

The Impacts of Simultaneous Disease Intervention Decisions on Epidemic Outcomes

Michael A. Andrews^{a,*}, Chris T. Bauch^{a,b}

^aUniversity of Guelph, 50 Stone Rd. E. Guelph, Ontario

^bUniversity of Waterloo, 200 University Ave. W. Waterloo, Ontario

Abstract

Mathematical models of the interplay between disease dynamics and human behavioural dynamics can improve our understanding of how diseases spread when individuals adapt their behaviour in response to an epidemic. Accounting for behavioural mechanisms that determine uptake of infectious disease interventions such as vaccination and non-pharmaceutical interventions (NPIs) can significantly alter predicted health outcomes in a population. However, most previous approaches that model interactions between human behaviour and disease dynamics have modelled behaviour of these two interventions separately. Here, we develop and analyze an agent based network model to gain insights into how behaviour toward both interventions interact adaptively with disease dynamics (and therefore, indirectly, with one another) during the course of a single epidemic where an SIRV infection spreads through a contact network. In the model, individuals decide to become vaccinated and/or practice NPIs based on perceived infection prevalence (locally or globally) and on what other individuals in the network are doing. We find that introducing adaptive NPI behaviour lowers vaccine uptake on account of behavioural feedbacks, and also decreases epidemic final size. When transmission rates are low, NPIs alone are as effective in reducing epidemic final size as NPIs and vaccination combined. Also, NPIs can compensate for delays in vaccine availability by hindering early disease spread, decreasing epidemic size significantly compared to the case where NPI behaviour does not adapt to mitigate early surges in infection prevalence. We also find that including adaptive NPI behaviour strongly mitigates the vaccine behavioural feedbacks that would otherwise result in higher vaccine uptake at lower vaccine efficacy as predicted by most previous models, and the same feedbacks cause epidemic final size to remain approximately constant across a broad range of values for vaccine efficacy. Finally, when individuals use local information about others' behaviour and infection prevalence, instead of population-level information, infection is controlled more efficiently through ring vaccination, and this is reflected in the time evolution of pair correlations on the network. This model shows that accounting for both adaptive NPI behaviour and adaptive vaccinating behaviour regarding social effects and infection prevalence can result in qualitatively different predictions than if only one type of adaptive behaviour is modelled.

Keywords: Epidemic Modelling, Vaccinating Behaviour, Non Pharmaceutical Interventions, Adaptive networks, Econophysics

*Corresponding Author

Email addresses: mandre04@uoguelph.ca (Michael A. Andrews), cbauch@uwaterloo.ca (Chris T. Bauch)

1. Introduction

Infectious disease outbreaks have the potential to cause unexpected burdens and panic in societies. For example, the outbreak of severe acute respiratory syndrome (SARS) in 2003 caused significant economic impacts across the world, despite lasting only six months [1]. Occurring unexpectedly, outbreaks such as the aforementioned SARS outbreak [1, 2], the Middle East respiratory syndrome outbreak in 2012 [3], Ebola outbreak in 2014 [4], or an influenza pandemic, which has happened as recently as 2009 [5], can be difficult to predict and can spread locally or globally and last anywhere from months to years.

Human behaviour can have a large impact on the spread of infectious diseases [6]. People have been observed to change their regular social routines in response to an epidemic, in order to reduce their risk of becoming infected [7, 8, 9]. The infection prevalence or incidence of a disease in a community serves to drive these behavioural changes, as an individual's perceived susceptibility generally rises along with these disease measures [6, 10, 11, 12]. There are two primary self protective intervention strategies susceptible members of a population can utilize to reduce their chances of contracting a disease. These are pharmaceutical interventions, such as vaccination, and non-pharmaceutical interventions (NPIs), such as social distancing and increased hand washing [13]. The usage of these intervention strategies are voluntary in many health jurisdictions, and so perceived risks play an important role in how often they are utilized [14].

Coupled disease-behaviour models combine human decision making behaviour with traditional transmission dynamics, helping to capture an additional, and often important, aspect of disease spread [6, 15, 16]. Behaviourally based models that incorporate NPIs and social distancing during an outbreak show that these practices can lower the attack rate of a disease [17, 18, 19, 20, 21, 22, 23, 24]. Suppressing an outbreak using these means can be very critical, as vaccines may not always be immediately available to the general population [25]. Modelling how NPIs are utilized can be approached in various ways by mathematical models. For example, Funk et al [19] allow an individual's level of awareness to the presence of a disease shape their usage of self-protective measures. Rizzo et al. model a population where susceptible individuals base their activity rates on the infection prevalence of a disease in the population or the infection incidence over a time step [20]. Similarly, Bagnoli et al. [21] and Del Valle et al. [17] have individuals lower their susceptibility according to the proportion of their contacts in a transmission network that are infectious, and to the infection prevalence, respectively. Poletti et al. [23, 24] incorporate imitation dynamics to model the behavioural changes of the population. Finally, Fenichel et al. [22] and Chen et al. [26] study models where individuals derive utility from engaging in social contact, but raise their risk of infection when doing so. In these aforementioned models, each individual's behaviour is shaped by the information they gather about the disease status of those around them. Thus, in these models, transmission dynamics depend heavily on the perceived risks that drive contact patterns.

Further approaches to mathematical models that integrate self protective behaviour into disease transmission utilize adaptive and multiplex networks. An adaptive network is a network whose edges between contacts change dynamically over time. Using these, Gross et al. [27], Shaw and Schwartz [28, 29] and Zanette and Risau-Gusman [30] allow susceptible nodes to rewire their existing connections away from infectious nodes at a given rate. **The approach of multiplex networks helps to model the many types of social networks individuals may use to acquire information, and Granell et al. [31] and Cozzo et al. [32] use these to study the impact of different information flows on the spread of epidemics.** On the other hand, Glass et al. [33] and Kelso et al. [34] use contact networks which include families, schools, and workplaces to study the effects of various NPIs such as school closures and staying at home while infectious.

47 Additionally, vaccines (if available) play a major role in reducing infection rates during an epi-
48 demic. Some mathematical models have shown that under voluntary vaccination, populations may
49 not reach sufficient uptake levels to stop an epidemic [35, 36]. However, under voluntary policies
50 in a network, Zhang et al. demonstrate that nodes with high degree can help to suppress disease
51 spread through their increased desires to vaccinate [37]. During an outbreak, complications may
52 arise when there are delays in vaccination. As a result of a delay, epidemic final size can increase
53 significantly [38], especially as the delay lengthens [39]. When considering the efficacy of a vaccine,
54 Wu et al. suggest through their model that a less effective vaccine causes vaccine uptake to increase
55 (to an effectiveness of about 50%), especially for more serious diseases [40]. Insights from the models
56 discussed above, as well as more empirically based research [41], have shown that perceived risks play
57 an important factor in an individual’s decision to protect themselves through vaccination. These
58 risks include perceived susceptibility to the illness and perceived risks associated with vaccinating
59 (due to potential side effects) [42, 43]. Much like NPIs, members of a population will base their
60 vaccination decisions on information they are able to gather about the disease during an outbreak.

61 Perceived risks surrounding a disease play a crucial role in vaccination and NPI decisions. Infor-
62 mation that shapes these perceptions is gathered by individuals in a population and may be derived
63 from local information [9, 8, 44] (such as social contact networks), or through global information
64 such as media reports about the population as a whole [44, 45]. We note that disease-behaviour
65 models like those discussed above do not typically consider the intervention strategies of vaccination
66 and NPIs simultaneously. However, it is clear that both are important factors in the spread of a
67 disease. Andrews and Bauch [46] have studied the interactions of these two disease interventions
68 with a utility based decision framework model in the context of seasonal influenza. In contrast to our
69 previous work that considers long-term, year-to-year dynamics, here we develop a disease-behaviour
70 **individual based** network simulation model to study interactions between vaccinating behaviour
71 and NPI behaviour and their impact on health outcomes during the course of a single, **and sudden**,
72 epidemic outbreak *of a novel, self limiting infection*, where perceived risks and social influence serve
73 as the primary drivers of individual behaviour. Moreover, we include parameters that allow con-
74 trolling the relative influence of local versus global information on behaviour. Our main objective is
75 to compare how our model predictions differ from predictions of models that capture behaviour for
76 only one of the two interventions, under various assumptions for (1) transmission probabilities, (2)
77 timing of vaccine introduction, and (3) vaccine efficacy, and how efficacy influences vaccine uptake.
78 Furthermore, we explore how the utilization of local versus global information regarding disease
79 spread and vaccine uptake can alter network wide outcomes.

