The impact of media coverage on the transmission dynamics of human influenza

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• Effects of media

- Effects of media
- The model



- Effects of media
- The model
- Analysis



- Effects of media
- The model
- Analysis
- Optimal controls



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- Adverse outcome



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- The model
- Analysis
- Optimal controls
- Adverse outcome
- Implications.













The media influences:

individual behaviour



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 individual behaviour (eg gift-chasing)



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- formation and implementation of public policy



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- formation and implementation of public policy (eg biometrics)



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- perception of risk



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- formation and implementation of public policy (eg biometrics)
- perception of risk (eg SARS in Chinatown).



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- Mass media are key tools in risk communication
- However, they have been criticised for making risk a spectacle.



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- This suggests that media have a direct and rapid influence on everyday understanding
- However, this has been revised in recent years.

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- Consumers might only partially accept a particular media message
- Or they may resist the dominant media messages altogether.

Media effects may sway people into a panic



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 Conversely, media may have little effect on more familiar diseases

(eg seasonal influenza).



Media in a crisis

• Media reporting play a key role in


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 - perception



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 However, state-controlled media are rewarded for creating an illusion of normalcy (eg embedded journalists).

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 - (eg climate change).



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- Media influences behaviour, which in turn influences media.

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- Misplaced fears of autism in the developed world have stoked fears of vaccinations against childhood diseases.

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- However, this may be especially problematic for vaccines
 - (eg HPV vaccine).

 We model the dynamics of influenza based on a single strain without effective crossimmunity



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- We include a vaccine that confers temporary immunity
- Vaccinated individuals may still become infected but at a lower rate than susceptibles
- Media converage is included via a saturated incidence function.






























$$\begin{aligned} \frac{dS}{dt} &= \Lambda + \omega V - (\theta + \mu) S - \left(\beta_1 - \beta_2 \frac{I}{m_I + I}\right) SI + \sigma R\\ \frac{dI}{dt} &= \left(\beta_1 - \beta_2 \frac{I}{m_I + I}\right) SI + \left(\beta_1 - \beta_3 \frac{I}{m_I + I}\right) (1 - \gamma) VI - (\alpha + \mu + \lambda) I\\ \frac{dV}{dt} &= \theta S - (\mu + \omega) V - \left(\beta_1 - \beta_3 \frac{I}{m_I + I}\right) (1 - \gamma) VI\\ \frac{dR}{dt} &= \lambda I - (\mu + \sigma) R \end{aligned}$$

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- m₁ is the media half-saturation constant
- β_i are the relative transmissibilities.

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- As many people become infected, effects of media are reduced
- ie message reaches a maximum number of people due to information saturation
- This also reflects the fact that the media are less interested in a story once it's established in society.



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- and an endemic equilibrium $(\hat{S},\hat{I},\hat{V},\hat{R})$ which only exists for some

parameter values.



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 If R₀>1 the DFE is unstable.

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(affecting the media half-saturation constant).



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Benefit of
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S=susceptible I=infected V=vaccinated *u*_v=vaccine control *u*_m=media control

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$$Benefit of uninfected populations$$

$$Weight constraint for infected populations$$

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 B₁ and B₂ can represent the amount of money expended over a finite period, or the perceived risk.

 u_{v} =vaccine control u_{m} =media control

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- a_{11} and b_{11} are lower and upper bounds for u_{ν}
- a_{22} and b_{22} are lower and upper bounds for $u_{\rm m}$
- The optimal controls are unique if t_f is small.

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Media has beneficial effect on vaccine



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Media has negative effect on vaccine



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- Suppose, initially, the media and the general population are unaware of the disease
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- New infected individuals arrive at fixed times
- We will ignore recovery in this simple model.

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- Suppose there are a critical number of infected individuals whereupon people become aware of the disease, via the media
- Above this threshold, susceptibles do not mix with infecteds
- However, vaccinated individuals mix significantly with infecteds
- Even though they may still potentially contract the virus.



• For I<I_{crit}, the model is

S=susceptible I=infected V=vaccinated Λ =birth rate μ =background death rate α =disease death rate ω =waning rate λ =recovery rate I_{crit}=vaccination panic threshold

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10

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- t_k are (fixed) arrival times of new infecteds
- This approximates low-level mixing
- If arrival times are not fixed, the results are broadly unchanged.
 S=susceptible I=infected V=vaccinated A=birth rate μ=background death rate α=disease death rate ω=waning rate λ=recovery rate

I_{crit}=vaccination panic threshold

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(at low rates).








• If I<I_{crit}, we can prove that

 μ =background death rate α =disease death rate λ =recovery rate I_{crit} =vaccination panic threshold



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where $\tau = t_{k+1} - t_k$

 If m⁺>I_{crit}, then the system will eventually switch from the lower region to the upper region.

 $\substack{\mu = \textit{background death rate } \alpha = \textit{disease death rate } \\ \substack{\lambda = \textit{recovery rate } I_{\textit{crit}} = \textit{vaccination panic threshold}}$



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- ie once trajectories enter the upper region, they will stabilise there
- If I*>m⁺, then the outcome will be worse than without media effects
- Thus, even in this extremely simplified model, the media may make things significantly worse.



Low-level mixing of susceptibles

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- Including these will increase the long-term number of infecteds



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- Including these will increase the long-term number of infecteds
- It will also increase the peak of the epidemic wave.





High-level mixing of susceptibles

• What if susceptibles mix with infecteds in more significant numbers?



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- If these effects are included in the upper region, then the wave peak occurs earlier



High-level mixing of susceptibles

- What if susceptibles mix with infecteds in more significant numbers?
- If these effects are included in the upper region, then the wave peak occurs earlier
- The long-term number of infecteds will also increase.





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- The driving factor here is overconfidence in an imperfect vaccine
- ie vaccinated people mix significantly more with infecteds than susceptibles do
- This may happen if people feel invulnerable, due to media simplifications around vaccines.

JORGE CHAM @ 2009

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Recommendations

- As scientists, we could all benefit from media training
- Messages need to be straightforward
- Plain language is crucial
- Speak in quoteable phrases, not paragraphs
- If you can't explain it...
 ...you didn't do it.



 Media simplifications can lead to overconfidence in the idea of a vaccine as a cure-all



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- The result is a vaccinating panic and a net increase in the number of long-term infected
- Thus, media coverage of an emerging epidemic can have dire consequences
- It can also implicitly reinforce an imperfect solution as the only answer.

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• eg people may ignore the media, de-linking the vaccination rate from the control.

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- The media are responsible for treating risk as spectacle, panic in the face of fear and oversimplifications in the absence of data
- While the media may encourage more people to get vaccinated, they may also trigger a vaccinating panic
- Or promote overconfidence in the ability of a vaccine to fully protect against the disease
- When the next pandemic arrives, the outcome is likely to be significantly worse as a result of the media.

Key References

• J.M. Tchuenche, N. Dube, C.P. Bhunu, <u>R.J. Smith?</u> and C.T. Bauch (2011). The impact of media coverage on the transmission dynamics of human influenza. BMC Public Health 11(Suppl 1):S5.

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