The Promise and Pitfalls of Systems Modeling: A Practitioner's Perspective

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NASEM Roundtable

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Topics

- Requirements for a useful and reliable systems model.

- The role of qualitative maps.

- Levels of evidence and the "possibility frontier". (Could Big Data/ AI help?)

- Obesity modeling: different issues → different models.

- Modeling equity and social justice.

- Effective modeling projects: approach to data, participants, apprenticeship.

DISCLOSURES
I have no financial conflicts to disclose.
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Models can help us think more expansively—
for better understanding and decision making
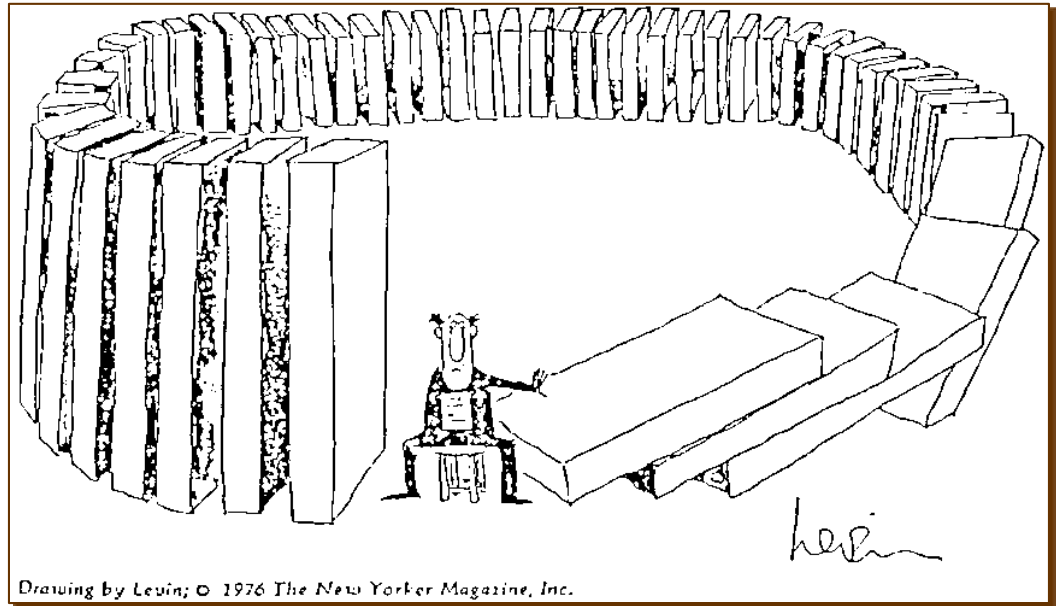
Drawing by Levin; © 1976 The New Yorker Magazine, Inc.

A model can get intervention impacts correct—and be useful for decision making—even if its baseline predictions are imprecise.

That's why "all models are wrong, but some are useful."

Sterman JD (2002). All models are wrong: reflections on becoming a systems scientist. *Sys Dyn Rev* 18(4):501-531.

Homer JB, Hirsch GB (2006). System dynamics modeling for public health: background and opportunities. *AJPH* 96(3):452-458.

Simulation approaches for systems modeling

System Dynamics (SD) Simulation	Discrete Event Simulation	Micro-simulation or Agent-based models
• **Compartmental (lumped)** • **Stock-flow cascades, feedback loops** • **Continuous time (longer time horizon)** • **Deterministic, but sensitivity testing gives an envelope of possibilities** • **1 run: seconds at most.**	• **Stochastic, operationally detailed** • **Discrete time (shorter time horizon)** • **1 run can be fast, but many runs required for summary findings.**	• **Micro-sim: individual actors <u>without</u> interaction (large N)** ➢ **Diverse patterns of attributes by individual** • **Agent-based: individual actors <u>with</u> interaction** ➢ **Diverse patterns of interaction (networks)** ➢ **Emergence of group or spatial clusters** • **1 run: often 1 hour or more.**

Different methods and emphases, but they all agree:

## Models should be testable, focused, and developed scientifically.

Homer JB (1996). Why we iterate: scientific modeling in theory and practice. *SD Review* 12(1):1-19.

