USING CITATION-MAPPING TO ASSESS ECONOMIC MODELS OF SCIENCE

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INTRODUCTION

• Dissertation: Consequences of importing economic ideas and methods into philosophy of science.

• Formal models of the division of cognitive labor in science substitute plausibility and robustness for empirical data.

• Without empirical data to establish representational or predictive accuracy, only weak inferences about science can be drawn.

• Citation analysis one way to inform models with data.

• Two examples from my project on CDL in climate science.

• Advantages and challenges of citation analysis.
TWO WAYS TO ASSESS MODELS WITH DATA

DATA → MODEL → DATA

Predictive Accuracy

DATA

Representational Accuracy

MODEL
WEISBERG: REPRESENTATIONAL ACCURACY

- Volterra principle: “A general pesticide will increase abundance of prey and decrease abundance of predators.”

- Data at the beginning: populations can be “described by coupled differential equations.”

- Model explores consequences of that.

- Robustness analysis at the end confirms results of model.
SCHELLING: PREDICTIVE ACCURACY

- Racial segregation can result from "mild" racial preferences.
- Individuals move if too many neighbours are of different race.
- Plausibility at beginning, confirmed by data at end.
ASSESSMENT IN FORMAL MODELS OF SCIENCE

DATA → MODEL ← DATA

Representational Accuracy

Predictive Accuracy
ASSESSMENT IN FORMAL MODELS OF SCIENCE

PLAUSIBILITY -> MODEL -> ROBUSTNESS

Predictive Accuracy

Representational Accuracy
PLAUSIBILITY: THOMA ON WEISBERG & MULDOON

• Weisberg and Muldoon: research communities composed of mavericks and followers.

• Thoma: Implausible that anyone would employ follower strategy:
  
  • Scientists can easily learn about the success of nearby approaches without investigating themselves.
  
  • Why would anyone be motivated to duplicate work for no epistemic benefit?
• Kitcher & Strevens: Self-interested scientists can achieve optimal divisions of labour between two research projects.

• Weisberg and Muldoon: Result not robust to changes in scientists’ knowledge of each others’ work.

• As radius of vision decreases, community diverges from optimal allocation.
WHY IS DATA IMPORTANT?

- Robustness analysis epistemically significant only to the extent that the model is representationally accurate.
  - Plausibility only weakly establishes representational accuracy.
- Plausibility epistemically significant only to the extent that the model is predictively accurate.
  - Robustness only weakly establishes predictive accuracy.
- Even if plausibility+robustness are informative about target systems, impossible to establish magnitude of effects without data.
  - To make normative claims about scientific practice, need to establish magnitudes.
MY PROJECT: COGNITIVE DIVISION OF LABOR IN CLIMATE SCIENCE
SUNDBERG'S CLAIMS

• Climate models are an obligatory passage point to climate policy.

• Data flows from experiments to models through parameterizations.

• Experimentalists often fail to translate their results into parameterizations that are useful to modelers.

• Climate science faces a coordination problem.

Sundberg, “Parameterizations as Boundary Objects on the Climate Arena” (2007).
Research Questions

• Is there really a coordination problem in climate science between modelers and experimentalists?

• What is the magnitude of this problem?

• If there is a problem, what is the cause?

  • Problem of education / communication?

  • Problem of incentives?
PARAMETERIZATION → AEROSOL CITATIONS COMPARED TO PARAMETERIZATION → RANDOM CITATIONS

240 Citations

571 Citations

1 SD

6 SD
MODELING THE CAUSE

• Assume there is a coordination problem. What is the cause?

• Observation: Citation counts follow power laws.

• Hypothesis: Rational scientists seeking to maximize citations will target papers narrowly.

  • Paper quality is group-relative, widely-targeted papers will have medium quality for many groups while narrowly targeted papers will have high quality for one group and low quality for others.

  • Maximizing quality relative to one group at the expense of others will maximize total citations.

• It is easier to target a paper narrowly at one’s own discipline.

