

# **The uses – and dangers – of models in informing public policy**

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## **Models are essential – but watch out for their weaknesses**

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**“All models are wrong”**

**“Some models are useful”**

**“Many models are dangerous”**

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## Some key uses of models

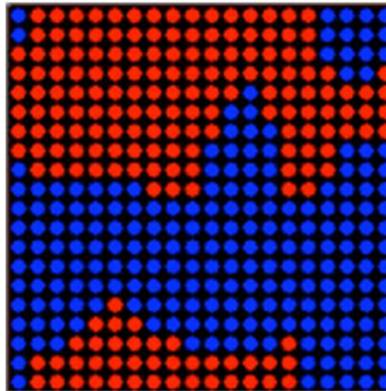
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- ❑ Allow predictions (most difficult and problematic)
- ❑ Improve understanding – especially of complex systems
  - ⌘ Lags, feedbacks, thresholds....
  - ⌘ Correlations are *not* enough in many cases
  - ⌘ Can provide a key insight by simplifying
  - ⌘ Example: Schelling segregation model
- ❑ Allow virtual experiments, facilitate negotiations
  - ⌘ What would happen if we...?
  - ⌘ Example: Sterman et al. climate models
- ❑ Make assumptions explicit – and open to debate
  - ⌘ Example: Bunn model of nuclear terrorism risk

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## Adaptive agents: Schelling's segregation model

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Source: Rauch, "Seeing Around Corners,"  
*The Atlantic*, April 2002

- ❑ Each agent prefers having at least two of its nearest neighbors be similar – moves if this is not the case
- ❑ Leads to almost total segregation

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## Some key dangers of models

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- ❑ Results that do not reflect reality can lead to terrible policy choices
  - ⌘ Adopting policies that work in the model but are ineffective (or counterproductive) in real life
  - ⌘ Rejecting policies that fail in the model but would have worked in real life
  - ⌘ Exaggerating some dangers, dismissing others
  - ⌘ Missing the questions the model doesn't ask
- ❑ “Model adequacy bias” or “Theory-induced blindness”
  - ⌘ Once we have a model, we tend to think it reflects reality – give more credence than the models often deserve
  - ⌘ We tend to ignore factors, influences, that aren't in the model
  - ⌘ Models reflect the biases, interests of those who make them
  - ⌘ Our theories and models shape our understanding of the world – for good and for ill (Example: rational-actor theories in economics)

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## Common model weaknesses

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- ❑ Unjustified assumptions
- ❑ Unjustified extrapolations from limited data
- ❑ Omission of major variables or system interactions
- ❑ Inclusion of structures/interactions that differ substantially from the system being modeled
- ❑ Inadequate representation and acknowledgment of uncertainty

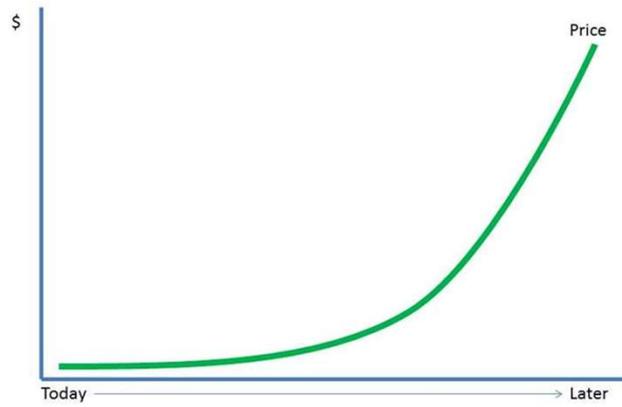
*Can you think of models in your experience that had one or more of these problems?*

*How does the way models are built and used reflect the underlying societal structures of power? Who has voice? Who gets to determine what kinds of questions are asked?*

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## Example: price of a non-renewable mined resource – traditional model

