



## Regular rates of popular culture change reflect random copying

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### Abstract

Almost by definition, “popular culture” reflects the effects of most people imitating those around them. At the same time, trends and fashions are constantly changing, with future outcomes potentially irrational and nearly impossible to predict. A simple null model, which captures these seemingly conflicting tendencies of conformity and change, involves the random copying of cultural variants between individuals, with occasional innovation. Here, we show that the random-copying model predicts a continual flux of initially obscure new ideas (analogous to mutations) becoming highly popular by chance alone, such that the turnover rate on a list of most popular variants depends on the list size and the amount of innovation but not on population size. We also present evidence for remarkably regular turnover on “pop charts”—including the most popular music, first names, and dog breeds in 20th-century United States—which fits this expectation. By predicting parametric effects on the turnover of popular fashion, the random-copying model provides an additional means of characterizing collective copying behavior in culture evolution.

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### 1. Introduction

As Boyd and Richerson (1985, p. 33) defined over 20 years ago, “culture is information capable of affecting individuals’ phenotypes which they acquire from other conspecifics by teaching or imitation.” Imitation is arguably the simplest form of culture transmission, termed unbiased transmission by Boyd and Richerson, which occurs when each individual acquires his or her behavior simply by copying from another individual within the population. Copying is a predominant human behavior (e.g., Gergely, Bekkering, & Király, 2004; Iacoboni et al., 1999) and is shared among primates (cf. Subiaul, Cantlon, Holloway, & Terrace, 2004). It can, thus, be useful to assume, as a null hypothesis in certain instances of social choice, that people

simply copy each other at random. In cases where choices have intrinsic value with respect to one another, it makes more sense to assume that cost–benefit decisions are made independently, with conformity potentially among the biases in making those decisions (e.g., Boyd & Richerson, 1985, 2005; Gintis, in press; Henrich, 2001, 2004; Henrich & Boyd, 2001; McElreath, Boyd, & Richerson, 2003; Shennan, 2002). This distinction is crucial to the nature of collective human behavior, in anything from voting, to corporate boardrooms, to deciding on a hunting strategy, as copying can tend toward baseless decisions, whereas independent decision making may lead to a rational, collective “wisdom” of a group (Surowiecki, 2004) and/or optimal solutions through a process analogous to natural selection (e.g., Crow & Aoki, 1982a, 1982b, 1984; Henrich, 2004). While there is a fairly large body of literature on group norms that arise as a consequence of identifiable costs and benefits of cultural traits, quantitative models of random copying of *neutral* cultural traits are relatively less well developed (see reviews by Eerkens & Lipo, 2005; Mesoudi, 58

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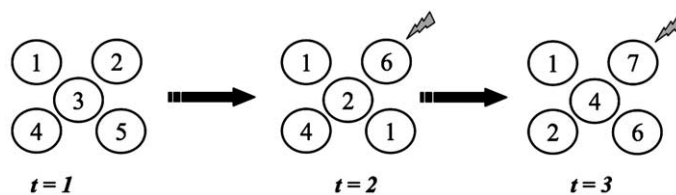


Fig. 1. A simple representation of the neutral-trait model. Shown are five individuals for three successive time steps. At each time step, we refresh the population with new individuals, and each is given a new copy of a variant (represented by numbers inside the circles). Each variant is assigned a new value by either (a) copying a randomly selected individual from the previous time step, with equal probability of choosing any individual, or (b) inventing a new variant (gray lightning bolts) with probability  $\mu$ , the fraction of innovators among the  $N$  individuals.

59 Whiten, & Laland, in press). Here, we focus on a particular  
60 prediction of the random-copying model, not to explain all  
61 human behavior, but to help identify it when it arises and  
62 further characterize the consequences of copying in collec-  
63 tive behavior.