80 2. Methods

81 2.1. Disease Dynamics

82 We consider a disease with a susceptible - infectious - recovered - vaccinated (SIRV) natural
83 history. Susceptible individuals may become infected by their infectious neighbours with probability
84 $P(N_{Inf}) = 1 - (1 - \beta)^{N_{Inf}}$ per day, where N_{Inf} is the number of infectious network neighbours, and
85 β is the transmission rate. Infectious individuals move to a recovered (and immune) state for the
86 remainder of the epidemic in a number of days sampled from a Poisson distribution with a mean of
87 7 days. Finally, susceptible individuals may choose to vaccinate and thus become immune for the
88 duration of the epidemic. Baseline parameter values were calibrated to obtain epidemic final size and
89 vaccine uptake trends within the plausible ranges of the corresponding measures in the United States
90 for the 2009 H1N1 influenza pandemic [47, 48], although we emphasize that we are not modelling

91 influenza in particular, but rather we intend our disease represent a hypothetical self-limiting, acute
 92 infection where individuals only lose natural immunity on a time scale of years. **We also assume**
 93 **that this is a novel strain of a disease, and individuals have no prior immunity - either**
 94 **natural or vaccine conferred.** Full details regarding network structure, transmission dynamics,
 95 and decision modelling appear in the following subsections.

96 2.2. Contact Network

97 The disease is transmitted on a network consisting of 10,000 nodes which was constructed by
 98 sampling from a large contact network derived from empirical contact data in Portland, Oregon
 99 [49]. Previous research has shown that the subnetwork is a good approximation to the full network
 100 [50]. This network's structure (**see Supplementary Information (SI) Figure 1**) remains static
 101 throughout an epidemic, and we assume that the edges in the network provide sufficient contact
 102 between individuals to allow potential disease transmission. **We also run simulations testing**
 103 **our primary results on two other types of networks: random networks and power law**
 104 **networks. For details regarding these results, we direct the reader to the SI.**

105 2.3. Non-Pharmaceutical Interventions and Vaccination

106 Susceptible individuals in the population may engage in self-protective behaviour in response to
 107 a growing epidemic. Their self-protecting activity is governed by both the presence of the disease
 108 itself [51] and by the social influence of their contacts and the population as a whole [23, 52]. To
 109 model this intervention use, we begin by allowing an individual to reduce their susceptibility to
 110 $\beta_{NPI} = (e^{-(\Phi + \Gamma_{NPI})})\beta$. Firstly, Φ is an individual's risk perception of the disease, given by

$$\Phi = \sigma f\left(\lambda, \frac{I_{Net}}{k}\right) + (1 - \sigma)f\left(\lambda, \frac{I_{Pop}}{N_{Pop}}\right), \quad (1)$$

111 where I_{Net} is the number of a given individual's contacts that have been infected, k is the node
 112 degree of the individual on the network, I_{Pop} is the number of individuals in the population that
 113 have been infected, N_{Pop} is the population size, and σ dictates how members of the population weigh
 114 information gathered from their contacts and the population as a whole. Finally, f is a function
 115 that determines an individual's response level to increasing infection incidence, given by

$$f(x, y) = 1 - \exp(-xy), \quad (2)$$

116 where x is a proportionality constant that governs the response dynamic (λ in (1)). **Since perceived**
 117 **risks only increase in our model (due to the relatively small timespan of one epidemic),**
 118 **we use this functional form. Also, it is an increasing function bounded between 0 and 1**
 119 **whose shape (or response of increasing perceived risk to incidence) can be governed by a**
 120 **single parameter. Similar functions have been used in the literature surrounding disease**
 121 **spread and self-protective behaviour, for example, see [19]. Secondly, Γ_{NPI_j} measures an**
 122 **individual j 's imitation of others who are utilizing self-protective NPI practices, given by**

$$\Gamma_{NPI_j} = \sigma f\left(\gamma, \frac{\sum_{i=1}^{k_j^{Vuln}} 1 - \exp(-(\Phi_i + \Gamma_{NPI_i}))}{k_j^{Vuln}}\right) + (1 - \sigma)f\left(\gamma, \frac{\sum_{i \neq j=1}^{N_{Pop}^{Vuln}} 1 - \exp(-(\Phi_i + \Gamma_{NPI_i}))}{N_{Pop}^{Vuln} - 1}\right), \quad (3)$$

123 where N_{Pop}^{Vuln} is the number of susceptible or vaccinated (potentially vulnerable) individuals in
 124 the population, k_j^{Vuln} is the number of susceptible or vaccinated neighbours individual j has,

125 $\frac{\sum_{i=1}^{k_j^{Vuln}} 1 - \exp(-(\Phi_i + \Gamma_{NPI_i}))}{k_{Vuln}}$ is the average amount of transmission rate reduction caused by self-protective

126 behaviour amongst an individual's susceptible neighbours, $\frac{\sum_{i \neq j=1}^{N_{Pop}^{Vuln}} 1 - \exp(-(\Phi_i + \Gamma_{NPI_i}))}{N_{Pop}^{Vuln} - 1}$ is the similar av-

127 erage reduction induced by the susceptible population as a whole, and γ is a parameter that governs
 128 the response strength of imitation behaviour. Equation (3) captures how individuals reduce their
 129 probabilities of becoming infected through observations of others doing the same. This includes imi-

130 tation of both network neighbours (σ), and imitation of how the entire population is behaving ($1 - \sigma$).

131 Thus, $0 < \exp(-(\Phi + \Gamma_{NPI})) \leq 1$ dictates how individuals lower their probabilities of becoming
 132 infected as they gain awareness of the epidemic by witnessing the disease spread throughout the pop-

133 ulation. **In our simulations, NPI use for each individual is updated non-synchronously**
 134 **in a new random order at the beginning of each day. Also, transmission rate reduction**

135 **through NPI use will typically be $\leq 50\%$ for any given individual, which is consistent**
 136 **with the available literature regarding the efficacy of NPIs [53, 54].**

137 If vaccines are available, members of the population may also choose to protect themselves from
 138 infection by receiving a vaccine. The decision to vaccinate becomes a more attractive option as
 139 vaccine uptake increases [55], and thus an individual's vaccination decision will depend both on
 140 their perceived risk of the disease as well as the decisions of others to vaccinate. We represent this
 141 as

$$\sigma \left(f \left(\lambda, \frac{I_{Net}}{k} \right) + f \left(\gamma, \frac{V_{Net}}{k} \right) \right) + (1 - \sigma) \left(f \left(\lambda, \frac{I_{Pop}}{N_{Pop}} \right) + f \left(\gamma, \frac{V_{Pop}}{N_{Pop}} \right) \right), \quad (4)$$

142 where V_{Net} and V_{Pop} are the numbers of a given individual's contacts and total number of indi-
 143 viduals that have been vaccinated, respectively. If we define $\Gamma_V = \sigma f \left(\gamma, \frac{V_{Net}}{k} \right) + (1 - \sigma) f \left(\gamma, \frac{V_{Pop}}{N_{Pop}} \right)$,

144 then (4) can simply be written as

$$\Phi + \Gamma_V. \quad (5)$$

145 Equation (5) combines an individual's risk perception of becoming infected, which is based on
 146 local and global information of disease incidence, with an individual's imitation of self protective
 147 behaviour, which also based on local and global information.

148 If on any day a susceptible individual's preference towards vaccinating, which we set as $\exp(-(\Phi +$
 149 $\Gamma_V))$, exceeds a given threshold, θ , then that individual will be transferred to the vaccinated compart-
 150 ment. Otherwise, this is interpreted as an individual being undecided, and they therefore remain
 151 susceptible. This process is similar to methods from decision field theory [56], where individuals
 152 update their preferences towards making certain decisions based on available information. If their
 153 preference toward making an action reaches a pre-defined level, a decision is then subsequently made.

