A simulation model of scientists as utility-driven agents

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Agent-based modeling (ABM), coordination, knowledge generation, reputation, scientific advancement, scientific competition, status competition, utility function

ABSTRACT

Agent-based simulations of science that account for the linkage between micro-level behavior of scientists and macro-level results of scientific competition are rather scarce. The approach of this simulation model is to link the motivation and behavior of scientists to knowledge growth and scientific innovations via the emergence of new knowledge fields. A new knowledge field is considered both to be a result of scientific competition and a representation of scientific advancement. This paper takes a closer look at the scientists' motivation and how they coordinate and add to scientific progress as utility-driven agents. Accounting for stylized facts of scientific competition, selected simulation results show how deep the processes of knowledge generation, reputation and scientific innovations are intertwined. As scientists are assumed to be of different utility types and have different aspiration levels, this approach is able to account for adaptive behavior of agents.

INTRODUCTION

The aim of the ABM is to show how scientists as utility-driven agents coordinate scientific competition. Coordination implies that even though science may exhibit biased results as reflected in the Matthew effect, the rules of scientific competition have nevertheless proved to be self-enforcing and well-designed in that they align the individual ambitions with the social purpose of scientific advancement (Vanberg, 2010). Individual scientists may follow the counter-norms of "emotional commitment, particularism, solitariness, interestedness, and organized dogmatism" (Mitroff, 1974), but after all, the *social* system of scientific competition remains robust in Merton's sense (Merton, 1973) as long it enhances the overall stock of knowledge. There is a long-standing debate among philosophers of science on how an individual epistemology can be aligned to a social epistemology. If one adopts the naturalist view that one has to account for the scientists' motivation and behavior in practice (Downes, 2001), it is generally agreed that scientists *are* in fact subject to different individual practices, (non-epistemic) motives and social influences (e.g., Bloor, 1991; Kitcher, 1993; Latour, 1987). The crucial question, however, remains a subject of discussion. How can consensus practices of scientific communities be derived from individual practices? The Naturalists' approach to align a rich cognitive conception of individual scientists with a scientific consensus building that heavily depends on neoclassical microeconomics and Bayesian decision theory has been subject to a lot of criticism (e.g., Downes, 2001; Mirowski, 1996; Sent, 1996).

The approach adopted here is to regard scientists not as utility maximizers of neoclassical economics who consistently base their reasoning on Bayesian decision theory. Rather, scientists are conceptualized as satisficing agents who are occasionally prone to biased reasoning and behavior. Thus, this paper follows a "thick" conception of individual agents, i.e. a claim about a rich psychological makeup of the agent and the relevance of context (Downes, 2001). Recently, research has been carried out in ABMs on science to account for biased behavior of scientists. Thurner and Hanel (2011) discuss biased behavior of agents in the coordination process of science, in particular how self-interested scientists affect the efficiency of the peer review mechanism. They show that referees who tend to reject better papers than their own and accept worse quality considerably reduce the average quality of accepted papers. This result is confirmed in a model by Squazzoni and Gandelli (2012). They also examine the effects of institutional factors on the quality and efficiency of peer-review. For instance, they show that increasing competition in a fragmented scientific community tends to foster evaluation bias and inefficiencies in the peer review process.

While these ABMs focus on the effects of motivational bias and institutional settings on the efficiency of the coordination mechanism, the model presented here intends to explain how individual scientists, who are prone to motivational and cognitive bias, are able via the coordination process of scientific competition to add to scientific advancement. The approach relates to the findings of Solomon (1992), who argues that a cognitive bias of scientists, in particular belief perseverance, leads to a distribution of research effort and thus contributes to the

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advancement of scientific debate. Especially when scientific problems are "ill-defined", a scientist is expected to support his special community of interest and to "(...) believe in his own findings with utter conviction while doubting those of others (...)" (Mitroff, 1974, p.592).

Scientific advancement is reflected in a growing body of scientific knowledge and its development by means of emerging knowledge fields and scientific innovations. To model this micro-macro-link is the intention of the model. It is an abstract simulation model which is based on plausible micro-level agent behavioral rules (Gilbert, 2008), yields stylized facts of scientific competition at the macro level and feeds back to the behavioral rules of micro-level-agents. To the knowledge of the author, so far there is no such model to link utility-driven micro behavior with the macro level of scientific advancement. This papers thus contributes to research that accounts for micro-macro interdependencies in scientific competition and the social embededdness of science (Edmonds et al., 2011). At first, this paper focuses on the motives and behavior of agents that drive the most important processes on the micro level. The mechanisms are simple, though powerful, and are able to reproduce a number of stylized facts of scientific competition. They are thus considered to be a suitable starting point for modeling the feedback processes between the macro and micro level.

