Emergent Cultural Signatures and Persistent Diversity: A Model of Conformity and Consistency

Jenna Bednar, Aaron Bramson, Andrea Jones-Rooy, and Scott Page
University of Michigan*

March 17, 2009

Abstract

How are cultures transformed when two cultures mix? Models contradict: Kuran and Sandholm conclude that cultural convergence is "unstoppable" (Kuran and Sandholm 2008:221). Other modeling approaches, stemming from Axelrod 1997, predict that diversity may be maintained but with segregation as a by-product. We present a multi-dimensional model of cultural formation that includes two forces that affect an individual: an internal pressure to be *consistent* and social pressure to *conform*. We find that interaction does not lead to homogeneity and the resultant persistent diversity does not depend on agents shunning those who are different. We further find that a preponderance of one force over the other actually slows convergence, rather than hastening it, suggesting that diversity will persist even in highly conformist societies, and that some degree of conformity will be evident even in the most individualistic ones. Finally, our model provides a candidate explanation for the emergence of cultural signatures, a topic not addressed in the existing literature.

Keywords: identity, diversity, coordination, dynamic equilibrium, agent based model

*This research was funded by AFOSR-MURI Grant 57100001867. We thank Paul Hartzog, Jennifer Miller, Len Sander, Casey Schneider-Mizell, and seminar participants at Stanford University for helpful conversations. Contact jbednar@umich.edu or spage@umich.edu.

Empirical research on cultural differences reveals three main findings. First, substantial inter-cultural differences exist: belief systems, behaviors, and mannerisms differ across cultures. Second, cultures exhibit signature characteristics that are socially meaningful and coherent: they cannot be dismissed as idiosyncratic. This consistency allows policy makers to anticipate and predict responses based on cultural affiliations and scholars to identify artifacts as belonging to particular groups. Third, despite the identifiability of group level signatures, individuals within groups vary substantially.

The literature on cultural differentiation and integration provides explanations for the first regularity.[1] Within-culture homogeneity arises through incentives to coordinate. Kuran and Sandholm (2008) show that even mild preferences for coordination produce community level homogeneity. Diversity across geographically disjoint groups is then explained by the near impossibility that two noninteracting populations would converge on identical behaviors. Axelrod's (1997) model of cultural emergence provides an alternative logic. He assumes that agents are more likely to interact with and be influenced by others like themselves (see also Centola et al. 2007, Klemm et al. 2003, Kitts et al. 2000, Friedkin and Johnsen 1997, Marsden and Friedkin 1993, Friedkin 1984).[2] Given that assumption, thick boundaries emerge within the population creating distinct, internally homogeneous cultures. In sum, one modeling approach concludes that cultural convergence is "unstoppable" (Kuran and Sandholm 2008:221), while the other implies that segregation is a by-product of persistent diversity. We offer a model where integrationist policies do not lead to homogeneity, and persistent diversity does not preclude continued interaction.

While existing models help explain the emergence and maintenance of diverse cultures, they provide no explanation for cultural signatures and contradict the observation that diversity persists within interacting populations. As structured, existing models cannot capture

[1] As Macy et al describe the problem: "the disproportionate homogeneity in social groups and the persistence of diversity across groups" (Macy et al. 2003:2).

[2] In addition to interaction and influence dynamics, many of these models show that variations in network configurations of agents and/or network dynamics (for example, cutting off completely relations with a neighbor with whom one shares no common traits) can also influence the extent to which global polarization and local convergence takes place.

coherence within any one culture because traits have no relationship to one another, implying that cultural blocks settle on particular traits idiosyncratically. Ethnographic research suggests that human cultures assume their signatures based on affinity between traits. Behavior in one context bleeds into other related contexts. Signatures, then, do not just distinguish one culture from one another, but allow actors within cultures to anticipate responses across domains. Second, because existing models focus on coordination, they cannot produce significant within-culture variation. This contradicts the empirical evidence. While an "American" cultural signature no doubt exists, people in the United States are not all the same. This heterogeneity runs deeper than simply the polarization of sub-cultures.[3]

If cultural models rely on coordination as their primary force, how can we expect one of them to produce diversity? We propose that the answer lies partly in the multi-dimensional nature of cultures. In our model, people do not attempt to coordinate on just a single action or behavior but attempt to do so on many. Suppose that people can tend to be open and welcoming or closed and private. In the context of any one domain of interaction (what modelers call a game)—say, in greeting a friend on the street—one can embrace warmly or nod. Not every member of a group will respond identically—some embracers will kiss two cheeks and others three, and some nodders may also extend a hand. Similar games apply to the care of children, road manners, and the behavior of store clerks. The existence of multiple games creates two effects. First, it allows a cultural signature, defined as consistent behavior across games, to exist.[4] Second, it makes the task of coordination much more difficult.[5]

[3]In coordination models, the result that people break into subcultures is a scaled down version of a global/local model of between-culture heterogeneity. In contrast, when we write of heterogeneity and diversity in this paper, we refer to differences between individuals in a population.

[4]Fisman and Miguel 2007 find a correlation between home country corruption levels and unpaid parking tickets issued to diplomats in New York City, and Miguel et al 2008 have found a correlation between a soccer player's tendency be penalized and the prevalence of violence in his home country; one hypothesis is that the hostile and aggressive behaviors learned as a young man in a violent environment resurface in the heat of competitive play.

[5]An analogy to keep in mind is the literature on spatial voting. With a single issue dimension, election-minded parties converge. With more than one dimension, they do not. The mechanism here differs slightly. With multiple cultural coordination domains, convergence still occurs but not within any reasonable time frame. Introducing even a small amount of noise prevents convergence altogether.

In this paper we construct a multiple domain cultural model that produces all three aforementioned macro-level regularities: differences between cultures, distinct cultural signatures, and diverse individuals. We assume that individuals have a desire to behave consistently as well as the standard incentive to coordinate. Consistency and conformity have strong empirical support. Incorporating both forces produces not just different cultures, but cultures that are distinct in socially meaningful and consistent ways—that is, cultural signatures.

To show how these two forces operate, we describe three models: a *pure conformity* model, a *pure consistency* model, and a *combined conformity/consistency* model. As we have no reason to believe that conformity and consistency matter equally, we also vary the weight across the two forces in the combined model. For each model we first omit the possibility of error, and then we include random errors and solve for equilibrium distributions of behavior.

The error-free, single force models produce intuitive results: in the pure conformity model, individuals adopt identical but internally inconsistent attributes. Whatever cultural differences exist arise from randomness (the odds of coordinating on the same attributes are low) or from different initial conditions (the attributes that are most prevalent initially tend to become the dominant cultural attributes). This simple social conformity (i.e., coordination) model can therefore explain inter-cultural heterogeneity as distinct equilibria of the coordination dynamic, but it cannot produce intra-cultural heterogeneity. Moreover, these equilibria cannot be interpreted as possessing a cultural signature.[6] Similarly, the error-free, pure consistency model produces consistent individuals but no intra-culture consistency. That is, it produces internally consistent individuals, but social coordination only arises by chance. Introducing error into each of these models has modest effects. Small amounts of noise produce small deviations from equilibrium.

When we introduce both forces of consistency and conformity to the model, the error-free version produces consistent individuals and coherent cultures but no within-cultural heterogeneity. However, the model takes a comparatively long time to converge, which suggests

[6]These findings are consistent with those of other conformity models, including those that allow for preferential interaction (Macy et al. 2003, Axelrod 1997, Rogers 1983, Hannan 1979, Barth 1969, Simmel 1955, and Homans 1950).

complex dynamics. Formal proofs of time to convergence verify that intuition. Further, when we add even small amounts of error to the combined model, we produce enormous within-culture heterogeneity. Thus, the full model connects two well established individual level behavioral assumptions from psychology—the individual desires to exhibit consistent and conforming behavior—with aggregate level empirical regularities well established by sociologists and political scientists: inter-cultural heterogeneity, predominant intra-cultural consistency (cultural signatures), and persistent intra-cultural diversity.

Each of these three regularities has implications for the study of political, economic, and social processes. Cultural differences are one candidate explanation for differences in political freedom and economic growth. The existence of meaningful cultural signatures is, we might even say, a necessary condition for a coherent area studies research agenda. Finally, within-culture heterogeneity has been shown to be a source of both conflict and innovation: the most fragile societies as well as the most economically robust tend to be diverse. Owing to the centrality of these three regularities in the study of politics and economics, making sense of their emergence and maintenance becomes an important question.

Finally, our mode of analysis makes an implicit methodological point that merits mention. Modelers often strive for simplicity. Here, we reveal a cost to oversimplification. The model containing both forces produces meaningfully distinct outcomes from either of its constituent models. One plus one does not equal two. This finding calls attention to the danger of carving out individual motivations and studying them in isolation and argues in favor of the exploration of richer models.

