Does Academia Evolve?
Evidence from Agent-Based Modeling and the Economics Discipline

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Abstract:

This paper explores the concept of academic science as a product of cultural evolution at multiple levels of selection, using the discipline of economics as a case study. Publication data from the top five economics journals are collected from the Web of Science database. An agent-based model is constructed in NetLogo, and simulations of the model are used to explore department-level evolutionary trends. Results suggest that departments are incentivized to encourage internal collaboration. The research herein is a first step toward a rigorous, computational approach to understanding academic science through an evolutionary lens.

1. Introduction

We live in a time of unprecedented global complexity, collectively facing challenges that call for coordinated action at every scale of society (Bulletin of the Atomic Scientists 2021; Steffen, Richardson, et al. 2015). When it comes to making sense of these issues, many researchers, commentators, activists, and others have lamented what the Doomsday project describes as a "threat multiplier: the continuing corruption of the information ecosphere on which democracy and public decision-making depend" (Birnbaum 2020; Bulletin of the Atomic Scientists 2021; Celliers and Hattingh 2020; Kapantai et al. 2021; Rebel Wisdom 2019; Treen, Williams, and O'Neill 2020). A crucial piece of this "information ecosphere" is science itself, which is widely regarded as the highest and most pure form of discovery and knowledge production. Unfortunately, little research has been done exploring the structure and function of scientific institutions and the role science plays and can play in solving critical societal problems. The goal in this paper is to take a first step toward a rigorous, computational exploration of scientific institutions, ultimately asking whether these structures are appropriate given the broad and complex landscape of issues facing communities.

In exploring this topic, the present paper explicitly takes an evolutionary perspective. Evolution by natural selection is most closely associated with the evolution of biological organisms, but the theory can be as well applied to complex communities of individuals, institutions, and their tools and products (such as universities) as it can to communities of cells, organs, and their various biological infrastructures. In fact, the scientific study of cultural evolution has grown over the last several decades, marked in part by the formation of the Cultural Evolution Society in 2015 (Bailey 2015; Henrich, Boyd, and Richerson 2008; Mesoudi 2016; Mesoudi, Whiten, and Laland 2006).

Equally important to the groundwork of this paper is multilevel selection theory ("MLST"), defined as "the notion that natural selection can operate *simultaneously* at different levels of the biological hierarchy" (Okasha 2006:75, emphasis in original). MLST provides for the possibility that science and scientific institutions may be simultaneously shaped by selection dynamics operating at the level of theories, as well as at the levels of individuals, universities, paradigms, and even countries, and that these levels of selection may exhibit complex interactions with one another. This MLST-enabled perspective encompasses previous ideas on the nature of the scientific endeavor. Included among these would be Karl Popper's ideas of competitive empirical falsification, weeding out weaker theories and selecting for the strongest, as well as Thomas Kuhn's recognition that the successful ideas in science are not only those that stand up to falsification, but also those that correspond with the dominant paradigm of the day or address a misgiving of that paradigm and launch a new one in its place (Kuhn 1962; Popper 1935). This paper abstracts from the potentially fractal scope of selective dynamics shaping science to specifically investigate natural selection at the levels of ideas, individuals, and universities.

One notable level of selection that is ignored in the current research is that of selection between academic disciplines. For simplicity, the current research focuses on economics, but future work should integrate multiple disciplines and sub-disciplines to explore those dynamics. Economics was chosen as a case study primarily because evolutionary models require a method for measuring fitness in a population, and economics researchers and departments can both be understood to maximize their prestige by seeking publication in top journals (May et al. 2021). Specifically, economists tend to measure success as publication in the top five journals, which are: *American*

Economic Review, Econometrica, Journal of Political Economy, Quarterly Journal of Economics, and *Review of Economic Studies* (Heckman and Moktan 2020). Two additional considerations influenced the choice of economics as the case-study discipline for this paper. First, it is speculated that due to their subject matter, economists may embrace competitive dynamics in their professional activities more than their counterparts in other disciplines. Second, in recent years economics has drawn criticism both from within and outside of its ranks, which may make the premise of this line of research more palatable: the discipline and the university structure that supports it are evolving entities which may no longer be adaptive for the "information ecosphere" writ large (Jaschik 2019; Orrell 2018).

With this background established, the central research question of this paper can be stated:

> *RQ: How and to what extent has the production of knowledge in the discipline of economics been shaped by an evolutionary process operating at multiple levels of selection?*

The primary method employed by this paper in answering this question is agent-based modeling. Agent-based modeling is a computational method that "simulates a field of interacting entities (agents) whose simple individual behaviors collectively cause larger emergent phenomena" (Gavin 2014). Agent-based models have been used to study topics as varied as climate change policy, innovation diffusion, and urban and architectural studies, among others (Axelrod 2006; Cao, Feng, and Wan 2009; Castro et al. 2020; Chen 2012; Kiesling et al. 2012). This is an appropriate tool in this context because it enables observation of the emergence of complex phenomena, and the evolution of the system of academic science is certainly too complex to be well understood from a top-down, analytic perspective alone. The agent-based model presented in this paper is built using insights from empirical economics publication data.

