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Learning, productivity, and noise: an experimental study of cultural transmission on the Bolivian Altiplano☆

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Abstract

The theory of cultural transmission distinguishes between biased and unbiased social learning. Biases simply mean that social learning is not completely random. The distinction is critical because biases produce effects at the aggregate level that then feed back to influence individual behavior. This study presents an economic experiment designed specifically to see if players use social information in a biased way. The experiment was conducted among a group of subsistence pastoralists in southern Bolivia. Treatments were designed to test for two widely discussed forms of biased social learning: a tendency to imitate success and a tendency to follow the majority. The analysis, based primarily on fitting specific evolutionary models to the data using maximum likelihood, found neither a clear tendency to imitate success nor conformity. Players instead seemed to rely largely on private feedback about their own personal histories of choices and payoffs. Nonetheless, improved performance in one treatment provides evidence for some important but currently unspecified social effect. Given existing

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experimental work on cultural transmission from other societies, the current study suggests that social learning is potentially conditional and culturally specific.

Keywords: Cultural evolution; Nonlinear dynamics; Experimental games

1. Introduction

Imagine a population living in an environment with two productive technologies. Both technologies are generally available and involve equal explicit costs. As an apt example, consider a group of subsistence pastoralists facing the option of herding either sheep or llamas. Any individual can use either technology during any period. Livestock yields have a random component, however, and individuals do not know which technology brings the highest average yield. Thus, on average, choosing suboptimally involves an opportunity cost. At one extreme, our featured pastoralists could simply flip a coin periodically to determine which animals to raise. Although a straightforward approach, short of actually biasing choices toward the suboptimal technology, it would minimize the productivity of each individual and, by extension, the economy. At the other extreme, each pastoralist could have a genetic variant coding for a strong desire to raise the livestock variety that happens to be optimal in the native environment. In this case, everyone generally makes the best choice, with or without experience, so long as the environment and set of available technologies remain constant. If some of our pastoralists decide to pick up and move, however, or if weather patterns change over time, the resulting environmental changes might render the old optimum suboptimal. Similarly, if some process of innovation or technology transfer introduces a new domesticate into the population, old technologies could become obsolete. In either case, genetic evolution may not be able to track the optimum over relevant time scales.

Between the extremes of randomization and genetic encoding lies a continuum of learning strategies. On the one hand, each individual could ignore her peers, experiment with both technologies individually, and rely exclusively on trial and error to estimate which option is best. In such a society, learned behavior depends only on private information, and each person effectively duplicates the efforts of every other. On the other hand, individuals could observe the behaviors and even livestock yields of their peers and could incorporate this information into their own decisions. The social information available and the way people use it will affect the actual distribution of behaviors in the population through time.

A key question concerns whether people discriminate in some way when they use social information. For example, if every individual indiscriminately picked another random person and blindly copied that person’s behavior, the distribution of behaviors in a large population would not change through time. In contrast, if every individual copied the behavior of a single individual who recently had an especially large payoff, the population would rapidly become fixed on this behavior. Both of these social learning rules are overly simplistic, but they illustrate the key difference between social learning that discriminates in some way and social learning that does not. The distinction is equivalent to the difference between biased and unbiased social learning examined by Boyd and Richerson (1985) and Richerson and Boyd (2005).

As a hypothesis about behavioral dynamics, biased social learning rests on weak assumptions. It depends on only two propositions: humans learn from other humans in ways that affect behavior, and they do not do so in a completely random fashion. Both of these propositions seem like truisms. Nonetheless, the nature of social learning is properly an empirical question, as is the nature of any interaction between individual learning and social learning. More to the point, simply concluding that social learning is not random leaves many possibilities on the table, and the differences matter. To sort among the many conceivable forms biased social learning could take, empiricism is essential.

