PERSPECTIVE

The golden age of social science

Anastasia Buyalskaya[a,1], Marcos Gallo[a], and Colin F. Camerer[a,b]

Edited by Matthew O. Jackson, Stanford University, Stanford, CA, and approved November 23, 2020 (received for review May 14, 2020)

Social science is entering a golden age, marked by the confluence of explosive growth in new data and analytic methods, interdisciplinary approaches, and a recognition that these ingredients are necessary to solve the more challenging problems facing our world. We discuss how developing a "lingua franca" can encourage more interdisciplinary research, providing two case studies (social networks and behavioral economics) to illustrate this theme. Several exemplar studies from the past 12 y are also provided. We conclude by addressing the challenges that accompany these positive trends, such as career incentives and the search for unifying frameworks, and associated best practices that can be employed in response.

interdisciplinarity | diverse teams | new data | difficult challenges

Social science is entering a golden age (1). A rise in interdisciplinary teams working together to address pressing social challenges, leveraging the explosive growth of available data and computational power, defines this moment. Each of these trends has been written about individually—the "big data revolution" has been transforming social science for several years (1), and the benefits of diverse teams are increasingly recognized and quantified (2, 3). We argue that it is the confluence of data, diverse teams, and difficult challenges which makes this a unique and exciting time for social scientists to tackle important research questions. Of course, there have been large team efforts in previous decades (4), but their frequency and breadth have increased recently.

Funding agencies have, in turn, recognized the need to support interdisciplinary teams. Fig. 1 presents evidence from multiinvestigator grants funded by the NSF of how interdisciplinary research is on the rise in social science. Given the difficulty in defining interdisciplinary work, federal agencies have chosen to use the number of grants provided to projects with multiple principal investigators as a proxy (5, 6). These data resonate with our idea of what interdisciplinarity means in this golden age: active collaboration among scientists with different training—meaning a diversity of perspectives is influencing the research—as opposed to one researcher passively borrowing ideas from other fields.

We hope our perspective will encourage scientists to take advantage of new datasets and form diverse collaborations to answer pressing questions. We direct these ideas especially to funding agencies and academic institutions, to convince them to provide more funding for this type of work. Ultimately, we wish to see an acceleration in work that addresses difficult challenges. For instance, the COVID-19 pandemic illustrates how large-scale problems will only be solved by many scientists contributing what they know best.

The Need for a Lingua Franca

The opening of disciplinary borders is akin to an increasing trade of methods, language, and knowledge across fields. This concept of trade is built on the premise that, like people and countries, each social science discipline has a different endowment (i.e., a historical mastery of tools and accumulated knowledge) and comparative advantage. Defining how the social science disciplines differ is difficult, but even a thumbnail sketch can clarify our ideas about comparative advantages and the value of trade. Hoping that the reader will appreciate that we overemphasize differences in fields (and ignore variation within them), we define them as follows. Anthropology seeks to understand cultural differences in human societies using ethnography, unearthing physical details of human development and exploring mathematical

[a]Division of Humanities and Social Science, California Institute of Technology, Pasadena, CA 91125; and [b]Computational and Neural Systems, California Institute of Technology, Pasadena, CA 91125

Author contributions: A.B. and C.F.C. designed research; A.B., M.G., and C.F.C. performed research; M.G. analyzed data; and A.B., M.G., and C.F.C. wrote the paper.

The authors declare no competing interest.

This article is a PNAS Direct Submission.

[1]To whom correspondence may be addressed. Email: abuyalsk@caltech.edu.

Published January 22, 2021.

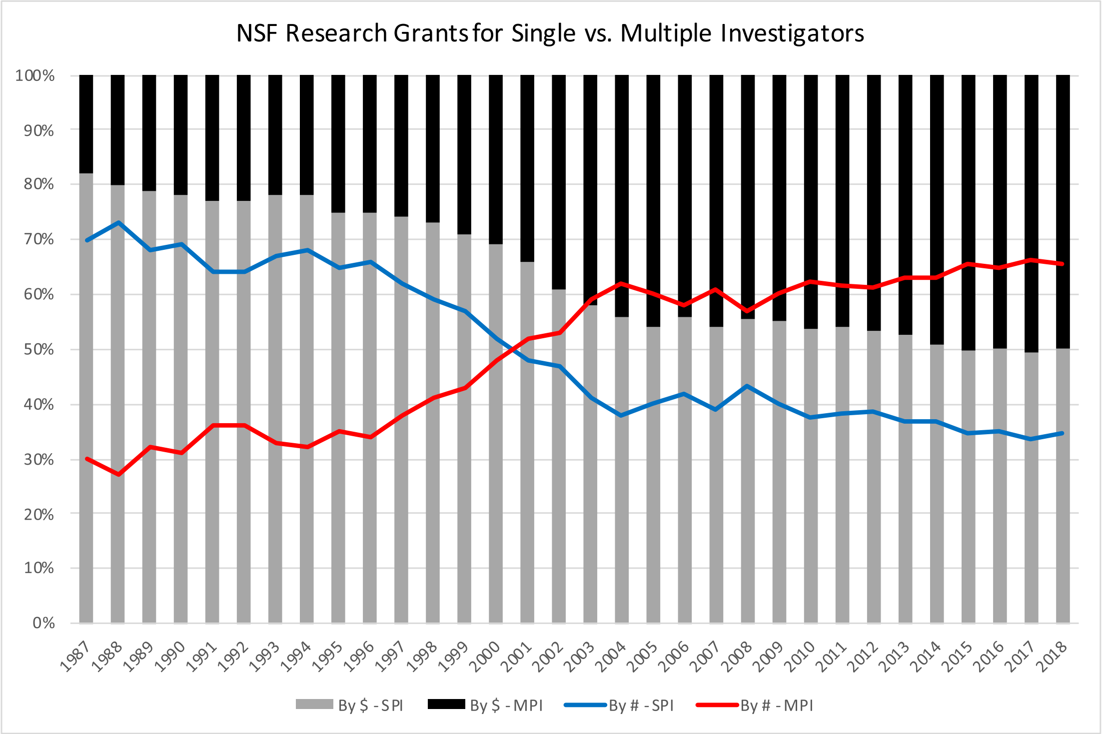

Fig. 1. Single (SPI) vs. multiple (MPI) investigator awards at the NSF, 1987 to 2018. Notice the trend toward awards with more than one PI, which the NSF considers to be the best current proxy for interdisciplinarity (6) (data source: refs. 5 and 7).

models of coevolution of culture and genes. Economics uses math-heavy methods to understand systemic (general equilibrium) outcomes of optimization of allocation of scarce resources, particularly money, in trading goods and services. Its main methods include theories rooted in preferences, beliefs, and constraints and analyses of field data. Political science studies formal systems of government, voting, juries, and law, which influence how people make consequential decisions collectively in different systems. Ideology is a central construct, with polls and surveys being a cornerstone method, although media and financial contributions data are increasingly used. Psychology seeks regularity in how people think and behave, with an emphasis on mechanisms and constructs such as memory, attention, and emotion. The main methods are laboratory experiments and psychometric or psychophysiological measures (though cognitive neuroscience uses a greater variety of newer methods). Finally, sociology investigates how the social world is created by and influences how people act in social groups at different levels of formal and informal aggregation. General ideas about functions of social structure are central but are not mathematized as in economics (e.g., economists might focus on allocative efficiency defined mathematically while sociologists might focus on social reproduction of elite success measured statistically or qualitatively).

Readers may view these highly reduced descriptions of their own fields as overly simplified, while perhaps believing that the descriptions of the other fields are not too bad. That perception itself illustrates why communication is a challenge for interdisciplinary work. Complicating trade is the fact that many words like "rationality," "trust," "discrimination," "hierarchy," "salience," and "power" are used across the social sciences, but in different ways. Their local meanings are understood by "native speakers" but often baffling to "traders" arriving from foreign scientific lands. Interdisciplinarity needs a common trade language across disciplines, a "lingua franca." In a useful lingua franca, all disciplines adopt the "best" language from whichever discipline has described an idea most effectively. In order for teams of researchers to effectively tackle the complex research questions of our time, they will need to work together to build a common vocabulary that enhances the efficiency of their trade and collaboration.

