**NSF Meeting and Recommendations for Research on Enhancing Socially and Behaviorally Modulated Mathematical Models for Human Epidemiology:**

**Conference Report**

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Eli P. Fenichel, and Timothy Reluga

Over the last two centuries, mathematical models have developed as tools in the description, forecasting, and analysis of the spread of infectious diseases. Beginning with the work of William Farr on smallpox (1840), public health researchers have used numbers and modeling to explain and predict the courses of epidemics. An important insight of early epidemiology was that mathematical theory helped scientists understand how the course of infection within a person and transmission to others can explain national and global epidemics. From Farr’s auto-regression models and Florence Nightingale's statistical analyses, to Ross-McKendrick compartmental models, to modern agent-based network models, a rich ecosystem of epidemic models can now inform statistical inferences, public policy design, and scientific research.

Because infectious disease epidemics are social processes, all epidemiological models contain behavioral assumptions. However, these assumptions are often implicit, and their relation to the knowledge accumulated in basic behavioral research is not always clear. The current paper summarizes a workshop designed to improve the conceptualization of impact of human behavior in epidemiological models.

The workshop started with seven pre-recorded plenary review presentations (see [videos](https://uofi.box.com/s/ge92bfv99qzg4msxqq2tdkbbza73sele)). Each presentation was followed by a plenary panel discussion (see notes attached), and three parallel open discussions in breakout rooms. Five of the seven plenary talks clarified how human behavior is incorporated into extant epidemiological models. The other two talks reviewed recent behavioral research with clear implications to epidemiological models. The meeting agenda and the list of attendees appear in the Appendix. The conference website is [here](https://giesbusiness.illinois.edu/bridging-disciplinary-divides-conference).

**Conceptualization of Human Behavior in the Leading Epidemiological Models**

The five plenary talks, summarizing extant epidemiological modeling, highlighted five main approaches to the conceptualization of human behavior: (a) classical models, (b) contact structure models, (c) rational choice models, (d) inductive game models, and (e) network and agent-based models.

Classical epidemiological models build on explicit assumptions concerning the spread of an infection and tend to lack explicit assumptions concerning human behavior relevant to transmission. Yet, the leading models include implicit behavioral assumptions. Specifically, they assume that individuals move through different health states. For example, in the basic “Susceptible, Infected, or Recovered” (SIR) model, the states are Susceptible, Infected, or Recovered with immunity (or removed), and the transition between these three states is captured parametrically. The parameters in classic SIR models are transmission and recovery rates. *When these parameters are neither time nor state varying, the resulting models impose strong implicit behavioral assumptions - namely that behavior is invariant to persons, situations, or times.*

Contact structure models extend compartmental models by parametrically capturing mixing rates among exogenous defined types. These models tend to capture non-time varying average behaviors differentiated by predetermined groups such as different ages, genders, or residence locations. *Implicit in this approach is the assumption that people might select their type (e.g., people who use drugs) before the estimation**of the groups’ parameters but do not change their type after the estimation.*

Rational choice models replace the static behavioral assumptions described above with the rationality assumption. This assumption implies*a decomposition of the underlying behavioral model into three factors: (1) the set of strategies that everyone can use; (2) the information the decision maker perceived and the subjective value (utility) of the feasible outcomes; and (3) the way individuals choose among their strategies.*

Inductive game models generalize rational models by adding specific biases and abstraction of learning. *For example, these models have been used to capture factors like anchoring and groupthink.*

Networks and agent-based models extend the models presented above by incorporating the environment, pre-existing contact patterns, incentives, and strategy of each individual. *Under one cognitive interpretation of this assumption, each agent observes the behavior of its neighbors (and maybe also more removed others) and tends to select the modal choice.*

**Examples of Behavioral Models and Questions that Can be Used to Improve Epidemiological Models and Disease Prevention**

The two behavioral plenary talks summarized two lines of behavioral research with clear implications to epidemiological models. The first line (Pronsky’s talk) focused on basic decision processes. This research suggests that people tend to rely on small samples of past experiences. This tendency implies bimodal reaction to rare risks. Where most people underweight rare risks (like the risk of infection), significant minorities tend to overweight certain rare risks (as in the risk of vaccination side effects).

The second behavioral plenary talk (Albarracin’s talk) addressed the impact of communications and behavioral interventions, centered first around the paradox that even though nobody doubts the impact of information on behavior and health behavior specifically, the actual impact of an informational message is close to 0. Therefore, we need to understand the conditions under which information has an influence, the temporal lag of this influence, and interactions with human behavior over time. In addition, we need to explicate and understand the impact of other interventions, including those that have the potential to impact behavior directly. This understanding must also be contextualized within the historic course of an epidemic and how to best match interventions to the stage of an epidemic.

**Open Questions, and Suggested Directions for Future Research**

The panels and breakout rooms discussions highlight four main obstacles to effective accumulation of knowledge between epidemiological modelers and behavioral scientists. First, the large volume of the behavioral literature, and the situation-specific nature of many of the hypotheses, imply that it is difficult for epidemiological modelers to identify the behavioral research that can help them improve their assumptions.Second, the technical nature of the leading epidemiological models, and the implicit nature of the behavioral assumptions, imply that it is difficult for behavioral scientists to propose refinements of the leading models. Third, the absence of a general model of behavioral prediction and change limits progress by a multiplication of studies of the same constructs with different names and frequent reinvention of the wheel due to disciplinary silos. Fourth, although the epidemiological data for some epidemics are available in real-time, large-scale efforts to collect behavioral data longitudinally are nonexistent.

We believe that NSF can help address this obstacle by encouraging the submission of proposals that explicitly present and compare alternative refinements of the leading epidemiological models and advance behavioral, social, and economic research that can contribute to those refinements. This report summarizes research ideas that emerge from the discussion in the breakout rooms. Those relevant to the Division of Mathematical Sciences appear below. Other ideas potentially relevant to other divisions (e.g., SBE) appear in the Appendix.

1. **Problem of epidemiological-modeling language.** An obstacle that the conference identified concerns the language of epidemiological models. Thus, one recommendation is to fund projects that translate epidemiological models into a language that social, behavioral, and economic scientists can understand and help refine. Projects that, for example, create new nomenclature that exists in the social, behavioral, and economic scientists will help to then refine the incorporation of behavior into the models. Another example involves the addition of “behavioral sensitivity analysis” to epidemiological analyses. Although we see the value of starting with the simplest model that captures the results (even if its behavioral assumptions are inconsistent with basic behavioral research), it is important to know if the predictions are sensitive to the replacement of the simplified assumptions with the assumptions suggested by the relevant behavioral literature.
2. **Problem of limiting, unrealistic assumptions within epidemiological modeling.** Another problem is that the assumptions of epidemiological models lack realism and precision. For example, SRI models often treat behavior as classes of individuals, such as people who use drugs, without more explicit recognition that people vary in the extent to which they perform a behavior as a function of contextual variables such as space, time, and interpersonal contexts. Therefore, future multi-disciplinary projects could review model assumptions more explicitly and investigate how to make improvements in these assumptions to make them consistent with reality. For example, research could tackle a particular limitation, seek a relevant theory, and test model improvements to offset the problem. Projects that uncover limitations and rigidity in modeling assumptions would also be worthwhile. For example, researchers could systematically evaluate whether models closely reflect reality through a combination of inductive and deductive methods, systematic review, and/or analyses of how models perform with data from different diseases, periods, or populations. This problem is complex and includes the different facets described below.
3. **Absence of a comprehensive, agreed-upon formulation of human behavior to incorporate into epidemiological modeling**. A problem that plagues the behavioral, economic, and social sciences is the lack of a comprehensive formulation of behavior that is shared across scientists and disciplines. Therefore, it seems desirable to encourage multi-disciplinary projects that select or build a broad, bold approach to explain behavior and health outcomes during a pandemic.
4. **Insufficient attention to basic behavioral, social, and economic research to build epidemiological models**. Another limitation is that there is no clear pipeline to ensure rapid, mutual influences between basic research in behavioral, social, and economic sciences, and epidemiological modeling. Studies testing specific basic processes to develop novel questions for epidemiological modeling seem worthwhile.
5. **Insufficient incorporation of model of policy decisions**. Although epidemiological models often present the outcome of different policy scenarios, how decisions are made is rarely modeled even though this aspect is key from an explanatory and intervention perspective. Thus, it would be useful to promote research on the factors that influence decisions and information use by policymakers and integration of these factors into epidemiological models.
6. **Inadequate incorporation of complex interactions between individual and cultural differences**. Another limitation is that individual behavior varies as a function of attitudes, norms, risk perceptions, and other motivational and cognitive factors that can interact with group differences, including culture. Thus, projects that model how the salience of cultural aspects (e.g., from race-targeted PSAs or neighborhoods with different demographic compositions) changes people use of internal representations (e.g., norms versus perceptions of risk) should be investigated. Research that compares performance of alternative epidemiological methods to model these questions should be particularly encouraged.
7. **Lack of nuance and absence of recognition that the outcome of a behavior can affect performance of that behavior in the future**. Traditional epidemiological models fail to provide nuanced depictions of behavior, especially when behaviors are correlated with outcomes. Therefore, it would be beneficial for researchers to work on projects that rely on social, behavioral, or economic theory to model recursive relations by which behavior affects outcomes but outcomes also affect behavior, sometimes in combination with policy interventions.
8. **Lack of theory for population level phenomena.** Human behavior models are quite sophisticated in individual behavior but naive in many other ways, including the population level kind of predictions. This problem may be ameliorated with research on the processes leading to different outcomes at the aggregate versus the individual levels and determining the effect of those processes on epidemiological models.
9. **Absence of systematic methods to define epidemiological models**. Another area for improvement identified during the conference concerns the lack of systematic, agreed-upon methods to define epidemiological models. For example, a project may tackle parameter selection and establish possible ways of balancing data-driven and theory-based approaches. Whereas data-driven approaches have limitations such as data completeness, bias, and sensitivity, adding complexity to the model increases computational burden. Tests of systematic methods to select parameters for epidemiological prediction are therefore desirable.

**APPENDIX**

**Other Research Ideas about SBE Research Relevant to Epidemics**

1. Studies that clarify the co-existence of insufficient sensitivity to the risk of pandemics, and oversensitivity to the risk of vaccination. These studies should examine the relationship of this pattern to basic research in decisions from experience.
2. Studies that use machine learning to predict vaccination rates.
3. Research on the failure to understand expert evaluation and its relation to the tendency to trust fake news.
4. Studies that integrate basic decision-making research that focuses on deviations from rational choice into epidemiological modeling.
5. Studies of the effect of experience on the way people treat objective data and expert’s evaluation of data.
6. Studies of the best enforcement policies for different regulations and clarification of the feasibility of enforcing different regulations.
7. Studies of the impact of enforcement and incentives on vaccination.
8. Studies of the way people learn from the experience of others in the context of pandemics.
9. Exploration of the conditions under which beliefs persist and the role of social pressure.
10. Studies that clarify the difference between predictions of short term and long-term epidemiological outcomes.
11. Implementation science projects in which a research group teams up with a government jurisdiction (e.g., a state or county) to design a policy test and then implement and study the policy.
12. Projects that study vaccination by integrating economic factors such as good distribution and incentivization and psychological variables that constitute immediate determinants of behavior.
13. Projects that integrate insights from behavioral prediction models into social network theory and research.
14. Research that collects longitudinal data to compare the impact of various behavioral, social, and economic variables at different points of a pandemic or at different phases of a given policy implementation (e.g., vaccination).
15. Research that combines longitudinal and experimental methods to develop a necessary and sufficient account for the role of behavior in epidemics, comparing different infections of varying characteristics (e.g., airborne versus sexual transmission).
16. Research using meta-analysis including individual-level synthesis to understand the impact of different interventions to control epidemics, particularly projects that compare cultures, nations, or demographic groups and seek to understand mechanisms of change.
17. Research on business and government processes related to privacy and information sharing to determine what improves data access and how actors make decisions about data sharing.
18. Projects that seek to understand variability in the social and/or economic impact of different diseases, particularly in combination with social health disparities.
19. Projects that study media impact on policy and citizens’ reactions, including research on social media, during an epidemic.
20. Research on the reasons for population noncompliance during an epidemic.
21. Research that separates different reasons for vaccination hesitancy and investigates ways of addressing it using a combination of experimental and modeling methods.
22. Projects designed to estimate and understand the impact of communication, both positive messages as well as misinformation/disinformation, on health behavior during a pandemic.
23. Research that uses computer science advances to better create or disseminate messages during a pandemic.
24. Projects that test different methods of tailoring information to individuals, including projects that use computational methods.
25. Research that uses experimental methods to identify the best interventions to increase vaccination.
26. Research that studies fatigue and passive responses in the population and how these vary with the stage of a pandemic.
27. Research on fear appeals and reactions to fear during a pandemic.
28. Studies of trust in information and how the public health system makes communication decisions, particularly in interaction with government factors and ideas about the democratic process.
29. Research on how changes in scientific information are communicated and the best methods of revising beliefs in response to such changes.
30. Research that tests theories of how different messages mix within a network or over time to produce positive or negative attitudes during a pandemic.
31. Studying how different government agencies interact to make decisions and the impact of those interactions and processes on the pandemic.
32. Research that innovatively integrates multiple data sources (e.g., social media, geolocation, survey) to test theories about interaction in networks.
33. Research that investigates the role of opposing forces in the decision to vaccinate (free ride vs. network peer effects) and integrates these forces into epidemiological models.
34. Research projects that use natural experiments and propose methods to address limitations such as the lack of a valid control group (i.e., everyone is being treated in natural experiments during epidemic/pandemic).
35. Research projects that investigate how to overcome data limitation. In particular, research that addresses lack of micro level data about behavior is necessary. A lot of modeling groups use publicly available data which is aggregated. But if behavior changes in an epidemic, this changes the dynamics even if the mean is constant.
36. Multi-disciplinary projects that investigate inconsistencies across disciplines in the definitions such as “rationality”.
37. Research projects that investigate how to deal with intertemporal forecasting in models with a rational decision maker and the model endogenously changes throughout time.
38. Research projects that investigate what should be included in utility function when the objective is maximizing utility. For example, should we have altruism in the case of COVID, when people are voluntarily social distancing?
39. Research projects that study the rules or aggregation for different psychological and behavioral variables. If you're deciding individually or as a family or a group, they're probably clear on differences between emotion and how that will transfer to the group. And something like deciding on a math problem, which is self-evidence. So, with one individual proposing that, that becomes the solution for the group.
40. Research projects that investigate how to use current agent-based models to add cognitive models that have value in them.

**SUPPLEMENT**

**Agenda Summary**

**Thursday, May 6**

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| --- | --- | --- |
| **EDT** | **CDT** | **Event** |
| 11:00 AM | 10:00 AM | Introduction (*Moderator*: Albarracin) |
| 11:20 AM | 10:20 AM | Epidemic modeling and behavior (*Plenary*: Eubanks; *Panelists*: Auld, Dangerfield, Sheeran; *Moderator*: Reluga) |
| 12:56 PM | 11:56 AM | Behavioral phenomena and their connection to epidemics (*Plenary*: Plonsky; *Panelists*: D’Onofrio, Finnoff, Gonzalez-Vallejo; *Moderator*: Erev) |
| 2:32 PM | 1:32 PM | Measuring response to policy changes and pathogen risks (*Plenary*: Murray; *Panelists*: Anderson, Bayham, Holtgrave; *Moderator*: Fenichel) |
| 4:08 PM | 3:08 PM | Network structure in epidemic models with behavior (*Plenary*: Fefferman; *Panelists*: Miller, Ognyanova; Vullikanti; *Moderator*: Reluga) |

**Friday, May 7**

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| **EDT** | **CDT** | **Event** |
| 11:00 AM | 10:00 AM | Introduction |
| 11:08 AM | 10:08 AM | Rational epidemic theory and game theoretic models (*Plenary*: Toxvaerd; *Panelists*: Gonzalez. Reluga, Werning; *Moderator*: Fenichel) |
| 12:44 PM | 11:44 AM | Connecting epidemic modelling to society (*Plenary*: Fenichel; Panelists: Sattenspiel, Tan, Tertilt; *Moderator*: Erev) |
| 2:20 PM | 1:20 PM | How communication and information lead to learning and behavior (*Plenary*: Albarracin; Panelists: Bauch; Palacios; Peters; *Moderator*: Erev) |
| 3:46 PM | 2:46 PM | Mini-Pitch Session |

*EDT = Eastern Daylight Time; CDT = Central Daylight Time*

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**Bridging disciplinary divides for behaviorally modulated**

**mathematical models in human epidemiology**

**May 6-7, 2021**

**Participant Biographies**

Daniel Ablin

***Master’s Student, Technion – Israel Institute of Technology***

Master's student in the area of game theory.

Or David Agassi

***Researcher, University of Haifa***

A young researcher, interested in the interaction between cognition, emotion, and human behavior.



Folashde Agusto

***Assistant Professor, University of Kansas***

I am a trained applied mathematician based in the department of Ecology and Evolutionary Biology at the University of Kansas; my work focuses on designing novel models to gain insight about emerging and reemerging infectious diseases of public health importance and how to mitigate the risks they pose to human health. My lab broadly addresses the following questions:

i) What are simple sustainable management strategies necessary to mitigate the risk from infectious diseases?  
ii) What are the effects of human behavior on disease spread and risk?  
iii) What are the evolutionary implications of host/pathogen interactions?  
I have designed and analyzed novel models for diseases like Ebola, avian influenza, bovine tuberculosis, Johne's disease, toxplasmagondii, Chikungunya, and malaria. My current work is on modeling tick-borne disease across the Great Plains, and understanding the role of human behavior on the transmission of COVID-19.



Dolores Albarracin

***Professor, University of Illinois at Urbana-Champaign***

Dolores Albarracin is an Argentine-American psychologist who studies social cognition, communication, and behavioral change. Her research (~ 180 publications and 6 books) has been recognized with an award for Outstanding Mid-Career Contributions to the Psychology of Attitudes and Social Influence from the Society of Social and Personality Psychology in 2018 and the Diener Award to Outstanding Mid-Career Contributions to Social Psychology from the same society in 2020.

Taylor Anderson

***Assistant Professor, George Mason University***

Dr. Anderson is an Assistant Professor in the Department of Geography and Geoinformation at George Mason University in Fairfax Virginia. Dr. Anderson develops novel spatial modeling and simulation approaches and implements these approaches to predict and analyze complex systems. Recently, Dr. Anderson and her team have been developing novel data-driven modeling approaches including agent-based models to better predict and understand the spread of COVID-19. The developed models provide support for decision-makers by exploring the effect of various policy interventions, human behavior, and mobility patterns on the number of COVID-19 cases and related deaths.

Andrew (Andy) Atkeson

***Professor, University of California, Los Angeles***

I have been working on behavioral SIR models to evaluate the impact of behavior on the dynamics of epidemics and in constraining our options for improving public health outcomes during an epidemic.



Chris Auld

***Associate Professor, University of Victoria***

Economist who specializes in applied microeconometrics, particularly applications in the study of health-related behavior.

Sharmistha Bagchi-Sen

***Program Director, National Science Foundation***

Sharmistha Bagchi-Sen holds a Ph.D. in geography from the University of Georgia. Her research interests include the geography of innovation, geographic implications of industrial evolution with a focus on biopharmaceuticals, agri-bio, and bioenergy sectors, energy transitions, foreign direct investment in the United States, and socioeconomic implications of urban-regional population shrinkage.