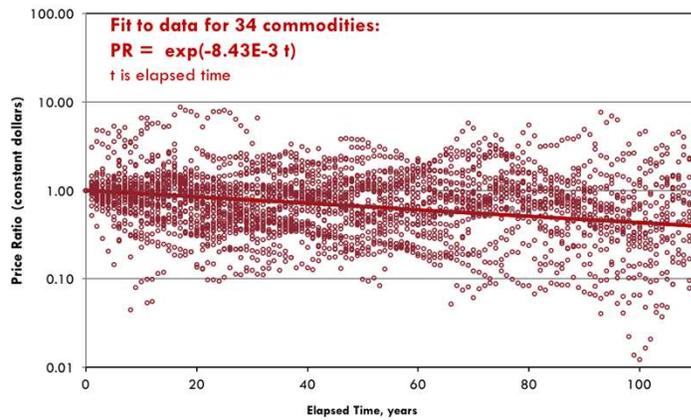
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## Real-world prices of mined resources

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## Some basics of typical models of infectious disease spread

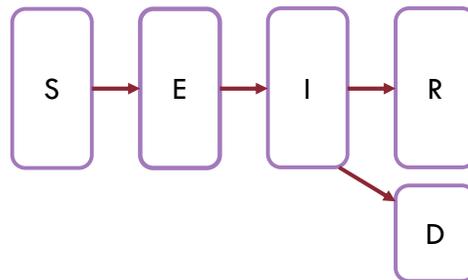
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- Key concept: the “reproductive number”,  $R_0$  (or  $R_t$  over time)
  - ⌘ Average number of people each infected person infects
    - $>1$  means exponential growth
    - $<1$  means decline
  - ⌘ Depends on:
    - How infectious the disease is, and how it's transmitted
    - How long people stay infectious, and whether they know they are infectious
    - What fraction of people are susceptible
    - How people live and behave (as affected by societal structures, fear, policies, other incentives)
- Was thought that at the beginning,  $R_0$  for COVID-19 was in the range of 2.2-2.7 in most places; latest data suggests 5.7 (at least in Wuhan) – ferocious growth

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## Some basics of typical models of infectious disease spread (II)

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- Population moves between categories – susceptible, exposed, infected, then recovered or dead
- Many assumptions in modeling this
  - ⌘ How many people will an “average” infected version come close to?
  - ⌘ How many of those become infected, on average?

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## What might help reduce $R_0$ ?

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- Meeting fewer people (social distancing)
- Meeting outside, not inside (ventilation)
- Wearing masks, washing hands, other barriers and decontamination (less transmission when people do meet and from surface contact)
- Testing, contact tracing, isolation (keeping the infected away from others)
- Special measures to protect those most at risk
  - ⌘ The old, immuno-compromised, those with key conditions
  - ⌘ People who can't social distance (homeless or poorly housed, retirement homes, essential workers...)

*How does focusing only on the average affect our thinking?*

11

## 1. How valid are the key assumptions?

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- Need to identify those assumptions most central to driving model results – then explore their basis
- How good is the evidence for those assumptions?
- Is there contrary evidence as well? Are there other explanations for the evidence?
- Is the model being asked to extrapolate to cases not covered by the data, where there is no experience?
- For COVID-19 models:
  - ⌘ We still don't fully understand what actions lead to what risk of infection – and what changes lead to what risk reduction
  - ⌘ We have quite limited data on some key factors:
    - How well do what forms of social distancing work?
    - How well do different types of masks work?

12

**Some evidence that masks block droplets from breath and speech**

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**But... some of the droplets escape**



Source: [japanesecreations.com](http://japanesecreations.com)

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## 2. How does the model do in representing the system's past behavior?

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- ❑ If the model can't reproduce the response to past events should doubt whether it will do well projecting the response to current or future events
  - ⌘ Example: climate models increasingly good at reproducing past climate – still have trouble explaining some past large excursions
- ❑ For COVID-19 models:
  - ⌘ Infection behavior appears to be different in important respects from flu, SARS, MERS...
  - ⌘ Can start to try to reproduce events in pandemic so far
    - But limited understanding of what was most important in causing rapid spread in some places and not others, rapid declines in some places and not others

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## 3. Can the modeler explain *why* the model behaves as it does?

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- ❑ ... and why the real world should be the same?
- ❑ If the model leads to a surprising result, is that result likely to be a new insight about the real world, or an artifact of the model?
- ❑ For COVID-19 models:
  - ⌘ One influential model showed that (within the model) near-universal mask use was highly effective – but only if introduced before 50 days, ineffective thereafter
  - ⌘ Real, or artifact? (Important, since well beyond 50 days now...)

