .

245 Finally, we can now rank different pathogens based on the average values of em-
 246 pirical resilience, which allows us to determine a set of parameters that are consistent
 247 with the estimated resilience (Figure 5A). Across all pathogens we consider, except
 248 for bocavirus and norovirus, we estimate that the average duration of immunity is
 249 likely to be short (< 6 years) across a plausible range of \mathcal{R}_0 . These rankings further

allow us to map each pathogen onto a set of parameters that are consistent with its empirical resilience (Figure 5A) and obtain a plausible range of susceptible replenishment rates for each pathogen (Figure 5B). However, we note that there is no one-to-one correspondance between susceptible replenishment rates and pathogen resilience, leading to a wide uncertainty in the estimates for susceptible replenishment rates (Figure 5B).

Discussion

The COVID-19 interventions have caused major disruptions to circulation patterns of both respiratory and non-respiratory pathogens, adding challenges to predicting their future dynamics. On the other hand, these interventions offer large-scale natural experiments for understanding how different pathogens respond to perturbations. In this study, we show that pathogen re-emergence patterns following COVID-19 interventions can be characterized through the lens of ecological resilience. Traditionally, ecological resilience measures how fast a system returns to a reference state following a perturbation. In the context of respiratory pathogens, resilience measures how fast epidemics return to their endemic cycles after interventions are lifted.

We use an attractor reconstruction approach to quantify how distance from attractor changes over time for each pathogen. By fitting a linear regression to log distances, we can estimate pathogen resilience and further predict when each pathogen will return to their endemic cycles. Consistency in resilience estimates across countries is particularly surprising given that each country imposed different intervention measures; this consistency provides robustness to our estimates. The ability to predict future epidemic patterns from resilience estimates also offers a new paradigm for epidemic forecasting. While this approach cannot predict the exact timing of outbreaks or epidemic patterns, it is nonetheless useful for predicting when epidemics will settle down to regular cycles after a large perturbation, such as COVID-19 interventions.

Our analyses suggest a possibility that several pathogens may have converged to different endemic cycles compared to their pre-pandemic epidemic patterns. Key examples include human metapnuemovirus, RSV, and bocavirus in Korea as well as RSV in Hong Kong. These changes may reflect permanent changes in behavior since 2020 or a shift in population-level immunity. However, it seems unlikely that permanent changes in behavior would only affect a few pathogens and not others. A shift in population-level immunity is plausible, as the emergence of SARS-CoV-2 and extinction of influenza B/Yamagata likely caused major changes in immune landscapes; however, we currently do not know how immunity, or lack thereof, from these pathogens would affect infection from other pathogens. Future studies should use detailed mechanistic models, coupled with behavioral and immunological data, to test these hypotheses and better understand post-pandemic dynamics of endemic pathogens.

290 We show that susceptible host dynamics shape pathogen resilience, where faster
291 replenishment of the susceptible population causes the pathogen to be more resilient.
292 For simplicity, we focus on waning immunity and birth as a main driver of the suscep-
293 tible host dynamics but other mechanisms can also contribute to the replenishment
294 of the susceptible population. In particular, pathogen evolution, especially the emer-
295 gence of antigenically novel strains, can cause effective waning of immunity in the
296 population; therefore, we tentatively hypothesize that faster rates of antigenic evo-
297 lution can also cause a pathogen to be more resilient. Future studies should explore
298 the relationship between the rate of evolution and resilience for antigenically evolving
299 pathogens.

300 Quantifying pathogen resilience also offers novel approaches to validating epi-
301 demiological models. So far, the majority of model validation in epidemiology is
302 based on the ability of a model to reproduce the observed epidemic dynamics and to
303 predict future dynamics. However, there can be plethora of models that meet these
304 criteria. For example, two major RSV models have been proposed so far to explain
305 biennial epidemic patterns: (1) a stage- and age-structured model that allows for
306 disease severity to vary with number of past infections and age of infection and (2)
307 a pathogen-interaction model that accounts for cross immunity between RSV and
308 human metapneumovirus. Since both models can accurately reproduce the observed
309 epidemic patterns, standard criteria for model validation do not allow us to distin-
310 guish between these two models. Instead, we can measure the empirical resilience
311 of each model by simulating various perturbations and compare them to estimates
312 of empirical resilience from data, using COVID-19 interventions as an opportunity.
313 Future studies should further investigate using pathogen resilience for validating epi-
314 demic models.

315 There are several limitations to our work. In particular, our estimates of pathogen
316 resilience and the associated ranking are necessarily crude. [SWP: *Limitation TBD*.]
317 Nonetheless, our study illustrates the utility of quantifying pathogen resilience for
318 understanding how different pathogens respond to perturbations.

319 [SWP: *Conclusion paragraph TBD*.]

320 Materials and Methods

321 Data

322 We gathered time series on respiratory infections from four different countries: Canada,
323 Hong Kong, Korea, and United States (US). As a reference, we also included time
324 series data on norovirus infections for available countries—in contrast to respiratory
325 pathogens, we expect gastrointestinal viruses, such as norovirus, to be less affected
326 by COVID-19 intervention measures.

327 Weekly time series of respiratory infection cases in Canada come from the Res-
328 piratory Virus Detection Surveillance System, which collect data from select labo-
329 ratories across Canada. We extracted the data from <https://www.canada.ca/en/>

330 public-health/services/surveillance/respiratory-virus-detections-canada.html.

332 Weekly time series of respiratory infection cases in Hong Kong came from the
333 Centre for Health Protection, Department of Health. We extracted the data from
334 <https://www.chp.gov.hk/en/statistics/data/10/641/642/2274.html>.

335 Weekly time series of respiratory infection cases in Korea came from Korea Disease
336 Control and Prevention Agency. We extracted the data from <https://dportal.kdca.go.kr/pot/is/st/ari.do>.

338 Finally, weekly time series of respiratory infection cases in the US comes from
339 the National Respiratory and Enteric Virus Surveillance System.

