Cultural Incubators and Spread of Innovation

Enrico R. Crema1,2,3\*

Mark W. Lake11

1UCL Institute of Archaeology

2Universitat Pompeu Fabra, Department of Humanities

3CaSEs - Complexity and Socio-Ecological Dynamics Research Group

\*Corresponding Author

**Key Words**: Cultural Transmission; Payoff-biased transmission; Payoff uncertainty; Spread of Innovation; Agent-Based Model

***Abstract***

Several forms of social learning relies on the direct or indirect evaluation of the fitness of cultural traits. Here we argue, via an abstract agent-based model, that payoff uncertainty, that is the correlation between a trait and the signal used to evaluate its fitness, plays a pivotal role in the spread of beneficial innovation. More specifically, we examine how this correlation affects the evolutionary dynamics of different forms of social learning and how each can generate divergent historical trajectories depending on the size of the sample pool. In particular, we demonstrate that social learning by copying the best model is particularly susceptible to a sampling effect caused by the interaction of payoff uncertainty, the number of models sampled (the sample pool) and the frequency with which a trait is present in the population. As a result, we identify circumstances in which smaller sample pools can act as cultural incubators that promote the spread of innovations, while more widespread sampling of the population actually retards the rate of cultural evolution.

**1. Introduction**

Social learning is one of the key processes underlying the spread of cultural traits in a living population. The last 30 years have seen productive application of models inspired by population biology to specific questions of interest to anthropologists, archaeologists and ethologists, including what evolutionary ‘problem’ social learning solves (Boyd and Richerson 1988, 1995, Perreault 2012; Plotkin and Odling-Smee 1982), the spread of innovations (Henrich 2001; Kandler and Steele 2009), the loss of cultural traits (Henrich 2004), the effect of population size on cultural complexity (Shennan 2001; Powell et al 2009, 2010) and the rationality of human decision-making (Bentley and Ormerod 2012). The latter, in particular, points to a convergence of interest with economists interested in bounded rationality which, although more commonly investigated using the mathematical apparatus of game-theory, exhibits population thinking (Boyd and Richerson 2000) in the explicit use of replicator dynamics to explore optimal strategies for copying with payoff uncertainty (Schlag 1998). In this paper we cross-cut some of these established themes by exploring the impact of population size/structure and payoff uncertainty on the early stages in the spread of innovations. Our finding augments the results of some existing studies (e.g. Baldini 2012, 2013; Lake and Crema 2012), but at least partially contradicts the results of others (Henrich 2004; Powell et al 2009, 2010; Shennan 2001), so we begin with a brief review of findings from the most immediately relevant recent literature on the value of social learning, the nature of payoff and success-biased social learning and how it is mediated by payoff uncertainty and population size and or structure.

*1.1. The value of social learning*

The textbook definition of social learning is copying some cultural trait from another individual rather than developing it by trial-and-error, thus as Mesoudi (2011, p.69) puts it, “people preferentially choose among existing traits found in the population without changing those traits”. The extent to which copying from others is unambiguously separable from trial-and-error — also called individual or ‘asocial’ (Laland 2004) — learning is debated in terms of the underlying psychological mechanisms (Heyes and Plotkin 1989) and may vary by context (Mesoudi et al 2014) and, indeed, the window of observation, since an individual can potentially copy a trait, modify it and then pass it on to another individual - so-called ‘guided variation (Boyd and Richerson 1985). Furthermore, it is now well understood that individual learning and social learning are interdependent at population level. Evolutionary epistemologists had long surmised that the function of social learning is to bring about adaptive responses to selective pressures over a timescale intermediate between (slow) natural selection and (fast) individual learning (Campbell 1974; Odling-Smee 1983, but see Kendal et al 2009 for a cautionary note), but it was Boyd and Richerson’s (1985, 1988) ‘costly information hypothesis’ which identified the selective benefit to individual organisms of social learning: that it incurs a lower cost than individual learning, provided that the rate of spatial and temporal variation in the environment is not so great as to render the socially learned information useless. Rogers (1988) subsequently demonstrated, however, that social learning does not increase the average fitness of the population as a whole, because imitators are selected against once their lower cost of learning is offset by the benefit of more accurate environmental tracking, in other words, when the fitness of the two types is equal. Further analysis (Boyd and Richerson 1995) upheld Rogers’ conclusions, with the result that research is now focussed on the existence of mixed equilibrium distributions of both individual and social learners (e.g. Kendal et al 2009; Rendell et al 2010) and a focus on the circumstances under which individuals should engage in social learning (Laland 2004; Kandler and Laland 2013; Kendal et al 2005; Kendal et al 2009).

*1.2. Social learning and payoff signals*

Even if beneficial social learning requires at least some individual learning, it is nevertheless clear that many behaviours are predominantly acquired by copying (Bandura 1977; Boyd and Richerson 1985). Laboratory experiments have revealed the extent to which human beings are cognitively predisposed to copy from others (Herrmann et al 2007) and the extent to which cultural norms reflect that predisposition has been demonstrated by comparative field studies (e.g. Rice and Feldman 1997; Hewlett et al 2002). Furthermore, Henrich (2001) demonstrated that biased social learning that excludes individual trial-and-error is required to account for the ‘S-shape’ curves that describe the uptake of the vast majority of well-studied innovations. There has been significant interest lately in the explanatory power of models based on random social copying (Bentley and Shennan 2005; Bentley and Ormerod 2012) and we include this in a variant of our model, but our principal interest is forms of social learning in which the selection of a cultural trait from a set of alternatives in a sample pool is biased by direct or indirect (Boyd and Richerson 1985) estimation of its ‘worth’.

Contemporary social learning nomenclature distinguishes ‘content’ bias from ‘context’ bias (Henrich and McElreath 2003). Content biases are those which arise from the intrinsic properties of a trait, either because learners have a psychological predisposition (either biologically or culturally determined) toward certain kinds of information, or because they engage in “more generalized cost-benefit calculation” (Henrich and McElreath 2003: 129). Recently, Mesoudi (2011: 67) has suggested that all 5 of the characteristics of successful innovations identified by Rogers (2003) can be considered forms of content-bias. Traits are more likely to be adopted if they are: (i) advantageous relative to existing traits; (ii) compatible with existing traits; (iii) simple enough that their use is easily learned; (iv) testable, so that their advantage can be discerned; and (iv) readily observable. Henrich and McElreath’s notion of “cost-benefit calculation” and Rogers’ “relative advantage” are both examples of what is elsewhere termed ‘payoff bias’ (Kendal et al 2009) and is the form of social learning most commonly studied by economists (e.g. Schlag 1998).

Context biases arise when learners utilise cues in the learning environment as proxies for the ‘worth’ of a trait: either its frequency or the characteristics of those individuals (models) who already have that trait. Frequency dependent bias occurs when the probability of an individual copying the most common trait is higher (conformism) or lower (anticonformism) than it would be if they randomly sampled the population of traits. Although frequency dependent social learning is in itself a low-cost form of learning, it is particularly susceptible to the trade-off, already discussed above, between low learning cost and the potentially high cost of failure to adequately track the environment (Wakano and Aoki 2007; Kandler and Laland 2013). The other form of context bias is model-biased social learning, which entails treating the prestige (Henrich and Gil-White 2001), success (Baldini 2012; Henrich and McElreath 2003), similarity, or some other property of a potential cultural model as a proxy for the ‘worth’ of a cultural trait which that model possesses.

