AMERICAN PSYCHOLOGICAL ASSOCIATION

Psychological Review

ISSN: 0033-295X

https://doi.org/10.1037/rev0000341

THEORETICAL NOTE

Hipsters and the Cool: A Game Theoretic Analysis of Identity Expression, Trends, and Fads

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Cultural trends and popularity cycles can be observed all around us, yet our theories of social influence and identity expression do not explain what perpetuates these complex, often unpredictable social dynamics. We propose a theory of social identity expression based on the opposing, but not mutually exclusive, motives to conform and to be unique among one's neighbors in a social network. We find empirical evidence for both conformity and uniqueness motives in an analysis of the popularity of given names. Generalizing across forms of identity expression, we then model the social dynamics that arise from these motives. We find that the dynamics typically enter random walks or stochastic limit cycles rather than converging to a static equilibrium. The dynamics also exhibit momentum, preserve diversity, and usually produce more conformity between neighbors, in line with empirical stylized facts. We also prove that without social network structure or, alternatively, without the uniqueness motive, reasonable adaptive dynamics would necessarily converge to equilibrium. Thus, we show that nuanced psychological assumptions (recognizing preferences for uniqueness along with conformity) and realistic social network structure are both critical to our account of the emergence of complex, unpredictable cultural trends.

Keywords: conformity, games on social networks, popularity cycles, social dynamics, uniqueness

Supplemental materials: https://doi.org/10.1037/rev0000341.supp

Popular cultural practices come into and out of fashion. Researchers have observed boom-and-bust cycles of popularity in music, clothing styles, automobile designs, home furnishings, given names, and even management practices (Abrahamson, 1991; Berger, 2008; Berger & Le Mens, 2009; Lieberson, 2000; Lieberson & Lynn, 2003; Reynolds, 1968; Richardson & Kroeber, 1940; Shuker, 2016; Sproles, 1981; Zuckerman, 2012). Popularity cycles appear to be driven by social influence, for example, by people adopting the music that their friends listen to or that they perceive as popular (Salganik et al., 2006; Salganik & Watts, 2008). At the individual level, people are constantly looking for new ways to express their preferred social identities (Berger, 2008; Chan et al., 2012; Hetherington, 1998; Rentfrow & Gosling, 2006). The resultant social dynamics do not typically converge to equilibrium. What are the social forces that lead to such perpetual change and novelty?

Social pressure to conform is a powerful force when behavioral patterns across a society shift in unison. Psychologists since Asch have recognized the remarkable strength of the conformity motive, stemming from a fundamental goal to fit in as part of a social group (Asch, 1955, 1956; Cialdini & Trost, 1998). The need-to-belong is a fundamental driver of social behavior (Baumeister & Leary, 1995; Gere & MacDonald, 2010). This social need makes people more sensitive to the behaviors of other people around them (Pickett et al., 2004). People tend to feel uncomfortable about considering, holding, and expressing beliefs that conflict with the prevailing views around them as well as about behaving oddly, in ways that might expose oneself as an outsider to the group (Golman et al., 2016; Rivis & Sheeran, 2003; Spears, 2021; Turner et al., 1987). Conformity helps people gain social approval (Cialdini & Goldstein, 2004). For example, people wear similar clothing styles as their peers in order to be socially accepted (Rose et al., 1994; Smucker & Creekmore, 1972).

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Thanks to David Zixi Chen, Andrew Gu, Cici Yidan Hu, Ashwin Konkimalla, Tzen-Hao Ng, and Andrew Wu for research assistance.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

The authors declare that they have no competing financial interests.

The data and code for the empirical analysis of given names, and the source code, social networks, and complete output data for the computational models have been made publicly available on OSF and can be accessed at https://osf.io/s4t6r/.

The analyses were not preregistered.

This research was presented at the Economic Research on Identity, Norms, and Narratives Conference in 2018; the Networks 2021 Conference; and the Learning, Evolution, and Games Conference in 2021. An early draft of the paper was posted to arXiv in 2019.

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Given the conformity motive alone, we might expect to observe convergence to an equilibrium in which society becomes monolithic, yet instead we actually observe persistent diversity.

Opposing the motive to conform is a similarly universal human need for uniqueness (Lynn & Snyder, 2002; Snyder & Fromkin, 1980). Standing out in some small way can help a person individuate himself (Maslach et al., 1985; Rios Morrison & Wheeler, 2010). The hipster striving to be cool departs from mainstream culture to assert individuality. While the desire to differentiate oneself clearly works against the desire to blend in (Imhoff & Erb, 2009), people simultaneously pursue assimilation and differentiation goals (Brewer, 1991; Chan et al., 2012; Hodges, 2017; Hornsey & Jetten, 2004). Chan et al. (2012) demonstrate that people choose distinctive attributes on one dimension of identity while conforming to prevailing behaviors on other dimensions of identity, thus aiming to be identifiable, but not identical. Such idiosyncratic displays of nonconformity, or small deviations from common patterns of identity expression, are judged positively (Bellezza et al., 2014; Warren & Campbell, 2014). People reassert their uniqueness specifically when mimicked by similar others (White & Argo, 2011). While there are certainly cultural differences in the interplay of conformity and uniqueness motives (Kim & Markus, 1999), both motives generally contribute to identity expression at some level, which may vary according to culture and context (Blanton & Christie, 2003; Vignoles et al., 2000; Yamagishi et al., 2008). Preferences for idiosyncratic behavioral patterns can preserve diversity in equilibrium (Smaldino & Epstein, 2015). Still, the question remains why behavioral patterns often do not remain in a stable equilibrium with everyone finding an optimal balance between distinctiveness and conformity. Why instead do behavioral patterns go through perpetual change, with particular behaviors cycling into and out of fashion as cultural trends play out?

One explanation, tracing back to Simmel (1957), is that an upper class tries to distinguish itself from the common folk while the common folk try to imitate them (see also Leibenstein, 1950). Accordingly, conformity may be particularly high among the middle class (Phillips & Zuckerman, 2001). In modern models of identity signaling, membership in one group may be preferable to membership in another, and people want to strategically distinguish themselves from those in the less-favorable group (Berger & Heath, 2007). The resulting dynamic of imitation and differentiation (or "chase-and-flight") can lead to fashion cycles (Pesendorfer, 1995; Tassier, 2004; Zhang et al., 2018). Undoubtedly, there are contexts in which elites initiate fashions and everyone else strives to imitate them, but empirical research shows that in many other contexts, groups with lower or equal status also strive to differentiate themselves (Berger & Heath, 2008). A dynamic of mutual differentiation, without imitation, cannot account for popularity cycles.

Other models of popularity cycles rely on people continually discovering new behaviors, which spread through the population and then get discarded, either through random imitation (Bentley et al., 2004, 2007), or with a motive for conformity or anticonformity (Acerbi & Bentley, 2014), or with the co-evolution of behavior and preferences (Acerbi et al., 2012). These models account for boom-and-bust cycles of popularity, but do not attempt to explain the source of the new behaviors that continually enter the model and keep the dynamics from converging to equilibrium.

This article explores a new account of the dynamics of cultural trends and popularity cycles. We show that along with conformity and uniqueness motives, a realistic network of social interaction may be a critical ingredient for complex social dynamics to emerge. Specifically, we show that reasonable adaptive dynamics, that would necessarily converge to a static equilibrium given random interactions in a well-mixed pool of people, instead typically enter random walks or stochastic limit cycles, and thus never converge, when interactions are restricted to individuals' local neighborhoods in their social networks. The social dynamics cannot converge in some cases as some people find more preferred expressions of identity, they disrupt others who observe them, making these other people dissatisfied with the identities they had previously been happy to express. The social network structure determines who are the innovators and who are the followers.

Popularity cycles in the expression of social identities display a number of empirical regularities, beyond the simple observation that they do not converge to equilibrium. They often preserve diversity, with different people expressing different identities (see Jetten & Hornsey, 2014). A hallmark pattern of social influence, that friends or acquaintances tend to behave similarly, holds for identity expression as well as other kinds of behaviors (Christakis & Fowler, 2013). Notably, friends display more similar attitudes than strangers, although they often assume they agree with each other while being unaware that they actually disagree (Goel et al., 2010). Commonalities in identity expression can extend across large communities—for example, there are regional correlations in the frequencies of given names across U.S. states (Barucca et al., 2015). Noncontroversial behaviors often spread more quickly through "weak ties" in loosely clustered networks (the strength of the weak tie being its tendency to serve as a bridge between groups with otherwise limited contact), whereas behaviors that require social reinforcement from multiple sources, for example, innovative health behaviors or participation in social movements, tend to spread more quickly through more tightly clustered social networks, in a process of "complex contagion" (Centola, 2010; Centola & Macy, 2007). As contagions spread, popularity cycles exhibit momentum—changes in popularity tend to persist in the same direction over time (Gureckis & Goldstone, 2009). Moreover, consistent with the motives we assume for our model, trends of rising popularity may spill over to other similar, but not identical, expressions of identity, while over-popularity actually decreases further adoption of particular expressions of identity (Berger et al., 2012). Here, we find that the social dynamics that emerge in our model with social network structure exhibit momentum, preserve within-group diversity, and usually produce more conformity between network neighbors.[1]

A natural theoretical approach for investigating social influence on decisions is to use game theory. The conformity motive in isolation would create a Keynesian "beauty contest," in which what is cool (like what is beautiful) is just what everybody else believes is cool (Keynes, 1936). The uniqueness motive in isolation would create a "congestion game," in which the objective is simply to be distinct from as many other people as possible (Rosenthal, 1973). Both games are known to be "potential games," for which convergence to a pure-strategy Nash equilibrium is practically guaranteed (Monderer & Shapley, 1996a, 1996b). When both motives coexist and the game is played on a realistic social network, however, the dynamics are more complex.

[1] In contrast, chase-and-flight dynamics between stratified social classes do not preserve diversity within the class that is trying to imitate the elite. And models that assume completely random drift cannot account for the empirical pattern that popularity cycles exhibit momentum.