The remainder of this article will proceed as follows. Section 2 will describe the empirical data and the details of agent-based model, as well as the simulations. In Section 3, the results of this research will be presented. Section 4 will provide further discussion, including limitations of this approach and directions for future research. Finally, Section 5 will offer a brief conclusion.

2. Methods

2.1. Empirical Data from Web of Science

The empirical data collected in this project comes from the Web of Science database, accessed via the Knowledge Lab at the University of Chicago.[1] All of the information available from publications at the top five economics journals was collected. The data contains publication and authorship information as far back as 1960, and data on authors' affiliations from 2008 to 2019. The dataset was filtered to only include the 20,563 publications with document type "article" (70% of the data), excluding book reviews (11%), notes (8%), meeting abstracts (5%), letters (2%), editorial material (2%), and other items (collectively 2%). **Table 1** displays some summary statistics from the resulting dataset.

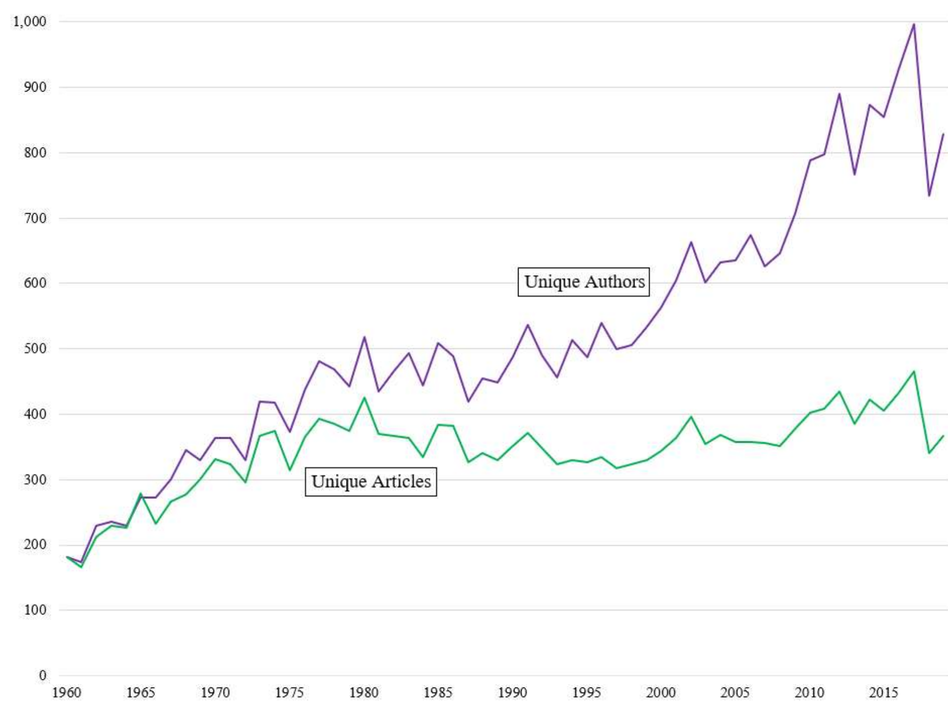
[1] To request access to this database contact Professor James Evans, director of the Knowledge Lab.

Table 1. T5 Economics Journals, Web of Science Summary Statistics

Journal	Number of Articles	Number of Unique Authors	Average Number of Authors per Paper	Average Bibliography Size
American Economic Review	8,723	9,148	1.8	20.7
Econometrica	3,569	3,586	1.7	24.9
Journal Of Political Economy	3,190	3,534	1.6	24.6
Quarterly Journal Of Economics	2,504	3,027	1.7	27.8
Review Of Economic Studies	2,577	2,998	1.7	26.6

A key insight collected from this empirical data that will be used in the construction of the agent-based model is the trend in the number of unique authors publishing in the top-five journals over time. As seen in **Figure 1**, while the annual number of articles published levels off after about 1980, the number of contributing authors continues to grow, particularly surging after about 1998.

Figure 1. Annual Number of Articles and Unique Contributing Authors, 1960-2019



A second insight from the empirical data that is used in the construction of the agent-based model is the distribution of articles across universities. **Figure 2** shows the most prolific institutions in economics, counting the publications by authors affiliated with each university department in the 11-year period from 2008 to 2019, when data on affiliations are available. While authors often have multiple affiliations, the model will require a single affiliation per author, so the most commonly appearing affiliation was used for each author to analyze the distribution. Because this research is primarily focused on idea-researcher-university dynamics, professional associations ("NBER", e.g.) and think tanks ("CEPR", e.g.) are excluded. Additionally, an exponential fit line is superimposed, which is estimated using the top 100 most prolific departments.[2] This fit summarizes the distribution and will be used to determine researcher-department affiliations in the agent-based model.