1 Meaningful Cultural Signatures and the Persistence of Internal Group Diversity

Survey research across social science disciplines has consistently revealed substantial differences between cultures. In fact, this inter-cultural variation provides a foundation for nearly all social scientific comparative studies. The nature of area studies research implicitly assumes recognizable and significant differences between behaviors of peoples in different geographical regions, be they informal societies, communities, cities, or countries. Inglehart, in summarizing The World Values Survey data, concludes that "cultural variation is ... relatively constant within a given society, but shows relatively great variation between different societies" (Inglehart 1997, p. 166).[7] The French, for example, tend to be more risk averse than Americans (Hofstede 1991), and Danish attitudes about well-being can be consistently distinguished from French, Italian, or Portuguese attitudes.

Complementing these survey results, psychological and economic experiments reveal systematic differences in patterns of thought across countries. Nisbett (2003) finds that citizens of Eastern Countries take context into account far more than Westerners and as a result are much more willing to accept logical contradiction. Henrich et al. (2001) study fifteen small-scale societies across five cultures, finding substantive evidence of inter-cultural behavioral variation. In another study Henrich (2000) finds that the economic behavior of Peruvian communities varies widely from the behavior of a Los Angeles control group, which suggests that "economic reasoning may be heavily influenced by cultural differences—that is, by socially transmitted rules about how to behave in certain circumstances (economic or otherwise) that may vary from group to group as a consequence of different cultural evolutionary trajectories" (Henrich 2000:973).

Despite observable cultural signatures, people within cultures differ widely. Not all German people think and act the same way, nor do all members of the Itza' or the !Kung. In fact, the differences within cultures are as substantial as the differences between them (Ingelhart 1997, Pelto and Pelto 1975, Thompson 1975, Graves 1970, Au 1999, Hofstede 1991). Au (1999) captures within-culture diversity related to work beliefs, finding that some countries that share similar cultural average scores can have wider or tighter spreads in the distribution of the population, and this variation may affect cross-cultural comparisons as much as the average. A simple plot of two factor scores of two countries from the World Values Survey data provides striking demonstration of all three regularities: inter-cultural diversity,

[7] On most variables he finds significant variation between country means. On cross cultural differences in life satisfaction over 64 countries, the United States life satisfaction mean is 7.7, based on a ten-point scale; across all 64 societies the means range from as low as 3.7 to as high as 8.2.

identifiable cultural signatures, and intra-cultural diversity (see graph in appendix).

Evidence of intra-cultural variation and our proposed explanation say nothing of its importance. Cultural, economic, and social behavior may differ in meaningful ways. Durham (1991) demonstrates variety in types of marriage custom within Tibetan culture. Thompson (1975) provides evidence of significant intra-cultural variation in willingness to accept delayed economic gratification between three communities in Uganda. A study of a series of six cultures across four continents by Mintun and Lambert (1964) and Whiting (1963) found that all but one variable on child rearing behavior was better captured by intra-cultural variation than by inter-cultural variation. In sum, within cultural differences matter as much as cross cultural differences, and for many of the same reasons.

2 Microfoundations: Conformity and Consistency

The development of a meaningful cultural signature implies that individuals within a community conform their behavior to match one another's, and also that there is some relationship that ties their behaviors and beliefs together from one activity or domain to the next, creating consistency across behaviors. In this section we describe and then model the two forces of social conformity and internal consistency.

Social conformity, the inclination to become more like those around oneself, can be unpacked into four distinct individual-level desires and incentives: (1) the desire to fit in with others, (2) the strategic benefit from coordination, (3) the incentive to free ride on the information of others, and (4) the tendency to interact with people similar to oneself. It is a well established observation in social psychology that people tend to mimic the behaviors, beliefs, and attributes of those with whom they interact. Social pressure can also impart desire to fit in with others (Bernheim 1994, Kuran 1995). And, if others positively reinforce conforming behavior, then conformity itself can become a conditioned response (Pavlov 1903, Skinner 1974). Finally, people who interact frequently act similarly, dress similarly, reveal similar preferences (Axelrod 1997), and react similarly to novel situations (Simon 1982).[8]

[8]Banduras' (1977) demonstrated that children imitate behavior they view on TV and Huesmann (1988,

Although conformity has several well accepted causes, attempts to identify the extent of conformity run up against an identification problem (Brock and Durlauf 2006). In addition to conforming, people also choose to be around those who act similarly, or *homophily*.[9] Homophily curbs group mergers because people avoid interacting with others who are not like themselves. Adding social influence to models of homophily exacerbates these effects: when individuals interact with others like themselves, and also actively become more similar to them, polarization between groups is even more pronounced. In our model we take the interacting groups as fixed and rule out the possibility of subcultures of this sort, acknowledging that the possibility of subcultures would create further intra-cultural heterogeneity.

Conformity need not be divorced from incentives. Individuals often mimic selectively, looking only to the behaviors of their more successful neighbors (Kennedy 1988). Moreover, common behavior need not imply conformity. People who face similar problems may construct similar solutions without imitating just as students who enroll in the same class and take identical exams may produce similar answers without copying. Seminal works in psychology by Pavlov (1903) and Skinner (1974) connect positive reinforcement and the conditioning of learned responses. Similar learning environments could, therefore, condition near identical behaviors. Along the same lines, institutions create a common set of incentives and constraints on behavior, which could encourage conformity (North 1990, Young 1998, Bednar and Page 2007).

Often institutions or the environment create strong incentives for identical behavior. If everyone else in a community shakes hands upon greeting, drives on the left side of the road, and speaks English, an individual benefits from doing the same. In these instances, the incentives to take the same action as others are economic as opposed to psychological and are therefore considered as strategic coordination games and not instances of conformity. Not all conformity, though, can be seen as economically based. This holds true even in economic contexts. Young and Burke (2001), for example, show that rather than choose

1998) showed that copied behaviors become encoded into children's their behavioral schemas.

[9]McPherson et al. (2001) review the scores of empirical studies. See also Schelling's (1971) discussion of preferences and racial segregation.

optimal contracts based on soil conditions, landowners and tenant farmers coordinate on common revenue sharing arrangements.

An incentive to conform also arises in uncertain situations, where individuals turn to others for behavioral clues (Tittle and Hill, 1967, Liska 1975). in general, the more observable one's behavior is to others, the more likely one is to conform to the majority behavior and/or the standing social norm (Liska 1975, Ajzen and Fishbein 1969, DeFleur and Warner 1969, Bowers 1968). If someone sees that everyone else has taken some action, she cannot help but draw inferences about the beliefs of others. This tendency can lead to herd behavior (Banerjee 1992) and information cascades (Bikchandani, et al 1993).

The second fundamental force that we consider in our model relates to an individual's desire to be consistent. Moral principles may undergird consistency. For example, ideology or religion may provide umbrella beliefs or a set of values to guide behavior that are unlikely to change significantly over time.[10] The drive to consistency may also be based on convenience: consistent behavior across domains reduces cognitive load.[11] Internal consistency, whether motivated by principles or cognitive burden, provides the linkage across dimensions necessary for a recognizable cultural signature.

Like conformity, the desire for consistency is also well established empirically. Psychological research shows that personal uneasiness with cognitive dissonance creates within individuals a desire for consistency; people find it difficult to behave differently in every situation (Festinger 1957, Ajzen and Fishbein 1980, Ross and Ward 1995, van Overwalle and Jordens 2002). Consistency extends to the political realm: Darmofal (2005) finds a citizen will tend to disagree with public policy expert's recommendations when they run counter to an individual's life experiences. Psychologists generally agree that individuals overcome cognitive dissonance by either restricting their behavior to be consistent with their attitudes or by changing their attitudes to match their inconsistent behavior (McGuire 1966, Singer

[10] Note that these umbrella beliefs do not imply perfect consistency. People are prone to idiosyncratic changes in behavior (or that what is "consistent" for one person might not be consistent for another), much as they might idiosyncratically copy a neighbor or not. The inclusion of errors in the second version of the model helps capture this.

[11] See Bednar and Page (2007) for a discussion of cognitive load and culture.

1966, Beauvois and Joule 1996, Aronson 1999, Harmon-Jones and Harmon-Jones 2002).

Research in neuroscience complements psychological evidence for consistency. The physiology of the brain may enforce minimal levels of consistency for the simple reason that repeated behaviors create cognitive pathways which funnel future thought and action (Gazzaniga 1999). This neurological evidence aligns with empirical studies that show when confronted with a novel situation, an individual often chooses a behavioral response that belongs to their existing repertoire (March 1991, Cavalli-Sforza and Feldman 1981).

Finally, at a more abstract level, consistency can be justified theoretically using the logic of cost-benefit analysis. Consistent behavior allows others to predict his/her next moves. Accurate predictions grease the wheels of economic and political institutions. In fact, one broadly-accepted role of culture is to help coordinate on equilibria. Some equilibria may be more focal than others based on their relationship to the wider culture (Calvert and Johnson 1997).