Cultural trends can be modeled more realistically as the dynamics of a game on a social network as social influence is mediated by a social network (Mason et al., 2007). Social influence on expressions of individual identity is transmitted whenever an individual observes another person whom he would like to identify with, so the relevant social network is defined by directed connections corresponding to observation. The connected components of the social network may correspond to distinct social groups, each with its own emergent subculture.

The desire for uniqueness within one's own social group should not be conflated with a desire for differentiation across groups (Chan et al., 2012). Our model features in-group conformity and uniqueness motives; it could be augmented with a desire for differentiation across groups, but for parsimony we assume that people care only about their fit within their own groups.

We now proceed to explore three mathematical models of identity expression based on dual motivations for conformity and uniqueness, looking to see if and when each model may produce popularity cycles. The first model introduces a mathematical characterization of these motivations, showing how they may coexist with each other, but simplistically assumes that everybody influences everybody else. Each subsequent model then incorporates a more realistic (and more complex) set of assumptions about social influence. The second model assumes that social influence is transmitted through a social network, so that people care about conforming and being unique only among the people they can observe. The third model assumes additionally that the social network itself evolves in tandem with expressed identities. Only the models with social networks (Models 2 and 3) can account for popularity cycles.

Model 1: Social Influence and Identity Expression in a Well-Mixed Population

We model the expression of social identity as a game played by a population of N individuals. Let us say there are m aspects of identity (or identity-relevant traits). Each person i adopts an expression of identity $x_i = x_{i,1}, \ldots, x_{i,m}$, where the choice of each expressed trait $x_{i,\mu} \in \{a..b\}^d$ can be represented as a tuple of d integers from some interval.[2] For example, in the case of choosing an outfit to wear, two traits could be the color of the shirt and the color of the pants, and three integers between 0 and 255 might correspond to shades of red, green, and blue that mix together to form any color in an "RGB-color system".

A person's degree of conformity in the population depends on the (Euclidean) distance between his expressed identity and the average (population mean) expression of identity, $\|x_i - \bar{x}\|$. A person's degree of uniqueness in the population depends on the number of others who express the exact same identity-relevant trait as him, averaged across all traits. For individual i and trait μ, denote the number of others who adopt his exact same expression of this trait as $n_{i,\mu}(X)$, where X is the entire population's profile of expressed identities, and let $n_i(X)$ denotes the average amount of shared traits, that is, $n_i(X) = \frac{1}{m}\sum_{\mu} n_{i,\mu}(X)$. Putting together the conformity and uniqueness motives, we model person i's utility given the profile of expressed identities as

$$u_i(X) = -\|x_i - \bar{x}\|^2 - \lambda n_i(X), \tag{1}$$

where λ is a parameter that describes the strength of the uniqueness motive relative to the conformity motive. This utility function describes a person whose goal is to be similar to everybody, yet the same as nobody. This preference leads people to differentiate themselves on some dimension of identity while conforming on other dimensions, as observed empirically (Chan et al., 2012).

We find empirical support for our proposed utility function by considering the popularity of given names, examining data on just one of the many forms of identity expression that we hope to encompass. We can embed given names in a vector space using distributional semantics models that capture relationships between words (including given names) according to their co-occurrence in a large corpus of text (see Bhatia, 2017). Specifically, we use the fastText algorithm (Mikolov et al., 2018) trained on Common Crawl data. This algorithm is based on co-occurrences of strings of characters, and thus associates related variants of phonetically similar names (e.g., Jesse and Jessie) and can handle rare names. We calculate the mean vector of American given names every year from 1880 to 2020 and then compute the Euclidean distance between each given name and this mean (for each year).

We first examine the relationship between these distances to the mean and the popularity of given names, measured as the percentage of babies receiving that name, in each year. Figure 1 presents scatter plots showing these distances and popularities for all names in the years 1900, 1950, and 2000, respectively. The scatter plots are overlaid on top of heat maps showing the number of different names with distances and popularities in subdivided intervals on these two dimensions, which helps us distinguish the number of different names in the high-density areas of the scatter plot. In each of the 3 years shown in the figure, most names have low-to-moderate distance from the mean and low popularity, but the vast majority of the most popular names have even lower distances from the mean. This pattern is consistent across all years. The correlation between the distance of a name from the mean and the popularity of that name in a particular year, averaged across all years, is −.13 (SD = .01). A t test shows the overall correlation to be significantly different from 0 ($p < .001$).

Next, for each name we examine the correlation between that name's distance from the mean and that name's popularity over time. Figure 2 shows graphs of the distance from the mean and the popularity over time for a representative name, "Wynona." The name grows in popularity during the beginning of the 20th century and then declines in popularity during the middle of the century, when it has higher distance from the mean than in the early years of the century. The correlation between the distance of "Wynona" from the mean and the popularity of "Wynona" is −.25. The average of these correlations across all names is −.29 (SD = .38), again significantly negative ($p < .001$). We thus see that babies are given names that are closer to the mean more frequently, and that names tend to become less popular when they are farther from the mean.

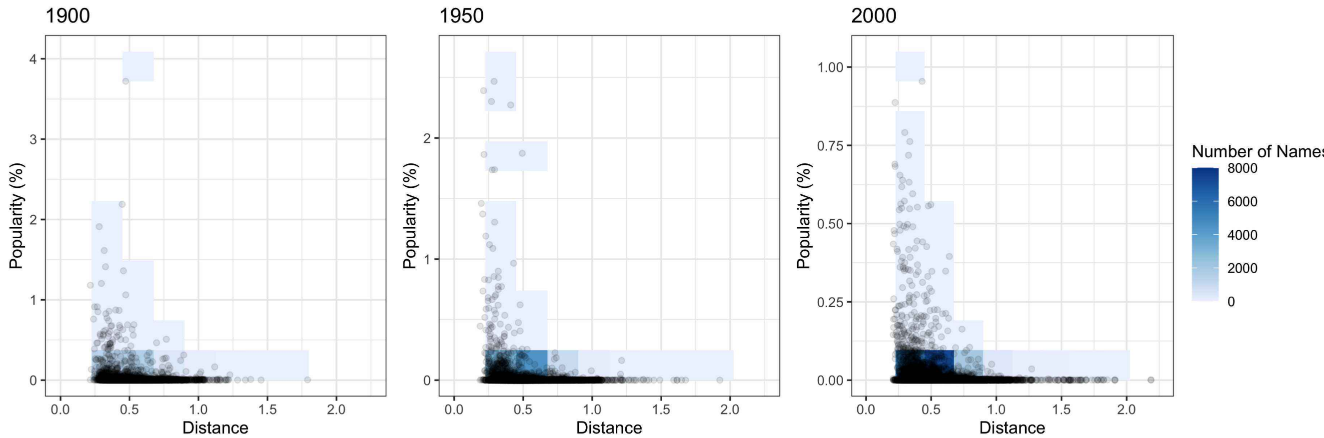
We also observe that new names enter into use over time (faster than old names disappear), while the most popular names tend to decline in popularity over time, as people look for unique names. For example, the most popular name in 1900 is given to almost 4% of babies born that year, whereas the most popular name in 2000 is given to less than 1% of babies that year, as shown in Figure 1.

To capture the dynamics of identity expression over time, we cannot assume that everybody immediately maximizes their utility. Instead, over time people may change their expressions of identity to

[2] The dimensionality d of the tuple and the boundaries of the interval $a..b$ can certainly vary for different traits, but we omit subscripts on these parameters specifying a particular trait to simplify the notation.

Figure 1

Euclidean Distance Between Each Name's Vector Representation and the Mean Name Vector, Along With the Popularity of These Names (i.e., The Percentage of Babies Receiving Each Name) in the Years 1900, 1950, and 2000



Note. Background shading indicates the number of names in each bin. See the online article for the color version of this figure.

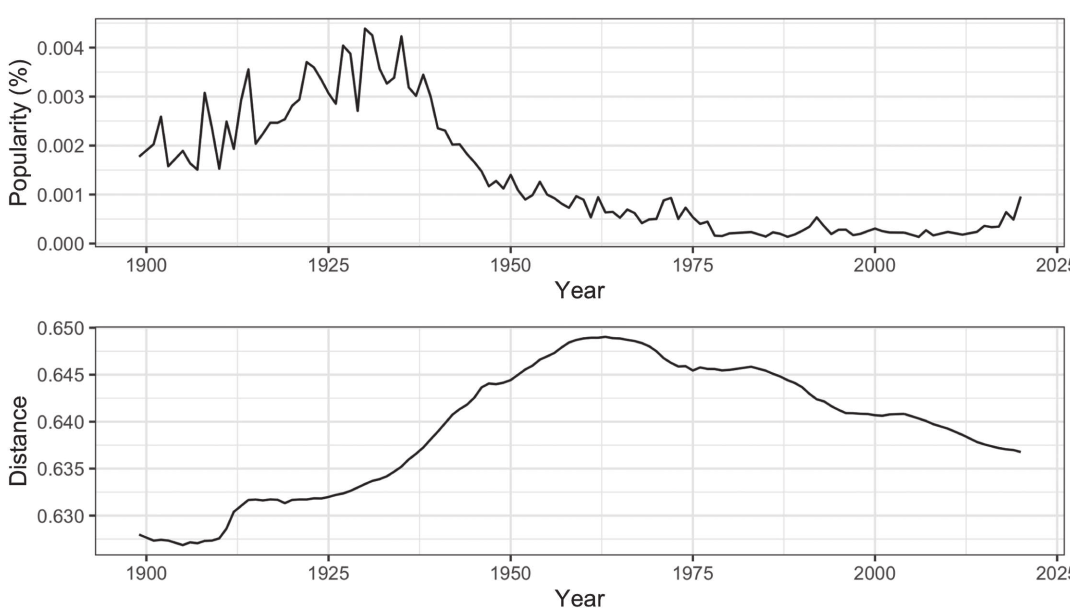
achieve higher utility. We need not fully prescribe this process, but assume only that people make changes that increase their own utility, in accordance with some *better-reply dynamics* (Friedman & Mezzetti, 2001; Monderer & Shapley, 1996b).