COORDINATION MECHANISMS IN SCIENCE

Stylized facts and characterization of a scientist

Scientists are presumed to gain utility from scientific insight (intrinsic motivation) and scientific reputation (extrinsic, non-monetary motivation). To achieve this, scientists are supposed to produce scientific output, i.e. publications. The distribution of publications per author is approximated by the Lotka distribution, saying that in a specific knowledge field the number of authors generating n scientific papers is proportional to $1/n^2$. This stylized fact has been verified in a number of papers, e.g. for economics (Cox and Chung, 1991). This effect is augmented by the law of decreasing returns, which in the context of scientific progress (Rescher, 1978) states that the more is already known in a scientific field, the smaller the scientific insights that are achievable. It is hypothesized that these two effects may lead to a considerable share of unsatisfied scientists, either in regard to scientific insight or reputation. One solution to the scientist's problem might be to initiate a new knowledge field, publish innovative articles and as the priority rule suggests, achieve disproportionally more credit than before. But a scientist might also choose to stick to one field of knowledge with only small scientific returns. In a nutshell, scientists are considered as heterogeneous as they have differing goals concerning scientific insight and reputation. They do not pursue lifetime utility maximization (Diamond, 1988), but have an aspiration level which they strive to achieve Simon (1955). The aspiration level may be defined in terms of private goals and/or determined by observable properties of other agents. After all, scientific advancement is rooted in the individual disposition of scientists who do not achieve their aspiration level. The concept of satisficing explicitly accounts for adaptive behavior of agents, for instance modeled in Brenner (2006) and Chang and Harrington Jr. (2006).

The present paper concentrates on heterogeneous scientists who are endowed with some basic rules of behavior and who coordinate their behavior in a social process, it abstracts from aspects of *how* scientists create and evalute new ideas (Gilbert, 2007; Watts and Gilbert, 2011), form networks of "invisible colleges" or adjust their lifecycle-productivity (Carayol, 2008; Levin and Stephan, 1991).

The scientist's utility function

As a scientist strives for scientific insight, he gains utility from his accumulated knowledge. The intrinsic utility of a scientist $u_{i,t}^{int}$ is assumed to be a function of his accumulated knowledge w driven by his cumulative productivity pr. The latter is a function of his publication activities pub exhibiting diminishing marginal returns. The function is assumed to have the following properties:

$$\begin{aligned} u_{i,t}^{int} &= f(w(pr(pub))) \qquad (1)\\ \partial f/\partial w &> 0 \\ \partial w/\partial pr > 0, \partial^2 w/\partial pr &< 0 \\ \partial pr/\partial pub_i > 0, \partial pr/\partial pub_{-i} &< 0 \end{aligned}$$

The accumulation of knowledge is a private disposition and thus unaffected by the accumulated knowledge of other scientists. However, for scaling purposes in the simulation model, the accumulated knowledge $w_{i,t}$ of scientist i is multiplied with a factor $\gamma = max(w_{-i,t})$. This yields a value $u_{i,t}^{int}$ in the interval $\in [0, 1]$.

$$u_{i,t}^{int} = \gamma * w_{i,t} \qquad (2)$$

Utility from reputation $u_{i,t}^r$ is considered a social disposition and assumed to decrease with the scientist's position according to his scientific output. Utility $u_{i,t}^r$ is defined by the ranking of scientists. The ranks ra are better (i.e. converge to a value of one) for those scientists who have many publications. To account for persistent ranking positions, a parameter of organizational inertia $(1 - \delta) \in (0, 1)$ is added. Rankings do not change if δ yields a value of 0. The closer δ converges to 1, the more ranking positions are proned to change and truly reflect the current publication activities. Utility from reputation is given by

$$\begin{aligned} u_{i,t}^r &= f(ra(pub, \delta)) \qquad (3)\\ \partial f/\partial ra < 0, \partial^2 f/\partial ra &< 0 \\ \partial ra/\partial pub &< 0 \\ \partial ra/\partial \delta &> 0 \end{aligned}$$