2.2. Agent-Based Model

The model consists of three types of agents and a variety of simple rules governing their actions and interactions, and is built in NetLogo, a software tool developed specifically for agent-based modeling (Wilenski 1999). The three agent types are **topics areas**, **researchers**, and **departments**.[3] This section proceeds by describing each of these in turn, followed by a description of the how the model executes a time-step. At the end of the section, **Figure 3** displays a screenshot of the NetLogo implementation of the model, which is available for access and exploration via github.

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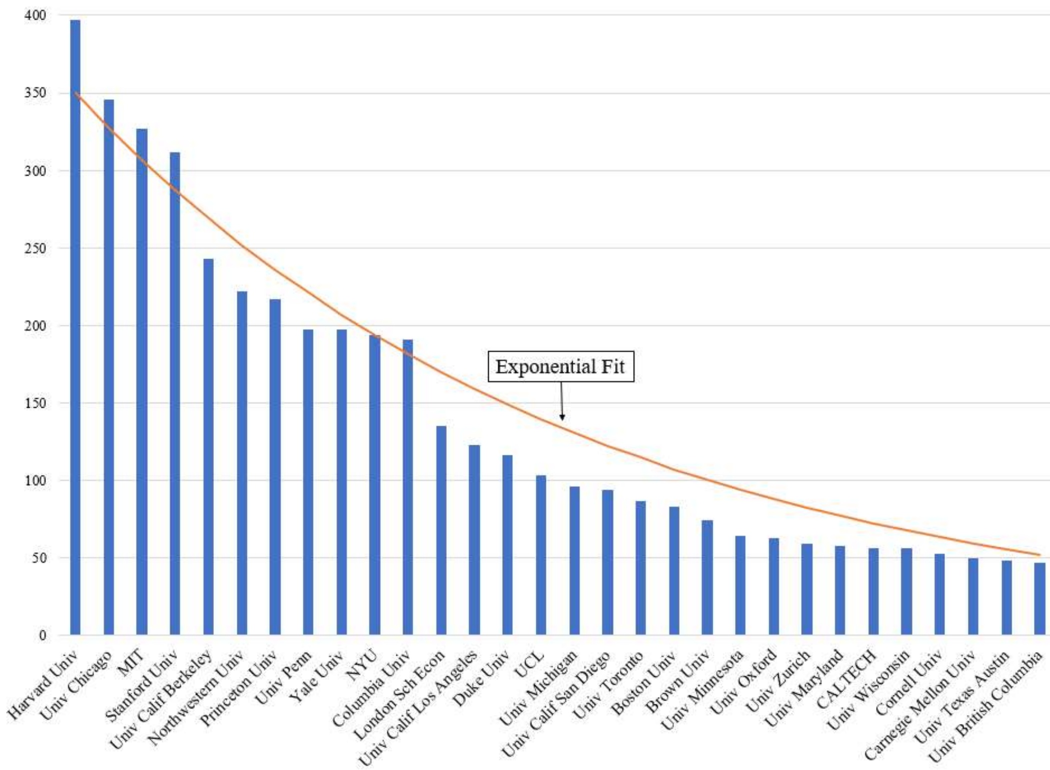
[2] The exponential fit is estimated as $\textit{Publications} = 373.49 \times e^{(-0.0656 \times \textit{Rank})}$, estimated using a weighted least squares regression with weights equal to the number of articles observed at each university.

[3] In this section, the first use of words that correspond to the agents and parameters of the model are in **bold font**.

Figure 2. Prolific Universities and Exponential Fit, 2008-2019



2.2.1. Topic Areas

The landscape of the model is a 40 by 40 grid of squares, each representing a single topic area of potential publication. Topic areas that are nearby in this grid are said to be similar in the idea space of the discipline, such that two publications related to labor economics would appear close to one another, and a publication in, say, national macroeconomic policy would appear further away, but no mapping to actual topics in economics is specified. The environment "wraps," such that squares along the bottom of the grid are treated as adjacent to those at the top, and the same is true of the left and right edges. Each topic area keeps track of its **potential**, a floating-point value that ranges from 0 to 100, representing the relative potential for influential publication in the topic area. In the visual representation of the model, the topic areas are shaded from bright green (representing high potential) to black (representing low potential).

At each time-step, the potential of every topic area is set to decrease by a fixed percentage, referred to in the model as **potential-decay.** The default value of this parameter is 98%, such that a topic area at 100 will move to 98 in the subsequent period. Potential also decreases if a researcher publishes in a topic area, reflecting the incentive for novelty in publication (Rehman 2018). On the other hand, potential increases following publication in a nearby topic area, reflecting the idea that new knowledge illuminates new directions for future research.

