A Model of Fads, Fashions, and Group Formation

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I develop a model of consumer behavior where agents purchase goods in order to signify personal characteristics. Agents purchase goods in order to imitate agents similar to them and agents they want to emulate. Depending on parameter values of consumer preferences the model generates stable groups, fads, and fashion cycles, or a mixture of both. The model is unique to the economic literature on fads in that the extinction of fads occurs endogenously in the model. *Complexity 9: 51–61, 2004*

Key Words: consumer behavior; fads; fashion cycles; imitation; social networks

1. INTRODUCTION

In this article I present a simple model of fashion cycles and fads. The basic idea is that owning or consuming some goods reveals meaning about their owners. Through this meaning the individual identifies herself with other agents in the population. As an example, an individual who buys Nike basketball shoes tells everyone "I'm someone who wants to be like Mike" And in buying Nike shoes the individual identifies herself with other Nike shoe buyers. Even beyond brand identification, the style of clothes or hair we each choose to wear helps others to identify a social grouping (skate-boarders and baggy pants for instance.) As an example consider the following story: "*Little Tree,* a coming of age story set in 1935 Tennessee, was rousingly received at a screening for college students. But in a discussion that followed, audience members conceded that they probably wouldn't [have seen] the film [on their own]." The students suggested they would be more likely to see another film, *Con Air*, because "We know all our friends would see *Con Air,* and I have to tell my pals I've seen it too."[1] This example illustrates individuals using the consumption of a consumer good, in this case the viewing of a film, in order to identify themselves with a group, in this case the type of person who would attend the film *Con Air*.

In addition to individuals being concerned with what groups they join, they also are concerned with who joins the groups they are already in. If too many people join your group, the social significance of belonging dissipates. This is one reason why social clubs, for example sororities and fraternities on college campuses or elite country clubs, limit

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[1]This story is from USA Today November 24, 1997, quoted from Farrell [1].

membership. In other instances the group members do not have control over who appears to be in their group. This is the case with fashions like clothing or hairstyles. For instance, a rebellious teen with green hair cannot control who else chooses to have green hair. And she would most likely change her hair color if suddenly all bankers dyed their hair green! In this way individuals choose some fashionable (or anti-fashionable) behaviors in an attempt to "belong," whether it is the hair style we choose, the shoes we wear, or the films we see.

If agents imitate each other in order to express an affiliation, there are at least three phenomena that may develop: First, all agents in the population may coordinate on one alternative. Second, another type of stable behavior may develop; agents may separate themselves into stable groups with each group acting in one particular way, or buying a particular good. Third, stable or unstable cycles may develop. These cycles are examples of what I am calling fads or fashion cycles. In this article I investigate what types of imitative behavior lead to fads and fashion cycles. I assume that there is a basket of goods that people may consume that conveys social meaning. We can call them Nike, Addidas, and Reebok, or Tommy, Levis, and the Gap, or short hair, long hair, and spiked green hair. I assume that each good is identical in its underlying quality. Thus the goods I consider are *functional alternatives* [2]. This should be noted in comparison to other models concerned with fads and buying cascades that consider the diffusion of innovations and new goods such as Watts [3].

When choosing among available goods, agents in my model consider standard economic variables such as price. And they also consider what the good signifies about their personal characteristics. This significance will be endogenously determined through the observation of the characteristics of other agents and the goods they buy. More specifically agents want to buy the same goods as other agents with characteristics similar to their own. And, agents want to buy the same goods as the people they want to emulate in the population. Thus agents imitate and are imitated by other agents in the model. Prices will be determined in a global market but information about what goods are owned by other agents will be determined locally. Agents will observe the behavior of a subset of the population. Depending on the parameters of the agents' utility function the model can generate stable groups, unstable fads and fashion cycles, or mixtures of both. Before continuing with the full specification of the model, I first discuss other work related to my model of fads and fashions.

2. DEVELOPING A MODEL OF FADS AND FASHIONS

The model I develop in this article combines ideas from two economics models and observations about fads and fashions from sociology and business. I now describe the underlying features of the model.

The model in this article is most closely related to Becker and Murphy [4]. In their model they assume that people come to prefer a good more as it becomes more popular. If more people buy or own a certain kind of good it becomes more valuable to the consumer. Let $Q = D(p, Z, Q)$. Q is quantity sold, p is price, and Z is other demand influences such as quality, etc. As price increases quantity demanded decreases, $D_p < 0$; call this the price effect. And as more people own a good quantity demanded increases, $D_Q > 0$; call this the popularity effect. Depending on how many people buy the good (or which effects dominates), the demand curve may be downward sloping (price effect dominates) or upward sloping (popularity effect dominates). It is easy to see that this model potentially can generate multiple equlibria for sufficiently large popularity effects.

Becker and Murphy [4] suggest that the occurrence of fads is due to the popularity effect. However, notice that the model is static. The population of agents may select an equilibrium where a good is popular, or they may select an equilibrium where a good is unpopular. But there is no reasonable story describing how one moves between the given equilibria unless one wants to hypothesize that random demand shocks move the economy from one equilibrium to the other. In other words their model does not describe how a fad begins or ends. In the model I describe below fads and fashion cycles appear and disappear endogenously out of the agent behavior in the model.