64 As we have shown in previous studies (Hahn & Bentley,  
65 2003; Herzog, Bentley, & Hahn, 2004), a highly useful null  
66 hypothesis for popular culture change can be a process of  
67 random copying between individuals, akin to the process of  
68 random genetic drift in population genetics. With its great  
69 potential for future modification and development, there are  
70 many ways in which the random-copying model, with the  
71 resources of population genetics theory to support and  
72 develop it, can make substantial contributions to social  
73 science. Large-scale shifts in popular preferences (e.g.,  
74 fashions) offer insight into general mechanisms of cultural  
75 change (Lieberman, 2000). Whereas the collective effect of  
76 independent decisions may be a sensible equilibrium,  
77 random copying is unpredictable, with no tendency toward  
78 an optimum. For example, a recent Internet-based socio-  
79 logical experiment (Salganik, Dodds, & Watts, 2006)  
80 demonstrated that popular success in music markets is as  
81 much a matter of social influence as of quality. A model that  
82 has proven surprisingly robust in explaining shifts in tastes  
83 assumes simply that the majority of individuals randomly  
84 copy the choices of others, with occasional innovation  
85 (Bentley, Hahn, & Shennan, 2004). In population genetics, a  
86 formal model of random copying between generations with  
87 mutation is called the neutral model (Kimura & Crow,  
88 1964). While developed to explain genetic variability, the  
89 neutral model has been effectively applied to ecological and  
90 cultural phenomena (e.g., Cavalli-Sforza & Feldman, 1981;  
91 Dunnell, 1978; Hubbell, 2001; Lang & Barlow, 1997; Lipo,  
92 Madsen, Dunnell, & Hunt, 1997; Neiman, 1995). It predicts  
93 that, inevitably, some variants will become highly popular  
94 simply due to imitation, not because they are in some way  
95 “better” than other variants. We have found that the  
96 assumption of random copying provides realistic predictions  
97 of the frequency distribution and change in frequency over  
98 time of such diverse phenomena as Neolithic pottery  
99 decorations (Bentley & Shennan, 2003), baby names (Hahn  
100 & Bentley, 2003), and dog breeds (Herzog et al., 2004).

101 The random-copying model assumes that there are  $N$   
102 individuals, each characterized by a behavioral/stylistic  
103 variant (Fig. 1). At each time step, we refresh the population

115 with  $N$  new individuals, and each is assigned a new variant by  
116 either (a) copying a randomly selected individual from the  
117 previous time step, with equal probability of choosing any  
118 individual, or (b) inventing a new variant with probability  $\mu$ .  
119 In each time step, most of the  $N$  new individuals are copiers,  
120 while a fraction  $\mu$  are innovators (with  $\mu$  being a dimension-  
121 less fraction, not a rate per time—by analogy, if a regular  
122 delivery of  $N$  oranges has 5% rotten oranges each week, the  
123 5% is a fraction, not a rate). The joint product of these two  
124 parameters,  $N\mu$ , provides a population-level measure of  
125 variation. Using this parameter and other results, the neutral  
126 model provides testable predictions concerning the change  
127 over generations in the number and relative frequencies of  
128 different variants (Gillespie, 1998).

129 Computer simulations of the neutral model show that the  
130 distribution of variant popularity levels (frequencies) fol-  
131 lows a power law function for small values of the innovation  
132 fraction  $\mu$ , and we have found that this prediction provides a  
133 fit to the distributions of modern cultural variant frequencies  
134 remarkably well (Bentley et al., 2004; Hahn & Bentley,  
135 2003), which fits the analytical predictions of Ewens (1972).  
136 An additional prediction of the neutral model is that if we  
137 follow a set of variants introduced in the same generation,  
138 the average of their frequencies stays the same over time,  
139 but the disparity (variance) in their frequencies increases  
140 (Hahn & Bentley, 2003). This provides a quantitative  
141 expectation that was used in a case study of registered  
142 purebred dog breeds in the United States (Herzog et al.,  
143 2004) to identify Dalmatians as an exceptional case that  
144 cannot be explained by simple random copying and, thus, to  
145 attribute the sudden popularity increase of Dalmatians to the  
146 rerelease of the Disney movie *101 Dalmatians*.

147 Another implication of the random-copying model is the  
148 consistency of change of variants or fashions. Here, we  
149 show that the random-copying model also predicts a  
150 regularity of turnover among particularly popular variants  
151 (fashions). Modern cultural data are commonly available in  
152 the form of “Top  $y$ ” lists of popularity, which represent the  
153 Top  $y$  highest-frequency variants. Several variables could  
154 affect differential turnover rates, including the length of the  
155 list (e.g., Top 10 vs. Top 40 songs), the rate at which new  
156 variants appear, and the population size. Our goal was to  
157 explore how the turnover rate on a Top  $y$  list, which we refer  
158 to as  $z_y$ , is affected by the length  $y$  of the list, innovation  
159 fraction  $\mu$ , and the population size  $N$ .