Although success bias is classified as a context bias because the learner evaluates a trait indirectly via its contribution to the reproductive fitness or material well-being of individuals who possess it (Baldini 2012; Henrich and McElreath 2003) there might be circumstances in which the result would not be very different from direct evaluation of the trait payoff, which is classified as a content bias. Indeed, the structural similarity of the two forms of bias is attested by the fact that the same game-theoretic analysis by Schlag (1998) is cited in both Henrich and McElreath’s (2003) discussion of success bias and Kendal et al’s (2009) discussion of payoff bias; in fact, there are no terms in Schlag’s model which would unambiguously differentiate the two forms of bias. Perhaps the best way of conceiving what is at stake in the attempt to differentiate payoff bias, success bias and prestige bias is to think in terms of a spectrum in which evaluation of the trait is increasingly prone to false inference about its true worth. Put another way, while all three biases entail paying attention to ‘payoff signals’, they differ in the likely correlation between the signal and the target trait owing to an increasing number of factors that may contribute to the generation of the payoff signal. Thus payoff biased social learning is vulnerable to stochasticity inherent in the use or performance of a trait, while success bias layers on top of this the possibility that the model is systematically better or worse equipped than the learner to use the trait. For example, a hunter might measure the advantage of a given target trait (e.g. the shape of an arrowhead) via the success (e.g. number of prey captured) of its bearer. This will, however, depend on the type of bow used, the strength and skill of the hunter and their knowledge of prey species, layered on top of stochastic factors that might equally affect both learner and model, such as the availability of the prey and sheer luck. All these factors will contribute to the payoff signal, so that two hunters with identical arrowheads will capture different numbers of prey. Prestige bias renders evaluation of the trait even more indirect because learners defer evaluation of the success of the model to others (Henrich and Gil-White 2001). For this reason, in our model we do not explicitly differentiate between payoff bias and success bias, preferring instead to focus on the magnitude of what, following Baldini (2012), Schlag (1998) and others, we simply label ‘payoff uncertainty’.

*1.3. The effect of payoff uncertainty*

Payoff uncertainty arises when the payoff signal is noisy, which may be because of inherent stochasticity and/or because the signal is also a function of the context in which it was generated, for example other cultural and biological traits possessed by the model, or the environment where the trait is manifest. A number of studies have modelled payoff uncertainty by assuming that a given cultural trait *g* generates a payoff signal *p* drawn from a parametric probability distribution *f*(*p*), such that the variance can be regarded as a measure of the correlation between the signal and the target trait.

Boyd and Richerson (1995) adopted a variant of this approach in a model designed to explore whether copying can increase the average fitness of learners by allowing individuals to learn more selectively in a changing environment. Boyd and Richerson modelled payoff uncertainty in the result of individual - rather than social - learning, such that the observed difference between the payoff of each of two traits is a normal random variable. In these circumstances learners can ensure greater accuracy by insisting on a greater difference between the observed payoffs before adopting the trait with the higher apparent payoff, but this will also result in more cases where the difference threshold is not met and so the result of their individual learning is indeterminate, in which case they copy a randomly chosen individual. What Boyd and Richerson found was that the average fitness of a population at equilibrium in terms of the frequency of copying could be higher than that of a population of learners who do not copy, but only for particular probabilities of environmental change.

Boyd and Richerson’s model employed unbiased social learning, but more recently Kendal et al (2009) described a model in which increasing the payoff associated with the novel trait allowed payoff-biased social learning to evolve in environments characterised by a higher probability of change. Although, as Baldini (2012) notes, Kendal et al’s model of payoff is not stochastic, there is nevertheless a sense in which the relative payoff of the two traits is at least a partial measure of the strength of the payoff signal. Baldini’s (2012) own model of the evolution of success-bias does employ stochastic payoffs, such that the successes associated with the two traits are independently and normally distributed. Baldini demonstrated that if the measure of success used by social learners is also that upon which natural selection acts to alter the frequency of social learning strategies, then increasing the strength of selection favours greater reliance on success bias since it effectively also increases the strength of the payoff signal by better differentiating the average payoffs of the competing traits.

Baldini’s model of success-bias assumes that the learner pays attention to the mean payoff of all the sampled models possessing each unique cultural trait, although the extent to which the learner actually favours higher mean payoffs is parametrised. This is a natural choice for a model extended to explore the evolution of success bias when the payoff signal is also that upon which natural selection acts, but as he concedes, it is not the only possible success-biased learning rule. Other possibilities include copying the most successful model (copy-the-best), copying a model who is more successful than the learner (copy-if-better) and copying with a probability that is proportional to how much more successful the model is relative to the learner (copy-proportionally) (Laland 2004).

The copy-the-best and copy-if-better rules both suffer from an inability to differentiate between “lucky and certain (or highly probable) payoffs” (Schlag 1998: 142). Indeed, Baldini (2013) has recently shown how a social learning strategy based on copying the best individual (Schlag 1999; Apesteguia et al 2007) can occasionally lead to the spread of suboptimal traits if trait payoff distributions overlap but the variance of the payoff is higher for the suboptimal variant. Furthermore, Lake and Crema (2012) have demonstrated that even if the variances are equal, payoff uncertainty can result in copy-the-best learning failing to identify a superior trait if it is rare simply because the rarer the superior trait is, the more likely that at least one model possessing the inferior trait will have obtained a higher payoff. It turns out that this sampling effect reduces the optimal amount of payoff-biased copy-the-best social learning when there is payoff uncertainty because it causes the early loss of innovations, although Lake and Crema go on to suggest (but did not formally explore) that this effect is also a function of the fraction of the total population of potential models that is actually sampled (the size of the 'sample pool').

Copy-proportionally serves to mitigate false inferences arising from the ‘lucky’ realisation of improbable payoffs (Schlag 1998), as does copying the best *average payoff* of each cultural variant (as per Baldini 2012; see also Schlag 1999). The latter ‘copy-the-best-average’ algorithm is not affected by the difference in payoff variance so long as the sampling is truly random such that models with higher payoff are no more likely to be used to evaluate the average payoff of each variant than other models. Although success-biased rules by which learners sample multiple models and then average the payoffs associated with competing traits have the advantage of suppressing false inference from improbable payoffs, Baldini (2012) has demonstrated that - perhaps counter-intuitively - they are also biased towards rare traits, with the effect that they can perform less well than unbiased learning when the optimal trait is common. Baldini observes that the bias towards rare traits is a consequence of the fact that by considering the average payoff of each variant, the choice between them is effectively made on the basis of only one observation per variant. Thus, for example, if trait A is twice as frequent as trait B, but both have the same payoff distributions, then the probability of choosing between them on the basis of their average payoffs is nevertheless close to 0.5; consequently, the rarer trait B will be chosen with greater probability than its frequency, so altering the trait distribution in favour of the rarer trait.

*1.4. The effect of population size*

The effect of population size on cultural evolution resulting from payoff / success-bias has been formally modelled in several studies (Henrich 2004; Powell et al 2009, 2010; Shennan 2001), with the general conclusion that larger populations promote cultural evolution by accelerating adaptive change and/or permitting the spread of more complex (harder to learn) cultural traits. A recent social learning experiment by Derex et al (2013) claims to provide empirical support for the positive effect on cultural evolution of increasing group size, although Andersson and Read (2014) have disputed this, pointing out that the experimental result that larger groups produced complex artefacts more frequently than smaller groups could simply be a sampling effect.

Shennan (2001) presented two models of the innovation and spread of fitness enhancing craft skills in different size populations. In both cases he modelled the fitness of an individual as the multiplicative sum of the states of each of a fixed number of craft attributes possessed by that individual. The states of these individual craft attributes could be altered by innovation, such that most innovations have relatively little effect but some have a significant effect (ibid. p6-7). In the first model craft attributes are passed vertically from parent to offspring, so that change in the frequency of any given attribute state is a function of the differential reproduction of the individuals who possess it and whose fitness is partially dependent upon it. The second model added oblique cultural transmission such that individuals probabalistically either aquire attribute states from their same sex parent or from a pool of *k* randomly chosen cultural models. If *k* = 1 social learning is effectively unbiased transmission, but if *k* > 1 the individual copies the most attractive individual among the *k* models, thus introducing a copy-the-best learning rule, albeit one that does not appear to include any evaluation of whether the model is actually better than the individual who is copying. This cultural transmission process occurs on a per-attribute basis, such that the most attractive individual among the *k* models is chosen with respect to the trait in question (ibid. p10). Using what he considered realistic parameters for hunter-gatherers, Shennan found that increasing the population size increased the long-term geometric mean fitness of the population, with the effect most pronounced for smaller sizes and less so for larger population sizes; this was true for both models. The effect of oblique transmission was to increase the absolute geometric mean fitness for any given population size (at least at the innovation rate for which explicit comparison is provided), but the positive effect of increasing population size decreases as the rate of oblique transmission is increased (ibid. fig 3).