2.2.2. Researchers

The next agent is the researcher. Researchers move through the idea space and operate individually and/or in collaboration with other researchers to produce publications, with the goal of maximizing **prestige.** The **prestige** parameter is also a floating-point value ranging from 0 to 100, and decays over time according to a parameter called **prestige-decay**, which has a default value of 95%. The main vehicle by which researchers gain prestige is publication. At each time-step, researchers decide whether they want to make progress toward a publication in their current topic area or forfeit any progress and move to a new topic area. Each researcher makes this decision by calculating their expected prestige for different actions and selecting the action with the highest expected prestige. Important parameters for this calculation are (1) **time-to-publish**, the number of time-steps it takes to reach publication (default six, corresponding to six months), (2) **foresight**, the number of time-steps into the future a researcher considers (default 24, corresponding to two years), and (3) **discount-rate**, the discount rate applied to future rewards (default 80%). At present, these parameters are set universally, but future work could allow for heterogeneity in these settings. Researchers are operating with incomplete information as they are unaware of how the topic space will shift over the coming periods due to movement and publication by other researchers.

Researchers may also collaborate with other researchers in their **vicinity**, defined by default as 6 units in the cartesian grid of 1,600 topic areas, where each topic area is a 1 by 1 square. Collaborating with other researchers linearly reduces the number of time-steps it takes to publish, but also divides the rewards of publication evenly among the collaborators. Potential collaborations are considered in much the same way as potential moves: by calculating expected prestige from alternative actions. In the visual representation of the model (**Figure 3**), collaborations are shown as blue links between researchers.

2.2.3. Departments

Researchers are assigned a department affiliation, following the exponential distribution derived from the empirical data as described in Section 2.1. In the visual representation of the model (**Figure 3**), the researchers' colors correspond to their departments, such that two red researchers are in the same department. Departments also have a **prestige** parameter, which is a floating-point value between 0 and 100 that decays over time at a default rate of 96%. Departments influence researchers' collaboration decisions via two parameters called **encourage-collaboration** and **internal-preference**. The former of these skews researchers' decisions toward (or away from) a preference for collaboration over independent work, and the latter skews researchers' decisions toward (or away from) a preference for collaboration with individuals of the same department.

Departments earn prestige when their constituent researchers publish, and at regular intervals also confer a prestige increase or decrease to their constituent researchers depending on the department's relative status.

Under the default settings, after every 12 time-steps, the departments in the bottom 50% of prestige rankings each have a 5% change of "inheriting" the encourage-collaboration and internal-preference settings of a department in the top 10%. This mechanism creates the evolutionary dynamic at the department level.