To summarize, empirical evidence shows that individuals tend toward both consistency and conformity. Note that we do not take consistency and conformity to be hard and fast rules but, rather, emphasize that they are two general forces that guide human behavior. Moment-to-moment, individuals can be as unpredictable in their behavior as they might be arbitrary in whom they imitate, but on the whole, they are generally consistent and they generally coordinate with others. Below, we present our model that captures these two forces that motivate human behavior. We show that these two simple pressures alone can generate the macro-observation of groups that are distinct from one another, that possess meaningful culture signatures, and that are characterized by persistent within-culture diversity.

2.1 General Structure of the Models

Our modeling framework assumes N agents, each represented by a vector of M attributes that take one of A values. Thus, we can characterize an agent as a vector of attributes $(a_1, a_2, \ldots a_M)$, where each $a_i \in \{0, 1, \ldots A\}$. These attributes might include behavior, dispositions, meanings, customs, attire and so on. Crucial to our model will be that attribute values have meaning enabling us to measure consistency. A person with two attributes, one valued zero and the other valued one is not consistent.

As in all models of cultural formation, individuals alter their attributes over time.[12] In our case, the agents follow *behavioral rules* applied in a model in which agents randomly match in pairs. Agents conform when they match the value of an attribute to that of of another agent. The desire to be consistent leads agents to match their value on one attribute to their value on another attribute. In the full model, agents try to conform *and* they try to be consistent.

2.2 Force 1: Internal Consistency

In the consistency model, agents adopt identical values on attributes. The desire for consistency can be captured in payoff form as an incentive to have as many attributes as possible take on the same value. Formally, let $s(a^j)$ equal the number of times the most common attribute appears in agent j's vector of attributes. We can write a *consistency payoff function*:

$$s(a^j) = max_{a \in A}\{|\ i\ |:\ a_i^j = a\}.$$

Given this payoff function, an omniscient optimizing agent would set all attributes to the same value. However, we assume that agents lack a holistic awareness of their inconsistencies. Our goal is to model the process through which the agents rid themselves of inconsistent attributes. In each period we randomly select an agent which applies the following *internal consistency rule*:

Internal Consistency Rule: *The agent randomly chooses two random distinct attributes and changes the value of the first attribute to match the value of the second.*

Clearly, repeated application of this rule eventually leads to consistency. We develop these single force models to understand the process more than the end result. To make that process as transparent as possible, we restrict attention to the case of binary attribute values.[13] Let

[12]Thus, these attributes are not *sacred* in the sense of Ginges et al. (2007).

[13]The extension to non-binary attributes is notationally burdensome but straightforward.

x denote the number of an agent's attributes with value one. Recall that M attributes exist in total. Thus, if $x = 0$ or $x = M$, the agent is *consistent.* In game theory, these consistent states would be called *equilibria*, while in dynamical systems they would be called *absorbing states.* Given our focus on process, we adopt the latter terminology.

This rule has the feature that the consistency is equally likely to increase as it is to decrease. Consider the special case where *exactly* one attribute has value one and all other attributes have value zero. Recall that the rule chooses two attributes and that only the first changes its value. For the consistency to *increase* the first attribute chosen must be the single attribute with value one, in which case, the agent becomes fully consistent. This occurs with probability $\frac{1}{M}$. For consistency to *decrease*, the *second* attribute selected has to be the single attribute with value one. The probability that the first attribute has value zero equals $\frac{M-1}{M}$, andthe probability that the second has value one equals $\frac{1}{M-1}$. The combined probability then equals $\frac{1}{M}$, which equal to the probability that consistency increased. We can now state the following lemma, whose proof relies on an extension of this logic.

Lemma 1 *Let x denote the number of M attributes whose values equal one. Applying the internal consistency rule, the probability that x increases or decreases by one equals:*

$$\frac{(M-x)x}{M(M-1)}$$

pf. For x to increase, the first attribute must be one of the $M - x$ attributes with value zero, and the second attribute must belong to one of the x attributes with value one. These events occur with probabilities $\frac{x}{M}$ and $\frac{M-x}{M-1}$. The proof for the case in which x decreases follows the same logic.

This lemma implies two characteristics of the dynamics. First, agents who are very inconsistent, i.e. who have nearly equal numbers of zeros and ones, relatively quickly become more consistent, but that agents who are nearly consistent may take relatively long to become fully consistent. Second, as mentioned above, the number of ones is equally likely to increase or decrease. Therefore, the process bounces around a lot before settling into an absorbing state. In technical terms, the rule can be said to produce an unbiased random walk in which the probability of movement slows near the two absorbing states.

2.3 Force 2: Coordination or Social Conformity

We next consider a model in which agents conform. In the conformity model, we define the payoff to agent j, $f(a^j, a^{-j})$, as the percentage of other agents whose attributes match those of agent j averaged across all attributes:

$$f(a^j, a^{-j}) = \frac{\sum_{k \neq j} \sum_{i=1}^{M} \delta(a_i^j, a_i^k)}{NM}$$

where $\delta(a_i^j, a_i^k) = 1$ if and only if $a_i^j = a_i^k$. In other words, $\delta = 1$ if the agents' values agree on the attribute and zero if they do not. We refer to this as the *conformity payoff function.* In the model, in each period, we randomly choose a pair of agents. Note that this differs from the internal consistency rule in which we chose a pair of *attributes.* The first agent chosen applies the *social conformity rule:*

Social Conformity Rule: *The first paired agent randomly chooses an attribute and sets the value of that attribute equal to the value that the other agent assigns to that attribute.*

This rule converges to full conformity if the agents update asynchronously (Page 1997). Like the internal consistency rule we established above, the social conformity rule also creates a random walk. The next lemma applies to a single attribute version ($M = 1$) of the model. The extension to the more general case is straightforward.

Lemma 2 *Let $M = 1$ and let y denote the number of N agents whose values on the attribute equal one. Applying the social conformity rule, the probability that y increases or decreases by one equals:*

$$\frac{(N-y)y}{N(N-1)}$$

The proof follows that of the consistency model because the processes are equivalent, suggesting a deeper symmetry that can be made formal.

Observation: *The internal consistency model applied to N agents with M attributes is equivalent to the social conformity model applied to M agents with a N attributes.*

In other words, a one dimensional conformity model is equivalent to a multidimensional consistency model. While the rules do reach absorbing states, the process is not fast and unidirectional but instead bounces back and forth, slowing near the absorbing state.

2.4 The Forces Combined: The Consistent Conformity Model

We now turn to the full model in which agents care about both consistency and conformity. We can characterize the payoff function to an agent j, π_j, as a convex combination of the payoff functions of the first two models:

$$\pi_j(a^j, a^{-j}) = \alpha s(a^j) \, + (1-\alpha) \, f(a^j, a^{-j})$$

where $\alpha \in [0, 1]$ denotes the relative weight on consistency. To model behavior we combine the previous two rules to create a single parameter family of rules $CC(p)$ where p denotes the probability that the agent applies the internal consistency rule. The parameter p may or may not equal α. As in the conformity model, in each period we randomly choose a pair of agents. The first agent in the pair applies the following behavioral rule:

Consistent Conformity Rule CC(p): *With probability p the activated agent applies the internal consistency rule and with probability $(1-p)$ the activated agent applies the social conformity rule.*

Note that this construction makes the consistency and conformity models special cases of this model, where $CC(1)$ is the consistency model and $CC(0)$ is the conformity model. The equilibria given the payoff function described above are the same as the absorbing states given our behavioral rule. They require all agents to choose the same value for each attribute. Other behavioral rules, in particular a myopic best response adjustment process, in which an agent only switches an attribute's value if it leads to a higher payoff, produce inefficient equilibria as well (Kuran and Sandholm 2008).

The next lemma characterizes the dynamics of the class of $CC(p)$ models. It states that the probability that an agent increases the number of attributes with value one depends on the number of attributes the agent sets to one (the consistency effect) and the number of other agents' attributes that equal one.

Lemma 3 *Assume a population of N agents with M binary attributes and an agent whose first x attributes take value one. Let S_i equal the number of other agents in the population who have value one on attribute i. The probability that x increases by one equals*

$$p\frac{x(M-x)}{M(M-1)} \; + \; (1-p)\frac{1}{M}\sum_{i=x+1}^{M}\frac{S_i}{N-1},$$

and the probability that x decreases by one equals

$$p\frac{x(M-x)}{M(M-1)} \; + \; (1-p)\frac{1}{M}\sum_{i=1}^{x}\frac{N-1-S_i}{N-1}.$$

pf: The proof follows from the first two lemmas.

As in the two single force models, this dynamic bounces back and forth and slows near the absorbing states. One important difference between this dynamic and the others is that it has far fewer equilibria (absorbing states). To see why, recall that M is the number of agents, N is the number of attributes, and A is the number of values per attribute. In the Consistency Model there are A^M equilibria, in the conformity model, A^N equilibria, but in the combined CC(p) model, only A equilibria. The fact that the Consistent Conformity model has far fewer equilibria does not necessarily imply that those equilibria will take longer to locate, but when we expose the dynamics we'll see that this in fact the case.