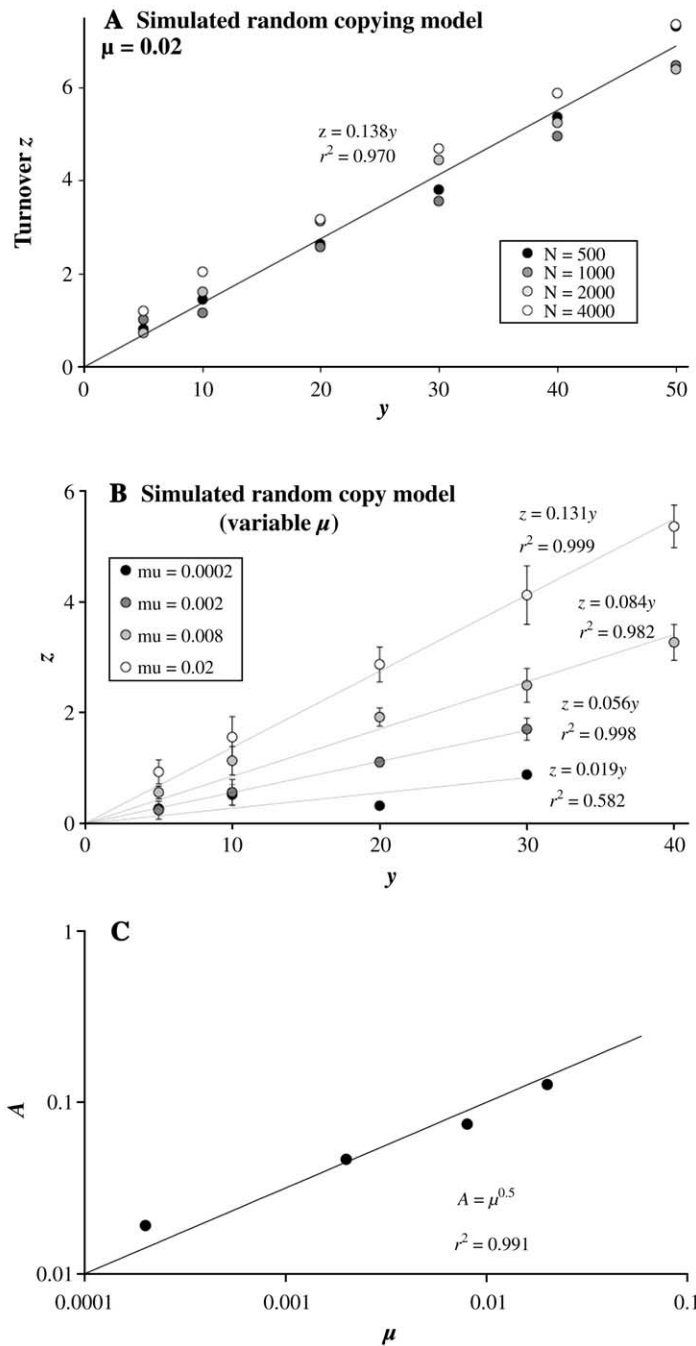


Fig. 2. Computer simulation of the random-copying model, showing the turnover rate  $z_y$  in the list of the Top  $y$  most-frequent variants, as a function of  $y$ . (A) Results for different numbers of individuals  $N$ , with the innovation fraction  $\mu$  constant at 0.02 for all runs. (B) Results, for each value of  $\mu$ , averaged from runs with  $N = 250, 500, 1000$ , and  $2000$  (error bars showing  $\pm 1\sigma$ ). (C) The slope,  $A$ , of each of the correlations in Panel B, versus  $\mu$ .

160 We are not aware of any direct analytical solution to this  
 161 problem since the sample includes only the most-frequent  
 162 variants, which means that we cannot simply assume, as for  
 163 an entire population at equilibrium, that the innovation rate  
 164 balances the loss rate. Our approach, therefore, was to use  
 165 computer simulation (Bentley et al., 2004; Hahn & Bentley,  
 166 2003), by which we run the random-copying model  
 167 using different numbers of individuals,  $N$ , and innovation  
 168 fractions,  $\mu$ . We then compared our simulation results to

real-world data sets involving pop music, baby names, and 216  
 dog breeds in the 20th-century United States. 217

## 2. Methods 218

As described in detail previously (Bentley et al., 2004; 219  
 Hahn & Bentley, 2003), we used a simple computer simu- 220  
 lation of the neutral model written in a Java-based simulation 221  
 package called RePast (v 2.0, <http://repast.sourceforge.net/>). 222