As related works account for an evaluation bias in the review process on the micro-level of scientific competition (e.g., Squazzoni and Gandelli, 2012; Thurner and Hanel, 2011), the parameter δ in this model can be interpreted as an evaluation bias on an aggregate level, i.e. how quick a scientific discipline credits new publications with corresponding ranks. It points to the fact that some disciplines are "tightly knit in terms of their fundamental ideologies, their common values, their shared judgments of quality, (...) and the level of their agreement about what counts as appropriate disciplinary content" (Becher and Trowler, 2001, p.59). Following Loch et al. (2001), utility from reputation yields a value in the interval $\in [0, 1]$ and specifies to:

$$u^{r}_{i,t} = 1 - \frac{(ra_{i,t} - 1)^2}{n_{j,t}} \tag{4}$$

with $n_{j,t}$ in (4) as the number of rank classes of scientists belonging to one community of scientists. Weighted utility from accumulated knowledge and reputation yields the overall utility function of a scientist. As Equation (5) shows, it is assumed that utility from knowledge and reputation are partial substitutes, with utility becoming zero when one of the terms is zero.

$$u_{i,t} = (u^{int}_{i,t})^{\alpha} * (u^{r}_{i,t})^{1-\alpha} \tag{5}$$
$$\alpha \in [0, 1]$$

It should be noted that although both utility from accumulated knowledge and from reputation are driven by publication activities, the interpretation is different. Intrinsic utility only aims at utility derived from significantly new findings which increase the stock of knowledge (outcome), whereas utility from reputation may also comprise "normal science" and equivalent types of output (Rescher, 1978).

Types of agents

According to the scientists' motivation reflected in their specific utility weights, it is assumed that scientists can follow three types of individual disposition. Scientists may

- put relatively more emphasis on reputation compared to scientific insight.
- put relatively more emphasis on scientific insight compared to reputation.
- be indifferent between reputation and scientific insight.

Apparently, the assignment of utility weights does not depend on a scientist's actual publication activity. The rationale for this is that there may be scientists who do appreciate knowledge enhancement more than reputational concerns, yet are not successful publishers. It implicitely asssumes that there are scientists who are willing to pay (with a low number of publications) for deviating from the prevailing norm, i.e. the model allows for non-conforming behavior (Brock and Durlauf, 1999). It is argued that scientists who show non-conforming behavior reveal a motivational and cognitive bias. Scientists who deviate from the prevailing scientific paradigm are assumed to constitute a group with a common focus. This common focus allows a new knowledge field to emerge.

Scientists cannot observe the individual disposition of other scientists. However, a scientist takes notice of the output of the scientific coordination process, concretely the number of publications and ranking of other scientists. This is the primary information that influences a scientist's strategy. Moreover, two parameters that reflect the context of a scientific discipline are considered: the degree of organizational inertia and the parameter of half life of scientific knowledge. While scientists can observe both parameters ex-post, they can act upon organizational inertia and adapt their strategies, whereas the parameter of half life is considered to be an exogenous parameter as explained in the next section.

```
initialize scientists and knowledge fields
link scientists to knowledge fields
initialize parameters
while simulation time < termination time
scientists
    publish
    update their knowledge stock
    update their ranks
    calculate utility from knowledge and reputation
if subgroup of scientists does not reach
utility threshold and conditions are met
scientists
    hatch a new knowledge field
    and link to it
end
plot graphics
calculate statistics
```

Table 1: Pseudocode of the simulation model

The scientist in action: outline of the simulation model

The pseudocode in Table 1 summarizes the simulation.

To initialize, n scientists are randomly assigned to one of j knowledge fields. In the current model, a scientist is never assigned to more than one knowledge field. It is assumed that separate knowledge fields may be incommensurable (Brock and Durlauf, 1999). Accordingly, the scientist has to decide which school of thought he wants to belong to, i.e. he makes an "investment" decision. Changing to other fields of knowledge is possible but costly.

All scientists who are assigned to one knowledge field constitute a scientific community. The fundamental activity to attain intrinsic and extrinsic non-monetary utility is to conduct research, i.e. to publish articles in the correspondig field. To model this process, Rauber and Ursprung (2008) used the hurdle model (see also Watts and Gilbert (2011) who used the Weibull distribution for related processes). As this model does not focus on the publication process itself and to keep the simulation as tractable as possible, publication activities are modeled as an adapted version of the lottery example borrowed from the Netlogo Models Library (Wilensky, 2004).