Here we present an experimental economic study designed to study how people learn individually and socially. Our study intersects with the subject matter of many disciplines, including the study of economic growth and its focus on innovation versus imitation (Aghion, Harris, Howitt, & Vickers, 2001; Barro & Sala-I-Martin, 2004), the sociological study of the diffusion of innovations (Henrich, 2001; Rogers, 1995), the study of learning in economics (Camerer & Ho, 1999; Camerer, 2003; Fudenberg & Levine, 1998; Merlo & Schotter, 2003; Schlag, 1998, 1999), evolutionary game theory and its pervasive assumption of payoff-biased imitation (Bowles, 2004; Gintis, 2000), the evolutionary theory of cultural transmission in humans (Boyd & Richerson, 1985, 2005; Cavalli-Sforza & Feldman, 1981; Henrich & McElreath, 2003; Richerson & Boyd, 2005), and the empirical study of social learning in animal behavior (Dall, Giraldeau, Olsson, McNamara, & Stephens, 2005; Fragaszy & Perry, 2003; van Schaik et al., 2003). The experimental setting is the scenario described above with two technologies and stochastic payoffs. The task is to test for two biases that have figured prominently in the literature on social learning: a tendency to imitate successful individuals (Henrich & Gil-White, 2001; Offerman & Sonnemans, 1998; Offerman & Schotter, 2005) and a conformist tendency to adopt the most common behavior in the population (Boyd & Richerson, 1982; Henrich, 2001; Henrich & Boyd, 1998).

2. Experimental methods

We conducted all experiments in September 2004 in seven communities in the high-altitude zone (ca. 3600–3800 m) of the Sama Biological Reserve in southern Bolivia. The estimated population of the entire reserve, in both the low-altitude and the high-altitude zones, is 5500 people (Bluske, 2004). In this study population, the basic economic activity is subsistence herding. Sheep are traditional, but llamas are rapidly growing in popularity. As a consequence, the basic choice of how to make a living in this area is analogous to our experiment. Two technologies are available, payoffs are stochastic, and people are not certain which technology is best on average. Although the two technologies in our experiment were simply “red” versus “green,” the analogy with the subsistence economy in this study population gives our experiment a high degree of external validity. Moreover, the choice of a nonstandard subject pool stems from a belief that behavioral experiments need to move beyond the confines of the standard university subject pool, as strongly suggested by recent cross-cultural studies in experimental economics (Henrich et al., 2001, 2004, 2005). Recent cultural evolution studies provide results from experiments similar to this one but conducted among university undergraduates in the United States (Baum, Richerson, Efferson, & Paciotti, 2004; McElreath et al., 2005) and Switzerland (Efferson, C., Lalive, R., Richerson, P. J., McElreath, R., & Lubell, M., unpublished data).

2.1. Technologies and payoff information

The two technologies in this experiment were "red" and "green" in the form of red and green index cards. On each card was a payoff in Bolivian centavos drawn from one of two truncated normal distributions with means 30 and 39. The color with mean 30 was suboptimal, while the color with mean 39 was optimal. The untruncated normal distributions had an S.D. of 12. Payoffs were truncated 2.5 S.D. above and below the means to prevent negative numbers from the lower tail of the suboptimal distribution. Truncation reduced the standard deviation of payoff distributions to slightly less than 12. Payoffs were also rounded to take integer values. Thus, the set of possible payoffs for the suboptimal color included the integers from 0 to 60, while the corresponding set for the optimal color included the integers from 9 to 69.

Because many people who live in Sama cannot read, we had a rubber stamp of a sheep made as a means of providing additional payoff information. The total range of possible payoffs was from 0 to 69. If a particular card had a payoff from the lower half of this interval (i.e., the integers 0–34), it also had one sheep stamp regardless of color. If the card had a payoff from the upper half (i.e., the integers 35–69), it had two sheep stamps. Thus, participants who could not read had the option of reducing the problem to identifying the color that brought two sheep stamps at the highest rate.

2.2. General procedures

Upon arriving in a community, we randomly assigned participants to either an individual learning treatment or one of two social learning treatments described below. Two stacks of cards, one green and the other red, were placed face down in front of each participant. Players were told that each card had a payoff in centavos, and that either color could bring high or low payoffs because the payoffs were "of luck." They were told that one of the two colors was better in the sense that it would bring high payoffs more often than the other. Players were told that, for those who could not read, the cards also had sheep stamps, with one sheep stamp indicating a small quantity of money and with two stamps indicating a large quantity of money. We told them that they would make 50 choices and, at the end of the experiment, they would be paid in real money by summing individually over all choices.