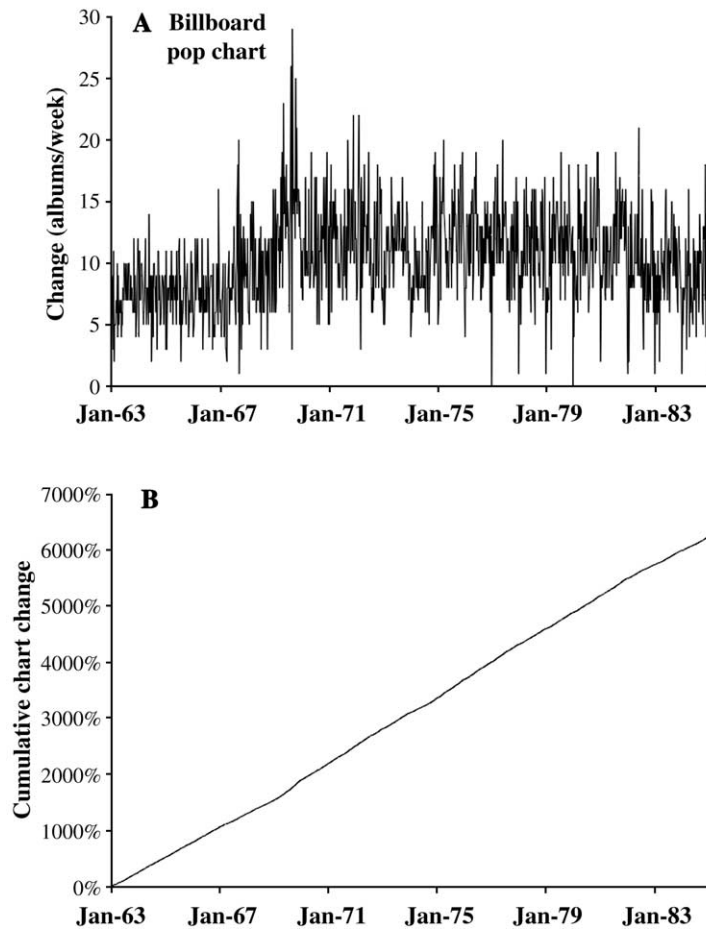


Fig. 3. (A) Weekly turnover on the Billboard Pop Chart, 1963–1985, in terms of the numbers of albums exiting the chart each week. (B) Cumulative change on the Pop Chart, in terms of the fraction of albums on the chart ( $z_y/y$ ) exiting each week. The denominator  $y$  in calculating this fraction was variable, as the chart was expanded from 150 to 200 in mid-1967, and the actual value of  $y$  varies slightly from week to week (due to albums' shared positions on the chart, etc.). The turnover rate averaged 5.6% per week for over 20 years. Adapted from Bentley and Maschner (1999).

223 As represented schematically in Fig. 1, the simulation begins  
 224 with  $I$  individuals that are assigned  $I$  different variants, which  
 225 are then subject to repeated copying and innovation (cf.  
 226 mutation). The simulation records the occurrence of every  
 227 variant to appear in the population throughout the run. At  
 228 every time step, the  $I$  individuals are replaced with  $I$  new  
 229 individuals, the majority of which receives a variant copied  
 230 at random from the previous time step, while the remaining  
 231 minority ( $N\mu$ , where  $\mu$  is the innovation fraction) invents a  
 232 novel variant (“innovation”). After running the simulation for  
 233 250 time steps to reach a quasi-equilibrium state, we  
 234 recorded all the variants present in the population and their  
 235 frequencies, for every other time step until Time Step 300  
 236 (25 total samples). At each sampling point, we recorded all  
 237 the variants present and their frequencies. We then created  
 238 Top  $y$  charts of varying sizes ( $y=5, 10, 20, 30, 40$ ) for each  
 239 of these samples. To determine the turnover rate among  
 240 the Top  $y$  most-frequent variants, we ranked the variants by  
 241 abundance for each sampled interval and then tabulated the  
 242 number of new variants to enter the Top  $y$  chart relative to the  
 243 previously sampled interval.

### 3. Results

279

The simulations all show that, after the transient phase  
 of the first 250 time steps, the turnover rate  $z_y$  of a Top  $y$  list  
 (the number of new variants to enter the Top  $y$  chart relative to  
 the previously sampled interval) finds a steady state, where it  
 fluctuates around a nominal average. In this steady state, as  
 Fig. 2A shows, the average turnover is linearly proportional  
 to the size of the list  $y$  ( $r^2=.970$ ). There is, therefore, a strong  
 dependence of turnover rate on the length  $y$  of the Top  $y$  list.

