Wrapping Up: Review and Looking Ahead

EES 4760/5760

Agent-Based and Individual-Based Computational Modeling

Jonathan Gilligan

Class #26: Thursday, December 2 2021

Final Week

Presentation Schedule

Tuesday Dec. 7:

- Maddie Allen
- Mostafa Farhadan
- Ben Gode
- Daniel Gonzalez
- Sarah Habeck
- Tanya Iyer
- Clark Kaminsky
- Nolan Siegel
- Tatiyanna Singleton
- ’Ana Stringer
- Robin Young

Thursday Dec. 9:

- Allister Barnes
- Zachary Bloom
- Marin Boyle
- Natalie Elliot
- Michelle Gordon
- Marisa Kim
- Davis Kornblum
- Tara Menon
- Yasmeen Minniefield
- Miguel Moravec
- Precious Ukachukwu

Presentations

- 5 minutes each plus 2 minutes for questions
- Structure:
  1. Start by describing your research question
  2. Briefly describe your model
  3. Describe the experiments you performed:
     - What outputs did you observe or measure?
     - What parameters did you change?
     - What did you see? (e.g., behaviorspace graphs or screenshots of the model)
  4. Conclusions
- General recommendations:
  - 5 slides, one minute each.
  - As much as you can, use figures (graphs, illustrations, images, etc.) instead of text.
  - Avoid slides with a lot of text
- You can’t say everything you did, so focus on the most interesting highlights.
- You can present what you did in depth in your paper.

Final Paper

- Write this up as though it were a scientific journal paper:
  1. Abstract (1 paragraph summary of the paper, focusing on highlights)
  2. Introduction
     - Research question and why it’s interesting
  3. Methods
     - Describe the model you started with and how you changed it to answer your research question
     - Describe the experiments you ran with the model.
     - Describe what outputs you measured
  4. Results
     - What did you see (graphs of output, pictures of turtles on patches, etc.)
  5. Discussion, conclusions:
     - What did you learn from the results of your experiment?
     - If you had more time, what would you do next with your model?
     - Do you think these results point to possible uses for your model?

Agent-Based Models for Policy Design

Prediction Markets

Who will be the 2016 Democratic nominee?

Top Predictions — 13815 Comments

Clinton 790	82¢	↓ 2¢
Sanders 1337	19¢	↑ 1¢

Who will be the 2016 Republican nominee?

Top Predictions — 67708 Comments

Trump 3087	46¢	↑ 1¢
Cruz 577	32¢	↓ 2¢

Who will win the 2016 U.S. presidential election?

Top Predictions — 9106 Comments

Clinton 481	59¢	NC
Trump 1226	20¢	↑ 2¢

Who'll win the Wisconsin Republican primary?

Top Predictions — 15959 Comments

Cruz 59	86¢	NC
Trump 106	15¢	↑ 1¢

Who'll win the Wisconsin Democratic primary?

