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Changes in variance and the canonical faculty productivity trajectory

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Extended Abstract

The quantity—and expectation—of a scholar's research output (their productivity) underpins major outcomes in scientific careers including hiring, awards, grant funding, and tenure. Recent work has shown that the "canonical trajectory" narrative, of a rapid early rise in productivity followed by a gradual decline, is misleading because although such a narrative appears across the average of many careers, few individuals exhibit such a trajectory. The causes of variability across career trajectories remains poorly understood, because prior attempts assumed the canonical trajectory was typical. Using random walk models, we characterize the structure of 2,085 productivity trajectories of computer scientists at 204 PhD-granting institutions spanning 29,119 publications between 1980 and 2016. We show that a decrease in individual productivity variance in the later career relative to the early career can explain both the canonical trajectory pattern and its variance across careers. Fitting an extended version of this model to our empirical data, we show that the remaining unexplained statistical patterns imply important non-Markovian dynamics within faculty careers, as well as unmodeled heterogeneity across careers.

A substantial literature spanning many decades and many fields has documented a "canonical trajectory" in scientific productivity over a career, in which a researcher's average productivity tends to rise rapidly to a peak in the early career followed by a gradual decline [1–3] (though see [4]). However, recent work has revealed that the canonical trajectory is not representative of most individuals, who instead exhibit a rich diversity of productivity trajectories [5]. Overestimating the prevalence of the average trajectory could lead to unfair penalties of individuals who deviate from the canonical trajectory. In fact, belief in the universality of the canonical trajectory has already influenced policies such as the now-defunct mandatory retirement age for US professors at the age of 70, which was motivated in part by a desire to increase overall scientific capacity.

The discovery that the canonical trajectory provides a misleading explanation for individual productivity patterns presents a puzzle: what mechanisms lead to such dramatic variability in the shape of individual productivity trajectories? Past explanations of the canonical pattern ranged from cognitive mechanisms to psychological development and economic mechanisms. However, these do not easily map onto the empirical reality of a broad diversity of productivity patterns. As a result, little is known about mechanisms that generate real individual productivity trajectories.

Here, we propose and investigate a parsimonious explanation: (1) individual faculty productivity fluctuates due to individually contingent factors from year to year, e.g., the beginning of a new collaboration, an experiment that fails, parenthood, changing institutions, etc., (2) within the context of larger-scale structural forces that drive the variability and central tendency of these factors over different career stages, such that productivity fluctuations are higher in the early career than in the later career, and this change in variance is sufficient to produce the canonical trajectory and much of the observed variability around it. We formalize this explanation as a probabilistic generative model that can simulate the evolution of individual faculty productivities based on parameterized randomness within distinct career stages (a parameterized random walk), and we validate the model against empirical data on the productivities of computer scientists at PhD-granting universities in the US and Canada (Fig. 1).

We produce two models—a simplified model, and a full one. The simplified model shows that simple changes of variance across a faculty career are sufficient to reproduce the canonical trajectory while preserving individual variability (Fig. 2). It crystallizes a set of sufficient conditions for producing the canonical patterns, and allows us to explore the space of possible average trajectories. The full model answers the question: to what degree does a model of this kind that is relatively realistic capture the details of real individual productivities? It validates the basic hypothesis—that a change in variance is sufficient for producing canonical trajectories (Fig. 3)—and reveals noteworthy limitations of a Markovian model of faculty productivity (Fig. 4).

In particular, even after parameterizing the model more fully, the discrepancies between the simulated and empirical trajectories indicate non-Markovian dynamics and unmodeled heterogeneity. We observe both more within-career variance and less across-career variance in the simulated data than compared to empirical trajectories. The greater variance within simulated trajectories compared to empirical trajectories leads us to consider as-yet unmodeled mechanisms that increase the inertia of faculty productivity above and beyond the one-year serial correlation in our random walks, such as the formation and persistence of research groups, which couples productivity across years. Similarly, the random walk model produces fewer years with zero papers than observed in the empirical data, implying that a state of zero productivity is "stickier" than our model allows, consistent with certain scientists transitioning into research-inactive states, such as teaching-intensive or administrative roles. We also observe less variance in cumulative productivity across faculty in our model than the empirical data, pointing toward the importance of unmodeled sources of heterogeneity across researchers, such as career roles, prestige, subfields, and gender. Faculty, especially in the later career, have access to multiple strategies beyond optimizing their productivity, such as focusing on service and teaching. These strategies simultaneously reduce the variance within careers, as well as increase the variance across careers.