Saunak Basu

***Graduate Teaching Assistant, University of Illinois at Urbana-Champaign***

I am a 4th year PhD student in Information Systems. My research interest includes social media analytics, crowdfunding platforms, healthcare IT and machine learning applications in econometric settings.

Chris Bauch

***Professor, University of Waterloo***

Chris Bauch studies mathematical and computer models of interactions between infectious disease dynamics and human behaviour, using a range of different approaches. Since 2003, he has published dozens of papers on the topic in PNAS, The Lancet Infectious Diseases, Science, Nature Communications, and other journals. Study systems have included influenza, measles, pertussis, COVID-19, HIV, smallpox, and chlamydia. He also works on health economic evaluation of vaccines using dynamic models.

Jude Bayham

***Assistant Professor, Colorado State University***

I am an economist with research interests at the intersection of public policy, human health, and the natural environment. I am currently an Assistant Professor in the Department of Agricultural and Resource Economics at Colorado State University and in the Department of Epidemiology at the Colorado School of Public Health. My research on infectious disease focuses on integrating economic principles of behavior and risk into epi models of communicable disease. During the COVID-19 pandemic, my research has focused on the empirical analysis of non-pharmaceutical interventions.

Nita Bharti

***Assistant Professor, Center for Infectious Disease Dynamics, Pennsylvania State University***

Dr. Nita Bharti investigates the underlying links between humans, pathogens, and the environment. Her work focuses on the dynamics of host-environment interactions that drive movement and contact patterns as they relate to pathogen transmission and access to health care. Dr. Bharti has a PhD in biology and an MA in biological anthropology.

Matthew Biggerstaff

***Epidemiologist, Centers for Disease Control and Prevention***

Dr. Matt Biggerstaff has been with CDC since 2006 and an epidemiologist with the Influenza Division since 2009. In this role, he leads CDC influenza forecasting and modeling activities and works to understand and evaluate how forecasting and mathematical modeling can complement influenza surveillance and inform seasonal and pandemic influenza public health actions. Dr. Biggerstaff also works to develop methods to assess the severity of influenza seasons and pandemics and leads studies to estimate the health and economic impact of influenza and influenza vaccinations. He has also led and supported CDC’s modeling and forecasting response to the COVID-19 pandemic since January 2020.

Man Pui Sally Chan

***Research Assistant Professor, University of Illinois***

I received my Ph.D. training in Psychology. My research interests focus on the underlying psychological mechanisms behind health-related behaviors and decisions in health care contexts. I approach these problems with a unique combination of psychology theory and data science by incorporating the analysis of surveillance data, secondary datasets, surveys, and social media data (big data) to model patterns of infections and changes in behaviors.

Dennis Chao

***Senior Research Scientist, Institute for Disease Modeling, Bill & Melinda Gates Foundation***

I have a background in Computer Science. I developed agent-based models of influenza, cholera, and dengue transmission. Now studying racial disparities in maternal mortality in the US.

Fred Chen

***Professor, Wake Forest University***

Fred Chen is a professor of economics at Wake Forest University. Prof. Chen teaches microeconomics, mathematical economics, and game theory. His main research interests involve the application of economic principles to issues in public health, population biology, and sustainability studies.

Avinash (Avi) Collis

***Assistant Professor, University of Texas at Austin***

Avinash (Avi) Collis is an Assistant Professor at the McCombs School of Business at the University of Texas at Austin. He is also a digital fellow at the MIT Initiative on the Digital Economy and the Stanford Digital Economy Lab. He holds a PhD in Management Science from MIT Sloan School of Management. He has done research on several COVID-19 projects including quantifying the danger and importance of re-opening various types of locations, measuring the social spillovers of shelter in place policies and behavioral interventions to increase uptake of COVID-19 vaccine.

Forrest Crawford

***Associate Professor, Yale University***

Forrest W. Crawford is an Associate Professor of Biostatistics, Statistics & Data Science, Operations, and Ecology & Evolutionary Biology at Yale University. He is affiliated with the Center for Interdisciplinary Research on AIDS, the Institute for Network Science, the Computational Biology and Bioinformatics Program, and the Public Health Modeling Concentration. His research focuses on mathematical and statistical problems related to discrete structures and stochastic processes in epidemiology, public health, biomedicine, and social science. He received the NIH Director's New Innovator Award in 2016.

Andie Creel

***Master’s Student, Yale University***

I am a current master of environmental science student at Yale School of the Environment. I will be staying at Yale to pursue my Ph.D. in natural resource economics and sustainable development, beginning in the fall.

Ciara Dangerfield

***Programme Manager, University of Cambridge***

I have worked in the area of epidemiology modelling for the past 10 years. Since 2015 my focus has been on linking economic and epidemiology modelling, with a particular focus on using real options approaches to identify the optimal timing of control measures. I am currently the programme manager for the JUNIPER (Joint Universities’ Pandemic and Epidemiological Research) consortium which is a consortium of modelling groups providing advice to the UK government on the COVID-19 pandemic.

Dominika (Dom) Dec Peevey

***PhD Student, Pennsylvania State University***

I am a third year Ph.D. student studying disease ecology at Penn State. I have been working with measles data and outbreaks during my master’s and currently, in my Ph.D. program. I am interested in infectious disease dynamics and ecology in general.

Himel Dev

***PhD Candidate, University of Illinois at Urbana-Champaign***

I am a PhD candidate in Computer Science at the University of Illinois at Urbana-Champaign (UIUC). Broadly, my interests lie in Applied Machine Learning (model design), Data Science (insight generation) and Economics (causal explanation). I work under the supervision of Prof. Hari Sundaram, studying the successes and failures of content-based platforms, such as Stack Exchange and Reddit.

Katharina Dittmar

***Program Director, National Science Foundation***

Katharina Dittmar is now Program Director, Division of Environmental Biology at the National Science Foundation (NSF).

Peter Dolton

***Professor of Economics, University of Sussex***

Professor of Economics. Special interest in health economics and econometrics. Just written a paper on modelling covid.

Alberto (Fuffo) d’Onofrio

***Independent Researcher***

I work in Biomathematics for 25 years, obtaining results not so bad (1st centile of the Stanford Research List, Google H Index: 41, Google Citations: 6000). I co-edited with Piero Manfredi the first book, ever published on Behavioral Epidemiology, and we coauthored with other colleagues the short book "Statistical Physics of Vaccinations". Married with Francesca, we have a son (Edouard) and a cat (Poucky).

Cheryl Eavey

***Program Director, National Science Foundation***



Ido Erev

***Professor, Technion – Israel Institute of Technology***

Ido Erev is the President of the European Association for Decisions Making. His research highlights a robust experience-description gap: people exhibit oversensitivity to rare events when they decide based on a description of the incentive structure, but experience reverses this bias and triggers underweighting of rare events. Comparison of alternative models favors the assumption that people tend to select the option that led to the best outcome in a small sample of similar past experiences. These observations imply that incentives are most effective when they ensure that the socially desirable behavior maximizes payoff, and minimizes the probability of regret.



Baltazar Espinoza

***Postdoctoral Research Associate, University of Virginia - Biocomplexity Institute***

Baltazar Espinoza is originally from Mexico, he got his PhD. in Applied Mathematics at Arizona State University. He is currently a postdoc at the Biocomplexity Institute and Initiative at the University of Virginia.

Stephen Eubank

***Professor, University of Virginia - Biocomplexity Institute***

For 25 years I have been modeling and simulating socio-technical systems, especially infectious disease epidemiology. I led one of the founding research groups of the NIH Models of Infectious Disease Agent Study (MIDAS) consortium. During this pandemic, a team at the Biocomplexity Institute has provided weekly briefings to the Commonwealth of Virginia and Dept. of Defense and participated in CDC modeling efforts.

Bita Fayaz-Farkhad

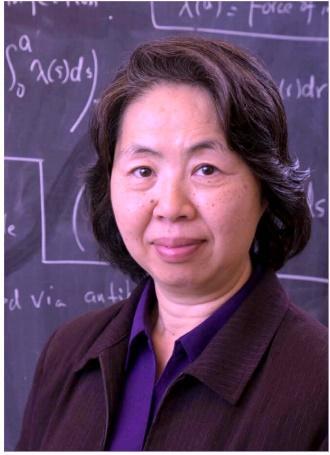
***Postdoctoral Research Associate, University of Illinois at Urbana-Champaign***

Bita Farkhad is an applied microeconomist and a postdoctoral researcher with a research focus broadly on the economics of health. Her research concerns how public programs and policies affect individuals’ health behaviors and involve the use of microeconometric methods to evaluate and inform public policy.

Nina Fefferman

***Professor, University of Tennessee, Knoxville***

Fefferman is a professor in both the Ecology and Evolutionary Biology and Mathematics departments at UT Knoxville, where she is an Associate Director of the One Health Initiative and the Director of the National Institute for Mathematical and Biological Synthesis (NIMBioS). Her research uses mathematical modeling to explore the behavior, evolution, and control of complex systems with application in areas from basic science (evolutionary sociobiology and epidemiology) to informing real-world policies and deployable technology (bio-security, pandemic preparedness, wildlife conservation, and cyber-security).



Zhilan Feng

***Professor of Math, Purdue University and Program Officer (DMS), National Science Foundation***

Zhilan Feng completed her Ph.D. in Mathematics at Arizona State University in 1994. Her areas of research include differential equations and dynamical systems and their applications in biology, ecology, and epidemiology. She has co-authored 3 books and over 120 research articles in these areas.



Eli Fenichel

***Professor, Yale University***

I am a natural resource economist. I have worked most of my career on the bioeconomics of infectious disease and how people respond to risk.

David Finnoff

***Professor, University of Wyoming***

Finnoff has developed coupled economic/ecological models to understand the tradeoffs facing policy makers considering recoveries of endangered species, to provide policy insight for systems faced with risk of invasive species, and for policy analysis in the face of native pests. Finnoff has also coupled economic and epidemiological models for policy analysis of the risk of infectious disease spread in human and wildlife populations.

Anna Gilbert

***Professor, Yale University***

Anna Gilbert received an S.B. degree from the University of Chicago and a Ph.D. from Princeton University, both in Mathematics. In 1997, she was a postdoctoral fellow at Yale University and AT&T Labs-Research. From 1998 to 2004, she was a member of technical staff at AT&T Labs-Research in Florham Park, NJ. From 2004 to 2020, she was with the Department of Mathematics (with a secondary appointment in Electrical and Computer Engineering) at the University of Michigan, where she was eventually the Herman H. Goldstine Collegiate Professor. In 2020, she moved to Yale University as the John C. Malone Professor of Mathematics and Professor of Statistics & Data Science.

Cleotilde (Coty) Gonzalez

***Research Professor, Carnegie Mellon University***

Cleotilde (Coty) Gonzalez is a Research Professor of Decision Sciences in the Department of Social and Decision Sciences and the Founding Director of the Dynamic Decision Making Laboratory (DDMLab) at Carnegie Mellon University. She is also affiliated to the Security and Privacy Institute (CyLab), the Center for Behavioral Decision Research (CBDR) and other research centers at Carnegie Mellon University. Her work focuses on the experimental studies and computational representations of the cognitive processes involved in decisions from experience in dynamic environments.

Claudia Gonzalez Vallejo

***Professor of Psychology, Ohio University***

Claudia Gonzalez Vallejo is Professor of Psychology at Ohio University with expertise in decision analysis, statistics, and the psychology of judgment and decision-making. She has prior experience in international affairs working for the United Nations Development Fund for Women (UNIFEM), and more recently at the US State Department, Bureau of Conflict and Stabilization Operations under the Jefferson Science Fellowship by the National Academies of Sciences, Engineering, and Medicine.

Matthew Gordon

***PhD Candidate, Yale University***

Matthew Gordon is a PhD candidate in environmental economics at Yale University. His current research focuses on the intersection of policy and behavioral responses to natural disasters.

David Holtgrave

***Dean and SUNY Distinguished Professor, University of Albany***

David Holtgrave, Ph.D., is the Dean of the University at Albany School of Public Health and SUNY Distinguished professor. His three-decade career in public health has included senior positions at CDC, Emory University and Johns Hopkins University, and he served on the Presidential Advisory Council on HIV/AIDS during President Obama’s administration.

Michael Johansson

***Biologist, Centers for Disease Control and Prevention***

Michael Johansson is a Biologist at the Centers for Disease Control and Prevention Dengue Branch and a Visiting Scientist at the Harvard TH Chan School of Public Health Center for Communicable Disease Dynamics. He uses statistical and mathematical modeling to investigate infectious disease dynamics and identify ways to improve surveillance, prevention, and control.

Haesung (Annie) Jung

***Postdoctoral Research Assistant, University of Illinois at Urbana-Champaign***

Annie Jung's research primarily focuses on prosocial behavior. She studies how social factors (e.g., prosocial model, social norms) affect prosocial development and variation across societies. She also studies how cognitive factors (e.g., construal level) affect individual preference to engage in different forms of prosocial behavior. Recently, she has extended her work to health domains, to examine how prosocial motivation impacts various health outcomes, including vaccination. Prior to joining the Social Action Lab, she earned her bachelor's and master's degree in psychology from Yonsei University (South Korea), and her doctoral degree in social and personality psychology from the University of Texas at Austin.

Jeremy Koster

***Program Director, National Science Foundation***

Jeremy Koster is a is a program director at NSF. He received his PhD. in Anthropology from Penn State University in 2007

Sicong (Zone) Liu

***Postdoctoral Researcher, University of Illinois at Urbana-Champaign***

Sicong is interested in the human self-regulation process. His past research focused on applying motor, cognitive, and neuroscience measurements and methods to understanding the optimization process of human performance. He is also interested in the mathematical approach in researching and aims to incorporate mathematical simulations in his future studies.

Amyn Malik

***Epidemiologist, Yale Institute for Global Health***

I am an infectious disease epidemiologist. I trained as a medical doctor before moving to epidemiology. My research interests are in area of respiratory infections mainly tuberculosis and COVID-19. I am also interested in ID modeling and transmission modeling.



Piero Manfredi

***Professor of Demography, University of Pisa, Italy***

After my training in demography i conducted most of my research in the population dynamics of infectious diseases and vaccination programs. Among my research areas: (i) the population dynamics of measles, (ii) the impact of demographic change on the transmission and control of infections, (iii) the measurement of contact patterns, (iv) the dynamics of varicella and herpes zoster. Since 2005 i have contributed to the development of the behavioural epidemiology of infectious diseases.

Katherine Meyer

***Professor Emeritus, Ohio State University and Program Director, National Science Foundation***

Dr. Katherine Meyer is Professor Emeritus of Sociology at The Ohio State University and Program Director of Social and Economic Sciences at the National Science Foundation. Her work examines social movements, religion, and social change in conflict, particularly in the Middle East.



Juan Meza

***Division Director, National Science Foundation***

I am currently serving as the Division Director at the National Science Foundation’s Division of Mathematical Sciences. My work focuses on applied mathematics (nonlinear optimization) and computational research, with an emphasis on methods for parallel computing.

Nolan Miller

***Helle Professor of Finance, University of Illinois at Urbana-Champaign***

Nolan Miller is the Daniel and Cynthia Mah Helle Professor in Finance at the Gies College of Business. An economic theorist by training, his more recent research has focused on understanding the impact of environmental variables on health.

Dina Mistry

***Network Scientist, Institute for Disease Modeling, Bill & Melinda Gates Foundation***

I am a network scientist currently working in the Epidemiology team at the Institute for Disease Modeling, a part of the Bill & Melinda Gates Foundation. I like studying people and why we do what we do. In particular, I have spent a lot of time thinking about how people interact in the physical world and how we can measure and model those interactions. My research has focused on characterizing and modeling the heterogeneity of social contact networks and mobility networks that are linked to the spread of infectious diseases and how this changes our understanding of disease dynamics.

Ujjal Mukherjee

***Assistant Professor, University of Illinois at Urbana-Champaign***

My research interests are focused towards healthcare analytics, particularly in the use of machine learning and statistical methods in healthcare problems, including precision medicine application in the area of cancer treatment, healthcare process and technology management. I have conducted in-depth field studies at large a large multi-specialty hospital in the Mid-western United States to study operational issues related to the effective use of surgical robots for delivering critical surgical care to OB/GYN and Urological patients. Apart from clinical research, I conduct methodological research in the area of statistics and machine learning such as high-dimensional quantiles, and Bayesian regularization methods for estimating sparse graphical networks. Recently I have been actively associated with COVID-19 research and mitigation activities as an active team member of the team of researchers from UIUC studying policy measures for mitigation of COVID-19.

Eleanor (Ellie) Murray

***Assistant Professor, Boston University***

Dr Murray is an Assistant Professor of Epidemiology at Boston University School of Public Health who focuses on improving methods for evidence-based decision-making and human-data interaction. Her work primarily focuses on applications to public health and clinical epidemiology, including applications to HIV, HPV, cancer, cardiovascular disease, psychiatric disorders, musculoskeletal disorders, social and environmental epidemiology, and maternal and adolescent health. Dr Murray also conducts meta-research evaluating bias in existing research. During the COVID pandemic, Dr Murray has been working on improving science communication about epidemiology and public health concepts and identifying and addressing barriers to equitable vaccination distribution and acceptance. Dr Murray is an Associate Editor for Social Media at the American Journal of Epidemiology, and can be reached on Twitter at @epiellie.

Pablo Andres (Andy) Neumeyer

***Professor of Economics, Universidad Di TELLA – Harvard Growth Lab***

Pablo Andres Neumeyer is a professor of economics at Universidad Torcuato Di Tella and a research associate at Harvard's Center for International Development. His research is in the fields of international finance, macroeconomics, and development. He obtained his Ph.D. in economics from Columbia University in 1992 and studied economics as an undergraduate at Universidad de Buenos Aires. He was Argentina's Central Bank's chief economist between February 2016 and June 2018.

Michelle O’Brien

***Research Scientist, Institute for Disease Modeling, Bill & Melinda Gates Foundation***

Michelle O'Brien has a Ph.D. in Sociology from the University of Washington, where she specialized in Demographic Methods. As a doctoral student, she worked on a team developing a survey-initialized agent-based model to assess the demographic consequences of violent conflict scenarios in Nepal. For her dissertation, she examined the long-term consequences of the Tajikistani Civil War for abortion and miscarriage, migration, and girls' education. Michelle works on the Family Planning team at the Institute for Disease Modeling to develop data-driven approaches to increase access to safe, effective, and voluntary family planning services.

Katherine (Katya) Ognyanova

***Assistant Professor, Rutgers University***

Katherine Ognyanova is an assistant professor at the School of Communication & Information, Rutgers University. Her research examines the effects of social influence on civic and political behavior, confidence in institutions, information exposure/evaluation, and public opinion formation. Ognyanova’s methodological expertise is in computational social science, network science, and survey research. She is also a co-lead of the COVID States Project ([www.covidstates.org](http://www.covidstates.org))

Connor Olson

***Graduate Research Assistant, Pennsylvania State University***

I am a second year math Ph.D. student at Penn State University. I work with Tim Reluga on disease modeling as well as studying topics in evolutionary biology.