The second economics model from which I borrow is the information cascades literature [5–7]. As an example consider the following story: A line of people stands in front of two restaurants. One restaurant is high quality; the other is low quality. People decide in turn which restaurant to enter without knowing the relative quality of each restaurant with certainty. They infer the quality through a private signal and the observation of the choices of the other agents. When it is an agent's turn to decide, she receives a private signal about whether restaurant A or B is the high quality one. The signal is noisy but informative. If restaurant A truly is the high quality restaurant, the probability the agent gets the high signal for restaurant A is greater than 1/2. Given the signal and observation of the decisions of the people deciding before the agent, the agent makes a choice. The authors of this literature show that with probability one everyone converges to choosing the same restaurant, but it may be the high or the low quality restaurant, depending on the order in which the signals arrive. Note that information in the model is derived from the observing the behavior of other agents. Many fads are generated by word of mouth through social networks, so much so that businesses actively pursue word of mouth marketing.[2]

[2] *See Farrell [1] or Rosen [8] for many examples.*

The information cascade models consider a much different scenario than the one I consider in this article. These models consider a situation where people imitate because it helps in the processing of information. People only have partial information of some item of interest to them, for example the quality of a restaurant. And they use observations of others to help them form a prediction. Imitation only occurs as an optimal strategy to a given problem. In the model I describe below people also imitate each other, but they do so because they directly derive utility from affiliation with other agents.

Note that neither of these economic models of fads and fashions describe the extinction of the trend. In contrast the descriptive models of sociologists generally ascribe the extinction of a fad as being due to a loss of uniqueness. For instance the life cycle of fads and fashions has been described as "discovery of the potential fad, promotion by discoverers and/or original consumers, labeling, dissemination, eventual loss of exclusiveness and uniqueness, and death by displacement" [2]. Once a trend becomes too popular the distinction of participating disappears for the early consumers or trendsetters, and they move on to something new. And many times the "new" fad is an old one; "fads are not born but rediscovered" [2].

Additionally fads and fashions many times follow a pattern of diffusion from high status individuals downward. As an example a study by Aguirre et al. [9] found that streaking was more likely to occur on a college campus if streaking had already occurred at a nearby prestigious college. Thus individuals imitate others they look up to by buying the same goods or imitating their behavior or actions. Hence the use of a famous personality as a spokesperson for a product or social cause.

Finally, individuals purchase goods in association with groups of friends. For instance Johnstone and Katz [10] found that small groups of friends influence each other's preference and taste in popular music. They conclude that personal relations play an important role in musical fads and fashions. Thus similar individuals influence each others' behavior. If your friends all listen to a specific type of music or watch a particular film you want to as well in order to take part in conversations and to fit in with your friends.

The model I describe below contains elements of all of these models. As in the information cascades model, the agents in my model receive information from local sources; they observe the purchases of people they contact in a specified geography. And, like the Becker and Murphy model, an agent's demand for a specific good will depend in part on the number of people buying the good. In addition the agents care about the characteristics of the people observed buying the good. Agents want to buy the goods that other people similar to them buy or that the people they want to emulate buy. They avoid buying the goods owned by people with whom they do not wish to associate or identify.

3. MODEL

Let there be a set of G goods described $\mathcal{G} = \{1, 2, \ldots G\}$, which are all equally desirable to the agent. Using one of the examples above, the goods may be thought of as three kinds of running shoes: Addidas, Nike, and Reebok from which agents must choose. Let Q_g be the quantity of agents who own a good of type g. Marginal cost is an increasing function of Q_g, $C(Q_g)$. Assume price is determined as in a perfectly competitive market such that $P_g = C(Q_g)$. Let there be a set of N agents. Each agent i has characteristics of two kinds: a set of J idiosyncratic types, $T_{i,j}$, each contained in (0, 1) and an attraction characteristic, A_i, also in (0, 1). These type characteristics may be thought of as personality characteristics. For instance suppose I may choose to spend time playing basketball or bowling. If I hate to bowl and love to play basketball, I prefer to have friends with similar preferences over these activities. Otherwise we will not spend much time together. Thus basketball players like basketball-playing friends and bowlers like to have other bowlers as friends. In contrast the attraction characteristic is a uniform ordering for all. If $A_i > A_j$, agent i is more attractive than agent j to everyone in the population. This characteristic may be thought of as the "coolness" or some intrinsic quality of the agent that is agreed upon by all.

Each agent must own one of the G goods described above. Denote the good owned by agent i as g_i. Each agent has a store of money available in each period to buy the good they desire, m_i. Each individual agent interacts with a set of other agents in the population. Call this the social network of agent i and label it Ω_i. The size of Ω_i is an even integer $k_i \in [0, N]$. Agents are arranged in a circle. Each agent is connected to $k_i/2$ agents in each direction with one exception: each connection of an agent can be replaced by a random member of the population. As in the Watts' small-world models [11] this happens to each individual connection with probability R_n.

Note that in my model not all connections are symmetric. Strictly imposing symmetry adds additional constraints on the distribution of k_i, which I do not wish to include in the model. In addition, in each period a given connection can be replaced for only the current period with a random agent with probability R_m. If this happens the agent reverts to the original connection in the following period. Random connections related to R_n are ongoing weak ties [11, 12]. Random connections related to R_m may be thought of as agents one observes only in a temporary scenario, such as people one notices when walking down a street that the agent does not know or other random meetings that may occur.