154 3. Results

155 3.1. Baseline Dynamics

156 The baseline scenario of our model (Table 1) simulates an outbreak in a population whose
 157 individuals may protect themselves from infection using NPIs or vaccination. We call this the

158 baseline scenario as it was calibrated to achieve plausible epidemic outcomes under the realistic
159 assumption that both vaccination and NPIs are available simultaneously. Henceforth, we will refer
160 to this scenario as the “combined scenario”, as both interventions may be used. If both intervention
161 options are available, the final size of the epidemic is lowest compared to when only one of the
162 two interventions are used, as expected (Fig 1a). We also compare the epidemic time series of the
163 combined scenario to hypothetical scenarios where there is no vaccine available over the course of
164 the outbreak (“NPI-only scenario”), or self-protective behaviour is completely ineffective (“vaccine-
165 only scenario”). We note that the NPI-only scenario gives similar infection rates as the combined
166 scenario for the first 3 weeks of the epidemic. This occurs because vaccine uptake in the combined
167 scenario is close to zero in the first few weeks, due to low perceived risks of becoming infected
168 while infection prevalence is still minimal, and therefore the differences between scenarios with and
169 without vaccination are small during this period of time. The implication of this is that delays in
170 vaccine availability in the first few weeks of an epidemic may not hinder vaccine uptake under a
171 voluntary vaccination policy. After this initial period, we observe consistently higher cumulative
172 infected for the NPI-only scenario over the combined scenario for the remainder of the epidemic.
173 The NPI-only simulations yield the greatest average cumulative infection incidence, as the response
174 from solely NPIs amongst susceptible individuals cannot match the disease mitigation of a perfectly
175 efficacious vaccine, in the long term (however, we note that the difference in cumulative incidence
176 is relatively small). In the vaccine-only scenario, infection incidence spikes rapidly but the epidemic
177 lasts a shorter amount of time than in the NPI-only scenario. The relatively rapid early spike in
178 total infected individuals is due to the lack of vaccine uptake in the first weeks of the epidemic, as
179 vaccination decisions are not activated until the perceived threat of becoming infected is sufficiently
180 high. In all these cases, self-protective behaviour serves to slow the spread of an epidemic, but
181 does not successfully reduce the final attack rate as significantly compared to when it is aided by
182 vaccination.

183 In the NPI-only scenario, NPI uptake amongst susceptible individuals is much more pronounced
184 than when vaccination is also an option (Fig 1b). This occurs for two reasons. Firstly, if vaccination
185 can occur, those that practice the strongest self protective behaviour due to having high levels
186 of perceived risk will be amongst the first to vaccinate. In turn, this will lower the average NPI
187 uptake amongst the remaining susceptible population. Secondly, if members of the population
188 are vaccinating, the spread of the disease will be suppressed causing perceived risks of becoming
189 infected to be lower. Thus, resulting NPI use will be less prominent. In the absence of vaccination,
190 transmission reduction through NPI use simply continues to rise along with the infection incidence
191 seen in Figure 1a. In the final vaccine-only scenario, total vaccine uptake is increased on average
192 (Fig 1c). Moreover, vaccine coverage begins to rise earlier in response to the rapid spike in infection
193 incidence that is observed when no transmission reduction is present through NPIs. Thus, when
194 NPI effects are not considered, predicted vaccine uptake is significantly higher.

195 *3.2. Transmission Rate*

196 Time series of infection prevalence corresponding to different transmission rates can help us
197 understand epidemic spread in our 3 scenarios (Fig 2). When the transmission rate is low, NPIs alone
198 are relatively effective at hindering the growth of the epidemic, lowering the peak infection prevalence
199 compared to the vaccine-only case (Fig 2a). For a transmission rate of $\beta = 0.00493$ per infectious
200 contact per day, simulations that utilize NPIs only or vaccination only result in the same epidemic
201 final size (Fig 2b). Although the peak infection prevalence in this scenario is larger for vaccine-only
202 simulations, the epidemic dies out more quickly compared to the NPI-only scenario, resulting in

203 the same cumulative infection incidence over the epidemic duration. For higher transmission rates,
204 the vaccine only scenario outperforms the NPI only scenario (Fig 2c). Although NPIs delay the
205 peak of the epidemic, infection prevalence dies out more slowly than when the population uses solely
206 vaccination instead. However, this highlights the importance of NPIs in epidemics where vaccination
207 may not be immediately available. Considering the combined scenario data in Fig 2c, which indicates
208 infection prevalence in simulations utilizing both NPIs and vaccination, the initial disease spread is
209 very similar to that of the NPI-only scenario. Only when individuals begin to vaccinate does the
210 infection prevalence in the combined scenario show quantitative difference to the infection prevalence
211 in the NPI-only scenario. Thus, as long as a vaccine is made available within a given time frame,
212 the final size can be expected to be the same due to the early activation of NPIs.

213 Vaccine timing plays a critical role in the health outcomes of the population during an epidemic,
214 across a range transmission rates (Fig 3). In the combined scenario (Fig 3a), a vaccine can be
215 introduced up to 20 days after the start of an epidemic for the epidemic final size to be roughly the
216 same as the scenario when a vaccine is available from day one, for baseline transmission rates. If
217 we disregard the use of NPIs (Fig 3b), the vaccine must be made available within 15 days before
218 we begin to observe larger epidemic final sizes. This effect is similar for $\beta = 0.006$ per infectious
219 contact per day. In the combined scenario, a vaccine must be made available within 15 days before
220 epidemic sizes increase. However, in the vaccine-only case, vaccine availability must occur within
221 just 10 days. Finally, for lower disease transmission, vaccine introduction timing has little impact
222 on infection incidence in the combined scenario. However, in the vaccine-only scenario, we see final
223 sizes begin to increase when availability occurs after 20 days. From these results, we also notice that
224 the rate of increase of epidemic final sizes corresponding to the timing of vaccine introduction are
225 much greater. For example, given the baseline transmission rate, the difference in infection incidence
226 between immediate vaccine availability and availability beginning on day 60 is $\approx 20\%$ in the vaccine-
227 only case. However, the same measure in the combined case is only $\approx 4\%$. Thus, the prediction
228 from these two modelling approaches of epidemic size induced by vaccine timing introduction differs
229 by about 16% of the entire population size.

230 Finally, we also consider measures for epidemic final size (Fig 4). When the transmission rate
231 is low, the final size is the same for the combined scenario as for the NPI-only scenario, but much
232 higher for the vaccine-only scenario (Fig 4a). Hence, for low transmission rates, NPIs on their own
233 can reduce final size as much as combined use of NPIs and vaccines, although the same is not true
234 for vaccines on their own. This is due to individuals promptly adopting NPIs, which are targeted at
235 the leading edge of the epidemic and quick to implement, curbing disease spread immediately. Also,
236 vaccine uptake is much larger in the vaccine-only scenario than in the combined scenario (Fig 4b).
237 In contrast, when the transmission rate is high, the final size is almost (but not quite) the same for
238 the combined scenario as for the vaccine-only scenario, but much higher for the NPI-only scenario.
239 Moreover, vaccine uptake is also nearly the same for both of the scenarios that include vaccination.
240 Hence, for high transmission rates, vaccines on their own can reduce final size almost as much as
241 combined use of NPIs and vaccines, although the same is not true for NPIs on their own. In the
242 case of NPIs, the NPI uptake amongst susceptible individuals does not change for $\beta > \sim 0.0045$, due
243 to the adoption of vaccination (Fig 4c). However, in the NPI-only scenario, susceptibility reduction
244 through NPIs continues to rise along with the transmission rate.

245 In summary, when transmission rates are sufficiently low, NPIs alone can be almost as effective
246 as having both vaccines and NPIs (whereas vaccination alone is relatively less effective), but when
247 transmission rates are sufficiently high, vaccines alone can be almost as effective as having both
248 interventions (whereas NPIs alone are relatively less effective).

249 *3.3. Vaccine Efficacy*

250 Vaccines are never 100% efficacious. For less effective vaccines, we can expect infection incidence
 251 and vaccination coverage to change as individuals in the population adapt to the quality of inter-
 252 ventions available to them. Thus, we explore the dynamics under various vaccine efficacies (denoted
 253 ϵ), and how they relate to vaccine coverage and epidemic final size with and without the additional
 254 impacts of NPIs (Fig 5). **We note that in our simulations, vaccines give full protection**
 255 **with probability ϵ , and no additional protection with probability $1 - \epsilon$.**

256 As vaccine efficacy decreases, the vaccine-only scenario overestimates the amount of vaccine
 257 uptake demanded by up to 16.5% of the population size relative to the combined scenario. We
 258 also observe that as vaccine efficacy decreases, the subsequent increase in vaccine coverage of the
 259 population is larger when NPI effects are not incorporated. For example, between efficacies of 100%
 260 to 50%, the combined scenario of the model predicts $\sim 3.5\%$ more of the population vaccinating,
 261 whereas with the vaccine-only scenario, simulations predict an $\sim 8\%$ increase. This effect is also
 262 seen with epidemic final size (Fig 5a). Across all efficacies, final size increase is only $\sim 1.5\%$ of the
 263 entire population size with combined NPI and vaccine utilization, and $\sim 5.5\%$ with only vaccination.
 264 Thus, we see that disregarding the impact of NPIs may lead to an overestimation of the population's
 265 vaccine demand and final epidemic size. Moreover, the increases in vaccine uptake and final size with
 266 decreasing vaccine efficacy may be less significant than what previous predictions which disregard
 267 NPI effects show [40]. Finally, when incorporating vaccination decisions and self protective behaviour
 268 simultaneously into the model, we observe that predicted levels of vaccine uptake are much smaller
 269 than when no NPIs are implemented (Fig 5b).