As a convention, a scientist is defined as someone who publishes at least one scientific paper. In the first period, each scientist produces a minimum of 1, and a maximum of 2 publications pub. The accumulated output a scientist produces yields the scientist's cumulative productivity $pr_{i,t}$ and is related to the maximum accumulated output of one of his fellows in his scientific community. In the following periods -according to the lottery example- the propensity to generate additional publications is higher for those scientists who already have a high cumulative productivity. Unless a scientist does not win the lottery, he will maintain his number of publications for the following periods. This assumption can be justified as one simulation run in the model does not intend to reflect a scientist's lifecycle-productivity (Levin and Stephan, 1991) but considers fluctuations within a lifecycle of scientific competition and thus accounts for the fact that no clear evidence exists for an increasing or decreasing overall average publication output per scientist (Wagner-Doebler, 2001). Since only a limited number of scientists will ever win the lottery, the number of publications per author approximates a skewed distribution (Lotka, 1926). Publication activities serves as the intrinsic motivation in that they enhance the scientist's accumulated scientific knowledge. Equation (2) can be specified for the simulation in that knowledge w of a scientist i grows according to

$$w_{i,t+1} = \theta * w_{i,t} + \sqrt{pr_{i,t} * pub_{i,t}} \qquad (6)$$

While there is consensus that publications serve as an indicator of scientific output, measuring *knowledge* is not only a problem in ABM models, but it is also a problem in the real world (Payette, 2011). The approach in (6) is justified as follows: The first term accounts for the fact that any scientific knowledge is subject to depreciation. Previous knowledge is thus multiplied with a constant half-life factor $\theta \in (0, 1)$. For instance, a half-life factor of .93 means that after a period of approximately 10 years, the scientific knowledge has lost half of its value in terms of topicality. The specification of θ is subject to the scientific discipline under consideration. As publications can be interpreted as the documentation of knowledge development, the second term describes the effectiveness of a scientist to transform scientific output (publications) into outcome (knowledge). $pr_{i,t}$ is calculated from the cumulated publications of a scientist in field j, normalized for the interval [0,1]. The higher his cumulated productivity $pr_{i,t}$, the higher the propensity to win the lottery in the next period and the more effective output is transferred into outcome. The square-root function represents the assumption that efforts to increase the knowledge stock in a specific knowledge field are subject to diminishing marginal returns (Koelbel, 2001).

Besides knowledge growth, publication activities serve to attain scientific reputation. Following Hopkins and Kornienko (2004) and Loch et al. (2001), ranks are the result of sorting the scientists' status weighted with a factor of organisational memory $(1 - \delta) \in (0, 1)$.

$$ra_{i,t} = (1 - \delta) * st_{i,t-1} + \delta * st_{i,t} \qquad (7)$$

Status st in (7) simply counts a scientist's fellows with less or strictly less publications and adds a minimum status value of 1 for each scientist. For each community of scientists, the status values are sorted in ascending order which yields rank $ra = 1$ for the scientist with the highest status. For scientists of one community who may have the same number of publications, it is allowed that they are assigned to the same rank. $(1 - \delta)$ reflects the organisational memory of a scientific *discipline*, i.e. it is defined for all knowledge fields of one discipline. The smaller δ is, the more a scientist benefits from his last period status and the harder it is for other scientists to achieve a higher status respectively.

Selected results on the influence of organizational inertia

Some simulation experiments have been conducted to test how δ influences the distribution of ranks in one specific knowledge field over one lifecycle (run) of scientific competition (35 periods). From the intuition it is sensible to believe that the more successful scientists group to the higher ranks while the scientists who do not stand out constitute the group with the lower ranks.

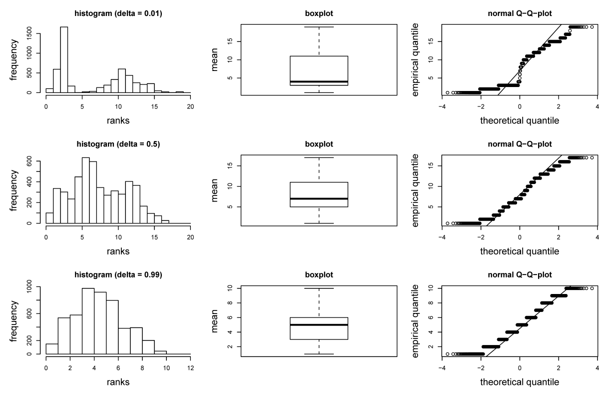

Figure 1: Frequency distribution of ranks for 50 scientists in period 35 based on 100 simulation runs