Definition 1 (Better-reply dynamics). At any given time t, one person i may consider switching from x_i to x_i'; he switches if and only if $u_i(X') > u_i(X)$; and for each person i and any best response x_i^* (to $X(t)$), the expected time until person i considers switching to x_i^* is finite.

The motivation for better-reply dynamics is that people are boundedly rational and adaptive (Gigerenzer, 2000). They can see what the people around them are doing and can search for something better (myopically), but they do not instantaneously react to changes in other people's behavior or anticipate these changes before they occur (Fiske & Taylor, 2013). Often they rely entirely on automatic, subconscious processing (Bargh & Chartrand, 1999). Almost all commonly assumed adaptive learning dynamics are particular specifications of better-reply dynamics (Hofbauer & Sigmund, 2003).

Figure 2

Euclidean Distance Between the Vector Representation of "Wynona" and the Mean Name Vector, as Well as the Popularity of the Name "Wynona" for Each Year the Name Was Given



Results: Social Dynamics in a Well-Mixed Population

Theorem 1. Suppose people derive utility from both their conformity and their uniqueness in the population, as in Equation (1). Then any better-reply dynamics necessarily converge to a pure-strategy Nash equilibrium.

The proof is presented in the Supplemental Materials. It follows from Lemma 1 in the Supplemental Materials, which identifies an exact potential function for this game. The existence of a potential function for the game means that any time that an individual finds a more preferred expression of identity, the shift in his own behavior necessarily moves the population as a whole toward a Nash equilibrium. Convergence to equilibrium is guaranteed as the value of the potential function can only increase as people adapt to each other, that is, all changes are toward an equilibrium.

Two examples of Nash equilibria, among many that exist, are shown in Figure 3. These equilibrium distributions of identity expression are approximately symmetric around a single centrally located peak as chosen expressions of identity all need to yield approximately the same utility in equilibrium—if any expression of identity generated higher utility, other people would want to adopt it; if it generated lower utility, people would give it up. (Minor deviations from perfect symmetry may arise from discrete-person effects.) The distributions are composed of a lot of people clustered near the mean and fewer people filling in around the periphery as the cost of being far from the mean (nonconforming) needs to be balanced against the cost of being less unique when near the mean.

Theorem 1 is a stark result that shows that our simple model makes a clearly unrealistic prediction. It says that in a well-mixed population, in the long run we will not see popularity cycles, perpetual change, or novelty. The fact that we do, in reality, observe popularity cycles, perpetual change, and novelty suggests that we should consider a more realistic model. We now consider the social dynamics that result from assuming that people care only about the expressed identities of their immediate neighbors in their social network. Naturally, people can only be influenced by the other people they can observe, and social influence thus must be mediated by the social network.

Model 2: Social Influence and Identity Expression in Social Networks

A social network is described by an adjacency matrix A where $a_{ij} = 1$ if person i observes, and thus cares about, person j's expressed identity (and equals 0 if not). Let $\eta(i) = \{j : a_{ij} = 1\}$ denotes the set of people that person i observes, that is, his neighbors.

Conformity among one's neighbors depends on distance from one's neighbors' average identity, $\bar{x}_{\eta(i)}$. Uniqueness among one's neighbors depends on the average amount of shared traits among one's neighbors (or, more precisely, the average across the different aspects of identity of the number of neighbors who express the same trait as oneself), denoted by $\tilde{n}_i(X; \eta(i))$. Thus, we now model person i's utility given the profile of expressed identities X and his set of neighbors $\eta(i)$ as

$$u_i(X) = -\|x_i - \bar{x}_{\eta(i)}\|^2 - \lambda \tilde{n}_i(X; \eta(i)). \qquad (2)$$

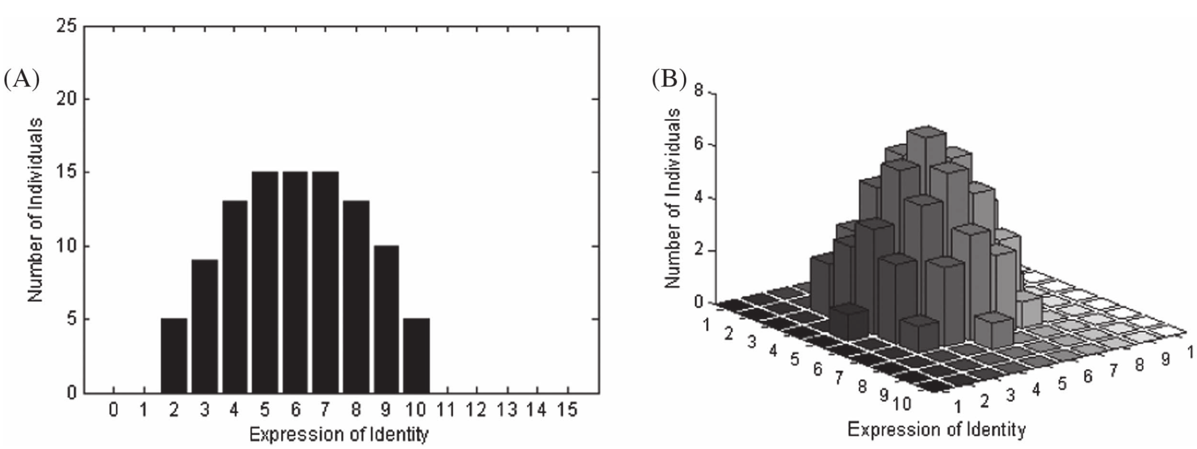
Results: Social Dynamics in Social Networks

Theorem 2. Suppose people derive utility from both their conformity and their uniqueness among their neighbors in a social network, as in Equation (2) with $\lambda > 1$ and $m = 1$. Then there exists a social network (i.e., an adjacency matrix $\hat{A}$) such that no pure-strategy Nash equilibrium exists and, thus, better-reply dynamics never converge to an absorbing state.

Proof. By construction. We provide an example of a social network with $N = 3$ people that illustrates the result. (Any larger social network that contains this network as an out-component

Figure 3

Two Nash Equilibria Distributions of Identity Expression for Populations of N = 100 Individuals



Note. We set $\lambda = 1.5$ for this illustration. (A) Expression of a single one-dimensional trait over the domain $\{0..15\}$. (B) Expression of a single two-dimensional trait over the domain $\{1..10\}^2$. By symmetry, the distributions can be shifted anywhere within these (or wider) domains, and many strategy profiles give rise to the same population distributions. Even after accounting for these symmetries, these Nash equilibria are not unique.

also suffices.) Let person 1 observes (only) person 2, person 2 observes (only) person 3, and person 3 observes (only) person 1. That is, the network is a cycle graph with length 3.

Observe that the best response correspondence for each person is as follows:

$$x_1^* \in \{x: \|x - x_2\|^2 = 1\}$$

$$x_2^* \in \{x: \|x - x_3\|^2 = 1\}$$

$$x_3^* \in \{x: \|x - x_1\|^2 = 1\}.$$

Each person wants to be one unit of distance away from the person he is observing. If we associate the parity of an expressed identity x with two colors (i.e., distinguish only whether the sum of its integer coordinates is even or odd), then each person wants to have the color different from the person he is observing. However, it is impossible for all three people to simultaneously choose best responses as (at least) one pair of them will always be the same color.[3]

In contrast to the result for the well-mixed population, which is guaranteed to converge to equilibrium, Theorem 2 says that there are social networks for which convergence to equilibrium is impossible, as no equilibrium can exist. For the simple cyclic network used to demonstrate the result, any individual finding his most preferred expression of identity necessarily makes the person observing him want to find a different expression of identity. Thus, with only local interactions in a social network, perpetually changing identity expression and popularity cycles become possible.

This result is consistent with the computational patterns generated by Smaldino et al.'s (2012) agent-based model of social identity dynamics arising from optimal distinctiveness theory. Their model also features conformity and distinctiveness motives (specified somewhat differently as opponent processes), and the incorporation of simple (lattice) social network structure in some cases leads to nonconvergence in that model as well.

Observe that the uniqueness motive is critical for obtaining our result. If we were to eliminate the uniqueness motive by setting $\lambda = 0$, then any homogeneous profile of expressed identities (with x_i identical for all i) would be a pure-strategy Nash equilibrium, regardless of the social network structure. Other models of conformity pressure with local interactions on networks, but with no uniqueness motive, also generally converge to equilibrium, although polarization is possible, with behavior varying between clusters, even without the uniqueness motive (Axelrod, 1997; Centola et al., 2007; Nowak et al., 1990). Here, the uniqueness motive along with the local interactions together allow for more complex social dynamics.

Still, Theorem 2 only provides an existence result constructed with a highly stylized, simplistic social network. It does not tell us whether complex social dynamics typically emerge from our model when people are connected by realistic social networks. Real social networks have community structure with high levels of triadic closure (i.e., clustering or transitivity)—people associate mostly in small, tightly knit groups (Girvan & Newman, 2002; Granovetter, 1973; Newman & Park, 2003). This community structure does not typically include the kind of isolated cycle invoked in the proof of Theorem 2. We now use computational modeling to explore the dynamics of our model on realistic social networks.

Realistic Social Networks

We used a variant of the Jin-Girvan-Newman algorithm (Jin et al., 2001) to create a sample of 25 directed social networks with positive levels of clustering and community structure and limited out-degree. The networks have $N = 100$ people, each of whom can observe up to a maximum of $z_{\max}$ neighbors. Connections are formed and broken randomly, with a tendency to begin observing specific individuals who currently either observe or are observed by others who one is already observing. [Real social networks exhibit both patterns of directed closure, Brzozowski and Romero (2011).] This tendency for clustering depends on a free parameter r. We varied r in {.01, .05, .1, .5, 1} and $z_{\max}$ in {3..7} to create the 25 networks. (see *Materials and Methods* in the Supplemental Materials for additional details.) Networks with higher $z_{\max}$ have more connections, and networks with higher r are more tightly clustered.