270 *3.4. Pairwise Correlations*

271 As an epidemic unfolds across a network, the status of the nodes will develop while the disease
 272 spreads and intervention decisions are made. As a result, the spatial structure of infected and
 273 susceptible individuals on the networks will evolve over time as well. The correlation between these
 274 pairs can offer insight on the vulnerability of the network to disease spread and how individuals
 275 react to infection prevalence according to the information available to them, which we control with
 276 the parameter σ . To measure the correlation between node pairs, we follow Keeling [57]:

$$C_{AB} = \frac{N_{Pop} [AB]}{k_{avg} [A][B]}, \quad (6)$$

277 where k_{avg} is the average node degree on the network. With this formulation, an increase in C_{AB}
 278 indicates an increase in correlation as the number of $[AB]$ pairs in the network relative to the number
 279 of type $[A]$ nodes and type $[B]$ nodes also increases. A value of $C_{AB} = 1$ indicates no correlation
 280 [57].

281 Considering the correlation between susceptible-infected ($[SI]$) pairs (Fig 6c), we observe a rapid
 282 initial spike in the network. This early increase is due to the first infected individuals spreading
 283 the disease to their network contacts, enabling more opportunities for transmission. As infection
 284 prevalence begins to peak (Fig 6a), infected individuals have a higher probability of being connected
 285 to a non-susceptible node, which results in the decline of C_{SI} in the network, as distinct clusters of
 286 infected and other infected, recovered or vaccinated individuals develop. However, the correlation
 287 rises again as infectious nodes recover and only a final few clusters of infected and susceptible nodes
 288 remain, more so for lower σ as those who vaccinated are less likely to be connected to an infectious
 289 node. Correlations of vaccinated nodes with nodes that are or have been infected, $[VI]$ and $[VR]$,

290 respectively, also show how network dynamics respond to different levels of σ (Fig 6d,e). When
 291 individuals base their decisions on local information, that is, on the basis of the number of infectious
 292 neighbours ($\sigma = 1.0$), C_{VI} and C_{VR} are higher. This indicates successful ring vaccination occurring
 293 in proximity to the infectious individuals. Under strong influence of local information, neighbours
 294 of infectious individuals develop a high perceived risk and decide to vaccinate earlier. Then, so-
 295 cial influences reinforce this vaccinating behaviour, resulting in clusters of vaccinated individuals
 296 around infectious individuals. However, when decisions are made more strongly based on popula-
 297 tion level infection prevalence ($\sigma = 0.5$), [VI] and [VR] pairs become less common in proportion to
 298 all vaccinated and infected/recovered nodes since vaccinations do not always occur on the epidemic
 299 front. The cumulative vaccine uptake under global information is higher than under local informa-
 300 tion, however, vaccine uptake increases more rapidly in the early stages of the epidemic under local
 301 information (Fig 6b). This reflects the efficiency of targeted vaccination under local information,
 302 where vaccines are administered to the contacts of infectious individuals so that infection spread is
 303 efficiently prevented. Finally, as the epidemic dies out and infectious nodes become rare, [VI] and
 304 [VR] correlations across varying levels of σ converge to similar values.

305 As σ decreases in our model, [SS] pairs become more common relative to the total number of
 306 susceptible nodes towards the end of an epidemic, increasing C_{SS} (Fig 6f). On the other hand, with
 307 higher σ , final values of C_{SS} continue to decrease. However, we note that during an epidemic, the
 308 opposite is true, albeit to a lesser extent. When $\sigma = 0.5$, vaccination occurs in locations other than
 309 the epidemic front, in turn decreasing C_{SS} compared to higher values of σ . Nonetheless, the ring
 310 vaccination observed with increased σ is more efficient than the more random vaccine allocation seen
 311 when $\sigma = 0.5$, for example, due to the disease only being able to spread along the network edges.

312 4. Discussion

313 We have developed and analyzed a model that simulates a population's adaptive self protective
 314 behaviour (use of NPIs and vaccination) in the face of a disease outbreak, in contrast to most previous
 315 approaches that model only vaccinating behaviour or only NPI behaviour. We allow an individual's
 316 actions to depend both on their perceived risk of infection developed from their experiences with the
 317 disease on the network (both from their network neighbours and from the population as a whole),
 318 as well as imitation of the behaviour of others in the population.

319 Surprisingly, when transmission rates are low, the NPI-only scenario offers comparable disease
 320 mitigation effectiveness to the combined scenario, while the vaccine-only scenario results in relatively
 321 larger epidemic sizes than either the NPI-only scenario or the combined scenario. For higher trans-
 322 mission rates, the opposite becomes true. That is, the vaccine-only scenario is almost as effective as
 323 the combined scenario for reducing infection incidence, but the NPI-only scenario fares worse. If a
 324 vaccine is not available immediately to the population at the start of an epidemic, epidemic mitiga-
 325 tion through adaptive NPI behaviour can curb the growth of an epidemic. Thus, if vaccination is
 326 made available to the population within a given time frame, health outcomes will be very similar to
 327 situations where a vaccine was always available. If, however, the effects of NPIs are not incorporated,
 328 then these time frames are comparatively shorter. Moreover, the increases in infection incidence for
 329 the vaccine-only scenarios are significantly higher the later the vaccine is introduced, resulting in in-
 330 creasingly higher predictions of epidemic final size. Finally, the impact of varying vaccine efficacy on
 331 both vaccine uptake and epidemic final size varies significantly between scenarios with and without
 332 adaptive NPI behaviour. The increases in both final size and vaccine uptake when vaccine efficacy
 333 is decreased are much higher for the vaccine-only scenario than the combined scenario. Hence, a

334 model of adaptive vaccinating behaviour that does not also account for adaptive NPI behaviour
335 will make very different predictions than a model that accounts for adaptive behaviour toward both
336 interventions. This again highlights the positive benefits of epidemic mitigation through adaptive
337 NPI behaviour.

338 From a network perspective, individuals basing their decisions to practice NPIs or become vac-
339 cinated based on the infection prevalence and behaviour in their infection contact network leads to
340 the most effective disease control. Pairwise correlations between vaccinated and infected nodes are
341 highest when this information gathering is possible, as those that vaccinate are typically connected
342 to infected nodes. **We also tested the main results with two additional types of networks:
343 random networks and power law networks (see SI). While the dynamics are qualita-
344 tively the same, the amount of change in epidemic final size or vaccine uptake with
345 differing vaccine delays or vaccine efficacies can depend on the specific network type.
346 Assumptions about network structure and transmission are an important consideration
347 - particularly when modelling a specific disease. For example, a transmission network
348 for influenza likely has a different structure than one that would be used to model HIV
349 transmission.**

350 In the combined scenario, epidemic final size is suppressed most effectively compared to when only
351 single interventions are possible. Also, when the effects of NPIs are not considered in our vaccine-
352 only scenario (an assumption which is common in previous behaviour-disease models focusing on
353 vaccinating behaviour), vaccine uptake predictions are higher compared to when these effects are
354 considered by our model, on account of counteractive feedbacks from NPI behaviour.

355 Our model includes some simplifying assumptions about behaviour-disease dynamics. For exam-
356 ple, NPI efficacy is poorly quantified in the epidemiological literature, and it is not always known in
357 what situations individuals may practice them most often. **Thus, we assume that NPIs for the
358 spreading disease are not used initially, but in reality there may be some baseline level
359 of NPIs used in the population due to other circulating diseases. Moreover, we do not
360 model the effects of NPI practices that infectious individuals may utilize, such as self
361 isolation. Instead, we make the assumption that infectious NPI use is absorbed into the
362 transmission rate.** Also, the network we used in our simulations could be extended to distinguish
363 family, friend, and work structures, where transmission rates to an individual can vary depending
364 on what category certain network contacts fall in. Similarly, age structure can be introduced into
365 the model. As children will be much less likely to effectively practice NPIs, disease transmission
366 in these groups may be more rapid than our model predicts. **Finally, we did not include the
367 impact of asymptomatic infections, and assumed all cases were identifiable in our main
368 results. However, we also considered a scenario where 50% of cases were asymptomatic
369 (see SI), and the primary results regarding vaccine efficacy and vaccine availability de-
370 lays across various transmission rates are qualitatively the same. Although the main
371 results are similar, in future work that aims to model a specific disease, accounting for
372 asymptomatic infections is an important factor.**

373 Through these experiments, we see that predictions of health outcomes and vaccine uptake in
374 a population can vary significantly when NPI use is, or is not, considered. It is important for
375 behaviourally based epidemiological models to incorporate the effects of transmission reduction
376 through this adaptive behaviour, as perceived risks of a disease will in turn be shaped by them -
377 subsequently altering the outcomes of an epidemic. The same is also true of models that focus on
378 modelling NPI behaviour, in populations where adaptive vaccinating behaviour could significantly
379 alter model predictions of NPI practices.