340 Empirical attractor reconstruction

341 Linear regression

342 Mathematical modeling

343 Throughout the paper, we use a series of mathematical models to illustrate the concept
344 of pathogen resilience and to understand the determinants of pathogen resilience.
345 In general, the intrinsic resilience for a given system is given by the largest real part
346 of the eigenvalues of the lineared system at endemic equilibrium. Here, we focus on
347 the SIRS model and present the details of other models in Supplementary Materials.
348 The SIRS (Susceptible-Infected-Recovered-Susceptible) model is the simplest model
349 that allows for waning of immunity, where recovered (immune) individuals are assumed
350 to become fully susceptible after an average of $1/\delta$ time period. The dynamics
351 of the SIRS model is described by the following set of differential equations:

$$\frac{dS}{dt} = \mu - \beta(t)SI - \mu S + \delta R \quad (2)$$

$$\frac{dI}{dt} = \beta(t)SI - (\gamma + \mu)I \quad (3)$$

$$\frac{dR}{dt} = \gamma I - (\delta + \mu)R \quad (4)$$

$$(5)$$

352 where μ represents the birth/death rate, $\beta(t)$ represents the time-varying transmission
353 rate, and γ represents the recovery rate. The basic reproduction number
354 $\mathcal{R}_0 = \beta(t)/(\gamma + \mu)$ is defined as the average number of secondary infections caused
355 by a single infected individual in a fully susceptible population and measures the
356 intrinsic transmissibility of a pathogen.

357 For this model, the intrinsic resilience corresponds to:

$$-\frac{\operatorname{Re}(\lambda)}{2} = \frac{\delta + \beta I^* + \mu}{2}. \quad (6)$$

³⁵⁸ Here, I^* represents the prevalence values at endemic equilibrium:

$$I^* = \frac{(\delta + \mu)(\beta - (\gamma + \mu))}{\beta(\delta + \gamma + \mu)}. \quad (7)$$

³⁵⁹ The susceptible replenishment rate is given by:

$$S_{\text{replenish}} = \frac{\mu + \delta R}{S^*}, \quad (8)$$

³⁶⁰ where $S^* = 1/\mathcal{R}_0$ represents the equilibrium proportion of susceptible individuals.

³⁶¹ When infection provides life-long immunity ($\delta \rightarrow 0$), the SIRS model becomes
³⁶² the SIR model. In this case, the intrinsic resilience is inversely proportional to the

³⁶³ In illustrating the impact of

³⁶⁴ **Supplementary Text**

Supplementary Figures

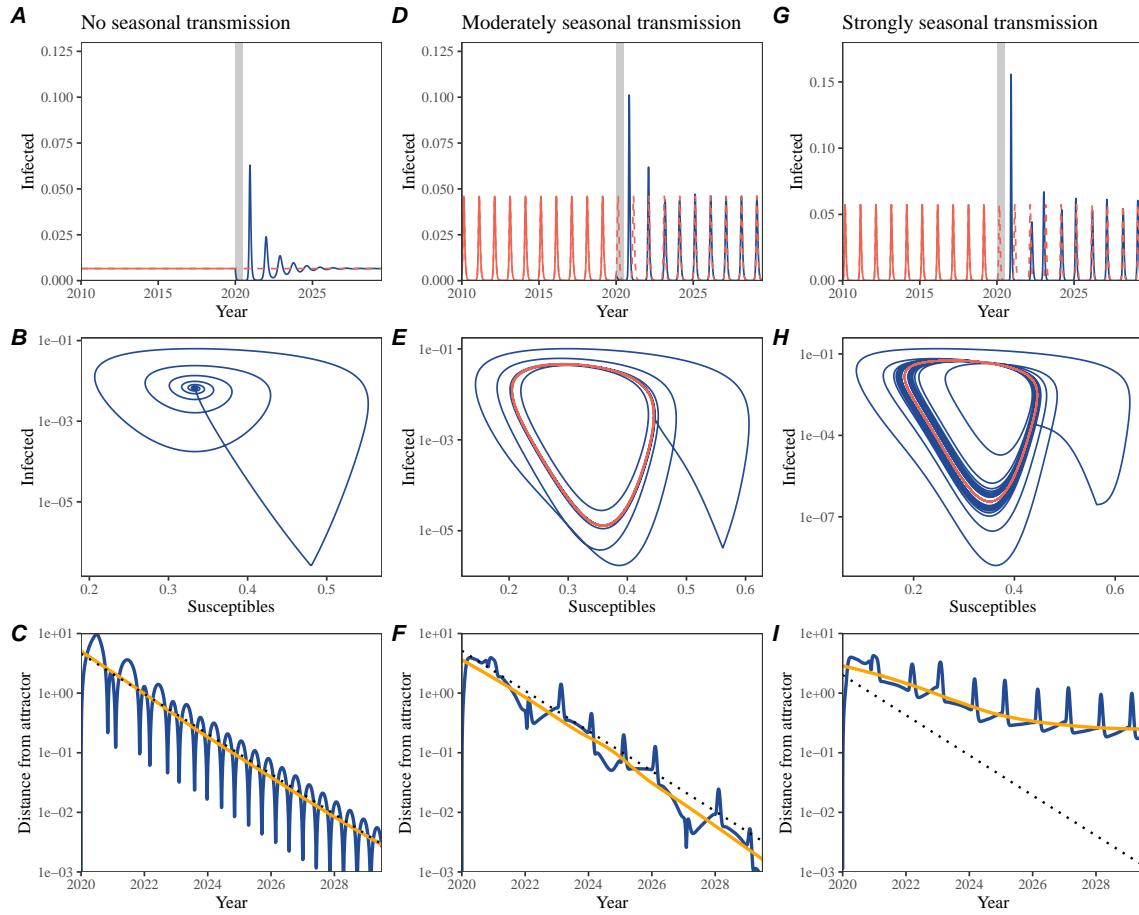


Figure S1: Impact of seasonal transmission on pathogen resilience. (A, D, G) Simulated epidemic trajectories using the SIRS model without seasonal forcing (A), with seasonal forcing of amplitude of 0.2 (D), and with seasonal forcing of amplitude of 0.2 (G). Red and blue solid lines represent epidemic dynamics before and after interventions are introduced, respectively. Red dashed lines represent counterfactual epidemic dynamics in the absence of interventions. Gray regions indicate the duration of interventions. (B, E, H) Phase plane representation of the corresponding model. Red and blue solid lines represent epidemic trajectories on an SI phase plane before and after interventions are introduced, respectively. (C, F, I) Changes in logged distance from attractor over time. Blue lines represent the logged distance from attractor. Orange lines represent the locally estimated scatterplot smoothing (LOESS) fits to the logged distance from attractor. Dotted lines are superimposed as a comparison to have the same slope as the intrinsic resilience of the seasonally unforced system.