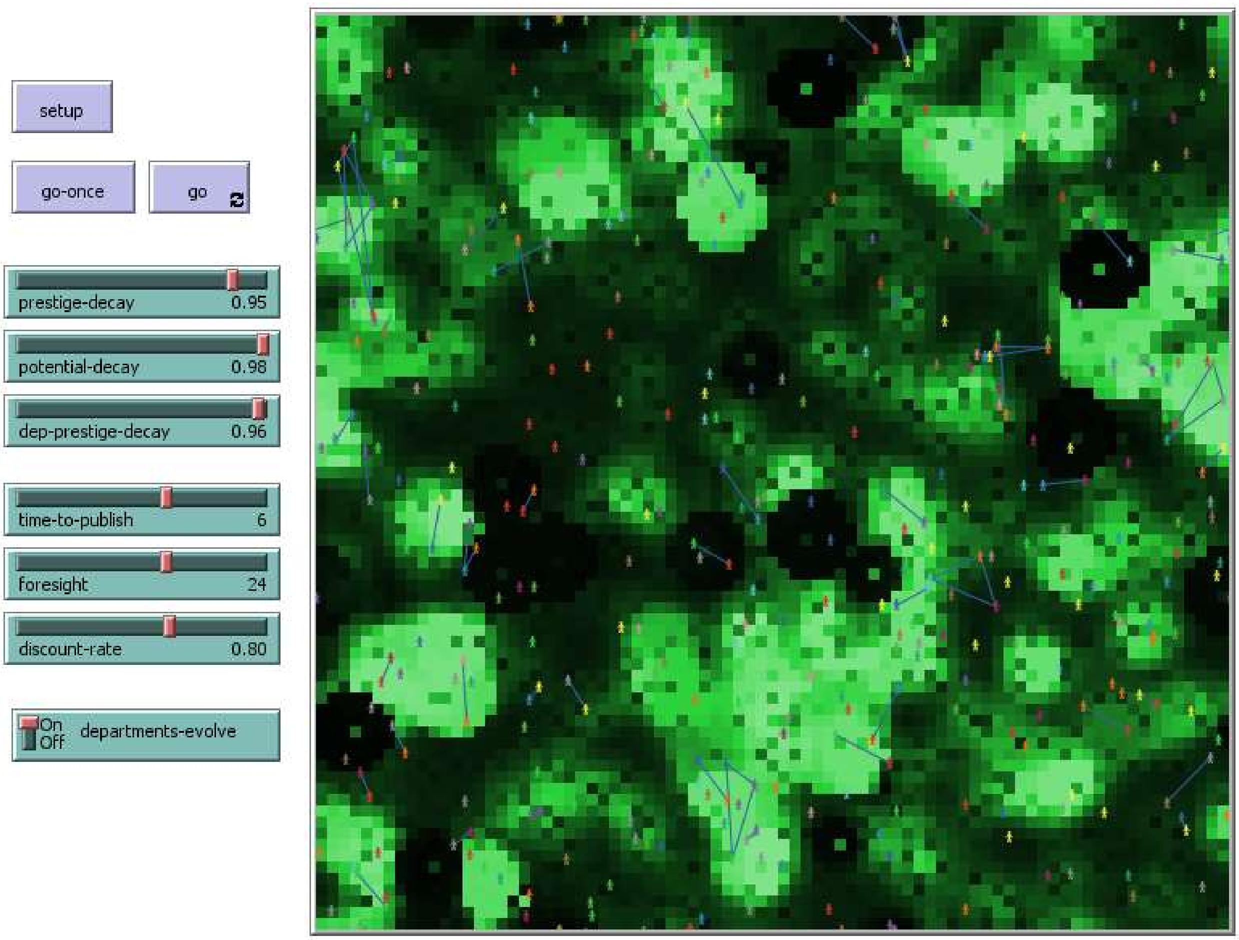
2.2.4. Execution of a time-step

To execute a time-step, the model proceeds by first dispersing a prestige benefit or loss to researchers depending on the relative prestige of their department. Second, researchers consider collaborations with other researchers in their vicinity, and if all parties agree, a collaboration is formed. Third, researchers decide whether to make progress on their current topic or reset their progress to move to a new topic. If a researcher is currently involved in a collaboration, any considered moves that would take them out of vicinity of their collaborators is considered with the context that the move would forfeit those relationships. Fourth, researchers and groups that have reached a sufficient level of progress to publish their work do so, collecting rewards to their prestige, increasing the prestige of their departments, and triggering updates to the topic area landscape. Finally, if the time-step is evenly divisible by 12, and if the setting **departments-evolve** is set to its default value of "On", then the bottom 50% of departments each have an independent 5% chance of "inheriting" the characteristics of one of the departments in the top 10%.

2.3. Simulations

With the model built, experiments can be run, but a full exploration of the behavior observed throughout the parameter space will be left for future work. Instead, the simulations presented in this paper seek to answer the central research question on the extent to which the development of the discipline of economics can be considered a multi-level evolutionary process. To do so, the model was run a total of ten times, five for each value of **departments-evolve.**

Figure 3. Visual Representation of the Agent-Based Model in NetLogo



Some additional settings were configured to align the model with the empirical data on the economics discipline. As has been mentioned already, a single time-step represents a single month.

These simulations therefore run for 720 time-steps, representing the 60-year period from 1960-2019. Additionally, an average of 1.5 new researchers are added each time-step from 1960 to 1980, and again from 2000 through 2019, reflecting the trend observed in the number of unique authors appearing annually in the Web of Science data (**Figure 1**). Finally, as has already been mentioned, the addition of new researchers (both initially and throughout the simulations) follows the exponential fit established in **Figure 2** when assigning department affiliations.

3. Results

The results of the simulations show a small amount of evidence for the multilevel selection phenomenon described in the introduction. **Figure 4** shows the annual average number of authors per publication in the empirical data and in the simulations, with the shaded regions showing the maximum and minimum values across the five simulations of each type. Clearly the simulations do not match the empirical data particularly well regardless of whether evolution at the level of university departments is included. At the same time, a comparison of the blue and green shaded regions does suggest that inclusion of department-level selection at least facilitates higher peaks of collaboration in the model.

The evolutionary trajectory of departments in the five simulations that allow for it show some interesting results. As shown in **Figure 5**, all five simulations tended to have increased average levels of the internal-preference parameter over time but decreased levels of the encourage-collaboration parameter. This suggests that departments benefit from internal collaboration significantly more than from cross-department collaboration.