380 **5. Acknowledgements**

381 This research was funded by a Natural Sciences and Engineering Research Council (NSERC)
382 Individual Discovery Grant to CTB.

Table 1: **Baseline Parameter Values.**

Parameter	Description	Value
λ	Constant governing awareness/risk perception of disease	1.5
γ	Constant governing behaviour imitation	0.5
θ	Vaccinating threshold	0.35
σ	Weighting for global versus local information	0.8
β	Transmission rate	0.005
N_{Pop}	Population size	10,000
I_0	Initial number of infectious persons	20
η	Mean infectious period, in days	7

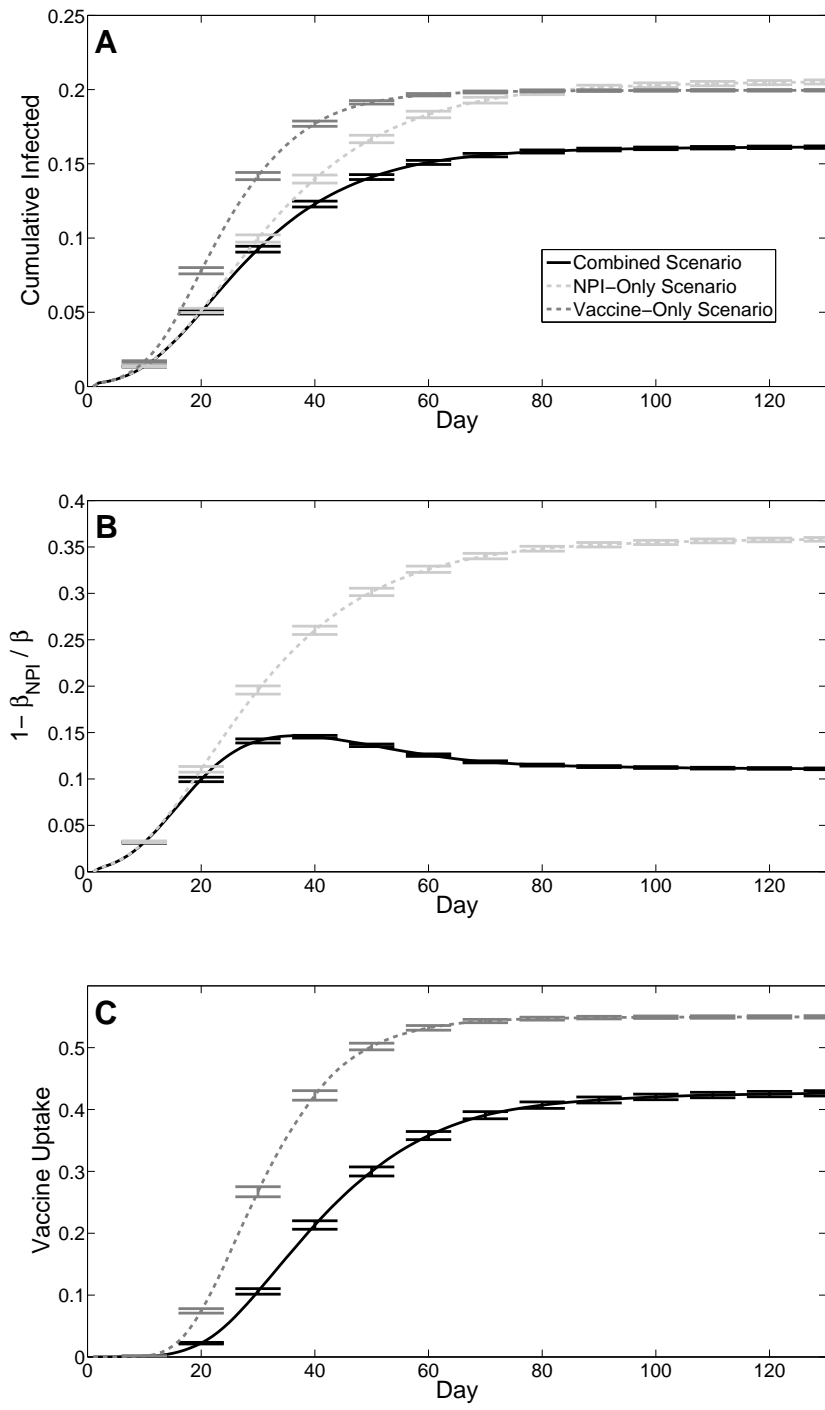


Figure 1: Time series of an epidemic, 95% confidence intervals shown every 10 days around the mean of 500 realizations. a) Cumulative infection incidence b) Transmission rate reduction due to self-protective behaviour (NPIs) amongst the susceptible population, c) Cumulative vaccine coverage.

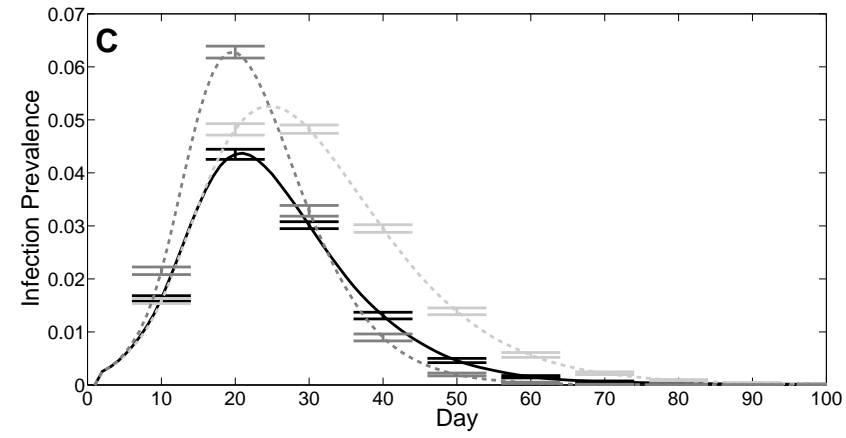
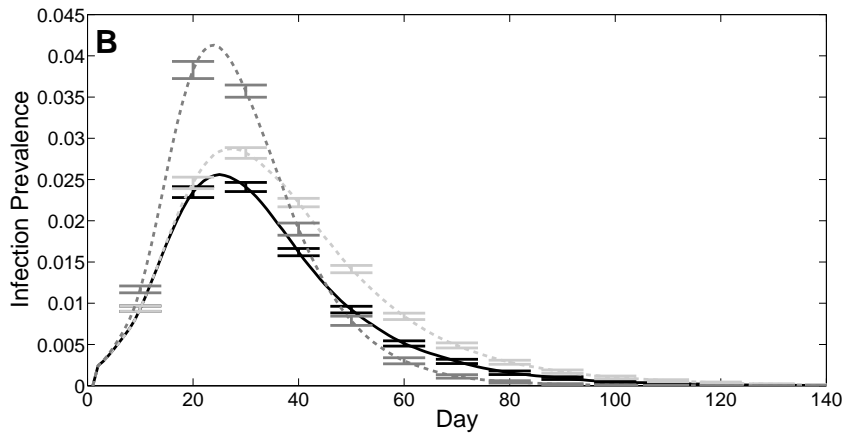
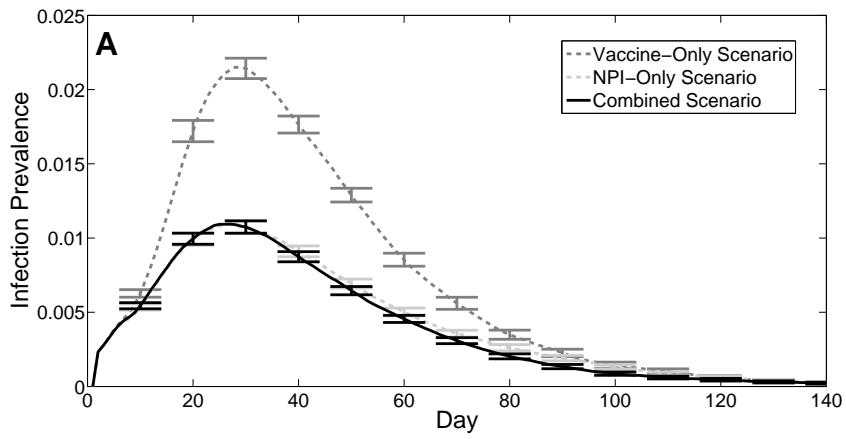


Figure 2: Time series of infection prevalence with the vaccine-only scenario, the NPI-only scenario, and the combined scenario. 95% confidence intervals shown every 10 days around the mean of 500 realizations. (a) $\beta = 0.004$ (b) $\beta = 0.00493$ (c) $\beta = 0.006$.