Mark Orr

***Associate Research Professor, University of Virginia – Biocomplexity Institute***

Mark Orr is a research associate professor in the Network Systems Science and Advanced Computing division. Orr was originally trained as a cognitive psychologist at the University of Illinois at Chicago. Orr received augmentation to this training with postdoctoral fellowships in computational modeling (Carnegie Mellon), neuroscience (Albert Einstein College of Medicine), and epidemiology/complex systems (Columbia University). Over the past decade, he has become heavily involved in understanding dynamic processes and drivers of risky behavior and decision making, primarily in a public health context, at the scale of the individual and populations. Orr is now currently expanding these ideas into other contexts and for other applications (e.g., DoD, DOE, DHS).

Damie Pak

***Postdoc, Pennsylvania State University***

I am a postdoc at Penn State University interested in using mathematical modeling for ecological processes.

Juan Palacios

***Postdoc, Massachusetts Institute of Technology***

Juan Palacios is currently a post-doctoral researcher at the Massachusetts Institute of Technology, in the Center for Real Estate. His research focuses on environmental economics, real estate and health economics. He is currently focusing on estimating changes in individual behavior in response to infection risk using experimental and quasi-experimental methods.

Prabasaj Paul

***Epidemiologist, Centers for Disease Control and Prevention***

I am an epidemiologist with the Mathematical Modeling Unit at the Division of Healthcare Quality Promotion, CDC. I have been on the Modeling Section of the CDC COVID-19 response since March 2020.

Mark Peecher

***Associate Dean of Faculty and Deloitte Professor of Accountancy, Gies College of Business, University of Illinois at Urbana-Champaign***

Mark E. Peecher, CPA PhD is the Associate Dean of Faculty, the Deloitte Professor of Accountancy, and the Academic Director of the Center for Professional Responsibility in Business and Society at the Gies College of Business at the UIUC. He specializes in psychology-based research about detection of deception, subconscious bias in judgment, and the assessment of risk. Mark currently serves as Co-Editor-in-Chief at Accounting, Organizations & Society. He also has served as editor at The Accounting Review and on editorial boards at Auditing: A Journal of Practice & Theory, Contemporary Accounting Research, The Accounting Review, and Issues in Accounting Education.

Malgorzata (Malgo) Pesznska

***Professor, Oregon State University and Program Director, National Science Foundation***

M. Peszynska is a rotating Program Director at the NSF-DMS; she is also a Professor at Oregon State University. Her field is applied and computational mathematics modeling, analysis, and simulation with real-life applications.

Ellen Peters

***Philip H. Knight Chair, University of Oregon***

Dr. Ellen Peters is the Philip H. Knight Chair and Director of the Center for Science Communication Research in the School of Journalism and Communication at the University of Oregon. She studies the psychology of human judgment and decision making and its links with effective communication techniques. She has published more than 150 peer-reviewed papers and is a fellow of the American Association for the Advancement of Science and other organizations. She has also worked extensively with federal agencies to advance decision and communication sciences in health and health policy and received an NIH Group Merit Award.

Ori Plonsky

***Assistant Professor, Technion – Israel Institute of Technology***

Ori Plonsky is a behavioral economist interested in prediction of behavior, topics on the boundary of data science and behavioral science, behavioral decision making, and behavioral policy design. He is an assistant professor in the Technion - Israel Institute of Technology, where in 2017 he obtained his Ph.D. He also holds a B.Sc. in Industrial Engineering and Management, B.A. in Economics and Management, and M.Sc. in Behavioral Science. Previously, he was a postdoctoral associate in the Center for Advanced Hindsight in Duke University and in the Israeli Democracy Institute.



Ellen Rafferty

***Health Economist, Institute of Health Economics***

Dr. Ellen Rafferty is a Health Economist with the Institute of Health Economics in Edmonton, Alberta, Canada. Dr. Rafferty’s research focuses on the epidemiologic and economic impact of public health policies, such as estimating the cost-effectiveness of immunization programs. She is currently helping lead the One Society Network, a cross-Canada team of economists and mathematical modelers whose goal is to integrate models and teams to evaluate the impact of infectious diseases and policy responses on all sectors of society.



Timothy (Tim) Reluga

***Associate Professor, Pennsylvania State University***



Eli Rosenberg

***Associate Professor, University of Albany***

Eli Rosenberg is an Associate Professor of Epidemiology at the University at Albany School of Public Health. Dr. Rosenberg’s research centers on applied and analytic studies that address current public health challenges in HIV, sexually transmitted infections, viral hepatitis, and emerging infectious diseases such as COVID-19, with a focus on surveillance, prevention, and social determinants. His work has been funded by and conducted in collaboration with the CDC, NIH, and New York State Department of Health.

Lisa Sattenspiel

***Professor, University of Missouri***

I have been working since the late 1970s on epidemic models with an emphasis on the importance of human social behaviors and the factors that bring people into contact and facilitate their spread. I originally developed mathematical models for the spread of infectious diseases in subdivided human groups and have switched over most of my work to agent-based simulations. I have modeled hepatitis A, HIV, measles, influenza, COVID-19, and other diseases in the US, a Caribbean island, Manitoba, Newfoundland and Labrador, and Alaska.

Sridhar Seshadri

***Professor, University of Illinois at Urbana-Champaign***

I work on modeling supply networks for risk management and on revenue management problems. Last several years, I worked on projects using large data and analytical techniques to inform policy on agriculture prices, growth of SME in manufacturing and healthcare operations.

Paschel Sheeran

***Professor, University of North Carolina at Chapel Hill***

Paschal Sheeran is a Professor in the Department of Psychology and Neuroscience at UNC-Chapel Hill. His research focuses on the intention-behavior 'gap' and interventions to improve the translation of intentions into health behaviors.

Eunha Shim

***Professor, Soongsil University***

My research focuses on computational modeling of infectious diseases including COVID-19 and intervention programs. I have worked on designing, analyzing, and simulating mathematical models of infectious diseases to inform public health policies and to project the potential impact of intervention strategies.

Brajendra (Braj) Singh

***Health Scientist, Centers for Disease Control and Prevention***

By training I am a population dynamics modeler. I have worked in the field of infectious disease dynamics modeling for more than 15 years. The infectious diseases that I have worked on include foot and mouth disease (e.g., 2001 FMD outbreak in the UK), Influenza-like illness, vector-borne diseases (lymphatic filariasis, dengue, Onchocerciasis). Currently I work on healthcare associated infections.

Rachel Slayton

***Lead, Mathematical Modeling Unit, Division of Healthcare Quality Control, U.S. Centers for Disease Control and Prevention***

Dr. Rachel Slayton is a PhD trained epidemiologist and infectious disease modeler. She leads a mathematical modeling unit focused on healthcare-associated infections and multi-drug resistant organisms in the U.S. Centers for Disease Control and Prevention (CDC)’s Division of Healthcare Quality Promotion, Epidemiology Research and Innovations Branch. She also serves as the Scientific Director for the Modeling Infectious Diseases in Healthcare (MInD-Healthcare) network and has co-led CDC’s COVID-19 mathematical modeling unit.



Hari Sundaram

***Associate Professor of Computer Science, University of Illinois at Urbana-Champaign***

My research is motivated by the need to solve large-scale collective-action problems. My group's research aims to understand human behavior at scale and empower individual decision-making. Our research contributes to applied machine learning, network science, and human-computer interaction.

Andy Tan

***Associate Professor, University of Pennsylvania***

Andy Tan (he/him) is Associate Professor of Communication at the Annenberg School for Communication and he leads the Health Communication & Equity Lab. Tan’s research program is aimed at advancing communication science to achieve health equity for all. His work examines the impact of marketing, media, and public health messages on health behaviors and outcomes among diverse populations including young adults, socioeconomically disadvantaged, and lesbian, gay, bisexual, and transgender (LGBT) populations. His research is informed by community-engaged research (CEnR) principles, persuasion and message effects theories, social determinants of health frameworks, minority stress and resilience frameworks, and implementation science. The goal of this work is to translate knowledge from communication science into scalable and culturally sensitive health interventions to alleviate tobacco- and cancer-related health disparities.

Troy Tassier

***Professor, Fordham University***

Troy Tassier, Ph.D., is Professor of Economics at Fordham University in New York City. He conducts research on the impact of social networks in economics and in public health outcomes and teaches courses on microeconomic theory and the economics of epidemiology.

Michele Tertilt

***Professor, University of Mannheim, Germany***

Michele Tertilt is a Professor of Economics at the University of Mannheim. Prior to joining the University of Mannheim, she was an Assistant Professor at Stanford University. For her research at the intersection of macroeconomics and family economics she has won numerous awards. Her recent work on the effects of COVID-19 on gender equality has received much attention in the media.

Florencia Torche

***Professor, Stanford University***

Florencia Torche is a social scientist with expertise in social demography, stratification, and education. Professor Torche’s scholarship examines inequality dynamics including intergenerational mobility, disparities in educational attainment, and assortative mating, among others. Her research also examines the influence of early-life exposures “starting before birth” on individual wellbeing and inequality. She is an elected member of the National Academy of Sciences, and the American Academy of Arts and Sciences since 2020.

Carlos Torelli

***Professor and Associate Head, Business Administration, University of Illinois at Urbana-Champaign***

Carlos Torelli is a professor of marketing, associate head of the department of business administration, and James F. Towey Faculty Fellow at the University of Illinois at Urbana-Champaign. His areas of expertise include global branding, cross-cultural consumer behavior, self-regulation, and persuasion. He looks to identify the key cultural factors that drive consumer behavior in a globalized economy and to uncover the underlying socio-cognitive processes for such culturally-driven behaviors. From 2016-2019, Torelli was a Center for Professional Responsibility faculty fellow, and from 2017-2020 he was executive director of Executive Education. He joined the University of Illinois in 2016, and earned a BE in civil engineering from Andres Bello Catholic University in 1986, an MBE from Simon Bolivar University in 1993, and an MBA from Marquette University in 1997. In 2007, he received his PhD in business administration from the University of Illinois at Urbana-Champaign.



Flavio Toxvaerd

***Economist, University of Cambridge***

Flavio Toxvaerd is an economist working on the economics of infectious diseases. Using techniques from epidemiology, dynamic optimization and game theory, he studies formal models of disease propagation with a special emphasis on equilibrium dynamics and the formulation of optimal policy.

Patricia Van Zandt

***Program Director, National Science Foundation***

Patricia Van Zandt graduated from Purdue University in 1992 with a Ph.D. in mathematical psychology. Her research interests include the development of Bayesian models for the analysis of human performance data, with a special emphasis on methods for analyzing data that contain contaminants and that arise from cognitive processes that change over time.

Anil Vullikanti

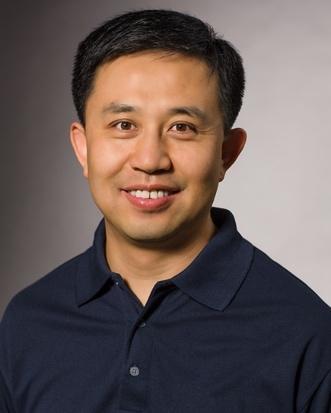
***Professor, University of Virginia***

Anil Vullikanti is a Professor in the Dept. of Computer Science and the Biocomplexity Institute at the University of Virginia. His research interests are in the broad areas of network science, dynamical systems, combinatorial optimization, and distributed computing, and their applications to computational epidemiology and social networks.

Junping Wang

***Program Director, National Science Foundation***

Dr. Wang is a program director at the Division of Mathematical Sciences, National Science Foundation. His research expertise is computational mathematics.



Shaowen Wang

***Professor, University of Illinois at Urbana-Champaign***

Shaowen Wang is Professor and Head of the Department of Geography and Geographic Information Science at the University of Illinois at Urbana-Champaign (UIUC). He has served as Founding Director of the CyberGIS Center for Advanced Digital and Spatial Studies at UIUC since 2013. His research interests focus on geographic information science and systems (GIS), advanced cyberinfrastructure and cyberGIS, complex environmental and geospatial problems, computational and data sciences, high-performance and distributed computing, and spatial analysis and modeling.

Ron Watkins

***Managing Director SHIELD Illinois & Associate Dean, Gies College of Business, University of Illinois at Urbana-Champaign***

Currently serving as Managing Director for SHIELD Illinois with responsibility for standing up testing statewide including seven labs, the distribution network, technology, supply chain, collections and external engagement. Prior Covid related responsibilities included selection of testing sites for Illinois Department of Public Health. Ron is also the Associate Dean for Strategy & Innovation at the Gies College of Business and a PhD student in Applied Health Sciences. His background has 10+ years in industry, 15 years in higher education, and a former active duty Army Officer.

Ivan Werning

***Robert Solow Professor of Economics, Massachusetts Institute of Technology***

Ivan Werning is an Argentinian economist with research focus in public finance and macroeconomics. He is the Robert M. Solow Professor of Economics at the Massachusetts Institute of Technology, where he has been since earning his PhD from the University of Chicago in 2002. He is a member of the American Academy of Arts and Sciences, a fellow of the Econometric Society, and a Research Fellow at the National Bureau of Economic Research.

Benjamin White

***Distinguished Fellow, University of Illinois at Urbana-Champaign***

I am a psychologist interested in health behavior prediction and change. My current work is on evaluating how interventions that try and change multiple behaviors work, as well as if these interventions have boundary conditions for efficacy. My other work has been on examining how community level factors predict behavior and change, as well as means of influencing persuasiveness of health communication.

Joseph Whitmeyer

***Program Director, National Science Foundation***

Joseph Whitmeyer has served as Director for the Sociology Program in the Division of Social and Economic Sciences within the Directorate of Social, Behavioral, and Economic Science at the National Science Foundation since July 2017. He earned a PhD in Sociology at the University of Washington in 1993 and a second PhD in Applied Mathematics at UNC Charlotte in 2010.

Youpei Yan

***Postdoc, Yale University***

My research intends to bridge economics and natural resources to provide analysis of human-environmental feedbacks that enables comparison between the value of nature and other resources. The framework is applicable to various human-environmental coupled systems in land use conservation, adoption of management practices in agriculture, mandating pollution abatement, and non-pharmaceutical interventions and infectious disease dynamics.

Yong Zeng

***Program Director, National Science Foundation***

Yong Zeng is a program officer in Statistics Program of DMS at NSF. His research interest includes statistical inference for stochastic processes, Bayesian methods and related computation, and statistical applications to genetics and network-traffic modeling, among others. He received his Ph.D. in Statistics from the University of Wisconsin-Madison in 1999.

Angela Zhang

***Research Assistant, University of Pittsburg***

Angela graduated from the University of North Carolina at Chapel Hill in 2018 with a B.S. in psychology and a second major in biology. Following graduation, she joined the Developmental and Motivation Research Lab at the University of Pittsburgh, where she works on longitudinal survey research examining adolescents’ motivation and engagement in math and science classes. Her current research interests lie in studying motivation and self-regulation in the context of health behavior and translating this research into interventions that

promote health behavior change. Beginning in the fall of 2021, she will be a graduate student in Dr. Dolores Albarracin’s Social Action Lab.

Henry Zhao

***PhD Candidate, Princeton University***

I am a PhD candidate in economics at Princeton University, and I focus on behavioral and political economics with applications to public health, information networks, and various sociological issues.

Siqi Zheng

***Professor, Massachusetts Institute of Technology***

Dr. Siqi Zheng is the STL Champion Professor of Urban and Real Estate Sustainability at the Center for Real Estate, and Department of Urban Studies and Planning at Massachusetts Institute of Technology (MIT). She is the faculty director of the MIT Center for Real Estate, as well as the MIT Sustainable Urbanization Lab. Prof. Zheng’s field of specialization is urban and environmental economics and policy, including environmental sustainability, and place-based policies and self-sustaining urban growth.

Yubo Zhou

***Lab Coordinator, University of California, Santa Barbara***

Yubo Zhou graduated from the UCSB, with a B.S. in Psychological & Brain Sciences and a B.A. in Philosophy. Currently, he is working in Yu Emotion Science (YES) Lab as the lab coordinator and post-Baccalaureate researcher.

**Notes from Breakout Rooms**

Instructions: Please take notes, if you can capture who said things. You may ask clarification questions for the purposes of notes. It is also fine to ask the group to take turns so that you can clearly capture the generated ideas. Please record the name of person as well as the comment in each row of the following table.