For each of these social networks, we repeatedly computed better-reply dynamics, specified with a simple random search for better replies based on the utility function in Equation (2) with λ in {0.5, 1.5, 5.0}, to see how often the dynamics converged to equilibrium within 1,000,000 time steps. (Different specifications of better-reply dynamics could lead to different patterns of identity expression, but they all share the property that their rest points are the Nash equilibria of the game, so our results should be robust across this class of dynamics.) For robustness, we considered three different specifications of the space of possible identities: first, $m = 1$, $d = 1$, and $\{a..b\} = \{0..99\}$; second, $m = 1$, $d = 2$, and $\{a..b\} = \{0..9\}$; and third, $m = 2$, $d = 1$, and $\{a..b\} = \{0..9\}$. (Higher dimensional spaces for identity expression would be more realistic, but are too computationally intensive to explore. We simply made the spaces large enough that everybody could express unique identities.) We repeated each computation 10 times, for a total of 2250 trials across the nine different parameter specifications and 25 networks. (see *Materials and Methods* in the Supplemental Materials for additional details.) If the dynamics did not converge within 1,000,000 time steps, we classified them as nonconvergent (for that trial). (We believe the cutoff at 1,000,000 time steps provides ample time for convergence, as we first computed the dynamics in the full, well-mixed population, for which Theorem 1 tells us that they must converge, and found that across 90 trials, the dynamics always converged within 2,000 time steps. We discuss additional checks on the sufficiency of 1,000,000 time steps below.)

Computational Results: Frequency of Nonconvergence

The frequency of nonconvergent trials varied with the parameters specifying the game and the network formation process, with the value of λ in particular playing a critical role. When $\lambda = 0.5$, the dynamics usually converged to equilibrium (68.53% of these 750 trials). Figure 4A shows the frequency of convergent trials for each of the 25 networks, for each of the three specifications of the space of identities, with $\lambda = 0.5$. Darker shading indicates higher frequencies of convergence. The frequency of convergence varies nonmonotonically with the maximum out-degree of the network $z_{\max}$. For $z_{\max} = 3$ or 4, the dynamics almost always converge, whereas for

[3] This is the case for any odd-length cycle, due to a basic mathematical theorem about graph coloring.

$z_{max} = 7$, the dynamics usually do not converge. Yet, there is more convergence with $z_{max} = 6$ than with $z_{max} = 5$.

When $\lambda = 1.5$, the dynamics usually did not converge (only in 18% of these 750 trials). Figure 4B shows the frequency of convergent trials for each of the 25 networks, for each of the three specifications of the space of identities, with $\lambda = 1.5$. Four of the networks with $z_{max} = 4$ usually converged (specifically, those with $r > .01$). A few of the other networks occasionally converged. Many never converged at all.

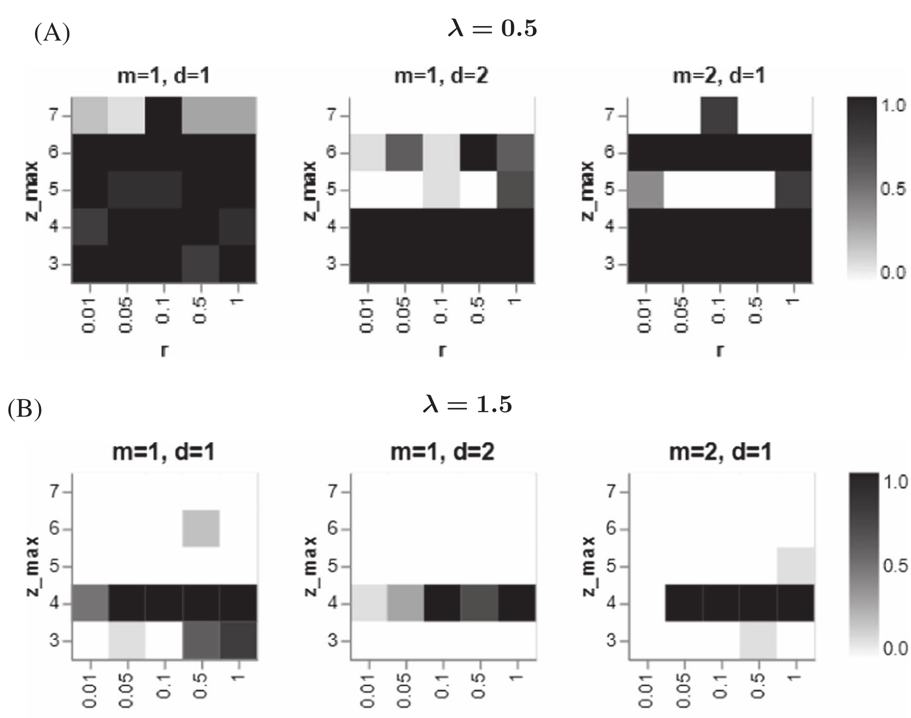
When $\lambda = 5$, the dynamics almost never converged. The only exception was the network with $z_{max} = 4$ and $r = 1$, which converged in all 10 trials with $m = 1$ and $d = 1$. However, none of the other 740 trials with $\lambda = 5$ converged. A stronger uniqueness motive (larger λ) appears to make convergence much less likely.

The results presented here leave room for two arguments raising concern that perhaps the dynamics would always eventually converge if they just had more time to continue running. First, it is surprising to see so many parameter specifications for which the dynamics sometimes converge and other times do not. We might have expected nonconvergent trials whenever there is no pure Nash equilibrium, but that whenever such an equilibrium exists and convergence is possible, it would eventually occur. Perhaps it just needs more time. However, even when a pure Nash equilibrium does exist, allowing the dynamics to converge in some trials, it is possible for the dynamics to enter a random walk on an absorbing subspace, from which it is no longer possible to reach the equilibrium. (i.e., the dynamics could sometimes move away from an equilibrium and then be unable to return to it.) This could explain the observed frequencies of convergence that are positive but still less than 100%. Still, a second cause for concern is that larger values of λ give the better-reply dynamics more possible states to explore when a neighbor adopts one's own identity. Thus, we should expect it to take longer to reach an equilibrium with larger values of λ. If the dynamics usually converge with $\lambda = 0.5$, might they be on their way, but not quite there yet, with larger values of λ?

A few additional pieces of data reassure us that most of the trials we have classified as nonconvergent are not artifacts of terminating the computation too quickly. First, for each trial we examine the fraction of individuals that are satisfied with their current identities every 1,000 time steps during the trial. Convergence to equilibrium occurs if and when everybody is satisfied. So, the trajectories of the percentage of satisfied individuals also reveal the times to reach equilibrium, when convergence occurs. Figure 5 shows the percentage of satisfied individuals over time for each trial with $m = 1$, $d = 1$, and varying λ, for networks with $r = 1$. Figures S3 and S4 in the Supplemental Material show the corresponding results with $m = 1$, $d = 2$ and with $m = 2$, $d = 1$, respectively. The results for networks with $r < 1$ look similar and are omitted. Across the board, when the dynamics do converge to equilibrium, they tend to do so quickly. Although the distribution of convergence times does have a fat tail, it certainly appears that convergence becomes less and less likely over time. Additionally, while the percentage of satisfied individuals appears to bounce around randomly, for many of the parameter values it appears to be bounded well below 100%.

Figure 4

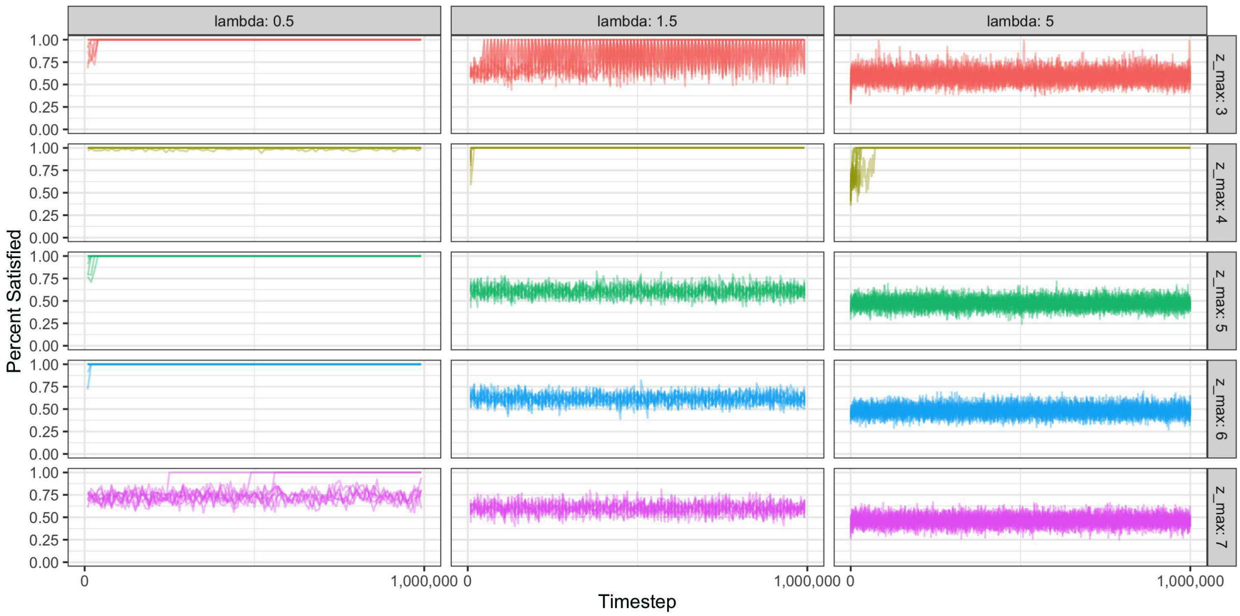
Frequency of Convergent Trials for Each Network



Note. Darker shading indicates higher frequencies of convergence. The trials with $\lambda = 5$ are omitted as they almost never converged.

Figure 5

Percentage of Individuals Satisfied Over 1,000,000 Time Steps for Each Trial With $m = 1$, $d = 1$, and Varying λ, for Networks With $r = 1$ and Varying z_{max}



Note. See the online article for the color version of this figure.