Shennan’s broad conclusion about the positive correlation between population size and cultural evolution was supported by Henrich’s (2004) model of the social learning of skills. Henrich modelled oblique transmission of skills in which individuals attempt to copy a skill from the most skilful individual in the population, in other words, using a copy-the-best social learning rule. He also analysed a variant which incorporated a fraction of vertical transmission, but this produced the same qualitative results. Importantly, and central to the claim that his model is “rooted in the cognitive details of social learning and inference” (ibid: 197), Henrich's model uses the Price equation, thereby explicitly incorporating the effects of both cultural selection and errors in social learning. In particular, he modelled the latter by drawing the skill-level achieved by the learner from a Gumbel distribution, such that the copied skill level is most likely to be lower than the model’s skill, but that there is nevertheless some non-zero probability of it being higher; in other words, Henrich assumed that social learning is mostly imperfect, but occasionally gives rise to improvements. By varying the mode, α, and dispersion, β, of the Gumbel distribution, Henrich was able to separately parameterise the difficulty of learning a particular skill (its complexity) and the likelihood that those attempting to copy it make similar or potentially very different errors (in a sense ease or difficulty of innovating). Henrich analysed the size of the population required for the change in average skill to be positive, that is, for there to be "cumulative adaptive cultural evolution" (ibid: 202), and found that it depends on the ratio between the difficulty of learning and ease of innovating. Skills that are more complex (large α) and/or more difficult to innovate (low β) are only be maintained or cumulatively improved in larger populations.

Shennan and Heinrich’s seminal contributions to understanding the importance of population size for cultural evolution have since been extended by Powell et al (2009, 2010). Powell et al were motivated by the same anthropological problem that initially motivated Shennan’s 2001 model, the so-called ‘explosion’ of cultural complexity at the European Middle-Upper Palaeolithic Transition. In order to explore the plausibility of demographic change as a prime driver of this transition, Powell et al (2009) re-implemented Henrich’s 2004 model, albeit with three changes. First, and of least significance for our purposes, they simplified the treatment of errors in social learning by collapsing α and β into one parameter. Second, they eschewed Henrich's simple oblique transmission model with one which they claim better captures a more realistic assumption that "cultural skills and behaviours are often first, and sometimes only, learned from parents" and also that "identification of the most skilled model will be inaccurate" (Powell et al 2009: supplementary material). This entails "vertical" unbiased copying of skills from individuals in the previous generation followed by "oblique" biased copying from individuals in the same generation (ibid.). The bias in the 'oblique' copying results from a social learning rule in which each individual attempts to copy a skill from among those models who have a higher skill-level than that which it inherited from the previous generation. The chosen model is selected probabilistically in proportion to the magnitude of the difference its skill-level and that of the learner. Third, Powell et al added spatial structure to the population by dividing it into G groups, each of size N, placed in an environment. Individuals can migrate between groups at a rate which is a function of the density, D, with which the groups are placed in the environment. Powell et al found that increasing the overall population size (a function of G, since N is fixed) does promote increased skill complexity, but the effect is most pronounced for smaller population sizes and is much diminished or even non-existent for larger populations sizes (ibid:fig. S2). In the latter case (G > 50) the principal determinant of population average skill-level is the amount of migratory activity. Experiments with a fixed and large number of groups demonstrated that the positive effect of increased inter-group migration on skill-level is greater for more complex skills, in the sense that as skills become harder to learn so increasing the migration rate has an effect that is the equivalent of greatly increasing the size of a single unstructured population. Although Vaesen (2012) has argued that the assumptions made by Powell et al mean that their model does not provide a sufficiently severe test of their substantive hypothesis, their results do nevertheless extend the set of specific learning rules for which it appears that there is a positive correlation between increasing population size and the rate at which payoff / success-biased social learning can drive cultural evolution. Furthermore, their study also points to the importance of population structure for this relationship.

*1.5. Combining payoff uncertainty and sampling effects*

We suggested above that payoff uncertainty potentially affects any form of social learning that makes use of a payoff-signal to evaluate the worth of a cultural trait, whether that is content-biased social learning such as payoff-biased learning or context-biased social learning such as success or prestige-biased learning. In all these cases a simple stochastic model of payoff can be used to capture the fundamental structural issue, which is the strength of the correlation between the observed payoff signal and the true ‘worth’ of the trait. As we have discussed, several studies employing such a model have demonstrated that payoff bias significantly affects the optimal amount of social learning in a range of different scenarios. Moreover, it is also now clear that the exact form of the social learning rule matters: copy-the-best can lead to false inferences when payoff uncertainty is high, whereas copy-the-best-average payoff is more robust, but on the other hand favours rare variants.

We have also documented how a separate strand of theoretical modelling has demonstrated that population size and/or structuremediates the effect of payoff / success-biased learning, and this appears to be true for both copy-the-best and proportional copying rules. Deleterious sampling effects caused by small population sizes are predicted to reduce the rate of adaptive cultural evolution and even lead to cultural trait loss. Larger populations, on the other hand, are predicted to support the social-learning of more complex traits even when the learning process is error prone, and increasing the migration rate in populations broken into subgroups also has this effect.It has recently been noted, however, that empirical studies do not unambiguously support these theoretical insights (Collard 2013). There are various possible reasons for this, ranging from the effect of population size being swamped by other factors, to the empirical studies not adequately measuring the interacting as opposed to total (census) population. The possibility that particularly interests us here is that existing models of the effect of population size/structure on cultural evolution do not adequately take account of the effect of payoff uncertainty on social learning. This is particularly problematic if Caldwell et al (2014) are correct in their supposition that social learning of human technology invariably involves payoff uncertainty because of the spatio-temporal separation of tool manufacture from tool use.

While it is clear from existing studies that both payoff uncertainty and population size/structure alter the effect of social learning on cultural evolution, it is striking that all the models reviewed above incorporate one or the other, but not both, so their interaction has not been fully explored[[1]](#footnote-2). Furthermore, in our discussion above we noted studies (Baldini 2012; Lake and Crema 2012) which provide reason to think that when payoff is uncertain the efficacy of particular forms of social learning can also be affected by the relative frequency with which a ‘better’ trait is present in a population. In particular, we have previously demonstrated that a rare better trait can be lost as a result of payoff uncertainty because of a sampling effect in which if enough models with the more common inferior trait are sampled it becomes probable that one of them will have a rare high payoff that is greater than the highest payoff exhibited among the smaller sample of models with the rare but better trait. This effect suggests to us a mechanism which could reduce the benefit of larger population sizes, or of higher migration rates between subgroups, especially when the better trait is rare, as would be the case in the earliest stages of the diffusion of an innovation. In section 2 of this paper we describe a model designed to explore exactly that possibility and in section 3 we present results which confirm that there are indeed scenarios in which certain payoff / success-biased social learning rules are predicted to produce faster rates of cultural evolution in smaller rather than larger populations. Moreover, it seems that smaller communities within populations can act as initial “cultural incubators” which promote the early survival of beneficial innovations, and we note the far-reaching significance of this in our concluding comments in section 4.

