EDUCATION

Complex Systems View of Educational Policy Research

Agent-based modeling and network analysis can help integrate knowledge on "micro-level" mechanisms and "macro-level" effects.

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Education researchers have struggled for decades with questions such as "why are troubled schools so difficult to improve?" or "why is the achievement gap so hard to close?" We argue here that conceptualizing schools and districts as complex adaptive systems, composed of many networked parts that give rise to emergent patterns through their interactions (*1*), holds promise for understanding such important problems. Although there has been considerable research on the use of complex systems ideas and methods to help students learn science content (*2*), only recently have researchers begun to apply these tools to issues of educational policy.

We roughly categorize existing education research into two categories, "mechanism based" and "effects based." Mechanism-based studies include ethnographies, case studies, and laboratory experiments that focus on understanding individuals and their interactions inside schools. Such work has provided insight into the motivation and cognition of students, teachers, and school leaders, as well as how social phenomena unfold inside schools (*3*, *4*). Effects-based research treats factors contributing to academic performance of schools as inputs that work together to yield a particular level of student achievement (*5*). By analyzing variation in quantitative observational data on inputs and outcomes (*6*), or through the execution of field experiments (*7*), effects-based research has increased our understanding of the relative importance of factors such as teacher-pupil ratio, family background, and teacher quality and has established effects (or lack thereof) of specific interventions designed to improve achievement.

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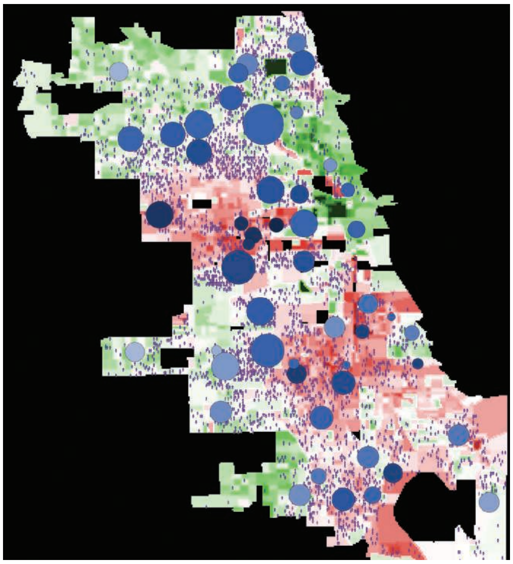

ABM of school choice in Chicago. Students, represented by small dots, are shown in their census block. Dark red indicates high-poverty locations; dark green, low. Each circle represents a school. Color reflects the expected academic performance of students attending the school, given the experimental conditions of the model. Light blue indicates high mean achievement; dark blue, low. Circle size is proportional to expected enrollment. For more information, see the text and (*32*).

What Works, How It Works

Despite of such successes, and as evidenced by the call for more "mixed-methods" designs (*8*), a key challenge facing education research is to integrate insights about "micro-level" processes with evidence about aggregate, "macro-level" outcomes that emerge from those processes. For example, suppose we have results of a well-executed experiment using a nationally representative sample of schools that indicates students in small classes perform better than those in large ones. Although it is tremendously helpful to know that, on average, students in small classes do better, this alone is not enough to fully understand what changes policy-makers and school leaders should implement.

One reason for this is the issue of heterogeneous treatment effects (*9*). If small class size mattered under certain conditions but not others, school leaders would need to understand what happened differently in some small classrooms that led to better student outcomes. Both mechanism- and effects-based research may be helpful here, examining differing contexts and how programs are implemented. But we still face the challenge of aligning micro-level accounts with aggregate data. This is all the more difficult when considering inherent impediments to understanding complex systems: Effects are disproportional to cause; cause and effect are separated in time and space; and properties of the macro-level system may be confused with properties of constituent, micro-level elements (e.g., attributing intelligence to individual ants when observing an entire ant colony intelligently gathering food) (*10*).

Additionally, we need to consider what are often referred to as "general equilibrium effects," i.e., the systemic implications of class-size reductions enacted at a large scale (*11*). For example, partly on the basis of results of a randomized field experiment in Tennessee, California mandated statewide class-size reductions. However, many school districts had to hire teachers with limited training and credentials because the supply of qualified teachers was too small to handle the sudden increase in demand (*12*). If identified a priori, we can try to account for such effects using econometric models estimated from observational data (*13*). Although such models can often help characterize particular equilibrium states of educational systems at a larger scale, we are still interested in an additional, policy-relevant step: how to best move the system from one equilibrium state to another. Regardless of how well we account for heterogeneous treatment and general equilibrium effects, complex systems methods can help bridge these aggregate outcomes to underlying mechanisms at work in the system, as well as discover new and unanticipated systemic consequences.