Before we present our analytic results, an example is instructive to demonstrate the tension between conformity and consistency. Suppose that two members of a society interact in three distinct contexts. In each context, a person can take a *fair* action, F, that equally splits resources, or take a *utilitarian* action, U, that produces a higher total payoff. Given these assumptions, we can describe an agent by a vector of length three consisting of F's and U's. Let's call these agents John and Jeremy, and assign them the following initial behavioral vectors:

$$\text{John: } (F, F, U)$$
$$\text{Jeremy: } (F, U, U).$$

Assume first that John and Jeremy apply the internal consistency rule. John may switch his third attribute so that his vector of attributes becomes (F, F, F). Jeremy, in contrast, may switch his first attribute so that his vector becomes (U, U, U). John and Jeremy would both achieve internal consistency and do so quickly.[14] Or, suppose John and Jeremy apply the external conformity rule. In this case, if John is activated first, and it is his second attribute that is selected, then John would switch his second attribute to U so that his vector becomes (F, U, U) The two agents have quickly reached conformity.

Now, assume that John and Jeremy apply both the internal consistency and the external conformity rules. John might first switch to (F, F, F). He may then meet Jeremy and switch to (F, U, F). However, he may then realize that he is being inconsistent and switch back to (F, F, F). Jeremy, meanwhile, may switch to (U, U, U) and then, aiming to conform, switch back to (F, U, U). Eventually, both John and Jeremy will be consistent and conform with one another but it would take much longer. Because conformity and consistency can pull in different directions, the time required to attain an equilibrium can be greatly increased.

3 Analytic Results

With the models specified, we now establish analytical claims on time to convergence. A meaningful cultural signature requires both conformity and consistency—otherwise, differ-

[14]Note that John could also change to (F, U, U) or (U, F, U) given the internal consistency rule, but at some point, he would have all three of his attributes taking the same value.

ences between groups would be meaningless. As the example above indicates, the emergence of signatures requires a high level of coordination. In this section we demonstrate how the process of cultural signature creation may be lengthy by considering a model without any errors. We then introduce errors and show that in equilibrium the model produces persistence of diversity within a coherent culture.

3.1 The Emergence of a Cultural Signature

We have argued that a cultural signature is more than coordination of attributes: those attributes must be linked together in a way that is meaningful to the agents. This connectedness can be provided by internal consistency. Therefore, both micromotives, social conformity and internal consistency, are necessary for the emergence of a meaningful cultural signature. In this section we study the time to convergence, where all agents assign the same value to all attributes. We begin by making the admittedly artificial assumption that no agent randomly alters any attribute—no one makes any mistakes—an assumption we relax in the next subsection. We compare the time to convergence in the three models—pure consistency, pure conformity, and the combined CC(p)—and find that the combined model, necessary for cultural coherence, takes far longer to converge. We also vary the weight of the two pure models within the CC(p) model, finding that the greater the imbalance, the longer the convergence takes.

At the aggregate, numerical level, time to convergence serves as a proxy for complexity of the underlying dynamics. More complex dynamic processes are more likely to amplify small errors. In our model time to convergence proves a *perfect* correlate to error amplification. Also, at the micro level, analyzing time to convergence reveals the dynamics of the process allowing us to understand why we see the outcomes we do when we add noise. Finally, analyzing time to convergence is standard practice in other disciplines that do not equate the existence of an equilibrium with its attainment. In studies of large systems, such as entire societies, the assumption that equilibria are attained may lead to highly problematic analyses. Thus, time to convergence merits attention on its own (Page 2008).[15]

We consider the simplest interesting case: two agents, two attributes, and two values per attribute (A=2, N=2, M=2). This very simple model is sufficient to show our two main results: (1) the Consistent Conformity model takes longer to converge than either of the other two models, and (2) its equilibrium in the model with errors has greater dispersion. We have performed a similar analysis for the three binary attribute, two agent model and find the same qualitative results to be quantitatively exaggerated.[16]

With two agents and two binary attributes, the systems can be in any one of sixteen states which can be sorted into five categories: the two agents can be in conformity and internally consistent (C&C), consistent but not conforming (CON), conforming but not consistent (CRD), one agent can be consistent but the other not, what we call off by one (OBO), or both can be inconsistent and lack conformity (NOT). Using the letters a and b to denote distinct attribute values, in Table 1 we define each category and its probabilities, given random assignment of attributes.

For the internal consistency rule, the probability that $x = 0$ equals the probability that $x = 2$ which is $\frac{1}{4}$. The other half of the time $x = 1$. If $x = 1$, then in the first period the two attributes are selected and one matches the other and as a result, the agent becomes consistent. By the symmetry argument the expected time to equilibrium in the consistency model must equal the expected time to equilibrium in the conformity model. Nevertheless, making the calculation in both models is instructive.

Consistency Model

In the consistency model, any configurations in the sets $C\&C$ and CON are equilibria. We first calculate the probability that any one of the other states moves to those states. If the

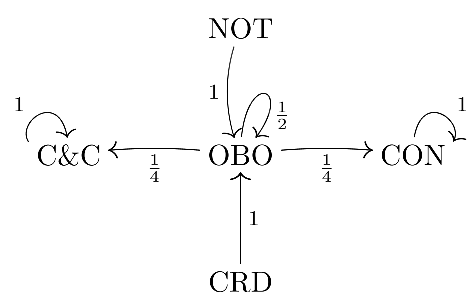
[15] The class of problems that we consider here has analogs in physics and computer science. Scholars in those fields have analyzed time to convergence as the number of attributes or agents grows very large. Using techniques developed by Bouchaud et al (1999), it can be shown that the time to convergence in the consistency model is of order M^2, and time to convergence in the conformity model with one attribute is of order M^2 (see appendix). The time to convergence for the Consistent Conformity Model can be shown to increase in order N^2M^2 for $p = 1/2$ (Page, Sander, and Schneider-Mizell 2007).

[16] These results are available from the authors.

Table 1: States of the System

State	*Agents*	*Prob*
Conformed & Consistent (C&C)	(a,a) (a,a)	$\frac{1}{8}$
Consistent Not Conformed (CON)	(a,a) (b,b)	$\frac{1}{8}$
Conformed Not Consistent (CRD)	(a,b) (a,b)	$\frac{1}{8}$
Off By One (OBO)	(a,b) (a,a)	$\frac{1}{2}$
Not Conformed Not Consistent (NOT)	(a,b) (b,a)	$\frac{1}{8}$

Figure 1: The Dynamics of the Internal Consistency Rule



initial state is in OBO, then the probability of staying in OBO equals one half, and the probability of moving to $C\&C$ or to CON equals one fourth. If the initial state is NOT or CRD, then it moves into OBO with probability one. We can write this information diagrammatically as shown in Figure 1.

We can use the information in this diagram to calculate the expected time to convergence.

Lemma 4 *With two agents and two attributes, the expected time to equilibrium for the Internal Consistency Rule is* $1\frac{3}{4}$ *interactions.*[17]

[17] Time is measured by the number of interactions (an interaction is one application of a rule) with each

pf: Let T_S denote the time (or expected time) to get to equilbrium from a given state. First, note that $T_{CON} = T_{C\&C} = 0$, since $C\&C$ and CON are absorbing states. Second note that the time to reach an absorbing state from a state in CRD or NOT equals one plus the time it takes to reach an absorbing state from OBO.

$T_{CRD} = T_{NOT} = 1 + T_{OBO}$

We calculate the expected time to reach an absorbing state from OBO as follows: With probability one half, the process takes only one time period. The other half of the time, the process remains in OBO, which means the time to an absorbing state equals one plus the time to an absorbing state from OBO. We can write this as follows:

$T_{OBO} = \frac{1}{2}(1) + \frac{1}{2}(1 + T_{OBO}) \ = \ 1 + \frac{1}{2}T_{OBO}$

Solving for T_{OBO} yields that $T_{OBO} = 2$. Therefore $T_{CRD} = T_{NOT} = 3$, so applying the internal consistency rule, the expected time to attain an absorbing state, T^{ICR}, equals $T^{ICR} = \frac{1}{8}(0) + \frac{1}{8}(0) + \frac{1}{8}(3) + \frac{1}{8}(3) + \frac{1}{2}(2) \ = \ 1\frac{3}{4}$.

Both the flow diagram and the algebraic proof show the potential for bouncing back and forth in the category OBO before reaching an absorbing state. Given the number of absorbing states, the oscillation is limited in duration.

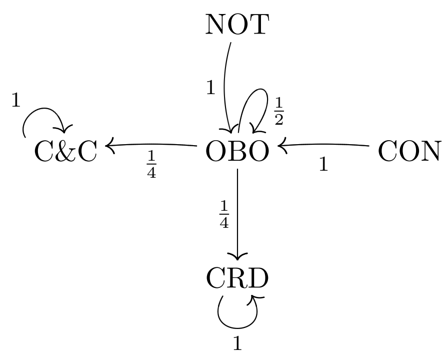
Conformity Model

We next construct a similar diagram for the dynamics created by the social conformity rule (see Figure 2). Therefore by symmetry the expected time to an absorbing state in this model is also $1\frac{3}{4}$ interactions.