Figure 4. Articles per Publication in Simulations and Empirical Data

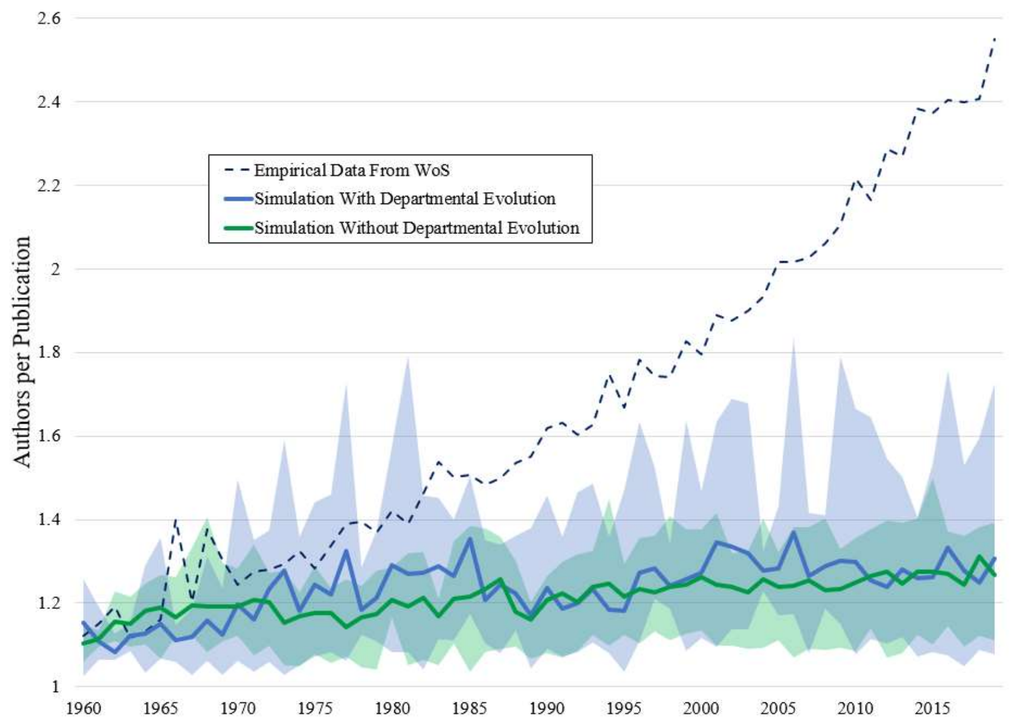
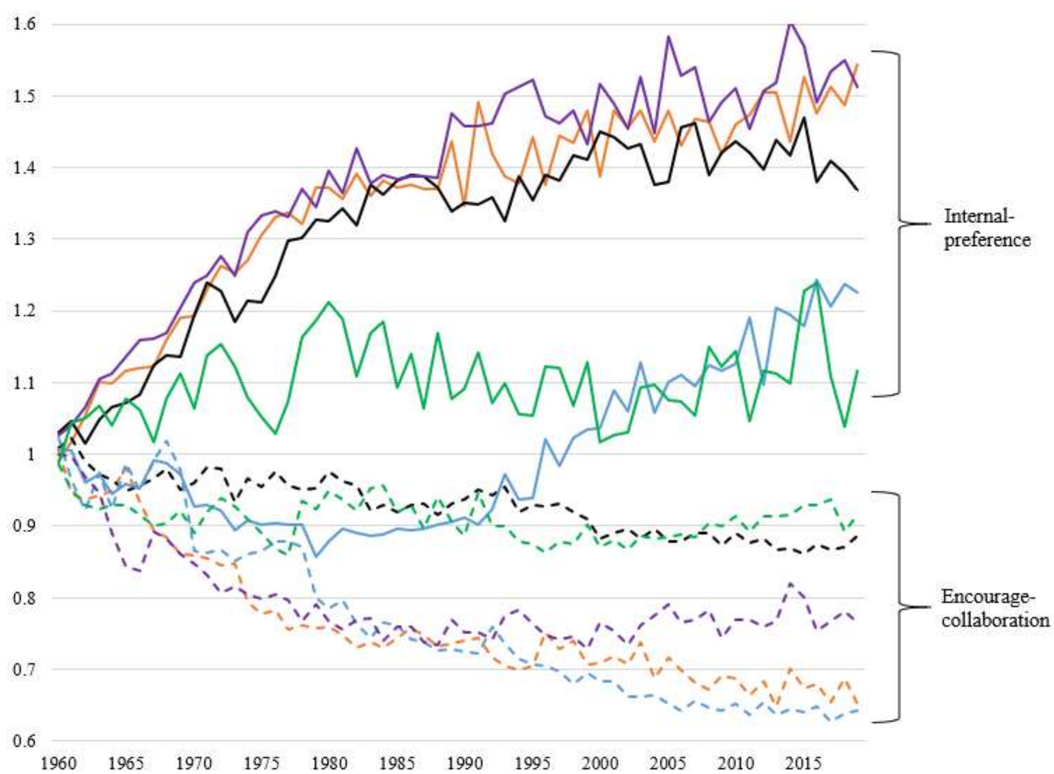


Figure 5. Simulated Evolutionary Trajectory of Department Characteristics



In addition to the simulation results, perhaps the most important result from this research is the model itself. The model represents a proof-of-concept for thinking about academia from an agent-based, evolutionary perspective. There are certainly many limitations to this approach to studying academia, as will be explored in the next section, but ideally the model developed will be used in future research to correct for these limitations and provide a useful lens on the continuing evolution of our knowledge-production systems.