Levy DT, Mabry PL, et al. (2010). Simulation models of obesity: a review of the literature and implications for research and policy. *Obesity Reviews* (17 pp.) doi:10.1111/j.1467-789X.2010.00804

Foresight UK obesity system map (2008)

Foresight
Obesity System Map

Expansive and causal but unfocused and untestable
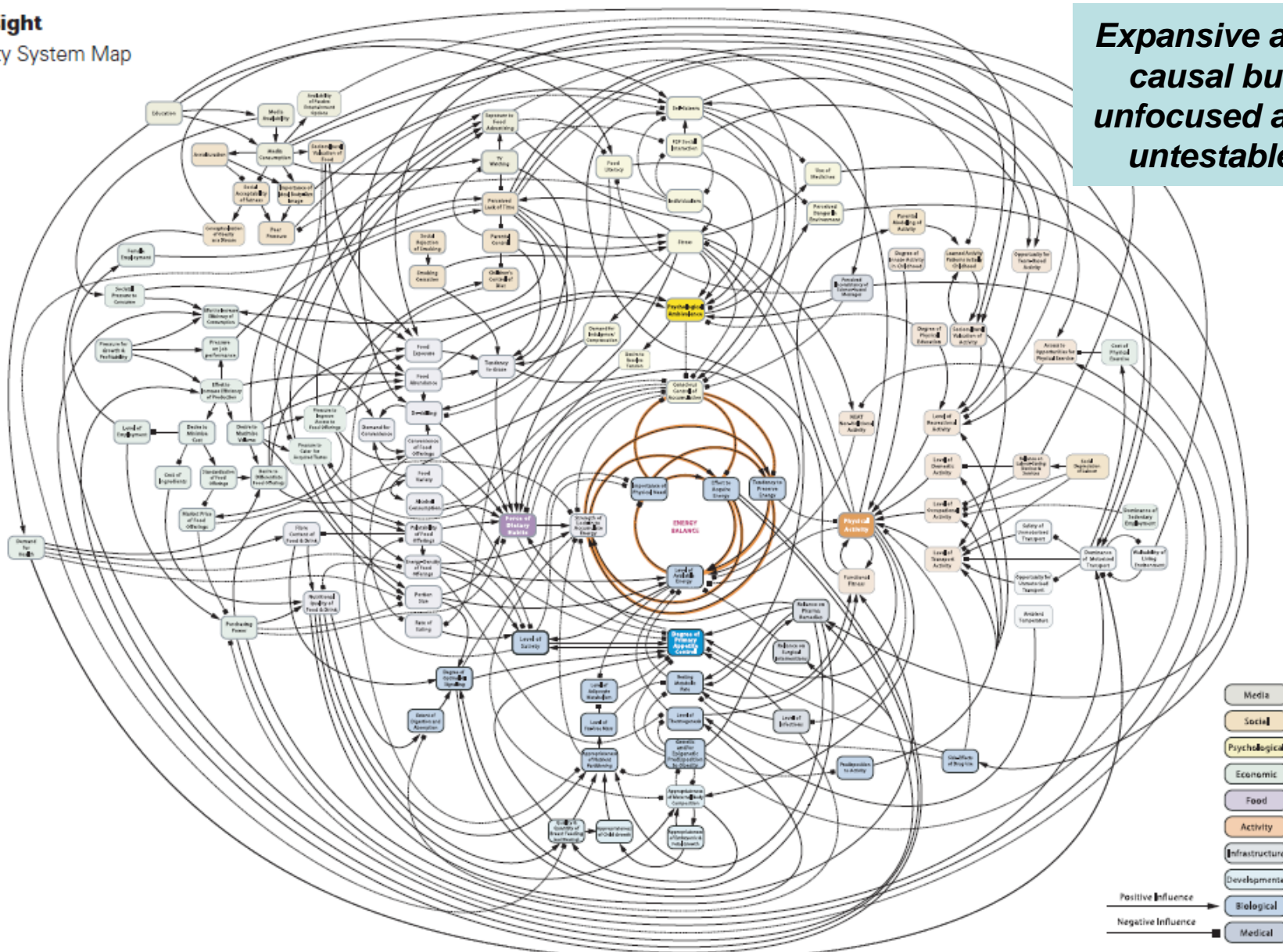
The role of qualitative maps and group modeling

