Spontaneous Specialization in a Free-Market Economy of Agents

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Abstract
In a free-market economy of software agents, information is produced, traded, and consumed by vast numbers of autonomous, self-motivated agents. An essential task in this economy is the retailing or brokering of information, whereby information is gathered from the right producers and distributed to the right consumers. This paper investigates one crucial aspect of a broker's dynamical behavior, its ability to specialize—i.e., to carve out a market niche for itself in a highly dynamic, potentially competitive environment—in the context of a simple information filtering economy.

1 Introduction
The coming synthesis of agent technology and electronic commerce offers the potential for a free-market economy of interacting agents to emerge on the Internet. Electronic commerce would reap all the benefits that agent technology can provide; at the same time, the "almighty dollar" would fill a crucial function as built-in motivator and facilitator for the adoption, success, and survival of agents.

Let us therefore suppose that the Internet is evolving toward a free-market information economy in which billions of software agents exchange a rich variety of information goods and services with humans and—much more commonly—amongst themselves [2, 4, 12, 14]. Is the emergence and survival of this economy guaranteed? The answer is far from clear. Within the context of market-driven optimization, a growing body of work demonstrates the success of economic mechanisms in coordinating the actions of agent populations [1, 3, 5, 11, 13]. But by definition, market-driven optimization presupposes a common overall goal to be striven for, in the form of a predefined measure of system performance, along with the implicit power of the system's designers to tune its parameters to help it achieve its optimum. In an open system like the Web, no such goal exists. Each agent has its own set of objectives, which may coincide with, conflict with, or (most probably) simply be incommensurable with, the goals of other agents [10]. The success or viability of the economy is determined on an agent-by-agent basis: if an agent can achieve its goals, the economy "works"; if not, it doesn't. Therefore the success of market-driven optimization can provide encouragement, but not proof, of a free-market agent economy's ultimate survival. Of even more concern is previous research on large systems of interacting, self-motivated software agents showing that they may be susceptible to the emergence of wild, unpredictable, disastrous collective behavior [8, 9].

All of the above motivates a general, wide-ranging study of economically motivated autonomous agents. In this and a pair of companion papers [6, 7], we have chosen to work within the context of a simple model of an information filtering economy, in which information brokers, which purchase selected information goods from a producer agent and resell them to selected consumers, play the central role. Ref. [7] examined the dynamics of the brokers' price-setting behavior in a competitive environment. This paper focuses on the complementary aspect of broker specialization, as measured by the brokers' individual selections of which, and how many, types of information good to carry.

In section 2, we describe the details of the model. Section 3 presents analytic results on specialization in an economy containing only one broker, which are then applied in section 4 to help understand the behavior of a multi-broker system. We close with a discussion of the overall results and of directions for future work.

2 A model news filtering economy
Our model system is an information filtering economy, first described in ref. [6]. It consists of a source agent that publishes news articles, C consumer agents that want to buy articles they are interested in, B broker agents that buy selected articles from the source and resell them to consumers, and a system infrastructure that provides communication and computation services to all agents. A diagram showing part of our model system is shown in Fig. 1. The ellipse at the top represents the source agent, brokers are in the middle, and consumers are at the bottom. Each agent's internal parameters (defined below) are printed inside its ellipse. The system is represented by the rectangle on the left. Solid lines represent the propagation of a sample article through broker 1. Broken lines indicate payment, and are labeled with symbols (explained below) for the amount paid.

The source agent publishes one article at each time step, and waits until that article has propagated through the system before publishing the next. It classifies articles according to its own internal categorization scheme, assigning
each a category index \( j \) when it is offered. The nature of the categories, and the number \( J \) of them, do not change. We represent this (hidden) classification scheme by a random process in which an article is assigned category \( j \) with fixed probability \( \alpha_j \). The set of all \( \alpha_j \) is the source’s category prevalence vector \( \alpha \). Each article labeled with its category index and offered for sale to all brokers at a fixed price \( P_b \).

For each article sold to each broker, the source pays a fixed transport cost \( P_T \).

Upon receiving an offer, each broker \( b \) decides whether or not to buy the article using its own evaluation method to select which category it is “interested in.” The broker’s evaluation method—which may involve a categorization scheme entirely different from that used by the source—is approximated by an interest vector \( \beta_b \), where \( \beta_{bj} \) represents the probability for \( b \) to purchase an article labeled with category \( j \). Analysis of the model [6] shows that it is in broker \( b \)’s best interest to set the \( \beta_{bj} \) individually to either 0 or 1.

When broker \( b \) purchases an article, it immediately sends it to a set of \( s \) subscribes, paying transportation cost \( P_T \) for each. Subscribers may examine the article, but must pay the broker \( P_b \) if they want the right to use (“consume”) it.

The broker’s internal parameters \( \beta_b \) and \( P_b \) are under its direct control.