Examples of lingua franca which originated in individual disciplines include an understanding of culture from anthropology, rational choice theory from economics, ideology from political science, laboratory experimental methods from psychology, and social networks from sociology. Besides these central constructs, powerful tools for quasi-experimental causal inference—which originated in psychology (8), created a boom through more sophisticated use of instrumental variables in economics starting in the 1990s (9), a little later in political science (10), and somewhat in parallel in computer science and statistics around 1995 (11)—have evolved as a methodological lingua franca across the social sciences.

A useful lingua franca, one which is to be a truly unifying framework, will need to cut through the technical jargon specific to any one field of origin in order to be widely accepted and used. Taking the time to build such a lingua franca will enable diverse teams to tackle multidimensional problems and create innovations for better health, wealth, and well-being (12). Drug addiction, obesity, sustainability and climate change, technology-driven changes in sociopolitical discourse, "fake news," and how artificial intelligence will change our world will never be fully understood by any one discipline working alone. Instead, making progress on these challenges will require understanding the institutional incentives, cultural norms, cognitive mechanisms, and social network effects that create and sustain these phenomena.

Interdisciplinary work has already helped make progress in fields including poverty, health epidemics, and mental health.

Learning from Case Studies

In the next section, we present two "case studies" of successful interdisciplinarity: social network science and behavioral economics. In both cases, interdisciplinary research led to the creation of new cross-disciplinary fields of inquiry built on the comparative advantages of contributing fields, inspiring a shared lingua franca, generating insights about human nature, and improving social outcomes. These cases originated decades ago, so they are not meant to illustrate the three features that we take to characterize the golden age. While the original research was not particularly propelled forward by large, diverse datasets or by a desire to tackle global challenges, recent research has moved in those directions (Figs. 2 *C* and *D* and 3*C*).

Social Networks

Social networks are our first case study of a successful interdisciplinary enterprise. Network analysis uses methods from physics, computer science, and applied math to analyze questions often studied by sociologists, anthropologists, and psychologists regarding how interpersonal relationships are formed and how behaviors, beliefs, and emotions are transmitted across connected individuals (13). One striking feature of network analysis is the diversity of scholars who have been active in researching this field from the beginning, and who continue to contribute to intellectual progress (see Fig. 2 for some examples). People from different fields, traditions, and countries have worked together on related research questions (14). Network analysis has been significantly enabled by the availability of novel datasets, such as social media connections, and data from increasingly "connected" devices such as fitness trackers with social aspects (15).

Notable contributors to the field of network analysis are Watts and Strogatz (16), who brought to light several key network properties, including that real-world networks are neither totally ordered (there are not always clear rankings between nodes) nor completely random (with all nodes having unequal probabilities of being connected with other nodes). Their work was important in getting the statistical physics community to recognize that their techniques could be applied to social settings, thus catalyzing an interdisciplinary turning point. It is worth noting that subsequent research, which flourished primarily in sociology, economics, and applied mathematics, did not necessarily follow directly from this original paper.

One attractive feature of network science is that simple mathematical models capture the core features of complex networks, allowing the study of network dynamics across a variety of phenomena. The seemingly unrelated affiliations between actors, power grid transmission lines, and the neural network of *Caenorhabditis elegans* can all be captured via a simple "small-world" network model, a mathematical graph in which the nodes (individuals) are not neighbors with most of the other nodes and yet all other nodes can be reached in a small number of steps (17–19).

Example 1: Revisiting Influence and Information Transmission. Collective behaviors are often studied at a static point in time, implicitly assuming that all individuals simultaneously make independent decisions. However, the heterogeneous process of information accumulation and integration prior to decision-making suggests that many decisions are actually made sequentially and that beliefs can be "transmitted" from one individual to the next. Given how many behaviors—from smoking to divorce to employment—are in fact "contagious" across individual groups, the dynamics of such contagion are of immense interest to social scientists. The field of cultural evolution has been modeling information transmission for several decades, using both epidemiological and social network models in their approach (24).

Broadly, social contagion models allow simulating the speed at which individuals receive information and how past interactions influence their future behavior (13). These models focus on a handful of key parameters, which can be grouped as 1) degree centrality, 2) eigenvector centrality, 3) diffusion centrality, and 4) betweenness centrality/bridging (18). While one might not wish to be central in an HIV infection network, centrality is viewed as an advantage in most social networks and is correlated with financial success (25) and well-being (26). Degree centrality captures "popularity," the sheer number of connections an individual might have, and the speed at which these individuals can easily transmit information to a wide group at once. Eigenvector centrality, which captures how many well-connected others one is connected to, has been used to study social status and scapegoats (27). Diffusion centrality is a measure of "reach," showing how well-positioned an individual is to spread and hear about information. Finally, betweenness centrality, or bridging, captures "social chameleons" who connect otherwise disparate groups. Interestingly, all of these positions appear to be context general: If an individual is central in one network, they are likely to be central in another, and so forth (18).

Each of these four "centralities" has different disciplinary origins: the idea of degree centrality began with sociologist and philosopher Georg Simmel (28); eigenvector centrality is a concept from graph theory, first used by mathematician Edmund Landau in an 1895 paper on chess tournaments (29); diffusion centrality became popular in recent literature by economists interested in the speed of information transmission (30); and betweenness centrality, or bridging, comes from sociology literature analyzing the creation and upkeep of social capital (31). In other words, the development of these social contagion models was itself an interdisciplinary enterprise from the beginning.

Since its creation, network analysis has allowed researchers to apply new tools while revisiting old questions about social influence. For example, researchers have investigated the types of individuals in a network to whom people gravitate, and hence may be more influential at spreading information of various types (26). Computational modeling methods have been used to show quicker consolidation of majority opinion and more successful spread of initially unpopular beliefs in populations characterized by greater susceptibility to social influence (32).

Other work using standard economic games has found that people give less money to those who are more socially distant (33). This has important implications when combined with the role that homophily plays in social networks, with many schools being heavily segregated by race, for example (34). Given the race-based economic disparity in many countries, this analysis has taught us that increasing the transfer and exchange of capital between people of different backgrounds must accompany efforts to interlink their social networks better.

Example 2: The Spread of Infectious Disease. Sociologists have been integral to guiding the development of network models, given how ubiquitously they help explain the spread of anything from disease to innovation (35). For example, most infectious diseases spread through human contact, making the study of