Agents have preferences over money, the type of good owned, and the members in their social network who own the same good as they do. A group for agent i is defined as the set of agents in Ω_i who currently own the same good as i. Note that groups are endogenously defined in the model. Potentially there are as many groups for each agent as goods in the population. But there may be fewer if some goods are not owned by any member of the population. There is a network value of owning each specific good. Agents want to own the same good as other agents who have similar idiosyncratic types and who have a high attraction value in their social network. More specifically let the network value of owning good g to agent i, $V_{i,g}$ be

$$V_{i,g} = \frac{\sum_{j\in\Omega_i}\sum_{t=1}^{J}[(1-\alpha_{i,t})(1-|T_i - T_j|)] + \sum_{j\in\Omega_i}\alpha_{i,a}(A_j)}{N_{i,g}}$$

for all agents j such that $g_i = g_j$, where $N_{i,g}$ is the number of agents in Ω_i who own good g. In other words $N_{i,g}$ is the set of agents in the social network of agent i who own the same good as i. $\alpha_{i,t}$ and $\alpha_{i,a}$ are preference parameters for having agents of similar idiosyncratic type and high attraction in the group of agent i. I can define an agent as the vector $I = (T_{i,1}, T_{i,2}, \ldots, T_{i,J}, A_i, m_i, g_i, \alpha_{i,t}, \alpha_{i,a})$.

The opportunity to buy a new good arrives to agents as a Poisson process, $(e^{\mu}\mu^{t})/t!$. When an agent gets the opportunity to update her good, she chooses the good that maximizes utility given by Cobb-Douglas preferences:

$$U_i = (m_i - P_g)^{\beta} V_{i,g}^{1-\beta}$$

such that $m_i - P_g \geq 0$, where m_i is the money the agent has and P_g is the price of the good as determined by demand in the previous period.

4. RESULTS

If restrictions are imposed such that agents are homogeneous in terms of money and the $\alpha_{i,t}$ and $\alpha_{i,a}$ parameters and each good has the same cost function some analytical results can be shown.

Proposition 1

When $\alpha_{i,a} = 0$ for all i, there exists at least one separating equilibrium where agents sort themselves into G stable non-overlapping groups of equal size.

Proof. To begin suppose that there are only two goods, x and y, and one type characteristic, $J = 1$. First note that the utility to agent i of good x (or y) decreases monotonically in the distance from T_i to the average value of T of the agents owning x (or y) and that price increases in the number of agents who buy the good. Now in the case where $G = 2$ there exists an equilibrium with $T^* = 0.50$ such that every agent with $T_i \geq T^*$ chooses good x if every other agent with $T_j \geq T^*$ chooses good x, and every agent with $T_i < T^*$ chooses good y if every other agent with $T_j < T^*$ chooses good y. Consider an agent who deviates. Any agent k with $T_k > 0.50$ who deviates to buy good y increases her distance from those buying the good she chooses and in deviating she increases the price for the good that she buys. Thus any agent who deviates gets utility that is strictly lower both in network value and in price.

The argument is trivially increased to G goods resulting in G groups of size N/G. For $J \geq 2$ the same logic applies. Separate a J dimensional space into G equally sized continuous partitions. It is an equilibrium if each agent in every partition buys the same good and the agents in no two partitions buy the same good. This is so because if any agent deviates and buys the good of another partition she increases her distance from the average consumer in her group and she increases the price of the good. Thus her utility is strictly lower by deviating.

Note that even though these sorting equilibria exist Proposition 1 tells us nothing about the ease with which agents are able to obtain them. It may be quite difficult for the agents to coordinate their behavior even when these equilibria exist. Proposition 1 considers the case where agents only care about the idiosyncratic type characteristics of the other agents. If instead agents only care about the attraction characteristic, we may get very different behavior. When $\alpha_{i,t} = 0.0$ for all i and t, there may not exist an equilibrium in the choices of goods by agents. This is demonstrated in the following example: Suppose there are two agents and two goods and that each agent has the same wealth, m. Agent 1 has $A_1 = 0.8$ and agent 2 has $A_2 = 0.2$. There are two cases: either each agent owns the same good or each agent owns a different good. If the agents own the same good, agent 1 can deviate to the other good and increase her utility by increasing the average value of A and by getting a lower price. Thus the agents owning the same good cannot be an equilibrium. Now, suppose the agents own different goods. Without loss of generality suppose agent 1 owns good Y and agent 2 owns good X. The utility of agent 2 is $(m - \mathrm{P}(1))^{\beta}(0.2)^{1-\beta}$ if she keeps good X and $(m - \mathrm{P}(2))^{\beta}(0.5)^{1-\beta}$ if she chooses to own good Y as does agent 1. So for a price function that increases sufficiently slowly, $P(2) - P(1)$, agent 2 is better off choosing to own the same good as agent 1. And, we know this is not an equilibrium from the first step. Thus the two agents enter into a perpetual cycle, with agent 2 chasing the good of agent 1 and agent 1 trying to avoid owning the same good as agent 2. Taken together Proposition 1 and the example illustrate that in order for the model to generate fads and fashions the agents must have nonzero values of $\alpha_{i,a}$. Fads and fashions develop when agents in the population buy the goods currently held by the high attraction agents. When too many low attraction agents own the same good as the high attraction agents, the high attraction agents move to a new good. And in doing so they potentially start a new trend.