Top Predictions — 3646 Comments

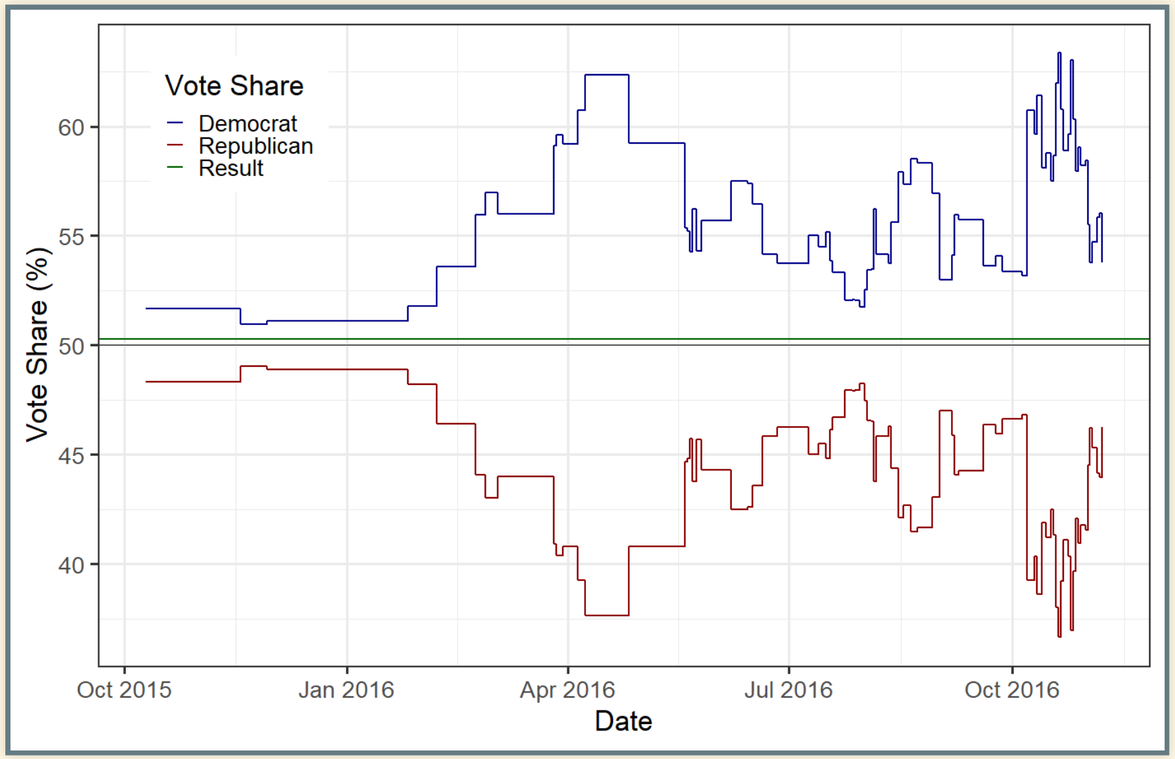
Sanders 20	88¢	NC
Clinton 18	13¢	↓ 1¢

Who'll win the Pennsylvania Republican primary?

Top Predictions — 592 Comments

Trump 1	69¢	NC
Kasich	22¢	↑ 2¢

Prediction Markets and Beliefs



- Predictions overestimated Clinton by ~5%
- Losers may re-evaluate beliefs
- Winners' beliefs reinforced