4. Discussion

Many of the limitations of this research stem from the fact that the production of knowledge in academia involves an extremely complex process, with many types of actors and many dynamics that must be abstracted away for the purpose of building a simple model. In the model each researcher can only be involved in one collaborative group at a time and can only make progress on one project at a time, and moreover, researchers are confined to a single topic area at a time. And of course, the idea space of any given discipline exists in higher dimensionality than the 2-d grid on which this model is built. These are obvious simplifications of the complex reality of academic work. It is also clearly a simplification to suggest that university departments influence their researchers only via a feedback effect in prestige and by influencing their collaboration preferences. Research universities have increasing come to compete with one another over the last several decades, but have also formed alliances, guilds, and other relationships and associations, which are not captured in this model (Musselin 2018). Future research can and should relax the strict assumptions that were necessary for the initial construction of this agent-based model.

Additionally, future work could explore the coevolution of academia with other major societal institutions, such as industry and government. As Henry Etzkowitz and Loet Leydesdorff wrote in 1998, "[t]he boundaries between public and private, science and technology, university and industry are in flux" (Etzkowitz and Leydesdorff 1998). Economics certainly overlaps with the world of private industry as well as with that of public policy, and it would be interesting to explore how these intricacies have shaped the discipline over time.

From a computational perspective, future research could more thoroughly explore the parameter space of the model. Currently, default values of parameters were set by trial and error to produce interesting and relatively realistic dynamic behavior between the agents in the model. For example, one goal that influenced the development of the model was to avoid having the potential of every topic area decrease to zero, which occurred at some levels of prestige-decay. Another similar goal was to avoid enormous collaborations that never break up. A rigorous exploration and discovery of the range of parameter values that create interesting dynamics would be a welcome addition to this line of research.

5. Conclusion

The general motivation of this paper has been the baseline understanding that human systems have both contributed to and been shaped by the "great acceleration" in population and economic growth that took hold in the middle of the 20th century and now threatens the ecological balance of the biosphere (Steffen, Broadgate, et al. 2015). One such human system is our system of producing and disseminating knowledge, of which academic science is a crucial subsystem. As a researcher at an academic university, I am invested in discovering the extent to which the current infrastructure of academic science will be resilient to the changes that will be brought about by the transition to a post-fossil fuel society, as well as the extent to which academic science has a role to play in smoothing that transition.

As a final note, in this line of inquiry, it is important to remember that academic science is not the only knowledge system ever invented by humans. Indigenous populations have been practicing knowledge production and information management in ways that do not degrade but rather enhance natural environments for millennia (Nicholas 2018). Future research should therefore also explore the lessons that indigenous knowledge systems have for the structure of academic science.

References:

Axelrod, Robert. 2006. "Chapter 33 Agent-Based Modeling as a Bridge Between Disciplines." Pp. 1565–84 in *Handbook of Computational Economics*. Vol. 2. Elsevier.

Bailey, Ashle. 2015. "Academic Integration & Policy Applications." *Evolution Institute*. Retrieved December 2, 2020 (https://evolution-institute.org/project/cultural-evolution-society/inaugural-workshop/).

Birnbaum, Emily. 2020. "Meet the Researchers and Activists Fighting Misinformation." *Protocol — The People, Power and Politics of Tech*. Retrieved May 29, 2021 (https://www.protocol.com/election-day-2020-misinfomation-disinformation).

Bulletin of the Atomic Scientists. 2021. *2021 Doomsday Clock Statement*.

Cao, Kai, Xiao Feng, and Hui Wan. 2009. "Applying Agent-Based Modeling to the Evolution of Eco-Industrial Systems." *Ecological Economics* 68(11):2868–76. doi: 10.1016/j.ecolecon.2009.06.009.

Castro, Juana, Stefan Drews, Filippos Exadaktylos, Joël Foramitti, Franziska Klein, Théo Konc, Ivan Savin, and Jeroen Bergh. 2020. "A Review of Agent-based Modeling of Climate-energy Policy." *WIREs Climate Change* 11(4). doi: 10.1002/wcc.647.

Celliers, Marlie, and Marie Hattingh. 2020. "A Systematic Review on Fake News Themes Reported in Literature." Pp. 223–34 in *Responsible Design, Implementation and Use of Information and Communication Technology*. Vol. 12067, *Lecture Notes in Computer Science*, edited by Marié Hattingh, M. Matthee, H. Smuts, I. Pappas, Y. K. Dwivedi, and M. Mäntymäki. Cham: Springer International Publishing.

Chen, Liang. 2012. "Agent-Based Modeling in Urban and Architectural Research: A Brief Literature Review." *Frontiers of Architectural Research* 1(2):166–77. doi: 10.1016/j.foar.2012.03.003.