**Session 1 Blue**

|  |  |
| --- | --- |
| **Person** | **Comment** |
| Stephen Eubank | To Flavio:  Situational assessment is real.  Why is vaccination rolling over right now? The rates  Is it hesitancy? Is it logistical problems?  A lot of things that economists know about analyzing distributing goods and incentivization  These insights could provide useful insights for models |
| Flavio Toxvaerd | One thing I found frustrating from UK experience.  The UK gov is split into modeling and behavioral group and another separate economic modelers- very little interaction b/w three streams.  One thing I tried to do is to incorporate three streams into one in my own efforts.  One complication for psychologists and behavior scientists- the way they work may not always lend themselves into modeling type of things. Economists in general seem to be more familiar with modeling. How do behavioral scientist think their insights can be useful for modeling during the pandemic? |
| Nina Fefferman | Things that psychologist and behavioral scientist prioritize from modeling approach can be different from those of epidemiologists.  Theories of psychology are not difficult to build into models but when trying to integrate them into conventional quantitative models- that translation gets difficult. |
| Nina Fefferman | Theory of planned behavior for example that deals with when are people willing to act on their beliefs. Components that can be quantified from the theory are perceived social norm – not actual but perceived, perception of behavioral control, etc.,  Not hard to input these constructs into computational models but then epidemiologists may not agree these constructs reflect or that’s how social behavior looks like from their perspective. So they could push back on integrating these factors into their models.  Psychology has beautiful work done in these models, but it is not expected and understood in the same way in other fields– not easily integrated into epidemiologists – they say that that is not how they themselves would build the model. How psychologist quantify constructs is different from how other fields like epidemiology would quantify the same constructs. |
| Paschal Sheeran | Breaking down people’s presuppositions could help. Models should be able to engage self-corrections. |
| Stephen Eubank | Particularly good time for this discussion – a lot of models suffer from the lack of rationality in people’s response during the epidemic. |
| Dolores Albarracin | It’s not a matter of lack of quantification because psychology always deals with quantification.  A potential issue is that not everyone in psychology think quantification itself means anything about how people think and behave.    For some fields the integration has been done, HIV studies has a lot of integration across the fields but maybe not other field like flu  There could be some epidemiologists who have not encountered this yet |
| Chris Bauch | The instinct in some behavioral scientists is that you throw in everything in the model, but this is not how things are done. Model selection should be more thoughtful. More thoughts should go into how we select parameters in models and using what criteria like parameter inference approach |
| Chris Auld | Some models are used for forecasting, some models are never useful for forecasting and do not capture reality but emphasize some parameter that modelers want to highlight. So we should think about what the goal the model is to understand how the reality works? |
| Stephen Eubank | We could try to understand the limitations of both approaches (storytelling vs. forecasting) and prioritize our goals. Engineers may have a modularizing problem.  Personally, I’ve be persuaded if shown a behavioral model that matched 20 different situation where the model can apply to – then, I would accept a larger model. Looking around places that build confidence in individual models –It is not hard to believe how they fit together |
| Andy Neumeyer | When you write a model, investing a lot of resources to understand empirical implications for individual behavior would be important.  Collecting the data that models say important, and even if other people say that’s not how to do it, it would still be useful still if you have a rich dataset. We should make an effort to challenge ourselves to collect, use, and understand disaggregated data and how people make decisions |
| Flavio Toxvaerd | Nice thing about epidemiology is that it is interdisciplinary in principle, we do not need one model but a host of models and then figure out which ones are most useful ones |
| Dolores Albarracin | It could be like proposing research projects that invite multiple disciplines to come up variety of constructs to explain x behavior of pattern and arrive at a comprehensive formulation that all disciplines agree |
| Hari Sundaram | In regard to disaggregated data, how do we go about issues of privacy and agency?  Although we have tremendous amount of data, I worry that we cannot use all because in the process of using this data, this dataset may covary with certain attributes like gender race. On top of that, what are the rights of individuals in the data |
| Stephen Eubank | Are you talking about privacy of people involved in data? Or potential sample biases? |
| Hari Sundaram | For example, GPS traces – what if people did not agree on data being aggregated on community level but state-level? There is no easy way to think about this right now but during the crisis, researchers are thinking we just use any data we have without clear consent but for public interest. |
| Paschal Sheeran | Easy answer is that if people say we do not want you to use my data, then we don’t use. |
| Stephen Eubank | This would one of the systematic barriers of epidemic models. Private companies have access to much rich data with participants having consented for public good in mind. Why cannot we use this data? |
| Chirs Bauch | This could be a barrier – we know there’s data, but we cannot access it.  Don’t know how to overcome that but is definitely huge barrier. |
| Stephen Eubank | CMU delphi group collect large data and publicize them– there’s still problems with sample and biases but not critical. But they did a very good job of making the data available. That makes a good point about how to build collaborations between researchers and private companies as well |
| Dolores Albarracin | All discussions good. But we could come up with research questions summarizing our discussions. For example, combination of longitudinal and experimental methods to develop a necessary and sufficient dataset to account for some behavioral epidemiological problems.    Others please add |
| Shaowen Wang | Evaluating data with several models of different graduality that would attract both social scientist and modelers as well as NSF |
|  |  |
| Chris Bauch | Adding to Dolores’s comment. Evaluating data with several models of different graduality that would attract both social scientist and modelers as well as NSF |
| Stephen Eubank | Has there been forecasting competitions in social science? |
| Paschal Sheeran | There has been a number in interventions – several mega-studies to promote vaccinations – very nice adjunct to the idea that Dolores is proposing as long as everyone plot in the various constructs. It would certainly to eye opening to get these constructs from different fields. |
| Dolores Albarracin | That would be advantageous. Language and definitions are all over the place – for example, behavioral economists are reinventing every terms that already have been coined in psychology – but they give new names in other fields. |
| Shaowen Wang | Data sharing across fields a big challenge but also an opportunity as long as people agree to work together. Semantics and syntax of data that we are dealing with - once disparities are broken, it’s much easier to work on integrating modeling efforts addressing #3    Addressing Harry’s comment – long standing questions on geo-privacy and info sharing. And how shared info should be used – throny problem in terms of getting the data treated properly. On that note, problem I would suggest related #1, how do we work across different communities to come up with model that examine different spatial scales? Regional national global levels? |
| Paschal Sheeran | First, capture behavioral data frequently to determine associations with rates of infection. Second, find what predicts the behaviors. Third, confirm the predictive factors by experiment? |

**Session 1 Green**

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| **Person** | **Comment** |
| Eli Fenichel | Purpose of this conference. The questions that we should focus on in these discussions. Doesn’t want anyone to say that we didn’t think big enough at this workshop. |
| Ciara Dangerfield | A point about question 3. Very UK focused, not perspective from everywhere. In the UK, with SPI-M model, they are given very specific questions like “what happens if we open pubs this day versus that day”. They are all mates, a lot used to be post-docs or PhD students of the PIs. All have a very similar perspective. Get invited to be on SPI-M, so they invite the people they know. Need a better way to construct these groups to get a better spread of disciplines. When starting to advise government, need to contest with other issues like government organizations not working together. How do you build those relationships? |
| Lisa Sattenspiel | Silo-ing is just as bad in the US as in the UK. A big barrier in interdisciplinary work, things need to go through a review process, and who do you get to give a review? Get slammed even if your work is not so bad if people on the review board aren’t familiar with your area. Need to get interdisciplinary teams of evaluators together. Need to cover all the aspects of research. Hard to do and doesn’t happen a lot. Interdisciplinarity has always been a problem and I don’t know how you deal with it. |
| David Finnoff | On the three questions, seem simultaneous in nature. Cannot deal with one or two but must tackle all three the tackle any one of them. |
| Ori Plonsky | Ciara was saying policy makers want answers on these specific questions. Not a barrier for epidemic modeling rather is a barrier as these are questions which are unlikely to be answered well using behavioral models. No real way anything behavioral can come in to answer questions this specific. In a sense, the barrier is some of the questions policy makers want answered are not the questions we can answer. We need to try to get policy makers to think differently. Rather than “what happens if I do A, B or C” get them to ask what can I do so that a goal happens? This is something we might be able to answer better. Don’t know how to predict behavior in any possible context but know some useful tips to predict behavior in specific circumstance under which behavior unravels. We need them to ask questions like “What do we need to do in order to get case counts down, what do we need to do to get people to socially distance.” These types of questions are what we can possibly answer better rather than “What happens under A rather than B.” No way a behavioral model can answer that. |
| Eli Fenichel | Are there specific research steps people have thought about that would push us forward in some of these directions? |
| Himel Dev | Regarding integrating social and behavioral factors into epi modeling is the absence of a shared vocabulary. Often, people use different vocab or taxonomy when talking about the same issue. Develop a shared vocab so people can communicate better. The other thing that I have been thinking about is the issue of modularity. Working as a group with different backgrounds can be challenging. Can we modularize the problem into different parts? Each develops own model, and can we make them communicate with each other in certain ways instead of developing one unified model? Baby steps for bridging the gaps between two disciplines. |
| David Finnoff | What are the most important questions to be answered? What metrics do you want to focus on, and what policies do you want to use to get there? Suite of policies, suite of outcomes. Focusing on those would be helpful. |
| Eli Fenichel | Problem with modeling is you have to choose what is a variable and what is a parameter. Are we concerned with loss of income, child abuse, death, mental health? How do you aggregate across those things? Is there a Venn Diagram which helps us sort out which types of models help with which kinds of questions and how they can be tied together? Often in epi modeling, you model cases, maybe deaths as a function of cases. Not the questions policy makers ask. Fundamentally different questions. |
| Ciara Dangerfield | Scientists in the UK are always very cautions that they are given specific policy questions. Cognizant of their role as scientists and their job to predict what the outcome of a policy. Up to the government to make the decision. Can be very challenging then. Don’t want the policy directing the science. They (policy makers) decide the policy and then cherry-pick modeling results to support this. |
| Eli Fenichel | Sometimes that would be easier, I think. The policies themselves are endogenous to the science that they get presented. |
| Ujjal Kumar Mukherjee | I think that what Ciara said in terms of policy makers making decision before the science and picking science to fit, need to consider from the science side what policy makers take into consideration to make their decisions. Considerations of policy makers are not incorporated into the model. Very few of the models made have had any real impact, as none of these models consider what the policy makers consider when making their decisions. |
| Eli Fenichel | Talk about policy makers when modeling as a monolith when modeling. Policy makers have different considerations. The interactions of these policy makers may be an interesting correction to worry about. |
| Sridhar Seshadri | Not just the policy makers. There are subgroups. Bankers want one thing; people in rural areas want another. The influence of these groups and how they react to information influence some of these issues. How groups react to information becomes very important. Which information is passed on to which decision makers? Through whom? Becomes very important in influencing the outcome. How suppliers react, how medical manufacturers react. Can say anything you want on the demand side, but if on the supply side, don’t know why there were shortages or delays or the thinking that went in to responding to this. Extend what Ujjal said to different constituencies. How do they react for their own local optimization? |

**Session 1 Red**

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| **Person** | **Comment** |
| Andrew Atkeson | One of the striking things about COVID is that it is associated with a huge behavioral and economic response, whereas other diseases have not. How can we test any theory or model against the full experience we have across other diseases? |
| Andrew Atkeson | The conquest of infectious disease is not cited as a major source of economic growth |
| Peter Dolton | In the past, most of the world didn’t know what was happening in the rest of the world. The availability of data was just not there and we need more of it understand any idea about what happened in the past. |
| Andrew Atkeson | There is a difference between a temporary threat and a permanent one. If it is temporary, I can avoid it. If a threat is going to be present always, you just have to get on with life. |
| Zhilan Feng | COVID has many types of policies that can be enforced and other contextual factors going on. Tuberculosis and other pandemics have never had these enforcements in place |
| Ellen Peters | People have very different actions and behaviors due to their emotional reactions within the context (fear breast cancer more than heart disease) beyond things like mortality rate |
| Andy Tan | Process of shifting, replacing, and enacting norms takes time to reach the tipping point past which everyone follows it. |
| Andy Tan | We need better ways of predicting how communication strategies for working with policy makers will work. Same for social media and news coverage. |
| Frederick Chan | More discussion will lead to the desire to include more things in our models. Important to keep in mind what can realistically be put into models for rapid modeling. What do we need vs. what can we put in |
| Nolan Miller | We have a lack of imagination in including those that have malicious noncompliance. We need to think more broadly about how people skirt the systems and models in place. |
| Jude Bayham | “Noncompliers” simply have a different set of incentives. Another systemic barrier is that there is different jargon used in every domain. |
| Ido Erev | Compliance is particularly interesting and needed. It was ignored in early COVID models but has been important once included. It needs to be thought of beyond just simple incentives |

**Session 2 Blue**

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| **Person** | **Comment** |
| Fenichel | Bayesian learning models – have you seen models where this is operationalized. Previous research looking at planting decisions by small farmers – even though they were biased, bias worked in their favor |
| Plonsky | All reinforcement learning models do this. Don’t explicitly take out things that happened a while back, but heavily discounted. Some evidence that recency not only thing that matters. Esp w rare events – people think rare events won’t repeat. Immediately after they think more likely to happen again, then less, and after a while, think it will come back. Haven’t seen this in Epi models. One nice property of reliance on small samples, in aggregate predicts well, although biases at individual level. But on average, assuming random sampling from the past, this does a good job. |
| Fenichel | So is there a research program to figure out what information is sticky? |
| Plonsky | In context of epidemics not sure. My research focuses on simple experiments. Some evidence that there is some bias towards extreme outcomes. But goes against underweighting rare events. Epidemics will definitely feature in future research. Extremely difficult questions, affected by personal experience, exact cues in the environment. In epi modelling, modelling the aggregate, psychologists like to model the individual. Makes epi modelling somewhat easier because aggregate is more important than the individual. |
| Palacios | Do we know a lot about spillovers of these events across people? Esp people not exposed to the same reality? If my friend is in Wuhan and I am not, how do I weight their experience? |
| Plonsky | Excellent question, short answer is I don’t know. In feb 2020, most info we had was descriptive. Much more difficult to get at for descriptive information. Prospect theory has a clear prediction – people will overweight rare events and panic. Not sure if this happened outside of China, but some people did. |
| Peters | Lot of research that suggests influenced by indirect experience – like media for example. If your buddy gets prostate cancer, all of your friends go get tested. Lots of little examples, but ways to test as well. We have some data that people who looked at numbers in the news every day, those people had much stronger emotional reactions, and took on more protective behaviors.  Some info is sticky, maybe because of repetition – whatever your tribe believes is very relevant, maybe bc you are exposed to it over and over. ex. People just look at numbers and news and those people tend to have much stronger emotion experience.  Question of what is sticky very important in many contexts  You might also be influence by experience, indirect influence by media.  Whatever you try to believe will finally become really sticky. It is beyond the pandemic too.  **Each of us as individuals are interested in the field, like I am very interested in emotion, communication, although I am interested in the model, but I don’t have enough knowledge for the model. That’s my barrier.** |
| Palacios | We have a lot of knowledge of what will happen in the short term with cases etc, but in other contexts like vaccine shortages seem to be unexpected, harder to predict. Evidence about events that are smoother – easier to predict vs ‘random events’ |
| Peters | Research that trends are important. People are very reactive to trends – trending up vs down. |
| Fenichel | What are systematic barriers to using these insights in epidemiological models? |
| Plonsky | How to integrate these ideas about small samples into epi models? One barrier – I’m not sure how to translate these insights into epi models that are being used today. Agent based, network, SIR – not sure how to integrate. This conference is all about this. Let’s see if we can integrate this one thing. I would be happy to see that come out of this conference |
| Peters | Lets take a topic that I’m interested in, but I’ll never know as much as an expert, but also need an expert that is interested in what I do, and we need to meet in the middle. Interested in modelling, but I don’t know enough about it. And I haven’t found a modeler who is interested in the types of things I’m talking about. |
| Bayham | Most of my work is in compartmental type models, but have been thinking about agent based models, you could have agents learn from their experience in the model. In compartmental not sure how we would do that, long path dependence, but in ABM could do that and maybe find interesting dynamics  Agent based model: I think about you have agents learn from the exampling model, but agent based model you might get some interesting circumstance there.  When we looking at the population, is that should just go to the average risk. |
| Plonsky | If you use the idea in compartmental models that people react to incentives, respond to ‘average risk’ all we are saying is that add another dimension that you respond to the probability of the risk. Don’t need to have explicit sampling etc.. End of day what you need is probability of risk. If I get infected I have very negative utility, but probability is very small – even if many people in the network are infected. |
| Bayham | In the aggregate, won’t this converge to just average probability |
| Fenichel | People don’t understand exponential processes. Paper I worked on never published, people deciding to get flu vaccine, after 7 or 8 years, state space of experiences is enormous, can’t actually compute probabilities. Love this idea that Ori is raising about small sample sizes – we don’t know what samples people are actually using. The data generating process creates these huge state spaces, people cant smooth over them |
| Plonsky | This is a great question, this is what I’d like to see happen here. |

**Session 2 Green**

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| **Person** | **Comment** |
| Claudia GV | We behave with certainty because we don’t fully grasp what ‘uncertainty’ means.  Example, we get vaccinated (which isn’t 100% protective), but we act like it’s 100%.  Different experience (e.g., vaccine) contribute to people’s perception of certainty, and one’s experience is not necessary what one is experiencing.      **We are constantly working in ‘between worlds’- we form assessments based on numerical values (lot of trackers, lot of numerical information) and we merge this with ‘experience that comes from descriptions and our own experience|.** |
| Ido Erev | What should we include in the model? |
| Nina Fefferman | (Answering Ido): For modeling, **we must parameterize how to internalize risk and uncertainty-** what are we asking for people?    There is a difference between misinformation and uncertainty. In her own words, ‘here may be a difference in observed actions and understanding of public behavior between the "certainty" being flawed about protection against illness and the "certainty" which is much closer to accurate for prevention of death.’ For instance, one’s goal (long vs. short term) and education background will affect the evaluation of behavior. So individual difference is an important factor to consider.  Nina Fefferman’s research is exploring how information from communication forms/social network construct individual view of risk which than influences your behavior. |
| Coty Conzalez | We need to develop a model to consider people’s experience and how it contributes to their behavior. |
| Claudia GV | **We must have a hybrid versions of a model that looks at what guides behavior such as personal experience (close one getting sick, city having a lot of cases) and what we learn from the multiple forms of communication (disease in different communities). Thinking about how to combine both elegantly is a key task.**  Important because policy-makers are experiencing the world like this, information comes in different format as well as experiences – it gets complicated- how do behavioral scientists help guide effective policies? |
| David Finnoff | There’s two aspects that must be incorporated into models:  1) **How to understand how people behave?**  - Specifically, if there’s different type of people, how prevalent are they in the society- where they are, are they operating in groups or individuals.  2) **How to involve those factors in the model.**  3) Bring in some simplest prospect theory into actual simple models of behaviors that can be used in the epi-type model. This still a question that have not been done completely  a) Modeling expected utility and risk preferences, doing that accurately seems to be challenging ? |
| Ido Erev | Psychologists and behavioral scientists have shown that expected utility theory is wrong- it doesn’t work. **Specifically, what is rationality in Covid** 19? One key is to look at Australia, China, and Isreael- look at how they responded differently and why. |
| Claudia | **Expand circles of our friends, creating interdisciplinary collaboration to refine models.** We need to listen to our friends in sociology, political science, anthropologists (culture)- behavioral decision is based on motivations, incentives work but it depends on different contexts (What are those, however?)    We need to enrich our model with cultural factors that could help people’s motivation in different context. |
| Ido Erev | Economic theory work up to a point- we got 75% of Israel vaccinated but that plateaued because no one is getting sick! Green pass is effective to 75 percent, if we have a new variant we must think again! |
| Nina Fefferman | **What motivate behavior? Will variant, new circulation force more vaccination or is there some other resistance?**    Strong assumption about variants being the reason why behavior will change, is it really because no one is getting sick (view of risk) that is leading to the plateau? |
| Claudia GV | Interestingly, is vaccine a ‘nutrient’ for Muslims in Ramadan? This has to do with value of culture- not all about risk. If I got vaccinated and get sick during Ramadan, can I drink water?  **Cultural patterns are important and well studied and should be incorporated into model**    **Lockdowns in Australia versus Southeast Asian countries- totally different approaches, cultural differences must be looked at!** We have enough data to support the robustness of cultural pattern in affecting people’s behavior. |
| Sridhar Seshadri | **I talk to people in India, Texas, rural parts, etc- there is large variability in beliefs- broad brush modeling is something I do not buy.** The main importance is ‘what actions are centrally enforceable’    Policymaker must lower the variation since in the same community- different opinions on what should be done.    Invisible hand phenomenon- make it more visible! Can I put a forcing action that the network stabilizes? |
| Claudia GV | It can backfire! Can do this with safety nets- lock downs cause economic difficulties and without good measures for taking care of the challenges as well as well coordinated actions- the lockdown is not effective!  Look at Chile    **These things can be modeled- they can speak to basic psychological/social factors** |
| David Finoff | The green pass cannot be pulled off in the US, look at rural USA (horrific, horrific response to policies) |
| Ido Rev | (counterpoint) In Israel, the Jewish community didn’t care about Covid, they still got vaccinated- the Jewish leaders said they can go to temple if they got the Green-Pass. **You can get people who were Covid-19 skeptics to get vaccinated based on incentives** |
| Claudia GV | **Culture is different but we need to find the incentives- how can we find this?** |
| Claudia Gonzalez-Vallejo | We have enough data to support the robustness of cultural pattern in affecting people’s behvior. |