16

## 4. How do the results of this model compare with the results of others?

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- ❑ Widely varying results should cast doubt
  - ⌘ Example: integrated assessment models of climate
- ❑ For COVID-19 models:
  - ⌘ Substantially varying projections of future spread
  - ⌘ Some increased convergence as more data becomes available, assumptions get more sophisticated and complex

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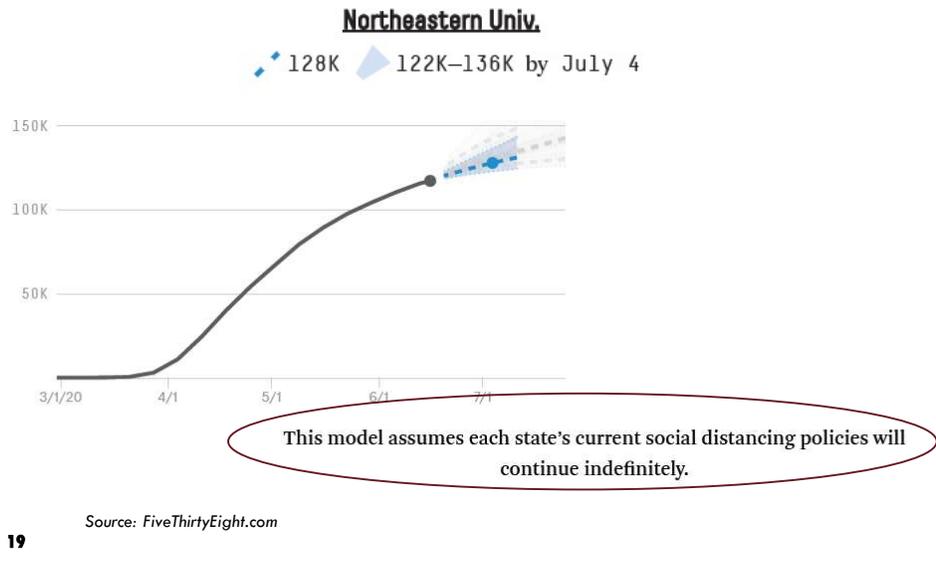
## 5. How well do the *pieces* of the model represent the real behavior?

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- ❑ Models of complex systems typically built from many particular sub-units
  - ⌘ Example: Models of clouds, oceans, atmosphere, land, biosphere, ice sheets, all interacting in climate models...
- ❑ For COVID-19 models:
  - ⌘ Many pieces
  - ⌘ An important one: how well does it capture changing behavior in response to policy and leadership statements?

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## Do the model pieces make sense?



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## 6. Does the model include key interactions that occur in the real world?

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- ❑ If key feedbacks, effects are not included, the models results are unlikely to be realistic
  - ⌘ Example: Many economic models of climate change don't include increased low-carbon R&D when there's a price on carbon
- ❑ For COVID-19 models:
  - ⌘ Do they include reduced social distancing as people get fed up, and get desperate for income?
  - ⌘ Do they include concentrations of risk where people can't social distance – e.g., retirement homes, the homeless?
  - ⌘ Do they include spread from infected people whose tests say they aren't infected?

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## 7. Does the model include interactions that do *not* seem like those in the real world?

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- ❑ Many models include interactions or effects quite different from those in the real world
  - ⌘ Example: Zebrowski model of nuclear theft risk
- ❑ For COVID-19 models:
  - ⌘ Unchanging behavior as risk reduces
  - ⌘ No variation in behavior from one person to another

21

## 8. Has the model been subject to peer review?

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- ❑ Peer review is highly imperfect – but >> better than nothing
  - ⌘ If complete models (and data sets) are not made available for external review – watch out!
  - ⌘ Initial reviewers often do not have time to look through papers (or models) in rigorous detail
  - ⌘ As models are used over time, including by other groups, issues tend to be identified
- ❑ For COVID-19 models:
  - ⌘ Lots of rush to get results out – for good reasons
  - ⌘ Peer review of some key journal articles apparently rushed – major controversies over some peer-reviewed results
  - ⌘ Some useful peer review of models now occurring
  - ⌘ But many unreviewed models in use