Subscriptions are represented by a subscription matrix \( S \), where \( S_{bc} = 1 \) if consumer \( c \) subscribes to broker \( b \), and \( S_{bc} = 0 \) if not. Subscriptions are maintained only with the consent of both parties and may be cancelled by either. For example, a broker \( b \) might not wish \( c \) to subscribe if the cost of sending articles exceeds the expected payment from \( c \), or \( c \) might not find it worthwhile to subscribe to \( b \) if the cost of siftng through lots of junk outweighs the benefits of receiving the rare interesting article. The requirement that the agreement be bilateral is represented by setting \( S_{bc} = \sigma_{bc}^h \sigma_{cb}^c \), where \( \sigma_{bc}^h = 1 \) if broker \( b \) wants consumer \( c \) as a subscriber and \( \sigma_{cb}^c = 0 \) if not; similarly, \( \sigma_{bc}^c = 1 \) if consumer \( c \) wants to subscribe to broker \( b \) and \( \sigma_{cb}^c = 0 \) if not.

Each consumer waits for articles to arrive from the brokers it subscribes to. When a consumer receives one or more copies of an article, it pays the computation cost \( P_C \) to evaluate whether it is interested in the article, then decides whether (and from whom) to buy it. Like the brokers, the consumers’ evaluation function is approximated by a stochastic process parametrized by an interest vector \( \gamma_c \); consumer \( c \) will be interested in an article labeled with category \( j \) with fixed probability \( \gamma_{cj} \). If a consumer is interested in an article, it then selects from the set of brokers it subscribes to the one broker \( b^* \) with the most attractive offer; we shall assume the most attractive offer is the cheapest one. The consumer then decides whether its interest justifies paying \( P_{bc} \) for that article. For reasons of simplicity, we model this decision process as follows: each consumer assigns a global constant anticipated value \( V \) to each article it is interested in. Then if \( V > P_{bc} \), it purchases the usage rights; otherwise it discards the article unused.

Each broker’s or consumer’s decision-making process may be expressed as an attempt to optimize its utility function, defined as the amount of net “value” or “utility”—however it may be measured—gained by making that particular decision. In the system described here, the expected utility per article for each broker and consumer may be explicitly formulated from the system variables. For consumers, the anticipated value \( V \) provides the fundamental benchmark for measuring utility. For brokers, the appropriate measure of utility is profit, defined in the usual way as revenue less expenses. General expressions for consumer utility and broker profit may be found in ref. [6].

In closing this section, let us observe that our model disregards a number of potentially interesting features of real information filtering systems. By assigning a single category index to each article, it disregards articles that fall into multiple categories. By having brokers and consumers evaluate each article independently of previous articles, it disregards the possibility of multiple articles containing redundant information. By assigning a constant value to each article purchased by each consumer, it disregards differences among consumers and among articles. By approximating the brokers’ and the consumers’ evaluation methods by stochastic functions, it disregards the advantages and difficulties associated with automatic evaluation of articles’ semantic content.

Each of these represents a refinement of the model which brings it closer to a real information filtering system. Nevertheless, they lie outside the scope of the present article. As we noted in the introduction, the focus of this article is the economic properties of the system, as opposed to the purely informational ones.

3 Specialization without competition

As we will see, a crucial first step in understanding specialization in a multi-broker economy is to consider the case of a single broker. In this section we analyze the profitability of a single broker as a function of the number of categories \( J \) that it carries, in the limit of a large consumer population \( C \rightarrow \infty \). Since \( B = 1 \), we drop the broker index \( b \) that the broker’s sale price is denoted by \( P \), its interest vector is \( \beta \) with elements \( \beta_{ij} \). The subscription matrix \( S \) is now a vector with elements \( S_{ij} \).

The broker utility \( W \) is given by (cf. ref. [6]):

\[
W = \sum_{j=1}^{J} \alpha_j \beta_j \left( \sum_{i=1}^{C} S_{ij}(\gamma_{ij}P - P_T) - P_S \right)
\]

(1)

The product \( \alpha_j \beta_j \) is the probability, per published article, that the broker will buy an article in category \( j \). The term in square braces is the expected net revenue per article
category \( j \). This breaks up into \( P_S \), the price the broker pays to the source for the article, and the sum over consumers \( c \), which gives the total revenue from sales of the article to consumers. For each subscribing consumer (i.e., \( S_c = 1 \)), the broker pays \( P_T \) to transport the article, while the consumer buys it with probability \( \gamma_c \), paying \( P \) to the broker if it does so.

Similarly, the utility for consumer \( c \) is given by:

\[ U_c = \sum_{j=1}^{J} \alpha_j \beta_j S_c \left[ \gamma_c (V - P) - P_c \right] \]  

Here, \( \alpha_j \beta_j S_c \) is the probability, per published article, that the consumer will be offered an article in category \( j \). For each article it is offered, it pays computation cost \( P_c \) to decide whether to buy it, which it does with probability \( \gamma_c \), receiving net value \( (V - P) \).