• Few papers will be targeted outside of home discipline.
### Citations of "Aerosol" Papers

- **PAPERS**: 4997
- **Mean**: 5.6
- **Median**: 3
- **10%**: 0
- **90%**: 13
- **99%**: 41
- **99.9%**: 146

![Graph showing the distribution of citations](image)

*Very long tail*
A SIMPLE MODEL

\( Q, Q_\omega, Q_\psi \in (0, 1) \)  

quality, internal quality, external quality

\( C, C_\omega, C_\psi \)  

total, internal, and external citation counts

\( A \in (\frac{1}{5}, \frac{1}{4}, \frac{1}{3}, \frac{1}{2}, 1, 2, 3, 4, 5) \)  

degree of specialization (1/5 and 5 are high)

\( q_\omega, i = q_i^a \quad q_\psi, i = q_i^1 \)  

specializing trades off between internal and external quality

\( c_\omega, i = \lambda (1 - q_\omega, i)^{-\frac{1}{\kappa}} - 1 \quad c_\psi, i = \lambda (1 - q_\psi, i)^{-\frac{1}{\kappa}} - 1 \)  

\( \lambda, \kappa \) parameters of Pareto (long-tailed) distribution.

Total citations is sum of internal and external citations.

\( c_i = c_\omega, i + c_\psi, i \)
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OTHER POSSIBLE MODELS

• Alternative causes (e.g. making papers useful to wider audiences takes more time).

• Alternative models of specialization.

• Agent-based simulations (papers accrue citations through time, papers take time to produce, authors have varying utility functions, authors have varying talent, authors discover papers through previous citation, adjustable reward structure).
CITATIONS AS DATA: ADVANTAGES

• Can parameterize/fit models with empirical data.
• Can test model predictions against empirical data.
• Can measure effect sizes.
CITATIONS AS DATA: CHALLENGES

- Time consuming.
  - Long execution times.

- Data access can be difficult.
  - Never get full coverage.

- Even with good datasets (eg. Web of Science), tracking citations can be difficult.
  - Messy data.

- Limited range of questions that can be answered.

- Don’t have access to counterfactual world (hard to use data at both ends of model).
Recent state minimum temperature records in the Midwest
State minimum temperature records were set or tied in Indiana (-37.0 degrees C) and Kentucky (-30.3 degrees C) in January 1994, and in Illinois (-37.2 degrees C), Iowa (-43.9 degrees C), Minnesota (-51.1 degrees C), and Wisconsin (-48.3 degrees C) in February 1996. The veracity of these temperatures was examined in the context of the large-scale synoptic situation, station location and history, observer, local terrain, instrumentation, and other factors related to extreme temperatures. New state minimum temperature records for states listed above were found to be acceptable; however, a state minimum initially reported for Michigan (-46.7 degrees C) in January 1994 was found to be unreliable and not accepted as a state record.


Lightman R A., 1963, WEATHERWISE, V16, P272

Dories N, 1985, AM WEATHER OBSERVER MAY, P3

Lublum DM, 1994, WEATHERWISE, V47, P44

*Midclim cl 1960, WEATHER CLIM IMP MIDW. V6, P3


Parker DE, 1995, ATMS RES, V37, P3, DOI 10.1016/0159-8095(94)0006-1

Parker DE, 1994, INT J CLIMATOLO, V14, P1, DOI 10.1002/10.37004102


Rinke B, 1996, COLDWAVE BREAKS RECO

Jordan P, 1985, ETLO416 US ARM CORPS

Schmidlin TW, 1980, WEATHERWISE, V39, P311

Stepanov N, 1958, MON WEA REV, V86, P6, DOI 10.1175/1520-0477(1958)086<0006:OTITOF>2.0.CO;2

Thomas M, 1953, WEATHERWISE, V16, P270

US DEP COMM, 1994, WEEKLY WEATHER CROP B, V81, P3

US DEP COMM, 1996, CLIM D, P0326

Weather FR H 1948, B AM METEOROL SOC, V29, P547

Williams J, 1994, 1995 US TODAY WEATHER
COUNTERFACTUALS

- Model requires specifying $\lambda$, $\kappa$ parameters for each distribution.

- Currently based on real data. Alternatively, use regression.

- Can’t double-dip: compare predictions with same data used to parameterize model.

- How to assess predictive accuracy?

- Need data other than citations at one end or the other, or substitute plausibility / robustness.

$$c_{\omega,i} = \lambda \left(1 - q_{\omega,i}\right)^{\frac{-1}{\kappa}} - 1$$

$$c_{\psi,i} = \lambda \left(1 - q_{\psi,i}\right)^{\frac{-1}{\kappa}} - 1$$
REFERENCES