22

## 9. Who says? What are the reputation, likely biases, of the modelers?

23

- ❑ As with any other expert opinion, the source matters
  - ⌘ Journal or institution with strong reputation?
  - ⌘ Source whose reliability has been demonstrated in the past?
  - ⌘ Potential biases?
  - ⌘ Example: Industry-sponsored models to downplay pollution effects, cigarette effects, climate problems...
- ❑ For COVID-19 models:
  - ⌘ Broad range of participants in modeling, making claims
  - ⌘ Ranges from highly reputable to conspiracy theorists -- hard to separate the wheat from the chaff

23

## 10. What's the uncertainty?

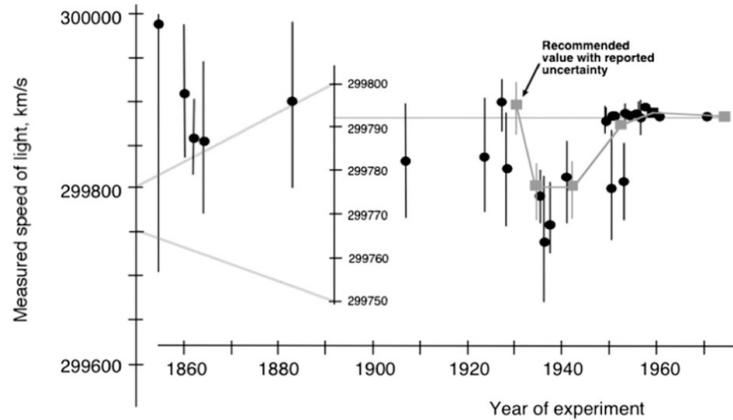
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- ❑ Human beings almost always underestimate uncertainty
- ❑ MANY sources of uncertainty in typical models
  - ⌘ Uncertainty in input parameters
  - ⌘ Uncertainty from model structure (MUCH bigger, and harder to test and evaluate)
- ❑ For COVID-19 models:
  - ⌘ Virtually every parameter highly uncertain
  - ⌘ Major additional uncertainties from simplifications in model structures

24

# There's uncertainty everywhere – even in estimating the speed of light

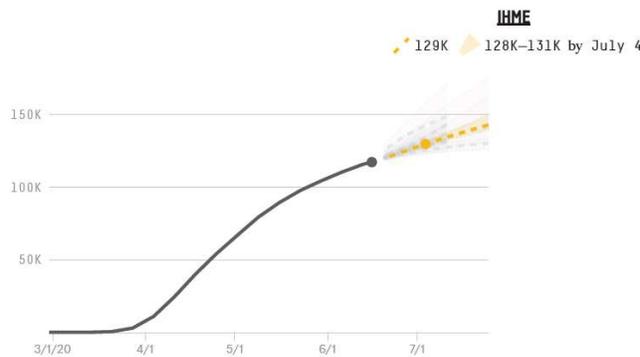
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Source: M. Granger Morgan, PNAS, 2014

25

# Assumptions... and uncertainty



This model combines anonymized mobile phone data and current social distancing policies to estimate how much contact exists between people in a given area. It assumes that current policies and movement patterns will continue until new infections drop to a very small number. The model was [changed significantly](#) on May 4.

Source: FiveThirtyEight.com

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## Example: The Kai et al. COVID-19 masking models

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- ❑ Study used 2 different models, adjusted to fit pandemic behavior in several locations
- ❑ Concluded >80% mask use could dramatically cut spread of disease
  - ⊗ Lower levels not effective
  - ⊗ Not effective if started after 50 days of pandemic
- ❑ Recommended immediate requirements for mask use
  - #masks4all

Widely reported:

VANITY FAIR

The New York Times



MSNBC

South China Morning Post



27

## Example: The Kai et al. COVID-19 masking models (II)

28

- ❑ How valid are key assumptions?
  - ⊗ Outcome driven crucially by assumed mask effectiveness (real mask use might be more or less effective)
  - ⊗ Worthwhile effort to test models/assumptions against data from pandemic so far
- ❑ Can the modelers explain surprising results?
  - ⊗ Ineffectiveness of lower levels of mask use easy to explain –  $R_0$  reduced, but not to  $<1$
  - ⊗ 50-day figure seems clearly an artifact of model conditions
- ❑ Who says?
  - ⊗ Authors not epidemiologists, study not yet published in journal
- ❑ Subject to peer review?
  - ⊗ Not when reported – may be undergoing review now