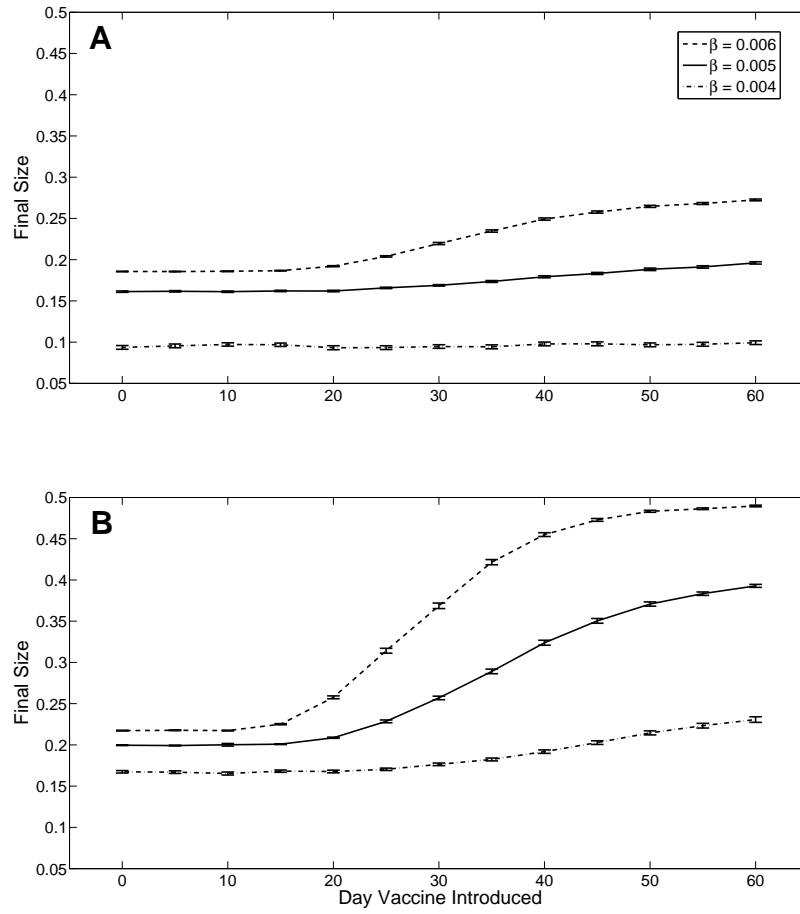


Figure 3: Epidemic final sizes with respect to when vaccination is made available. (a) With NPIs. (b) Without NPIs

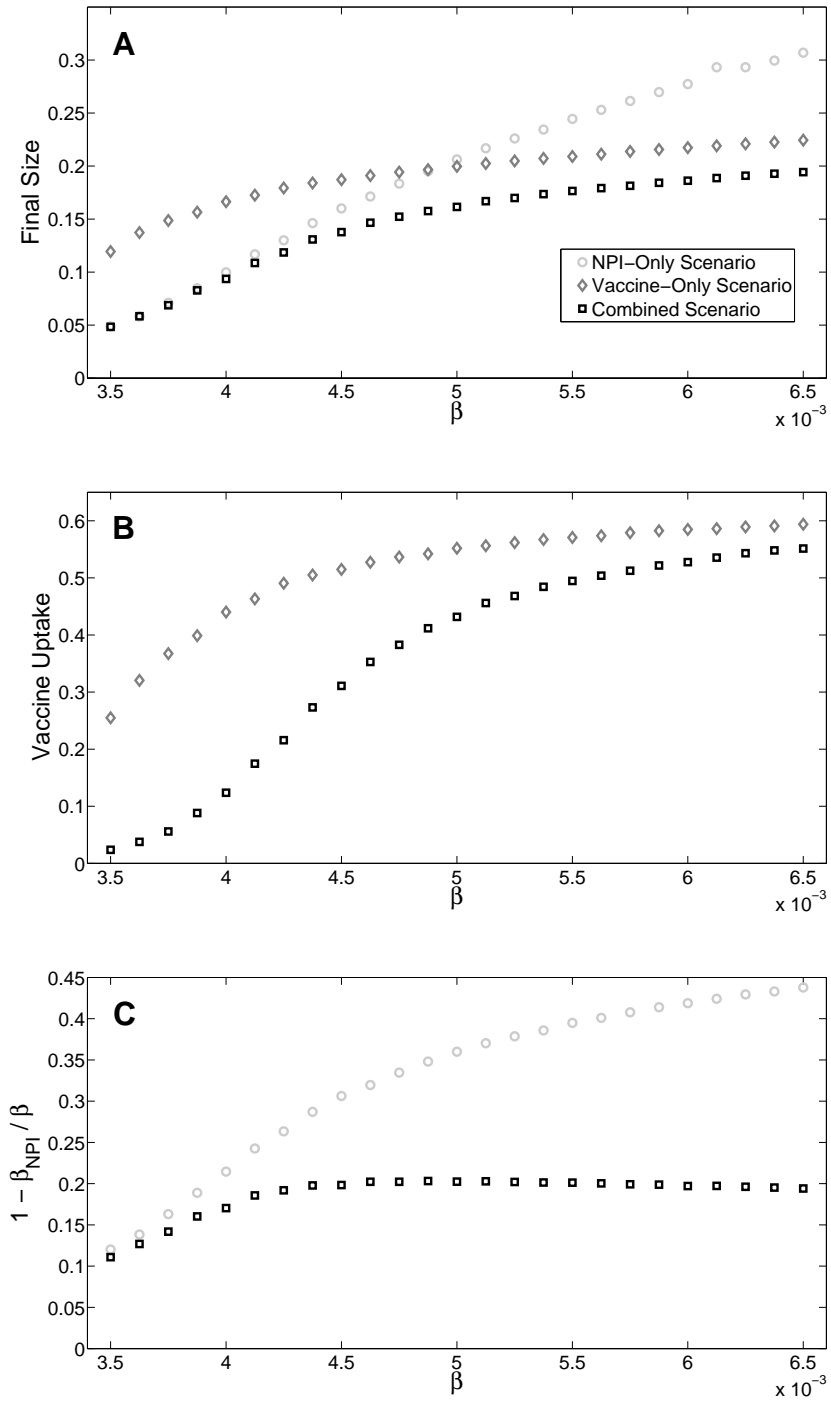


Figure 4: Epidemic measures with respect to transmission rate. (a) Epidemic final size. (b) Vaccine uptake. (c) Transmission rate reduction amongst susceptible individuals.

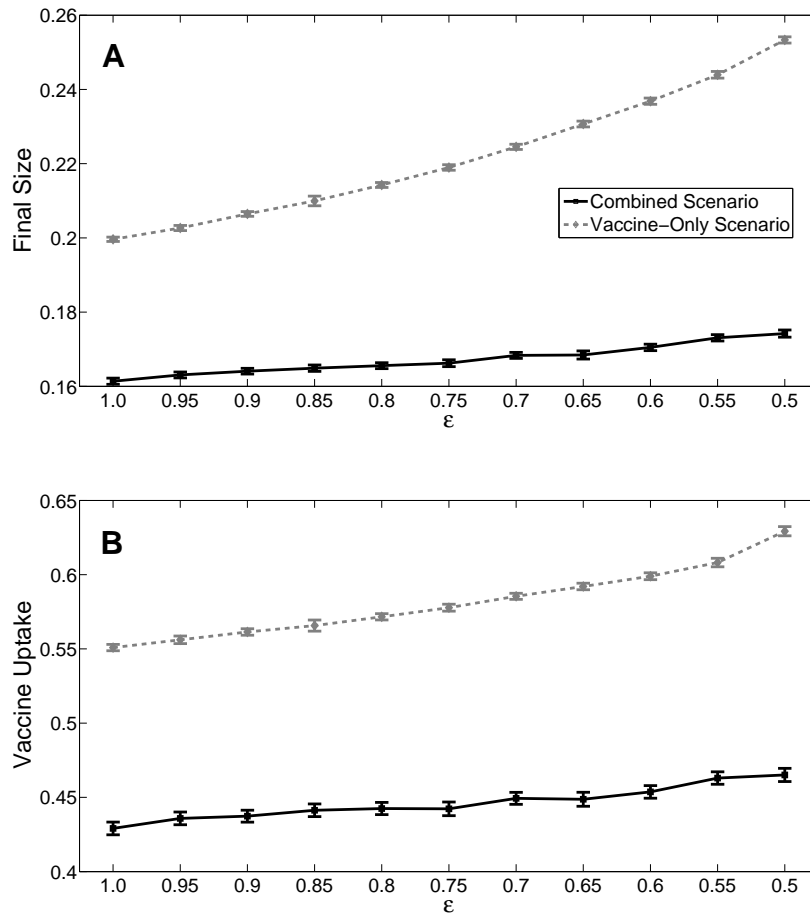


Figure 5: Effects of vaccine efficacy between scenarios with and without NPIs on (a) Vaccine uptake, and (b) Final epidemic size.