"Qualitative mapping introduces circular causality and provides a medium by which people can externalize mental models and assumptions and enrich these by sharing them." - E Wolstenholme (1999)

"We agree that system description through mapping can be a useful activity. It improves the process of thinking about the structure underlying a problem. However, maps are notoriously unreliable tools for behavioral inference. Only through formal testing can one solidly bridge the gap from structure to behavior." - Homer & Oliva (2001)

"Participatory or group modeling was created to enrich and strengthen the modeling process, not water it down or simplify it. It wasn't supposed to be a way to shortcut the hard work of modeling, nor to open the door to using maps instead of testable, quantitative models."
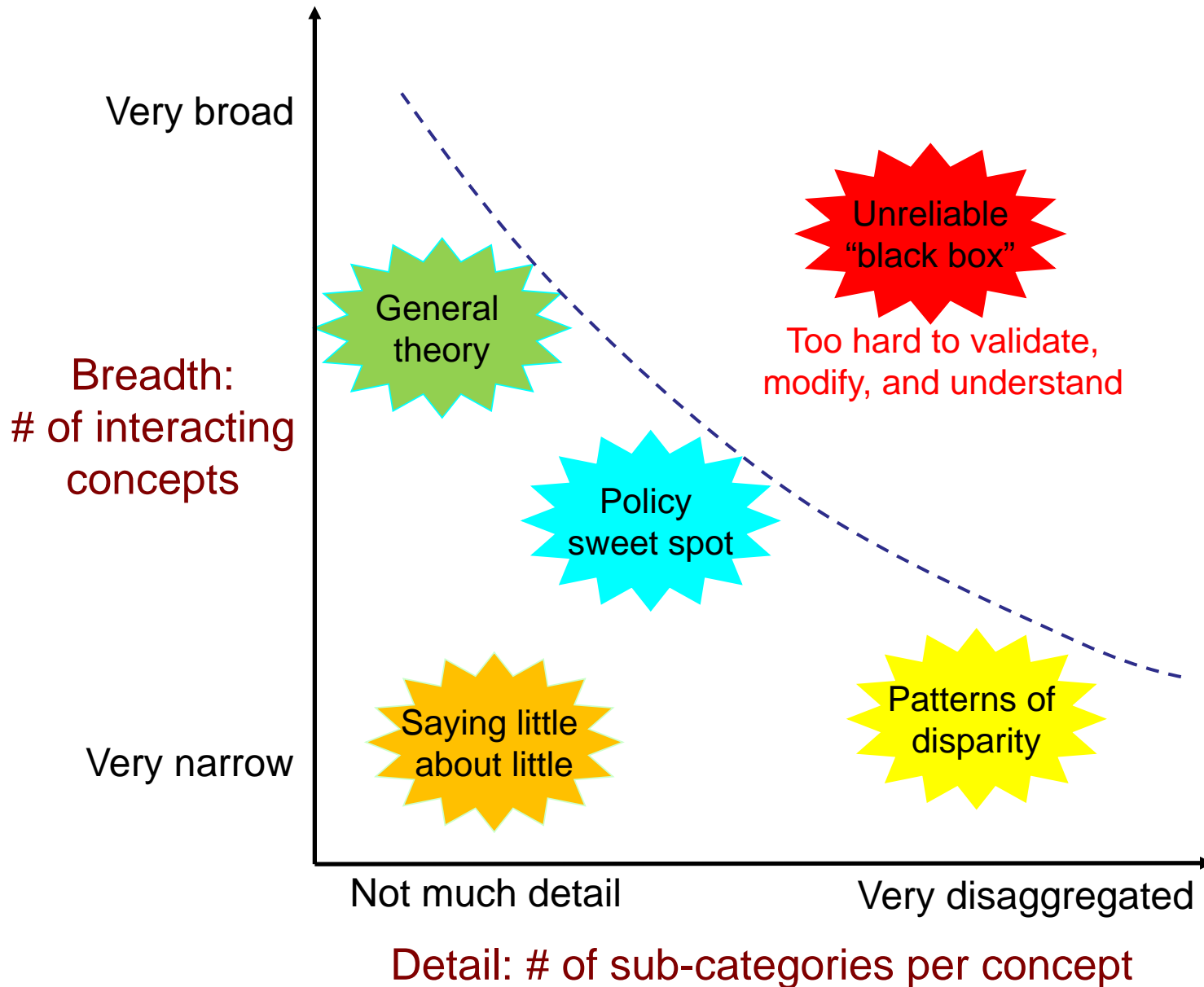
- G Richardson quoted in Homer (2019)

Wolstenholme EF (1999). Qualitative vs. quantitative modelling: the evolving balance. JORS 50:422-428.