As can be seen in the upper row of Figure 1, the distribution of ranks is bipolar when there is a high degree of organizational inertia. In this case, the histogram shows that on the aggregate level, scientists stay pretty separated over the periods of time, and the rank they take at the beginning is rarely prone to change. As δ rises, the frequency disribution converges to a normal distribution, i.e. the ranks change over time and their distance tends to get smaller. However, as the size of a scientific community slightly changes in each simulation run, the results can only show some basic mechanism which prevail on an aggregate level.

The implication of using a factor of organisational inertia $(1 - \delta)$ is to show that even though a scientist may achieve a high number of publications, this does not necessarily imply an equivalent ranking value. For instance, if $(1 - \delta)$ is close to 1, in the case of two scientists both of whom have a certain number of publications, only the one with the higher rank in previous periods gets rank 1. This was verified in a simple correlation analysis. As the increasing (negative) correlation coefficients show in Table 2, the smaller the parameter for organizational inertia, the closer the ranking reflects the scientists' current publication activities. It should be noted that the negative signs of τ are attributed to the fact that the smallest rank number represents the best rank.

δ	τ	z-value
0.01	-0.6831274	-59.03
0.5	-0.7906952	-69.79
0.99	-0.8133727	-69.86

p-value $<$ 2.2e-16 in all cases

Table 2: Kendall's rank correlations

The aspiration level of scientists and scientific advancement

Looking at the scientists' aspiration level in terms of the knowledge stock, a scientist is said to be satisfied if his knowledge stock grows. In the reference model, the overall amount of publications rises faster than the individual amount of publications, indicating that there is a natural crowding of knowledge fields over time. Thus the cumulated productivity $pr_{i,t}$ decreases for all scientists who do not win the lottery. This again leads to decreasing returns of knowledge growth $\Delta w = \frac{w_{i,t} - w_{i,t-1}}{w_{i,t-1}}$.

In general, knowledge growth becomes zero when the depreciation of the accumulated knowledge stock as defined in the first term of Equation (6) is faster than new output is transferred to knowledge (second term in Equation (6)). This process reflects the fact that the more that is already known in a specific knowledge field, the more effort has to be spent to attain substantially new findings (Rescher, 1978). As mentioned before, unsatisfied agents have the possibility to initiate a new knowledge field. Scientists who engage in a new knowledge field do not necessarily have to stem from the same community of scientists. At first, a new knowledge field is expected to be smaller than existing ones. With a lower number of competitors, they tend to attain a higher cumulated productivity and rank as defined in Equation (6) and Equation (7). As their cumulated productivity and knowledge increases, the propensity to win the lottery for additional publications rises as well. This process reflects two stylized facts of scientific competition: First, when a knowledge field is young, the scientific insights that are achievable are greater (Rescher, 1978) and second, scientists being the first to publish in a specific field attain higher reputation due to the priority rule (Merton, 1957).

For a new knowledge field to emerge, (1) there must be a minimum number of scientists who did not reach their aspiration level in regard to knowledge growth, (2) this state must have lasted for a minimum number of periods, and (3) the agents need a minimum capacity, i.e. knowledge, to engage in scientific search. The rationale for the latter condition results from the fact that scientific innovation is costly in terms of effort and risk and requires a minimum amount of scientific capital to successfully initiate a new field after all.

So far, the simulation model accounts for the first two conditions (see Table 3). The minimum number of unsatisfied agents is set to ten scientists, i.e. 10 per cent of the population of one scientific discipline. This reference value follows a study by Fagerberg and Verspagen on the emergence of the field of innovation studies in the 1960s which finds that the number of influential authors to engage in this new field can be traced back to a group of this size. The rationale for a minimum group size is that some degree of shared knowledge and common focus among unsatisfied scientists has to be developed before a new knowledge field is able to thrive (Fagerberg and Verspagen, 2009). This process takes time and therefore, a number of periods is necessary to let unsatisfied agents adjust their research efforts. In the simulation model, this start-up time is defined as periods with zero growth of knowledge for the scientists under consideration. The number is set to four, spanning a maximum period of two successive scientific evaluations. Taking the values as noted in Table 3 as input parameters for a test run, a simulation has shown that out of 100 runs, 71 times one new knowledge field emerges in a lifecycle of 35 periods. Subsequent analysis will test the sensitivity of the parameters used here.