The trajectories of the percentage of satisfied individuals suggest that the trials we have deemed nonconvergent really would never converge, but of course there can be no guarantee. With $N = 100$ individuals choosing among 100 possible identities, it is simply not computationally feasible to check every possible scenario. However, with $N = 8$ individuals choosing among eight possible identities, it is feasible to exhaustively search for equilibria. We created an additional social network using the same algorithm with $z_{\max} = 3$ and $r = 1$, but with $N = 8$. Once again, the better-reply dynamics with $\lambda = 5$ and $m = 1$, $d = 1$, and $\{a..b\} = \{0..7\}$ did not converge. We, then, exhaustively searched every profile of identities on this space and verified that no pure Nash equilibrium exists. This guarantees that the dynamics would never converge. This network does not contain an isolated odd-cycle, which our proof of Theorem 2 relied on, but it provides another example that shows that nonconvergence is possible, and moreover can occur with realistic network structure.

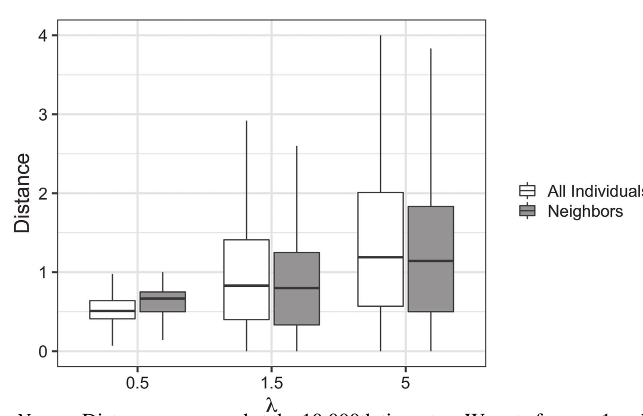
We interpret these results to mean that when the uniqueness motive is sufficiently strong, the dynamics on realistic social networks usually will not converge. However, if the uniqueness motive is too weak, individuals feel little pressure to differentiate themselves, and they may settle into an equilibrium with overlapping identities.

Computational Results: Conformity

We further explore the dynamics by observing the trajectories of identity expression over the initial 10,000 time steps. Clearly, because of the uniqueness motive, there will always be some diversity of identity expression. As the uniqueness motive gets stronger, that is, as λ increases, we expect to observe less conformity. Sure enough, this is the case. Figure 6 displays the distributions of the distances from individuals' identities to the average identity in the population and to the average identity of their neighbors in the network, $\|x_i - \bar{x}\|$ and $\|x_i - \bar{x}_{\eta(i)}\|$, respectively, measured at the 10,000th time step, for $m = 1$, $d = 1$, and varying λ, aggregating trials across the different networks. Figures S5 and S6 in the Supplemental Materials show the corresponding results for $m = 1$, $d = 2$ and for $m = 2$, $d = 1$, respectively.

Figure 6

Box Plots Showing Distances From Individuals' Identities to the Average Identity of All Individuals in the Population and to the Average Identity of Their Neighbors in the Network



Note. Distances measured at the 10,000th time step. We set , for $m = 1$ and, $d = 1$, and varying λ, and aggregating trials across the different networks.

We first compare the average distance to the population mean expressed identity across different values of λ. The average distance to the population mean increased from 0.59 ($SD = 0.57$) when $\lambda = 0.5$ to 0.99 ($SD = 0.83$) when $\lambda = 1.5$ to 1.45 ($SD = 1.13$) when $\lambda = 5$. (All differences are statistically significant with $p < .001$ in t tests.) We then compare the average distance to one's neighbors across different values of λ. The average distance to one's neighbors increased from 0.61 ($SD = 0.26$) when $\lambda = 0.5$ to 0.85 ($SD = 0.58$) when $\lambda = 1.5$ to 1.25 ($SD = 0.86$) when $\lambda = 5$.

We also check whether the expressed identities display the signature empirical pattern associated with social influence: do individuals express identities that are more similar to their network neighbors' identities than to the average member of the population as a whole? The differences between the distances to the population mean identity and to the mean of one's neighbors' identities appear to be small in Figure 6, but they are all statistically significant with $p < .001$ in paired t tests. For $\lambda = 1.5$ and $\lambda = 5$, individuals do indeed express identities that more closely resemble the people they observe than others in the population. Yet for $\lambda = 0.5$, individuals are actually more similar to unobserved others than to their network neighbors. There is little diversity across the entire population in these trials.

Computational Results: Momentum and Contagion

Next we look for momentum in the dynamics. For simplicity, we restrict this analysis to trials with $m = 1$ and $d = 1$. As a measure of momentum over time, we compute $\sigma_{100}(t) = \frac{1}{100}\sum_{t'=1}^{100} \Delta x(t) * \Delta x(t + t')$, where $\Delta x(t)$ is the change in identity expression of the individual who searched for a better reply at time step t. We take the average momentum for a trial to be the average value of $\sigma_{100}(t)$ for $1000 \leq t < 9900$. (We exclude the first 1,000 time steps as they tend to be noisy.) Figure 7 shows the average momentum on each network for varying λ, aggregated over 10 trials. We observe that average momentum is always positive ($M = .0096$, $SD = .31$), indicating that changes in identity expression tend to persist in the same direction over time.

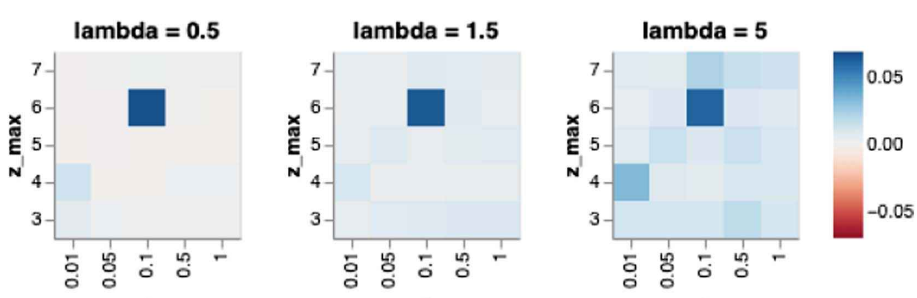
Figure 7 also shows clear differences in the average momentum across the different networks. Most prominently, we observe particularly strong momentum on the network with $r = 0.1$ and $z_{max} = 6$. This finding is robust across multiple trials, not the result of a single outlying trial, but appears to be specific to this particular network. (We created another network with the same parameters, $r = 0.1$ and $z_{max} = 6$, to see if this result would replicate. It did not. In the attempted replication, the average momentum aggregated over 30 trials across the same λ values was .006.) We examined the network's properties (available in the Supplemental Materials) hoping to explain why strong momentum develops on this network, but the network does not appear to have unusual characteristics or structure.

We use multiple linear regression to assess how momentum depends on our parameters r, z_{max}, and λ. Table 1 reports the results. We find that average momentum is increasing in λ and z_{max}. Intuitively, higher values of λ make individuals willing to make larger shifts in their identity to remain unique, which generates stronger momentum. Higher values of z_{max} mean that a single person's change in identity affects more of the other people in the network who observe that change, which also generates stronger momentum.

We were particularly interested in how average momentum depends on r, as this distinguishes a complex contagion from a simple contagion. Recall that a complex contagion describes the case that substantial social reinforcement is necessary to change behavior, whereas behavior spreads more easily in a simple contagion. Thus, clustering of the social network provides pathways for social reinforcement that are critical for complex contagions, but which are redundant and unnecessary for simple contagions (Centola & Macy, 2007). So, in a simple contagion, there would be greater momentum when there is less clustering (smaller r), whereas in a complex contagion, there would be greater momentum when there is more clustering (larger r). Alas, we find no significant linear trend here. Qualitatively, it appears that momentum is the strongest for an intermediate level of clustering, but this speculative finding might just reflect the observation of particularly strong momentum on the single network with $r = 0.1$ and $z_{max} = 6$. At an intuitive level, as social influence from multiple neighbors combines additively in our model (i.e., each neighbor shifting in a given direction adds steadily to the social pressure to shift in that same direction), our social dynamics may be in a border zone between simple contagion and complex contagion. When behavior choices are binary, additional neighbors changing their behavior can either be substitutes for each other or complements with each other in the production of social influence, corresponding to simple

Figure 7

Average Momentum on Each Network for Varying λ, With m = 1 and d = 1, Aggregated Over 10 Trials



Note. In all cases, the average momentum is positive. Darker shading indicates greater momentum. See the online article for the color version of this figure.

Table 1
Linear Regression of Average Momentum

Effect	Estimate	*SE*	*p*
λ	.0051	.0001	<.001
z_{max}	.0007	.0001	<.001
r	−.0001	.0001	.291
Constant	−.002	.0005	<.001
Observations	6,675,000		
R^2	.0002		
Adjusted R^2	.0002		
Residual standard error	.3062	(df = 6,674,996)	
F statistic	430.8	(df = 3; 6,674,996)	<.001

contagions and complex contagions, respectively, but in our model, expressions of identity may vary incrementally along one or more dimensions. With additive social influence involving neither substitutability nor complementarity among neighbors, our dynamics resist easy categorization as either simple or complex contagion.

Model 3: Co-Evolution of Identity Expression and Social Networks

Up to this point, we have considered identity expression on fixed social networks, but social networks themselves evolve over time. There is ample empirical evidence that people are more likely to form (and less likely to dissolve) all kinds of relationships with people who are more similar to them—a pattern of social network dynamics known as homophily (McPherson et al., 2001). By first forming the social networks and then considering the dynamics of identity expression on these fixed networks, we could capture a form of social influence, but we could not capture homophily. Yet empirical research suggests that homophily in the formation of social connections has equal or even stronger effects on patterns of similarity between friends compared to social influence (Cohen, 1977; Kandel, 1978).[4] We now consider integrating the dynamics of identity expression with the dynamics of social network formation, to incorporate homophily.