For each choice, the card from the top of the relevant stack was turned over and placed upright on top of any chosen cards of the same color from previous periods. After the experiment, players responded to a brief questionnaire individually and were then paid.

Because Bolivian currency is difficult to obtain in large quantities in denominations of less than 50 centavos, total payoffs were rounded up to the nearest 50-centavo increment. These various numbers were chosen, in part, to ensure that the average total payoff approximated 20 Bolivianos, which was the area's going rate at the time for a day's worth of unskilled labor. The following describes how procedures varied by treatment. Table 1 summarizes the information available to players in each treatment.

2.3. Individual treatment

Participants were in a private room without other participants. They communicated their choices to the experimenter either verbally or via gestures. After each stated choice, the experimenter turned the appropriate card over for the participant to see. With the exception of one blind man who participated in this treatment, the experimenter did not announce the payoff. The optimal color and the color on the player's right side were randomized over individuals.

2.4. Best-color treatment

A given group entered a private room, usually in the community school building or church, where the experiment would take place. Each individual sat in front of a large cardboard box containing her own two stacks of cards. In addition to the individual payoff information discussed above, players were also told that, at the end of each period, they would learn the color chosen by the player who had received the highest payoff that period. To conduct the experiment, two experimenters encircled the room asking each individual which color she wanted to choose. The individual reached inside the box without speaking and pointed. One of the experimenters turned the appropriate card over inside the box for the participant to observe. The other experimenter recorded the color chosen and the payoff. After all players had made a choice in a given period, the data-recording experimenter announced the color that had produced the highest payoff for that period based on the centavo information contained on each card. The experimenter did not announce the associated payoff, and so players only observed their own individual payoffs. The concept of a period was easily conveyed with the Spanish word "vuelta," which implies one pass around the room. Although the possibility was not discussed up front, a handful of periods produced two-color ties for the highest payoff. When this outcome occurred, the data-recording experimenter simply explained that two players had received the same highest payoff with one choosing red and the other choosing green. Ties for the highest payoff involving the same color were never announced, although, theoretically, two greens tying for the highest payoff is not the same situation as one green producing the best payoff. Individuals were asked to remain silent during the experiment. The optimal color was randomized over experimental groups, and the color on the right side within each box was randomized over individuals. All individuals within a group, however, had the same optimal color, and this fact was explained at the beginning of each experimental session. This treatment included a group of 4, a group of 5, a group of 6, and four groups of 11.

Table 1
A summary of the information available in the three experimental treatments

Treatment	Private feedback	Social feedback ($t \geq 2$)
Individual	Realized payoff	None
Best color	Realized payoff	Color with highest payoff
Total distribution	Realized payoff	Distribution of colors

Social information was only provided in the two relevant treatments in Periods 2–50.

2.5. Total distribution treatment

This treatment was identical to the best-color treatment with two exceptions. First, after each period, the experimenter announced the number in the group choosing green and the number choosing red. Second, this treatment involved five groups of 11.

3. Basic results, statistical methods, dynamics, and model selection

For each player, we calculated a mean payoff per period. These quantities differ by experimental treatment [analysis of variance: $F(2, 159)=5.491$, $p=.005$]. Fig. 1 shows that a higher proportion of players typically chose optimally under the total distribution treatment as compared to individual and best-color treatments.

Table 2 records the mean payoff per period with 95% confidence intervals (95% CIs).

As Table 3 shows, the mean payoff per period in the total distribution treatment is significantly greater than those in both the individual and best-color treatments, while the same quantities for the individual learning and best-color treatments are not significantly different.