Rather than attempting to enumerate and model each possible mechanism driving faculty productivity, a difficult undertaking due to the unavailability of crucial data about how faculty expend their effort, we show that a dynamic model that places assumptions on the entire population of scientists, rather than on individuals, can yield important insights about scientific productivity. We produce dynamic models that fulfill the two main empirical criteria: that (a) the average faculty productivity follows the canonical trajectory, and (b) individual scientific career trajectories exhibit a wide diversity, rather than all following the average. Our key insight is that a change in individual faculty variance is sufficient to meet both of these criteria.

References

[1] H. C. Lehman, *Age and Achievement*. Princeton University Press, 1953. [2] W. Dennis, "Age and productivity among scientists," *Science*, vol. 123, no. 3200, 1956. [3] A. M. Diamond, "The life-cycle research productivity of mathematicians and scientists," *J. Gerentol.*, vol. 41, no. 4, 1986. [4] S. Cole, "Age and scientific performance," *Am. J. Sociol.*, vol. 84, no. 4, 1979. [5] S. F. Way, A. C. Morgan, A. Clauset, and D. B. Larremore, "The misleading narrative of the canonical faculty productivity trajectory," *Proceedings of the National Academy of Sciences of the USA*, vol. 114, no. 44, 2017.

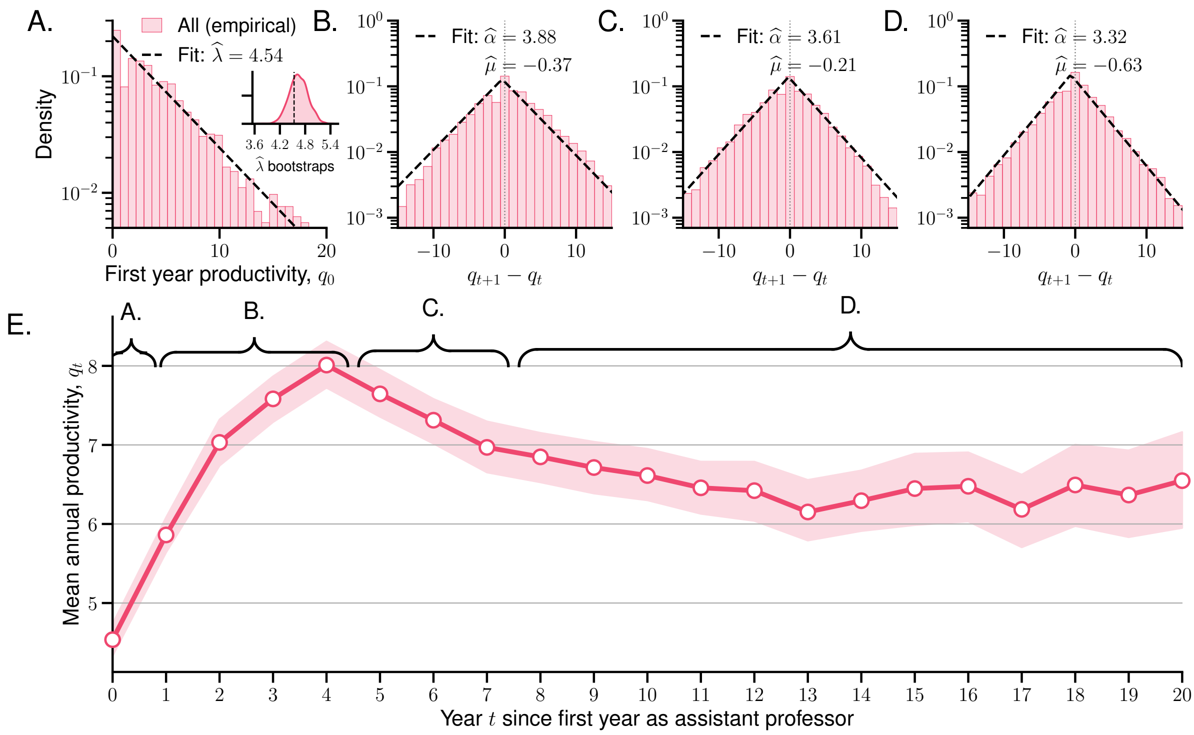

Figure 1: **Empirical criteria for model**. (A) An exponential distribution provides an accurate fit for the distribution of first-year productivity, showing the empirical data (pink histogram) and fitted exponential distribution (dashed black line). The inset displays the estimated rate parameter against the density of estimated rates in 1000 bootstrap replicas. (B-D) The density of productivity increments are linear on a log scale across a range of groupings over time, and can be modeled by a Laplace distribution. The empirical data is shown as pink histograms and the fitted Laplace distributions are shown as a dashed black line. (E) The average productivity for faculty rapidly rises and then gradually levels off. Depicted are means of time-adjusted productivity for each career age and 95% bootstrap confidence intervals. The brackets indicate the range of increments that were grouped together for the density plots: (A) productivity in year zero, (B) increments of productivity in years 1–4, (C) years 5–7, (D) years 8–20.