We see that increasing $\alpha_{i,t}$ increases the likelihood of forming stable groups while increasing $\alpha_{i,a}$ may decrease stability in the model. Thus there is a tension in the interaction of $\alpha_{i,a}$ and $\alpha_{i,t}$. In the next subsection I investigate how changing the relative values of $\alpha_{i,a}$ and $\alpha_{i,t}$ affects the model behavior.

4.1. Base Simulations

Simulations of the model described above serve two primary purposes: First, equilibrium groups may exist but that does not imply that agents are able to find them. Second, the analytical results above only consider the end points of the preference parameters. The behavior of the agents in the model is much more difficult to analyze for interior parameter values and when the strict assumptions of Proposition 1 and the previous example are relaxed.

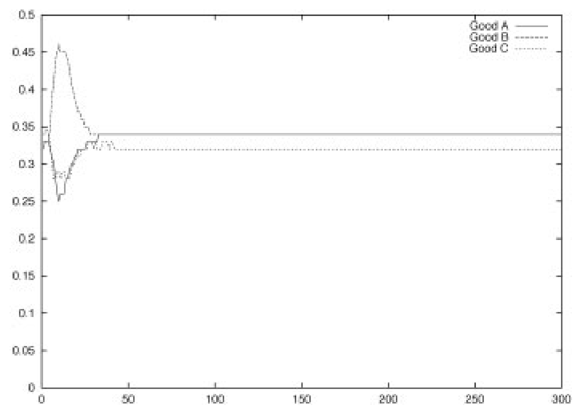
In this set of simulations there will be one type characteristic and one attraction characteristic. These are both uniformly distributed over (0, 1). The values of the preference parameters will be constant across all agents. Recall that we are interested in how the model behavior changes as the relative values of $\alpha_{i,a}$ and $\alpha_{i,t}$ change. Because there is only one type characteristic, normalize the preference parameters such that $\alpha_{i,a} + \alpha_{i,t} = 1$. And, let $\Lambda = \alpha_{i,a}$ for all i and thus $\alpha_{i,t} = 1 - \Lambda$ for all i. Thus Λ defines the relative values of $\alpha_{i,a}$ and $\alpha_{i,t}$. Λ is large when agents place a high value on the attraction characteristic of the other agents and a low value on the type characteristic. Λ is low when agents place a low value on the attraction characteristic and a high value on the type characteristic. As we change Λ, we investigate the importance of $\alpha_{i,a}$ relative to $\alpha_{i,t}$.

All simulations in this subsection consider random permanent networks, $R_n = 1.0$, with no random meetings, $R_m = 0.0$. I will consider changes to the network structure in a later subsection. There are 1000 agents in all the simulations. The size of an agent's network is uniformly distributed from 25 to 50. The price of good g is determined by the log of the number of agents currently owning good g. I set $\beta = 0.1$. I begin by looking at the fraction of the population who own each good for various levels of Λ. Figure 1 shows that for $\Lambda = 0.0$ the agents quickly find an equilibrium with each good being owned by approximately 1/3 of the population. Similar behavior occurs for values of Λ up to approximately 0.5. When I increase Λ further, the results change. Figure 2 shows the fraction of the population owning each good when $\Lambda = 0.6$. Here agents do not find an equilibrium and we begin to see fads and fashion cycles develop. When Λ is increased even further (Figure 3), more pronounced fads and cycles result.

Remember, $R_m = 0.0$ in these simulations. Thus the models are completely deterministic once the agent characteristics and social networks are assigned. It is not randomness that is creating the instability; the deterministic decisions of the agents are creating the instability. When Λ is high, agents try to buy the same good as the agents with a high attraction characteristic. Suppose there is a good such that the average attraction of the agents owning that good is high. When a sufficient number of agents with low attraction buy this good, the average level of attraction decreases for this good. Thus agents with the highest attraction eventually become better off buying another good where their high attraction value has a larger effect. Because of this effect, the agents with high attraction characteristics in the model become "trend-setters." However, these trend-setters are endogenously determined in that the trend-setting agents do not have trend-setting as a specific goal.

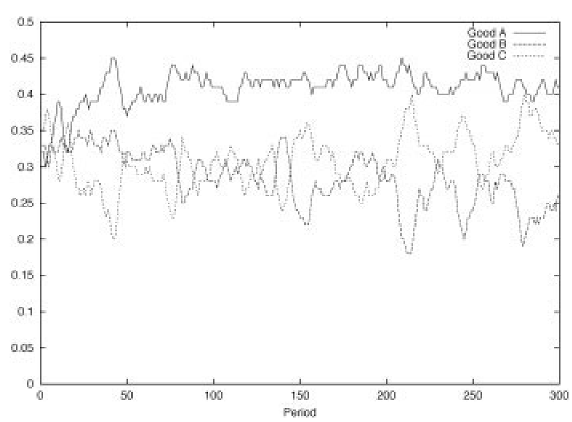
Next I consider the characteristics of the individuals that buy each good. I do this in order to better show the relationship between the fads and fashion cycles discussed in the previous paragraphs and the stability or instability of

FIGURE 1



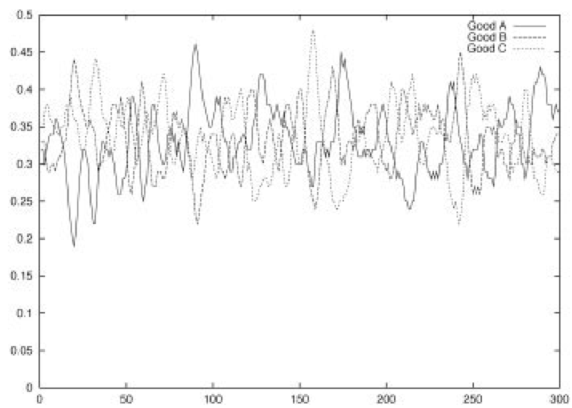
Fraction of Population Owning Good when $\Lambda = 0.0$.