28

## An over-simplified idea (model) of how masks might work

29

- ❑ Suppose  $R_t$  would otherwise be  $\sim 2-3$
- ❑ IF:
  - ⊗ Infected person's mask reduces chance of infection at each contact by 50%
  - ⊗ Non-infected person's mask reduces their chance of infection by 50%
  - ⊗ Almost everybody is wearing masks when in contact with others
- ❑ Then masks might reduce risk of infection by 75%, cut  $R_0$  to  $< 1$



Source: Spencer Platt/Getty Images

29

## 10 questions for policymakers to ask in considering model results

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1. How valid are the key assumptions?
2. How does the model do in reproducing the system's past behavior?
3. Can the modeler explain why the model behaves as it does, and why the real world should do the same?
4. How do the results of this model compare with the results of other more or less independent models?
5. How well do the pieces of the model represent the real behavior of the real things they are modeling?

30

## 10 questions for policymakers to ask in considering model results (II)

31

6. Does the model include key interactions that the policymaker can guess would occur in the real world?
7. Does the model include interactions and effects that do not seem to correspond to those in the real world?
8. Has the model been subject to peer review?
9. Who says? What is the reputation, and what are the likely biases, of those who made and are using the model?
10. What's the uncertainty?

31

## Humility → Adaptive management

32

- Uncertainty reigns – we don't really know what the results of major policy shifts will be
- Where possible, need to look for “adjust as you learn” strategies – shifting in response to results, developments
- Here, too, need for balance, understanding the system
  - ⌘ In some cases, “doing a little to see how it works” may not work – may need a larger initial shift to get the desired system response
  - ⌘ Small changes may be worse than none in some cases (e.g., sending a signal that's all you can do)
  - ⌘ Some situations may be highly non-linear – small change may have one effect, twice as much may have dramatically different effect
- Nevertheless, should always look for adaptive, flexible approaches, avoid rigid lock-ins

32

## Use the tools – but careful, they’re sharp!

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“No sensible policymaker would base the globe’s future on a single model, a single set of computer runs, a single viewpoint, or a single national, ethical, or disciplinary perspective.”

-- William Nordhaus, 2008

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## For further reading...

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Maggie Koerth, Laura Bronner, and Jasmine Mithani, “Why It’s So Freaking Hard to Build a Good COVID-19 Model,” *FiveThirtyEight.com*, March 31, 2020

<https://fivethirtyeight.com/features/why-its-so-freaking-hard-to-make-a-good-covid-19-model/>

Afreen Siddiqi and Kaveri Iychettira, “What Policymakers Should Ask Modelers,” *Project Syndicate*, April 21, 2020

<https://www.project-syndicate.org/commentary/predictive-models-four-questions-for-policymakers-by-afreen-siddiqi-and-kaveri-iychettira-2020-04?barrier=accesspaylog>

C. Avery et al., “Policy Implications of Models of the Spread of Coronavirus: Perspectives and Opportunities for Economists,” *NBER*, April 2020

<https://www.nber.org/papers/w27007>

“Masking Protects Your Community. Not Just You” <http://dek.ai/masks4all/>

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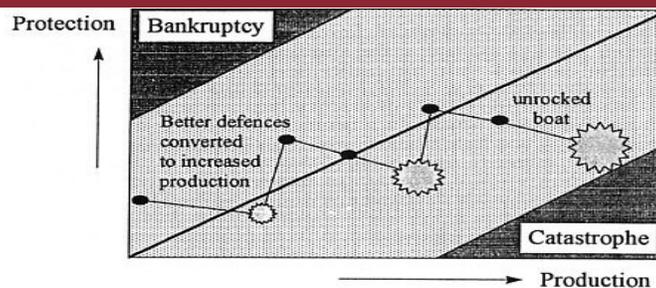
## Backup slides if needed...