https://doi.org/10.1073/pnas.2002923118

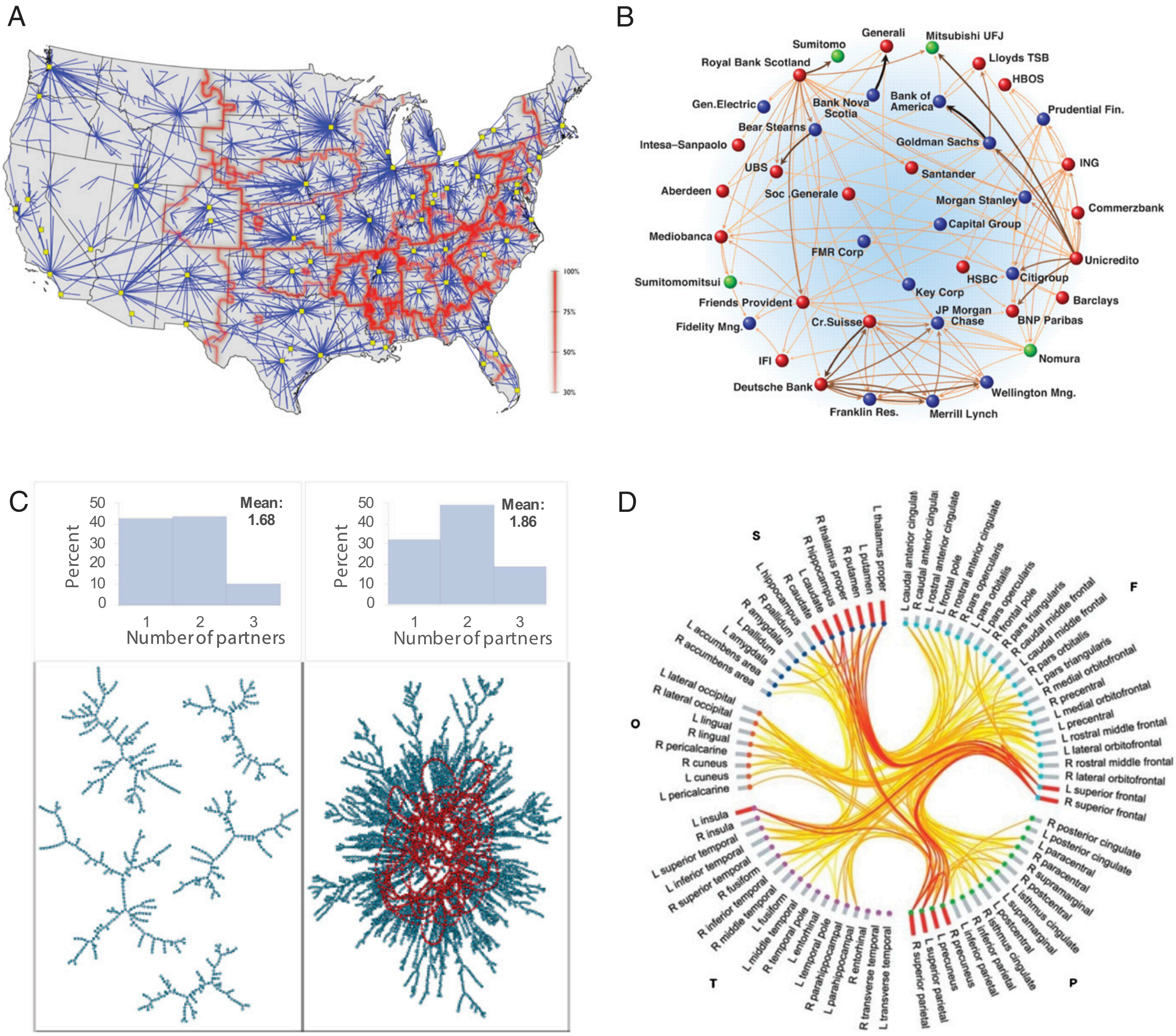

Fig. 2. (*A*) A network of human traffic reveals cities that are important nodes (in yellow) and effective borders (in red). Reprinted from ref. 20, which is licensed under CC BY 4.0. (*B*) A network of international financial institutions. Edges symbolize mutual shareholdings. From ref. 21. Reprinted with permission from AAAS. Note the high connectivity among nodes that can create systemic risk and network vulnerability. (*C*) Effects of the distribution of sexual partner concurrency on network connectivity. Adapted with permission of McGraw Hill LLC from ref. 22; permission conveyed through Copyright Clearance Center, Inc. Note how a slight increase in average concurrent partners (from the top left to right histograms) dramatically impacts the number of nodes in the largest component of the network. (*D*) A network of brain regions where edges represent developmental increases in streamline density. Reprinted from ref. 23, which is licensed under CC BY 4.0.

infection a natural place to apply network analysis. One of the first and longest-used models of disease spread, known as the SIR model, was introduced by Kermack and McKendrink in 1927 (36). This simple model assumes three "types" of people in the population of interest: susceptibles ("S"), infected ("I"), and recovered ("R"). The model has a number of necessarily simplifying assumptions, including that people can only be infected once before they move into the "R" group and are thereafter considered forever immune to the disease, and that only two people can come into contact at one point in time.

More recently, Kretzschmar and Morris, following discussions with people who described how disease was "actually spreading" during a trip to Uganda, worked to create better ways to model the spread of HIV. Specifically, their new model handled multiple connections (multiple sexual partners) at once—something which is still closer to the norm than the exception in several societies (37). The model confirmed that small variations in concurrency (simultaneous sexual partners) can have dramatic effects on a population's vulnerability to HIV (38). Morris's team continues to collaborate across disciplines (with sociologists and statisticians, she is a professor of both), as well as across geographies (with several collaborators in Africa), to improve models of the spread of infection and apply them to new and better datasets.

Epidemiological models are at the scientific center of the current COVID-19 pandemic, and many versions have been proposed. One interdisciplinary group developed a "risk source" model that uses population flow from a disease epicenter to predict infections in other locations, controlling for gross domestic

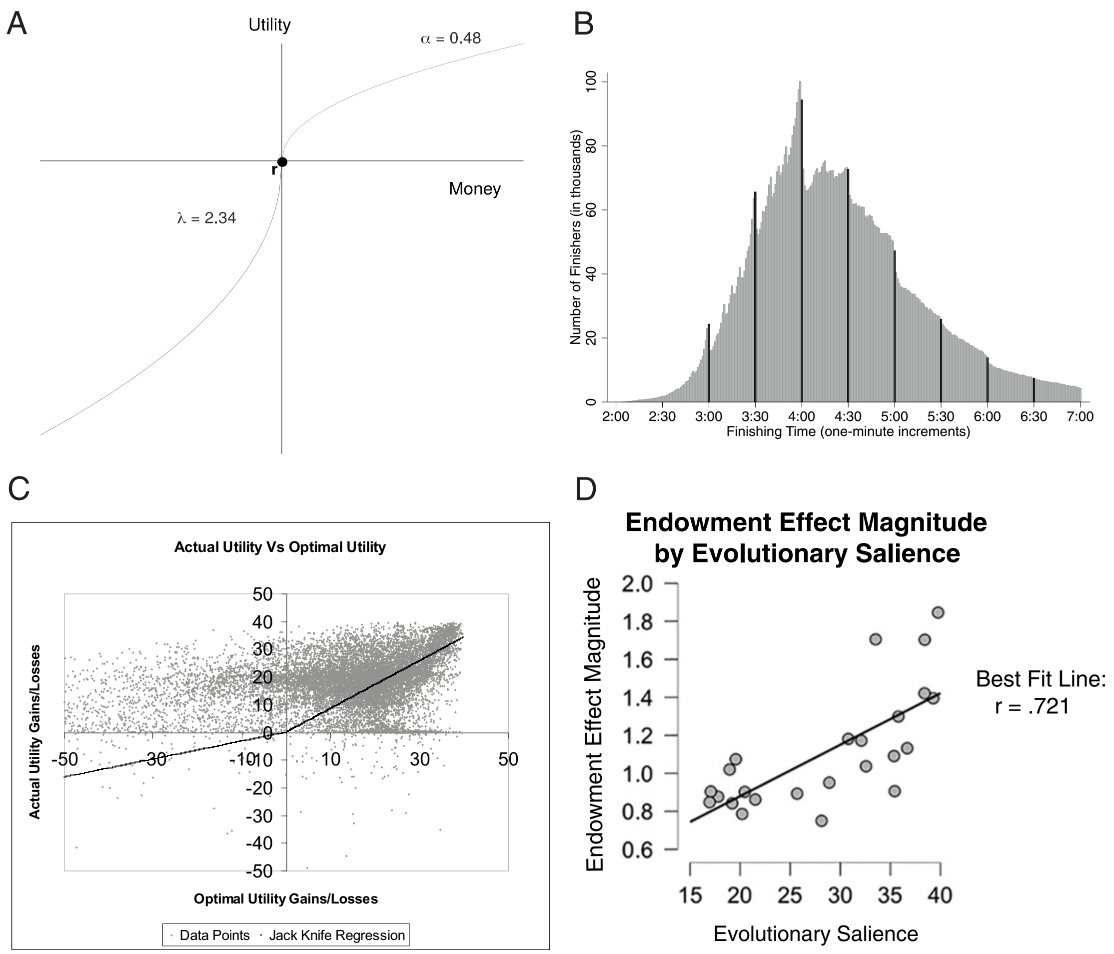

Fig. 3. Loss aversion. (*A*) The gain–loss utility function over money derived from group parameters estimated from risky choices. Reprinted with permission of The Institute for Operations Research and the Management Sciences from ref. 66; permission conveyed through Copyright Clearance Center, Inc. (*B*) The distribution of marathon race finishing times. Reprinted with permission of The Institute for Operations Research and the Management Sciences from ref. 67; permission conveyed through Copyright Clearance Center, Inc. Note the peaks at round numbers. (*C*) Actual point values in each period, plotted against optimal conditional point values from consumption choices, in a 50-period savings experiment [previously unpublished using data from Brown et al. (68)]. Note how few actual point values (*y* axis) are negative even when optimal point values (*x* axis) should be negative. (*D*) Human endowment effects (selling–buying price ratios) are correlated (*r* = 0.72) with evolutionary salience of 24 items (only 2 used in previous studies). This finding reflects trade between behavioral economics, evolutionary psychology, and cultural anthropology. Reprinted from ref. 69, with permission from Elsevier.