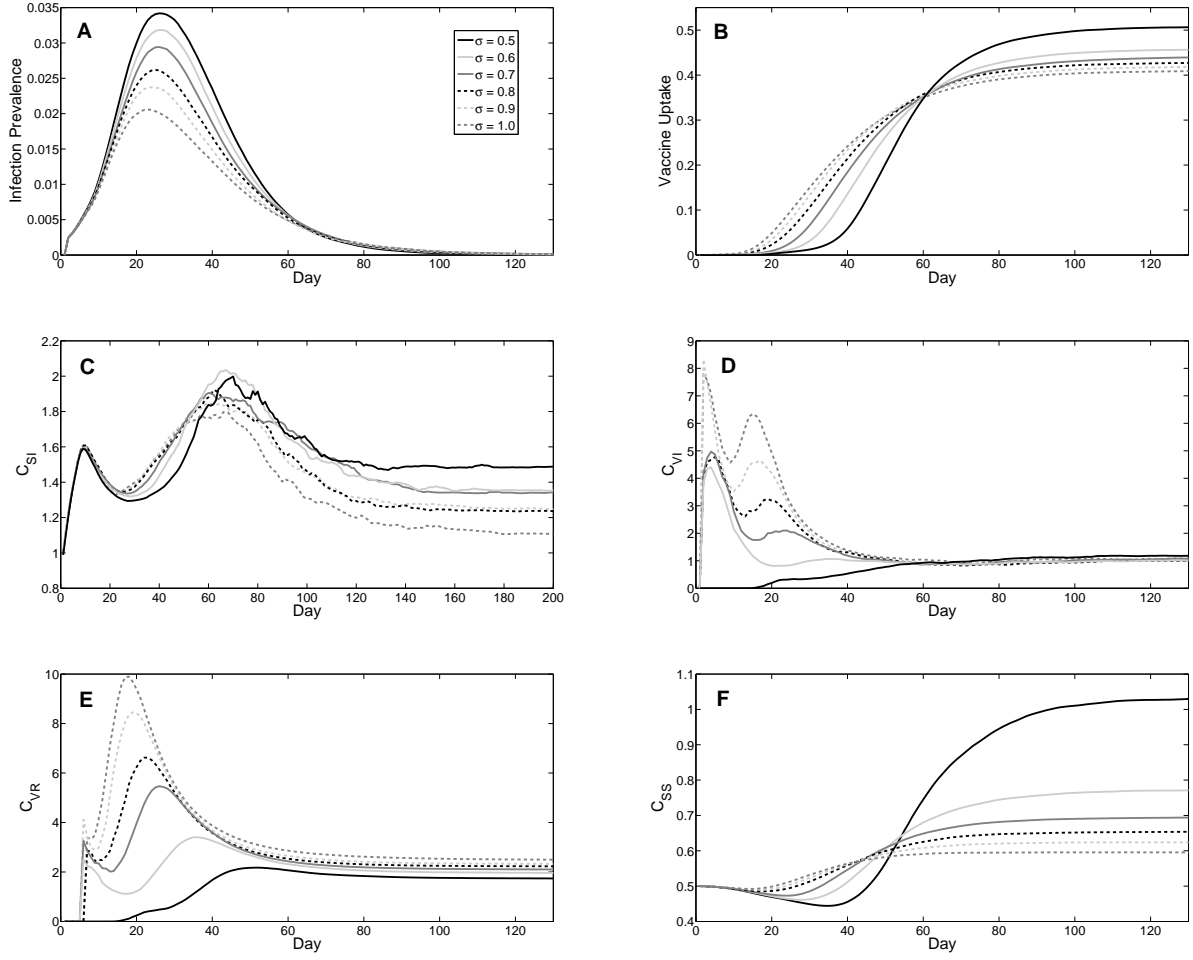


Figure 6: Time series of epidemics over different values of σ , the weighting for global versus local information. (a) Infection prevalence, (b) Vaccine uptake, (c) Correlation between SS pairs, (d) SI pairs, (e) VI pairs, and (f) VR pairs. Lines show the average values over 500 realizations.

383 **References**

- 384 [1] P. Y. Lee, D. B. Matchar, D. A. Clements, J. Huber, J. D. Hamilton, E. D. Peterson, Economic
385 analysis of influenza vaccination and antiviral treatment for healthy working adults, *Annals of*
386 *Internal Medicine* 137 (4) (2002) 225–231.
- 387 [2] H. Pearson, T. Clarke, A. Abbott, J. Knight, D. Cyranoski, SARS: What have we learned?,
388 *Nature* 424 (2003) 121–126.
- 389 [3] A. Balkhair, K. A. Maamari, F. B. Alawi, The struggle against MERS-CoV (the novel coron-
390 avirus), *Oman Medical Journal* 28 (4) (2013) 226–227.
- 391 [4] WHO Ebola Response Team, Ebola virus disease in west africa - the first 9 months of the
392 epidemic and forward projections, *The New England Journal of Medicine* 371 (2014) 1481–
393 1495.
- 394 [5] M. P. Girard, J. S. Tam, O. M. Assossou, M. P. Kieny, The 2009 A(H1N1) influenza virus
395 pandemic: A review, *Vaccine* 28 (2010) 4895–4902.
- 396 [6] S. Funk, M. Salathé, V. A. A. Jansen, Modelling the influence of human behaviour on the
397 spread of infectious diseases: A review, *Journal of the Royal Society Interface* 7 (50) (2010)
398 1247–1256.
- 399 [7] J. T. Lau, X. Yang, E. Pang, et al., SARS-related perceptions in hong kong, *Emerging Infectious*
400 *Diseases* 11 (3).
- 401 [8] T. Philipson, Private vaccination and public health: An empirical examination for U.S. measles,
402 *The Journal of Human Resources* 31 (3).
- 403 [9] A. Ahituv, V. J. Hotz, T. Philipson, The responsiveness of the demand for condoms to the local
404 prevalence of AIDS, *The Journal of Human Resources* 31 (4).
- 405 [10] D. P. Durham, E. A. Casman, Incorporating individual health-protectice decisions into disease
406 transmission models: A mathematical framework, *Journal of the Royal Society Interface* 9 (68)
407 (2012) 562–570.
- 408 [11] O. de Zwart, I. Veldhuijzen, G. Elam, Perceived threat, risk perception, and efficacy beliefs
409 related to SARS and other (emerging) infectious diseases: results of an international survey,
410 *International Journal of Behavioral Medicine* 16 (2009) 30–40.
- 411 [12] D. Koh, K. Takahashi, M.-K. Lim, et al., SARS risk perception and preventive measures,
412 Singapore and Japan, *Emerging Infectious Diseases* 11 (4) (2005) 641–642.
- 413 [13] Centers for Disease Control and Prevention, Nonpharmaceutical Interventions (NPIs), [http:](http://www.cdc.gov/nonpharmaceutical-interventions/)
414 [//www.cdc.gov/nonpharmaceutical-interventions/](http://www.cdc.gov/nonpharmaceutical-interventions/) (August 2012).
- 415 [14] G. B. Chapman, E. J. Coups, Predictors of influenza vaccine acceptance among healthy adults,
416 *Preventive Medicine* 29 (1999) 249–262.
- 417 [15] C. Bauch, P. Manfredi, A. d’Onofrio, Behavioral epidemiology of infectious diseases: An
418 overview, in: P. Manfredi, A. d’Onofrio (Eds.), *Modeling the Interplay Between Human Behav-*
419 *ior and the Spread of Infectious Diseases*, Springer, 2013, Ch. 1, pp. 1–19.