Etzkowitz, Henry, and Loet Leydesdorff. 1998. "The Endless Transition: A 'Triple Helix' of University-Industry-Government Relations: Introduction." *Minerva* 36(3):203–8.

Gavin, Michael. 2014. "Agent-Based Modeling and Historical Simulation." *Digital Humanities Quarterly* 008(4).

Heckman, James J., and Sidharth Moktan. 2020. "Publishing and Promotion in Economics: The Tyranny of the Top Five." *Journal of Economic Literature* 58(2):419–70. doi: 10.1257/jel.20191574.

Henrich, Joseph, Robert Boyd, and Peter J. Richerson. 2008. "Five Misunderstandings About Cultural Evolution." *Human Nature* 19(2):119–37. doi: 10.1007/s12110-008-9037-1.

Jaschik, Scott. 2019. "Economics and Its Main Association Face Criticism." Retrieved May 30, 2021 (https://www.insidehighered.com/news/2019/01/03/economics-and-its-main-association-face-criticism).

Kapantai, Eleni, Androniki Christopoulou, Christos Berberidis, and Vassilios Peristeras. 2021. "A Systematic Literature Review on Disinformation: Toward a Unified Taxonomical Framework." *New Media & Society* 23(5):1301–26. doi: 10.1177/1461444820959296.

Kiesling, Elmar, Markus Günther, Christian Stummer, and Lea M. Wakolbinger. 2012. "Agent-Based Simulation of Innovation Diffusion: A Review." *Central European Journal of Operations Research* 20(2):183–230. doi: 10.1007/s10100-011-0210-y.

Kuhn, Thomas S. 1962. *The Structure of Scientific Revolutions*. Chicago: University of Chicago Press.

May, Ann Mari, Mary G. McGarvey, Yana van der Meulen Rodgers, and Mark Killingsworth. 2021. "Critiques, Ethics, Prestige and Status: A Survey of Editors in Economics." *Eastern Economic Journal* 47(2):295–318. doi: 10.1057/s41302-021-00188-6.

Mesoudi, Alex. 2016. "Cultural Evolution: A Review of Theory, Findings and Controversies." *Evolutionary Biology* 43(4):481–97. doi: 10.1007/s11692-015-9320-0.

Mesoudi, Alex, Andrew Whiten, and Kevin N. Laland. 2006. "Towards a Unified Science of Cultural Evolution." *Behavioral and Brain Sciences* 29(4):329–47. doi: 10.1017/S0140525X06009083.

Musselin, Christine. 2018. "New Forms of Competition in Higher Education1." *Socio-Economic Review* 16(3):657–83. doi: 10.1093/ser/mwy033.

Nicholas, George. 2018. "After Thousands of Years, Western Science Is Slowly Catching Up to Indigenous Knowledge." *YES! Magazine*. Retrieved June 1, 2021 (https://www.yesmagazine.org/democracy/2018/02/26/after-thousands-of-years-western-science-is-slowly-catching-up-to-indigenous-knowledge).

Okasha, Samir. 2006. *Evolution and the Levels of Selection*. Oxford University Press.

Orrell, David. 2018. "The Economics Debate: The Problem Isn't Bad Economics, It's Bad Science." *Evonomics*. Retrieved May 30, 2021 (https://evonomics.com/bad-economics-science-heterodox-orrell/).

Popper, Karl. 1935. *The Logic of Scientific Discoveries*. London and New York: Taylor & Francis e-Library.

Rebel Wisdom. n.d. "The War on Sensemaking, Daniel Schmachtenberger."

Rehman, Jalees. 2018. "Novelty in Science – Real Necessity or Distracting Obsession?" *The Conversation*. Retrieved May 31, 2021 (http://theconversation.com/novelty-in-science-real-necessity-or-distracting-obsession-84032).

Steffen, Will, Wendy Broadgate, Lisa Deutsch, Owen Gaffney, and Cornelia Ludwig. 2015. “The Trajectory of the Anthropocene: The Great Acceleration.” *The Anthropocene Review* 2(1):81–98.

Steffen, Will, Katherine Richardson, Johan Rockström, Sarah E. Cornell, Ingo Fetzer, Elena M. Bennett, Reinette Biggs, Stephen R. Carpenter, Wim de Vries, Cynthia A. de Wit, Carl Folke, Dieter Gerten, Jens Heinke, Georgina M. Mace, Linn M. Persson, Veerabhadran Ramanathan, Belinda Reyers, and Sverker Sörlin. 2015. “Planetary Boundaries: Guiding Human Development on a Changing Planet.” *Science* 347(6223). doi: 10.1126/science.1259855.

Treen, Kathie M. d’I., Hywel T. P. Williams, and Saffron J. O’Neill. 2020. “Online Misinformation about Climate Change.” *WIREs Climate Change* 11(5). doi: 10.1002/wcc.665.

Wilenski, Uri. 1999. *NetLogo*. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.