product and population size. Using Chinese cell phone geolocation data, they found that, over time, the spreading pattern of severe acute respiratory syndrome coronavirus 2 can be associated with the pattern of population outflow from Wuhan. The model led a daily risk score to identify high-transmission areas at a very early stage (39). More recently, another interdisciplinary team compared three epidemic models in fitting time-series government data. They found that an SIR model best fits the data going into the peak of the disease and that all three models show the importance of social distancing in mitigating the negative effects of the pandemic (40).

Summary. Network science would have been less successful without scientists from different disciplines borrowing ideas and communicating in a shared language about constructs and methods. Innovation in network science has benefited from the wide network of researchers who share a lingua franca, transmit high-fidelity information, and bring diverse perspectives to the table.

Networks and their properties are fundamentally interesting because they underpin such a wide range of phenomena. Unlike behavioral economics, there was less conflict among those studying networks because the concept of a network was so obviously appealing and useful from the start (i.e., there was no interdisciplinary conflict about whether people "were networked" as occurred about whether people "were rational"). Furthermore, while sociologists studied networks first (14), the difficult question of what networks arise when people have scarce social bandwidth and can choose network links was cracked by economists (41). Moreover, the increasing availability of large, novel datasets that capture connections between individuals, such as social media and online communication data, has truly turbo-charged network science.

Behavioral Economics

Economics has arguably shown the most dramatic shift toward a golden age in terms of citation patterns (42). It has been increasingly citing other social sciences ("importing") and is also being cited more ("exporting" citations) by other social science fields, particularly political science and sociology from 1970 to

https://doi.org/10.1073/pnas.2002923118

1990 and psychology starting in 2000. One notable case study comes from behavioral economics, which uses evidence and methods from other social sciences—psychology in particular—to analyze natural limits on human computation, willpower, and selfishness (43). These analyses make new predictions about field data, leading to novel suggestions about how markets work and what policies might be effective. Analyzing such limits is of interest because conventional rational choice theory assumes maximization of subjective values ("utilities") and Bayesian integration of information, often over a long time horizon and accounting correctly for risks.

However, research over the past few decades has shown that, in reality, people often do not act that rationally. Granted, rational choice theory was always intended to be useful rather than realistic. Behavioral economists aimed to have theories that are more realistic and more useful. At first, there was substantial hostility toward the behavioral approach, largely because it was not clear how models using only preferences, beliefs, and constraints could incorporate psychology (44, 45). Thaler and others (46) used an "insider" approach (47). They took rational choice theory as a simple benchmark, identified important empirical "anomalies" that could not be sensibly explained by that benchmark and added extra ingredients sparingly to explain the anomalies and make new predictions. The first step was to begin with highly controlled laboratory experimental evidence to convince skeptics and establish plausible alternative theories. The researchers then explained and predicted field data. Alternative theories with a small number of added parameters were developed so that rational and behavioral predictions could be compared (48).

Example 1: Loss Aversion. Conventional economic analysis typically relies on expected utility theory, a model which assumes that people choose risks by weighing subjective utility of prospective outcomes of each risk by their probabilities and choosing the risk with the greatest expected utility. In their influential "prospect theory," Kahneman and Tversky proposed a more psychologically plausible alternative: that outcomes are subjectively valued by their gains and losses relative to a reference point (49). In addition to reference dependence, prospect theory incorporated the idea that potential losses may be weighted disproportionately more than gains. This "loss aversion" is measured by a parameter, λ, the ratio of gain utilities to loss utilities (or to marginal utilities), which is around 1.9. Loss aversion has been used to explain different phenomena, including 1) taking financial risks in laboratory experiments (50), 2) why stocks historically return so much more than bonds (51), and 3) why there is a gap between high prices demanded to sell goods and lower prices paid to buy the same goods, an "endowment effect" (52). Psychologists also found effects of emotions (53), cognitive sequencing (54), and attention (55) on endowment effects.

Cognitive neuroscientists have found evidence for loss aversion in neural circuitry (56), including dissociations between circuitry valuing gains and losses (57) and an unusual tolerance of losses in patients with amygdala damage (58). Political economists have used loss aversion to understand bargaining concessions (59), elections (60), and trade policy (61). Fig. 3 illustrates estimates of loss aversion using large datasets (marathon running times) and interdisciplinary perspective (the cultural anthropology concept of evolutionary salience correlating with the strength of loss aversion).

While behavioral economists have not been keenly interested in the evolutionary and cultural origins of phenomena like loss aversion (62), there is evidence that loss-aversion and endowment effects are present in monkeys (63) and great apes (64)—though only for food and not for other valued goods (e.g., tools). Others found an unusual lack of endowment effects among market-isolated Hadza villagers in Tanzania (an example of behavioral economics trading with anthropology) (65). These data indicate that loss aversion or its behavioral implications are not universal and show why a wider scope of data are needed.

Loss aversion contributes to a "status quo bias," an exaggerated tendency to choose a suggested default or stick with a status quo (70). This insight has impacted public policy. Countries in which organ donation is the default and people must "opt out" have higher donation rates than those with opt-in donation (71). The first impactful application of default bias is the "Save More Tomorrow" (SMART) plan (72). In this plan, companies autoenroll workers into tax-advantaged 401(k) plans (unless they opt out) and invest a fraction of their next pay raise into the plan (so their paycheck does not go down and create a subjective loss). These plans have increased savings substantially (73). The SMART plan became a poster child for many types of "nudges," designed choices that help some people make better decisions at a low cost to others who are fine on their own (74, 75).

Example 2: Social Preferences. Humans are the most prosocial species of all, often helping genetically unrelated individuals at a cost to ourselves. Psychological theories of comparisons between self and others, beginning in the 1960s (76), planted the seed for studying social preferences in other disciplines. Behavioral economics later contributed new mathematical functions and data.

Game theory is a lingua franca for this understanding by offering canonical strategic interactions that can be used to dissect elements of prosociality (76). For example, in the "ultimatum game" a proposer offers a share of a known amount of resources, such as $10, to a responder (77). If the responder accepts the offer, they collect their money, and the proposer keeps the rest, but if the responder rejects the offer, everyone gets nothing. Rejecting an offer shows negative reciprocity—a willingness to sacrifice resources to harm an unfair person. Negative reciprocity can also be collective: In one study, police effectively solved fewer criminal cases after losing a wage arbitration (78).

As the ultimatum game caught on across social sciences, other games quickly followed, highlighting different psychological motives (1, 79, 80): 1) dictator allocations, in which the responder must accept the offer (measuring altruism and norm sensitivity but not reciprocity); 2) trust games, in which a first mover invests money that is multiplied, taking a social risk to potentially benefit both parties, gambling that the second mover will share the total gain (81, 82); and 3) many-person gift-exchange labor markets in which firms prepay wages and hope that workers exert effort which is costly to workers but benefits the firms (83).

These economic games are now widely used across social sciences. An interdisciplinary team, mostly anthropologists, used economic games to study cross-cultural sociality in small-scale societies (84). They learned that stronger sharing norms (which were punished by ultimatum rejections) were associated with societal cooperation, such as building houses together, and with the extent of market trading.