Our simulation results also showed that under the  
 assumption of random copying, the turnover rate is  
 predicted to be independent of the population size  $N$ , as  
 varying  $N$  from 250 to 2000 in the simulations (Fig. 2A) had  
 no significant effect on the turnover rate ( $r^2=.003$ ). In sum,  
 the average turnover in the simulated random-copying  
 model can be described simply as

$$z_y = Ay, \quad (1)$$

where  $A$  is a constant, such that  $z_y$  is largely independent of  
 $N$ . At the same time, the simulation results show that  $z_y$

296  
297

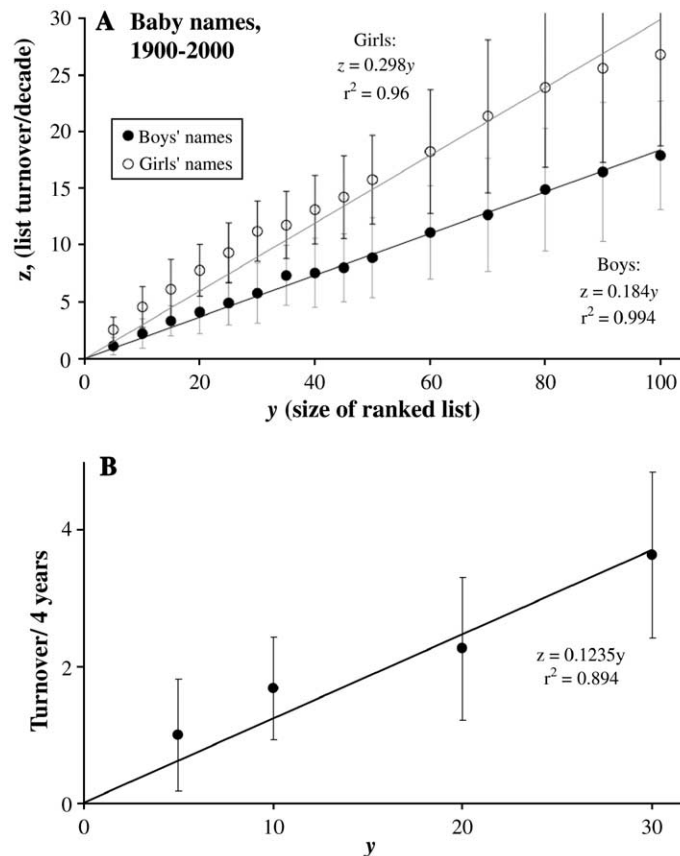


Fig. 4. Turnover rate of Top  $y$  charts, plotted against  $y$ , the size of the list, for (A) boys' names (filled circles) and girl's names (open circles) and for (B) dog breeds. For baby names, the turnover rates are per decade and averaged over the 20th century. For dog breeds, the turnover rates were calculated based on 4-year intervals. Error bars show  $\pm 1\sigma$ .

298 does depend on the innovation fraction  $\mu$  (Fig. 2B). In fact,  
 299 as Fig. 2C shows, the constant  $A$  is simply proportional to  
 300  $\mu$ , with an  $r^2$  of .991 ( $p < .005$ ). Hence, we find the  
 301 simple relation:

$$z_y = y\sqrt{\mu}. \quad (2)$$

302 **303** An example that appears to exhibit characteristics of the  
 305 random-copying model involves the Billboard "Top 200"  
 306 Pop Chart (Bentley & Maschner, 1999; Whitburn, 1985)—  
 307 hereafter, the "Pop Chart"—a mainstream record of popular  
 308 music in the United States. The number of new albums (or,  
 309 equivalently, the number of exiting albums) per week on the  
 310 Pop Chart jumped erratically about a nominal average—  
 311 rather like the "El Farol" problem of how many people visit  
 312 a bar from night to night (Arthur, 1999)—of around 7–  
 313 8 albums per week from 1963 to 1967 when the Pop Chart  
 314 had 150 albums. This average then increased to around 11  
 315 albums per week after 1967, when the Pop Chart was  
 316 expanded to 200 albums (Fig. 3A). The change in the chart  
 317 size brought about a proportional change in the turnover  
 318 rate: when the Pop Chart was made 33% larger (from 150 to  
 319 200), the turnover rate increased by 38% (from about 8 to  
 320 about 11 albums per week).