Homer J, Oliva R (2001). Maps and models in system dynamics: a response to Coyle. SD Review 17(4):347-355.

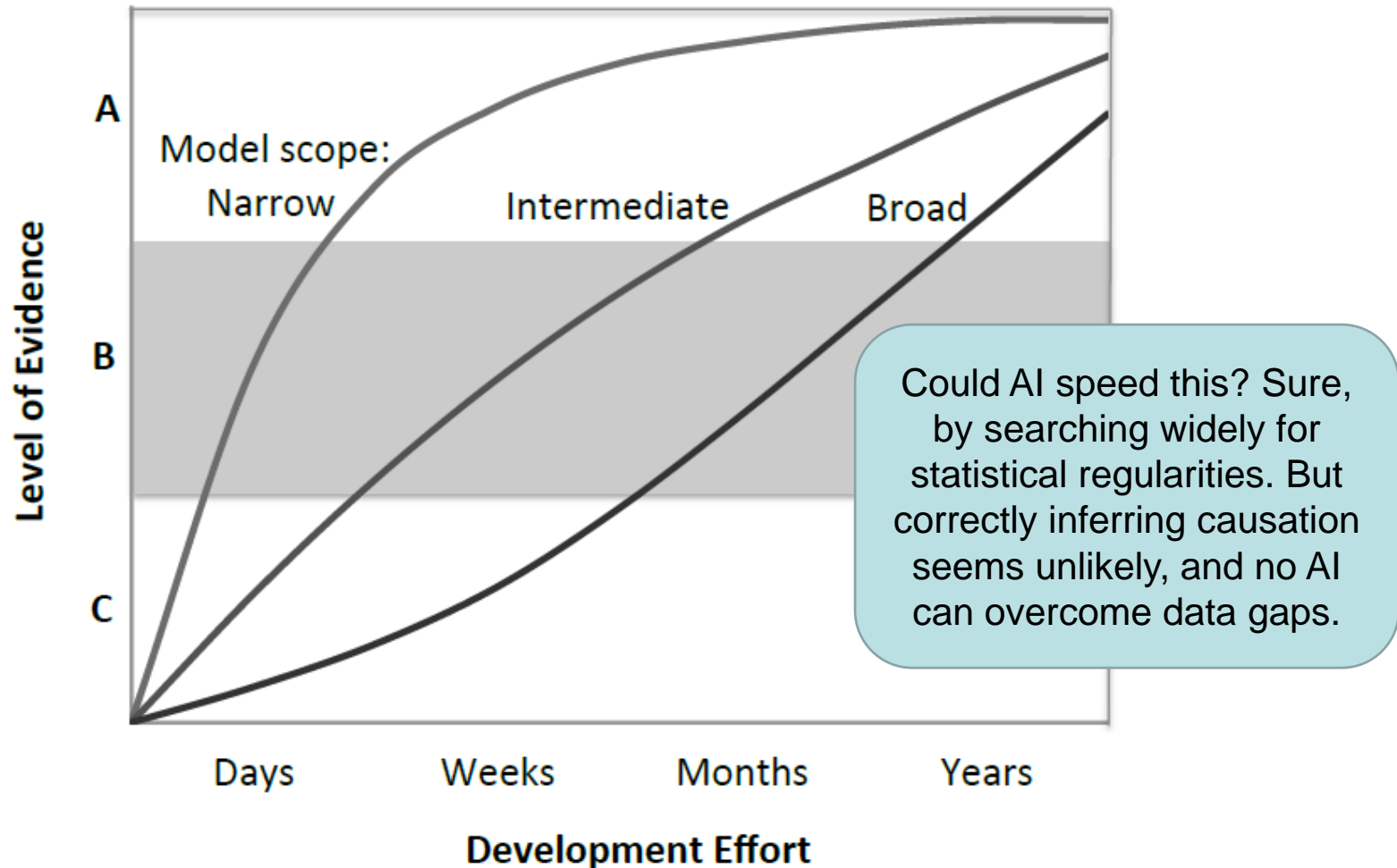Homer J (2019). Group model building: a dialogue (with George Richardson). SD Society Blog, September 2019.