As interest in these games grew, the sociological lingua franca of a "norm" got imported widely. Norms are informal social rules that are expected to be followed and usually informally self-enforced by social punishment for deviations (even absent legal enforcement). In dictator allocation games, for example, people

Table 1. Highlighted papers

Summary	Primary subfield(s)*	Data
Inequality is associated with the intergenerational transmission of wealth across small-scale societies (98).	Anthropology, economics	Multigenerational measures of three types of wealth
Greater exposure to war increases religiosity (99).	Anthropology, biology, economics	Surveys in postconflict societies
Rwandans use the mobile phone network to transfer "mobile money" to those affected by unexpected economic shocks (100).	Economics	Mobile phone usage
Brain responses to emotionally evocative images predict political ideology (101).	Political science, neuroscience, psychiatry	Functional MRI
Genetic data can predict economic and political preferences (102).	Political science, economics, psychology, sociology	Genetic data (genome-wide association study)
Musical preferences and personality traits are linked (103).	Psychology, marketing	Facebook likes
Bystanders will help in public conflict (104).	Psychology, sociology	Closed-circuit television footage
Social networks strongly influence exercise habits (15).	Sociology	Fitness tracking and social networks
Predicting scientific paper impact from conventionality and novelty of citations (105).	Sociology, economics, operations, physics	New bibliometrics: Web of Science citation, impact data

*Authors' departmental affiliations are used for disciplinary identification.

have different subjective norms about what is fair to share. Their sharing is closely tied to what they think the norm is (85), reflecting "good manners" rather than altruism (86).

Cognitive neuroscientists have also used these games to identify circuitry implementing prosociality (87) and associating brain lesions with abnormal social preference (88). Knowing more about social preferences has not contributed immediately to solving social problems at the scale that "nudging" has. However, experiments have suggested social forces that could enhance prosociality. For example, allowing people to punish others who have behaved antisocially seems to increase cooperation (89), although the results vary cross-culturally (90). New evidence has also invigorated understanding of charitable giving (91). In the future, diagnostic tools will likely emerge from a better understanding of sociality, with applications ranging from psychiatry, methods to develop empathy, and perhaps analytics matching people to jobs.

Summary. Before the growth of behavioral economics, it was commonly said that moving away from rational optimization would lead to an unfalsifiable theory in which "anything can happen." However, psychology showed that what happens is captured by psychological principles; something specific—not "anything"—happens. Loss aversion originated from perceptual psychology and early prosociality theories came from social psychology. Experimental economics added more general mathematical and game-theoretic structure. In general, behavioral economists won over skeptics through the mantra that "the easiest way to win an argument is to run another experiment or another statistical regression" (43). In many areas of behavioral economics and finance, large datasets played an important role, including more recently, multisite laboratory and field experiments (90, 92). A treasure trove of experimental data came about as nudges and other ideas were implemented by "behavioral insight teams" in governments on every continent, currently just over 200 (93), to create better outcomes for citizens and consumers.

More could be done integrating behavioral economic methods with biological and cultural origins of preferences, norms, and cognitive limits (94) and extending beyond Western, educated, industrialized, rich, and democratic (WEIRD) societies (84), which do not represent all human activity.

A Spotlight on Specific Studies

This section shines a spotlight on research from the past 12 y that epitomizes the golden age of social science. We begin with one study of drug trafficking. Table 1 then presents nine other studies which are also good examples.* Each of these papers combines features of 1) active collaboration between researchers from different disciplines, 2) using new types of data, and 3) answering important and difficult questions. The Table 1 papers are about topics from exercise habits to social inequality and use diverse new datasets from genetics, brain imaging, browsing history, and more.

Magliocca et al. (95) analyzed international drug trafficking in Central America (Fig. 4). The researchers tested an agent-based model against a database of estimated illicit drug flows from 2000 to 2014. The model successfully captures many of the underlying trends across time and countries in trafficking flow and interdiction. It reproduces two effects known as the "balloon" effect (when trafficking spreads into new areas) and the "cockroach" effect (when trafficking routes become fragmented after big drug busts) (95).

This study illustrates practice and promise in the golden age. Their team was nine coauthors from seven universities, one government organization, and a coauthor who remained anonymous to protect confidential sources. Their affiliations span geography, politics, biology, and earth sciences. This interdisciplinarity was essential to a model that did not leave out anything crucial, by using ideas from geography of crime (which focus only on where illegal drugs are made and used) and transaction costs, since logistics and risks of shipping are crucial, and vertical integration of the value chain. Their analysis includes strength of political governance (e.g., police corruption), economic inequality that drives the poor to produce narcotics, and geographic remoteness. Their approach imports new ideas from behavioral economics about learning (96) and salience (97) of trafficking events, predicting spatial and temporal patterns of cocaine flow tested with an impressive, classified dataset. The model can be used to analyze how different policies will hypothetically change trafficking, prices, and drug use, a challenging problem of global importance.

*We first heard this phrase used by Adam Gurri (https://theumlaut.com/the-golden-age-of-social-science-has-begun-d7555098ac72).