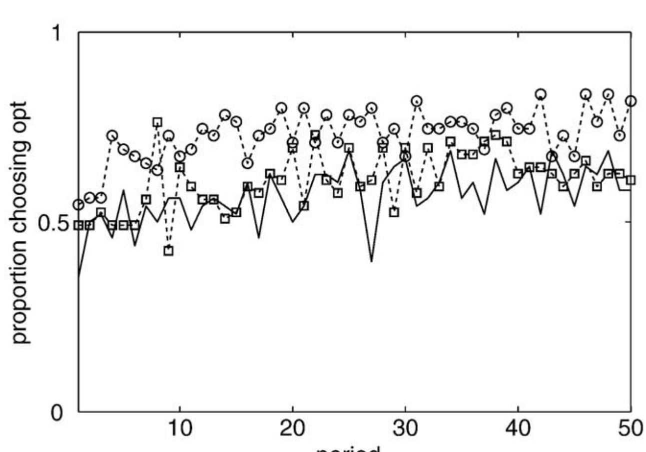

Fig. 1. The proportion of players choosing the optimal color, by period, for each of the three treatments. The solid line represents individual treatment, the dashed line with squares represents best-color treatment, and the dashed line with circles represents total distribution treatment.

Table 2
Mean individual payoff (with 95% CI), by period, for each of the three treatments

Treatment	Sample size	95% CI
Individual	48	34.952±0.503
Best color	59	35.386±0.740
Total distribution	55	36.498±0.698

To examine the structure of this difference in choices and payoffs, with a particular focus on how the difference relates to social information, we developed an a priori set of dynamic models to fit to each of the three data sets. Each model makes specific assumptions about how changing information, both private and social, affects the choices players make through time. Given a set of such models, the task is to identify the model that fits the data best. This approach is well established in the experimental economics literature on learning, and Camerer (2003) provides a broad overview. The question is fundamentally empirical in the sense that the researcher seeks a model that summarizes the observed data better than some set of alternate models (Camerer & Ho, 1999).

With a few exceptions, the models we used were theoretical models of individual learning from the economics literature (Camerer & Ho, 1999; Fudenberg & Levine, 1998) and social learning models from the cultural evolutionary literature (Boyd & Richerson, 1985). The basic approach is to take a model developed for theoretical purposes, introduce a noise structure, and fit the model to the data using maximum likelihood (Efferson & Richerson, 2006; McElreath et al., 2005). Appendix A presents a detailed description of how we accomplished this for the present study. Here we simply describe the models we fit to a particular data set and summarize the results qualitatively. First, however, we briefly discuss how we compared alternate models.

To compare alternate models, we fit all models using maximum likelihood and, as a model selection criterion, we used a derivative form (AIC_c) of Akaike (1973) criterion, discussed in Burnham and Anderson (2002, p. 66). The basic idea behind the Akaike criterion is the following. Some process generated the data at hand. We do not know this process, but based on past research, we have various candidate models that we think represent this process more or less well. Because models are models, however, and not reality, summarizing reality with a model always results in loss of information. The Akaike criterion selects the model from a specified set of models that is estimated to lose the least amount of information (Burnham & Anderson,

Table 3
Multiple comparisons (Tukey–Kramer) of individual mean payoff, by period, in all combinations of two treatments

Treatment 1	Treatment 2	Lower bound	Estimate	Upper bound
Individual	Best color	−1.559	−0.434	0.690
Best color	Total distribution	−2.688	−1.545	−0.402
Total distribution	Total distribution	−2.196	−1.111	−0.026

The estimate indicated is the estimated difference in the individual mean payoff under Treatment 1 minus the same quantity under Treatment 2. The lower and upper bounds for this estimate at α=.05 are also shown.

2002). In this regard, it is an "information-theoretic criterion." In practical terms, it selects the model that yields the best maximum likelihood value, but it includes a penalty for adding parameters that one has to estimate with the same amount of data. Thus, in loose terms, the question is not "Can we improve the fit with a more complex model?" but rather "Can we improve the fit per unit of added complexity?" Burnham and Anderson (2002), Forster and Sober (1994), and Hilborn and Mangel (1997) provide extensive overviews of information-theoretic criteria like the Akaike criterion and their many advantages over more conventional approaches to data analysis rooted in hypothesis testing. Efferson and Richerson (2006) discuss the use of the Akaike criterion specifically with respect to the experimental study of social learning.