**2. Modelling cultural transmission with uncertain payoff signals**

We first describe a model of the cultural transmission of discrete traits whose payoff is variable, such that individuals have imperfect knowledge of the true worth of traits possessed by others in the population. Three variants of this model differ according to the learning rule employed, which is one of: random copying (unbiassed transmission), copy-if-better and copy-the-best. We provide a commentary on aspects of the model and then go on to outline our experimental design.

2.1. *The model*

Consider a population of *N* individuals, each possessing a cultural trait *g* represented by an integer, and a payoff signal *p* that varies at each time-step and is a function of *g*. We assume that neither *g* nor *p* affects the reproductive fitness of the agents (i.e. *N* is held constant), and that transmission occurs synchronically rather than sequentially (i.e. transmission is inter-generational). At each discrete time-step, *t*, all individuals undertake thefollowing:

1. *Expression of the payoff-signal*: a payoff signal *pi*is emitted by each individual as a random draw from a normal distribution with mean *gi* and standard deviation *σ*. We assume that *σ* is equivalent for all values of *g*.
2. *Social learning*: With some probability *z*, each individual, *i*, engages in social learning which may result in it copying a trait from a model chosen from among *k* individuals who comprise the sample pool, *Si*. The choice of model and decision whether to adopt the model's trait is governed by one of three learning rules (all individuals use the same learning rule in any given experiment):

* 1. *Unbiased transmission* (UB).The focal individual, *i*, randomly selects a model, *j*, from the sample pool and adopts that model's trait irrespective of its properties or payoff.
  2. *Copy*-if-better (CIB). The focal individual, *i*, randomly selects a model, *j*, from the sample pool. It then compares its own payoff, *pi* with the model's payoff, *pj*, and adopts the model's trait only if *pj > pi*.
  3. *Copy-the-best* (CB). The focal individual selects the model, *m*, with the highest payoff, *pm,* among the *k* individuals in the sample pool *Si*. The focal individual subsequently compares its own payoff, *pi*, with that of the model and if *pi* < *pm*, it copies the cultural trait *gm* of the model.

1. *Innovation.* For the sake of simplicity we assume that all innovations are beneficial and incremental. Innovation occurs with frequency *μ* and consists of an update of cultural trait *gi* by an amount *b* so that at time *t*, *gi*(*t*) = *gi*(*t-1*) + *b*. Note that we allow for convergence, so two agents can, with probability *μ2*, independently reach the same *g(t)*if they had also the same *g(t-1).*

As discussed in section 1, the stochasticity of the payoff signal (*σ*) is a direct proxy for the correlation between *g* and *p*. When *σ*=0, there is no uncertainty in the payoff, and agents are assumed to be capable of fully isolating the adaptive performance of a given cultural trait, and hence can correctly identify whether a variant is 'better' or the ‘best’, depending on the social learning rule. With increasing values of *σ*, the correlation declines and consequently traits that are less beneficial can potentially be associated with a payoff signal that is higher than that associated with other more beneficial traits.

*Unbiased transmission* provides a benchmark expectation for a comparative assessment of the two social learning rules that incorporate selection.. *Unbiased transmission* (UB) assumes a copying process in which only the frequencies of the variants determine their probability of adoption (Bentley et al 2004). The *copy-the-best* rule (CB) involves a process of selection (the identification of the individual in the sample pool who has the highest payoff, *p*) and evaluation (comparison between the focal individual and model's payoff signals) prior to copying. Copy-if-better (CIB) offers a compromise between the undirected random copying of unbiased transmission and the strongly directed copy-the-best rule. On the one hand there is no directed selection of the model (which is picked at random from the sample pool), but on the other hand copy-if-better retains the element of evaluation in that the model's trait is adopted only if it has a higher payoff, *p* than the focal individual's current trait. We noted in section 1 that Powell et al (2009), doubting the realism of the copy-the-best rule, implemented a form of copy-if-better social learning in which individuals have an opportunity to copy a better skill with a probabilty proportional to the magnitude of improvement it represents. It could be argued that for Powell et al the probabilistic copying provides a partial implementation of payoff uncertainty, in the sense that higher skill-levels are more likely to be perceived as worth copying, but on the other hand, it does not ultimately capture the uncertainty about which models have higher skills. Our version of copy-if-better allows payoff uncertainty to dictate the accuracy of inference about which models have higher skills and is more weakly directed than Powell et als' rule, but on the other hand should be less susceptible to false inference from rare payoffs than both their rule and the copy-the-best rule.

An important element in our model is the parameter *k*, the number of individuals in the sample pool. This allows us to relax the assumption that social learning is unconstrained by physical or cognitive constraints (i.e. that cultural transmission is panmictic) since implies that the sampling capacity of the focal individual is finite, perhaps as a function of cognitive capacity (cf. Dunbar 1993), or the result of cultural isolation caused by distance (cf. Premo and Scholnick 2011). Both Shennan (2001, second model only) and Lake and Crema (2012) parameterised the size of the sample pool, but neither subjected it to systematic exploration and Shennan was not, in any case, concerned with the effect of payoff uncertainty. Powell et als' (2009) use of discrete groups (subpopulations) connected by migration is analogous to specifying finite sample pools with non-identical but partially overlapping membership, but again, they were not explicitly concerned with the relationship between sample pool size and payoff uncertainty. The parameter *k* can be loosely interpreted of as the size of the strongly interacting social clique who learn from one-another, which potentially varies from the entire population of size *N*, to diads comprising just 2 individuals; however, in our formalisation we always exclude the focal individual (the one who is learning) from the sample pool, so *k* can take values from *N-*1 to 1. In this way our model assumes that the focal individual never attempts to copy from itself, although it can subsequently evaluate a candidate trait against its own trait (in copy-the-best and copy-if-better social learning). Consequently, model selection and evaluation (the decision to adopt a candidate trait) are explicitly treated as separate parts of the social learning process.

*2.2 Experimental design*

In this paper we present the results of two experiments. The first explores how different values of *σ* (uncertainty in the payoff signal), *k* (the size of the sample pool) and the social learning rule interact to affect the earliest stage of beneficial innovation. Our specific concern is to establish the probability that a rare beneficial innovation is lost from the total population, *N*, as a result of sampling effects. We achieve this by assuming that there is one innovator who has a superior trait and that all other individuals in the population share an inferior trait (with lower *g* and therefore lower mean *p*). For simplicity we assume that the innovation and the existing trait both have the same payoff variance, *σ*. In this first experiment we are not concerned with population structure, so in all cases *N* = *k* + 1. In other words, the sample pool is simply the entire population minus the focal individual, and thus by altering *k* we are effectively altering the population size. In this way the results can be compared with those obtained by Shennan (2001) and Henrich (2004)[[2]](#footnote-3).

The second experiment focuses on different values of *σ* (uncertainty in the payoff signal), *k* (the size of the sample pool) and the social learning rule interact to determine the long-term rate of cultural evolution. The latter is measured as the median value of *g* after a pre-defined number of time-steps. In other words, we seek to identify conditions where, holding constant the rates of innovation (*μ*) and the amount of improvement (*b*), we see the fastest spread of beneficial cultural traits. Furthermore, in this case we abandon the assumption of panmixia and instead explore the effect of population structure. We achieve this by implementing the model as a simple agent-based simulation in which we randoml place the agents in a bounded space and define the sample pool of each focal agent as its *k* nearest-neighbours. Thus, when *k* < *N* - 1 we model some degree of isolation by distance whereas when *k = N* - 1 we model a panmictic population. Note that modelling the membership of the sample pool as a fixed number of neighbours (rather than, say, those falling within some euclidean search radius) guarantees a fixed size sample pool per agent and, importantly for interpretation of *N*, that there are no completely isolated population subgroups. Since in this experiment we hold the total population, *N*, constant and vary *k*, we are no longer modelling the effect of population size *per se*, but rather the completeness which the population is sampled. In that regard this second experiment is closer to some of the experiments conducted by Powell et al (2009) than it is to the earlier studies of Shennan (2001) and Henrich (2004), although of course it is different in its very explicit treatment of payoff uncertainty.