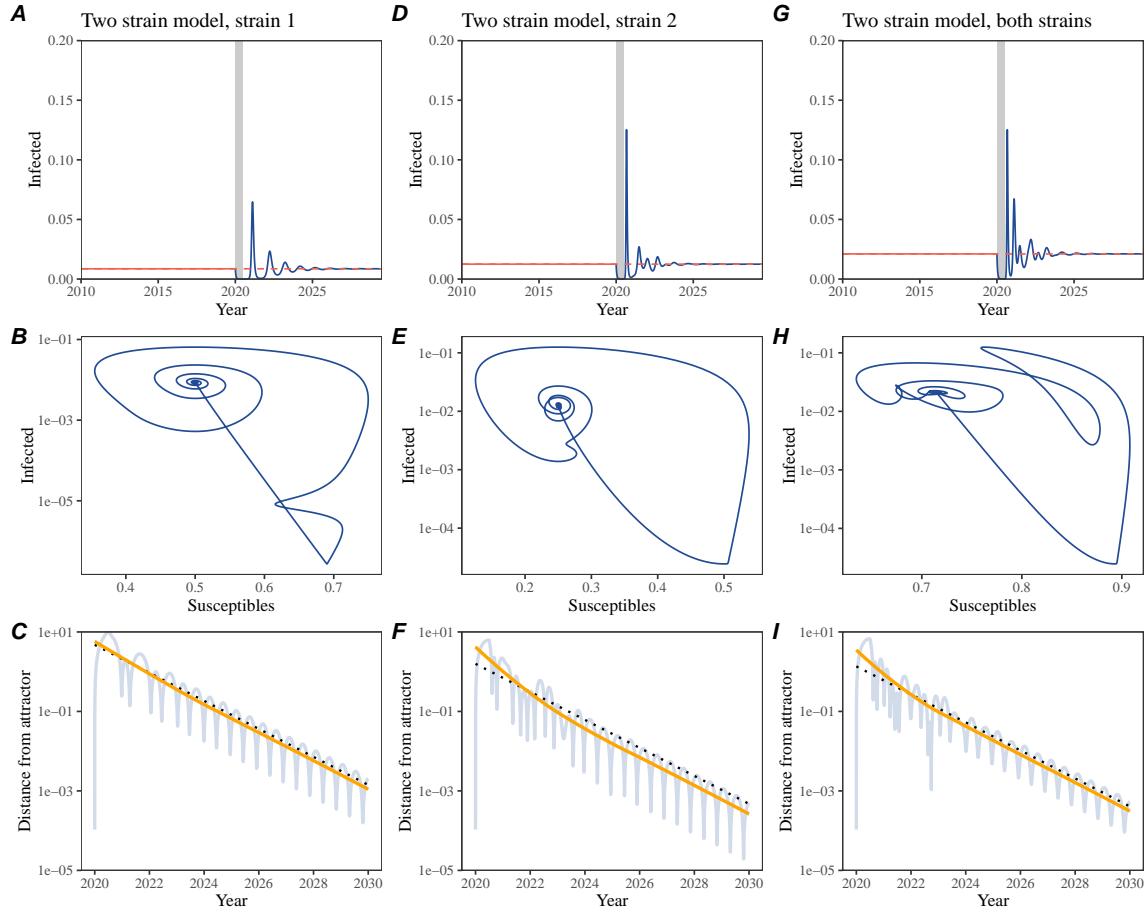


Figure S2: Conceptual framework for measuring pathogen resilience following NPIs for a multi-strain system without seasonal forcing. (A, D, G) Simulated epidemic trajectories using a multi-strain system without seasonal forcing. Red and blue solid lines represent epidemic dynamics before and after interventions are introduced, respectively. Red dashed lines represent counterfactual epidemic dynamics in the absence of interventions. Gray regions indicate the duration of interventions. (B, E, H) Phase plane representation of the corresponding model. Red and blue solid lines represent epidemic trajectories on an SI phase plane before and after interventions are introduced, respectively. (C, F, I) Changes in logged distance from attractor over time. Blue lines represent the logged distance from attractor. Orange lines represent the locally estimated scatterplot smoothing (LOESS) fits to the logged distance from attractor. Dotted lines are superimposed as a comparison to have the same slope as the intrinsic resilience of the seasonally unforced system.