The "possibility frontier" of reliable modeling

Effort-time-data required for reliable modeling
as affected by model scope

Could AI speed this? Sure, by searching widely for statistical regularities. But correctly inferring causation seems unlikely, and no AI can overcome data gaps.

Homer J (2014). Levels of evidence in system dynamics modeling. *Sys Dyn Rev* 30:75-80.

A life-course "BMI transitions" model (CDC 2005):
to infer caloric gaps and compare prevention vs. treatment

Dynamic Population BMI Framework
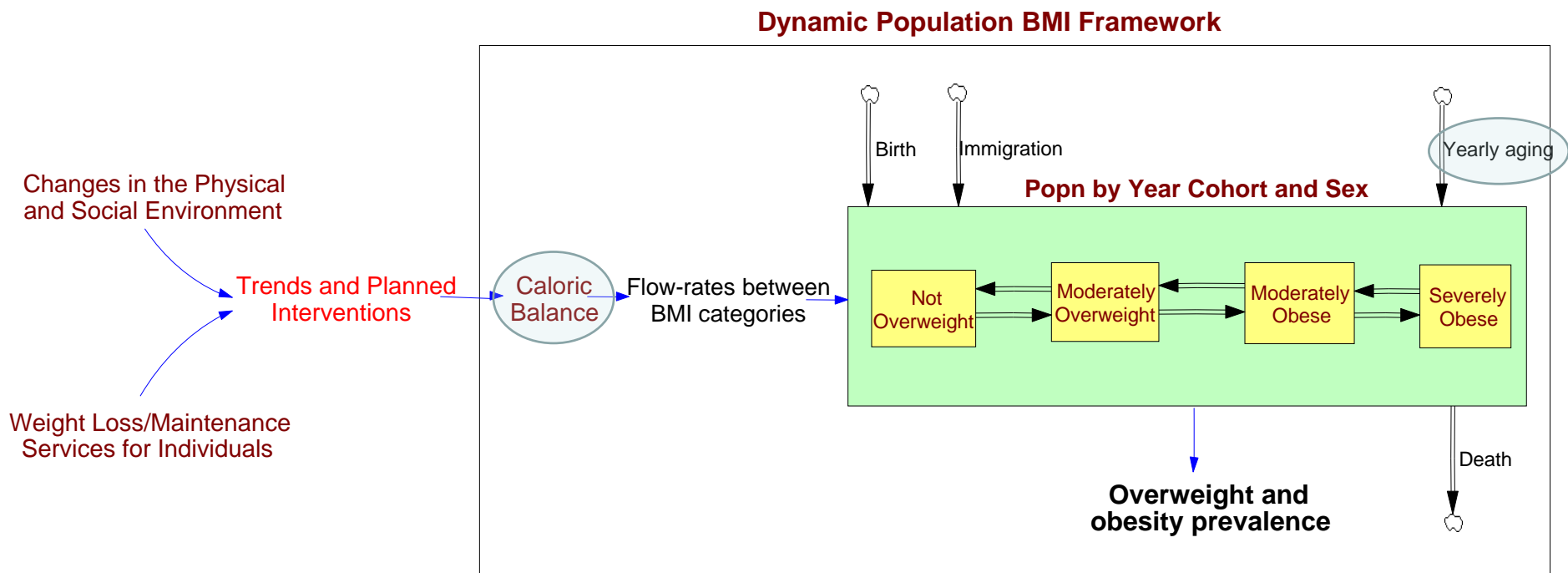
Longitudinal data sources:

NHANES (1971-2002): BMI prevalence for 20 age/sex categories, median BMI & height per category.

NHANES (2001-02): 1-year weight change by age/sex category in adults (upflows/downflows).