**Session 2 Red**

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| **Person** | **Comment** |
| Tim Reluga | How do we operationalize small sample size effects into a model? |
| Lisa Sattenspiel | Nowadays there is a strong tendency to downplay small-scale effects, because we don’t know how to properly scale these results up to bigger situations. |
| Chris Bauch | Combining machine learning and mathematical models can be helpful to deal with mobility and social science data and help with small scale issues. Machine learning algorithms (like Alpha Go beating humans) can identify patterns/strategies that humans can’t even comprehend at first. Non-linear dynamics have large right hand side variables but we can progressively fit the model to a dataset that uses the best terms to deal with the data. Thus we can discover a model from the data. |
| Tim Reluga | So we can pick up patterns using small scale behavioral data and use the algorithm to scale up to a larger scale model. |
| Andrew Atkenson | Large scale aggregate models tend to have weird measurement errors. It’s rare to see an assessment in statistical work and inference. In macro, even with a simple linear model to study simple questions like disease growth rate, weekday effects, reporting lags, and other measurement errors can cause systemic biases in the data. Even doing Bayesian inference, this noise is not taken into account and treated formally. The smoothing process would still fail under a linear model. |
| Alberto d’Onofrio | Modeling and understanding static behavior is difficult, and understanding dynamic behavior is even harder. The integration between he classical mathematical modeling and machine learning from the behavioral part can be a good strategy, since the problem of COVID is that we know little of modeling and we ignore too much from the real data exploration. |
| Tim Reluga | Do any of your models treat the population as segmented in terms of beliefs? Individuals being pro-vaccine or anti-vaccine, perhaps. |
| Alberto d’Onofrio | Overweighting side effects (of vaccination) and underweighting the risks of COVID need some work to be adapted in the model. |
| Hari Sundaram | The issue with behavioral data is that human behavior is heavy-tailed. Many models do not have sufficient regularization to the distributional aspects of the data, so these models end up picking up the effect of very high outliers. These models are good at predicting types of behavior, but bad at predicting WHO will do it. From a policy perspective this is problematic because it makes intervention strategies difficult to design. |
| Troy Tassier | One difficulty with empirical studies is we can observe behavior but can’t see “why” -- Empirical difficulty separating things like people’s preferences, beliefs, network effects, and economic constraints. This makes it hard to inform policies. |
| Chris Bauch (final summary) | Small scale individual processes like personal history are hard to be represented in the aggregate data. Social media data and mobility can be used with machine learning to narrow the gap in epidemic models. We also discussed how machine learning might fail and how measurement errors should be addressed, particularly surrounding small scale data. |

**Session 3 Blue**

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| **Person** | **Comment** |
| Before breakout session |  |
| Eleanor Murray | Reviewed her talk.  Challenges in running randomized trials.  Propose simulation/mathematical models as a solution when we do not have good data for example early days of the pandemic. The problem might be most of the time they are not realistic, so how can we make sure inferences we make are informative in real world |
| Taylor Anderson | Static human behavior assumption is a problem for COVID-19 era. People change their behavior. This change is not national change. There is a geographic heterogeneity that needs to be accounted for. Need to add geo-related behavior.  Policy works at one place not another place.  Is the best solution to add more realistic assumptions? More realistic assumptions add computational problem and increases assumptions |
| Jude Bayham | What are the costs and benefits of a policy? It is an important question.  Expectation of policy makers; there are challenges in policy analysis.  It is hard to identify best measure during COVID.  Defining policy and the way enforced is difficult too.  Policy analysis is hard because of presence of feedbacks and expectations.  Policy->behavior->outcome but also other relations risk perception-> behavior or outcome->risk perception , etc    Datasets  American time use survey: problem is there are delays.  Mobile devices: no demographics and it has bias.  Social media: nice because you can do sentiment analysis but hard because of its biases.  Which mobility measure to use?  What motivates people?  What are the tradeoffs?  Update data structure with real time data? |
| David Holtgrave | How we can model that satisfies the model assumptions  We can model policies sometimes because we have good data.  When we do not have that other ways like threshold analysis could be used  Back of envelope calculation sometime for example syringe exchange programs to see how much you save by avoiding 3 infections.    Parameter selection problem (his paper in 2004)  HIV prevention among black gay man that had a smaller cost saving because have poor access to care.    Ensemble model of MMWR vaccine from CDC critics  There should some requirements for how to report things – very difficult to understand how it’s done and what goes in the model. |
| Eleanor Murray | Can we get answer from past models? More than 5000 vars, so many relations so hard to use. Not replicable too. It may work with past data but not with recent data. |
| Stephen Eubank | Can we use natural experiment to get causal effect? Are there social scientists who can comment on their experience on use of natural experiments to understand behavior and causal systems |
| Jude Bayham | Depends, no one is untreated during COVID-19 - natural experiments are much harder because no one is really untreated, and you don’t have control who gets treatment versus not |
| Eleanor Murray | Validity of IVs problem. Violation of exclusion.    In Epidemiology, natural experiments are less used because the type of questions that interest epidemiologists often cannot be addressed by conducting natural experiments. Lots of focus have been on individual actions and natural experiments provide little understanding for that. Maybe for group level questions but for individual level questions not so much.  There are also some issues inherent in them – we see classic “rainfall is instrument for everything” (?) kind of approach. I would be interested in seeing them more in use though.  Match the type of questions we want to ask and what types of questions natural experiments are answering |
| Rachel Slayton | To David-  I appreciate your realistic view of MMWR as a product and its limitations. I also appreciate your efforts to dig in to github to figure out what goes in MMWR. We always want to learn more about how to present these information and how these analysis are being informed and doing so transparently. We also want people to understand the underlying structures.  The value of ensemble and individual model: we did a lot of that for forecasting efforts – thank you for your thoughts and comments |
| David Holtgrave | I think CDC has now and historically moved forward the mathematical modeling and doing policy analysis and over the years, units formed to focus on this, and agency communication is important. In the 90s in the CDC, the MMWR office was just outstanding: common feedback is make it a bit shorter. These need to be very tight concise documents for scientists and public to consume. |
| Breakout room Blue | Breakout room leader/leaders: Dolores Albarracin |
| Dolores Albarracin | Has there ever been an attempt to systematically evaluate whether models closely reflect situation in reality? Full circle of how models ultimately influence reality which might include comparing several models - |
| Lisa Sattenspiel | I did a review chapter and a book on Foot and mouth disease – I didn’t do a systematic study but there has been a lot of modeling on what to do earlier on in the epidemic and what decisions need be made – the decisions informed by the models ended up being killing a lot of cattle- highly controversial decisions – because nobody thought about the social and economic side effects -farmers and people’s livelihood were destroyed because of this epidemiological decisions based on models.    This is an interesting case because the modeling approach informed decisions that ended up being successful in controlling the epidemic but it’s unclear whether the epidemic was on its way down anyway. The model still had unintended consequences because of not paying attention to social economic side of things. One of the best examples of how model was actually successful in affecting policy but wasn’t successful in addressing other unintended consequences. |
| Eli Fenichel | I can think of two other examples. Microeconomic policy that’s all model-driven, not cross sectional but time-series.  The other example is using modeling to estimate fish stocks. Recommendations from this model follow a lot of biological targets but that’s very narrow and make people unhappy |
| Dolores Albarracin | Impact of modeling on various decision ability and then use of similar modeling efforts in the future with different circumstances produce some disastrous outcome.  To model the impact of policy needs to model it comprehensively |
| Lisa Sattenspiel | History will show that modeling in covid-19 pandemic has produced mixed results. It was really nice in the early days of the epidemic when the world is recognizing what epidemiologists do but the downside of it was that the estimates were so off with the uncertainty of the pandemic that public confidence decreased and did not perceive epidemiology modeling better than it used to be – it would be interesting to study how effective modeling has been for the COVID-19 pandemic but it’s early to do so yet |
| Dolores Albarracin | What would it take to study this? One way is to reporting models and their implications and documenting policy that were developed from different models – systematic review of models and policy formation and its consequences |
| Stephen Eubank | Need a review of policies. The model published by Rachel (CDC) on Ebola was criticized for exaggerating the threat but at least the model received a lot of attention |
| Rachel Slayton | Agree that’s why we tried doing time-series to get the validity but there were so many other purposes that the model was being used for which needed validation longitudinally. |
| Dolores Albarracin | What model are you using now? |
| Rachel Slayton | We had calls from modeling experts. Had group present individual models and estimate the effectiveness of these models in comparison with ensemble models. These efforts were documented in public domain.  How other decision makers use modeling also varies. Under the previous administration it could have been different process -individual models were more used than ensemble or multiple models. |
| Eli Fenichel | Ensembles models – there’s network efforts of researchers and the models are not always independent. -how do you address this?  Achieving high fidelity of models to run forecasts – how do we understand the causal effect of these models, informing things like, if we had done this policy how would that have changed the trajectory? How do we go about defining model matrix? |
| Rachel Slayton | Forecasting has an analysis on the way right now – still working on the method.  Also, we’re looking at the correlation between models and how that ought to be addressed in ensemble models? That gets at the non-independent issue. Understanding the relative contribution of each model.    In terms of the ability to address causal inferences, it’d be useful to develop a set of scenarios and educate decision makers how needs to be done. This is totally different from forecasting and should be evaluated in a different way. Would want to see directions are correct, not necessarily the numbers. Multiple interventions are at different levels and that’s harder. I love to understand how you all think. How to develop new tools to capture heterogeneity. |
| Dolores Albarracin | What are you measuring on interval scale? – forecast? |
| Rachel Slayton | Standard prediction intervals quantile each group has to provide, such as I have 95% certainly this would be upper bound and lower bound.  Number of quantiles groups put together and quantities for individual outcomes we’re predicting is combined in ensemble approach |
| Eli Fenichel | How far? |
| Rachel Slayton | We go for 4 weeks – incidence deaths, cumulative deaths, incidence hospitalization and etc., some groups did submit longer forecasts and evaluated their performances.  Performance sometimes degrades even when models are right – when their prediction interval capture the value rather than actually information about the trajectory - which is more important to do next rather than getting a good number by chance |
| Eli Fenichel | Using a time-series model auto regressive moving average model could be models you can use |
| Stephen Eubank | That’s one class of model in ensemble modeling approach |
| Dolores Albarracin | Could add subjective measures to models. Adding more interdisciplinary perspectives in these modeling approaches – perhaps then these forecasts would add credibility and usefulness? |
| Rachel Slayton | We can evaluate some of that putting things out there publicly. There may be other uses that we’re not aware of - understanding how the model is used would need more digging after the pandemic. Forecasting workgroup started with influenza. Trying to hear what local health departments are using the model for. These folks we have talked with the most during the pandemic – who else have been using the models is of great interest to me |
| Stephen Eubank | Scenario based modeling is really not new concept even in public health.  Modeling was required to target profile assumptions (e.g., pharmaceutical companies) |
| Eli fenichel | How do we arrive at this decision? What goes in as parameters?    Does the way we frame overarching objective of the model affects what parameters we use and whether it would be affected by time-varying function? |
| Stephen Eubank | I think it’s a chicken and egg problem in lot of instance. We don’t know what parameters are until we do sensitivity analysis of the outcome, but we cannot do sensitivity analysis until we decide what parameters to add in the model. So it is iterative |
| Eli Fenichel | What about you Taylor? |
| Taylor Anderson | From individual based modeling perspective, we try to keep as micro level as possible so that we’re not forcing any patterns that come out of the model. Potentially using domain experts to guide for that – a lot uncertainty during covid about what these values are and what they should be so at this point expert knowledge is the best way to go |
| Coty Gonzalez | From the Cognitive modeling perspective – could be different from Eli’s perspective.  Parameters are factors that influence the behavior of the model from cog science – parameters that are theoretically driven (e.g., decay of memory over time) those are often calibrated to human data and depending on the model parameters could be very different and impact the model in many different ways but it’s really the question of whether parameters can be calibrated to human data that exists or whether they are theoretically driven. Parameters are expected to be lever that are going to modify the behavior of the model. |
| Taylor Anderson | The models that we are developing right now is mobility – how often do people leave the home, where do they go, what do they do? We’re trying to use data-driven approach.  That brings up more questions about data completeness, bias, sensitiveness.  The point of interest users go are usually public spaces and those that they spend money on – you’re missing out on many other parameters that are not relevant to the above.  That’s just one layer – we also have disease spread layer and socioeconomic factors of individuals. |
| Stephen Eubank | Minimum requirement is that represent each of the policy levels in the models and parameters for each of them. |
| Rachel Slayton | And natural history of pathogens in interest too. You really have to understand how pathogens and patterns of infections change over time and how it differentially affects different subpopulations. |
| Stephen Eubank | Sometimes we have to introduce new interactions in the model. You start with aggregated model and then somebody tells you some parameters are correlated with some demographic factors. Then you have to add those in the model. |
| Taylor Anderson | I like your comment How questions and models changed over time based on the purposes and needs of the models |
| Stephen Eubank | Models can change with the purpose of the model; you may need to add or drop variables    That could be in the review of how models influence policy decisions.  What models do they end up selecting and use?  Do policy makers actually want forecasting or simply yes or no evaluations of policy?    Something else:  You have to understand jurisdictions that policy makers are in and rather than to talk about models that apply to overall state level or other jurisdictions |
| Dolores Albarracin | Some barriers to achieving the goals we talked about? |
| Taylor Anderson | With individual agent-based modeling, our barriers are computational issues when increasing the complexity of the models. Adding things like human behavior and decision-making, response in small scales that will increase computational burdens – running these models in parallel is just difficult – if you want to scale up, it’s expensive and limited – overcoming issues with computational efficiency is challenging |
| After breakdown session |  |
| Nina Fefferman (red group) | We had a discussion about scales involving different types of behavior and coupling that with different types of models. We discussed the Idea of agent-based modeling that could inform understanding behavior and that could impact policy decisions.  Scales of impact that we want to make. What level of understanding we want? Fine-scale vs. coarse scale. What are the opportunities from the available large-scale data and associated dangers such as exploitation |
| Dolores Albarracin (blue group) | We had an interesting discussion about the potential of studying the impacts of different models on parameter selection, policy decisions, and society. E.g., Systematic review of how models impact policy decisions    Issues of barriers – the issue of complexity of the models – particularly when we’re trying to model individual behavior at nationally level – need more funding to overcome the computational complexity |
| Jude Bayham (green) | Use of natural experiments depends on the questions that you are asking – in certain contexts with reasonable control. then we talked about the scope of research in informing policy and how several of us have been engaged in advising policy makers at some level and scope and the time frame you have to operate under, and the quality of work you can produce in a relatively short time-frame. We also discussed measurement of response from a lot of dataset available now but how to distill which of those contains the most useful signals.  Political economy – factors determining policy makers’ decisions – Alberto’s paper on game theory and how governments may set policies strategically. We left thinking about how we take data and empirically test some hypotheses surrounding this. |

**Session 3 Green**

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| **Person** | **Comment** |
| Dave Finnoff | What are the ways to deal with everyone being treated in natural experiments during epidemic/pandemic? |
| Jude Bayham | There are opportunities to find treatment and control groups through policy discontinuities  There is no one who doesn’t have a treatment effect during COVID  An issue: how quickly question arise and how quickly answers are needed  There were a lot of models with bells and whistles, but we fall on a simpler model that is easily adaptable for policy questions  Policy Qs: What’s hospital capacity? What’s mobility mean? How will people get vaccinated? Threshold analysis.  We should not have policy influence the research agenda. |
| David Holtgrave | I’m a fan of, even once the policy window’s closed, still do the peer review paper.  Have a self-analysis: what did I do in two days? What did I do for a publisher paper? Where they similar?  In New York, lots of models. But the most helpful calculation was the positivity rate which is the division of two numbers.  (Jude: you could linearly forecast on that for a week and it wouldn’t be that bad of a projection) |
| Chris Bauch | How can we incorporate social science and disease?  Research topic: response of human systems to policy changes  There are coupled human disease systems. Human system that a lens to a disease system and vice versa.  Actional questions: data on population response to policies that can be incorporated in models about how human systems react in a disease landscape |
| Jude Bayham | I had high hopes that “stay at home” metrics (from cell phones) would be a sufficient statistic for mobility, but I’m not sure now.  What are the statistics now that we’re out of the first couple of rushed months?  It’s not symmetric (mobility and spread). At the beginning, we saw less mobility and less spread. Now, we see increased mobility and don’t see the commensurate increase.  Why do we see the immediate change? That’s a remaining empiric question? |
| Dave Finnoff | What if you haven’t enforced this type of policy for many years?  What’s the right baseline to use to compare to? What data do you use for that baseline? |
| Sridhar Seshadri | There may be an opportunity to use transfer learning and utilize machine learning with flu data.  The flu data provided power to prediction. At the beginning of the pandemic, we didn’t know how COVID was working so we could do transfer learning.  We also need to pay more attention to negative results. Ex. COVID didn’t start from the west coast and spread east. That was a negative result.  It’s helpful for us to focus on finding negative results in order to know what didn’t happen rather than precisely knowing what did. |
| Ujjal Kumar Mukherjee | We tried to use testing as a tool and asked how we may be utilizing tests since we can control for tests.  Question of optimal allocation of tests when scare. But we didn’t have enough data on current tests, so we utilized flu data as transfer data  Used data on past instances and transfer it to current situation since we didn’t have enough data on current to get helpful inferences.  Used this to model the spread of disease in a spatial read of locations based on past experiences.  Use past to model future when needed. |
| Jude Bayham | Were you ever able to predict the curves (*inflection points*)? |
| Ujjal Kumar Mukherjee | No, we were not really able to predict the curves. We were mostly predicting were resources needed to go  We were typically predicting out 15 days to a month. |
| Jude Bayham | Our team wrestled with: Do we try to build a model that anticipates a policy implementation  We know that the government would put in place a policy response (closing restaurants). Should we try to build a model that takes that into account? |
| Ujjal Kumar Mukherjee | We did build out scenario predictions so that we could share that  Build models on tested and untested, built lock down and non-lockdown.  We also used twitter sentiments on mass wearing a social distancing and it was representative of zip code.  Many of these models try to explain and predict. We don’t talk much about prescriptive models, finding out what nudges work better than others. |
| Sridhar Seshadri | Did some optimal control theory.  The problems are linear, and the cost is linear, so we found bang-bang solutions  Shut down everything, stay open. Test everyone, not bulk testing |
| Jude Bayham | Research Q: how did policy makers make decisions? |
| Ujjal Kumar Mukherjee | India: Political economy needs to be in here  They should lock down India for 15 days  But the politicians implicitly take into account who they’re talking to  We fail to incorporate those in models, but they play a large role in the system |
| Jude Bayham | Political economy is necessary here |
| David Holtgrave | Three questions on policy makers:  How do they seek information? Where did they get it from?  How did they process the information? People helping them, aids?  When they communicate the decision, how do they communicate it? Individuals, population? Gain frame? Loss frame? |
| Ori Plonsky | Good game theory paper out there on this  Policy makers are rational agents  Theory paper (which is where we have to start)  https://www.medrxiv.org/content/medrxiv/early/2020/05/27/2020.05.26.20112946.full.pdf |
| Matt Gordon | Ex of research Q: who got classified as essential workers, where and why? |