321 If we assume that a consistent fraction of the population  
 322 are innovators, then we can apply Eq. (1), which predicts

323 that the fraction of Pop Chart turnover  $z_y/y$ , in terms of the  
 324 percentage change in the composition of the Pop Chart per  
 325 week, will be constant. Indeed, the Pop Chart turnover was  
 326 remarkably steady at 5.6% per week for over 20 years  
 327 (Fig. 3B). Unfortunately, we cannot systematically test  
 328 different values of  $y$  because our source (Whitburn, 1985)  
 329 only gives the date each album entered the Pop Chart and  
 330 the date it exited, rather than the position of each album  
 331 week to week. However, as Fig. 3B shows, there is no  
 332 visible change in the fractional turnover rate,  $z_y/y$ , when the  
 333 Pop Chart was expanded from 150 to 200 in mid-1967.  
 334 Given that the population of the United States increased  
 335 almost 70% during this time, from about 150 million  
 336 in 1960 to about 250 million in 1990, and assuming a  
 337 commensurate increase in albums sold, it appears that the  
 338 steady turnover on the Pop Chart was independent of  $N$ , in  
 339 line with the random-copying model.

340 Our next real-world example involves popular baby  
 341 names, as recorded by the U.S. Social Security Adminis-  
 342 tration (<http://www.ssa.gov/OACT/babynames/>) by ranking  
 343 the 1000 most common boys' and girls' names in each  
 344 decade of the 20th century. The rates at which new names  
 345 appeared on the list averaged  $182 \pm 52$  female names and  
 346  $133 \pm 26$  male names per decade. Taking these turnover  
 347 values as measures of  $z_y$ , we find the turnover rate for

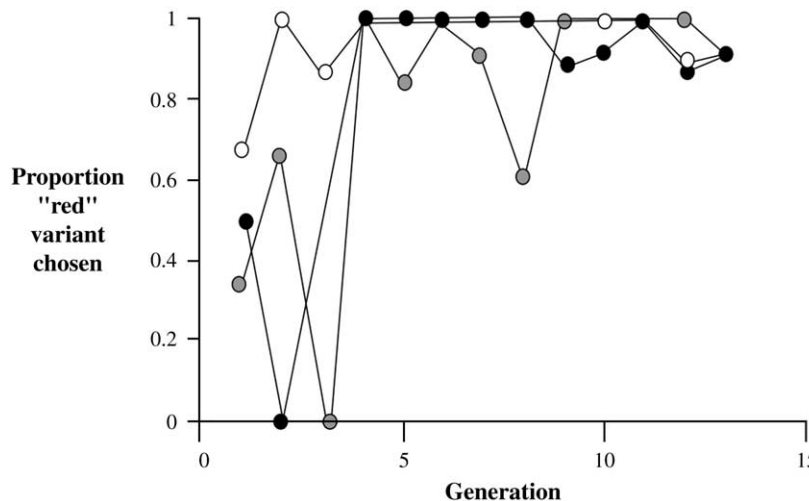


Fig. 5. Representative results of a cultural microevolution experiment by Baum et al. (2004), in which participants, in groups of four, solved puzzles that were coded either red or blue. In each generation, the player in the group who took the longest time in solving the puzzle was replaced by a new person. In the run shown in this figure, the payoffs for solving red puzzles was greater than those for blue, and as a result, red clearly becomes the predominant choice, although there is constant renewal of the population. The experiment shows how an intergenerational “tradition” results when there is a payoff advantage for a particular choice. Adapted from the study of Baum et al. (their Fig. 1C), showing the results of three typical sessions out of the six performed under the same parameters.

348 female names to be 1.37 times (182/133) that for male  
 349 names. The difference appears to be real and not by  
 350 statistical chance, as the rate for female names was higher  
 351 for every decade of the 20th century (Hahn & Bentley,  
 352 2003). The higher turnover rate for female names in each  
 353 decade implies more innovation in naming girls, as is clear  
 354 in other studies (see Fryer & Levitt, 2004; Levitt & Dubner,  
 355 2005, pp. 179–204; Lieberman, 2000).

356 As seen by the numbers of new names to enter the Top 20,  
 357 Top 100, Top 500, and Top 1000 lists in each decade,  
 358 the turnover rate clearly increases as  $y$  increases, for both  
 359 boys’ and girls’ names. Averaged over all decades of the  
 360 century, the resulting linear relationship with  $y$  (Fig. 4A) is  
 361 as predicted by Eq. (1), for both girls’ ( $r^2=.96$ ) and boys’  
 362 ( $r^2=.99$ ) names. According to Eq. (2), each slope (0.259 for  
 363 girls’ names, 0.176 for boys’ names) corresponds to the  
 364 square root of the innovation rate  $\mu$ , yielding a century-  
 365 averaged innovation parameter of 0.067 for girls’ names and  
 366 0.031 for boys’ names, for decadal sampling (since real-  
 367 world events occur in time rather than orderly “generations,”  
 368 the calculated innovation parameter is a relative measure  
 369 of the frequency of innovation for the sampling interval,  
 370 e.g., per decade).