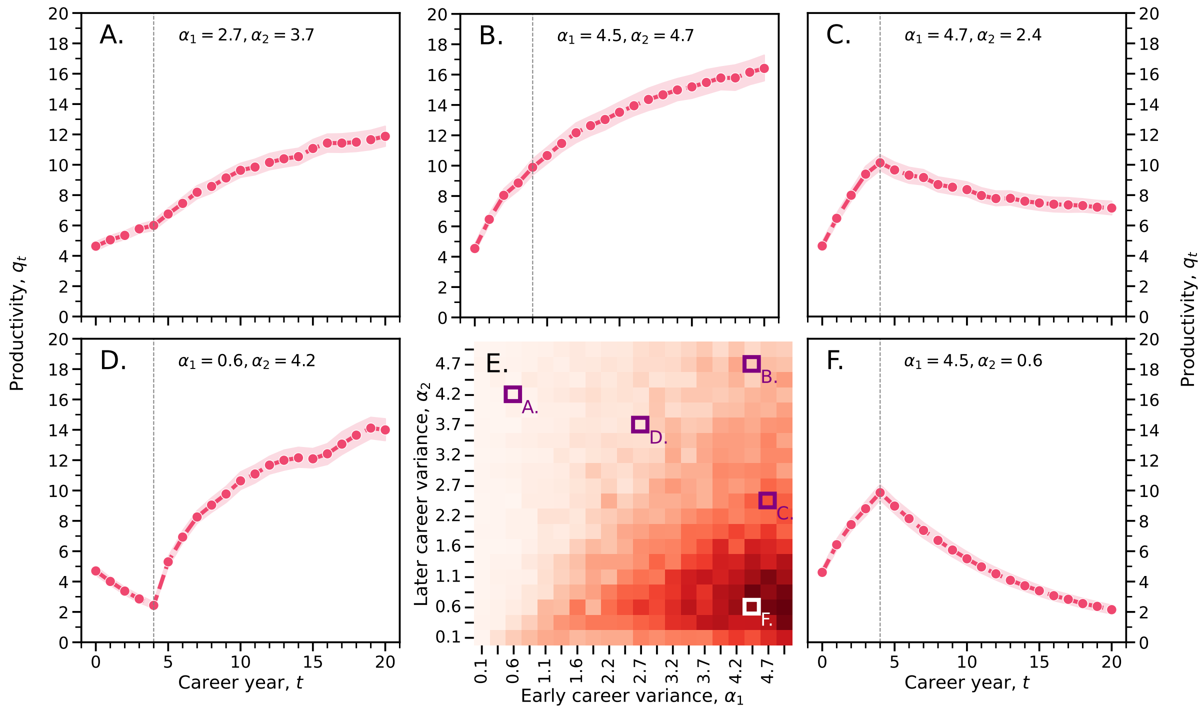

Figure 2: Reproducing canonical trajectories with a simplified model. In the simplified model, the random walk is completely determined by two variance parameters, α_1 for the first five years of the career, and α_2 for the remaining fifteen years. (E) Simulating $N = 400$ trajectories for each pair of α_1 and α_2 with $\mu = -1$ fixed, we display the fraction of those trajectories that are canonical. Some regions of the parameter space generate non-canonical trajectories (A, B, D), while others generate more canonical trajectories on average (C, F). Shaded intervals denote 95% confidence intervals for $N = 1000$ simulations at those parameters.

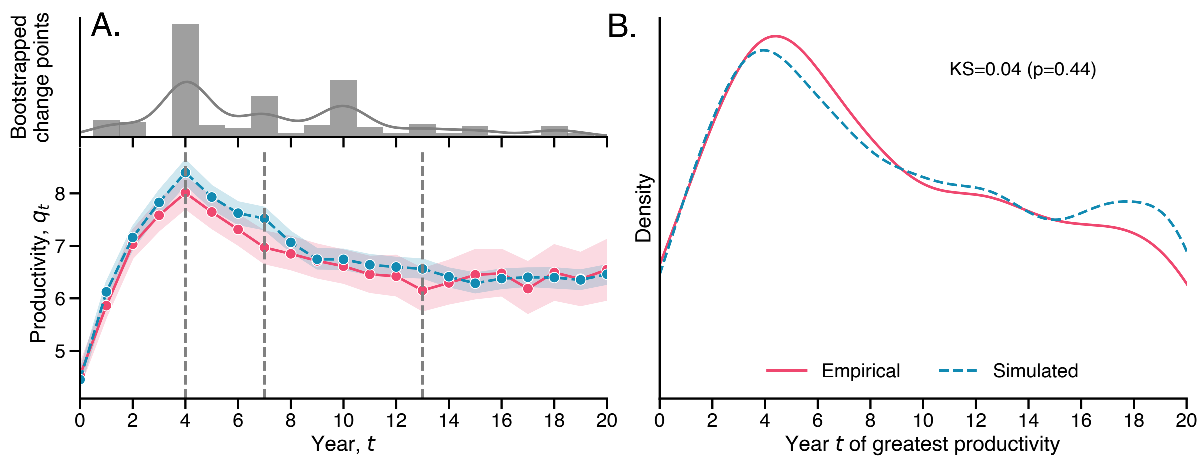

Figure 3: Model fit vs. empirical data. In the full model, we perform model selection to determine the location of up to four change points in the career, where the random walk has different mean and variance parameters for each career stage. (A) Simulations produced by the maximum likelihood estimates of the fitted full model (where career stages are drawn with dashed gray lines at years 4, 7, and 13) match the empirical trajectory on average. Shaded intervals denote 95% confidence intervals. Bootstrapping individuals in the data and refitting the model 1000 times, the distribution of the top change points on each run are plotted above. (B) The distribution of the years with greatest productivity among the full trajectories is similar to the distribution of the years with greatest productivity within simulated trajectories.