[Table 1]

**3. Results**

*3.1. Experiment 1: Loss of a beneficial innovation*

When the mode of social learning is unbiased we can calculate the probability of the population loosing the innovation, <pbloss>, as follows. First, recall that we assume that one individual has innovated a better trait, B, and all other *N*-1 individuals possess an inferior trait, A. Recall also that we fix k = *N*-1, which means that individuals do not copy themselves. The probability that the population looses B is the product of the probability, <pilb>, that the innovator looses B by copying A and the probability, <poncb>, that none of the other *N*-1 individuals copies B from the innovator. Considering each in turn:

<pilb>=*z*, because the innovator will always loose B if it engages in unbiased social learning as all other individuals from which it can learn have trait A;

<poncb>=(1-*z*/*k*)*k*, because the the probability of any one of the *N*=*k*-1 individuals who are not the innovator copying trait B is 1-*z*/*k.*

It follows that <pbloss>= *z*(1*-z/k*)*k.*

This solution does not, however, allow for the possibility that each of the individuals who has trait A might gain B, not by copying it from the innovator, but by convergent innovation of its own. Although this possibility might be remote (but perhaps less so for simpler traits), we take a conservative stance by incorporating it: if the innovation is lost even with the possibility of convergence then the probability of loosing it without convergence would be even higher. Assuming that copying trait B and independently innovating it are not mutually exclusive possibilities and that the probability of convergent innovation is *c*, then by the law of addition, the probability of any one individual who is not the original innovator acquiring the trait B is: *z*/*k*+*c*-c*z*/*k*.

Substituting this revised formulation back into our original solution we find the probability of trait B being lost from the entire population to be:

<pbloss>= *z*(1*-z/k+c-cz*/*k*)*k*

Copy-with-payoff-weighted-frequency additionally takes account of the payoff signal, and hence can be considered a weighted version of unbiased learning. In this case the expected probability of losing an innovation is equal to 1-*zgi*/(*gi+kgk*), where *gi* and *gk* are equivalent to the average payoff signal of the focal agent and the pool of teachers respectively. When *gi*=*gk* we obtain the same result as unbiased learning, as only the frequency of a given variant determines the probability of its adoption.

We solve the probability of innovation loss during copy-the-best social learning by simulating the expected probability that a random draw with mean *gi is* smaller than the highest value from *k* random draws from a normal distribution with mean *gk,* assuming that the payoff variance is fixed and equal[[3]](#footnote-5) to *σ*. We explore this probability by holding the difference *gi* – *gk* to unit, and sweeping *σ* (from 0 to 3 with an increment of 0.02) and *k* (1 to 150 with an increment of 1). For each of the resulting 22,500 parameter combinations we run 12,500 simulations, and compute the proportion of runs where the condition *pi*<max(*pk*) is satisfied. The results (fig.1) show how an increasing stochasticity in the payoff-signal of cultural traits (*σ*) and a larger sample pool (*k*) are strongly detrimental to the survival of the beneficial trait as a consequence of the sampling bias.

[Figure 1]

A comparison of the three kinds of social-learning shows (fig.2) that when σ is small the probability of beneficial trait loss during copy-the-best learning decreases dramatically compared to unbiased learning and learning by copying-with-payoff-weighted-frequency, demonstrating the potential evolutionary advantages of copy-the-best social learning. In all cases, however, high values of k are detrimental to the retention of the novel trait, although the rate by which this negative effect increases is different for each of the different forms of social learning.

[Figure 2]

*3.2. Experiment 2: Spread of innovation over space*

The results of the first scenario suggest that when social learning uses a copy-the-best rule, a decreased correlation between *g* and its corresponding payoff signal *p (i.e.* lager *σ*) can lead to smaller sample pools better supporting the retention of rare, beneficial traits. However, small *k* implies also a smaller chance that a beneficial innovation occurs within the social clique (sample) in the first place. We thus face two contrasting forces: low *k* promotes the retention of beneficial innovations, but decreases the probability of detecting such innovations; high *k* increases the probability of erroneously selecting suboptimal traits present at higher frequencies, but also increases the probability that a beneficial innovation is present (and thus available to be copied) within the social clique.

We explore the balance between these two contrasting forces in a spatially structured population with a constant density, where *k* becomes the local interaction radius. High values of *k* allow wider interaction, increasing the probability that a sampled model possesses a beneficial mutation, while low values of k produce more localised interaction with a concomitantly lower probability of innovation loss. We use Latin hypercube sampling (McKay et al 1979) to ensure uniform coverage of a parameter space comprising 50,000 unique combinations, with *σ* bounded between 0 and 3, *k* between 1 and 300, and fixing *N* to 1,000, *b* and *z* to unit, and *μ* to 0.005. Figure 3 shows the relationship between the final median cultural trait and the size of the sample pool/interaction radius (*k*)for different ranges of *σ*.When *σ* is close to zero (that is when the correlation between the payoff signal and the underlying trait is high), panmixiapromotes the immediate diffusion of beneficial traits over larger distance. However, with increasing values of *σ*, the beneficial effect of a larger interaction radius is counterbalanced by the increasingly detrimental role of sampling bias, effectively shifting the optimal range of *k* to increasing smaller values (fig.4).

[Figure 3]

[Figure 4]

The results shown in figures 3 and 4 clearly indicate the detrimental effect of sampling bias with large k and the positive effect of isolation by distance. We further explore this scenario by allowing agents to engage in different amounts of social learning, which we achieve by sampling values of z in the range 0 to 1. Elsewhere (Lake and Crema 2012) we have noted that lower values of z can be beneficial when the payoff variance is high, essentially showing an effect that is very similar to that of k. Figure 5 illustrates the joined effect of k and z for the three forms of cultural transmission. Once again, unbiased social learning and copying-with-payoff-weighted-frequency exhibit no variation in the median cultural trait as a function of σ and k, although higher values of z appear to promote a higher rate of cultural evolution for the latter form of social learning. Social learning by copying-the-best produces a rather different result in which the median cultural trait declines sharply with increasingly high values of σ, and switches from higher to lower values of k around σ=0.6. The effect of z and its symmetric relationship with k is more complex. When σ < 0.5, the best option is to have a high frequency of social learning with the largest number of potential teachers. On the other hand, when σ is high (2.5<σ<3), the best combination is mid-high z/low k. When k is high, however, low z becomes beneficial as an alternative route for retaining beneficial innovation (see also fig.6).

[Figure 5]

**4. Discussion and conclusion**

Beneficial traits often fail to spread through a population as a result of key events occurring at the earliest stage of adoption. The decision making of early adopters can potentially drive long-term evolutionary trajectories, often leading to the permanence of suboptimal traits and the loss of more beneficial ones. This is particularly likely to occur when it is difficult to measure the value of each variant and, consequently, the comparative advantage of a novel trait is hard to evaluate (Rogers 2003). The increased learning costs of cumulative knowledge (Mesoudi 2011), a decreased investment in individual learning (Whitehead and Richerson 2009), and early chance events (Greve and Seidel 2014) can all lead to the retention of suboptimal traits and slow-down in the rate of cultural evolution. Here we suggest that a social learning strategy centred on the imitation of a smaller subset of highly visible, successful individuals (the ‘best’) can also generate a decrease in the rate of cultural evolution. The dynamics we demonstrate closely resemble what economists refer to as *survivorship bias* (Elton et al. 1996), a particular form of sampling bias where only highly positive payoff signals of a given behaviour are considered, hindering the correct evaluation of the full spectrum of a cultural trait. Indeed, our simulation experiments show that when payoff is highly uncertain and the sample pool of potential cultural models is larger there is bias favouring the retention of suboptimal traits present at higher frequency. As a direct consequence, since novel variants will always initially have a lower frequency, there is an intrinsic advantage for traits that are common and whose value is measured via payoff signals that have high variance.