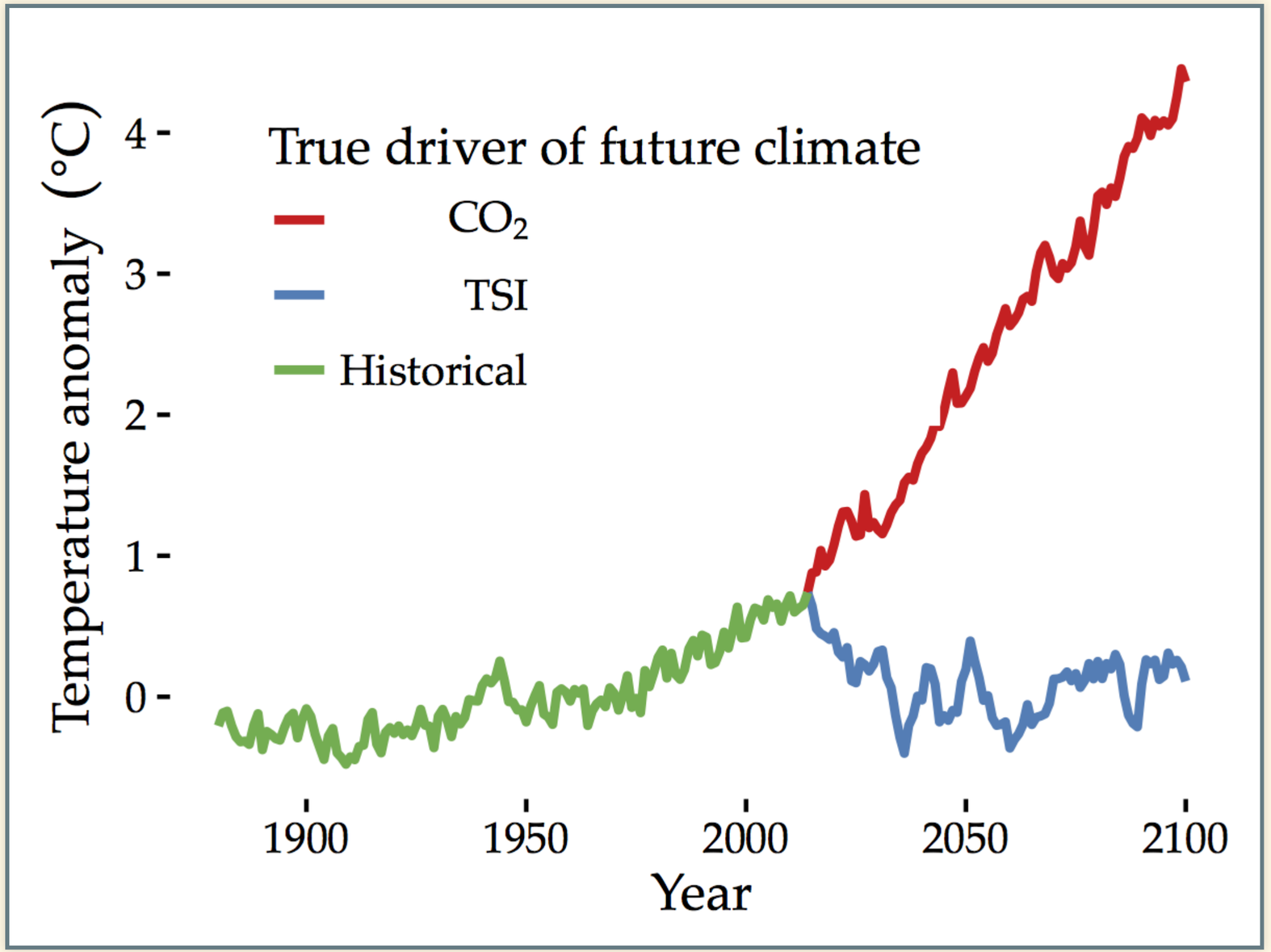
Climate Change and Prediction Markets

- From 1990–2013, increasing scientific confidence that recent warming is mostly caused by human activity.
  - From very uncertain in 1990 to 95% certain in 2013.
- **But**, public's beliefs did not change much.
  - Distrust of scientists
  - People who distrust scientists may trust markets
- Prediction markets: "Put your money where your mouth is"
  - Efficient information aggregation.
  - Do they also change beliefs?

Prediction Market Simulation

- Research Question:
  - *Might prediction markets be useful for increasing convergence of climate beliefs?*
  - *If so, under what conditions?*
- Why simulation?
  - Real prediction markets focus on near term events.
    - Difficult to extrapolate to climate case.
  - We can observe traders' actions, but not their beliefs
- Simulation modeling informed by climate and economic theory to study potential of prediction markets for producing agreement.