**Session 3 Red**

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| **Person** | **Comment** |
| Nina Fefferman | Collisions: when a thing is being affected by two different things. Apparent competition in ecology |
| Ido Erev | Worries me is that I study simple situations. A model that can capture 11 games with only three parameters, COVID-19 needs more parameters |
| Nina F. | My research is not data driven, it is either mathematical or practical. Thresholding: how do you get just enough information to inform real time decision making |
| Tim Reluga | Dismissing SIR models for agent-based models because agent-based models have less assumptions, which I don’t agree with. |
| Nina F | The Ferguson model was an off-the-shelf flu model rather than something new |
| Ido Erev | Doesn’t a flu model include behavioral changes? There is a parameter in the model for that. |
| Tim R | You can have people switch between behaviors in the model (SIR model) |
| Ido Erev | If we know the popular models that are useful we could know how to improve them |
| Nina F. | There are models that do this, Dr. Reluga’s for example. Add vaccine uptake, avoidance of illness, etc are now becoming classic in the way economics and SIR models can be coupled. We don’t need to start from scratch but we have a building block available |
| Tim R | Are the models shown in the talk before incompatible with dynamical models? |
| Chris Auld | There are statistical and () issues in doing this. Policy changes are not provided randomly |
| Ido E | Behavioral economics does a lot of experiments and then fitting a model to this information. Could you do this with infectious disease? Compare the policy implementations and other behavioral components and see if you can reproduce the data between multiple countries |
| Tim R | There are all sorts of different dynamics between different countries – ex. Matt Ferrari’s dataset for measles in Africa. |
| Nina F. | Regional construction of emotional behavior |
| Paschal Sheeran | How rigid social norms and how people adhere to those social norms in regards to mortality from COVID-19 paper. Coming to terms with a model that doesn’t include human behavior. |
| Tim R | Imagine all people are balls in a box, if you touch a red ball you turn red. This does depend the timing of the disease and interactions (direct/indirect contact). This all relies on the R0 or transmission rate – this is difficult to interpret and understand and it’s the only one that accounts for behavior |
| Paschal S | Can we fit a model that accounts for historically collected data to help understand current models? |
| Nina F | The most useful versions of these would be large scale time series or behavior data, these types of data sets are privacy violations and there is an ethical barrier to publishing this type of data. You end up such specific questions it becomes an instant of something rather than generalizable. We don’t have repeated data sets at different time points with the similar situation. There are real barriers with how we can engage with these types of datasets. |
| Paschal S | The UK collects information about drinking and smoking every month, and they know when stuff is changing. We don’t have the data to enable the modelling that we need. |
| Nina F | Data free modelling can still be helpful  (Everyone agrees) |
| Brajendra Singh | In the US there are groups that are using artificial populations to overstep the privacy issue |
| Chris Auld | A lot of groups are using publicly available data which is aggregated. But we don’t care about average behavior. If behavior changes in an epidemic, this changes the dynamics even if the mean is constant. Without microdata we are limited in what we can do in terms of modelling. |

**Session 4 Blue**

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| **Person** | **Comment** |
| Peter Dolton | Are there any data about natural world, any network observed before COVID, during and after Covid? We need a baseline of network that is beforehand.  I am interested in using the model to identify the thing. Who you know, which friends you know, and impact of Covid has been?  I’ve worked on Adhealth data – but not surveyed at the right time. Interested in econometric model to identify network effects but challenging. |
| Nina Fefferman | Aware of a few datasets being gathered in real time. Katherine mentioned in panel – don’t know if they have the baseline.  Some small-scale work on relative psychology of salience of factors – group at Princeton looking at that. |
| Troy Tassier | College and K-12 schools might be good place to have these data. Perhaps the places to collect data. Surveys of friendship data. |
| Hari | One challenge we are dealing with, is the causality.  Running experiments on networks like in local neighborhood. The empirical data we get is very challenging, how you sample network of neighborhood. At least for us, we found if your network neighborhood take risky behaviors, also have correlated with it, taking more risky behaviors. |
| Peter Dolton | Can you in fact find the instrument. If it is the networking data, will be hard to get into experiment.  You dont observe in social areas, these things you won’t know when you just go social media.  Folks at Adhealth must be bursting to do this. Information over 20 years or more, not sure they have the money.  You don’t observe all of their behavior on twitter if they don’t tweet it. We ideally need Adhealth people to survey exactly what behavior, views, opinions, etc were. |
| Nina Fefferman | It is not just the straightforward of impact and time evaluation. Real world observational studies, it won’t be in the wild observation.  Dynamics evolve in real time. Not static impact but timed evolution is self-referential. Smaller pieces can be teased apart |
| Hari | Basically create 8 alternative worlds. The idea was 8 experimental worlds and observe the evolution of these world gradually. |
| Matt Gordon | cell phone data is an interesting data source that fits some of Nolan’s criteria, and 2 one issue that comes up with applying data to network theory is how well a sample of nodes (whether random or not) will approximate the structure of the true network |
| Paschal | Nina, your mathematician but you trained to do traditional academic work. |
| Nina Fefferman | Marry the basic research and policy research. We are not all interested in the same questions. Mathematical sociology. Here are the things people who work mathematical, might not be what needed by policymaker.  Data collection Peter suggested is crucial but expensive. That’s the part, I would love us to know. |
| Peter Dolton | Network of friendship, do we have these references.<https://science.sciencemag.org/content/311/5762/854.abstract?casa_token=-TI2tQKM9OMAAAAA:IQhE-soket-La6FVHnnIcpkbxm6TxKRElPo1xvxQ363CDBYXU2Z9wtm7YXiuzsRkXVAUrlZ2bxfvkQw> |
| Hari Sundaram | Also the approximating to the thing you measured. It is not a easy thing to sample.  Covid tweets – how to sample network neighborhoods? Ego correlates with tweeting about risky data. Covariate but probably not causal.  Whether sampling approximates global or local structures depends on questions. Doesn’t even account for whether network is dynamic or not |
| Nolan Miller | Network belongs to the left side or the right side. Maybe something you want to control for.  Not sure whether network should be left hand variable or right hand |

**Session 4 Green**

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| **Person** | **Comment** |
| Ido Erev | Interesting to suggest that people are more likely to vaccinate if their friends are vaccinated” which is opposite of what Game Theory predicts (you don’t get vaccinated when your friends are vaccinated because your friends will keep you safe). In the meanwhile, there are other incentives. How would you model them at the same time. |
| Katherine Ognyanova | If people are trying to game the system that is more on the global scale, the decision to get vaccinated may be more local (did my friends get severe symptoms, etc.) |
| Ido Erev | It’s a known phenomenon that in some area, very few people vaccinate while others vaccinate a lot. **You model with different incentives, how would you model that? How do you model with incentives and network?** |
| Katherine Ognynova | First thing to know- ask some questions for the full motivation for vaccination? Are people not getting vaccinated because other people are getting vaccinating? This might not be the main reason, vaccine hesitancy may be based more on ideology?  **You could model in network sense where the individual adoption threshold by both the immediate surrounding/social cues around you and with the average levels around the community.**    If you want to explore the Game Theory case, you can model with the incentive to not vaccinate rising proportional to people in your community who are vaccinated |
| Chris Auld | There’s been some work that looks at **“Should I get vaccinated if everyone else is vaccinated?”.** This can get some weird results (especially with imperfect vaccine) and the system can behave in weird ways. I wonder if you (Katherine) have any insights? How do individuals factor in all incentives, esp. when these factors are in conflict? |
| Katherine Ognynova | Looking at others’ influence as a group is not good because of the within-group heterogeneity. |
| Ido Erev | **What are the robust things about network- what situations does imitation (if my friends get vaccinated, I get vaccinated) arrive?** Future research should be able to predict |
| Anil | Two forces in his network research: At the node there is the cost of infection based on who else is diseased/vaccinated state of others and structural cost (do I benefit if I imitate others or do I get a cost if I go against)    There’s interesting structural properties of the network- found in analysis, vaccination cost/infection cost/benefits from compliance- completely theoretical exercises- not clear how to make succinct statements from pure theory.    Can Theoretical constructs like networks be verified with data. |
| Sridhar Seshadri | Let’s look at Solar panels model- the person is deciding on estimating the rate of learning based on individuals and the people around them- explains the diffusion.    In some learning models, like whether to adopt a technology or not. In situations that we have two technologies that are co-evolving we found it hard to understand how one’s choice are influenced by others’. |
| Ujjal Kumar Mukrherje | I think Harding/Hurting (???both note-takers are not certain about this term) behavior can be a way to look at it- vaccination, what is the actual cost. The cost is about uncertainty (helpful/harmful- should I take it or not take it).    Harding talks about information cost, if my friends are taking It, I will take it because they are alive and I will be alive.    Source of Harding on network setting is more information/uncertainty perspective- psychological cost of information uncertainty |
| Ido Erev | You can look at it different ways though. It can be Harding, because you friend take it, you take it. But I can see a case where you get vaccinated, because you want to go places with your vaccinated friend (aka: green pass). Information doesn’t seem to sound important as an intervention target because it is from internet. - you’re probably getting vaccinated because of incentives not information. |
| Ujjal Kumar Murkherje | True, but I’m talking about information as I am talking about uncertainty |
|  | (from note-taker [Zone]: I think overall the session is not as rich as other sessions in discussion. The moderator was not aware of her task initially. Also, the Q&A seems random to some degree by each person throwing in their own research experience but not necessary solve each other’s questions.) |

**Session 5 Blue**

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| **Person** | **Comment** |
| Troy Tassier | Question for Lisa: You do a lot of agent-based modeling. Do you have any take on the rationality discussion? |
| Lisa Sattenspiel | Agent-based modeling à thinking about choices that people are making all the time, but Lisa’s work is not within any particular framework à more using knowledge of human behavior as an anthropologist (understanding of variation among cultures, different attitudes, different ways people behave in different kinds of environments) |
| Ori Plonsky | Question for Lisa: What are the basic assumptions you make in your modeling (about people’s choices)? |
| Lisa Sattenspiel | Not a huge amount of choice in the models, though there is some  Mostly been doing historical modeling of 1918 flu in a fishing community in Newfoundland à uses historical information about how fishing boats were set up, who ran the boats, households; knowledge from the ethnographic literature about how often men will go out to fish, whether women will help them à creates the basis for decisions à if the behavior is likely to be variable à set up probabilities for what people choose to do based on the ethnographic literature (not based on a theoretical model) |
| Ori Plonsky | Your probabilities are based on actual historical data? Do you use the mean probability? |
| Lisa Sattenspiel | Yes, uses the mean probability |
| Ori Plonsky | There’s no show of value or anything for if each agent gets something? |
| Lisa Sattenspiel | No |
| Ori Plonsky | Would be interesting to know how to use agent-based models to add cognitive models that have value in them |
| Lisa Sattenspiel | Depends on what you’re trying to model  Doesn’t know enough about economic models to know how the value fits in; how does that work in an economic model? |
| Troy Tassier | Does network-based modeling à agents are thinking in a game theoretic, strategic formulation with information coming from different sources (can have population-level information, local-level information) à optimize based on what your information set is |
| Ori Plonsky | What do you optimize? What is the objective? |
| Troy Tassier | Standard rational choice, economics type situation  Based on your own experience, the experience of people within your network, or the experience of people in a population, how likely are you to be infected, what is the cost of vaccination à try to optimize your utility  You may have different sets of information depending on where within a network you live |
| Chris Bauch | Giving an example of how you might operationalize this approach: Assume population is all vaccinators or non-vaccinators à at each timestep, each person talks to one neighbor à people of different opinions compare payoffs (payoffs may be based on a homogeneous cost, or each agent could have a cost associated with the vaccine based on a past history of having an adverse reaction to the vaccine) à if they can get a higher payoff by switching strategies, they switch strategies with a certain probability (perhaps proportional to the gain in payoff) |
| Paschal Sheeran | Changing your mind is based on discussion and interaction; is there space for rates of vaccination within one’s network? |
| Chris Bauch | Different models use different approaches  You could look at the population-level of vaccination, or you could look at your neighborhood à if you see a lot of people vaccinated in your neighborhood, you might infer a lower probability of infection |
| Troy Tassier | There may be a certain number of people in your neighborhood for whom you know their vaccination status, but you don’t know the vaccination status of everyone in your neighborhood; however, you can more easily observe how many people are infected (ex. Rates of school absenteeism, number of people who are sick) à can have different levels of information in the model both at the network level and global population level à look at differences in behavior |
| Lisa Sattenspiel | Can do the same kind of thing with the type of modeling Lisa does  It’s an implicit network, but agents can check with other agents around them about their behavior and change their behavior based on what’s going on around them |
| Jude Bayham | Are the agents forward-looking? Are they solving some dynamic optimization problem? |
| Lisa Sattenspiel | Not in Lisa’s models |
| Chris Bauch | Usually not; usually based on the current status, sometimes the history |
| Troy Tassier | No; based on history or current status  In network models, really difficult to think about optimal forecasting |
| Ori Plonsky | Question for Chris and Troy: You’re using fixed payoffs? It’s not a distribution? |
| Troy Tassier | Yes; usually have an expected payoff; making an estimation of probability of being infected based on your neighborhood or history; have a payoff of being healthy or being sick; use expectations of becoming infected to weigh payoffs |
| Ori Plonsky | Can also integrate probability of success into models, which should, in the case of infections, have large consequences on the decisions that people make  Seems most natural to use an agent-based modeling framework |
| Chris Bauch | Are you thinking about prospect theory in particular? |
| Ori Plonsky | Thinking about the opposite of prospect theory, which predicts overweighting of rare events; however, when people learn from experience, we see the opposite (people underweight rare events)  First order would be to integrate the probability of success; the second order, when you assume a reliance on small samples, then you get a bi-modal distribution (a lot of people underweighting rare events, with a minority of people overweighting rare events) à could do a lot of interesting stuff in network models à in certain neighborhoods, you get people overweighting rare events; in other neighborhoods, people underweight rare events à network modularity |
| Chris Bauch | Could get a patchwork of echo chambers |
| Ori Plonsky | Can get echo chambers of people who overweight the rare event, are panicking and buying up toilet paper  Can see different phenomena emerging in different locations in the network |
| Chris Bauch | Is there empirical support for small sample bias in the toilet paper phenomenon? |
| Ori Plonsky | If a significant minority of people overweight rare events and panic, that changes the incentive for other people in the network to panic as well even if most people think panicking is stupid |
| Troy Tassier | Like an irrational bank run |
| Ori Plonsky | The interaction between social learning, how the way other people react changes your incentives, and reliance on small samples can all be integrated into an agent-based model |
| Lisa Sattenspiel | Missouri is a patchwork state; some enclaves where everyone wears a mask; other enclaves where no one wears a mask; also characteristic of vaccination and other things related to COVID-19  The model Ori is talking about may be able to better capture that kind of patchwork structure |
| Jude Bayham | Same with Colorado |
| Ori Plonsky | There is also a selection issue; people tend to choose to live in certain environments where their neighbors are similar to them |
| Lisa Sattenspiel | You can’t assume everyone’s the same because they’re not  If your goal is to design models that allow you to assess different strategies, the better you can model the underlying populations and their variability, the better your strategies will be |
| Ori Plonsky | If you can create a model that accurately shows these enclaves, you can create a baseline for when the epidemic hits |
| Jude Bayham | In these network models, are there ever general equilibrium economic models ever layered on top where you have endogenous prices, markets clearing? |
| Chris Bauch | Hasn’t seen that; usually, people who build network models are interested in those things as outputs rather than inputs; interested in what kind of behaviors might emerge from a network model  Could imagine a network model with network transmission but the vaccine demand by individuals is governed by a supply and demand function dictated by the total number of vaccinators in the population à transmission is localized but market dynamics are mass action |

**Session 5 Green**

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| **Person** | **Comment** |
| Gonzalez | The concepts of the models and the parameters of these models are different from the behavioral models.    The other thing is, what is the social side that is important and to incorporate into these models and which level. So, there is discussion about the generic models, whether we want to do it at the individual or group level. Whether the models capture individual behavior, and I do believe the diversity and variability of the behaviors are very important for these models. |
| Chen | The best way to think about the distinction about normative and productive…is the issue of rationality vs. bounded rationality. That’s actually one dimension, and then the distinction between productive and normative that’s actually different dimensions. In economic, we are looking for equilibrium behaviors vs. what is socially optimal. Equilibrium is are what we predict will happen, and then we have a notion of what is normatively [blast?]. That’s the social optimal. And so, we want to compare the two to see if the equilibrium gets to the social optimal.    We also have the fully rational and bounded rational approach. A good way to think about it is like a two 2-by-2 box. The fully rational model would give you predictions different from boundedly rational models. Now there are plenty people, like behavioral economics, who study non-Bayesian learning who study behaviors that are not fully rational. They actually parameterize their model.    So the more sophisticated work nowadays can parameterize the level of rationality. And the challenge for the behavioral sciences for the empirical studies is what are actually those parameter values that we should then put into our model. |
| Eubank | The rational actors are not going to give you the kind of nuanced depiction of behavior that would really be appropriate, especially when behaviors are correlated to, to outcomes.    Like people who decide not to get vaccinated are going to have a different experience than people that do. Maybe there's a way to combine that with this level of dis-aggregation of representing behavior. The cognitive models will be parameterized in some way by right [white?] individuals. So this individual will have a different cognitive experience reaction than another individual. |
| Chen | The productions are not necessarily very robust because it depends on how you specified a boundedly rational model. The fully rational approach has been very popular and dominant because that framework's foundation is strong, but behavioral economics don't have a super solid foundation upon which to make a robust production [predictions?]. |
| Gonzalez | The behavioral economic models cannot capture really many ways in which humans can be irrational. But, there are many ways in which humans can be irrational.    Capturing of the learning process in adoptive [adaptive?] process is very important. And a lot of the behavioral economics models prescribed rules or determining what are the different possibilities in which people can be rational. Because there are millions of ways, so what we need to do is being able to capture things in an adoptive [adaptive?] way in which those irrational behaviors emerge...and particularly models that are learning models that are able to take into account particular individualized experiences, and also to predict the rationality. And the parameters should be able to capture that level.    I think that's a major challenge is to integrate those with the bigger picture of epidemiological models. The epidemiological models are quite sophisticated, but very naive in terms of human behavior. And the human behavior models are quite sophisticated in individual behavior, but very naive in many other ways, including the population level kind of predictions. The challenge is precisely sort of bringing these two together. |
| Chen | A lot of behavioral economic models now parameterized the level of like bounded rationality, or the level of bias in the models. So that by changing a parameter values, you can get fully rational or a fully naive version. There are lots of different ways you can write down a boundedly rational behavioral model. |
| Ivan | The question is always, we know people who are rational are, but what is the key question? In the case of an epidemic, there are so many forms of rational. |
| Albarracin | The term is a problem for a psychologist -- why would we have to submit or make judgements about rationality, it's, I think, extremely demeaning. The term rationality, I think it weren't abandoned, it would fly better in terms of how the communication with psychology.    One aspect that we do consider is reasoning; another part is automaticity. And the fact that people are not even making decisions. |
| Gonzalez | Human behavior is important to have that optimal or baseline or at that optimal level so that we can figure out how far humans are from optimal, not to claim that humans are irrational or optimal, but to determine in which ways we differ from those optimal behaviors.    Automaticity emerges from experiencing consistent situations and that doesn't mean that people are not making decisions. They are just making automatic decisions. |
| Albarracin | Some are clearly practice decisions, but in other cases, factors that are incidentally linked environmentally. And not because you made a decision in response and then became automated. |
| Obrien | When we get into sort of rationality, that’s not a zero one decision that these agents are making. They're selecting from a huge range of options to control some part of their health.  And optimization is a little less clear because we have to sort of decide what is optimal for these agents, which is not ideal. |
| Ivan | It is uncleat what the main parts are from worrying about the risks, of going into a store or the risks to people you're gonna contact in future. It is interesting to know what the main thing is that's that we have to add to that? |
| Albarracin | To integrate these different lines of research, perhaps first collecting/coming up with some kind of list of, of the factors. We do have risk estimates but they are not hugely impactful at all times. |
| Ivan | A large part of economics is aggregating up individual behaviors and seeing how they influence each other. So let's say if everyone's preventing being very careful, then maybe I have less of an incentive to be careful because I think, you know, everyone's going to be careful for me. They're going to wear their mask. I don't have to wear mine. That would just be, you know, off the cuff example. |
| Albarracin | I really liked this, this idea, something that we could propose for it to NSF? Something like a call to study the rules or aggregation for different psychological and behavioral variables.    If you're making a decision individually or as a family or a group, they're probably pretty clear on differences between emotion and how that will transfer to the group. And something like making a decision on a math problem, which is fairly self-evidence. So with one individual proposing that, that becomes the solution for the group |
| Gonzalez | It would bring several areas together, social networks and cognitive science in particular. To scale up our cognitive models, who behavior, which are at the individual models to networks, it will require social network people here, like Nina, for example, um, and many ideas. So, the interdependencies among people scale up in non-linear ways. |
| Chen | There are a lot of the things we can throw in a model, but ultimately, we need to know what we're trying to achieve. And some ways we need to know what our objective is because like we want to improve epidemiological models. How do we want to measure the goodness of fit? What are we trying to achieve? You have to make modeling choices depending on what your final objective. Because without a clear, we could sit here and argue about what we want to add into a model, but we're just not gonna get any closer. |