Lemma 5 *With two agents and two attributes, the expected time to equilibrium for the Social Conformity Rule is* $1\frac{3}{4}$ *interactions.*

interaction taking one time step. Hence, time is really a measure of the iterations of the model irrespective of the computational complexity of the iteration.

Figure 2: The Dynamics of the Social Conformity Rule



pf: follows from above.

Notice that the diagram above is identical to Figure 1 except that the states CRD and CON have changed places. When we combine the two dynamics, the absorbing states will be the intersection of the absorbing states of these two models. This implies that the dynamics will take much longer to settle into an absorbing state.

CC(p) Model

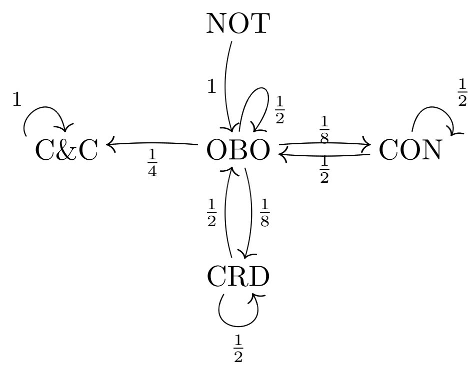
Next, we consider the combined coordination/consistency model, or $CC(p)$. In the diagram below, we show the case where $p = \frac{1}{2}$. The diagram for this model, Figure 3, combines the diagrams for the previous two models. Notice that the only absorbing state (equilibrium) is $C\&C$. Using Figure 3, we can state the following claim.

Lemma 6 *With two agents and two attributes, the expected time to equilibrium for the CC(p) Rule is* $1\frac{7}{8} + \frac{1}{p(1-p)}$.

pf: see appendix.

We can combine these three lemmas to state our first substantive result:

Figure 3: The Dynamics of the Combined Rule where $p = \frac{1}{2}$



Claim 1 *With two agents and two attributes, the expected time to equilibrium in the combined model is strictly greater than either the social conformity or internal consistency models.*

pf: Follows directly from Lemmas 4, 5, and 6.

The combined model is a family of models, where we can vary the probability that either rule is applied when an agent and attribute are activated. We can also use Lemma 6 to establish a second substantive claim and corollary that compare the time to convergence as we vary the probability that the consistency rule is invoked:

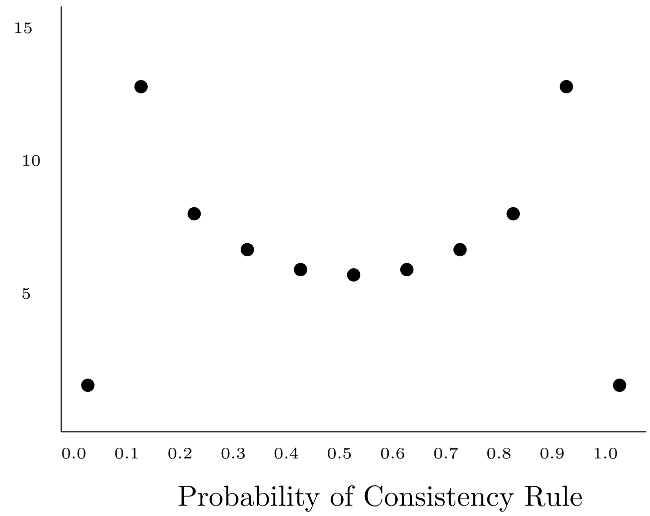
Claim 2 *In the CC(p) model, the time to convergence is minimized at* $p = \frac{1}{2}$.

Corollary 1 *For* $p \in (0, 1)$*, the time to convergence increases as* $p \to 0$ *or* $p \to 1$.

pf: Straightforward from Lemma 6.

Given that we have equal numbers of agents and attributes, if both conformity and consistency are possible behavioral rules, the time to convergence is minimized when they are equally weighted. The time to convergence grows as either one becomes more likely to be invoked. If a population of agents mostly conforms, but occasionally strive for internal

Figure 4: Expected Time To Equilibrium: Two Person Model



consistency, the population will take much longer to settle into a common set of attributes than if they weighted the two motivations equally.

We can compare the expected time to equilibrium in the three models—including the full family of submodels in CC(p)—graphically. Recall that the internal consistency model and the social conformity model are special cases of the combined model, where $p = 1$ or $p = 0$, respectively. Figure 4 shows the expected time to equilibrium as a function of the probability of applying the consistency rule. Note first that the expected time to equilibrium is far shorter in the conformity model and the consistency model than in the $CC(p)$ model, as established by Claim 1. Note also that with the execption of the two special-case endpoints, the expected time to equilibrium is *minimized* in the $CC(p)$ model at $p = \frac{1}{2}$. For comparison, the time to convergence at $p = \frac{1}{2}$ is $5\frac{7}{8}$ interactions; this value is more than three times the time to convergence in the other two cases. Also note the non-linearity of the time to convergence—what we have taken to calling the "smile" curve—due to the increasing time produced by an unbalanced weighting of the two rules.

The three flow diagrams reveal the two reasons why the consistent conformity model takes so much longer to converge than either the conformity model or the consistency model. First, as already proved, the consistent conformity model has fewer absorbing states. Whereas Figures 1 and 2 both have two categories of absorbing states, Figure 3 has a single category of absorbing states. Second, the individual processes of the pure conformity model and the pure consistency model head directly to their respective absorbing states. The only possible delay that can occur in either of those single processes is the system remaining in state OBO. In contrast, the consistent conformity model can move away from the lone absorbing state, from CRD to OBO to CON and back to OBO, and thus considerably slowing convergence.

When convergence in a system is extremely slow, we should not expect the system to be in equilibrium. If a system is prone to shocks or errors, then it is even less likely to reach equilibrium. One might argue that if an equilibrium exists, then the system would eventually reach it. However, when the number of interactions required to attain an equilibrium is sufficiently large, as we might expect it to be in real cultures, then other factors will likely intervene before equilibrium can ever be reached. Furthermore, missteps along the path can result in substantial and perpetual deviations from the equilibrium. Thus, we can interpret the slow time to convergence as predictive of intra-cultural heterogeneity. We make that connection more formal in the next section, where we show that the introduction of even very small amounts of noise can have very large effects.

3.2 The Persistence of Diversity

The inclusion of errors is a standard assumption in learning and conformity models. These models still attain equilibria, but they equilibria are not longer static. Instead, the system reaches an equilibrium distribution over states (Young 1998). For example, in the limit the conformity model could spend 95% of the time in conformity state and 5% of the time in the category OBO. That would be an equilibrium distribution but not a static equilibrium. In all of the models we consider, we obtain unique equilibrium distributions.

To capture errors, we assume that with some small positive probability, ϵ, an agent randomly changes an attribute's value rather than applying its behavioral rule. We are interested in how the two forces singly and jointly magnify these errors. One might expect that adding noise at a level ϵ would create an equilibrium distribution in which approximately ϵ of the agents are out of equilibrium. And in the Consistency Model and the Conformity Model, we find something close to that. In the Consistent Conformity Model, however, the behavioral rule magnifies the noise term. Small errors lead to substantial heterogeneity on a par with what is seen in empirical data within cultures.

Consistency Model

First, we consider the consistency model. It suffices to consider a single agent, which allows us to reduce our five states to three. We can let CNS denote the union of the states CON and $C\&C$. These represent the states where the agents are consistent. We can then combine the NOT and CRD into the state NCN. In this state, neither agent is consistent. This gives a Markov Process defined over three states CNS, NCN, and OBO. We can write the Markov Transition Matrix as follows:

		$T+1$		
		CNS	OBO	NCN
	CNS	$1-\epsilon$	ϵ	0
T	OBO	$\frac{1}{2}$	$\frac{1-\epsilon}{2}$	$\frac{\epsilon}{2}$
	NCN	0	1	0

This gives a system of equations that characterize the dynamic equilibrium.

$$P_{CNS} = (1-\epsilon)P_{CNS} + \tfrac{1}{2}P_{OBO}$$

$$P_{OBO} = \epsilon P_{CNS} + \tfrac{1-\epsilon}{2}P_{OBO} + P_{NCN}$$

$$P_{NCN} = \tfrac{\epsilon}{2}P_{OBO}$$

Solving these equations gives

$$P_{CNS} = \frac{1}{1+2\epsilon+\epsilon^2},\ P_{OBO} = \frac{2\epsilon}{1+2\epsilon+\epsilon^2},\ P_{NCN} = \frac{\epsilon^2}{1+2\epsilon+\epsilon^2}$$

These last three equations characterize the dynamic equilibrium. The proportion of agents in the consistent state, CNS, equals approximately $\frac{1}{1+2\epsilon}$, which is approximately

$1 - 2\epsilon$. In other words, ϵ error translates into 2ϵ of the population on average not in the error-free absorbing state.