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## Risk management: avoiding both complacency and bankruptcy

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Source: James Reason, *Managing the Risks of Organizational Accidents* (Ashgate, 1997)

- Imaginary organization starts with protection emphasis
- Complacency leads to increasing shift toward production emphasis until incident occurs
- Long period with no incidents can lead to catastrophe – unless means put into place to counter complacency

36

## Tight coupling and “normal accidents”

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- ❑ “Normal accidents” theory: Accidents will occur inevitably – be “normal” – in systems that are:
  - ⌘ Complex (so we don’t understand all their interactions)
  - ⌘ Tightly coupled (so a problem in one part of the system affects other parts faster than controllers can respond)
  - ⌘ Argument: redundancy won’t solve the problem, may make it worse (by making systems more complex)
- ❑ Potential solutions:
  - ⌘ Make systems less complex, better understood
  - ⌘ Make coupling looser
- ❑ How much insight does this theory offer?
  - ⌘ Was tight coupling a key part of 2008 financial crisis, Deepwater Horizon spill, Fukushima...?

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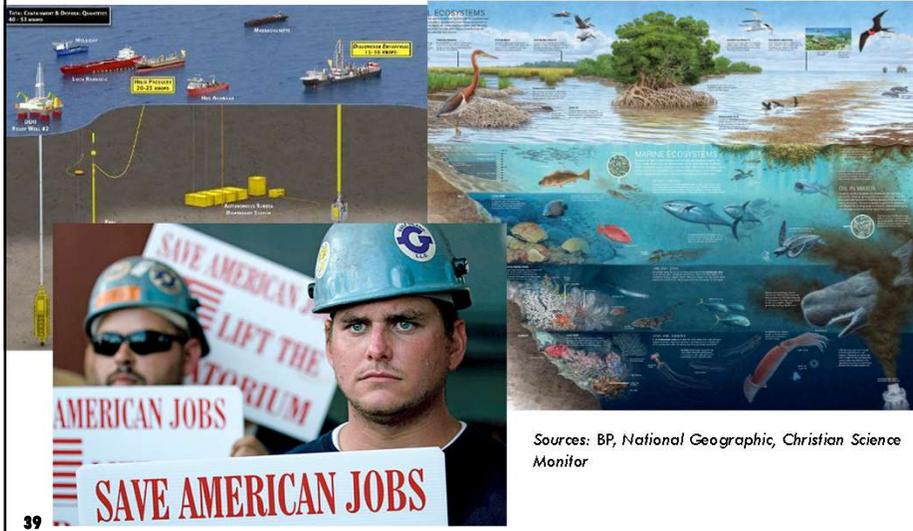
## Policy problems as complex systems

38

- ❑ Complex systems
  - ⌘ Many parts
  - ⌘ Interactions which are not fully understood
  - ⌘ Emergent properties – different from the sum of the parts
- ❑ Some key properties relevant for policy:
  - ⌘ Stocks and flows
  - ⌘ Feedbacks: positive (decreases stability), negative (increases stability)
  - ⌘ Thresholds
  - ⌘ Tight coupling vs. loose coupling
- ❑ Some types of system analysis often used for policy
  - ⌘ Networks
  - ⌘ Adaptive agents

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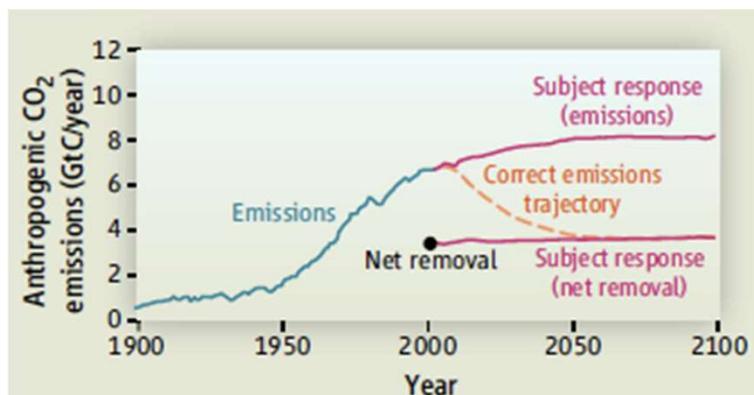
## Complex, intersecting, technical, ecological, economic, political systems



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## Misunderstanding stocks and flows