DISCUSSION AND OUTLOOK

The utility-driven approach presented in this paper is a fruitful approach to unfold the mechanism on the micro and macro level. Two basic processes that drive the scientist's utility have been presented in this paper: At first, the process of knowledge generation that accounts for the depreciation of accumulated knowledge and diminishing marginal returns of efforts, and secondly, the process of how organizational inertia influences the scientists' reputation. Since it is argued that different utility types of

Parameter description	Example values
Initialization	
No. of knowledge fields within one scientific discipline	2
No. of scientists	100
No. of time steps	35
Parameter for half life of scientific knowledge θ	0.93 ($\approx$ 10years)
Parameter for organizational inertia $(1-\delta)$	0.5
Assignment of parameter α in utility function	random $\in [0,1]$
Maximum no. of additional publications for "lottery winner" in each period	2
Emergence of new knowledge field	
Minimum no. of scientists to engage in new knowledge field	10
No. of periods (start-up time) until a new knowledge field can emerge	4
No. of times a new knowledge field emerges within 100 runs	71

Table 3: Parameters for the simulation model

scientists exist, some of them engage in new knowledge fields and add to the advancement of science. This is explicitly accounted for in the simulation model. In the previous section the point was made that the attainment of knowledge growth or reputation is costly since any kind of effort (time, money, etc.) has to be spent on these activities. This effort represents a disutility that has to be accounted for. From what has been said so far, two aspects have to be considered. For some scientists, it may be worth sticking to a specific knowledge field. They are able to take advantage of scale effects in that each additional publication is less costly and reduces the disutility of effort. On the other hand, as a specific knowledge field grows and tends to get more crowded, each additional publication yields smaller returns. Scientists consider this as a trade-off decision. Accordingly, as scientists represent different utility types, they are presumed to differ in their decisions and willingness to take the risk of engaging in new knowledge fields. The extent of disutility is determined by the resources that each scientist is endowed with. On the macro level, the budget allocation is a special representation of the institutional setting within which the process of scientific coordination unfolds. As budget allocation policies have recently been subject to change, enforcing the competitive or market-like character of science, considerable effects are expected concerning the coordination result of scientific competition. In the context of the simulation model, budget allocation policies are interpreted as a selection environment that not only affect the decisions of scientists, but implicitly act on the motives of scientists (utility types). It is hypothesized that a growing share of risk-averse utility types and imitative behavior emerges. This is argued to have a negative effect on the coordination results, in particular the scientists' propensity to engage in innovative research and, by means of emerging knowledge fields, contribution to the stock of scientific knowledge.

REFERENCES

Becher, T. and Trowler, P. (2001). *Academic Tribes and Territories: Intellectual Enquiry and the Culture of Discipline*. Open University Press, Buckingham, 2nd Edition.

Bloor, D. (1991). *Knowledge and social imagery*. University of Chicago Press, Chicago, 2nd Edition.

Brenner, T. (2006). Agent Learning Representation: Advice on Modelling Economic Learning. In: Tesfatsion, L. and Judd, K., Editors, *Handbook of Computational Economics: Agent-Based Computational Economics*, Pages 895–947. Elsevier.

Brock, W. A. and Durlauf, S. N. (1999). A formal model of theory choice in science. *Economic Theory*, 14(1):113–130.

Carayol, N. (2008). An Economic Theory of Academic Competition: Dynamic Incentives and Endogenous Cumulative Advantages. In: Albert, M., Voigt, S., and Schmidtchen, D., Editors, *Conferences on New Political Economy*, Volume 25, Pages 179–203. Mohr Siebeck, Tuebingen, 1st Edition.

Chang, M.-H. and Harrington Jr., J. E. (2006). Agent-Based Models of Organizations. In: Tesfatsion, L. and Judd, K., Editors, *Handbook of Computational Economics: Agent-Based Computational Economics*, Pages 1273–1337. Elsevier.

Cox, R. A. K. and Chung, K. H. (1991). Patterns of Research Output and Author Concentration in the Economics Literature. *The Review of Economics and Statistics*, 73(4):740–747.

Diamond, A. M. (1988). Science as a rational enterprise. *Theory and Decision*, 24:147–167.