FIGURE 2



Fraction of Population Owning Good when $\Lambda = 0.6$.

FIGURE 3



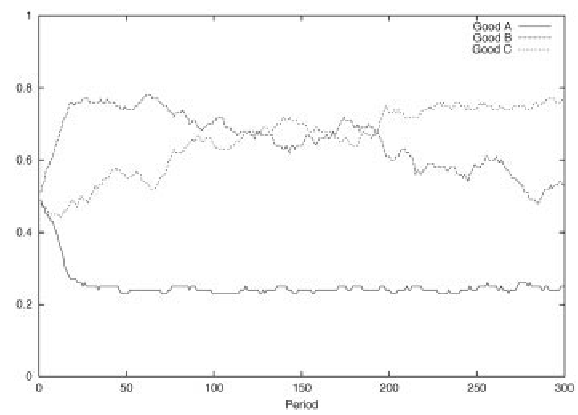
Fraction of Population Owning Good when $\Lambda = 0.8$.

groups. We can view the amount of group formation across time by calculating the average value of T_i for each member of the population who owns good x, $N_{t,x} = \Sigma_{i=1}^{N_i} T_i / N_g$ for all i owning x for each period. Figures 4–6 show the levels of $N_{t,x}$ for three runs of the simulation: one where $\Lambda = 0.0$ (no fads), one where $\Lambda = 0.6$ (small fads), and one where $\Lambda = 0.8$ (large fads).

As can be seen in the figures, when $\Lambda = 0.0$ the agents sort themselves into distinct groups associated with each good. The agents owning good A tend to have low values of T_i; the agents owning good C have intermediate values; and the agents owning good B have high values on average. As I increase the parameter Λ, the groups become more difficult to distinguish. For instance, in Figure 5 the agents appear to have three clear groupings at periods 50 and at period 300. But between periods 100 and 200 there are only two groups; the agents with low values of T_i buy good A, and everyone else buys goods B and C, with no clear distinction between the agents owning them. As I increase Λ further, no group distinctions exist (Figure 6).

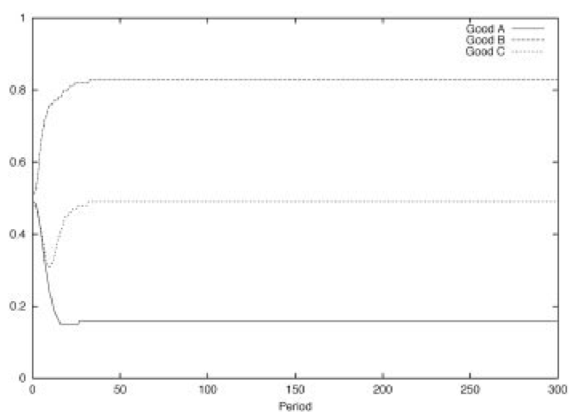
Up to now the distinction of groups has been done by eye. We can quantify the level of group formation by calculating the sum of the absolute differences of the average agent type across the goods. So, in the case with $G = 3$ one would calculate $D = |N_{t,1} - N_{t,2}| + |N_{t,1} - N_{t,3}| + |N_{t,2} - N_{t,3}|$. If the groups are perfectly sorted there will be partitions at 1/3 and 2/3. Thus the values of $N_{t,x}$would be: $(1/3)/2 = 1/6$, $[(2/3) - (1/3)]/2 + 1/3 = 1/2$, and $[1 - (2/3)]/2 + 2/3 = 5/6$. Then the value measured for the amount of group formation in this example is: $D = |1/6 - 1/2| + |1/6 - 5/6| + |1/2 - 5/6| = 4/3$ if the agents are perfectly sorted by the type characteristic.

FIGURE 5



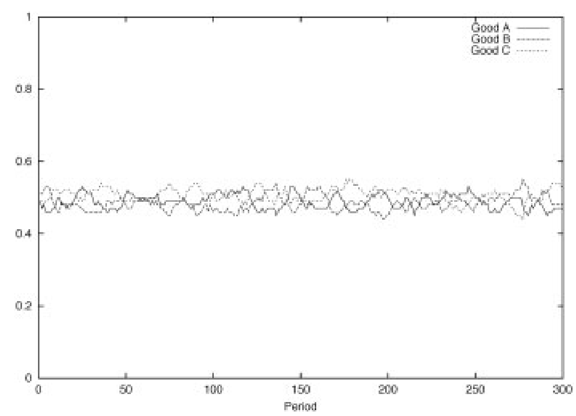
Levels of $N_{t,x}$ with $\Lambda = 0.6$.