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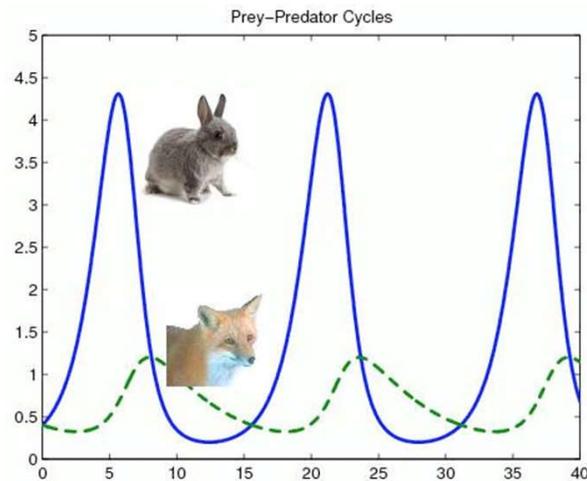


Source: John Sterman, "Risk Communication on Climate: Mental Models and Mass Balance," *Science*, 24 October 2008, Vol. 322, pp. 532-533.

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## Non-linear behavior: e.g., predator-prey models

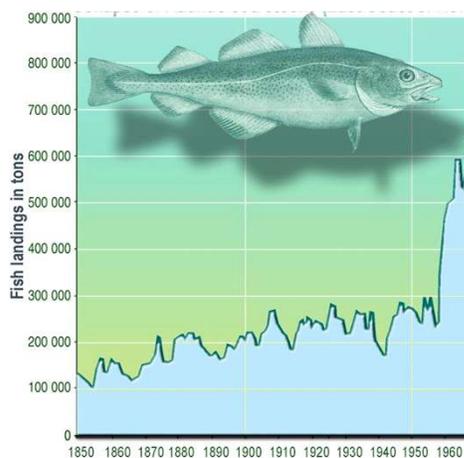


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Source: Scholarpedia.org

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## Sometimes the past doesn't predict the future: watch out for tipping points!

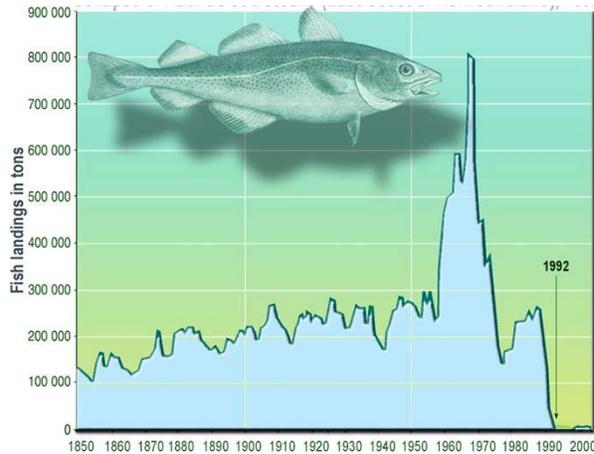


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Source: Millenium Ecosystems Assessment

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## Sometimes the past doesn't predict the future: watch out for tipping points!



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Source: Millenium Ecosystems Assessment

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## A critical element – understand the *incentives* of players in the system

46

- In response to a policy intervention your PAE proposes:
  - ⊗ What incentives will program managers have to implement it one way rather than another?
  - ⊗ What incentives will line workers have?
  - ⊗ What incentives will recipients or targets of the policy have? How will they respond, and how will that affect the intervention's success?
  - ⊗ What would you do in that position? (Ask yourself this again and again as you go...)

46

## Policy resistance – many flavors

47

- ❑ “Moral Hazard” – reducing risks causes more dangerous behavior
  - ⌘ E.g., people wearing seatbelts drive faster
- ❑ Elements of some policies are self-defeating
  - ⌘ E.g., staff cuts to improve budget picture lead to more overtime and more costly production problems
- ❑ Push-back by affected actors reduces effectiveness
  - ⌘ E.g., industry pressure to weaken regulations or enforcement

*Policymakers must seek to understand the policy system well enough to anticipate, plan for key elements of policy resistance*

47

## Be on the alert for system effects in policy problems...

48

- ❑ Seek to understand the overall system context for each policy problem you're addressing
  - ⌘ Especially what all participants have *incentives* to do
- ❑ Look out for feedbacks and policy resistance
- ❑ Look out for non-linear behavior, possible thresholds
- ❑ See if you can identify small changes to the system that might have high leverage (e.g., critical nodes in a network, or changing key incentives)
- ❑ Seek to design policies for sustainability:
  - ⌘ Structure incentives so that participants have interests in making the system keep working
  - ⌘ Structure processes to enable system to learn and adapt

48