The shape of the payoff distribution we examined here assumes an additive interaction of its generative constituents (i.e. the target trait and everything else contributing to the payoff signal), but a multiplicative interaction yielding a skewed distribution (Limpert et al 2001) is also possible. In this scenario the correlation between the target traits and its payoff signal would be reduced and the association between the two even harder to disentangle. Although there are good reasons to believe that in many behavioural domains the payoff signal is normally distributed (Frank 2009), some empirical data on prestige and success do indeed show a positively skewed distribution, for example income (Drăgulescu and Yakovenko 2001) and number of academic citations (Gupta et al 2005). We suspect that such asymmetric and right-tailed payoff distributions would further strengthen the effect of survivorship bias, promoting the retention of suboptimal traits even more frequently than already observed with our model based on normally distributed payoffs.

The most important implication of our results is that smaller, but not too small, social cliques can, perhaps counter-intuitively, promote the survival and spread of beneficial variants. Previous studies (Shennan 2001; Henrich 2004) have demonstrated that drift and low fidelity social learning can increase the accidental disappearance of existing beneficial traits and the retention of suboptimal variants in very small populations, but here we have shown that a large population size can also be detrimental to the rate of cultural evolution. Our results demonstrate that when payoff is uncertain, the relationship between population size and the rate of cultural evolution is no longer monotonic, but favours social cliques of intermediate size. This result is broadly consistent with recent network analysis (Montanari and Saberi 2010) which found that innovations spread faster in locally connected networks rather than larger well-integrated social infrastructures.

It is worth noting, however, that although the detrimental effect of increasing *k* is striking, the rate of cultural evolution for *copy-the-best* social learning is still comparatively higher than either pure *unbiased* social learning or its *payoff-weighted* variant. This advantage is only eroded at the largest values of *k* that we explored, when the rate of cultural evolution driven by copy-the-best social learning became almost indistinguishable from that driven by *copying-with-payoff-weighted- frequency*. Empirical values of *k* are difficult to estimate, although we might expect that for most part of human history it was comparatively small and close to our cognitive limits on the maintenance of stable social relationships (ca 150, Dunbar 1993). Consequently, for much of human history, *copy-the-best* social learning might have been more effective than other social learning strategies even despite the non-monotonic relationship with population size. However, the situation might be different today, since the exponential development of information technology over the last 50 years has greatly increased the pool of potential social models, quite possibly creating scenarios beyond those we modelled here. Any concomitant slow-down in cultural evolution would not be visible in absolute terms (since the rate of cultural evolution would be still increasing given the larger *N*), but we would expect the effect of survivorship bias to become stronger, and the advantage of a social learning strategy restricted to the identification of few successful individuals to greatly decrease relative to alternative social learning strategies.

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**Tables**

Table 1: Model parameters and values used in the two experiments.

|  |  |  |  |
| --- | --- | --- | --- |
| **Symbols** | **Description** | **Experiment 1** | **Experiment 2** |
| *N* | Number of agents | 2-151 | 1,000 |
| *gi*(t) | Cultural trait of the agent *i* at time-step *t.* | - | - |
| *pi*(t) | Payoff signal of the agent *i* at time-step *t.* | - | - |
| *σ* | Uncertainty of the payoff signal. | 0-3, by 0.02 | 0-3 |
| *z* | Frequency of social learning. | 1 | 1, 0-1 |
| *k* | Size of the sample pool of potential model agents. | 1-150 | 1-300 |
| *μ* | Innovation rate. | - | 0.005 |
| *b* | Amount of beneficial innovation. | 1 | 1 |

**Figure Captions**

Figure 1: Probability of beneficial innovation loss as a function of payoff-signal uncertainty (σ) and the observed number of potential social teachers (k).

Figure 2: Probability of beneficial innovation loss for different forms of social learning as a function of k.

Figure 3: Relationship between k and median g for different ranges of σ (yellow=unbiased transmission; blue=copy-with-payoff-weighted-frequency; red=copy-the-best; darker colours for each set indicate higher v within each range)

Figure 4: Optimal range of k (i.e. the 95% confidence interval of k for the top 5% of median cultural trait values) for different intervals of σ (yellow=unbiased transmission; blue=copy-with-payoff-weighted-frequency; red=copy-the-best).

Figure 5: Relationship between k, z, and ḡ for copy-the-best social learning with high payoff-signal uncertainty (2.5<σ<3).