- 420 [16] Z. Wang, M. A. Andrews, Z.-X. Wu, L. Wang, C. T. Bauch, Coupled disease-behavior dynamics
421 on complex networks: A review, *Physics of Life Reviews*.
- 422 [17] S. Del Valle, H. Hethcote, J. Hyman, C. Castillo-Chavez, Effects of behavioral changes in a
423 smallpox attack model, *Mathematical Biosciences* 195 (2005) 228–251.
- 424 [18] T. C. Reluga, Game theory of social distancing in response to an epidemic, *PLOS Computational*
425 *Biology* 6 (5).
- 426 [19] S. Funk, E. Gilad, C. Watkins, V. A. A. Jansen, The spread of awareness and its impact on
427 epidemic outbreaks, *Proceedings of the National Academy of Sciences of the United States of*
428 *America* 106 (16) (2008) 6872–6877.
- 429 [20] A. Rizzo, M. Frasca, M. Porfiri, Effect of individual behavior on epidemic spreading in activity-
430 driven networks, *Physical Review E* 90.
- 431 [21] F. Bagnoli, P. Liò, L. Sguanci, Risk perception in epidemic modeling, *Physical Review E* 76.
- 432 [22] E. P. Fenichel, C. Castillo-Chavez, M. G. Ceddia, G. Chowell, P. A. G. Parra, et al., Adaptive
433 human behavior in epidemiological models, *Proceedings of the National Academy of Sciences*
434 *of the United States of America* 108 (15) (2011) 6306–6311.
- 435 [23] P. Poletti, B. Caprile, M. Ajelli, A. Pugliese, S. Merler, Spontaneous behavioural changes in
436 response to epidemics, *Journal of Theoretical Biology* 260 (2009) 31–40.
- 437 [24] P. Poletti, M. Ajelli, S. Merler, Risk perception and effectiveness of uncoordinated behavioral
438 responses in an emerging epidemic, *Mathematical Biosciences* 238 (2012) 80–89.
- 439 [25] E. Check, Avian flu special: Is this our best shot?, *Nature* 435 (2005) 404–406.
- 440 [26] F. Chen, M. Jiang, S. Rabidoux, S. Robinson, Public avoidance and epidemics: Insights from
441 an economic model, *Journal of Theoretical Biology* 278 (2011) 107–119.
- 442 [27] T. Gross, C. J. D. D’Lima, B. Blasius, Epidemic dynamics on an adaptive network, *Physical*
443 *Review Letters* 96.
- 444 [28] L. B. Shaw, I. B. Schwartz, Fluctuating epidemics on adaptive networks, *Physical Review E* 77.
- 445 [29] L. B. Shaw, I. B. Schwartz, Enhanced vaccine control of epidemics in adaptive networks, *Physical*
446 *Review E* 81.
- 447 [30] D. H. Zanette, S. Risau-Gusman, Infection spreading in a population with evolving contacts,
448 *Journal of Biological Physics* 34 (2008) 135–148.
- 449 [31] C. Granell, S. Gómez, A. Arenas, Dynamical interplay between awareness and epidemic spread-
450 ing in multiplex networks, *Physical Review Letters* 111.
- 451 [32] E. Cozzo, R. A. B. nos, S. Meloni, Y. Moreno, Contact-based social contagion in multiplex
452 networks, *Physical Review E* 88.
- 453 [33] R. J. Glass, L. M. Glass, W. E. Beyeler, H. Min, Targeted social distancing design for pandemic
454 influenza, *Emerging Infectious Diseases* 12 (11) (2006) 1671–1681.

- 455 [34] J. K. Kelso, G. J. Milne, H. Kelly, Simulation suggests that rapid activation of social distancing
456 can arrest epidemic development due to a novel strain of influenza, *BMC Public Health* 9 (117).
- 457 [35] R. Vardavas, R. Breban, S. Blower, Can influenza epidemics be prevented by voluntary vacci-
458 nation?, *PLOS Computational Biology* 3 (5).
- 459 [36] C. T. Bauch, A. P. Galvani, D. J. Earn, Group interest versus self-interest in smallpox vaccina-
460 tion policy, *Proceedings of the National Academy of Sciences of the United States of America*
461 100 (18) (2003) 10564–10567.
- 462 [37] H. Zhang, J. Zhang, C. Zhou, M. Small, B. Wang, Hub nodes inhibit the outbreak of epidemic
463 under voluntary vaccination, *New Journal of Physics* 12.
- 464 [38] Y. Yang, J. D. Sugimoto, M. E. Halloran, N. E. Basta, D. L. Chao, et al., The transmissibility
465 and control of pandemic influenza A (H1N1) virus, *Science* 326 (2009) 729–733.
- 466 [39] M. Z. Gojovic, B. Sander, D. Fisman, M. D. Krahn, C. T. Bauch, Modelling mitigation strategies
467 for pandemic (H1N1) 2009, *PMC Canadian Medical Association Journal* 181 (2009) 673–680.
- 468 [40] B. Wu, F. Fu, L. Wang, Imperfect vaccine aggravates the long-standing dilemma of voluntary
469 vaccination, *PLOS One* 6.
- 470 [41] N. T. Brewer, G. B. Chapman, F. X. Gibbons, et al., Meta-analysis of the relationship between
471 risk perception and health behaviour: The example of vaccination, *Health Psychology* 26 (2)
472 (2007) 136–145.
- 473 [42] R. Roberts, Q. Sandifer, M. Evans, M. Noland-Farrell, P. Davis, Reasons for non-uptake of
474 measles, mumps, and rubella catch up immunisation in a measles epidemic and side effects of
475 the vaccine, *BMJ* 310 (1995) 1629–1639.
- 476 [43] P. H. Streefland, Public doubts about vaccination safety and resistance against vaccination,
477 *Health Policy* 5 (2001) 159–172.
- 478 [44] E. Klein, D. L. Smith, C. A. Gilligan, Economic incentives and mathematical models of disease,
479 *Environment and Development Economics* 12 (2007) 707–732.
- 480 [45] T. R. Berry, J. Wharf-Higgins, P. Naylor, SARS wars: An examination of the quantity and
481 construction of health information in the news media, *Health Communication* 21.
- 482 [46] M. A. Andrews, C. T. Bauch, Disease interventions can interfere with one another through
483 disease-behaviour interactions, *PLOS Computational Biology* 11.
- 484 [47] S. Shrestha, D. Swerdlow, R. Borse, V. Prabhu, L. Finelli, et al., Estimating the burden of 2009
485 pandemic influenza A (H1N1) in the United States (April 2009–April 2010), *Clinical Infectious
486 Diseases* 52 (2011) S75–S82.
- 487 [48] Centers for Disease Control and Prevention, Flu Vaccination Coverage, United States, [http:
488 //www.cdc.gov/flu/fluview/coverage-1213estimates.htm](http://www.cdc.gov/flu/fluview/coverage-1213estimates.htm) (April 2015).
- 489 [49] Network Dynamics and Simulation Science Laboratory, Synthetic data products for societal
490 infrastructures and proto-populations: Data set 1.0, Tech. rep., Virginia Polytechnic Institute
491 and State University (2008).

- 492 [50] C. R. Wells, C. T. Bauch, The impact of personal experiences with infection and vaccination
493 on behaviour-incidence dynamics of seasonal influenza, *Epidemics* 4 (2012) 139–151.
- 494 [51] M. Z. Sadique, W. J. Edmunds, R. D. Smith, W. J. Meerdink, O. de Zwart, et al., Precautionary
495 behavior in response to perceived threat of pandemic influenza, *Emerging Infectious Diseases*
496 13 (9) (2007) 1307–1313.
- 497 [52] C. T. Bauch, Imitation dynamics predict vaccinating behaviour, *Proceedings of the Royal So-*
498 *ciety B Biological Sciences* 272 (1573) (2005) 1669–1675.
- 499 [53] E. L. Larson, Y. hui Ferng, J. Wong-McLoughlin, S. Wang, M. Haber, S. S. Morse, Impact of
500 non-pharmaceutical interventions on uris and influenza in crowded, urban households, *Public*
501 *Health Reports* 125 (2) (2010) 178–191.
- 502 [54] J. J. Sheehan, P. J. Mott, B. W. Sisk, J. W. Arbogast, C. Ferrazzano-Yaussy, C. A. Bondi,
503 Alcohol-based instant hand sanitizer use in military settings - a prospective cohort study of
504 army basic trainees, *Military Medicine* 172 (11) (2007) 1170–1176.
- 505 [55] S. Bhattacharyya, C. T. Bauch, “wait and see” vaccinating behaviour during a pandemic: A
506 game theoretic analysis, *Vaccine* 29 (2011) 5519–5525.
- 507 [56] J. R. Busemeyer, J. T. Townsend, Decision field theory: A dynamic-cognitive approach to
508 decision making in an uncertain environment, *Psychological Review* 100 (3) (1993) 432–459.
- 509 [57] M. J. Keeling, K. T. Eames, Networks and epidemic models, *Journal of the Royal Society:*
510 *Interface* 2 (2005) 295–307.