Conformity Model

We can perform a similar analysis for the conformity model. Let CDC equal the union of the two states in which the two agents have confromed, CRD and $C\&C$, and let NCD equal the union of the states in which they have not, NOT and CON. We can write the Markov Transition Matrix as follows:

$$\begin{array}{cc|ccc} & & & T+1 & \\ & & CDC & OBO & NCD \\ \hline & CDC & 1-\epsilon & \epsilon & 0 \\ \text{T} & OBO & \frac{1}{2} & \frac{1-\epsilon}{2} & \frac{\epsilon}{2} \\ & NCD & 0 & 1 & 0 \end{array}$$

This matrix is identical to the one for the Consistency Model up to a relabeling of the states. Therefore, the equilibrium equals

$P_{CDC} = \frac{1}{1+2\epsilon+\epsilon^2}$, $P_{OBO} = \frac{2\epsilon}{1+2\epsilon+\epsilon^2}$, $P_{NCD} = \frac{\epsilon^2}{1+2\epsilon+\epsilon^2}$

These equations can be interpreted the same as the previous ones: introducing an error of size ϵ produces an equilibrium that has on average 2ϵ of the agents not in the error-free model's absorbing state.

CC(p) Model

For the Consistent Conformity Model, the effect of errors becomes amplified. To analyze this model requires all five categories of states. We can write the Markov Transition matrix between those states as follows

$$
\begin{array}{cc|ccccc}
 & & & & T+1 & & \\
 & & C\&C & OBO & CRD & CON & NOT \\
\hline
 & C\&C & 1-\epsilon & \epsilon & 0 & 0 & 0 \\
 & OBO & \frac{1}{4} & \frac{(1-\epsilon)}{2} & \frac{p+\epsilon-\epsilon p}{4} & \frac{1-p-\epsilon p}{4} & \frac{\epsilon}{4} \\
\mathrm{T} & CRD & 0 & 1-p+\epsilon p & p-\epsilon p & 0 & 0 \\
 & CON & 0 & p+\epsilon+\epsilon p & 0 & 1-p-\epsilon+\epsilon p & 0 \\
 & NOT & 0 & 1 & 0 & 0 & 0
\end{array}
$$

The following system of five equations characterizes the equilibrium.

$P_{C\&C} = \frac{1}{1+4\epsilon+\epsilon^2+\alpha\epsilon+\alpha^{-1}\epsilon}$, $P_{OBO} = \frac{4\epsilon}{1+4\epsilon+\epsilon^2+\alpha\epsilon+\alpha^{-1}\epsilon}$, $P_{CRD} = \frac{\alpha\epsilon}{1+4\epsilon+\epsilon^2+\alpha\epsilon+\alpha^{-1}\epsilon}$

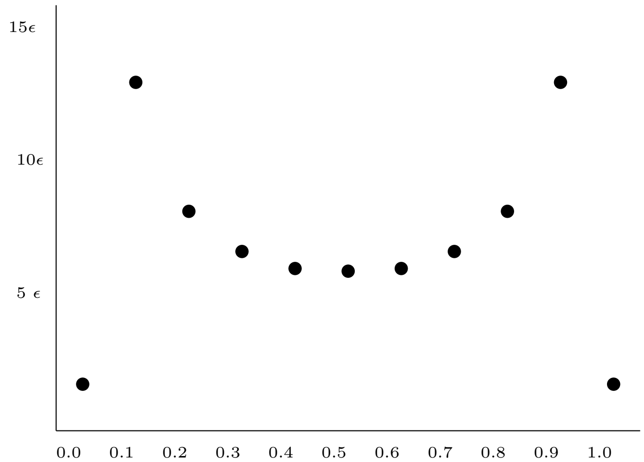
$P_{CON} = \frac{\alpha^{-1}\epsilon}{1+4\epsilon+\epsilon^2+\alpha\epsilon+\alpha^{-1}\epsilon}$, $P_{NOT} = \frac{\epsilon^2}{1+4\epsilon+\epsilon^2+\alpha\epsilon+\alpha^{-1}\epsilon}$

Where $\alpha = \frac{(p+\epsilon-\epsilon p)}{(1-p+\epsilon p)}$ which equals the ratio of the probability of moving from OBO to CON to the probability of moving from OBO to CRD. Interpreting these equations requires some care. Note first, and most importantly, that the proportion of time in the absorbing state equals approximately, $\frac{1}{1+(4+\alpha+\alpha^{-1})\epsilon}$. For small ϵ this is approximately $1-(4+\alpha+\alpha^{-1})\epsilon$. A little math shows that $(\alpha+\alpha^{-1})$ is greater than or equal to two. Thus, an error of ϵ implies that, on average, *at least* 6ϵ of the population is not in the error-free absorbing state. Not only does diversity persist, but at much higher rates than the level of error.

Note second that the higher α, the more time the system will spend in CON. The lower α, the more time that the system will spend in CRD. Finally, note that setting $p = \frac{1}{2}$ maximizes the time spent in the consistent conformity state ($C\&C$). Figure 5 shows the percentage of the time the system spends outside of state $C\&C$ as a function of p for a given error level ϵ. If we let p go to 0 then α converges to ϵ and the system spends half of the time outside of the state $C\&C$. Similarly, if we let p go to 1 then α converges to $\frac{1}{\epsilon}$, and the system again spends half of the time outside of the state $C\&C$. Thus, even for very small errors, if one dynamic outweighs the other, the system can spend almost half of its time out of equilibrium.

Except for the units on the y-axis, this figure matches figure 4 exactly. The equivalence, modulo a rescaling, of the time to equilibrium and the distance to the perfectly conformed

Figure 5: Distance to Conformed and Consistent Equilibrium: Error Model



and consistent equilibrium is an artifact of our model. But the correlation between the two generally hints at an important insight: the longer the time to equilibrium, the more complex the dynamics. The more complex the dynamics, the larger the potential effects of error.

We can summarize these results in the following claim:

Claim 3 *With two agents and two attributes, the average proportion of time not spent in an absorbing state in the social conformity or internal consistency models approximately equals* 2ϵ*. In the combined model, the average proportion of time not spent in an absorbing state is at least* 6ϵ *and can approach one-half for any* ϵ*.*

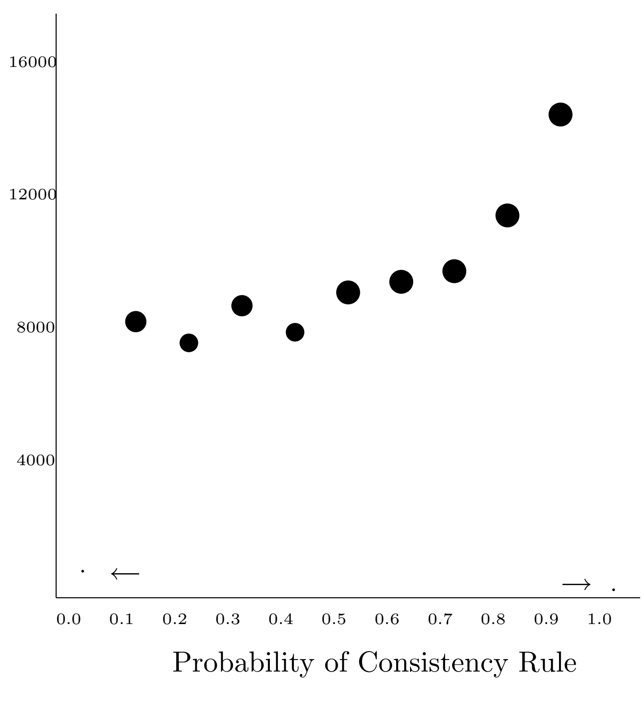
This claim establishes that small amounts of error produce substantial heterogeneity in the combined model. It also establishes that the model is capable of producing agents who are somewhat consistent and somewhat coordinated. A natural question to ask is whether this result scales: Do similar findings hold with larger number of agents and attributes? We provide a statistical answer to that question next using numerical experiments.

4 Numerical Experiments

We use numerical experiments to test the robustness of our results to an increase in the number of agents and attributes. We varied the number of agents from two to one thousand, the number of attributes from two to ten, and the number of values per attribute from two to six.[18]

We present two sets of computational experiments. In the first set, we measure the time to convergence in the error-free model. In the second set, we measure levels of consistency and conformity in the models with errors. Figure 6 shows the time to convergence as a function of p for a model with one hundred agents, ten attributes, and six values per attribute. The results are averages of over fifty trials. All of the differences are statistically significant. The arrows point to the values for $p = 0$ and $p = 1$, which are otherwise easy to overlook.