Bridging the Gap

Applying a complex systems perspective to education research parallels the recent use of complex systems methods to model the spread of epidemics (*14*). Traditionally, one relied on (i) detailed case studies that traced social con-

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tacts of a few infected individuals to identify the origin of an outbreak and elucidate infection mechanisms (*15*), or (ii) theoretical studies assuming large "perfectly mixed" populations where differences in infection mechanisms were simplified to aggregate measures of susceptibility and infectiousness (*16*). More recent work utilizing agent-based modeling (ABM), which allows modelers to "run" scenarios involving interconnected agents over discrete time steps to discover the emergence of macro-level properties, has helped link theoretical and case studies. Researchers now understand epidemics as macro-level outcomes that depend on relational, micro-level properties of the system, such as the structure of the contact network (*17*) and the reactions of agents to changing conditions (*18*). Such work has aided the development of antiviral drug distribution and quarantine strategies (*19*).

Although operationalizing rules governing individual behavior in educational systems may be more difficult than specifying micro-level rules of disease transmission, techniques for studying complex systems can complement more traditional approaches to education research in at least two ways. The first way is through visualization techniques, measures, and algorithms that facilitate network characterizations of social context. Although network characterizations are not new in social science (*20–22*), recent advances are particularly useful for education research. New tools for visualization of longitudinal network data enable researchers to connect fine-grained observations of classroom interactions, such as the content of student conversations, to emergent outcomes such as classroom discipline (*23*). Algorithms and measures developed to identify "communities" in networks (*24*) can identify boundaries of potentially influential social groups as they emerge from interactions driven by the local school context (as opposed to a priori categorizations of students into groups of "scholars," "athletes," etc.). Such techniques can be applied to widespread, existing data, enabling large cross-context analysis. For instance, one study used a network clustering algorithm to identify adolescent peer groups from class schedules and showed in a national sample of U.S. high schools that girls are more sensitive to social influence with respect to enrollment in mathematics courses (*25*).

The second way complex systems methods complement existing research is through the use of ABM, providing insights into how individual and group-level behaviors relate to systemwide phenomena (*10*, *26*). To illustrate the potential of ABM, consider school choice reform. Empirical research on programs that give households more choice is inconclusive, with methodological concerns arising for both observational and experimental studies (*28*). Computation has enabled work addressing the systemic effects, and related policy implications, of programs. For example, economists have used computational general equilibrium (CGE) simulations to identify features likely to minimize "cream-skimming" of top students by private schools in systems where government-issued vouchers are used to pay for private schooling (*29*).

ABM can extend such research by addressing questions pertaining to the paths between equilibrium points, such as whether a transition to choice might make a system worse before it gets better and for how long and for whom it is worse. Moreover, ABM enables investigation of a broader range of agent-level behaviors, including rules for students and schools that more directly correspond to behaviors observed from mechanism-based studies and agent-level data (*30*, *31*). We have used student- and school-level data from Chicago Public Schools to initialize an ABM that allows households to choose among all public schools in a district (see the figure). In one set of computational experiments, we allowed for schools with a greater "value-added" (ability to increase student test scores) to enter the district and varied the manner in which students ranked schools. When students valued a school's previous test scores much more than its geographic proximity, it became more difficult for new schools of higher, but initially unknown, value-added to survive. Consequently, a micro-level rule that one might surmise should aid district improvement (placing a relatively high value on school achievement) can also limit district-level performance in certain conditions (*32*). Future models could be used more directly to design school choice programs. For instance, by calibrating the model with more detailed information about the distribution of household decision-making rules, one could identify locations for new schools that would most increase district-level achievement.

By providing tools to characterize and quantify relationships between individuals and to investigate how individual actions aggregate into macro-level outcomes, a complex systems approach can help integrate insights from different types of research and better inform educational policy. Education research must establish not only what works but also how and why it works.