FIGURE 4



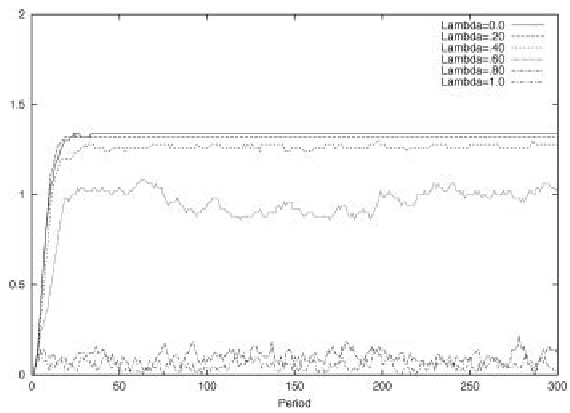
Levels of $N_{t,x}$ with $\Lambda = 0.0$.

FIGURE 6



Levels of $N_{t,x}$ with $\Lambda = 0.8$.

FIGURE 7



Group formation as measured by *D*. As Λ increases groups formation becomes less distinct and disappears when Λ approaches 1.0.

Figure 7 shows the amount of group formation, as measured by *D*, for various levels of Λ. As predicted by Proposition 1, when agents do not care about the attraction values of the agents, $\Lambda = 0$, the agents in the simulation are able to sort themselves into stable groups. As expected the amount of group formation falls as preferences for the attraction variable, Λ, increases. For intermediate values of Λ the agents form less clearly defined groups and for the two highest values of Λ the agents do not form any groups.

There are two important features of this subsection to highlight: First the agents with a high attraction level, A_i, act as trend-setters. If one good develops that is bought by agents with a higher level of average attraction, other agents with lower A_i begin to buy that good in order to be in the same group with the highly attractive agents. As more low attraction agents choose to buy the good, the benefit of owning that good diminishes. At some point the benefit diminishes enough that the agents with high attraction quit buying the "cool" good and begin buying other goods. Eventually enough highly attractive agents coordinate on the same good and the cycle begins again. Second many fads occur because of the development of new products. Note that fads occur in the model in this article without the introduction of new or improved goods. The agents in this model create fads and fashions endogenously through their attempts to associate and dissociate with other agents. Low attraction agents attach themselves to high attraction agents through imitation. But high attraction agents flee from associating with the low attraction agents who follow them. Thus the fads in this article are similar to fashion trends where a style becomes popular and then unpopular for a length of time, and then reemerges as popular style at some time in the future.

4.2. Robustness

In the previous subsection we saw that the model exhibits fads and fashion cycles for a given parameter setting and a high value of Λ. In this subsection I test the range of parameters that generates fads and fashion cycles. In order to do so I need a measure of the degree of cycles that occur. Because the cycles we observe are essentially fluctuations around a mean, one direct measure of the degree of the fluctuations is the standard deviation. I calculate the standard deviation of each good over the last 200 periods of each of 20 runs for each parameter setting and average the results.[3]

I begin by separating the effect of the fluctuations due to price changes and the demand driven fluctuations. I do so by comparing the outcomes using the parameters above to the same outcomes but with a fixed price for each good that is equal to the price at the average demand for each product. In other words I fix the price for each good at the price where each good is owned by one-third of the population. Table 1 displays the standard deviation across each of these runs.

Note in Table 1 that the price changes have a very small effect on the dynamics of the system. It appears that for low values of Λ allowing the price to increase as the quantity sold increases reduces the magnitude of the cycles (compare the values for $\Lambda = 0.4$.) But for other values there is not any measurable effect. A second effect of pricing in the model is the effect of the parameter β, which sets the agent's

[3] *I use only the last 200 periods in order to allow the systems that will settle into a stable equilibrium time to do so.*

TABLE 1

Effect of Pricing

Λ	0.0	0.2	0.4	0.6	0.8	1.0
Std dev fixed price	0.0000	0.0001	0.0024	0.0270	0.0451	0.0463
Std dev variable price	0.0000	0.0000	0.0017	0.0246	0.0453	0.0460

TABLE 2

Price Sensitivity

β	0.1	0.3	0.5	0.7	0.9
Std dev	0.0246	0.0241	0.0230	0.0213	0.0189

preference for money versus goods. Recall that as β increases agents are more price sensitive. Table 2 shows the effect of changing β, holding all other parameters constant. As you can see, as β increases, the fad and fashion cycles decrease in magnitude. As agents become more price sensitive fad and fashion cycles decrease.

Taking these two robustness comparisons together, we see that the effect of a price increase as goods become more popular plays a small role in the extinction of a fad or fashion trend. Primarily the extinction of a trend is demand driven in the model. In other words, the supply side of the model plays a small role unless agents are extremely price sensitive.

Next I examine changes in the average waiting time of the agents to update their choice of good, μ. Table 3 shows that this parameter plays a very minor role in the magnitude of the cycles. If agents wait longer to update their product, there is a small decrease in the magnitude of the cycles. (Compare the standard deviations for $\mu = 1$ and $\mu = 9$.)