Figure 6: Time to Convergence in Number of Periods



[18]We wrote two separate programs, one in C and one in Repast (a java-based modeling toolkit). We used the faster C program to sweep the attribute values, and the Repast program to generate the graphs that you see in the paper. We also tested our models against the analytic results presented in the paper.

Our theoretical results suggested that the time to convergence should increase as p approaches zero and one. Here, we only see that phenomenon as p approaches one because the number of agents is far larger than the number of attributes. The probability of applying the consistency rule must be very small before we would expect to see the time to convergence to increase given the greater need for conformity.

All of the models converge, but the magnitude of the time to convergence differs substantially. In the conformity model and the consistency model, the system converges in a few hundred periods. The consistent conformity model can take more than fifteen thousand periods to converge. Our model is abstract enough that we cannot attach any specific span of time to a period; time is simply the number of agent actions. However, if we set each period equal to one day, then this difference translates into the difference between a year and more than forty years.

In the second set of experiments we test to see whether errors have a much larger effect in the Consistent Conformity Model. To make this comparison we need some measures of consistency and conformity. In constructing these measures, we refer back to notation we used in constructing payoff functions. Recall that $s(a^j)$ equals the number of times the most common attribute appears in agent j's vector of attributes. We can write

$$s(a^j) = max_{a\ inA}\{\mid i \mid :\ a_i^j = a\}$$

$$\text{pconsistent } = \frac{\sum_{j=1}^{M} s(a^j)}{AM}$$

Thus, *pconsistent* takes on values in the closed interval between zero and one, with perfectly consistent agents taking the value one.

We define *pconformity* to be the average of the *conformity payoff functions.* Recall that the conformity payoff function equals the average number of agents who agree with the agent's attribute values.

Table 2: Percentage of Conformity and Consistency (Models with Error)

	p = 0.0				p = 0.5				p = 1.0			
	pconformity		pconsistent		pconformity		pconsistent		pconformity		pconsistent	
noise	mean	stdev	mean	stdev	mean	stdev	mean	stdev	mean	stdev	mean	stdev
0	1	0	0.360	0.082	1	0	1	0	0.200	0.016	1	0
0.005	0.736	0.064	0.373	0.044	0.354	0.081	0.556	0.067	0.199	0.012	0.970	0.009
0.01	0.585	0.052	0.376	0.030	0.299	0.037	0.510	0.033	0.200	0.012	0.946	0.012
0.02	0.482	0.044	0.376	0.023	0.269	0.017	0.483	0.017	0.201	0.012	0.904	0.017

$$f(a^j, a^{-j}) = \frac{\sum_{k \neq j} \sum_{i=1}^{M} \delta(a_i^j, a_i^k)}{NM}$$

where $\delta(a_i^j, a_i^k) = 1$ if and only if $a_i^j = a_i^k$

$$\text{pconformity} = \frac{\sum_{j=1}^{M} f(a^j, a^{-j})}{M}$$

Thus, if the entire population has conformed, then the value of *pcoordinate* equals one. The table below gives the values of *pconsistent* and *pconformity* for each of the three models under various levels of agent error for a model with ten attributes and five values per attribute and 100 agents.

Table 2 shows the average percent values and standard deviations of inter-agent value difference (pconformity) and intra-agent value difference (pconsistent) over the last 1000 interactions of 100 runs with 100 agents, 10 features, 5 values per feature and a total run time of 5,000,000 interactions per run. Notice that with no errors, the CC($\frac{1}{2}$) model converges to a consistent and coordinated state as we expect, and the two pure models (the equivalent of CC(0) and CC(1)) converge unproblematically, as predicted by the theory. These results serve as a benchmark and a check on the accuracy of the computer programs.

Importantly, for the $CC(\frac{1}{2})$ model, the introduction of even the tiniest bit of noise (0.005) leads to substantial heterogeneity both between agents (only 35.4% conform) and within agents (55.6% are consistent), displaying far more diversity than in the other two models (73.6% conform and 97% are consistent). A little noise has a much larger effect when both forces operate.[19] These computational experiments show that the insight generated in the simpler mathematical model—that the effect of noise when both forces are in play greatly exceeds the sum of the individual effects—becomes even more pronounced for larger systems. Thus, even small amounts of error may frustrate a society of people who wish to conform and be consistent.

While our model offers an explanation for the emergence of cultural signatures and internal cultural diversity, it remains consistent with models based upon Axelrod (1997) that support differences between cultures. Two runs of any coordination game models (including ours) are very unlikely to produce the same outcomes. Thus, if we treat one run of the model as the United States, and a second run of the model as Germany, then we will naturally see two different "cultures" emerge, each with its own signatures. And because our model includes conformity, we also see that its distinct signatures are meaningful and consistent with the broader fabric of behaviors in that society. Also because of consistency, we see the persistence of diversity within each culture. As different runs of the model produce different outcomes, the model naturally provides an explanation for inter-cultural diversity—differences in initial conditions and different paths lead to diverse outcomes. Consistent with Axelrod (1997), even when these cultures interact, group distinctions persist.

5 Conclusion

This simple model produces within-cultural heterogeneity, cross cultural differences, and meaningful cultural signatures. The model also shows that varying the weights of the forces slows convergence and increases diversity. This finding helps us to understand why some cultures exhibit more diversity than others: if pressures to conform or be consistent are higher or lower, we'll see different levels of diversity. These results can be counterintuitive but emerge as a result of nonlinear effects of convergence in the combined model. Furthermore, the presence of more or fewer "errors" (such as propensities towards missteps, misinformation,

[19] Comparing results for cases with noise = 0.005, the p-value for a test of the difference of means for conformity for the p=0.0 and p=0.5 models is 2.23×10^{-304} and the p-value for a test of the difference of means for consistency for the p=0.5 and p=1.0 models is 1.61×10^{-831}.

or confusion) in different systems would respectively promote or inhibit diversity.

In addition, our results suggest a reconsideration of the measures of diversity. First, the greater the likelihood of error, the less conformity we should see. We might speculate that informational systems provide a crude proxy for the transmission error of cultural traits. Closer relations between individuals would push in the opposite direction. Second, in a society in which the relative tendency to conform is high relative to the tendency to be consistent, people may be less consistent but more similar. Thus, whether one culture appears more or less heterogeneous depends on the type of questions asked in a survey. If survey questions ask about an existing behavior, we'd expect a higher conforming society to appear less heterogeneous. However, if the questions are hypothetical, the lack of consistency may give respondents a variety of possible behaviors to apply in the novel context. Depending on the questions asked, a less individualistic society, like Japan, could appear more heterogeneous than a highly individualistic society like the United States.

Our model also has implications for a range of organizational forms beyond the standard conception of "culture" as a characteristic of nations. Within corporations, for example, people face incentives to conform as well as to be consistent, though for reasons that differ slightly from those we described above. Relatedly, members of a political party also desire conformity and consistency, and these two desires may result in the analogous effects: differences within and between parties as well as coherent party ideologies. In a party version of the model, attribute values would represent participants' ideal points in policy or preference space. The internal consistency rule would capture the individual desire for a consistent ideology, and the social conformity rule would capture the collective desire for party cohesiveness. The simplicity of our model means it could be reasonably extended in a number of ways to be sensitive to any particular constraints in different contexts in which it is relevant.

One implication of our results is that consistent cohesiveness cannot emerge without top down encouragement or even enforcement.[20] Within any organization or collection of people, be it an interest group, a community organization, or an academic department, these

[20] As presented, the model considers random mixing and no central transmission of desired attributes.

two forces probably operate. Absent strong central control, diversity should reign.[21] This finding agrees with what we see in the real world: few (if any) groups converge to a state of consistent conformity, but meaningful cultural signatures do emerge.