4. Results

4.1. Results for individual learning treatment

We fit a total of six models to the individual learning data set. The simplest of these involved a constant probability of choosing the optimum in every period over all players. We also fit three models that do not explicitly incorporate individual histories of choices and payoffs but allow for a phenomenological description of trends and autocorrelated choices. Lastly, we fit two models that explicitly incorporate each individual's particular history of choices and payoffs. These models are called "attraction" models because they assume that the more money a player has made by choosing a particular option in the past, the stronger will be her attraction to it in the future. We describe the models and results in detail in Appendix B.

Based on this model-fitting exercise, players in this treatment did learn individually, although they tended to switch colors frequently from one period to the next. Learning can be seen in Fig. 1 because the proportion of individual learners choosing optimally increased steadily through time. The strong tendency to switch behaviors from one period to the next, however, prevented attraction models from fitting well. Attraction models incorporate individual choice and payoff histories and thus predict that a color generally producing higher payoffs (i.e., the optimal color in this experiment) will typically have a stronger and stronger attraction as time passes. In essence, players learned in this treatment, but the tendency to switch colors outweighed information processing as we model it with two standard attraction models from the economics literature (Camerer, 2003).

4.2. Results for best-color treatment

We fit the same individual learning models described above to this data set. We additionally used these individual learning models as a basis for models that combine individual learning and social learning. Social learning in this case takes the form of imitating the color that produced the highest payoff in the social group in the previous period. This model-fitting strategy is based on the following reasoning. The models combining individual and social learning often involve additional parameters beyond pure individual learning models. If the social learning component of the combined models does not sufficiently summarize systematic features of the data, the Akaike criterion will penalize these models for estimating relatively useless additional parameters associated with social learning. In such a case, pure individual learning models will fit better. If a combined model fits the best, it would mean that imitating success as we model it in Appendix A is a form of social learning that summarizes important features of the data.

As we explain in Appendix A, the two attraction models without social learning best summarize the data for the best-color treatment. This result has two implications. First, unless our models of imitating the best color from the previous period are completely inappropriate, players in this treatment apparently ignored the valuable social information provided to them. Social information was valuable in the sense that the announced best color in a given period was usually the color that was actually optimal for the session in question. Because payoffs were random, on occasion, the color that produced the highest payoff in a given period would be the color with the lower expectation (i.e., the suboptimal color), but this outcome was relatively uncommon. Appendix A includes a model that explains why this will generally be true. Second, although players in this treatment apparently relied on individual feedback, they did not learn individually in the same way as players in the individual learning treatment. In the best-color treatment, attraction models fit better than the other individual learning models. In the individual treatment, attraction models fit much worse relative to simple phenomenological models that do not account for individual choice and payoff histories. This result implies some kind of interaction between the social context and how players learned as individuals.

4.3. Results for total distribution treatment

The results for the total distribution treatment are analogous. In this case, to develop combined models of individual and social learning, we worked with three different models of frequency-dependent social learning: unbiased social learning and two different forms of conformity. Appendix A describes these models and Appendix B describes the results of the analysis in detail. As in the best-color treatment, the two attraction models without any social learning fit the best. Once again, this result suggests that players did not consistently use the social information provided in this treatment in any way captured by our models. Moreover, this information was valuable, as in the best-color case, because the color in the majority in any given period was almost always the color that was optimal for that session. This is because players in the total distribution treatment were learning individually. As a consequence, most of the players in a group in a particular period chose the color that was actually optimal, and so the group-level information we provided exaggerated the effects of individual learning into a valuable social signal. In short, conformity would have been an effective approach to making money.

4.4. Paradox and a posteriori analysis

The results above introduce a paradox. Relative to the individual treatment, the best-color treatment did not produce an effect in terms of optimality and average payoffs, but the total distribution treatment did. Learning in the best-color treatment as pure individual learners who ignored social information (an interpretation that the model-fitting exercise supports) could explain the lack of effect in the best-color treatment. The model-fitting exercise, however, also suggests that players in the total distribution treatment ignored social information and essentially learned as pure individual learners. What then is responsible for the observed increase in optimality and average payoffs in this latter treatment?