References and Notes

1. J. H. Holland, *Hidden Order: How Adaptation Builds Complexity* (Perseus Books, Cambridge, MA, 1995).
2. On using complex systems principles to transfer knowledge between scientific domains, see (*33*); on the cognitive difficulties of understanding complex systems, see (*34*); and on understanding scientific phenomena by constructing agent-based models, see (*10*, *35*).
3. C. E. Coburn, *Am. Educ. Res. J.* **43**, 343 (2006).
4. D. K. Cohen, *Educ. Eval. Policy Anal.* **12**, 311 (1990).
5. E. P. Lazear, *Q. J. Econ.* **116**, 777 (2001).
6. G. Hong, S. W. Raudenbush, *Educ. Eval. Policy Anal.* **27**, 205 (2005).
7. G. D. Borman, N. M. Dowling, C. Schneck, *Educ. Eval. Policy Anal.* **30**, 389 (2008).
8. R. B. Johnson, A. J. Onwuegbuzie, *Educ. Res.* **33**, 14 (2004).
9. J. J. Heckman, *J. Polit. Econ.* **109**, 673 (2001).
10. U. Wilensky, M. Resnick, *J. Sci. Educ. Technol.* **8**, 3 (1999).
11. In economics, "general equilibrium effects" refers to the rippling changes that occur as a result of a change in a focal market after supply and demand reequilibrate in related markets. Most effects-based research is done under the alternate assumption of "partial equilibrium," which does not account for such feedback. See (*13*).
12. L. Mishel, R. Rothstein, Eds., *The Class Size Debate* (Economic Policy Institute, Washington, DC, 2002).
13. J. J. Heckman *et al.*, *Am. Econ. Rev.* **88**, 293 (1998).
14. J. M. Epstein, *Nature* **460**, 687 (2009).
15. C. H. Hennekens, J. E. Buring, *Epidemiology in Medicine* (Little, Brown, Boston, 1987).
16. R. M. Anderson, R. M. May, *Infectious Diseases of Humans: Dynamics and Control* (Oxford Science Publ., Oxford, 1992).
17. D. E. Woodhouse, *et al.*, *NIDA Res. Monogr.* **151**, 131 (1995).
18. C. Chen, C. Yang, S. Jin, *Agent-Based Modeling and Simulation on Emergency Evacuation* (Springer, Berlin, 2009).
19. V. Colizza, A. Barrat, M. Barthelemy, A.-J. Valleron, A. Vespignani, *PLoS Med.* **4**, e13 (2007).
20. A common line of analysis involves using measures of an individual's location within a social network to test hypotheses about the role of social structure in determining his or her performance. For example, one can test whether the association between peer influence and student achievement is moderated by the extent to which a student's friends are also friends with each other. See (*21*), and for a review outside of education, see (*22*).
21. S. Maroulis, L. M. Gomez, *Teach. Coll. Rec.* **110**, 1901 (2008).
22. R. S. Burt, *Res. Organ. Behav.* **22**, 345 (2000).
23. J. Moody *et al.*, *Am. J. Sociol.* **110**, 1206 (2005).
24. R. Guimerà, L. A. Nunes Amaral, *Nature* **433**, 895 (2005).
25. K. A. Frank, *et al.*., *Am. J. Sociol.* **113**, 1645 (2008).
26. J. Miller, S. E. Page, *Complex Adaptive Systems: An Introduction to Computational Models of Social Life* (Princeton Univ. Press, Princeton, NJ, 2007).
27. U. Wilensky, NetLogo (CCL, Northwestern University, Evanston, IL, 1999); http://ccl.northwestern.edu/netlogo/.
28. D. Goldhaber, E. Eide, *Educ. Eval. Policy Anal.* **25**, 217 (2003).
29. D. Epple, R. Romano, *Int. Econ. Rev.* **49**, 1395 (2008).
30. Agents in CGE models are assumed to be constrained optimizers, with decision-making taking place within a single time period. Typically, households pick schools and levels of tuition spending that maximize utility. Schools choose levels of inputs for an "education production function," such as per pupil spending, that maximizes profits. The characteristics of the resulting equilibrium are compared across different parameterizations of the model. For a review, see (*31*).
31. T. J. Nechyba, *Natl. Tax J.* **56**, 387 (2003).

32. We thank the Chicago Public Schools and the Consortium on Chicago School Research for their assistance. The model was developed in the NetLogo ABM platform (*27*). A working paper, including full details on the model, can be downloaded at http://ccl.northwestern.edu/papers/choice.pdf.

33. R. Goldstone, U. Wilensky, *J. Learn. Sci.* **17**, 465 (2008).
34. M. Resnick, *J. Learn. Sci.* **5**, 1 (1996).
35. U. Wilensky, K. Reisman, *Cognit. Instruc.* **24**, 171 (2006).

36. The authors acknowledge the support of the NSF and the Searle Foundation.

10.1126/science.1195153