371 Finally, we obtained data from the American Kennel  
 372 Club on the annual number of new puppy registrations in  
 373 the United States for all recognized breeds (Herzog et al.,  
 374 2004). This is a large (a total of 52,806,268 registrations  
 375 from 1926 to 2004) and highly accurate index of the relative  
 376 popularity of purebred dog breeds over the past five  
 377 decades. Using these data, we created multiple Top  $y$  lists  
 378 for each year since 1926 by listing and comparing the set of  
 379 top registered dog breeds in order of decreasing frequency  
 380 for the year. For each year in the study, we used the total  
 381 number of dogs registered as our measure of  $N$ . By

sampling lists of different sizes,  $y$ , at regular time intervals, 382  
 we then determined the turnover rate in each list per 4 years 383  
 (sampling every year would leave too many zeros in the 384  
 time series). 385

The number of different dog breeds registered in the 386  
 United States has increased from 73 breeds in 1926 to 150 387  
 breeds in 2004. Nonetheless, throughout this time period, 388  
 the pattern is as predicted by the random-copying model, 389  
 which is an increase in turnover rate,  $z_y$ , as  $y$  increases. As 390  
 Fig. 4B shows, the turnover rate  $z_y$  for dog breeds shows a 391  
 convincing ( $r^2=.894$ ) linear relationship with  $y$ , and the 392  
 slope of 0.124 corresponds via Eq. (2) to an innovation 393  
 parameter  $\mu$  of 0.015 for 4-year sampling. 394

#### 4. Discussion 395

In accord with the evidence of copying behavior in 396  
 downloading music (Salganik et al., 2006), the random- 397  
 copying model provides a simple, parsimonious explanation 398  
 for the steady turnover of modern baby names, dog breeds, 399  
 and pop music albums over much of the 20th century. As is 400  
 often noted in the social sciences, many models can fit the 401  
 data, and we do not rule out the possibility that other models 402  
 could be devised to fit the patterns we have shown. We 403  
 advocate random copying as a null model firstly because it 404  
 appears to be the absolute simplest model capable of 405  
 replicating the data patterns at the societal scale and, 406  
 secondly, because its two mechanisms, innovation and 407  
 random copying, are the two most basic elements of 408  
 unbiased culture transmission as defined by Boyd and 409  
 Richerson (1985). In fact, there is growing evidence that in 410  
 situations where cultural transmission occurs predominantly 411  
 from one individual to another, a neutral or “random- 412  
 copying” model is the best null model against which 413

414 real-world cultural variants can be compared (e.g., Bentley  
415 et al., 2004; Bentley & Shennan, 2003, 2005; Hahn &  
416 Bentley, 2003; Herzog et al., 2004; Lipo et al., 1997; Lynch,  
417 1996; Neiman, 1995; Simkin & Roychowdhury, 2003). Use  
418 of this model in future studies will make it easier to test for  
419 more detailed effects, including those of race (e.g., Fryer &  
420 Levitt, 2004), geography, and/or class. A recent study within  
421 the publishing industry (Lulu.com, 2006), for example,  
422 shows a decreasing life expectancy of books on bestseller  
423 lists since the 1950s (equivalent to an increasing turnover  
424 rate), which, by comparison with the random-copying  
425 model, would suggest an increase in innovation, perhaps  
426 as books can be published more and more quickly in  
427 response to public topics and tastes.

428 As Baum, Richerson, Efferson, and Paciotti (2004, p.  
429 306) point out, while there is a wealth of research on  
430 individual-level mechanisms of social learning, there is a  
431 need for more discussion by social scientists of how cultural  
432 traditions change over time at the population level. Applied  
433 here on the societal scale, the random-copying model simply  
434 assumes a constant proportion of innovators in the  
435 population, as often assumed in epidemiological models  
436 applied to binary-choice culture change (e.g., Dodds &  
437 Watts, 2005; Watts, 2002). Of course, innovation, that is,  
438 creativity, is an enormous topic (e.g., Martindale, 1975,  
439 1986, 1999) that we are not attempting to explain at the  
440 individual, psychological level. As we move outward in  
441 scale, however, new quantitative effects emerge (Anderson,  
442 1972), particularly with regard to the collective effects of  
443 society (e.g., Ball, 2004; Barabási, 2005; Le Bon, 1896).  
444 Baum et al., for example, conducted an empirical investi-  
445 gation of “cultural microevolution” on the scales as small as  
446 four individuals, which is an important bridge to the societal  
447 scale we are investigating here (we discuss their results  
448 below). At the societal scale, creative innovation generates  
449 what is effectively “quasi-random” variation as Martindale  
450 (1986) described it.