Arkansas school K-12 assessment (2004-05): 1-year weight change in kids (upflows/downflows).

Census (1970-2000 and projected): population, death, birth, immigration.

Homer J, Milstein B, Dietz W, Buchner D, Majestic E. (2006) Obesity population dynamics: exploring historical growth and plausible futures in the U.S. 24th International SD Conference, Netherlands.

Findings from the 2005 study

- Caloric imbalance vs. 1970 has been only 1-2% (<50 cal./day) within any given age, sex, and BMI category.

- Impacts of changing environments on adult obesity take decades to play out fully through the aging structure: "carryover effect".

- Youth interventions will likely have relatively small impact on future adult obesity.

- Ideal policy would combine preventive interventions with effective weight loss options for people with obesity.

Other modelers have taken a similar calorie-based "BMI transitions" approach:

Wang YC, Colditz GA, Kuntz KM (2007). Forecasting the obesity epidemic in the aging U.S. population. *Obesity* 15(11):2855-2865.

Fallah-Fini S, Rahmandad H, et al. (2014). Modeling US adult obesity trends: a system dynamics model for estimating energy imbalance gap. *AJPH* 104(7):1230-1239.

Other SD models addressing obesity

- Individualized weight management strategy.[1]

- Food market transformation.[2]

- Population obesity affecting diabetes onset and progression *[CDC]*.[3]

- Population obesity as part of a causal chain from modifiable risk factors to hypertension, hyperlipidemia, diabetes, and CVD *[CDC]*.[4]

  - Including the carryover of some habits from childhood to adulthood.

  - Addressing different regions of the country, allowing a comparison of historically advantaged and disadvantaged areas.

- Population obesity as part of a causal chain from social determinants to overall morbidity and mortality at a county level *[ReThink Health]*.[5]

[1]Hamid TKA (2009).*Thinking in circles about obesity*. Springer: New York.

[2]Struben J, Chan D, Dube L (2014). Policy insights from the nutritional food market transformation model. *Ann NY Acad Sci* 57-75.

[3]Jones A, Homer J, et al. (2006).Understanding diabetes population dynamics. *AJPH* 96(3):488-494.

[4]Hirsch G, Homer J, et al. (2014). Using simulation…for reducing CVD risks. *AJPH* 104(7):1187-1195.

[5]Milstein B, Homer J (2020). Which priorities for health and well-being stand out…in large urban counties? *Milbank Quarterly* 98(2):372-398.