Modeling the co-evolution of behavior and social network structure can give us insight about how social influence and homophily interact and reinforce each other. Together, they can generate surprising emergent patterns. For example, Centola et al. (2007) have shown that homophily in forming and maintaining social connections on top of conformity pressure transmitted through the social network can preserve cultural diversity between social groups (see also Holme & Newman, 2006; Kozma & Barrat, 2008). Cultural differences can then lead to different network structures (Muthukrishna & Schaller, 2020; Smolla & Akçay, 2019). Models of the co-evolution of identity expression and social network structure typically assume only a conformity motive. We depart from this existing literature by introducing the additional motive for demonstrating uniqueness. The uniqueness motive contributes to the emergence of popularity cycles here, as cultural trends develop momentum and often do not converge to equilibrium.

Our model of co-evolving identity expression and social networks relies on the same utility function we used above, given in Equation 2. Now, at each time step an individual can either consider a change in his own identity or a change in the network neighbors he observes. (We assume each consideration is equally likely.) In the former case, the individual randomly considers a new expression of identity. In the latter case, the individual considers forming a new connection either to a randomly selected other person or specifically to another person who already has a link (in either direction) with someone he already has a connection to (i.e., with a tendency toward triadic closure), and if the focal individual already had as many relationships as he could handle, he simultaneously considers breaking an existing connection. (In reality, limits on the number of relationships an individual can handle are likely to be somewhat more flexible, but this stylized model parsimoniously captures the clustering and bounded out-degree that characterize social networks.) Critically, the individual only accepts changes to his identity or to his social network if they increase his utility. (An exception is made for the first network connection that each individual considers forming, which is always accepted, as the utility function is not well-defined if the individual has no connections at all.) See *Materials and Methods* in the Supplemental Materials for additional details about the process. The model effectively brings together Jin et al.'s (2001) social network formation process with the preferences about identity expression that we have proposed here, and incorporates homophily by only allowing changes to one's social network that increase utility. The assumed tendency toward triadic closure may induce considerable additional homophily by reinforcing the effects of homophily in initial network connections or social influence on multiple neighbors, as empirically observed (Kossinets & Watts, 2009).

We investigate whether our earlier results are robust in this model of co-evolving identities and social network ties. We ran 30 trials each with $\lambda = 0.5$, $\lambda = 1.5$, and $\lambda = 5$. When $\lambda = 0.5$, 23% (7/30) of the trials converged to equilibrium. When $\lambda = 1.5$ or $\lambda = 5$, none of the trials converged to equilibrium. These results are consistent with our earlier results for the fixed social networks.

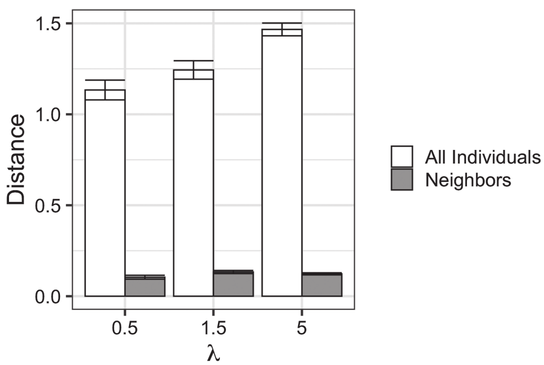
We again compare the conformity among network neighbors to the conformity in the population as a whole. Figure 8 shows the average distances to the population mean identity and to one's neighbors' mean identity, measured at the end of the trial, for each λ, aggregating across the 30 trials. We find that expressed identities are significantly more similar to one's neighbors' identities than to the population mean identity in all three cases. The differences here are much starker than they were in the comparisons on the fixed social networks as the social networks that endogenously form here are not necessarily fully connected. When people sort themselves into nonoverlapping social groups, the distance between the groups' mean identities tends to be larger than the variance of identities within a group.

We again look for momentum in the dynamics. This time we simply compute the percentage of successive changes to identities that are in the same direction over the duration of each trial. Averaging across the trials, well above half (59%, 95% CI [58.2%, 59.9%]) of shifts in identity are in the same direction as the previous one. When we restrict to changes in identity within the largest connected component of the network after the first 10,000 time steps, it jumps to almost always (99.4% of successive shifts, 95% CI [99.37%, 99.45%]) going in the same direction. Thus, the finding of significant

[4] Empirically disentangling social influence and homophily is challenging (see Aral et al., 2009; Levitan & Visser, 2009; Shalizi & Thomas, 2011; Steglich et al., 2010).

Figure 8

Average Distance to the Population Mean Identity and to One's Neighbors' Mean Identity, Measured at the End of the Trial, for Each λ, Aggregating Across the 30 Trials



Note. The error bars correspond to the standard errors for the means.

momentum carries through from our earlier results for the fixed social networks.

Discussion

These results tell us that with local interactions on realistic social networks, the interplay of conformity and sufficiently strong uniqueness motives produces social dynamics for identity expression that are indeed typically nonconvergent. People continually change their expressed identities, and certain forms of expression come into and out of fashion in unpredictable cycles. Popularity cycles are inherently unpredictable in the model as people typically have multiple better replies (and even multiple best responses) to choose from in the face of most profiles of their neighbors' identity expression. The multiplicity of paths the dynamics could take leaves room for idiosyncrasy.

Our findings help us to understand the role of social networks and local interaction in the dynamics of cultural trends. Popularity cycles, perpetual change, and novel expressions of social identity should be expected when people observe their neighbors in realistic, directed social networks and care about being unique as well as fitting in. While popularity cycles are often attributed to chase-and-flight dynamics arising from asymmetric imitation and differentiation, complex social dynamics of identity expression may also arise from our alternative specification of conformity and uniqueness preferences and social network structure.

Consider, for example, popularity cycles in given names, as seen in the rise and fall in the popularity of the names "Jennifer" and, subsequently, "Jessica," or the recent popularity of "Emma" following that of "Emily" (Berger et al., 2012). These popularity cycles do not appear to reflect chase-and-flight dynamics. We cannot identify a clearly demarcated group chasing the trends, for example, that wants to assimilate their kids with the other "Emily"s, or a group exhibiting flight, for example, that opts for "Emma" instead of "Emily" to avoid an undesirable association. Moreover, there would be no reason to choose a name like "Emma," that is so similar to "Emily," if the only goal was differentiation. Rather, it appears that parents are drawn to a trendy name, but look for a similar name that is more unique. (They may be quite surprised when that name becomes so popular too.) The proposed account of popularity cycles driven by concurrent conformity and uniqueness motives, with social influence transmitted through a social network, better fits this scenario.

Recognition of conformity and uniqueness as opposing, but not mutually exclusive, motives is also part of optimal distinctiveness theory (Brewer, 1991; Leonardelli et al., 2010). The theory posits that people form collective identities by choosing to associate themselves with social groups. They can simultaneously pursue assimilation and differentiation goals by viewing themselves as members of groups that provide both a sense of belonging and a sense of distinctiveness. Their desired social identities may shift according to their prioritization of these motives (Pickett et al., 2002). Optimal distinctiveness theory deals with group affiliation and collective identities as fundamental constructs. In contrast, our concept of social identity expression operates at the level of the individual. In our view, collective identities emerge at the level of the group based on their members' individual identities. From the alternative, similarly valid perspective, we could propose that individual identities emerge from a psychological process of finding consonance between the collective identities of the many groups that an individual affiliates with at any point in time. Connecting these perspectives requires deeper understanding of how people choose to associate with or withdraw from social groups, and how this relates to social network structure. While this integration remains beyond our present grasp, we find it useful to have complementary theories aimed at different levels of social identity (Postmes et al., 2005; Turner & Oakes, 1986).

We use game theory and computational modeling here to describe social dynamics with mathematical precision. Social phenomena do not always reflect individual preferences (Schelling, 1971), but understanding individuals' motives is critical to understanding social dynamics. Mathematical modeling helps us understand the relationship between psychological motives and aggregate social dynamics when interactions generate nontrivial feedbacks. Our work here is part of a tradition of formal modeling of identity expression and fashion (Acerbi et al., 2012; Miller et al., 1993; Smaldino & Epstein, 2015; Smaldino et al., 2012, 2015; Strang & Macy, 2001; Tassier, 2004). This approach yields us deep theoretical insight, and we hope it inspires more research leading to further insights into social dynamics and identity expression.

References

Abrahamson, E. (1991). Managerial fads and fashions: The diffusion and refection of innovations. *Academy of Management Review*, *16*(3), 586–612. https://doi.org/10.2307/258919

Acerbi, A., & Bentley, R. A. (2014). Biases in cultural transmission shape the turnover of popular traits. *Evolution and Human Behavior*, *35*(3), 228–236. https://doi.org/10.1016/j.evolhumbehav.2014.02.003

Acerbi, A., Ghirlanda, S., & Enquist, M. (2012). The logic of fashion cycles. *PLOS ONE*, *7*(3), Article e32541. https://doi.org/10.1371/journal.pone.0032541

Aral, S., Muchnik, L., & Sundararajan, A. (2009). Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences*, *106*(51), 21544–21549. https://doi.org/10.1073/pnas.0908800106

Asch, S. E. (1955). Opinions and social pressure. *Scientific American*, *193*(5), 31–35. https://doi.org/10.1038/scientificamerican1155-31

Asch, S. E. (1956). Studies of independence and conformity: I. A minority of one against a unanimous majority. *Psychological Monographs: General and Applied*, *70*(9), 1–70. https://doi.org/10.1037/h0093718

Axelrod, R. (1997). The dissemination of culture: A model with local convergence and global polarization. *Journal of Conflict Resolution*, *41*(2), 203–226. https://doi.org/10.1177/0022002797041002001

Bargh, J. A., & Chartrand, T. L. (1999). The unbearable automaticity of being. *American Psychologist*, *54*(7), 462–479. https://doi.org/10.1037/0003-066X.54.7.462

Barucca, P., Rocchi, J., Marinari, E., Parisi, G., & Ricci-Tersenghi, F. (2015). Cross-correlations of american baby names. *Proceedings of the National Academy of Sciences*, *112*(26), 7943–7947. https://doi.org/10.1073/pnas.1507143112

Baumeister, R. F., & Leary, M. R. (1995). The need to belong: Desire for interpersonal attachments as a fundamental human motivation. *Psychological Bulletin*, *117*(3), 497–529. https://doi.org/10.1037/0033-2909.117.3.497

Bellezza, S., Gino, F., & Keinan, A. (2014). The red sneakers effect: Inferring status and competence from signals of nonconformity. *Journal of Consumer Research*, *41*(1), 35–54. https://doi.org/10.1086/674870

Bentley, R. A., Hahn, M. W., & Shennan, S. J. (2004). Random drift and culture change. *Proceedings of the Royal Society of London. Series B: Biological Sciences*, *271*(1547), 1443–1450. https://doi.org/10.1098/rspb.2004.2746

Bentley, R. A., Lipo, C. P., Herzog, H. A., & Hahn, M. W. (2007). Regular rates of popular culture change reflect random copying. *Evolution and Human Behavior*, *28*(3), 151–158. https://doi.org/10.1016/j.evolhumbehav.2006.10.002

Berger, J. (2008). Identity signaling, social influence, and social contagion. In M. J. Prinstein & K. A. Dodge (Eds.), *Understanding peer influence in children and adolescents*. Guilford Press.