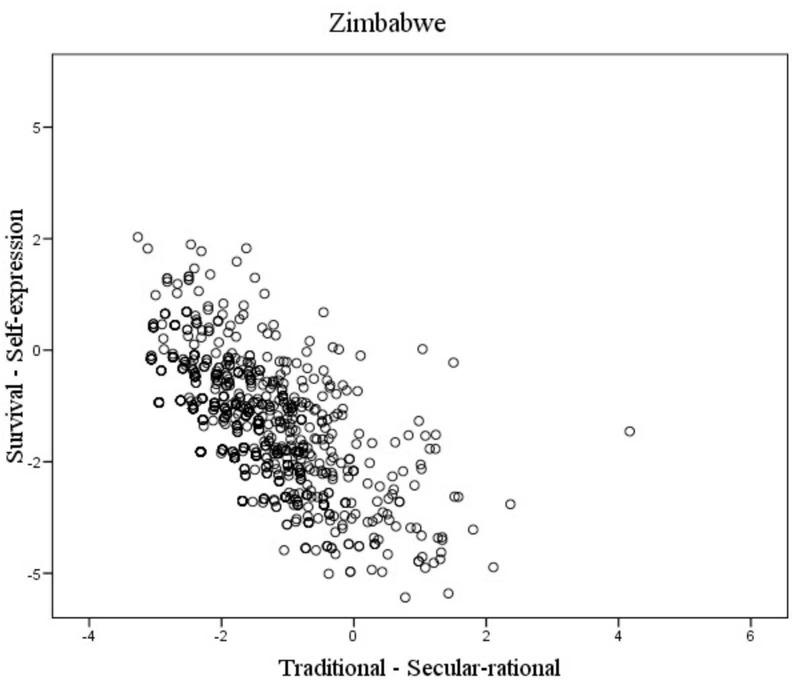
Finally, we want to be clear that we do not attach negative normative significance to the persistence of intra-group heterogeneity. To the contrary, the lack of convergence, be it in a society, a political, party, or an organization, may, on balance, be a good thing. It may promote innovation in the form of cultural evolution. This tension between conformity and consistency maps to related tensions between "exploiters versus explorers", "conformers versus nonconformers", and "scroungers versus producers" and may produce stability through variation (March 1991, Kameda and Nakanishi 2002, Boyd and Richerson 2001, Rogers 1995, Nisbett and Ross 1980, Tindall 1976, Weick 1969, Campbell 1965, Axelrod and Cohen 2000, Roberts and Zuni 1964). Diverse societies may also better produce knowledge and be more adept at problem solving and prediction (Wallace 1991, Page 2007). Overall, diverse societies may be more robust, as they have the potential to adapt to new and changing circumstances (Bednar 2006). In contrast, societies that lack intra-cultural diversity may be prone to collapse (Diamond 2005). Thus, the persistence of diversity in the face of two homogenizing forces may prove as serendipitous as it is paradoxical.

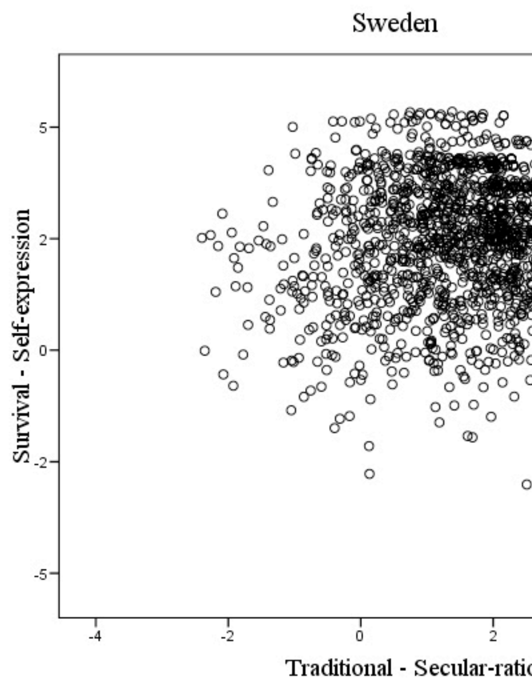
[21] Note that that control would need to be very strong, as our model shows a preponderance of incentives to conform typically slows convergence.

Appendix

Plot of within-culture variation

We generated the graphs below using data from the World Values Survey (Inglehart and Welzel 2005). On the x-asis the Traditional – Secular-rational dimension captures how important religion is to respondents in each country. High scores on this dimension correspond with high values placed on concepts like family, tradition, and deference to authority. On the y-axis the Survival – Self-expression dimension captures the differences in responses on questions related to materialist or post-materialist values. High scores correspond with high values placed on concepts like diversity, imagination, tolerance, environmental protection, and involvement in political and economic life, as well as with high interpersonal trust. Not only do responses differ considerably between countries, but also that responses from Sweden demonstrate greater within-culture diversity. These factors aggregate multiple responses from each individual, so were the variation due to random error, within country variation would be very small.





Claim 4 *The expected time to convergence for the consistency model with binary values and M attributes for a random starting point is of order M^2 periods.*

pf: (Courtesy of Len Sander) Let x denote the number of attributes with value 1. Let T_x be the time to convergence if at location x. Let m_x be the probability of increasing or decreasing the number of attributes with value 1. By the previous claim, these probabilities are equal. After one time period, the expected time has to be one period less. Therefore, we have the following equation:

$$T_x - 1 = m_x T_{x+1} + m_x T_{x-1} + (1 - 2m_x) T_x$$

This reduces to

$$-1 = m_x[(T_{x+1} - T_x) - (T_x - T_{x-1})]$$

Recall from Claim 1 that $m_x = \frac{(M-x)x}{M(M-1)}$. For large M we can approximate this as $m_x = \frac{(M-x)x}{M^2}$. Let $p(x) = \frac{x}{M}$, so that $m_x = p(x)[1 - p(x)]$. We then can rewrite $T_{x+1} - T_x$ as

$$\frac{1}{M} \cdot \frac{(T(p(x+1)) - T(p(x))}{\frac{1}{M}}$$

For large M, this converges to $\frac{\partial T(p(x))}{\partial p}$. It follows that we can write the following approximation:

$$(T_{x+1} - T_x) - (T_x - T_{x-1}) \ \sim \ \frac{1}{M}\left[\frac{\partial T(p(x))}{\partial p} - \frac{\partial T(p(x-1))}{\partial p}\right]$$

Which in turn we can approximate as

$$\frac{1}{M^2}\frac{\partial^2 T(p(x)}{\partial p}$$

We can therefore approximate our initial difference equation as

$$-1 = p(x)[1 - p(x)]\frac{1}{M^2}\frac{\partial^2 T(p(x))}{\partial p}$$

Rearranging terms and simplifying notation gives

$$\frac{\partial^2 T(p)}{\partial p^2} = -\frac{M^2}{p(1-p)}$$

We also have that $T(0) = T(1) = 0$. The solution to this differential equation is

$$T(p) = M^2 \left[p \log(\frac{1}{p}) + (1-p) \log(\frac{1}{1-p}) \right]$$

which completes the proof.

We can state a similar result for the conformity model.

Corollary 2 *The expected time to convergence for the conformity model with binary values and N agents converges for a random starting point is of order N^2 periods.*

pf: follows from our earlier observation of equivalence and the previous claim.

Proof of Lemma 6:

We can write the following equations.

$T_{C\&C} = 0$

$T_{OBO} = 1 + \frac{1}{4}T_{C\&C} + \frac{1}{2}T_{OBO} + \frac{p}{4}T_{CON} + \frac{(1-p)}{4}T_{CRD}$

$T_{CON} = 1 + (1-p)T_{OBO} + pT_{CON}$

$T_{CRD} = 1 + pT_{OBO} + (1-p)T_{CRD}$

$T_{NOT} = 1 + T_{OBO}$

By substitution, these equations imply that

$T_{CON} = \frac{1}{1-p} + T_{OBO}$, and $T_{CRD} = \frac{1}{p} + T_{OBO}$

These in turn imply that

$T_{OBO} = 1 + \frac{1}{2}T_{OBO} + \frac{p}{4(1-p)} + \frac{(1-p)}{4p} + \frac{1}{4}T_{OBO}$

This reduces to

$T_{OBO} = 4 + \frac{(1-2p+2p^2)}{p(1-p)}$

Substituting back into the other equations gives

$T_{CON} = 4 + \frac{(1-p+2p^2)}{p(1-p)}$, $T_{CRD} = 4 + \frac{(2-3p+2p^2)}{p(1-p)}$, $T_{NOT} = 5 + \frac{(1-2p+2p^2)}{p(1-p)}$

Therefore the average time to convergence equals

$$\frac{1}{2}\left(4 + \frac{(1-2p+2p^2)}{p(1-p)}\right) + \frac{1}{8}\left(4 + \frac{(1-p+2p^2)}{p(1-p)} + 4 + \frac{(2-3p+2p^2)}{p(1-p)} + 5 + \frac{(1-2p+2p^2)}{p(1-p)}\right)$$

Which reduces to

$1\frac{7}{8} + \frac{1}{p(1-p)}$

For the special case $p = \frac{1}{2}$, these equations become

$T_{OBO} = 1 + \frac{1}{4}T_{C\&C} + \frac{1}{2}T_{OBO} + \frac{1}{8}T_{CON} + \frac{1}{8}T_{CRD}$

$T_{CON} = 1 + \frac{1}{2}T_{OBO} + \frac{1}{2}T_{CON}$

$T_{CRD} = 1 + \frac{1}{2}T_{OBO} + \frac{1}{2}T_{CRD}$

$T_{NOT} = 1 + T_{OBO}$

By substitution, these equations imply that $T_{CON} = T_{CRD} = 2 + T_{OBO}$. Which in turn implies that $T_{OBO} = 1 + \frac{1}{2}T_{OBO} + \frac{1}{2} + \frac{1}{4}T_{OBO}$. This is an equation in a single variable, T_{OBO}. Solving gives equation gives $T_{OBO} = 6$. Substituting back into the other equations gives $T_{CON} = T_{CRD} = 8$ and $T_{NOT} = 7$. Therefore the average time to convergence equals $\frac{1}{2}(6) + \frac{1}{8}(8+8+7) = 5\frac{7}{8}$.

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