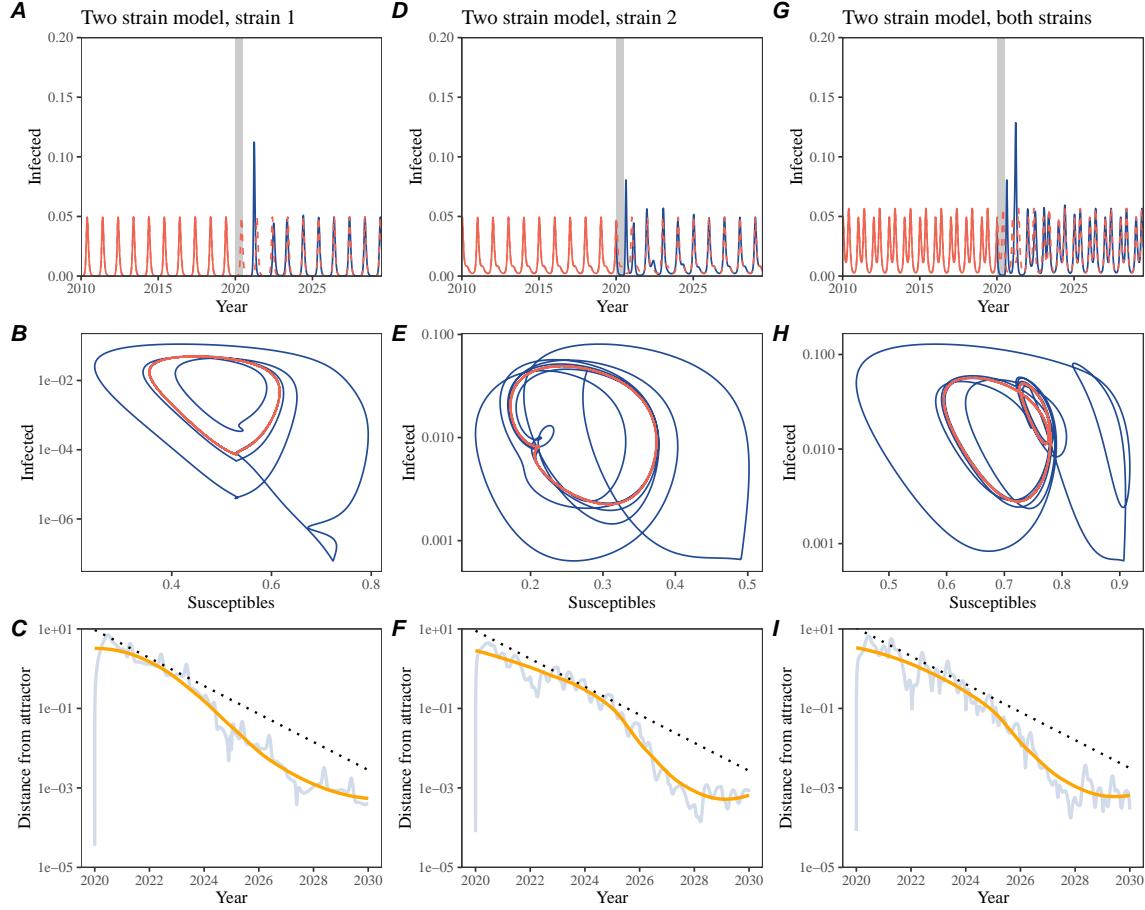


Figure S3: Conceptual framework for measuring pathogen resilience following NPIs for a multi-strain system with seasonal forcing. (A, D, G) Simulated epidemic trajectories using a multi-strain system with seasonal forcing (amplitude of 0.2). Red and blue solid lines represent epidemic dynamics before and after interventions are introduced, respectively. Red dashed lines represent counterfactual epidemic dynamics in the absence of interventions. Gray regions indicate the duration of interventions. (B, E, H) Phase plane representation of the corresponding model. Red and blue solid lines represent epidemic trajectories on an SI phase plane before and after interventions are introduced, respectively. (C, F, I) Changes in logged distance from attractor over time. Blue lines represent the logged distance from attractor. Orange lines represent the locally estimated scatterplot smoothing (LOESS) fits to the logged distance from attractor. Dotted lines are superimposed as a comparison to have the same slope as the intrinsic resilience of the seasonally unforced system.

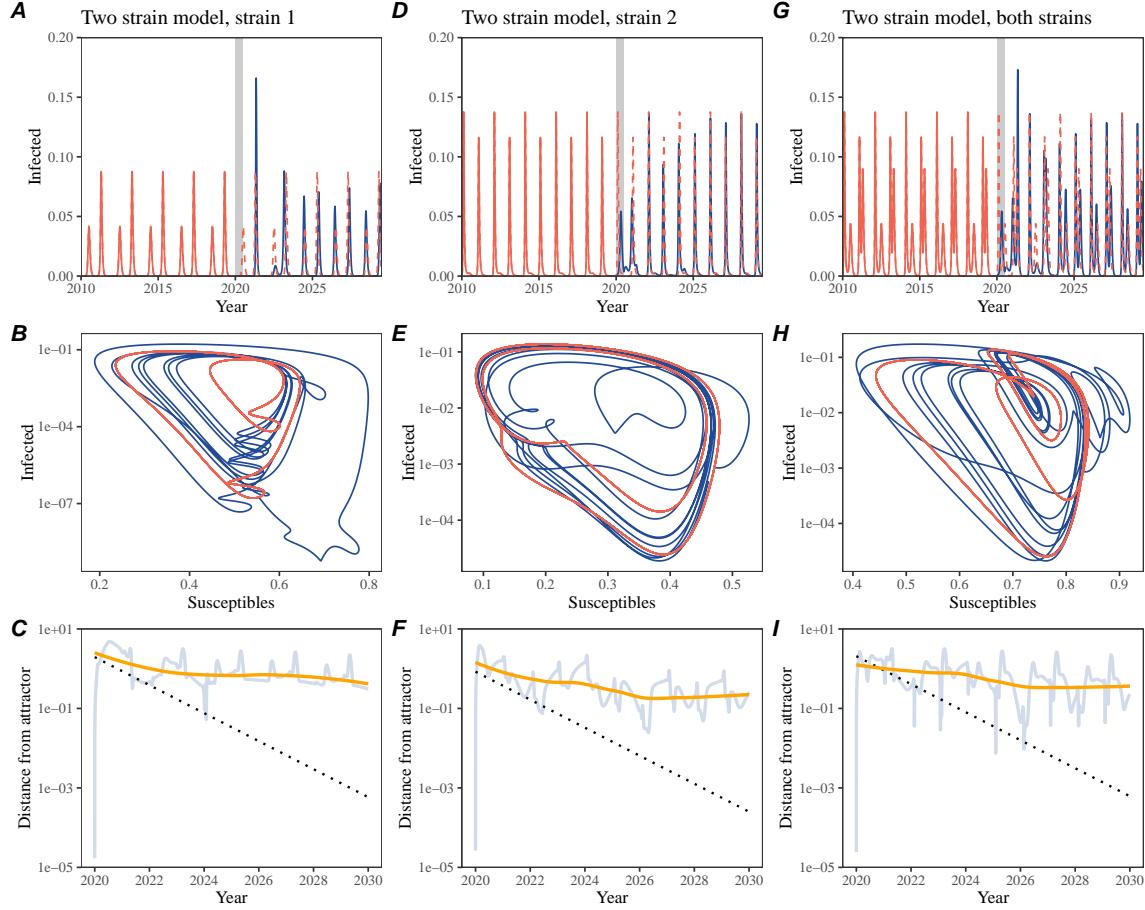


Figure S4: Conceptual framework for measuring pathogen resilience following NPIs for a multi-strain system with strong seasonal forcing. (A, D, G) Simulated epidemic trajectories using a multi-strain system with seasonal forcing (amplitude of 0.4). Red and blue solid lines represent epidemic dynamics before and after interventions are introduced, respectively. Red dashed lines represent counterfactual epidemic dynamics in the absence of interventions. Gray regions indicate the duration of interventions. (B, E, H) Phase plane representation of the corresponding model. Red and blue solid lines represent epidemic trajectories on an SI phase plane before and after interventions are introduced, respectively. (C, F, I) Changes in logged distance from attractor over time. Blue lines represent the logged distance from attractor. Orange lines represent the locally estimated scatterplot smoothing (LOESS) fits to the logged distance from attractor. Dotted lines are superimposed as a comparison to have the same slope as the intrinsic resilience of the seasonally unforced system.