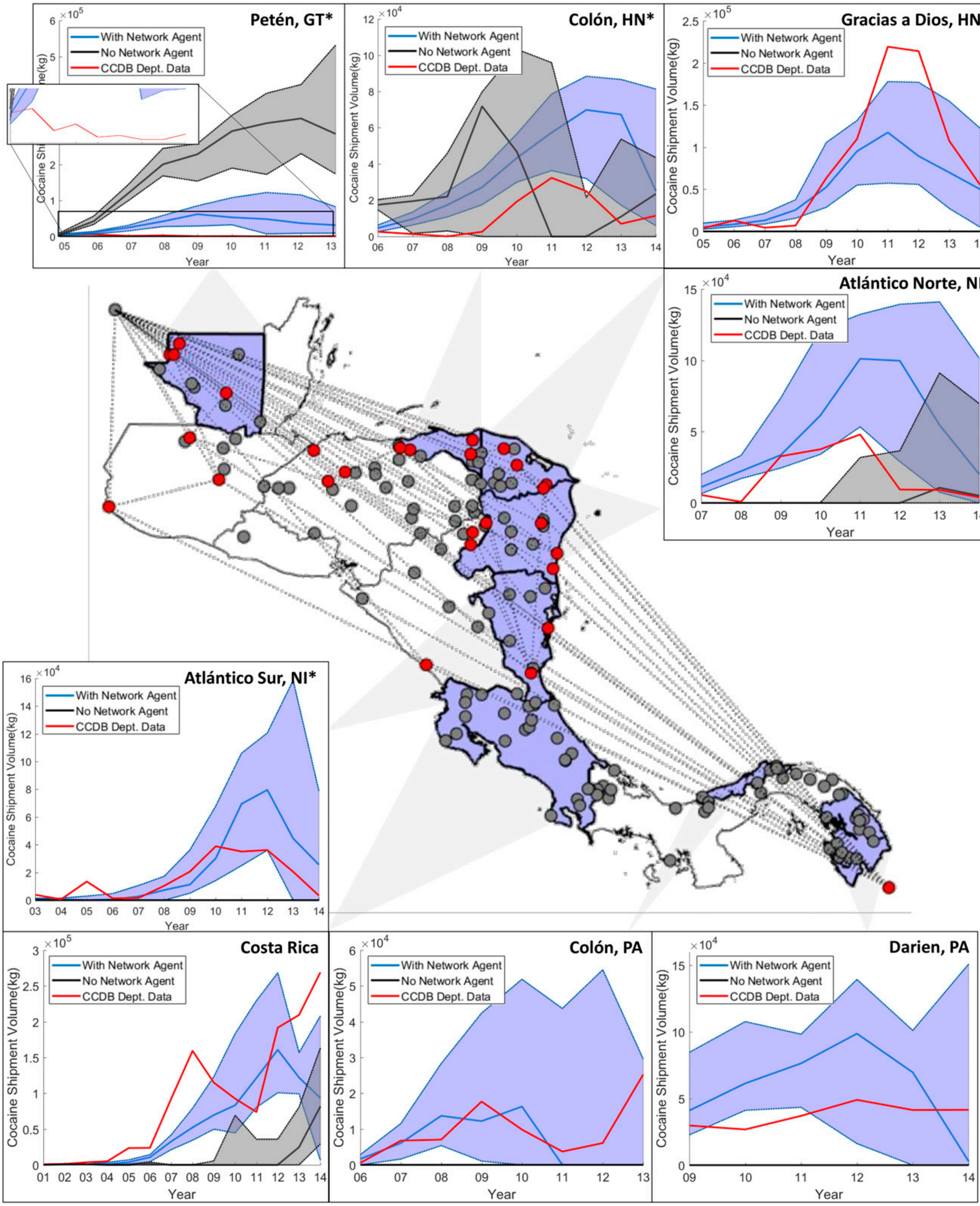

Fig. 4. Central America modeling domain (*Center*) with an example simulated narcotrafficking network consisting of inactive nodes (gray circles), active nodes (red circles), and trafficking routes between each active node (dashed lines). The most southern and northern nodes outside of the model domain represent supply (e.g., Colombia) and demanding nodes (e.g., Mexico), respectively. Around the periphery, comparisons of subnational cocaine shipment volumes (blue regions in the map) reported at the administrative level of departments in the Consolidated Counterdrug Database (CCDB) (red line) and median volumes simulated by model versions with (blue line) and without (black line) a network agent. Shaded regions represent the bounds of the second and third quartiles of simulated cocaine volumes. Departments were selected to include at least one location per country and on the basis of having at least 5 y of continuous observations reported in CCDB. Reprinted from ref. 95, which is licensed under CC BY-NC-ND 4.0.

Table 1 presents nine other studies we believe to be similarly emblematic of the golden age of social science.

Conclusion and Challenges

We hope this paper encourages scholars to pursue more interdisciplinary projects. However, this type of research also presents new challenges. The following obstacles disproportionately concern teams working on questions that cut across disciplines—we review each one and provide best-practice recommendations.

- The question of silos between journals, or where and how information is accumulated, can be a special challenge for teams who are used to contributing to traditionally disparate disciplines. Many journals cater solely to the readership of a specific discipline or discipline subfield, with authors citing papers predominantly from like-minded journals. While cross-citation is on the rise, it is not guaranteed that interdisciplinary work will make equal contributions across fields, presenting the possibility of losing valuable insight with relevance to one of the fields. We encourage more journals to seriously consider and publish high-quality interdisciplinary research, even when it falls outside their traditional sphere of work. In the meantime, we encourage scholars to consider that an interdisciplinary project may produce multiple papers, such that all disciplines which contributed to the research will benefit from knowledge accumulated in the project.
- Closely tied is the question of career incentives and authorship. Academics are often encouraged to remain focused on contributing to their respective subject areas, which means working with other academics in the same subfield and publishing in specialized journals (see previous point). Furthermore, differences in authorship norms across disciplines (such as the strong emphasis on solo-authored papers in economics) make some young researchers reluctant to join projects where bigger teams are better. If interdisciplinary work is to continue to thrive, hiring and promotion practices will need to adjust to value contributions in large teams that reach diverse journal audiences. In training and hiring new PhDs, we encourage departments and organizations to consider ways to expose trainees to more breadth in social science and develop better ways to evaluate interdisciplinary research.
- Interdisciplinarity possesses unique challenges for "open science"—that is, the sharing of procedures, data, and code intended to make research more widely accessible—because different social science disciplines often have different tools and norms. As Stodden et al. note, "Current reporting methods are often uneven, incomplete, and still evolving" (106). However, this challenge is now widely recognized, and efforts are underway to improve open science in practice. We encourage researchers, especially new PhDs, to see this as an opportunity to define best practices for how the relevant sharing of data and code should be done.
- Another challenge is the creation of unifying frameworks to explain behaviors across disciplines. Better theories will constrain the number of explanations that could be derived from big data by setting appropriate priors for hypotheses. An expansion of methodological approaches alone will not increase scientific knowledge unless there is common lingua franca or, even better, genuinely unifying frameworks. Social science would benefit from evolutionarily plausible theories that provide ultimate (function) and proximate (mechanism) explanations. We encourage trade-minded scholars to be humble and open to learning from other social scientists who have long histories of concepts and methods to share.

The obstacles discussed above are not to be downplayed, but there is reason to be optimistic: Our increasingly connected age means that knowledge from other disciplines is much easier to access. To that end, here are some ways we can measure success in the years to come: more respected journals will seek out and publish work from diverse teams using unique datasets, more young scientists will engage in interdisciplinary research (thanks to improved institutional practices regarding career progress and encouragement from provosts and senior faculty), and more established scientists will engage in interdisciplinary work (thanks to increased interest from funding agencies). Most importantly, scholars will increasingly focus on difficult questions—ones that may have been avoided historically because their complexity made them impossible to tackle from one discipline alone—and social science will be more impactful together than the sum of any one subdiscipline working on its own.

Data Availability. There are no data underlying this work.

Acknowledgments

We thank Fred Blum, Jerry Davis, Jonathan Katz, Joseph Henrich, Philip Hoffman, Keri Leigh Merritt, Scott Page, Duncan Watts, our editor, and two anonymous referees for constructive comments and discussions. We thank the T&C Chen Center (Fellowships for M.G., A.B., support for C.F.C.), the Behavioral and Neuroeconomics Discovery Fund at Caltech and MacArthur Foundation (for C.F.C.), NSF Social, Behavioral and Economic Sciences award 1851902 (supporting M.G., C.F.C.), NSF award 1851745 (for C.F.C.), and especially Trilience (for C.F.C.) for financial support for research on this topic.

1 M. J. Salganik, *Bit by Bit: Social Research in the Digital Age* (Princeton University Press, 2018).
2 S. E. Page, *The Diversity Bonus: How Great Teams Pay off in the Knowledge Economy* (Princeton University Press, 2017).
3 P. Smaldino, C. O'Connor, Interdisciplinarity can aid the spread of better methods between scientific communities. https://osf.io/cm5v3, doi:10.31222/osf.io/cm5v3. Accessed 10 November 2020.
4 R. Costanza *et al.*, The value of the world's ecosystem services and natural capital. *Nature* **387**, 253–260 (1997).
5 National Science Board, Report to Congress on interdisciplinary research at the National Science Foundation. https://www.nsf.gov/nsb/publications/2018/nsb201915.pdf. Accessed 1 July 2020.
6 National Academy of Sciences, National Academy of Engineering, and Institute of Medicine, *Facilitating Interdisciplinary Research* (National Academies Press, 2005), vol. 11153.
7 National Science Foundation, National Science Foundation's merit review process fiscal year 2018 digest. https://www.nsf.gov/nsb/publications/2020/nsb202013.pdf. Accessed 1 July 2020.
8 T. D. Cook, D. T. Campbell, *Quasi-Experimentation: Design & Analysis Issues for Field Settings* (Houghton Mifflin, 1979).
9 J. D. Angrist, A. B. Krueger, Instrumental variables and the search for identification: From supply and demand to natural experiments. *J. Econ. Perspect.* **15**, 69–85 (2001).
10 A. J. Sovey, D. P. Green, Instrumental variables estimation in political science: A readers' guide. *Am. J. Pol. Sci.* **55**, 188–200 (2011).
11 J. Pearl, Causal diagrams for empirical research. *Biometrika* **82**, 669–688 (1995).
12 D. J. Watts, Should social science be more solution-oriented? *Nat. Hum. Behav.* **1**, 0015 (2017).