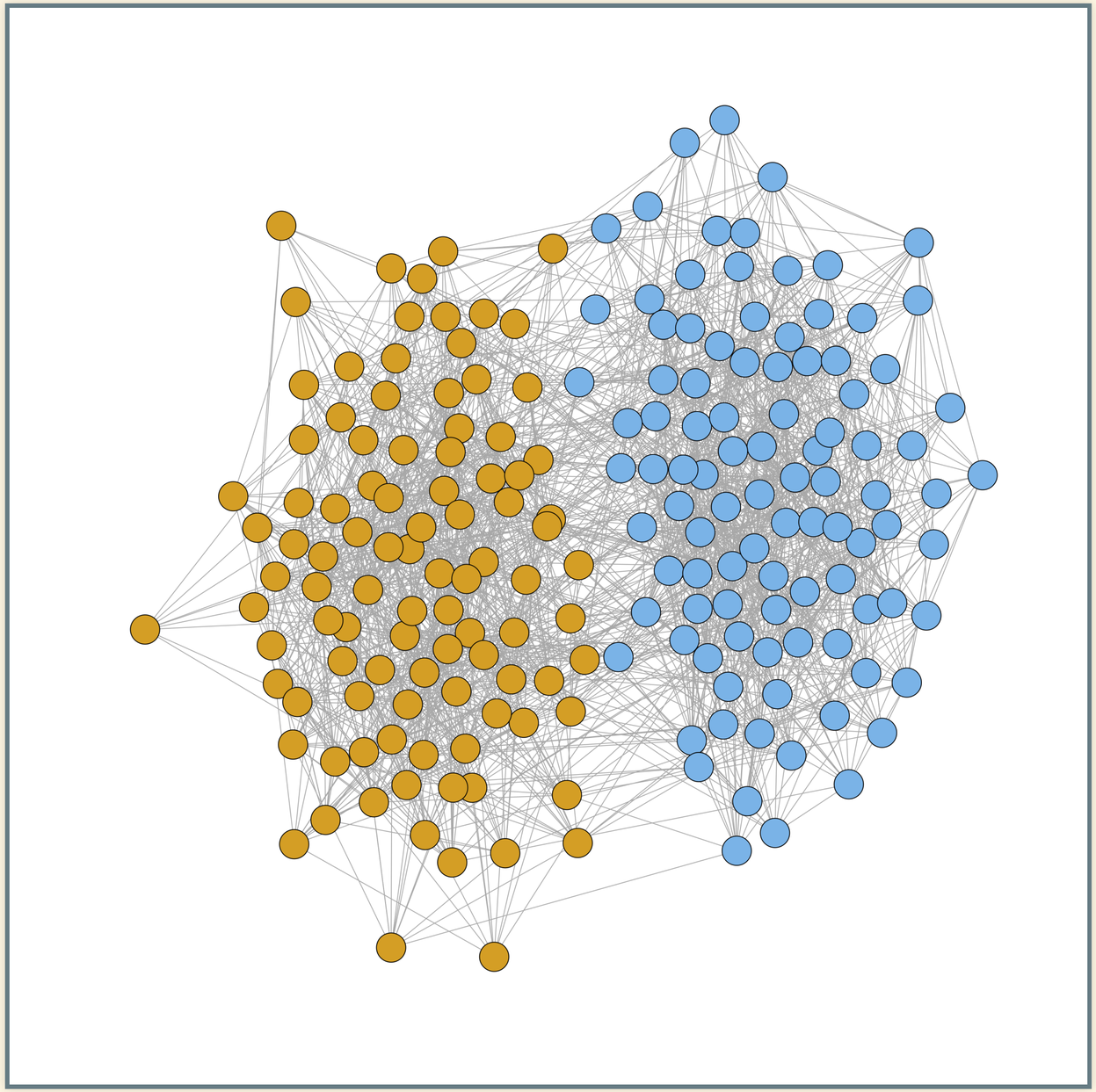
Two Alternate Realities



Trader Beliefs

- Initialize traders with half believing each cause of climate change.
  - CO_2 or Total Solar Irradiance?
- Traders using correct model may not make accurate predictions
  - *Functional form* correct, but must calibrate parameters on noisy temperature records.