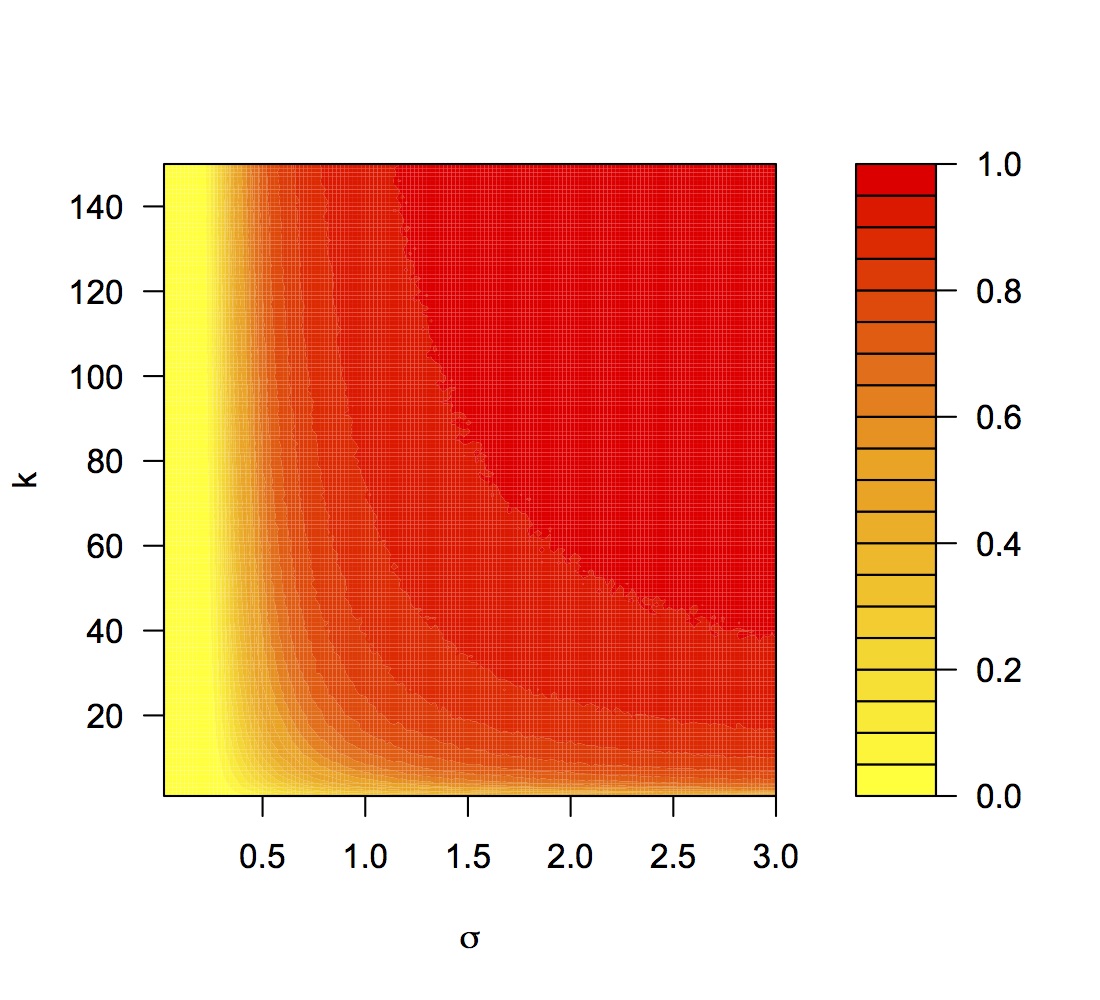
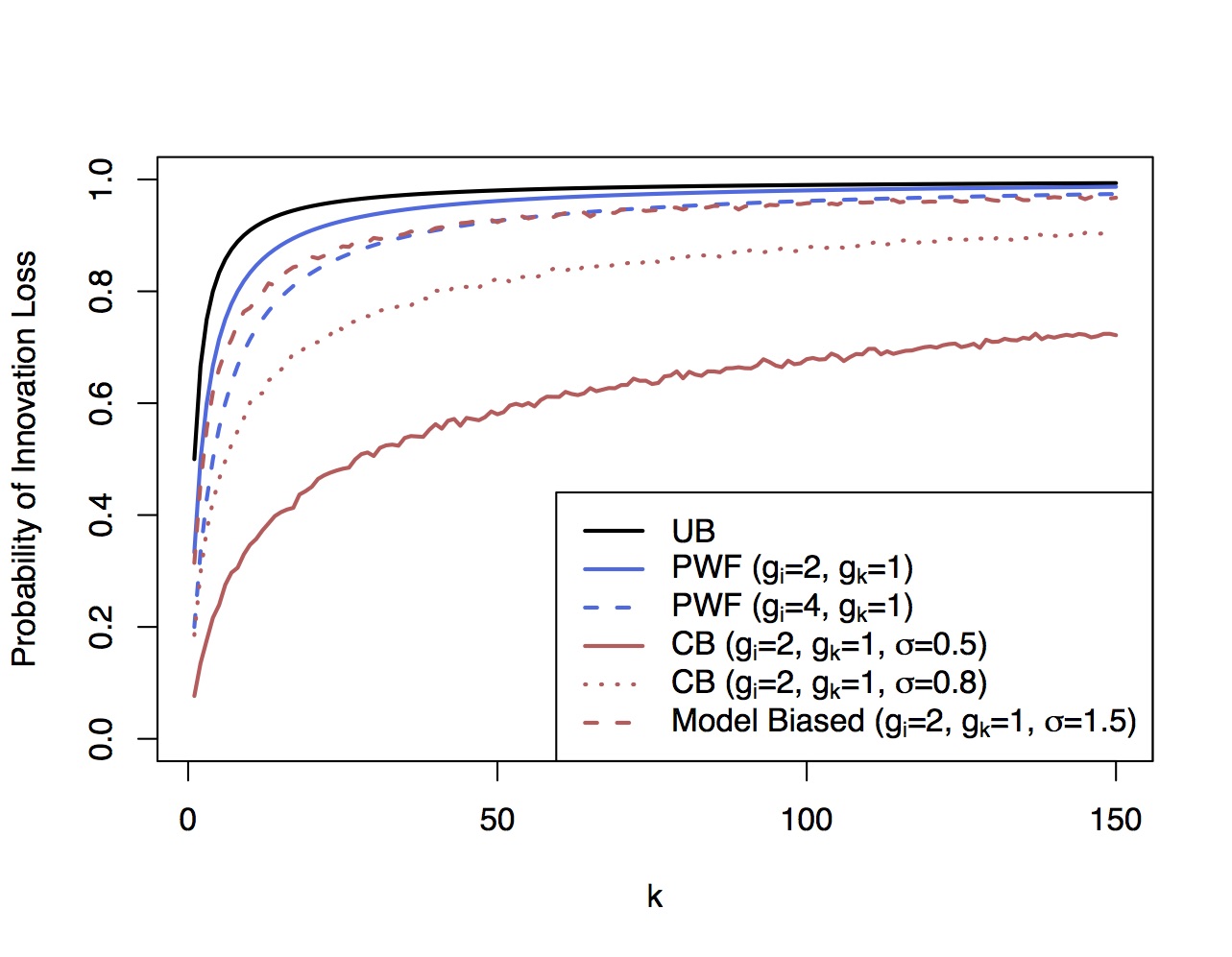