Next I investigate how the average number of agents in a social network affects the magnitude of fads and fashions. Recall that in the simulations above the maximum number of members of an agent's social network was equal to 50. Here I vary the number of other agents in an agent's social network. Note that there are potentially two effects in terms of the average network size. First, at the local level, as the average network size increases, agents are able to collect more information on population trends. Second as the average size of the network increases, the properties of the aggregate social network change. For instance when the maximum network size is 25, the average distance between all pairs of agents in the population is 2.69. As the average network size increases, the average network distance decreases (2.22 for a maximum network of 50 and 1.93 for a maximum network of 100.) Thus as network size increases,

TABLE 3

Agent Waiting Time

μ	1	3	5	7	9
Std dev	0.0271	0.0229	0.0246	0.0230	0.0212

TABLE 4

Network Size

Maximum Network Size	25	50	100
Std dev	0.0254	0.0246	0.0141

each agent is closer on average to other agents in the population. A second characteristic of networks is clustering. Essentially, clustering measures the likelihood that two individuals j and k are connected given that both are connected to i. For the networks considered here the clustering is 0.019, 0.037, and 0.073 for a maximum network size of 25, 50, and 100, respectively.

I display the results of changing the maximum network size in Table 4 for $\Lambda = 0.6$. As the average size of agents' social networks increases the magnitude of the cycles decreases. As agents are able to gain more information and are closer to other agents in the population, the cycles are smaller. Lastly, I allow every agent to be connected to every other agent. Thus all agents have perfect information on every other agent in the population. In this case the standard deviation is 0.0044. Even if agents have perfect information about all other agents in the population, fad and fashion cycles still exist.

Finally, I compare the magnitude of fad and fashions cycles when the number of goods increases. Table 5 compares the behavior of the model with five goods versus three goods. For low levels of Λ, when agents are trying to sort into groups, there are larger cycles with five goods than with three goods. This is because the agents essentially face a more difficult problem. They must sort into five groups instead of three groups. However when Λ is large, the agents care less about sorting into groups and more about holding the good that is held by the highly attractive agents. Because the cycles occur across a larger number of goods, the highly attractive agents have more options because the less attractive agents chase them across goods. Thus the highly attractive agents jump out of a fad earlier than when there are fewer options. And, the magnitude of the fad and fashion cycles is smaller.

Overall we see that there is a wide range of parameters that exhibit fad and fashion cycles in the model. Price variations and increasing the waiting time of agents plays a small role in decreasing the magnitude of fads and fashion cycles. Increasing the information of agents by increasing the number of other agents they observe or increasing the number of fashion goods decreases the magnitude of fads and fashions. But fad and fashion trends still exist across all parameter settings except for low levels of Λ, as in the base simulations.

TABLE 5

Increasing the Number of Goods

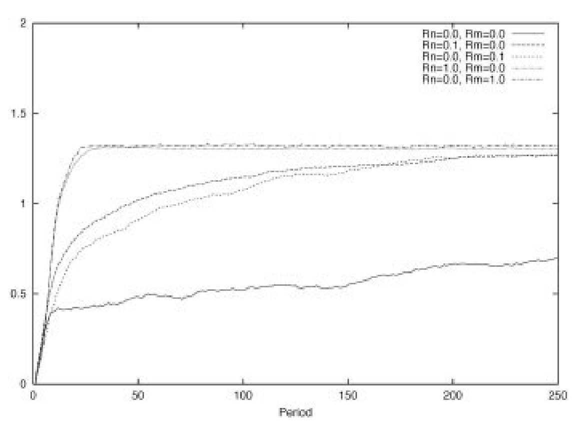
Λ	0.0	0.2	0.4	0.6	0.8	1.0
Std dev three goods	0.0000	0.0000	0.0017	0.0246	0.0453	0.0460
Std dev five goods	0.0000	0.0009	0.0159	0.0244	0.0284	0.0283

4.3 Network Dynamics

In this subsection I investigate whether and how the structure of the networks in which an agent interacts with other agents affects the dynamics of fashions and the formation of groups. I do this by altering the network parameters of the model, R_m and R_n. All runs of the model in this subsection have $\Lambda = 0.3$. I chose this value because it is on the border of where group formation begins to break down. Thus in this section I will be investigating what network structures allow (or encourage) stable groups to form and what network structures encourage unstable cycles.

Figure 8 displays the average value of group formation, D, over 20-simulation runs for five different network configurations each. In one set of runs the networks are completely regular. Every agent is connected to $k_i/2$ neighbors in each direction. In two of the sets of runs the networks are completely random. Of these one has all connections being purely random meetings each period, $R_m = 1.0$ and $R_n = 0.0$. In the other, the model has purely permanent random connections, $R_m = 0.0$ and $R_n = 1.0$. The other two are intermediate cases similar to small world networks. These have mostly regular networks but small amounts of randomness. Specifically one has $R_m = 0.0$ and $R_n = 0.1$ and the other has $R_m = 0.1$ and $R_n = 0.0$. Again, network size is uniformly distributed [25, 50]. Specific characteristics of the networks are as follows: Average path length = 2.22, 2.63, and 8.34 for R_n equal to 1.0, 0.1, and 0.0, respectively. Average clustering for these networks = 0.037, 0.544, and 0.738 for R_n equal to 1.0, 0.1, and 0.0.,[4] respectively.

FIGURE 8



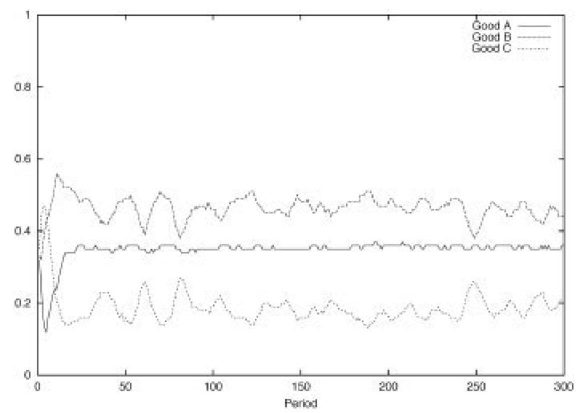
Amount of group formation for various network structures.