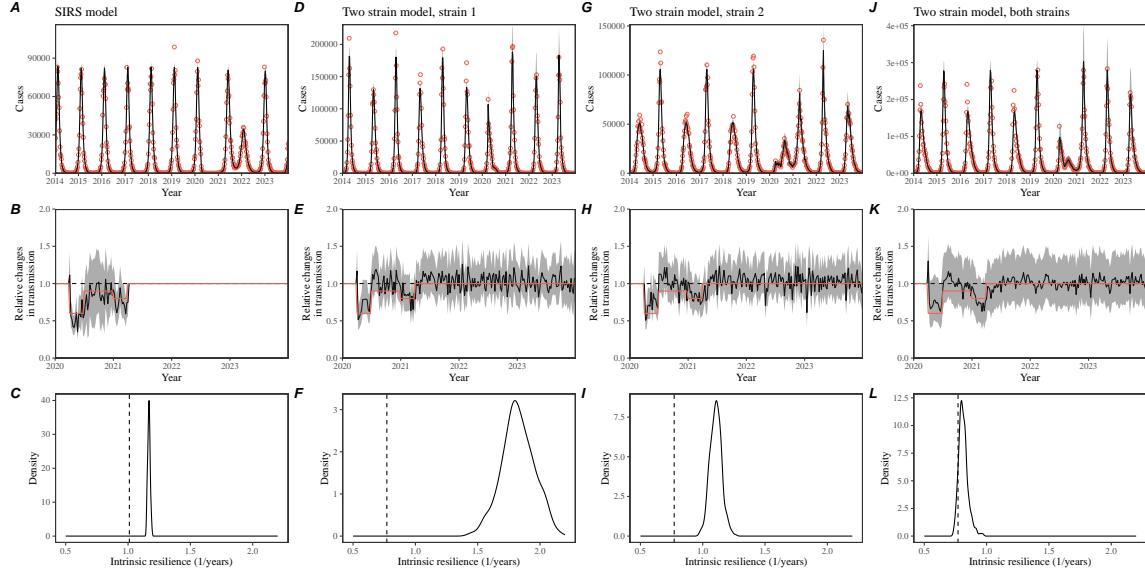


Figure S5: Mechanistic model fits to simulated data and inferred intrinsic resilience. (A, D, G, J) Simulated case time series from corresponding models (red) and SIRS model fits (black). (B, E, H, K) Assumed changes in transmission due to COVID-19 interventions (red) and estimated changes from the SIRS model (black). Solid lines and shaded regions represent fitted posterior median and 95% credible intervals. (C, F, I, L) True intrinsic resilience of the seasonally unforced system (vertical lines) and the posterior distribution of the inferred intrinsic resilience from the SIRS model (density plots).

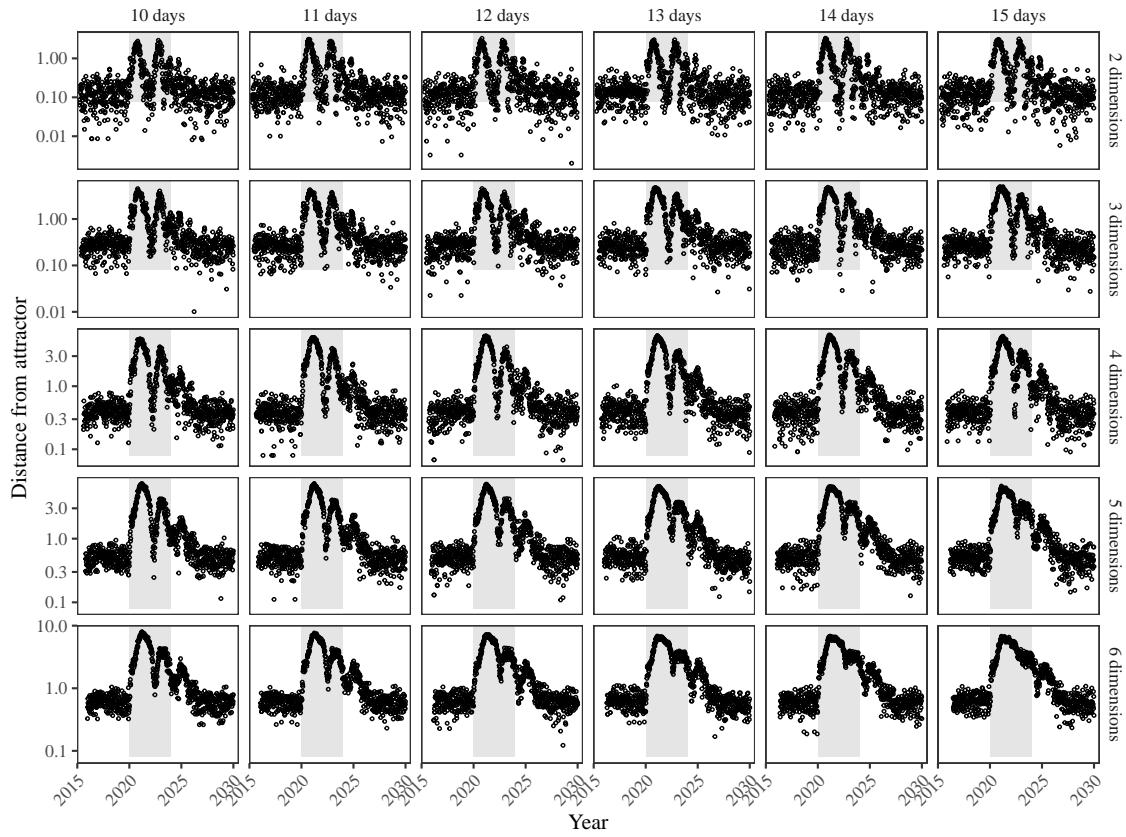


Figure S6: Sensitivity of the distance from attractor to choices about embedding lags and dimensions. Sensitivity analysis for the distance-from-attractor time series shown in Figure 3E in the main text by varying the embedding lag between 10–15 days and embedding dimensions between 2–6 dimensions.