Social Network



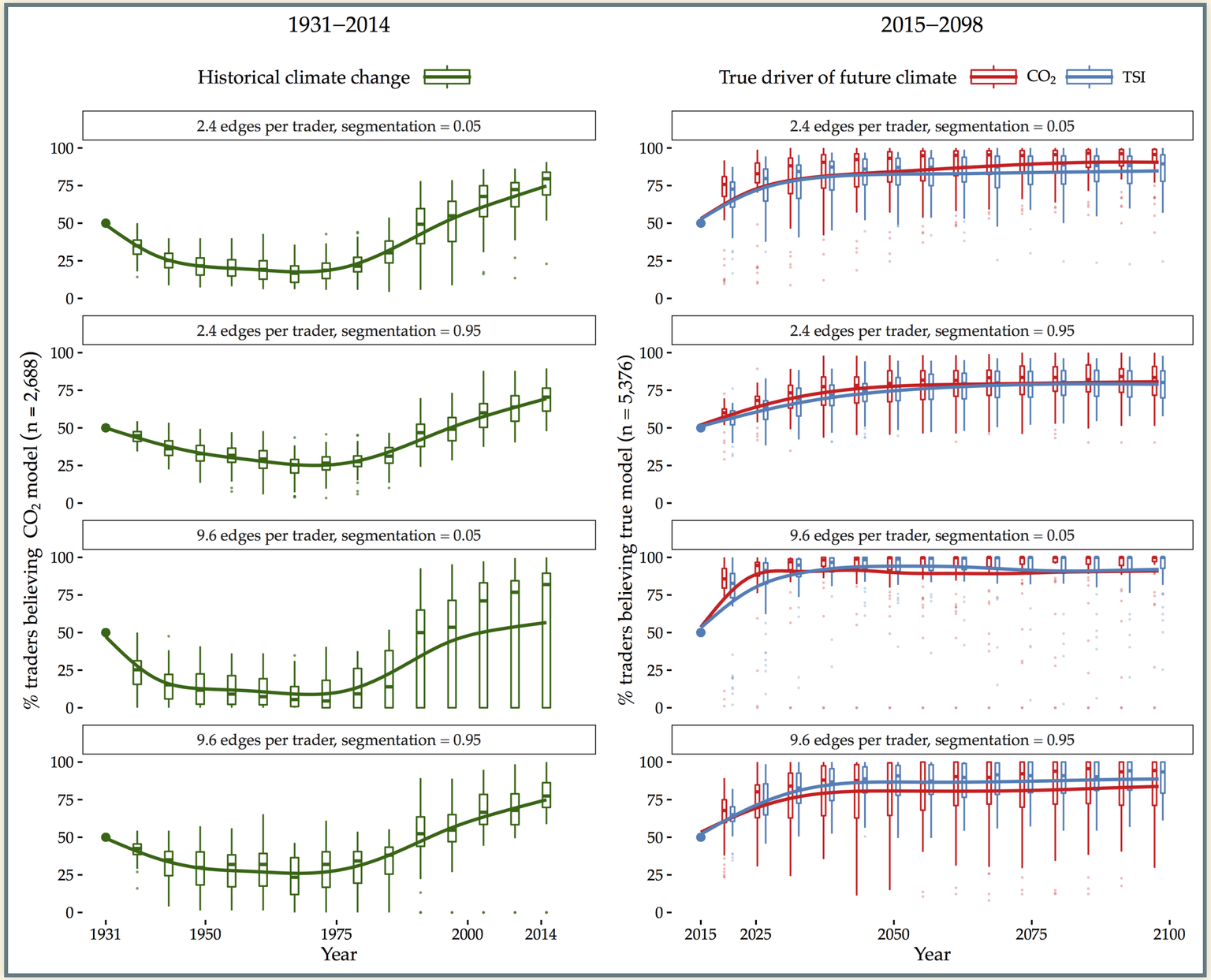
Simulation Model

1. Traders estimate forecasting model.
2. Six years of trading
3. Payoffs at end of 6 years.
4. Decide whether to adopt beliefs of wealthiest neighbor in social network.
5. Repeat

Trading Sequence

- Securities represent temperature ranges.
  - At maturity, pay $1 if temperature is within range
- Each year, traders use last year's T to update personal model
  - Predict probabilty distribution $p(T)$ for T at maturity date
  - Assign expected value to temperature securities.
- Continuous double-auction:
  - Each trader takes a turn:
    - Picks a random security in portfolio to sell (willing-to-accept price, WTA)
    - Picks a random security to buy (willing-to-offer price, WTO)
  - Trading whenever **one trader's WTO $\geq$ another trader's WTA**