Berger, J., Bradlow, E. T., Braunstein, A., & Zhang, Y. (2012). From karen to katie: Using baby names to understand cultural evolution. *Psychological Science*, *23*(10), 1067–1073. https://doi.org/10.1177/0956797612443371

Berger, J., & Heath, C. (2007). Where consumers diverge from others: Identity signaling and product domains. *Journal of Consumer Research*, *34*(2), 121–134. https://doi.org/10.1086/519142

Berger, J., & Heath, C. (2008). Who drives divergence? Identity signaling, outgroup dissimilarity, and the abandonment of cultural tastes. *Journal of Personality and Social Psychology*, *95*(3), 593–607. https://doi.org/10.1037/0022-3514.95.3.593

Berger, J., & Le Mens, G. (2009). How adoption speed affects the abandonment of cultural tastes. *Proceedings of the National Academy of Sciences*, *106*(20), 8146–8150. https://doi.org/10.1073/pnas.0812647106

Bhatia, S. (2017). Associative judgment and vector space semantics. *Psychological Review*, *124*(1), 1–20. https://doi.org/10.1037/rev0000047

Blanton, H., & Christie, C. (2003). Deviance regulation: A theory of action and identity. *Review of General Psychology*, *7*(2), 115–149. https://doi.org/10.1037/1089-2680.7.2.115

Brewer, M. B. (1991). The social self: On being the same and different at the same time. *Personality and Social Psychology Bulletin*, *17*(5), 475–482. https://doi.org/10.1177/0146167291175001

Brzozowski, M. J., & Romero, D. M. (2011). Who should i follow? Recommending people in directed social networks. In L. A. Adamic, R. A. Baeza-Yates, & S. Counts (Eds.), *Proceedings of the international AAAI conference on web and social media, ICWSM*. AAAI Press. http://www.hpl.hp.com/research/scl/papers/follow/follow.pdf

Centola, D. (2010). The spread of behavior in an online social network experiment. *Science*, *329*(5996), 1194–1197. https://doi.org/10.1126/science.1185231

Centola, D., Gonzalez-Avella, J. C., Eguiluz, V. M., & San Miguel, M. (2007). Homophily, cultural drift, and the co-evolution of cultural groups. *Journal of Conflict Resolution*, *51*(6), 905–929. https://doi.org/10.1177/0022002707307632

Centola, D., & Macy, M. (2007). Complex contagions and the weakness of long ties. *American Journal of Sociology*, *113*(3), 702–734. https://doi.org/10.1086/521848

Chan, C., Berger, J., & Van Boven, L. (2012). Identifiable but not identical: Combining social identity and uniqueness motives in choice. *Journal of Consumer Research*, *39*(3), 561–573. https://doi.org/10.1086/664804

Christakis, N. A., & Fowler, J. H. (2013). Social contagion theory: Examining dynamic social networks and human behavior. *Statistics in Medicine*, *32*(4), 556–577. https://doi.org/10.1002/sim.5408

Cialdini, R. B., & Goldstein, N. J. (2004). Social influence: Compliance and conformity. *Annual Review of Psychology*, *55*, 591–621. https://doi.org/10.1146/annurev.psych.55.090902.142015

Cialdini, R. B., & Trost, M. R. (1998). Social influence: Social norms, conformity and compliance. In D. Gilbert, S. Fiske, & G. Lindzey (Eds.), *The handbook of social psychology, vols. 1 and 2.* , McGraw-Hill. https://doi.org/10.1037/0022-3514.58.6.1015

Cohen, J. M. (1977). Sources of peer group homogeneity. *Sociology of Education*, *50*(4), 227–241. https://doi.org/10.2307/2112497

Fiske, S. T., & Taylor, S. E. (2013). *Social cognition: From brains to culture*. Sage Publications.

Friedman, J. W., & Mezzetti, C. (2001). Learning in games by random sampling. *Journal of Economic Theory*, *98*(1), 55–84. https://doi.org/10.1006/jeth.2000.2694

Gere, J., & MacDonald, G. (2010). An update of the empirical case for the need to belong. *Journal of Individual Psychology*, *66*(1), 93–115.

Gigerenzer, G. (2000). *Adaptive thinking: Rationality in the real world*. Oxford University Press.

Girvan, M., & Newman, M. E. (2002). Community structure in social and biological networks. *Proceedings of the National Academy of Sciences*, *99*(12), 7821–7826. https://doi.org/10.1073/pnas.122653799

Goel, S., Mason, W., & Watts, D. J. (2010). Real and perceived attitude agreement in social networks. *Journal of Personality and Social Psychology*, *99*(4), 611–621. https://doi.org/10.1037/a0020697

Golman, R., Loewenstein, G., Moene, K. O., & Zarri, L. (2016). The preference for belief consonance. *Journal of Economic Perspectives*, *30*(3), 165–188. https://doi.org/10.1257/jep.30.3.165

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360–1380. https://doi.org/10.1086/225469

Gureckis, T. M., & Goldstone, R. L. (2009). How you named your child: Understanding the relationship between individual decision making and collective outcomes. *Topics in Cognitive Science*, *1*(4), 651–674. https://doi.org/10.1111/j.1756-8765.2009.01046.x

Hetherington, K. (1998). *Expressions of identity: Space, performance, politics*. Sage Publications.

Hodges, B. H. (2017). Conformity and divergence in interactions, groups, and culture. In S. Harkins, K. Williams, & J. Burger (Eds.), *The oxford handbook of social influence* (pp. 87–105). Oxford University Press.

Hofbauer, J., & Sigmund, K. (2003). Evolutionary game dynamics. *Bulletin of the American Mathematical Society*, *40*(4), 479–519. https://doi.org/10.1090/S0273-0979-03-00988-1

Holme, P., & Newman, M. E. (2006). Nonequilibrium phase transition in the coevolution of networks and opinions. *Physical Review E*, *74*(5), Article 056108. https://doi.org/10.1103/PhysRevE.74.056108

Hornsey, M. J., & Jetten, J. (2004). The individual within the group: Balancing the need to belong with the need to be different. *Personality and Social Psychology Review*, *8*(3), 248–264. https://doi.org/10.1207/s15327957pspr0803_2

Imhoff, R., & Erb, H.-P. (2009). What motivates nonconformity? Uniqueness seeking blocks majority influence. *Personality and Social Psychology Bulletin*, *35*(3), 309–320. https://doi.org/10.1177/0146167208328166

Jetten, J., & Hornsey, M. J. (2014). Deviance and dissent in groups. *Annual Review of Psychology*, *65*, 461–485. https://doi.org/10.1146/annurev-psych-010213-115151

Jin, E. M., Girvan, M., & Newman, M. E. J. (2001). Structure of growing social networks. *Physical Review E*, *64*(4), Article 046132. https://doi.org/10.1103/PhysRevE.64.046132

Kandel, D. B. (1978). Homophily, selection, and socialization in adolescent friendships. *American Journal of Sociology*, *84*(2), 427–436. https://doi.org/10.1086/226792

Keynes, J. M. (1936). *General theory of employment, interest and money*. Harcourt Brace. https://doi.org/10.2307/2143949

Kim, H., & Markus, H. R. (1999). Deviance or uniqueness, harmony or conformity? A cultural analysis. *Journal of Personality and Social Psychology*, *77*(4), 785–800. https://doi.org/10.1037/0022-3514.77.4.785

Kossinets, G., & Watts, D. J. (2009). Origins of homophily in an evolving social network. *American Journal of Sociology*, *115*(2), 405–450. https://doi.org/10.1086/599247

Kozma, B., & Barrat, A. (2008). Consensus formation on adaptive networks. *Physical Review E*, *77*(1), Article 016102. https://doi.org/10.1103/PhysRevE.77.016102

Leibenstein, H. (1950). Bandwagon, Snob, and Veblen effects in the theory of consumers' demand. *The Quarterly Journal of Economics*, *64*(2), 183–207. https://doi.org/10.2307/1882692

Leonardelli, G. J., Pickett, C. L., & Brewer, M. B. (2010). Optimal distinctiveness theory: A framework for social identity, social cognition, and intergroup relations. *Advances in Experimental Social Psychology*, *43*(100), 63–113. https://doi.org/10.1016/S0065-2601(10)43002-6

Levitan, L. C., & Visser, P. S. (2009). Social network composition and attitude strength: Exploring the dynamics within newly formed social networks. *Journal of Experimental Social Psychology*, *45*(5), 1057–1067. https://doi.org/10.1016/j.jesp.2009.06.001

Lieberson, S. (2000). *A matter of taste: How names, fashions, and culture change*. Yale University Press.