In the figure one can see that except for the case of purely regular networks, $R_m = 0.0$ and $R_n = 0.0$, the agents sort themselves into stable groups.[5] And in the case of both of the purely random networks and purely random meetings, they do so almost immediately. In the two small-world-type networks agents also manage to find stable groups, but it takes them a significantly greater amount of time to do so. Elsewhere it has been suggested that more random networks may increase the spread of fads because the short characteristic distance between agents allows for fast diffusion. However it should be noted that the fadish goods in those models are new innovations, not existing goods as studied here. The authors study how quickly the new goods diffuse in the population dependent on the network structure in which agents interact. The short characteristic distance between agents in more random networks generally allows diffusion to happen quickly. But here, because of the same short characteristic distance between agents, more random networks allow for fast coordination and thus group formation. When the distance between agents is too long, as in the example of purely regular networks, by the time the one subset of the population coordinates on a good, agents in another part of the network may have coordinated on a good that contradicts the decision of another part of the network. In my model random networks facilitate group formation and thus make it more likely that the agents form equilibrium groups and dampen the force to create fads and fashion cycles. One last thing to note in regard to this section is that for high enough levels of Λ no network

[4] *Note that network statistics are not relevant for the case, where $R_m = 1.0$ and $R_n = 0.0$ or the case, where $R_m = 0.1$ and $R_n = 0.0$. In these cases there isn't a specific network; there are only random meetings between agents that do not persist across periods.*

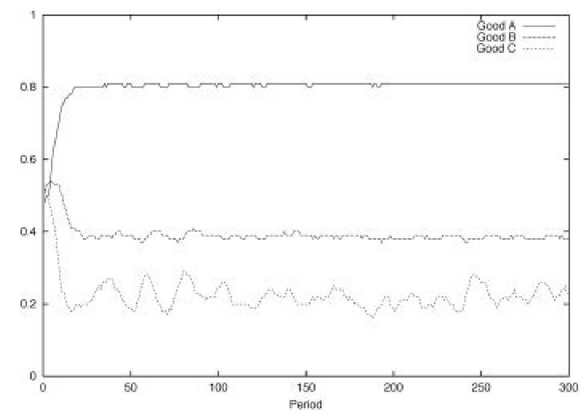
[5] *Although the $R_n = 0.0$, $R_m = 0.0$ case appears to be increasing at the end of the figure it asymptotes at approximately $D = 0.8$.*

FIGURE 9



Proportion of population owning each good when the value characteristic of agents is correlated with income, $A_i = m_i/N$.

FIGURE 10



Average A_i of agents owning each good.

structure allows for the creation of groups. For instance if agents only care about the attraction variable of other agents, $\Lambda = 1.0$, there may be no equilibrium on which to coordinate as mentioned earlier.

4.4. Segregated Equilibria

In this section I describe how preferences for the attraction characteristic of the agents may create segregated equilibria under certain assumptions. Here I assume that the attraction characteristic is a direct function of wealth, $A_i = m_i/N$. Thus more wealthy agents are considered more attractive by all agents. I also assume that the goods have different cost functions. Thus they have different prices for the same quantity purchased. I am going to let good A be an expensive good; good B will be an intermediately priced good; and good C will be an inexpensive good. Specifically let the price of Good A be given as N_A; let the price of Good B be given as $N_B/10$; and let the price of good C be $N_C/20$. I run the simulations with $\Lambda = 1.0$. Thus in the previous cases there would not be stable equilibrium groups. But here, as one can see in Figure 9, the agents do reach an equilibrium and in a short amount of time. Looking more closely at the characteristics of who is buying which goods, Figure 10, reveals that the agents with the most money have separated themselves apart from the other members of the group.

Here because the agents with the highest attraction characteristic also have the highest income, they are able to form an exclusive group. This suggest that if individuals are trying to emulate affluent individuals, fashion cycles are more likely to exist in less expensive items. We would not expect to see fashion cycles in memberships at exclusive golf clubs, high end cars, or affluent neighborhoods. Instead, fashion cycles are more likely to occur in less expensive items like clothing and toys.

5. CONCLUSION

Imitative behavior is generally described as one of the primary factors influencing the creation of fads and fashion cycles. However this is somewhat puzzling because imitative behavior many times leads to stable homogeneity. Here I present a model where imitative behavior may lead to homogeneity, segregation into distinct groups, or fad and fashion cycles. In addition other economic models do not adequately explain why fads die. The model contained in this article generates the endogenous extinction of a fad. Once a fad becomes too popular the distinction associated with participating in the fad dissipates and the fad subsequently disappears.

The model in this article is purposely simple and several additional features could be added: First, agents could be allowed to own more than one good. This may make sorting into groups more or less difficult. The agents have an additional means to coordinate groups but the problem they attempt to solve becomes more difficult. Second, the agents in the model are homogeneous in many ways. Additional diversity of agents could be studied by allowing agents to have different preferences for goods or preferences for the characteristics of group members. And these could change across time. As an example, individuals may become less concerned about image as they grow older. Third, new goods could enter and exit the market. This feature would likely increase the amount and extent of fads in the model.

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