**Session 5 Red**

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| **Person** | **Comment** |
| Andrew Atkeson | Tim, I was very interested about what you said about phases of disease and control of it. Could you expand on it? |
| Ido Erev | I am also very interested in talking about definitions of rationality in Economics and Psychology. This is important  What is the definition in epi-economics |
| Tim Reluga | Mutation of behavior is very different from mutation of virus. Behavior is more continuous and adaptable, virus is the limited slow process and it has to do with differences in scenarios. |
| Andrew Atkeson | You said in early phase of evolution of disease stochastic and we can control it but there is threshold that beyond that it is not possible |
| Tim Reluga | Yes, once it starts to be transmitting in large numbers in community you cannot snuff it out in the way that you could earlier |
| Andrew Atkeson | Here is definitely difference between zero case and one thousand cases. But once you get to one case, why does it matter |
| Tim Reluga | It is stochastic at low numbers, there is threshold, fuzzy phase transition |
| Andrew Atkeson | Even if it is stochastic, the expected transition rates why is controlling that not concentrates the scale? The reason why I am asking this is that it impacts what optimal policy is.    You have population, you want some policy (school closure, mask wearing) to reduce transmission rate to get the rate below 1. There is a fraction that is infected then you need to put some resources and money  If you double infected people and double resources, do we get the same impact or not? If not why not? |
| Zhilan Feng | I think, in the beginning when you have few cases you can trace cases to stop spread  After some point when you have a lot of cases , tracing would not be effective |
| Andrew Atkeson | Why not? Just hire more people  The model that I have seen.  It takes 1 person to make this many calls to trace this many contacts  If you twice the people you can trace the twice of that many contacts. Yesterday I saw estimated to be 300,000 people. Why did not we hire 300,000 or 400,000 |
| Zhilan Feng | Because every person make contact so many people, go shopping etc. Then you must quarantine all those people. |
| Andrew Atkeson | It should scale linearly |
| Tim Reluga | I agree |
| Andrew Atkeson | Epidemiologists say this all the time that this cannot be done and I have not seen any explanation why this cannot be done. |
| Ido Erev | I think we should talk about big problem, big picture |
| David Finnoff | I think it is a behavioral and policy-making question. Question for you Tim, How you include rational behaviors in your models? I do not care about the definition of rationality.  How are you incorporating behavior in decision making? |
| Tim Reluga | Individual behavior is described by Markov process with tunable parameters, but agent optimize… |
| David Finnoff | So there are feedbacks on the Markov chain    About this concept of rationality, if you have this rational decision maker, maybe not great description of people and How would you move from that which is very complicated structure? For example you have network change in front of decision maker, so how do you deal with intertemporal forecasting of these decisions but your model endogenously changes throughout time.    Flavio, You have those rational decision-makers, how would you deal with the network structure changes due to the decision making and how to deal with it across time. Like those initially optimal results no longer being optima due to the change of the network. |
| Flavio Toxvaerd | Most of my work uses well mixed populations. I have not done it but there should be a way to do it  Network based models, the ones I have seen do not have intertemporal maximization so they look at consequences of location of different individuals within the networks and so on  In principle, I do not think why it should not be possible. I suspect it should take simulation work. |
| David Finnoff | Is there any possibility for network inconsistency overtime?  You make your best choices through time then your network changes then what you thought would be optimal no longer is optimal then it blows up all maximization stuff |
| Flavio Toxvaerd | I have not done such models and I do not see any practical solution to a problem of such complexity. But you can add random components there. |
| Ellen Peters | I just wanted to go back to the question of what is the definition of rationality for economists.  Normative models are logical models that what people should do  From decision psychology point, it is like the difference between expected utility theory and prospect theory  How is it different for you? |
| Flavio Toxvaerd | Rationality just means behavior is according to your preference. I think prospect theory is about rationality because I define rationality more broadly (e.g., someone rationally decide to behave irrationally) |
| Andrew Atkeson | If we want to do prediction, you can side step a lot of these questions about definitions and do some modifications of statistical models to incorporate some anticipated response useful for forecasting  Some dirty secret of macroeconomics  A lot of time purely statistical models for forecasting do better than our structural models  The use of structural models is for doing counterfactuals for things that we do not observe in the data  I call that story telling    But for forecasting you do not have to be very philosophical |
| Ido Erev | We definitely use rationality differently  So the question is not people are rational or not  But what is useful for this meeting is we want to make assumptions more explicit and less implicit  When you develop Epi models incorporating rationality, we necessarily need to involve factors that are rational, which make the models impossible to reject. |
| Tim Reluga | I’m using expected values when talking about rationality. |
| Peter Doloton | Let’s take all this back to the data  What we want to do at the end of the day is we want to predict how many cases, deaths, how many resources we would need.  That rises the question of how do we marry the data with theories Favillio was talking about.  The underlying thing of all these that we talk about brings up the standard problem in Econometrics which is endogeneity of behavior. That is probably what we should be doing next |
| David Finnoff | My understanding of rationality was consistent choice under the same condition which is very broad.  The reason we bring up this a lot in Economics is that the individual level is all over across the board but in terms of average across the large population that kind of assumption does not do bad. It is hard to optimize the parameters in models, but I think we need to have a starting point and later improve. |
| Eli Fenichel | I put a book in the chat which is my favorite explanation of rational choice theory and aligns with what David just said (Gilboa, I., 2009. Theory of Decision under Uncertainty. Cambridge University Press, New York.)  The goal of what we need is condition on choices we have made in a model of what is fixed and what is allowed to vary is parameters in decision space of the agents ate not situationally dependent. That purges to kind of endogeneity that Peter was talking about  This has been a problem in epidemiological models, the way they have used behavior is highly confounded measures. Some of the smartest epidemiologists have mentioned can we turn behavior off. As we look at the data there is no such thing. A lot of confusions are coming from mathematical definition, conceptual definition, and behavioral definition in epi modeling.  The only way to turn it off is North Korean policy dictator tells people do not change from what you were doing |
| Ellen Peters | If rationality is being consistent with preferences. My question is how about preference reversal? Not only psychologist study it, economist also study and show it.  About the modeling average, how much do want to get the average given all the differences that are out there? Some of those differences will be taken care of by controls like demographics, but what if some of those differences that are not in your data and turns out to be what you need to predict some other things |
| Eli Fenichel | With nonlinearity the average behavior does not get the average payoff. This is the problem with just using the average. |
| Peter Doloton | That is why exactly we need econometrics. Even if we have perfect models and take to the models. Simply because the data is mismeasured whatever model you want to use there is a role for econometrics. |
| Andy Neumeyer | In Columbia, they took a lot of mitigating behavior and look for the average behavior. |
| Michele | For many economists, rational choice means maximizing utility. The question is what do put in the utility. I am providing the point that we should thinking about what utilities are. Should we have altruism in the case of COVID now, people voluntarily are social distancing |

**Session 6 Blue**

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| **Person** | **Comment** |
| Michele Tertilt | To Ellen- how do you think psychology can help economic and epidemiology models? |
| Ellen Peters | We study psychological process- understanding psychology underlying behavior and use this knowledge to motivate behavioral change but also to improve society in some way – and we have accumulated a lot of data on these processes.  In terms of models –some of our data can figure out things that are missing in models in economics and epidemiology, and what need to be added in the models.  The language (different terms used across disciplines) can be a barrier though. |
| Ido Erev | In economics, you need to have some assumptions about behavior to build models.  Hopefully, psychologists can help us come up with good assumptions and justify our assumptions. But given we use different languages – I saw people in economics take concepts from psych and use it in ways I would never do. e.g., loss aversion works only in one-shot decisions (as shown by psychological experiments) and not repeated decisions – However, a lot of economists apply loss aversion in repeated decisions as well – which is incorrect.  The benefit of this meeting is that we can talk to psychologists about these assumptions, and we can use that insights into our models. |
| Timothy Charles Reluga | Challenge for us (Mathematician) is that –  I can make a model for behavior that is rational but has no basis of facts of psychology. |
| Paschal Sheeran | How many parameters can we add in your model - Can we put trust in government as parameters in models? That has been shown to predict a lot of behavior during the pandemic (e.g., support for mask-wearing, social distancing and etc.,) |
| Timothy Reluga | Distribution of choices? |
| Ido Erev | Something more basic-  In each model you have to assume equilibrium that some people make mistakes and behave randomly – not fixed parameters – people change their behavior often.  Basic psychology would tell you the probability that people will deviate. |
| Timothy Charles Reluga | What about learning? people learn from their experience over the course of the epidemic and how we apply these changes in the model |
| Ido Erev | We want to learn more about implicit behavioral assumptions about people (which we get from psychology) |
| Timothy Charles Reluga | Basic assumptions in epidemiology models are mostly physical (e.g., movement)– we know where they are, where they spend time |
| Ido Erev | Parameters of move – economists can help you predict when these properties will change across different situations |
| Michele Tertilt | Going back to Paschal’s questions about trust in gov - I think that would be too abstract.  As an economist, cost in government is vague but once we think about something concrete- one dimension of trust in government. |
| Ellen Peters | from psych – not sure why trust in gov is abstract – it is an observed variables and quantified. We already know from a lot of data that trust in gov shapes behavior (covid-19 preventive behavior). it is not deterministic; we have an expectation |
| Ido Erev | We have different perspective – when talking about adding trust in government as a parameter – we would focus more on the specific feedback people get from the government as proxies of trust (e.g., free food) – something more basic.  what kind of feedback people get from gov (as a variable that could affect trust in gov)– these are the things should go in as parameters |
| Paschal Sheeran | Support for trump in 2016 and prevention behaviors – strong predictive correlation |
| Ido Erev | Feedback is important, |
| Timothy Charles Reluga | But this correlation emerged at some point during the pandemic – Trump voting is independent of epidemic in the beginning. Then- emergent correlation between voting in a presidential election and how you act around your neighbors.  That’s what we need to be able to predict, if we can get predicted this- we would have a better handle on how the epidemic would progress.  how can we predict these things and put them in parameters before?  Where to draw the line? |
| Michele Tertilt | Interesting question about heterogeneity. Do parameters change over time.  Traits that could change – things that cannot capture easily |
| Ido Erev | In Israel, it’s interesting because liberals believe less of COVID-19 – opposite from US.  There is an equilibrium, for some group of people, they form a belief, you move with your friends. Depending on countries will make different groups.  Different countries – different groups showing different patterns |
| Paschal Sheeran | Are we getting close to having good empirical data to model this? |
| Ellen Peters | It’s hard to figure out if we can predict these division in groups? |
| Timothy Charles Reluga | Do liberal believe more in science in Ido – In israel? |
| Ido Erev | Too liberal that they do not believe in science |
| Ido Erev | I agree that trust is important, but we should go for something easier to predict |
| Ellen Peters | How could have predicted this trump effect? Even if in psychology we did not predict – he ended up having a cult – there is something in that sort of thinking that could have predicted this phenomenon |
| Ido Erev | Multi equilibrium kind of situation  For white paper, we can propose collecting data from different countries-how same parameters in different cultures will lead to different conclusions about covid-19 and interventions for government or policy. We would expect polarization from different cultural groups. |
| Timothy Charles Reluga | Comment on Jewish community in the US. Hasidic Jewish community went from transition of vaccine hesitant to being vaccine willing. |
| Ido Erev | Jewish community in New York – sent children schools even during school closures because if they do not go, they worry that their kids will become less religious. But vaccination they love it because if they get vaccinated, they can go to school. They’re very rational -work well in models and easy to predict. Their behavior is less about concerns for COVID-19 but they support whatever that could keep their religious beliefs going. |
| Timothy Charles Reluga | Certain characteristic about Jewish that could have predicted this outcome? |
| Ellen Peters | Interesting opinion article shared.  How Israel Successfully Combated COVID-19 Vaccine Hesitancy.<https://www.npr.org/2021/04/20/989015624/how-israel-successfully-combatted-covid-19-vaccine-hesitancy>.  How they’re getting information about vaccines is very different also. |
| Ido Erev | They get information mainly from Rabi which they have great trust in.  Green pass – major success in Israel. Worked well for religious orthodox |
| Ido Erev | To Ellen-  For some reason kids in the school they are not sick (those sent to school during covid-19 in Jewish communities) experts are not sure why- they could have been sick but unnoticed. Perhaps their transmission rate is low |
| Ido Erev | In Israel, our green passport is not mandate but it is just checks about covid19 test once a week – so people would go vaccinate because this is a pain. So this proves that you do not always have to force people – let them do what they want. It is hard for them to at least object to testing and if they want to avoid testing, they will just go and get vaccinated. |
| Blue room summary | How psychology can help economics and epidemiology models in general  We need some data from psychology, measurement, and what dimensions of heterogeneity are we getting wrong in economics and epidemiology models.  We talked about parameters – for example, trust in government would be something that psychologists would be interested in putting in as parameters in models but not in other fields. We talked about how specific these parameters should be.  Politics and distancing seems to be very related in the US – could have this been predicted or that could be changed? What are the ways that we could have predicted this?  Using models to understand vaccine hesitancy – issue of green passes, incentives- differences of these interventions and efficacy in different countries.  Topic of Israel-Extreme liberal wing are actually refusing vaccine but opposite in the US. Interesting dichotomy to observe.  We use parameters to predict something but how we predict behaviors that go into these parameters in the first place. Integration of factors affecting behaviors could be one way – combinations of communication, behavior, policy, media, networks. |

**Session 6 Green**

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| **Person** | **Comment** |
| Eli Fenichel | One thing we didn’t touch on is the communication strategy. Communication can itself be a policy. During h1n1 there was no stay-at-home order but there was messaging to influence behavior. It is interesting what information sticks and has an effect. |
| Flavio Toxvaerd | Same experience in epidemiology - as these are not voluntary behaviors since we told them to do so, and they think communication is intervention. But we don’t think of those as mandates.  There is variation in communication on mask wearing: when early on we wanted to protect limited PPE stocks and then later we wanted to promote masks for everyone, this gives conspiracy theories something to point to. There are also lessons from HIV: the actual risks were small for any individual but aggregate effects were significant, so there was perhaps a dangerous overemphasis on the risks in order to promote pro-social behavior and achieve public health goals. |
| Eli Fenichel | There doesn’t seem to be good language to describe the difference between voluntary and compelled behavior, which leads to critics like unemployment as a voluntary vacation. When we think about people responding situationally, taxes and fines are the same mechanically but have different labels. |
| Chris Bauch | The chance to use public health interventions may have deteriorated as individuals’ faith in doctors (versus online sources) has decreased  Sweden an example of communication versus behavior, their ‘herd immunity’ strategy is often discussed as a country that didn’t lock down. People compare outcomes between Sweden and France who did lock down as being drastically different in this sense -- but mobility drops in Sweden are comparable to places with lockdowns, so people still independently made these choices. |
| Flavio Toxvaerd | This seems like an example of individuals having incentives that are not perfectly aligned with social welfare, since the magnitude of distancing is lower in places without formal restrictions. And perhaps Swedish people are culturally disposed to socially distancing? |
| Ori Plonsky | To Eli’s questions, definitely strategy in communication has important implications, but as Sweden shows for certain settings like COVID it’s not enough so it feels like the easy way out for policymakers: give people information they’ll do the right thing and that’s it so we don’t have the lobbyists on our backs to avoid lockdowns.  It was so much easier to talk to government officials about communication strategies than about behavioral implications. |
| Eli Fenichel | What’s communicated to the public when the policymaker is only talking, like in a cheap-talk model? Do people just think the whole thing is not very serious? Are there any co-messages going on here? |
| David Finnoff | In our sample (we oversampled Wyoming), we found iinformation doesn’t budge people. The information is cheap and easy. It doesn’t work on most people. People may need a portfolio of policies. |
| Ori Plonsky | It’s easier to talk to governments about nudges because there are things that they can do without getting politicians involved. It’s not about money or laws, so it’s easier to just broadcast messages and hope they work. We can use nudges if we can’t use incentives. We have data to test people with RCT to get vaccinated. We have only 1-2% differences from baseline. If there are incentives from media or through text messages, it increases threefold. Communication with incentives is important. |
| Eli Fenichel | So what can we do? What are the barriers? |
| Ori Plonsky | Broader social impact: we can get people to voluntarily act responsibility if we align the incentives with what we understand works. When the probability of reward for doing the right thing is very high, then it works. |
| Michelle O’Brien | One of the barriers is that there is a huge cultural difference in uptake about the incentives.  Compliance is hugely different based on not only incentives but also people’s past experiences with government sanctions and what regulation really means.  Where and for whom and how impactful are these policies? |
| David Finnoff | We tried to build a food web model based upon some principles of behavior, where through the aggregation of agents’ behavior, important variables like prices are determined. We tried to apply that in the ecological setting. Then you could track perturbation through the system, and understand both the behavioral decision-making rules and how these aggregate into important outcomes. This can be quite challenging in a representative agent model. |
| David Finnoff (session summary) | We had in in-depth conversation about the importance of communication. Specifically, communication as a policy variable. Often times, in policy talks, it’s key for policy makers because it’s cheap and avoids some other political forces. Does it work? It does with some people to certain degrees, but we need to understand the behavioral impacts more precisely. |