Downes, S. M. (2001). Agents and Norms in the New Economics of Science. *Philosophy of the Social Sciences*, 31:224–238.

Edmonds, B., Gilbert, N., Ahrweiler, P., and Scharnhorst, A. (2011). Simulating the Social Processes of Science. *Journal of Artificial Societies and Social Simulation*, 14(4):14.

Fagerberg, J. and Verspagen, B. (2009). Innovation studies - The emerging structure of a new scientific field. *Research Policy*, 38(2):218–233.

Gilbert, N. G. (2007). A generic model of collectivities. *Cybernetics & Systems*, 38(7):695–706.

Gilbert, N. G. (2008). *Agent-based models*. Quantitative applications in the social sciences. Sage Publications, Los Angeles.

Hopkins, E. and Kornienko, T. (2004). Running to keep in the same place: Consumer choice as a game of status. *American Economic Review*, 94(4):1085–1107.

Kitcher, P. (1993). *The Advancement of Science*. Oxford University Press, New York.

Koelbel, M. (2001). Das Wachstum der Wissenschaft in Deutschland 1650-2000. In: Parthey, H. and Spur, G., Editors, *Wissenschaft und Innovation. Wissenschaftsforschung. Jahrbuch 2001*, Pages 113–128. Gesellschaft fuer Wissenschaftsforschung.

Latour, B. (1987). *Science in action*. Harvard University Press, Cambridge.

Levin, S. G. and Stephan, P. E. (1991). Research Productivity over the Life Cycle: Evidence for Academic Scientists. *The American Economic Review*, 81(1):114–132.

Loch, C., Huberman, B., and Uelkue, S. (2001). Status Competition and Group Performance. In: Lomi, A. and Larsen, E. R., Editors, *Dynamics of Organizations*. Cambridge, MA: The M.I.T. Press.

Lotka, A. (1926). The frequency distribution of scientific productivity. *Journal of Washington Academy Sciences*, 16(12):317–324.

Merton, R. K. (1942 (1973)). The Normative Structure of Science. In: *The Sociology of Science: Theoretical and Empirical Investigations.* University of Chicago Press, Chicago.

Merton, R. K. (1957). Priorities in scientific discovery. *American Sociological Review*, 22:635–659.

Mirowski, P. (1996). The economic consequences of Philip Kitcher. *Social Epistemology*, 10:153–169.

Mitroff, I. I. (1974). Norms and Counter-Norms in a Select Group of the Apollo Moon Scientists: A Case Study of the Ambivalence of Scientists. *American Sociological Review*, 39(4):579–595.

Payette, N. (2011). For an Integrated Approach to Agent-Based Modeling of Science. *Journal of Artificial Societies and Social Simulation*, 14(4):9.

Rauber, M. and Ursprung, H. W. (2008). Life Cycle and Cohort Productivity in Economic Research: The Case of Germany. *German Economic Review*, 9(4):431–456.

Rescher, N. (1978). *Scientific Progress*. Pittsburgh University Press. German Edition: Wissenschaftlicher Fortschritt, de Gruyter, Berlin 1982.

Sent, E. (1996). An economists glance at Goldmans economics. *Philosophy of Science*, 64:139–148.

Simon, H. (1955). A Behavioral Model of Rational Choice. *Quarterly Journal of Economics*, 69:99–118.

Solomon, M. (1992). Scientific rationality and human reasoning. *Philosophy of Science*, 59:439–455.

Squazzoni, F. and Gandelli, C. (2012). Saint Matthew Strikes Again: An Agent-based Model of Peer Review and the Scientific Community Structure. *Journal of Informetrics*, 6:265–275.

Thurner, S. and Hanel, R. (2011). Peer-Review in a World with Rational Scientists: Toward Selection of the Average. *The European Physical Journal B*, 84:707–711.

Vanberg, V. (2010). The 'science-as-market' analogy: a constitutional economics perspective. *Constitutional Political Economy*, 21:28–49.

Wagner-Doebler, R. (2001). Rescher's Principle of Decreasing Marginal Returns of Scientific Research. *Scientometrics*, 50:419–436.

Watts, C. and Gilbert, N. (2011). Does cumulative advantage affect collective learning in science? An agent-based simulation. *Scientometrics*, 89:437–463.

Wilensky, U. (2004). Netlogo Lottery Example from Netlogo Library / Code Examples. Online: http://ccl.northwestern.edu/netlogo/.

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