Figure 1

Figure 2

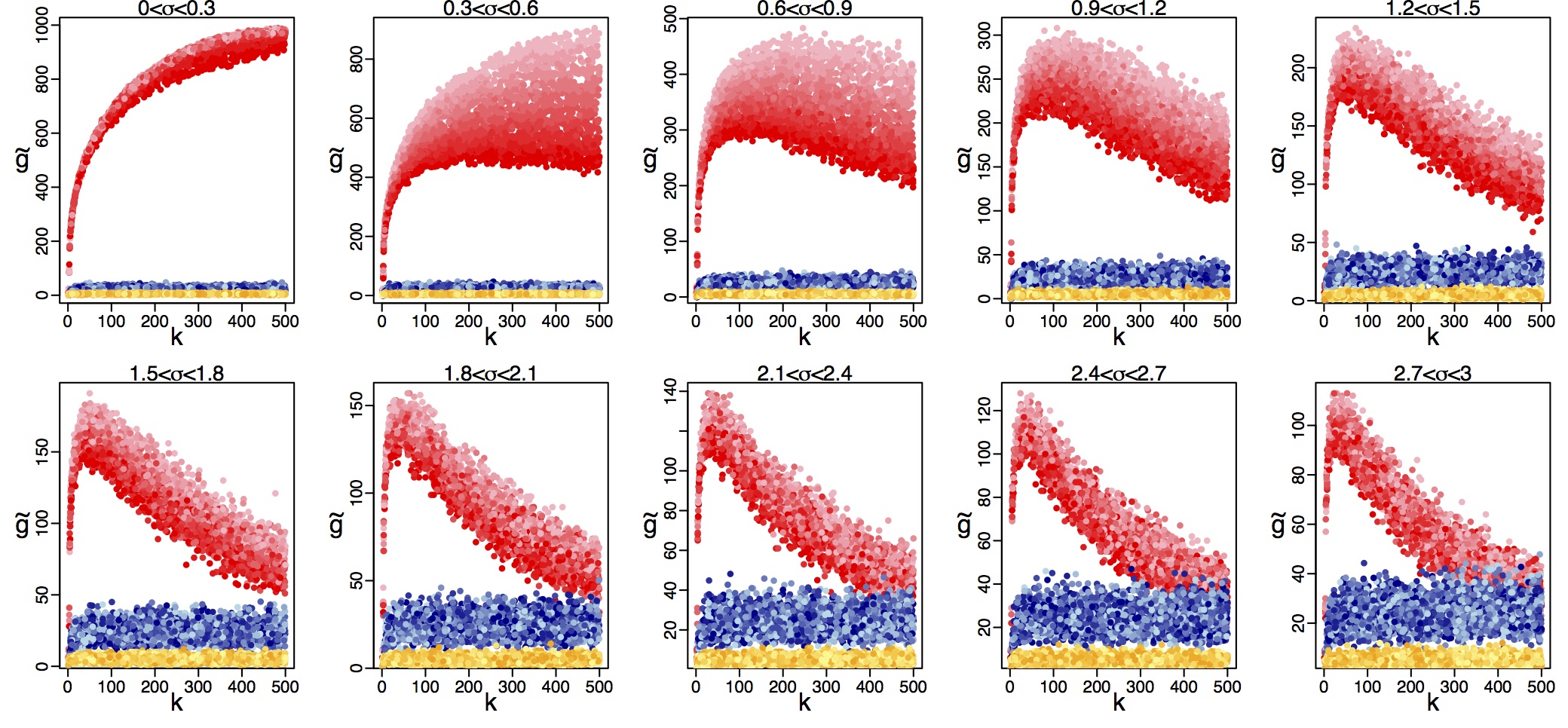


Figure 3

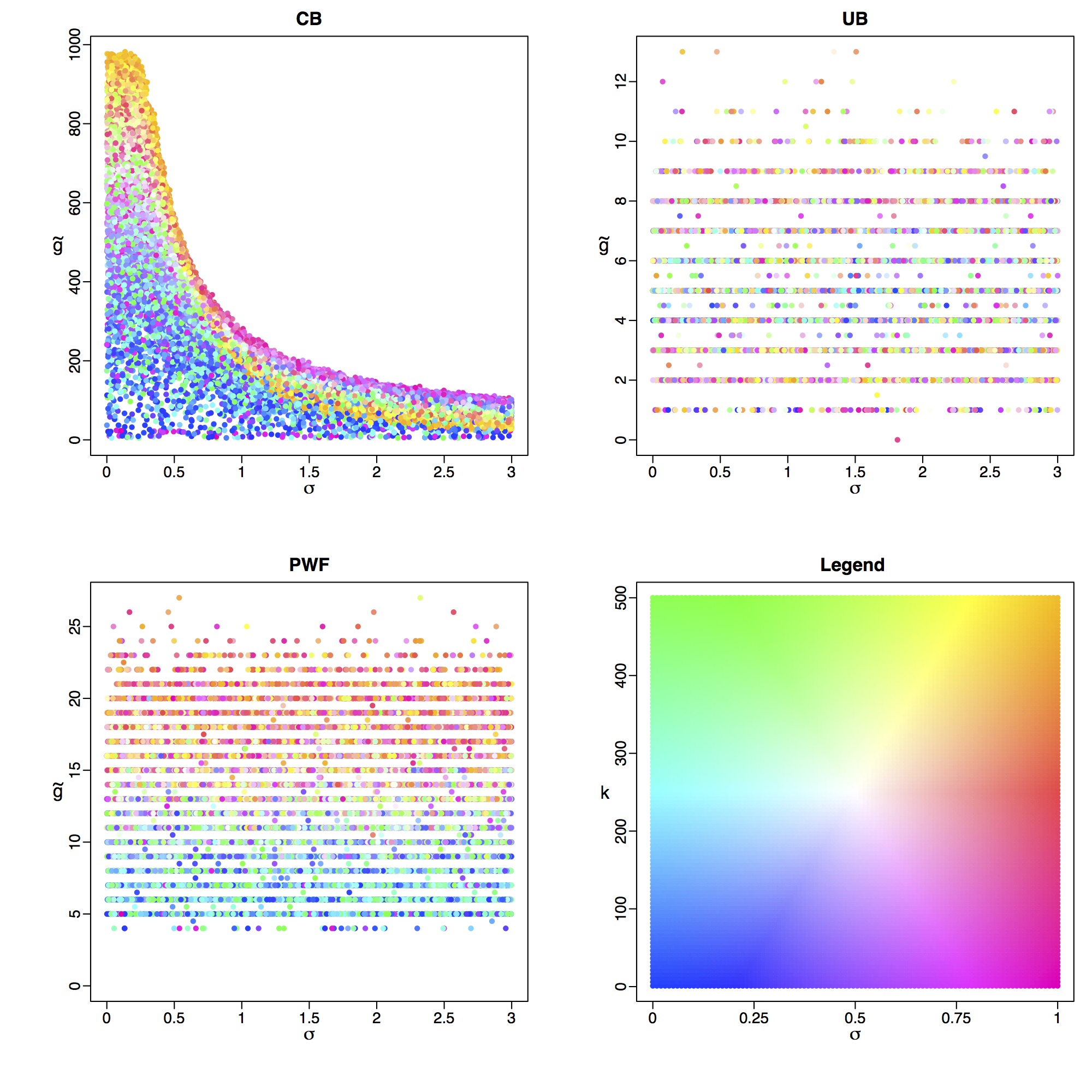
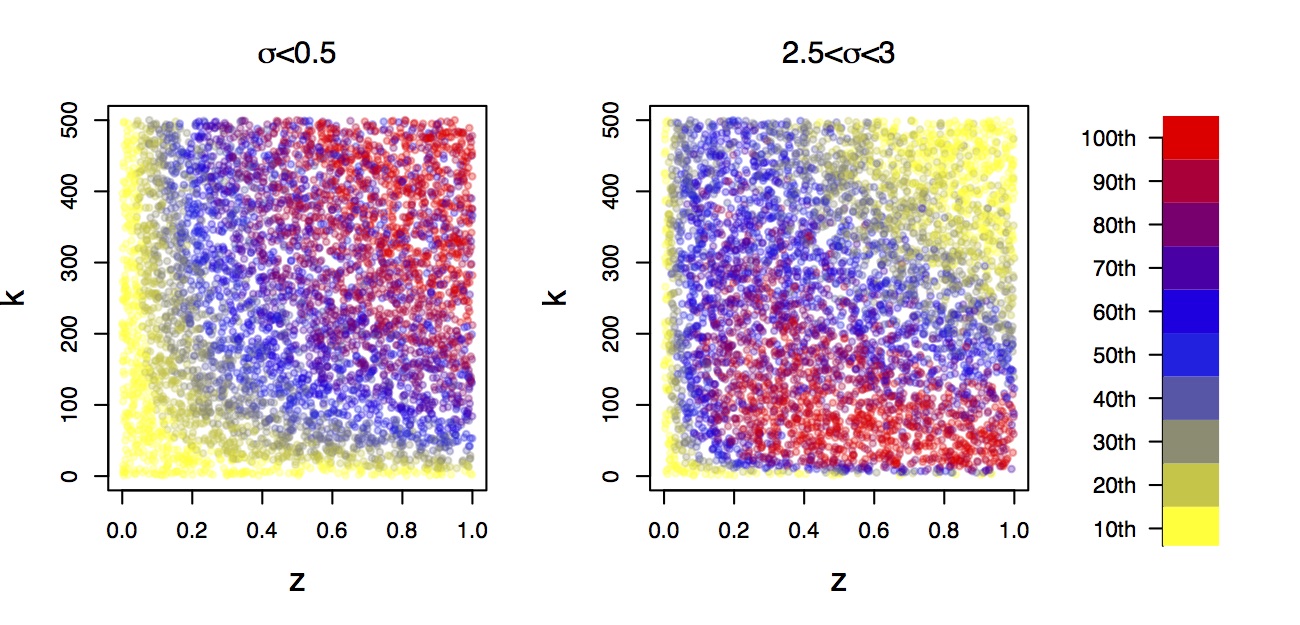


Figure 4

Figure 5

1. Appendix D of Henrich (2004) presents a variant of his model in which selection of the cultural model is based in an indirect cue for the underlying skill, but this is not explored in the body of the paper and, in any case, he was not concerned with population structure. [↑](#footnote-ref-2)
2. Although if one is concerned with absolute numbers it should be noted that both Shennan and Henrich report results for N/4, reflecting their shared assumption that individuals predominantly learn from same-sex parents (Henrich adds a further 20% reduction to reflect the reduced likelihood of learning from the oldest potential models). This is really just scaling for the purposes of anthropological comparison; indeed, although both Shennan and Henrich refer to N/4 as the "effective population" they do not mean that in the technical sense of it being equal to the size of a Fisher-Wright population that would exhibit the same amount of drift. [↑](#footnote-ref-3)
3. Notice that the second distribution is mathematically equivalent to a Gumbel distribution with mean *α* and location *β*, where *α* is the inverse cumulative distribution function of a normal distribution with mean *gk* , standard deviation *σ* and probability *1-1/k* and *β* to the same inverse cumulative distribution function with probability *1-1/ek* minus *α*. [↑](#footnote-ref-5)