**Session 6 Red**

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| **Person** | **Comment** |
| Dolores | Some of the language in econ (like rationality or morality) could represent a barrier to merging multiple domains/ideas |
| Dolores | Terms like Moral Hazard I eliminate due to them not being palatable in the public health community |
| Frederick Chan | We can’t expect or develop a general model that will solve all kinds of problems. It is going to be problem specific model development. From a public health perspective, what is the objective? |
| Andy Tan | The intention of creating a model is to inform the quality of the decisions that policy makers or other agents might be relying on to recommend/avoid specific actions. So a decision aid to maximize public benefits, minimizing consequences |
| Frederick Chan | There is a difference between predicting mortality and infection vs what are the public benefits, what are the unintended consequences? I feel like the model should focus on the predictability and then the interpretation should be based on morality and those other lenses |
| Dolores | Public health is about the behavior, the population, and the context. There is little focus on generality. Each situation is absolutely unique |
| Dolores | Behavioral and social variables are not typically included in most epidemiological models, though there might be nuances in how they reach that conclusion. It is perhaps true for some behaviors (e.g., flu), but does not seem true for HIV. They focus on specific behaviors rather than the idea that infectious diseases just diffuse. |
| Frederick Chan | One example of how economists can clear up these confusions would be that describing some things as irrational is incorrect. Example – It may be rational to vaccinate if everyone else is already vaccinated, or based on their own personal values. |
| Dolores | Just using the idea of this is still rationality does not help us because there are two different outcomes |
| Dolores | What does it mean to improve models? Policy relevance and utility are one. Including behavior may not really improve forecasting and predictive power. The validity of the models might improve. |
| Folashade Agusto | Behavior might not help with the prediction, but can help with understanding the trajectory and patterns of the model. The fact that most epidemic models do not think of behavior and the models are not incorporating people’s beliefs (e.g., Ebola). These other features are important and necessary for a global outlook on the disease |
| Frederick Chan | The hardest part of being a modeler is that they need to be parametrized and estimated. Theoretically you can include whatever you want but the difficulty is in actually including it in the model. To improve these models we need to focus on the nitty-gritty |
| Dolores | There are multiple models of behavior that are reasonably predictive. But the data are scarce. What is available are things like the annual reports from the CDC. |
| Dolores | Summary: General vs. specific models and the interplay in those. One aspect of those is whether the model is specific if we never compare it. There is also the issue of what should be done with the model to improve it (policy, utility, beliefs, practices). Finally, data needs and the desire for a national effort to track these psychological features. |

**Session 7 Blue**

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| **Person** | **Comment** |
| Dolores Albarracin | Would be interesting to measure the actual impact of information and persuasive communications  We do see their impacts in the real world, but when we measure them, they tend to be modest, especially just factual information (persuasive communications do better)  But there is more to it (overlap of multiple sources and so on) |
| Ori Plonsky | Question for Ellen: Why is there the discrepancy between the college students partying and the 58% of the population who were still very worried about COVID-19 in December? |
| Ellen Peters | College students vs. the American public |
| Ori Plonsky | So, they’re just different people (the majority are worried, but the minority are not) |
| Ellen Peters | College students are very different from other groups of people; tend not to be particularly worried about COVID-19 (are at lower risk of getting it and suffering from it); many are completely unconcerned; some are worried only for other people but not themselves  The general American public is more worried overall about COVID-19 |
| Hari Sundaram | There’s been a lot of interest in coming up with highly sophisticated models for prediction. We’ve talked about how machine learning can incorporate behavioral techniques, etc.  However, it seems like we don’t have as nuanced of an approach regarding how we tell people how they should behave. Why should everyone be told the same thing? How can we have sophisticated techniques of telling people the things that we think are crucial for them to make the decisions that are relevant to the pandemic? |
| Dolores Albarracin | It’s a great idea to improve the methods for tailoring messages, but we’re constrained but what NSF asked us to do |
| Paschal Sheeran | Messages are actually remarkably effective given what they’re up against (people could get angry/reactance, threatening their identity, threatening what they want to do)  Our messages need to get around a lot of barriers to be effective; maybe machine learning could help us to calibrate |
| Hari Sundaram | Advertisers are already using highly sophisticated techniques to tell each person something slightly different  Science should do the same thing to make messages more effective |
| Ellen Peters | Could machine learning help us sort through a variety of different techniques in order to effectively tailor messages to different types of people? |
| Hari Sundaram | Yes, that’s what advertising does |
| Ellen Peters | Would need a compendium of different ways of communicating; need to know the effects of those communications on different types of people; need a huge amount of data, but machine learning could help us figure out the right techniques to tailor messages |
| Ori Plonsky | Maybe could use machine learning to predict numeracy based on internet activity and then target messages based on numeracy level  This method would not require as much data |
| Hari Sundaram | Highly abstract comic-like infographics tend to work really well (people empathize with the comic character as opposed to having a highly detailed, fleshed out representation that creates distance)  What are the different cues that create empathy?  How do we tell stories that are highly individualized? |
| Dolores Albarracin | There is a lot of tailoring already in health communication; using this method would be great |
| Paschal Sheeran | Do we know how many randomized controlled trials of behavior change interventions we’ve conducted over the course of the pandemic? |
| Dolores Albarracin | Quite a few on messaging (majority are not super successful)  Largest done by Katy Milkman (5% increase in flu vaccination behavior when we tell people we have a vaccine reserved for them)  Very difficult to move even intentions to get the COVID-19 shot |
| Paschal Sheeran | Surprised by the lack of randomized controlled trials so far in the pandemic (lots of observational studies but seem to be fewer attempts to actually change people’s behavior) |
| Dolores Albarracin | Have effects primarily from making the vaccine mandatory (seems to be the most effective kind of message) (similar to Green Pass in Israel) |
| Andy Tan | Maybe look at influences of exposures through people’s media utilization phenotype and look at subsequent behavior over time |
| Dolores Albarracin | Could be one layer to look at; would need to model the collective impact of all these sources that are validating certain types of information |
| Paschal Sheeran | Could pursue the behavior change for good model that Milkman and Duckworth use à invite teams of researchers to generate interventions and then invite other researchers to predict the likely outcomes of those interventions à run the interventions and see the results  Have few competitive tests of different strategies to change people’s behavior |
| Dolores Albarracin | Tried that approach before (came up with every possible strategy to change intentions to get a COVID-19 shot), and none of the strategies had any effect (though the study had lots of power)  Maybe target a population that is actually going to a place to get vaccinated (need actual adoption rate) |
| Paschal Sheeran | Maybe try running some of the conditions again (could have different results now that getting the vaccine is a real possibility instead of hypothetical) |
| Dolores Albarracin | During the original study, getting the vaccine wasn’t hypothetical, but the supply was very limited  Could try again now that the vaccine is more available |
| Paschal Sheeran | There was another mega-study about increasing gym attendance using a text message intervention à no effect |
| Steven Eubank | Was it that none of the interventions had any effect, or did they all have the same effect? |
| Paschal Sheeran | Text message intervention had a modest effect over the first month, but effect didn’t stick after the text messages stopped |
| Amyn Malik | Currently working with Facebook and UNICEF country offices to conduct a targeted messaging trial looking at intention to get the COVID-19 vaccine (sentiment analysis on posts within a geographic location à sending targeted messages based on what people are posting about vaccines/their feelings about vaccines in different locations) (initially measuring intention but could follow up by looking at behavior later) |
| Andy Tan | Could we (ethically) use bots on social media to share information from reliable sources with vaccine hesitant people so they can have at least incidental exposure to accurate information?  Compare against a control condition where bots share random, unrelated news |
| Ellen Peters | Could also tailor bots to make them seem more trustworthy to the individual |
| Andy Tan | To make the bots more believable, could have some proportion of posts unrelated to COVID-19 |
| O’Brien | Would need to somehow measure change in a vaccine hesitant social media user |
| Andy Tan | Could invite the social media user to a study and ask them to self-report on those behaviors |
| Juan Palacios | Maybe use location data to determine if people go to vaccine sites |
| Hari Sundaram | Need to be very careful in how we train bots; if you just train them on a large corpus, even if it’s ecologically valid, it’s possible that the words that the bots learn can covary with attributes like race and ethnicity |
| Paschal Sheeran | Facts alone don’t change people’s minds, but sharing personal experiences can help bridge divides à people can learn to respect one another’s opinions and become more willing to interact and engage with each other |

**Session 7 Green**

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| **Person** | **Comment** |
| Tertilt 00:00 | Couldn't the Canadian data be just kind of pandemic fatigue? |
| Bauch 00:54 | There's a number of reasons that can determine if behavior becomes more or less adherent to the second wave. And they all work in the direction of less caution. So there were a lot of strong, pressures, including fatigue that were just making people over the world less less reactive in the second wave. |
| Tertilt 01:44 | Novelty wearing off and fatigue are conceptually quite distinct to the costs of the protective behavior. It's maybe some kind of convex cost function and that's the reason. |
| Bauch 02:23 | It might even be related to macroeconomic factors, you know, some have speculated that, well, the other thing that happened in the fall was that many central banks decided to stop printing so much money. Novelty wears off monotonically and data builds cumulatively, but the fatigue can come and go depending on opening and closing phases. |
| Sattenspiel 03:43 | You might be able to get insight on this by looking at the 1918, uh, situation. It turns out that in many parts of the world, there was a pretty sizable wave in 1920. |
| Bauch 07:16 | That kind of suggests that we have not only fatigue to deal with, but amnesia. People will want to forget this in a few years. |
| Finnoff 09:50 | How the impact of budget constraints on the ability to absorb? And it might not necessarily just be fatigue. It's just that you can't financially afford to not expose yourself after a certain point or for like you can do it for a certain amount of time, but there's just other constraints which kind of force you. And you could interpret that as fatigue or just giving up, but it might be that your, your hands being forced. |
| Tertilt 11:16 | Those people who are officially on unemployment, I mean, those who were officially unemployed, they actually large chunk of them getting more money than they would have without the pandemic. So there's already some discussions on part of the slow rate or recovery could be even faster if we weren't paying as much on unemployment insurance right now, but I realize not everyone has access to that. |
| Bharti 12:53 | Unemployment was a, was a risk factor of not being able to quarantine. So people who were unemployed and more likely to, to have to go out not be able to say something else |
| Auld 13:34 | How would we formalize the notion of fatigue? There's no rational explanation for why people are no longer social distance saying they're just tired of it. It's just off the marginal cost of spending a day at home is increasing. Then this is exactly what we would expect. So is there a difference? Is fatigue something above and beyond what I had or is it not, is it just the same thing? |
| Tertilt 14:02 | In economic models, it could be like a mental capital stock or something that at some point, part of it is just a regular cost. And that could be some kind of a mental capital stock for a while. You can do without seeing your friends and your family. Capital stock depreciates over time. |
| Bauch 16:15 | Pandemic fatigue is just an umbrella term for a lot of effects. Some people need the social interaction more than others. That creates problems in terms of formalizing it because it is such a catch-all term for many different factors that all tend to be correlated with how long you've been in this. |
| Finnoff 17:33 | There was some notion of this bundling and communication can work. But, with the one-off communication that we've used bundling didn't matter. There were certain things that were better on their own than without. The portfolios I would think would be like coming up with what, what are for certain situations, what are good portfolios does this information have to be repeated; that's like a key, you can get away with a one-off blast or you got to just swamp them, that portfolio and how it's delivered, it seemed to be really important. |
| Sattenspiel 18:22 | A really interesting research question that would fit this would be, how can you frame the message in such a way that you realistically communicate the situation without the negative consequences of people overreacting to something? It still is a problem with the news media, just repeating things that are half true. How do you frame this message so that you can minimize the social and psychological responses and deal with the problems that have to be dealt with without having that extra veneer on top? |
| Sattenspiel 20:24 | Think about the situation as Ebola and, the fear there was because a few people who were a few Americans at least came back from Africa and Ebola showed up in hospitals in the US and the whole country just, just, panicked. How do you frame news about infectious disease outbreaks without scaring everybody; how do you realistically communicate about the real risks that people face? |
| Tertilt 21:12 | Some of the panic is needed to get people to change their behavior and to respond appropriately, in the context of HIV. So in some sense, this sort of misperception this panics kind of help in some sense to fight the diseases. |
| Sattenspiel 22:00 | That's what framing is all about. How do you communicate the situation in a way that is most effective for public health purposes or whatever your goal without, without lying to people? |
| Bharti 23:08 | I think the lies on in both directions are important. So the misinformation to overreact versus the misinformation to underreact were both important in shaping the response to this pandemic. The misinformation to under-react has been more harmful and has allowed transmission to propagate differently and more intensely.    Some of the early on overreaction is our retrospective estimate. The under reaction and the misinformation not to take it seriously was demonstrably more damaging. And that was very politically skewed. |
| Finnoff 24:49 | We have a long history of manipulating information. I don't know about deliberately misinforming people, but delaying releases of information. Probably there is a policy lever. We did some work with a SIRS model and, and observed versus unobserved immunity. And if you, if people know that they're going to be immune than they get risky. Like we know they're, I'm immune, I'm going to get risky.    So maybe not letting people know they're going to be immune or keeping it well, this unknown efficacy of masks or vaccines that might actually be useful with wide swaths of people, because it just kind of puts a damper on some of that behavior. |

**Session 7 Red**

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| **Person** | **Comment** |
| Ido Erev | Effect of Facebook might have been different than we thought it was.  Give the same message to the public, the impact wouldn’t be very big. To choose people have particular message. If you just push them a little bit more will be very effective. |
| Eli Fenichel | Cambridge Analytica seemed to be awfully good at microtargeting information. If you submerge yourself in an ecosystem – does the messaging have a strong effect or is it endogenous – you choose to submerge yourself. How costly to get someone to unsubmerged  Notion of being able to use communication. Not just social work, but do those sorts of dataset will help us to understand the structure of people? |
| Erev | If you message to public effect is not very large, but if you can better target, you can have bigger effect. Easier to push a little bit more than to push them in the opposite direction.  Not sure how well it can be used for covid, how well can we push people who don’t believe in vaccination |
| Eli Fenichel | The notion of being able to use communication – do the network datasets help us think about stratification of people – what are the relevant strata |
| Chen | How fine grained should the model be? What is the objective? If were interested in the effect of messaging on certain type of people maybe need that level of detail, but if its at the broader level of can we predict the number of cases correctly, might be more helpful to have a more parsimonious model. |
| Eli Fenichel | If you’re worried about herd immunity, is it helpful to use this data to think about assortative mixing. Jude and I built contact matrices out of ATUS data, get multiple waves just because US society is not well mixed  Is that helpful to use these data to mixing big effect. Will you be persistent to have these things? Five different attributes, no matter how you get it, you have different waves. US society is not well mixed. E.g., Ultra wealthy vs. labor  The texture content will help us unpack that from social media data. |
| Bayham | There are natural pockets in the population |
| Feng | What is assortative mixing |
| Eli Fenichel | Like mixing with likes. Interesting bit of that is labor market relations. Might have assortative mixing by ultra wealthy and low skilled laborers. If ultra wealthy employ some low skill labors might be some mixing across groups but not homogenous. |
| Erev | Our research is doing something like this on a small scale. Before zoom conferences I would only talk to people like me, but this breakout room style, I’m forced to talk to other people. Can we do something large scale? My daughter only mixes with people like her, but maybe we keep some portion on zoom to encourage different types of mixing |
| Feng | Mostly mixing withing grade levels |
| Eli Fenichel | My hypothesis is that more mixing withing socio economic classes but across grades. Wealthy kids more likely to mix with kids from their own class but in different grades, than someone from different class in their same grade. Maybe theres a market for lemons problem here – been thinking about this with respect to vaccines as well. You drive out good information.  Is there a market for lemons in media? Fox is not high quality, but their bottom line is good. Seem to be doubling down on low quality content. Is better quality wthin Fox getting pushed out |
| Chen | Not a quality problem, but a social effect. Nature of market to attract viewers, more profitable to have polarizing viewpoints. Whatever sells, media companies will go that way. Maybe more of a sorting problem, rather than quality.  If I know there are lots of risky people there, I am more likely to stay in, more risky people are there. You got sorting of really risky people are there. Positive feedback mechanism. If you have that, you just keep going.  We don’t need psychology unless different cognitive thing leads to different cognitive aspect. |
| Fenichel | But within that sorting is the lemons process at play? |
| Erev | There is a lemon problem that I don’t want to talk to someone smarter than me, because they can convince me of anything |
| Chen | I see what you mean Eli – connection to Kramer problem. If theres a lot of risky people out there, I’m more likely to stay in, then more risky people out there. |
| Fenichel | Yea or bifurcating in that if theres private information, I’m just going to stay out of this market. Explained Akerlof paper. Kramer fatalism process is kind of similar. If I know that process is going on, I’m kind of screwed |
| Chen | Positive feedback process, multiple equilibria. Circling back to the theme of the conferences, we don’t need psychology to inform this process, I’m still wondering what are we trying to achieve here. |
| Erev | Solution to the lemon problem is that you buy the car if you can get insurance. Change the incentive structure to make sure people don’t lose too much from buying used car. So you can change the rules, which is also a learning process. |
| Feng | I like that question, what is the purpose of this. We really want to improve epidemiological modeling. Most don’t incorporate social behavior explicitly, treat as some kind of constant.  We would like to incorporate those specifically to make better assessments. Better policy evaluation, better forecasts. Improve utility of existing models. |
| Fenichel | I don’t know if that’s the problem. One of the things that’s solidified in my mind is modeling the behavior of policy makers, and how they are influenced by the science that’s presented.  No model of policy makers. Some health department with a mission – reduce mortality and morbidity. The fed – manage unemployment and inflation. Could have a situation where fed is pumping money into econmy while CDC tells people stay home don’t go shopping. How important is it that these things are better coordinated.  In late 70s series of papers about whether Fed could achieve targets without Congress’s cooperation. Mathematical conditions about whether they can pull this off, but very strong conditions. Might need that analysis to better understand how we as a society respond to an epidemic. |
| Feng | From point of view of funding agency, we cannot control how policymakers will respond. CDC want to take information from mathematical models.  If we can present some interesting mathematical tools that they can take into account, we can hopefully make some contribution |
| Fenichel | Take a behavioral agent – he’s school is closed, and they’re getting a stimulus check – are these consistent incentives? |
| Chen | From CDCs perspective – they want to see if people can come up with better models. Like Netflix competition for better recommendation algorithm. Need some scoring mechanism to see if people can come up with something better. |
| Erev | Need some training dataset. Maybe NSF can come up with some training dataset… |
| Feng | This is not NSF effort, it is DMS/MB – our interest with SBE, there is different division for data. We don’t have money to fund those – for that research need something for different programs. |
| Fenichel | We’ve talked about CDC, but also housing, unemployment – do we only care about those in the extent they affect disease dynamics, or care about them in themselves. |
| Feng | We care about those to the extent they help better predict disease dynamics, better capture real life. |
| Fenichel | There are policymakers that we can influence, whos mandate is not public health – its unemployment, or poverty, or racial equality. That interacts with epidemic but do we care about those if we can get the epidemic right. Its not clear you need to model that level of details |
| Chen | That’s why its so important to specify whats’ important. Sounds like Zhilan is saying we really want to get case counts right |
| Fenichel | If we do what other policies… We convinced congress that childcare was essential to preventing deaths, without forecasting. Epidemic. Causal effect doesn’t necessarily need most robust fully specified model |
| Chen | You have a valid point but you just need to understand NSF’s mandate – get case counts right. |
| Feng | We are not just for CDC, but we want to have a practical use for this. |
| Fenichel | The goal of a governors office – might also value better models, but their definition of better might be different from CDC. We did a very similar model on childcare, and Senate picked that up and used it as important argument for funding childcare in CARES act. Lots of people here been talking with governors office – they have more authority over NPIs. |
| Feng | CDC is not only one we want to convince. If you can provide whitepaper that can convince utility of this, we can convince our supervisors. Want to build capacity.  CDC’s perspective, they want to have someone can have useful model. Who can come up with the robust algorithm? We need to provide to the NSF and CDC that can use for it. |
| Fenichel | Next pandemic will look different. Need to build capacity, get people to think about these things how they interact. Will need new models. Will need people ready to think about those things. |