https://doi.org/10.1073/pnas.2002923118

13 D. J. Watts, P. S. Dodds, Influentials, networks, and public opinion formation. *J. Consum. Res.* **34**, 441–458 (2007).
14 L. C. Freeman, *The Development of Social Network Analysis: A Study in the Sociology of Science* (Empirical Press, 2004).
15 S. Aral, C. Nicolaides, Exercise contagion in a global social network. *Nat. Commun.* **8**, 14753 (2017).
16 D. J. Watts, S. H. Strogatz, Collective dynamics of 'small-world' networks. *Nature* **393**, 440–442 (1998).
17 N. A. Christakis, J. H. Fowler, *Connected: The Surprising Power of Our Social Networks and How They Shape Our Lives* (Little, Brown, 2011).
18 M. O. Jackson, *The Human Network: How Your Social Position Determines Your Power, Beliefs, and Behaviors* (Pantheon Books, 2019).
19 D. J. Watts, The "new" science of networks. *Annu. Rev. Sociol.* **30**, 243–270 (2004).
20 C. Thiemann, F. Theis, D. Grady, R. Brune, D. Brockmann, The structure of borders in a small world. *PLoS One* **5**, e15422 (2010).
21 F. Schweitzer *et al.*, Economic networks: The new challenges. *Science* **325**, 422–425 (2009).
22 M. Morris, S. Goodreau, J. Moody, "Sexual networks, concurrency, and STD/HIV" in *Sexually Transmitted Diseases*, K. K. Holmes, Ed. (McGraw-Hill Medical, 2008), pp. 109–125.
23 S. T. E. Baker *et al.*, Developmental changes in brain network hub connectivity in late adolescence. *J. Neurosci.* **35**, 9078–9087 (2015).
24 P. J. Richerson, R. Boyd, The role of evolved predispositions in cultural evolution. *Ethol. Sociobiol.* **10**, 195–219 (1989).
25 R. S. Burt, D. Ronchi, Teaching executives to see social capital: Results from a field experiment. *Soc. Sci. Res.* **36**, 1156–1183 (2007).
26 S. A. Morelli, D. C. Ong, R. Makati, M. O. Jackson, J. Zaki, Empathy and well-being correlate with centrality in different social networks. *Proc. Natl. Acad. Sci. U.S.A.* **114**, 9843–9847 (2017).
27 M. E. Weaverdyck, C. Parkinson, The neural representation of social networks. *Curr. Opin. Psychol.* **24**, 58–66 (2018).
28 G. Simmel, O. Rammstedt, G. Simmel, *Soziologie: Untersuchungen über die Formen der Vergesellschaftung* (Suhrkamp, 1992).
29 I. J. Schoenberg, "Publications of Edmund Landau" in *Number Theory and Analysis*, P. Turán, Ed. (Springer, 1969), pp. 335–355.
30 M. O. Jackson, *Social and Economic Networks* (Princeton University Press, 2008).
31 L. C. Freeman, A set of measures of centrality based on betweenness. *Sociometry* **40**, 35–41 (1977).
32 M. Muthukrishna, M. Schaller, Are collectivistic cultures more prone to rapid transformation? Computational models of cross-cultural differences, social network structure, dynamic social influence, and cultural change. *Pers. Soc. Psychol. Rev.* **24**, 103–120 (2019).
33 N. Candelo, C. Eckel, C. Johnson, Social distance matters in dictator games: Evidence from 11 Mexican villages. *Games (Basel)* **9**, 77 (2018).
34 S. Currarini, M. O. Jackson, P. Pin, Identifying the roles of race-based choice and chance in high school friendship network formation. *Proc. Natl. Acad. Sci. U.S.A.* **107**, 4857–4861 (2010).
35 G. F. Davis, H. R. Greve, Corporate elite networks and governance changes in the 1980s. *Am. J. Sociol.* **103**, 1–37 (1997).
36 W. O. Kermack, A. G. McKendrick, A contribution to the mathematical theory of epidemics. *Proc. R. Soc. Lond. A* **115**, 700–721 (1927).
37 M. Kretzschmar, M. Morris, Measures of concurrency in networks and the spread of infectious disease. *Math. Biosci.* **133**, 165–195 (1996).
38 M. Morris, M. Kretzschmar, Concurrent partnerships and the spread of HIV. *AIDS* **11**, 641–648 (1997).
39 J. S. Jia *et al.*, Population flow drives spatio-temporal distribution of COVID-19 in China. *Nature* **582**, 389–394 (2020).
40 A. L. Bertozzi, E. Franco, G. Mohler, M. B. Short, D. Sledge, The challenges of modeling and forecasting the spread of COVID-19. *Proc. Natl. Acad. Sci. U.S.A.* **117**, 16732–16738 (2020).
41 M. O. Jackson, A. Wolinsky, A strategic model of social and economic networks. *J. Econ. Theory* **71**, 44–74 (1996).
42 J. Angrist, P. Azoulay, G. Ellison, R. Hill, S. F. Lu, Inside job or deep impact? Extramural citations and the influence of economic scholarship. *J. Econ. Lit.* **58**, 3–52 (2020).
43 R. H. Thaler, From cashews to nudges: The evolution of behavioral economics. *Am. Econ. Rev.* **108**, 1265–1287 (2018).
44 Part 2: The Behavioral Foundations of Economic Theory. *J. Bus.* **59**, no. 4 (1986).
45 R. H. Thaler, *Misbehaving: The Making of Behavioural Economics* (W. W. Norton & Company, 2016).
46 G. Lowenstein, C. Camerer, M. Rabin, Eds., *Advances in Behavioral Economics* (Princeton University Press, 2004).
47 N. Geiger, The rise of behavioral economics: A quantitative assessment. *Soc. Sci. Hist.* **41**, 555–583 (2017).
48 S. DellaVigna, "Structural behavioral economics" in *Handbook of Behavioral Economics: Applications and Foundations 1*, D. Bernheim, D. Laibson, S. DellaVigna, Eds. (Elsevier, 2018), vol. 1, pp. 613–723.
49 D. Kahneman, A. Tversky, Prospect theory: An analysis of decisions under risk. *Econometrica* **47**, 263–291 (1979).
50 U. Gneezy, J. Potters, An experiment on risk taking and evaluation periods. *Q. J. Econ.* **112**, 631–645 (1997).
51 S. Benartzi, R. H. Thaler, Myopic loss aversion and the equity premium puzzle. *Q. J. Econ.* **110**, 73–92 (1995).
52 D. Kahneman, J. L. Knetsch, R. H. Thaler, Experimental tests of the endowment effect and the coase theorem. *J. Polit. Econ.* **98**, 1325–1348 (1990).
53 J. S. Lerner, D. A. Small, G. Loewenstein, Heart strings and purse strings: Carryover effects of emotions on economic decisions. *Psychol. Sci.* **15**, 337–341 (2004).
54 E. J. Johnson, G. Häubl, A. Keinan, Aspects of endowment: A query theory of value construction. *J. Exp. Psychol. Learn. Mem. Cogn.* **33**, 461–474 (2007).
55 S. Bhatia, R. Golman, Attention and reference dependence. *Decision (Wash. D.C.)* **6**, 145–170 (2019).
56 S. M. Tom, C. R. Fox, C. Trepel, R. A. Poldrack, The neural basis of loss aversion in decision-making under risk. *Science* **315**, 515–518 (2007).
57 J. Yacubian *et al.*, Dissociable systems for gain- and loss-related value predictions and errors of prediction in the human brain. *J. Neurosci.* **26**, 9530–9537 (2006).
58 B. De Martino, C. F. Camerer, R. Adolphs, Amygdala damage eliminates monetary loss aversion. *Proc. Natl. Acad. Sci. U.S.A.* **107**, 3788–3792 (2010).
59 R. McDermott, Prospect theory in political science: Gains and losses from the first decade. *Polit. Psychol.* **25**, 289–312 (2004).
60 A. Alesina, F. Passarelli, Loss aversion in politics. *Am. J. Polit. Sci.* **63**, 936–947 (2019).
61 P. Tovar, The effects of loss aversion on trade policy: Theory and evidence. *J. Int. Econ.* **78**, 154–167 (2009).
62 O. D. Jones, "Why behavioral economics isn't better, and how it could be" in *Research Handbook on Behavioral Law and Economics*, J. C. Teitelbaum, K. Zeiler, Eds. (Edward Elgar Publishing, 2018).
63 V. Lakshminaryanan, M. K. Chen, L. R. Santos, Endowment effect in capuchin monkeys. *Philos. Trans. R. Soc. Lond. B Biol. Sci.* **363**, 3837–3844 (2008).
64 P. Kanngiesser, L. R. Santos, B. M. Hood, J. Call, The limits of endowment effects in great apes (Pan paniscus, Pan troglodytes, Gorilla gorilla, Pongo pygmaeus). *J. Comp. Psychol.* **125**, 436–445 (2011).
65 C. L. Apicella, E. M. Azevedo, N. A. Christakis, J. H. Fowler, Evolutionary origins of the endowment effect: Evidence from hunter-gatherers. *Am. Econ. Rev.* **104**, 1793–1805 (2014).
66 A. Baillon, H. Bleichrodt, V. Spinu, Searching for the reference point. https://aurelienbaillon.com/research/papers/pdf/reference_point.pdf. Accessed 12 February 2020.
67 E. J. Allen, P. M. Dechow, D. G. Pope, G. Wu, Reference-dependent preferences: Evidence from marathon runners. *Manage. Sci.* **63**, 1657–1672 (2017).
68 A. L. Brown, Z. E. Chua, C. F. Camerer, Learning and visceral temptation in dynamic saving experiments. *Q. J. Econ.* **124**, 197–231 (2009).
69 C. B. Jaeger, S. F. Brosnan, D. T. Levin, O. D. Jones, Predicting variation in endowment effect magnitudes. *Evol. Hum. Behav.* **41**, 253–259 (2020).
70 W. Samuelson, R. Zeckhauser, Status quo bias in decision making. *J. Risk Uncertain.* **1**, 7–59 (1988).
71 E. J. Johnson, D. Goldstein, Medicine. Do defaults save lives? *Science* **302**, 1338–1339 (2003).
72 R. H. Thaler, S. Benartzi, Save more tomorrow: Using behavioral economics to increase employee saving. *J. Polit. Econ.* **112**, S164–S187 (2004).
73 R. Chetty, J. N. Friedman, S. Leth-Petersen, T. H. Nielsen, T. Olsen, Active vs. Passive decisions and crowd-out in retirement savings accounts: Evidence from Denmark. *Q. J. Econ.* **129**, 1141–1219 (2014).
74 C. Camerer, S. Issacharoff, G. Loewenstein, T. O'Donoghue, M. Rabin, Regulation for conservatives: Behavioral economics and the case for 'asymmetric paternalism'. *Univ. Pa. Law Rev.* **151**, 1211 (2003).