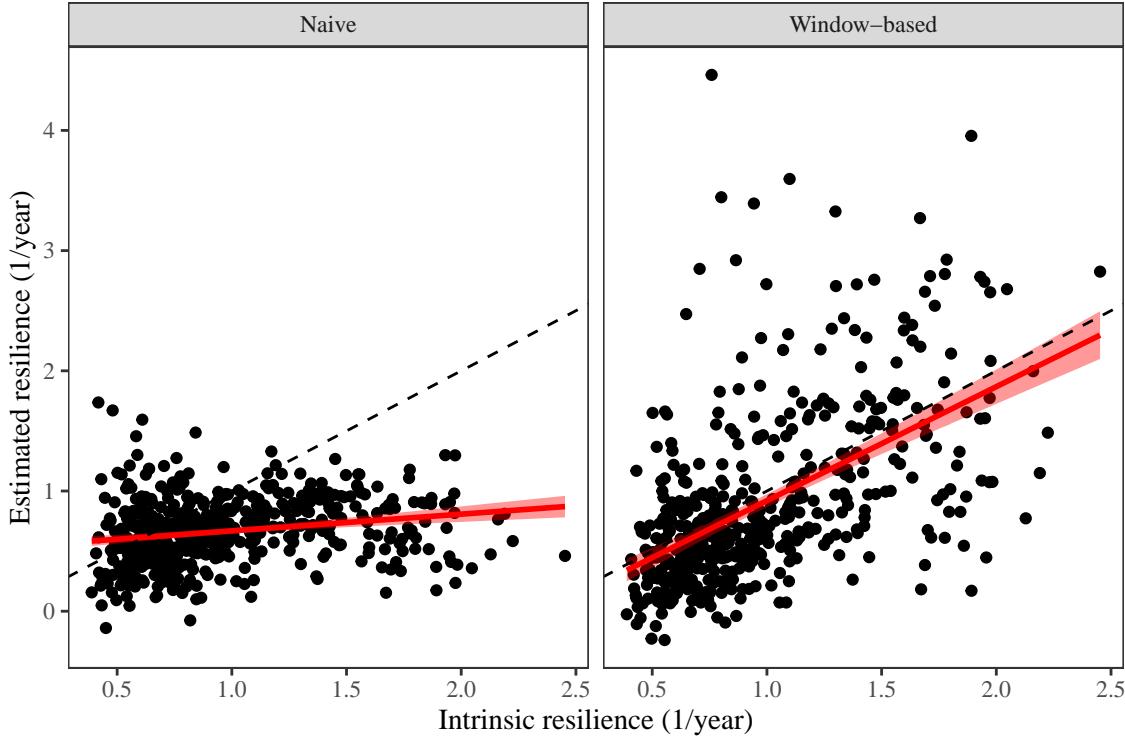


Figure S7: Impact of fitting window selection on the estimation of empirical resilience. We simulate 500 epidemics using stochastic SIRS model with randomly drawn parameters and randomly generated intervention impacts. For each simulation, we reconstruct the empirical attractor based on the approach outlined in Figure 3 and estimate the distance from attractor. The naive approach fits a linear regression on a log scale, starting from the maximum distance until the end of the time series. The window-based approach tries to select an appropriate window by smoothing the distance estimates and finding a time period when the smoothed time series crosses pre-determined threshold, relatively to the maximum distance; then, a linear regression is fitted by using the raw distance within this time period.

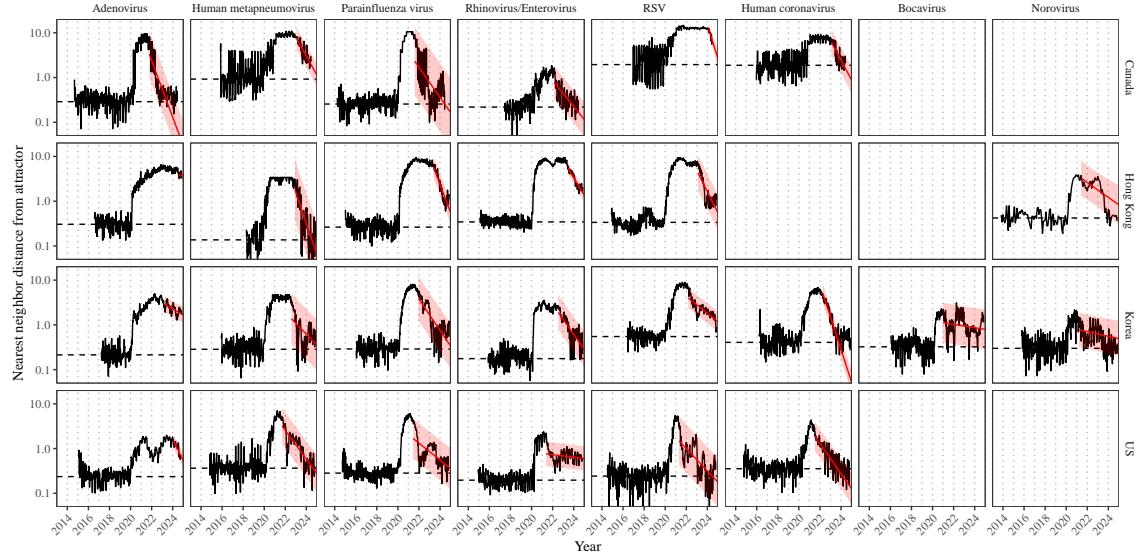


Figure S8: Estimated time series of distance from attractor for each pathogen across Canada, Hong Kong, Korea, and the US. Black lines represent the estimated distance from attractor. Red lines and shaded regions represent the linear regression fits and corresponding 95% confidence intervals. Dashed lines represent the average of the pre-pandemic nearest neighbor distances.

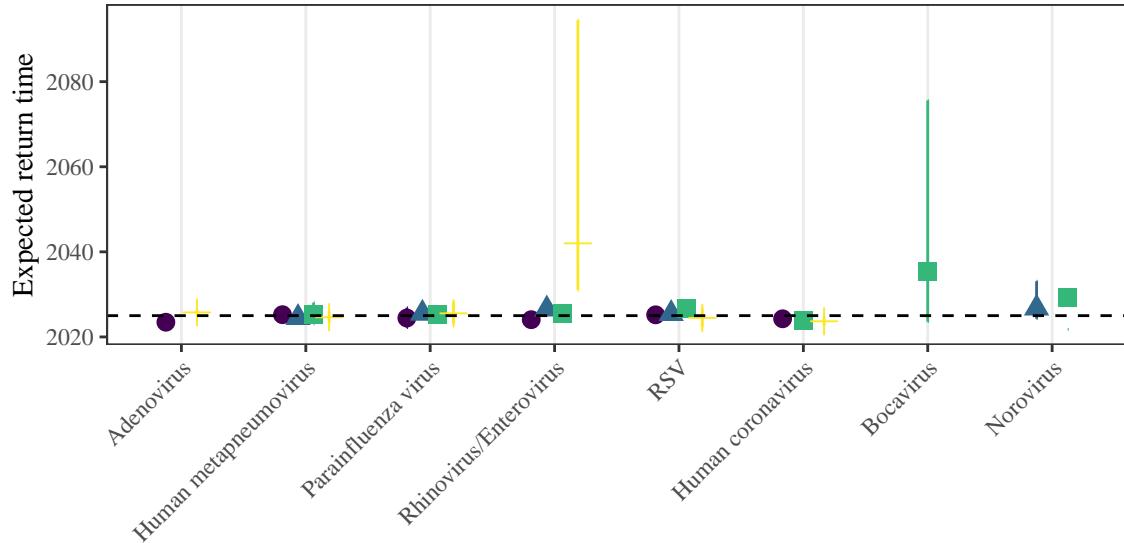


Figure S9: **Predicted timing of when each pathogen will return to their pre-pandemic cycles (zoomed out).** The dashed line in panel B indicates the end of 2024 (current observation time). Error bars represent 95% confidence intervals.