One possibility is a type of interaction psychologists refer to as social facilitation (Galef, 1988). Social facilitation is a form of learning in which learners do not acquire or use information from others. Rather, the presence of others encourages more efficient individual learning. For example, being in a group might cue individuals in a way that leads them to feel that they need to do well at the task. They might, as a consequence, try harder to estimate which color is optimal. Such an effect might explain why participants in the total distribution treatment performed better than those in the individual treatment, despite so little evidence that they used the information embedded in the social signal. In support of this interpretation, the model-fitting exercise indicates that players learned differently based on their private feedback in the individual treatment, where attraction models did not fit well, and based on their private feedback in the total distribution treatment, where attraction models did fit well. This difference seems especially salient in light of the fact that attraction models represent a more sophisticated use of private feedback than the other models under consideration. Nonetheless, if social facilitation is the only relevant mechanism behind the difference between the individual and the total distribution treatments, why then did placing players in groups in the best-color treatment not have the same effect? The absence of an effect here suggests that an additional mechanism is at play in the total distribution treatment.

In particular, Fig. 1 shows that the increase in optimal choices in the total distribution treatment seems to have come only in the first six or seven periods. In these periods, the proportion of players choosing the optimal technology rose quickly, relative to the other two treatments, but subsequently, there is no obvious difference in the trends found in the three treatments. To investigate this, we fit all of our models for the total distribution data set to the first seven periods only. Two results came out of the analysis. First, attraction models no longer fit the best, but rather the same phenomenological models that fit the individual treatment best also best fit the data from the first seven periods of the total distribution treatment. Second, the results suggested that players may have been using conformity in the first seven periods, but the limited amount of data produced confidence intervals too large to draw any firm conclusions for or against a social learning effect. On a related note, McElreath et al. (2005) conducted a similar experiment and found a strong interest in social information in early periods that waned rapidly as the experiment progressed.

5. Discussion and conclusion

Some simple facts best illustrate the value of the group-level information provided in the two social treatments. In the best-color treatment, across seven experimental sessions, the announced highest-paying color was the true optimum 274 of 350 times. Even more dramatically, in the total distribution treatment, a majority of players in the group chose the optimal color 237 of 250 times. Thus, in both experiments, social information aggregated a lot of individual noise into a valuable signal that reliably pointed toward the optimal color. Yet, on balance, model fitting provided little evidence that players used this signal. The one possible exception involved the initial periods of the total distribution treatment. Our analysis strongly suggests that information use was distinctive in these periods, and this difference accounts for the higher average payoffs for players in this treatment.

What we can say is that, in the first few periods of the total distribution treatment, some kind of interaction between individual learning and social situation produced an increase in optimal choices with a corresponding increase in productivity. The net effect over all 50 periods was modest because the increase in optimality was confined to the early stages of the experiment. The difference in absolute productivity, however, could be substantial in a real-world setting involving aggregation over hundreds or thousands of individuals and multiple time periods.

In the final analysis, we suspect that variation in social learning will have a kind of metastructure that will require a sustained experimental program to unpack. The current experiments found an interaction between social setting and behavior that affected payoffs, but the effect was not readily attributable to biased social learning. In contrast, Baum et al. (2004), Efferson et al. (unpublished data), and McElreath et al. (2005) found considerable evidence for cultural traditions in the laboratory and biased social learning. This kind of variation across studies could be part of a larger structure governing social learning. After many years of economic experiments on social preferences, for example, we now have some sense of how these preferences and their aggregate effects depend on and interact with the institutional setting, culture, and framing (Camerer, 2003; Camerer & Fehr, 2006; Fehr & Fischbacher, 2003, 2004; Henrich et al., 2004). We anticipate that the experimental study of social learning will prove to be similarly rich with subtleties.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.evolhumbehav.2006.05.005.

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