A model of community actions/conditions (incl. equity) in response to a shock like COVID-19
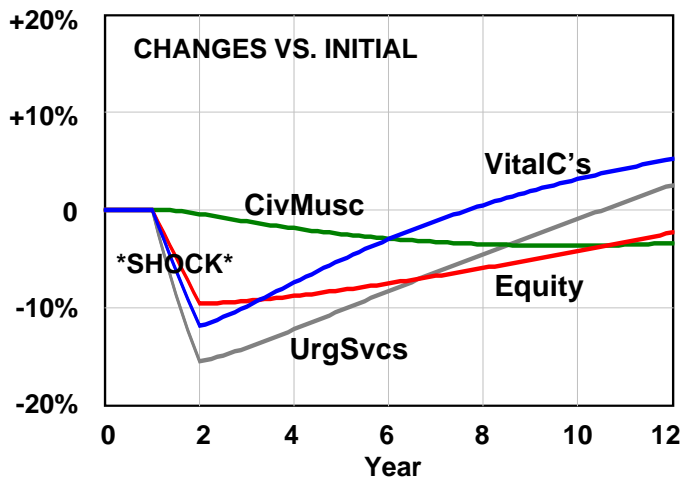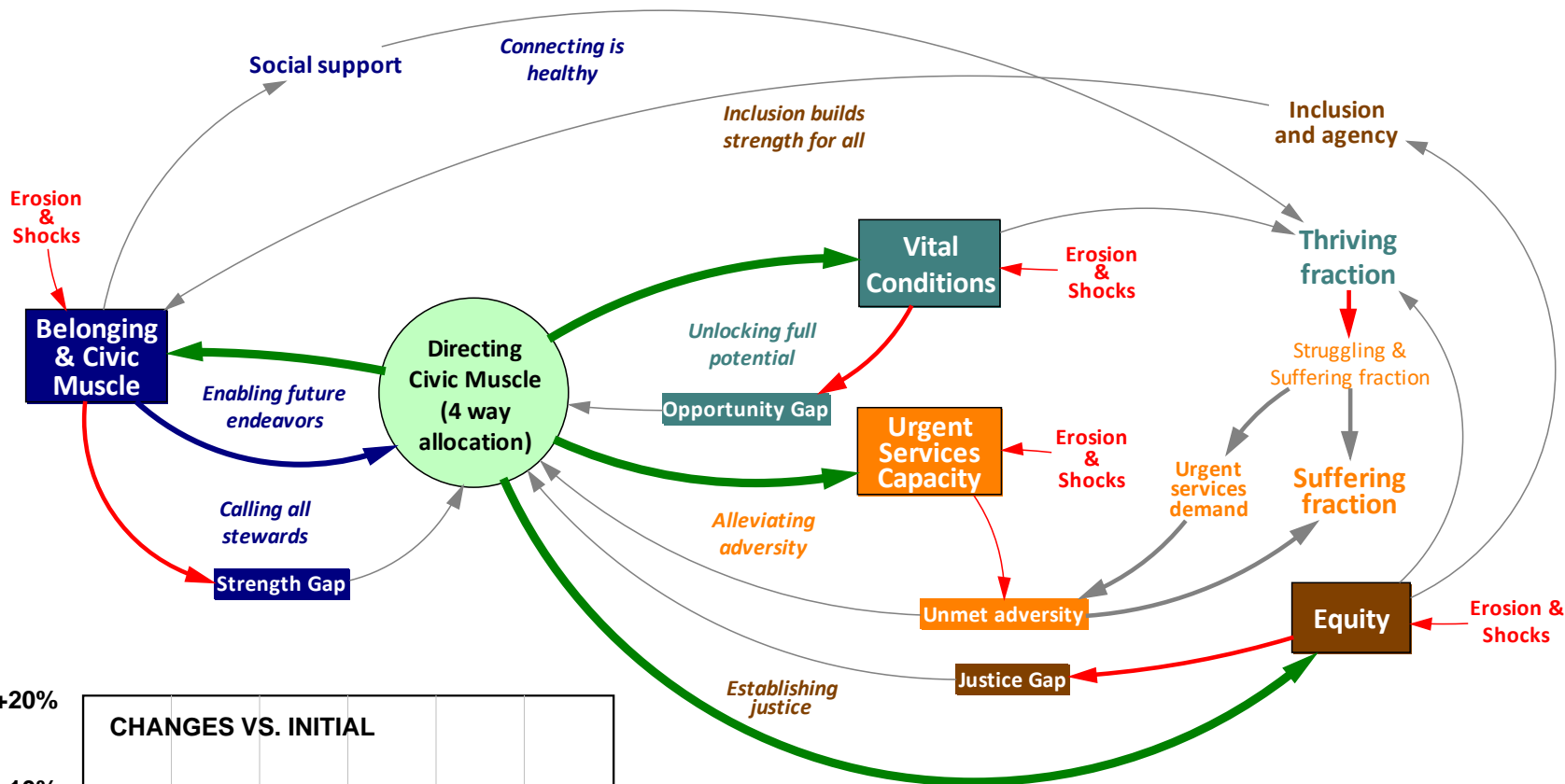
Work in progress for ReThink Health. Based loosely on CDC's Healthy People 2030 Well-Being Framework, initialized to US averages using data from County Health Rankings and Gallup Well-Being Survey.

We need local case studies and longitudinal data to move this from a thought-provoking "toy" to a more serious tool.

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Blueprint for an ideal (well-funded, year-plus) systems modeling project

Follow best practices for building, testing, documentation.*

Anchor to well-established datasets, plus best studies.

Data analyst plus statistician.

Team with stakeholders, DMs, and SME advisors.

Keep other thought leaders in the loop.

Junior modelers as apprentices (mentorship).

*Homer J (2019). Best practices in SD modeling, revisited. *SD Review* 35(2):177-181. Rahmandad H, Sterman JD (2012). Reporting guidelines for simulation-based research in social sciences. *SD Review* 28(4):396-411.

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