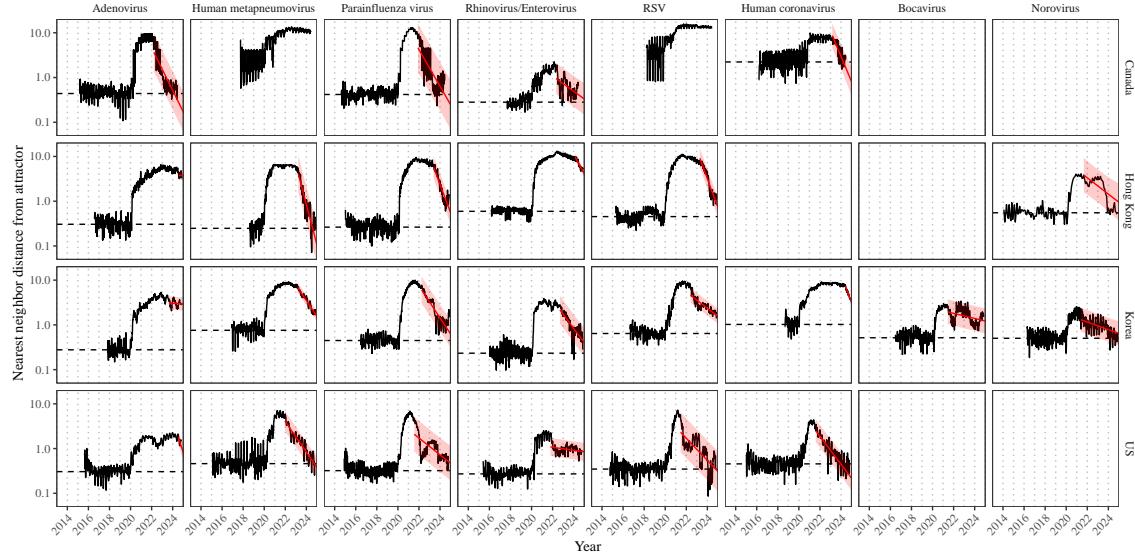


Figure S10: Estimated time series of distance from attractor for each pathogen across Canada, Hong Kong, Korea, and the US using higher embedding dimensions. Black lines represent the estimated distance from attractor. Red lines and shaded regions represent the linear regression fits and corresponding 95% confidence intervals. Dashed lines represent the average of the pre-pandemic nearest neighbor distances. A lower threshold is used for determining embedding dimensions with the false nearest neighbors approach, thereby yielding a higher embedding dimension.

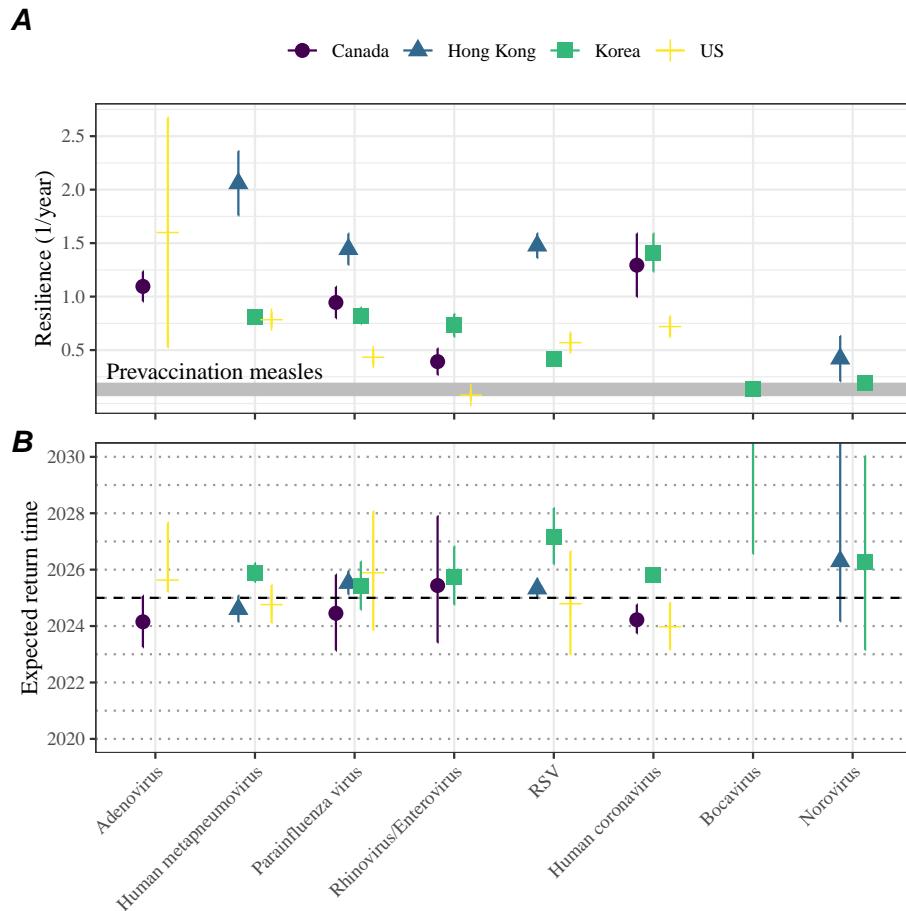


Figure S11: Summary of resilience estimates using higher embedding dimensions. (A) Estimated pathogen resilience. The gray horizontal line represents the intrinsic resilience of pre-vaccination measles dynamics. (B) Predicted timing of when each pathogen will return to their pre-pandemic cycles. The dashed line in panel B indicates the end of 2024 (current observation time). Error bars represent 95% confidence intervals. A lower threshold is used for determining embedding dimensions with the false nearest neighbors approach, thereby yielding a higher embedding dimension.