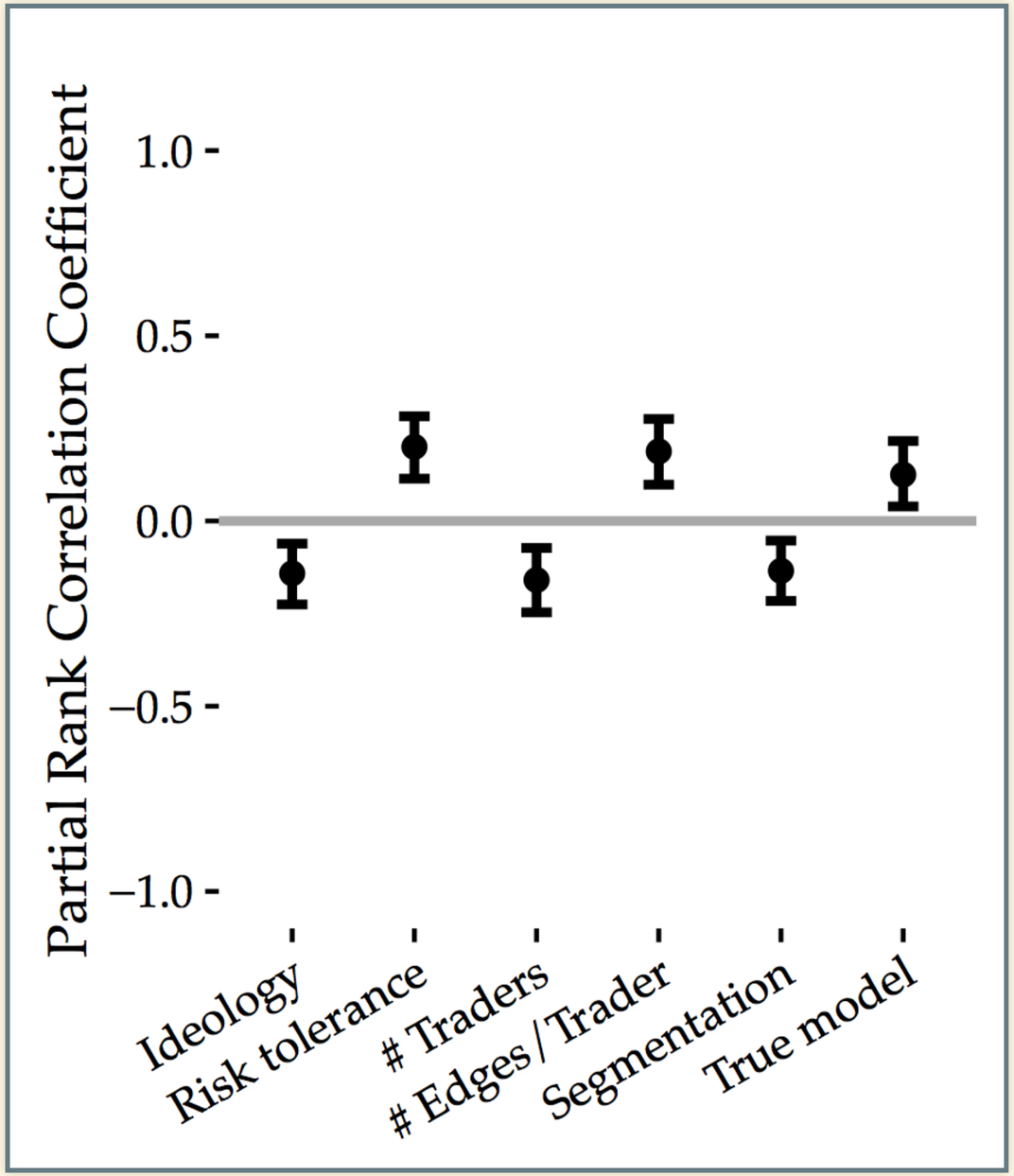
Convergence Over Time



Market Parameters

- Ideology: resistance to changing beliefs
- # traders: size of market
- # edges per trader: density of social network
- Risk tolerance: aggressive WTO, WTA prices, greater risk of not finding counterparty.
- Segmentation: is social network an echo chamber?
- True model: 1 for CO_2, 0 for solar irradiance.

Sensitivity Analysis Results



Conclusions

- It appears that traders in a climate prediction market would converge to the correct belief about the cause of climate change.
- Convergence is much faster if social networks effectively link people with different beliefs.
  - Echo chambers inhibit learning
  - In a highly connected network, convergence to correct belief takes about 10 years.
- Results are not very sensitive to any of the parameters.

Next Steps

- Working with faculty in Law School & Owen School of Management to set up a real prediction market.