75 R. H. Thaler, C. R. Sunstein, *Nudge: Improving Decisions about Health, Wealth, and Happiness* (Penguin Books, 2009).
76 D. M. Messick, C. G. McClintock, Motivational bases of choice in experimental games. *J. Exp. Soc. Psychol.* **4**, 1–25 (1968).
77 W. Güth, R. Schmittberger, B. Schwarze, An experimental analysis of ultimatum bargaining. *J. Econ. Behav. Organ.* **3**, 367–388 (1982).
78 A. Mas, Pay, reference points, and police performance. *Q. J. Econ.* **121**, 783–821 (2006).
79 G. F. Loewenstein, L. Thompson, M. H. Bazerman, Social utility and decision making in interpersonal contexts. *J. Pers. Soc. Psychol.* **57**, 426–441 (1989).
80 C. Camerer, E. Fehr, "Measuring social norms and preferences using experimental games: A guide for social scientists" in *Foundations of Human Sociality*, J. Henrich *et al.*, Eds. (Oxford University Press, 2004), pp. 55–95.
81 J. Berg, J. Dickhaut, K. McCabe, Trust, reciprocity, and social history. *Games Econ. Behav.* **10**, 122–142 (1995).
82 C. Camerer, K. Weigelt, Experimental tests of a sequential equilibrium reputation model. *Econometrica* **56**, 1–36 (1988).
83 E. Fehr, G. Kirchsteiger, A. Riedl, Does fairness prevent market clearing? An experimental investigation. *Q. J. Econ.* **108**, 437–459 (1993).
84 J. Henrich *et al.*, "Economic man" in cross-cultural perspective: Behavioral experiments in 15 small-scale societies. *Behav. Brain Sci.* **28**, 795–815, discussion 815–855 (2005).
85 E. Krupka, R. A. Weber, The focusing and informational effects of norms on pro-social behavior. *J. Econ. Psychol.* **30**, 307–320 (2009).
86 C. Camerer, R. H. Thaler, Anomalies: Ultimatums, dictators and manners. *J. Econ. Perspect.* **9**, 209–219 (1995).
87 E. Tricomi, A. Rangel, C. F. Camerer, J. P. O'Doherty, Neural evidence for inequality-averse social preferences. *Nature* **463**, 1089–1091 (2010).
88 I. Krajbich, R. Adolphs, D. Tranel, N. L. Denburg, C. F. Camerer, Economic games quantify diminished sense of guilt in patients with damage to the prefrontal cortex. *J. Neurosci.* **29**, 2188–2192 (2009).
89 T. Yamagishi, The provision of a sanctioning system as a public good. *J. Pers. Soc. Psychol.* **51**, 110–116 (1986).
90 B. Herrmann, C. Thöni, S. Gächter, Antisocial punishment across societies. *Science* **319**, 1362–1367 (2008).
91 S. DellaVigna, J. A. List, U. Malmendier, Testing for altruism and social pressure in charitable giving. *Q. J. Econ.* **127**, 1–56 (2012).
92 A. Cohn, M. A. Maréchal, D. Tannenbaum, C. L. Zünd, Civic honesty around the globe. *Science* **365**, 70–73 (2019).
93 OECD, Behavioural insights. https://www.oecd.org/gov/regulatory-policy/behavioural-insights.htm. Accessed 15 January 2020.
94 S. Bowles, S. Polanía-Reyes, Economic incentives and social preferences: Substitutes or complements? *J. Econ. Lit.* **50**, 368–425 (2012).
95 N. R. Magliocca *et al.*, Modeling cocaine traffickers and counterdrug interdiction forces as a complex adaptive system. *Proc. Natl. Acad. Sci. U.S.A.* **116**, 7784–7792 (2019).
96 C. Camerer, T. H. Ho, Experience-weighted attraction learning in normal form games. *Econometrica* **67**, 827–874 (1999).
97 P. Bordalo, N. Gennaioli, A. Shleifer, Salience theory of choice under risk. *Q. J. Econ.* **127**, 1243–1285 (2012).
98 M. Borgerhoff Mulder *et al.*, Intergenerational wealth transmission and the dynamics of inequality in small-scale societies. *Science* **326**, 682–688 (2009).
99 J. Henrich, M. Bauer, A. Cassar, J. Chytilová, B. G. Purzycki, War increases religiosity. *Nat. Hum. Behav.* **3**, 129–135 (2019).
100 J. E. Blumenstock, M. Fafchamps, N. Eagle, "Risk and reciprocity over the mobile phone network: Evidence from Rwanda" (NET Institute Working Paper No. 11-25, 2011).
101 W.-Y. Ahn *et al.*, Nonpolitical images evoke neural predictors of political ideology. *Curr. Biol.* **24**, 2693–2699 (2014).
102 D. J. Benjamin *et al.*, The genetic architecture of economic and political preferences. *Proc. Natl. Acad. Sci. U.S.A.* **109**, 8026–8031 (2012).
103 G. Nave *et al.*, Musical preferences predict personality: Evidence from active listening and facebook likes. *Psychol. Sci.* **29**, 1145–1158 (2018).
104 R. Philpot, L. S. Liebst, M. Levine, W. Bernasco, M. R. Lindegaard, Would I be helped? Cross-national CCTV footage shows that intervention is the norm in public conflicts. *Am. Psychol.* **75**, 66–75 (2019).
105 B. Uzzi, S. Mukherjee, M. Stringer, B. Jones, Atypical combinations and scientific impact. *Science* **342**, 468–472 (2013).
106 V. Stodden *et al.*, Enhancing reproducibility for computational methods. *Science* **354**, 1240–1241 (2016).

https://doi.org/10.1073/pnas.2002923118