Lieberson, S., & Lynn, F. B. (2003). Popularity as taste: An application to the naming process. *Onoma*, *38*, 235–276. https://doi.org/10.2143/ONO.38.0.2002560

Lynn, M., & Snyder, C. R. (2002). Uniqueness. In C. R. Snyder & S. J. Lopez (Eds.), *Handbook of positive psychology* (pp. 395–410). Oxford University Press. https://doi.org/10.1037/0021-843X.86.5.518

Maslach, C., Stapp, J., & Santee, R. T. (1985). Individuation: Conceptual analysis and assessment. *Journal of Personality and Social Psychology*, *49*(3), 729–738. https://doi.org/10.1037/0022-3514.49.3.729

Mason, W. A., Conrey, F. R., & Smith, E. R. (2007). Situating social influence processes: Dynamic, multidirectional flows of influence within social networks. *Personality and Social Psychology Review*, *11*(3), 279–300. https://doi.org/10.1177/1088868307301032

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, *27*(1), 415–444. https://doi.org/10.1146/annurev.soc.27.1.415

Mikolov, T., Grave, E., Bojanowski, P., Puhrsch, C., & Joulin, A. (2018). *Advances in pre-training distributed word representations* [Conference session]. Proceedings of the International Conference on Language Resources and Evaluation (LREC 2018), Miyazaki, Japan. https://www.aclweb.org/anthology/L18-1008.pdf

Miller, C. M., McIntyre, S. H., & Mantrala, M. K. (1993). Toward formalizing fashion theory. *Journal of Marketing Research*, *30*(2), 142–157. https://doi.org/10.1177/002224379303000202

Monderer, D., & Shapley, L. S. (1996a). Fictitious play property for games with identical interests. *Journal of Economic Theory*, *68*(1), 258–265. https://doi.org/10.1006/jeth.1996.0014

Monderer, D., & Shapley, L. S. (1996b). Potential games. *Games and Economic Behavior*, *14*(1), 124–143. https://doi.org/10.1006/game.1996.0044

Muthukrishna, M., & Schaller, M. (2020). Are collectivistic cultures more prone to rapid transformation? Computational models of cross-cultural differences, social network structure, dynamic social influence, and cultural change. *Personality and Social Psychology Review*, *24*(2), 103–120. https://doi.org/10.1177/1088868319855783

Newman, M. E., & Park, J. (2003). Why social networks are different from other types of networks. *Physical Review E*, *68*(3), Article 036122. https://doi.org/10.1103/PhysRevE.68.036122

Nowak, A., Szamrej, J., & Latané, B. (1990). From private attitude to public opinion: A dynamic theory of social impact. *Psychological Review*, *97*(3), 362–376. https://doi.org/10.1037/0033-295X.97.3.362

Pesendorfer, W. (1995). Design innovation and fashion cycles. *American Economic Review*, *85*(4), 771–792. https://www.jstor.org/stable/2118231

Phillips, D. J., & Zuckerman, E. W. (2001). Middle-status conformity: Theoretical restatement and empirical demonstration in two markets. *American Journal of Sociology*, *107*(2), 379–429. https://doi.org/10.1086/324072

Pickett, C. L., Gardner, W. L., & Knowles, M. (2004). Getting a cue: The need to belong and enhanced sensitivity to social cues. *Personality and Social Psychology Bulletin*, *30*(9), 1095–1107. https://doi.org/10.1177/0146167203262085

Pickett, C. L., Silver, M. D., & Brewer, M. B. (2002). The impact of assimilation and differentiation needs on perceived group importance and judgments of ingroup size. *Personality and Social Psychology Bulletin*, *28*(4), 546–558. https://doi.org/10.1177/0146167202287011

Postmes, T., Haslam, S. A., & Swaab, R. I. (2005). Social influence in small groups: An interactive model of social identity formation. *European Review of Social Psychology*, *16*(1), 1–42. https://doi.org/10.1080/10463280440000062

Rentfrow, P. J., & Gosling, S. D. (2006). Message in a ballad: The roles of music preferences in interperosnal perception. *Psychological Science*, *17*(3), 236–242. https://doi.org/10.1111/j.1467-9280.2006.01691.x

Reynolds, W. H. (1968). Cars and clothing: Understanding fashion trends. *Journal of Marketing*, *32*(3), 44–49. https://doi.org/10.1177/002224296803200308

Richardson, J., & Kroeber, A. L. (1940). Three centuries of women's dress fashions, a quantitative analysis. *Anthropological Records*, *5*(2), 111–153. https://digitalassets.lib.berkeley.edu/anthpubs/ucb/text/ucar005-003.pdf

Rios Morrison, K., & Wheeler, S. C. (2010). Nonconformity defines the self: The role of minority opinion status in self-concept clarity. *Personality and Social Psychology Bulletin*, *36*(3), 297–308. https://doi.org/10.1177/0146167209358075

Rivis, A., & Sheeran, P. (2003). Descriptive norms as an additional predictor in the theory of planned behaviour: A meta-analysis. *Current Psychology*, *22*(3), 218–233. https://doi.org/10.1007/s12144-003-1018-2

Rose, G. M., Shoham, A., Kahle, L. R., & Batra, R. (1994). Social values, conformity, and dress. *Journal of Applied Social Psychology*, *24*(17), 1501–1519. https://doi.org/10.1111/j.1559-1816.1994.tb01560.x

Rosenthal, R. W. (1973). A class of games possessing pure-strategy Nash equilibria. *International Journal of Game Theory*, *2*(1), 65–67. https://doi.org/10.1007/BF01737559

Salganik, M. J., Dodds, P. S., & Watts, D. J. (2006). Experimental study of inequality and unpredictability in an artificial cultural market. *Science*, *311*(5762), 854–856. https://doi.org/10.1126/science.1121066

Salganik, M. J., & Watts, D. J. (2008). Leading the Herd astray: An experimental study of self-fulfilling prophecies in an artificial cultural market. *Social Psychology Quarterly*, *71*(4), 338–355. https://doi.org/10.1177/019027250807100404

Schelling, T. C. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology*, *1*(2), 143–186. https://doi.org/10.1080/0022250X.1971.9989794

Shalizi, C. R., & Thomas, A. C. (2011). Homophily and contagion are generically confounded in observational social network studies. *Sociological Methods & Research*, *40*(2), 211–239. https://doi.org/10.1177/0049124111404820

Shuker, R. (2016). *Understanding popular music culture*. Routledge.

Simmel, G. (1957). Fashion. *American Journal of Sociology*, *62*(6), 541–558. https://doi.org/10.1086/222102

Smaldino, P. E., Calanchini, J., & Pickett, C. L. (2015). Theory development with agent-based models. *Organizational Psychology Review*, *5*(4), 300–317. https://doi.org/10.1177/2041386614546944

Smaldino, P. E., & Epstein, J. M. (2015). Social conformity despite individual preferences for distinctiveness. *Royal Society Open Science*, *2*(3), Article 140437. https://doi.org/10.1098/rsos.140437

Smaldino, P. E., Pickett, C. L., Sherman, J., & Schank, J. (2012). An agent-based model of social identity dynamics. *Journal of Artificial Societies and Social Simulation*, *15*(4), 1–17. https://doi.org/10.18564/jasss.2030

Smolla, M., & Akçay, E. (2019). Cultural selection shapes network structure. *Science Advances*, *5*(8), Article eaaw0609. https://doi.org/10.1126/sciadv.aaw0609

Smucker, B., & Creekmore, A. M. (1972). Adolescents' clothing conformity, awareness, and peer acceptance. *Family and Consumer Sciences Research Journal*, *1*(2), 92–97. https://doi.org/10.1177/1077727X7200100203

Snyder, C. R., & Fromkin, H. L. (1980). *Uniqueness: The human pursuit of difference*. Plenum Press.

Spears, R. (2021). Social influence and group identity. *Annual Review of Psychology*, *72*(1), 367–390. https://doi.org/10.1146/annurev-psych-070620-111818

Sproles, G. B. (1981). Analyzing fashion life cycles: Principles and perspectives. *Journal of Marketing*, *45*(4), 116–124. https://doi.org/10.2307/1251479

Steglich, C., Snijders, T. A., & Pearson, M. (2010). Dynamic networks and behavior: Separating selection from influence. *Sociological Methodology*, *40*(1), 329–393. https://doi.org/10.1111/j.1467-9531.2010.01225.x

Strang, D., & Macy, M. W. (2001). In search of excellence: Fads, success stories, and adaptive emulation. *American Journal of Sociology*, *107*(1), 147–182. https://doi.org/10.1086/323039

Tassier, T. (2004). A model of fads, fashions, and group formation. *Complexity*, *9*(5), 51–61. https://doi.org/10.1002/cplx.20037

Turner, J. C., Hogg, M. A., Oakes, P. J., Reicher, S. D., & Wetherell, M. S. (1987). *Rediscovering the social group: A self-categorization theory*. Basil Blackwell.

Turner, J. C., & Oakes, P. J. (1986). The significance of the social identity concept for social psychology with reference to individualism, interactionism and social influence. *British Journal of Social Psychology*, *25*(3), 237–252. https://doi.org/10.1111/j.2044-8309.1986.tb00732.x

Vignoles, V. L., Chryssochoou, X., & Breakwell, G. M. (2000). The distinctiveness principle: Identity, meaning, and the bounds of cultural relativity. *Personality and Social Psychology Review*, *4*(4), 337–354. https://doi.org/10.1207/S15327957PSPR0404_4

Warren, C., & Campbell, M. C. (2014). What makes things cool? How autonomy influences perceived coolness. *Journal of Consumer Research*, *41*(2), 543–563. https://doi.org/10.1086/676680

White, K., & Argo, J. J. (2011). When imitation doesn't flatter: The role of consumer distinctiveness in responses to mimicry. *Journal of Consumer Research*, *38*(4), 667–680. https://doi.org/10.1086/660187

Yamagishi, T., Hashimoto, H., & Schug, J. (2008). Preferences versus strategies as explanations for culture-specific behavior. *Psychological Science*, *19*(6), 579–584. https://doi.org/10.1111/j.1467-9280.2008.02126.x

Zhang, B., Cao, Z., Qin, C.-Z., & Yang, X. (2018). Fashion and homophily. *Operations Research*, *66*(6), 1486–1497. https://doi.org/10.1287/opre.2018.1744

Zuckerman, E. W. (2012). Construction, concentration, and (dis)continuities in social valuations. *Annual Review of Sociology*, *38*, 223–245. https://doi.org/10.1146/annurev-soc-070210-075241

Received December 16, 2019
Revision received September 17, 2021
Accepted October 10, 2021 ■