451 An alternative to the random-copying model is clearly  
452 some form of selection or that people choose the variant  
453 with the highest payoff with respect to some benefit (e.g.,  
454 Baum et al., 2004; Boyd & Richerson, 1985; Gintis, in  
455 press; Henrich, 2001, 2006; Henrich et al., 2006). In the  
456 case of the phenomena we have investigated here—baby  
457 names, pop music, and dog breeds—we see no evidence for  
458 inherent benefits of one variant over another. As Baum et al.  
459 (2004) recently showed through experiments on groups of  
460 four participants, the stronger the payoff is for choosing one  
461 particular variant over another, the stronger is the “tradition”  
462 that evolves in bringing that choice to be the most popular,  
463 which is passed on to the newcomers of each generation  
464 (Fig. 5). Henrich (2001) and many others (e.g., Boyd &  
465 Richerson, 1985; Dunnell, 1978; Gintis, in press) have made  
466 similar predictions—when variants are not neutral—then,  
467 we expect the most beneficial choice to rise to popularity  
468 and remain until a superior choice becomes available. Hence,  
469 we would not expect constant, population-independent

turnover among cultural variants if they were being selected 470  
according to intrinsic value, although a future study of Top  $y$  471  
charts of nonneutral cultural variants could reveal intriguing 472  
and unexpected aspects of their turnover. 473

474 Finally, it might be argued that none of the variants we  
475 have studied is truly neutral for various reasons—certain  
476 famous pop artists have clear advantages over newcomers,  
477 for example, or people tire of old fashions in favor of new  
478 ones (cf. *pronovelty bias* in Boyd & Richerson, 1985). This  
479 is true, and it is the reason Herzog et al. (2004) could  
480 identify Dalmatians as being selected among dog breeds  
481 against a background of neutral evolution. To say that things  
482 evolve neutrally means that, of the variants observed, all  
483 behave in a neutral fashion. If they were all positively  
484 selected compared to some unseen variant, they would still  
485 all behave neutrally with respect to one another because  
486 fitnesses are always relative. Hence, the inevitable fact that  
487 newcomers have a lower fitness is not inconsistent with the  
488 model. It would be interesting in the future to investigate the  
489 effects of people getting tired of old fashions by intro-  
490 ducing some sort of pronovelty bias among individuals  
491 (cf. Shennan & Wilkinson, 2001) or by adding intrinsic  
492 value to variants to introduce elements of selection, which  
493 could even decay with time (cf. Dorogovtsev & Menedes,  
494 2000). At this stage, however, the aim of the proponents of  
495 the neutral model (Bentley et al., 2004; Bentley & Shennan,  
496 2005; Hahn & Bentley, 2003; Herzog et al., 2004; Hubbell,  
497 2001; Lipo et al., 1997; Neiman, 1995; Shennan &  
498 Wilkinson, 2001) is still to establish the random-copying  
499 model as an appropriate basis for making these added  
500 alterations. For all its simplicity, the neutral model replicates  
501 a remarkable range of patterns of cultural transmission. In  
502 this study, our main aim is to show that while added rules  
503 can always be imposed to engineer the results, the random-  
504 copying model produces constant turnover *on its own*,  
505 which we find unexpected, somewhat counterintuitive, and,  
506 therefore, significant.

507 In conclusion, our simulations of the random-copying  
508 model indicate that the population size  $N$  should not  
509 significantly affect the turnover rate on the pop charts.  
510 The time-averaged turnover rate in Top  $y$  charts is linearly  
511 proportional to the chart size  $y$  and the square root of the  
512 innovation fraction  $\mu$ . Hence, while prediction of the next  
513 big popular success may be impossible (Salganik et al.,  
514 2006), predicting the frequency distribution (Bentley et al.,  
515 2004; Hahn & Bentley, 2003) and turnover rate is relatively  
516 straightforward. Since such regular turnover is not neces-  
517 sarily expected when independent, rational decisions are  
518 made, random copying may be identifiable in research of  
519 markets and cultural change. The neutral model could also  
520 be useful for assessing situations where copying and  
521 continual, yet directionless, turnover may be undesirable,  
522 as in politics or academic publishing. For these reasons  
523 and more, further research on random copying should be  
524 of high priority for the study of culture evolution and  
525 collective behavior.

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