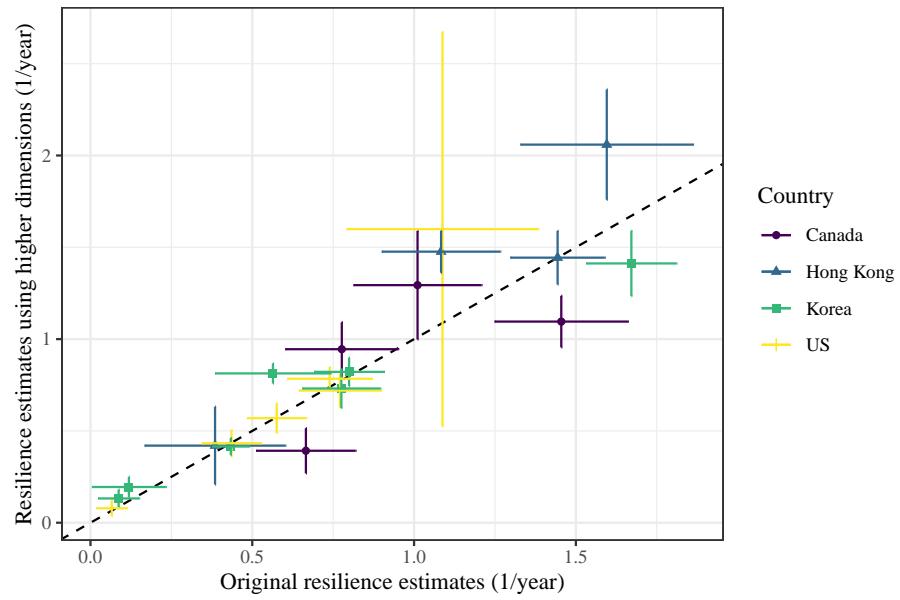


Figure S12: **Comparison of resilience estimates.** Each point represents a resilience estimate for a specific pathogen at a specific country. The x values represent the original resilience estimates presented in Figure 4. The y values represent the original resilience estimates presented in Supplementary Figure S11.

366 **References**

- 367 [1] Edward A Bender, Ted J Case, and Michael E Gilpin. Perturbation experiments
368 in community ecology: theory and practice. *Ecology*, 65(1):1–13, 1984.
- 369 [2] Anthony R Ives and Stephen R Carpenter. Stability and diversity of ecosystems.
370 *science*, 317(5834):58–62, 2007.
- 371 [3] Marten Scheffer, Jordi Bascompte, William A Brock, Victor Brovkin, Stephen R
372 Carpenter, Vasilis Dakos, Hermann Held, Egbert H Van Nes, Max Rietkerk,
373 and George Sugihara. Early-warning signals for critical transitions. *Nature*,
374 461(7260):53–59, 2009.
- 375 [4] Stuart L Pimm. The structure of food webs. *Theoretical population biology*,
376 16(2):144–158, 1979.
- 377 [5] Michael G Neubert and Hal Caswell. Alternatives to resilience for measuring
378 the responses of ecological systems to perturbations. *Ecology*, 78(3):653–665,
379 1997.
- 380 [6] Lance H Gunderson. Ecological resilience—in theory and application. *Annual
381 review of ecology and systematics*, 31(1):425–439, 2000.
- 382 [7] Vasilis Dakos and Sonia Kéfi. Ecological resilience: what to measure and how.
383 *Environmental Research Letters*, 17(4):043003, 2022.
- 384 [8] Jeanne C Chambers, Craig R Allen, and Samuel A Cushman. Operationalizing
385 ecological resilience concepts for managing species and ecosystems at risk.
386 *Frontiers in Ecology and Evolution*, 7:241, 2019.
- 387 [9] Rachel E Baker, Sang Woo Park, Wenchang Yang, Gabriel A Vecchi, C Jessica E
388 Metcalf, and Bryan T Grenfell. The impact of COVID-19 nonpharmaceutical
389 interventions on the future dynamics of endemic infections. *Proceedings of the
390 National Academy of Sciences*, 117(48):30547–30553, 2020.
- 391 [10] Gabriela B Gomez, Cedric Mahé, and Sandra S Chaves. Uncertain effects of the
392 pandemic on respiratory viruses. *Science*, 372(6546):1043–1044, 2021.
- 393 [11] Mihaly Koltai, Fabienne Krauer, David Hodgson, Edwin van Leeuwen, Marina
394 Treskova-Schwarzbach, Mark Jit, and Stefan Flasche. Determinants of RSV
395 epidemiology following suppression through pandemic contact restrictions. *Epi-
396 demics*, 40:100614, 2022.
- 397 [12] Sang Woo Park, Brooklyn Noble, Emily Howerton, Bjarke F Nielsen, Sarah
398 Lentz, Lilliam Ambroggio, Samuel Dominguez, Kevin Messacar, and Bryan T
399 Grenfell. Predicting the impact of non-pharmaceutical interventions against
400 COVID-19 on *Mycoplasma pneumoniae* in the United States. *Epidemics*,
401 49:100808, 2024.

- 402 [13] Eric J Chow, Timothy M Uyeki, and Helen Y Chu. The effects of the COVID-19
403 pandemic on community respiratory virus activity. *Nature Reviews Microbiology*, 21(3):195–210, 2023.
- 405 [14] Georgiy V Bobashev, Stephen P Ellner, Douglas W Nychka, and Bryan T
406 Grenfell. Reconstructing susceptible and recruitment dynamics from measles
407 epidemic data. *Mathematical Population Studies*, 8(1):1–29, 2000.
- 408 [15] Bärbel F Finkenstädt and Bryan T Grenfell. Time series modelling of childhood
409 diseases: a dynamical systems approach. *Journal of the Royal Statistical Society
410 Series C: Applied Statistics*, 49(2):187–205, 2000.
- 411 [16] Floris Takens. Detecting strange attractors in turbulence. In *Dynamical Sys-
412 tems and Turbulence, Warwick 1980: proceedings of a symposium held at the
413 University of Warwick 1979/80*, pages 366–381. Springer, 2006.
- 414 [17] Alan Hastings, Karen C Abbott, Kim Cuddington, Tessa Francis, Gabriel Gell-
415 ner, Ying-Cheng Lai, Andrew Morozov, Sergei Petrovskii, Katherine Scran-
416 ton, and Mary Lou Zeeman. Transient phenomena in ecology. *Science*,
417 361(6406):eaat6412, 2018.
- 418 [18] Matthew B Kennel, Reggie Brown, and Henry DI Abarbanel. Determining
419 embedding dimension for phase-space reconstruction using a geometrical con-
420 struction. *Physical review A*, 45(6):3403, 1992.
- 421 [19] Eugene Tan, Shannon Algar, Débora Corrêa, Michael Small, Thomas Stemler,
422 and David Walker. Selecting embedding delays: An overview of embedding
423 techniques and a new method using persistent homology. *Chaos: An Interdis-
424 ciplinary Journal of Nonlinear Science*, 33(3), 2023.