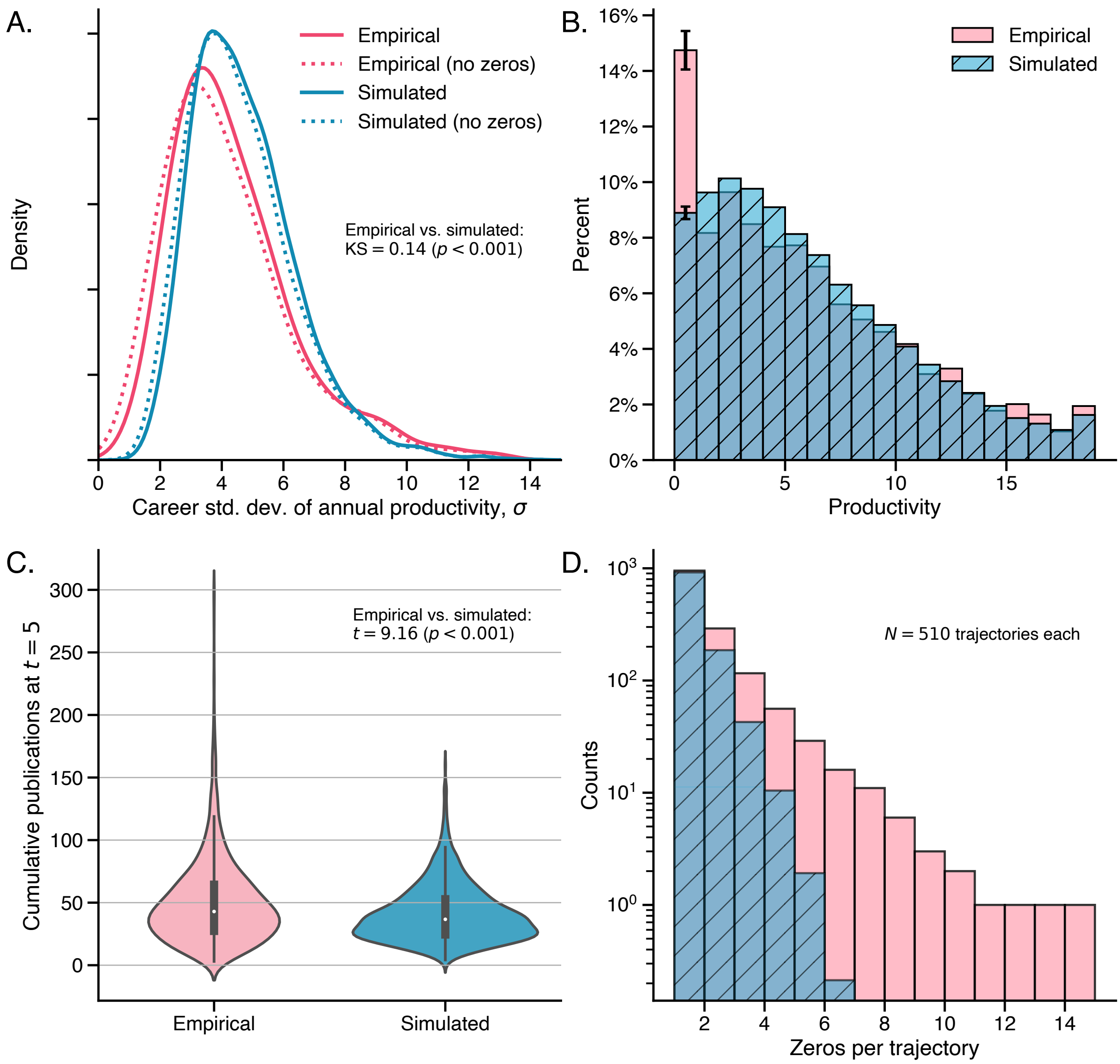

Figure 4: Deviations of full model from empirical data. (A) Standard deviations of full empirical trajectories are generally smaller on aggregate than SDs of simulated trajectories, even once we omit zeros. Empirical vs. simulated test is performed on distributions without zeros omitted. (B) Among full trajectories, the distribution matches the simulated data closely except at zero. The probability of seeing zero is much greater in the empirical data than our model predicts. Drawn in black are binomial 95% Wald confidence intervals for the probability of seeing zero publications. (C) By career year 5, the simulated trajectories tend to have fewer publications than the empirical publication, and the difference is especially pronounced among the most productive individuals. (D) A similarly number of simulated and empirical trajectories have exactly one zero, but more empirical trajectories exhibit more than one zeros than the simulated trajectories, decaying with a broader tail than an exponential distribution.