These can be simplified somewhat. First we note that the broker’s utility is maximized by setting \( \beta_j = 1 \) for each category in which its net revenue is positive, and \( \beta_j = 0 \) for all others. Note, however, that categories \( j \) for which \( \beta_j = 0 \) are effectively removed from the system, since the broker never purchases articles in those categories. Therefore, without loss of generality, we consider the case where \( \beta_j = 1 \) for all \( j \) and reinterpret the number of categories \( J \) as the number of active categories—i.e., those categories that actually show up in the system. The broker activates or deactivates a category \( j \) by setting \( \beta_j \) to 1 or 0, respectively. It is also necessary to rescale the \( \alpha_j \) to preserve the normalization \( \sum_{j=1}^{J} \alpha_j = 1 \).

We can summarize a consumer’s interest vector by its effective interest level \( \overline{\gamma}_c \equiv \sum_{j=1}^{J} \alpha_j \gamma_j \). This is the probability that a consumer will be interested in a randomly selected article offered by the broker. A little algebra now gives simplified forms of the broker and consumer utilities:

\[ W = \sum_{c=1}^{C} S_c (\overline{\gamma}_c P - P_T) - P_S \]
\[ U_c = S_c (\overline{\gamma}_c (V - P) - P_c) \]  

If both brokers and consumers set their subscriptions independently to optimize their utilities (i.e., they pursue a game-theoretic solution), it can be shown (cf. ref. [6]) that the subscription vector element \( S_c \) depends only on the broker’s price \( P \) and \( \overline{\gamma}_c \), and is given by

\[ S_c (\overline{\gamma}_c, P) = \Theta (\overline{\gamma}_c P - P_T) \Theta (\overline{\gamma}_c (V - P) - P_c) \]  

where \( \Theta \) is the step function: \( \Theta (x) = 1 \) for \( x > 0 \), and 0 otherwise. The first term represents the veto power of the brokers, who only want subscribers for whom the expected income \( P T \overline{\gamma}_c \) is greater than the cost \( P_T \). The second term on the right represents the veto power of the consumers, who only subscribe to brokers providing expected net value \( \overline{\gamma}_c (V - P) \) that exceeds cost \( P_c \).

The only remaining free variables are the number of active categories \( J \) and the broker’s price \( P \). To determine the values of \( P \) and \( J \) that optimize the broker’s profitability, it is necessary to specify the consumers’ effective interest levels \( \overline{\gamma}_c \). We will examine two extreme cases: a uniform distribution, in which the consumer interest levels \( \gamma_c \) are uniformly distributed on the interval \( 0 \leq \gamma_c \leq 1 \), and an “all or nothing” distribution in which a consumer is either completely interested (\( \gamma_c = 1 \)) in a category with probability \( \nu_c \), and otherwise completely uninterested (\( \gamma_c = 0 \)).

First let us re-express the broker’s profitability in terms of its expected income per consumer \( I(J, P) \):

\[ W(J, P) = CI(J, P) - P_S \]  

In a sufficiently large consumer population, the first term dominates for any finite source price \( P_S \). Therefore the value of \( I(J, P) \) is the determining factor in the broker’s optimal behavior.

### 3.1 Uniformly distributed consumer interests

If the consumer interest levels \( \gamma_c \) are distributed uniformly, the broker profitability per consumer \( I(J, P) \) can be calculated analytically in the limit \( C \to \infty \), if we make the assumption that \( \alpha_j = 1/J \) for all \( j \), i.e., all categories are equally prevalent. This makes all categories equally profitable, effectively replacing the question of which categories to offer with the simpler one of how many to offer. Fig. 2 shows the result in the form of profit cross-sections \( I(J, P) \) vs. \( P \) for \( J = \{1, 2, 3, 10\} \), for a characteristic choice of extrinsic costs \( P_C, P_T \) and consumer value \( V \).

![Figure 2: I(J, P) vs. P for J = 1, 2, 3, 10, when P_T = P_C = 0.29, V = 1.](image-url)

Focusing for the moment on the curve for \( J = 1 \), we observe that the profit per customer has a single peak at \( P^* \approx 0.61 \). As \( P \) increases beyond \( P^* \), the broker’s profit is reduced as fewer and fewer consumers purchase articles. On the other hand, as \( P \) decreases away from \( P^* \), the broker’s profit per customer per article is less.

More important, however, is the fact that as the number of categories \( J \) increases, the profitability value at the peak changes drastically. The analytic solution shows that \( P^*(J) \) is a strictly decreasing function of \( J \), and \( P^* \to \frac{P_T}{2} \) as \( J \to \infty \). In other words, the broker can always charge a higher price if it offers fewer categories. However, the number of consumers actually buying articles, and hence profit per consumer, may increase or decrease with the number of offered categories. For \( J = 1 \), the peak profit per customer is \( I(1, P^*) \approx 0.062 \), while for \( J = 10 \), the peak value is \( I(10, P^*) \approx 0.021 \). Evidently, for optimal profit, the broker should not automatically offer as many categories as possible. In this case, for example, the best situation is \( J = 2 \), because it has the highest peak, even though the overall curve is not universally higher than other curves for arbitrary \( J \).

The dependence of the broker’s profit on the number of categories is summarized in Fig. 3. It shows the peak...
profit per customer $I(J, P^*)$ vs. $J$, for three different settings of $P_C$ and $P_T$, with $V = 1$. For $P_C = P_T = 0.35$ and $P_C = P_T = 0.29$, the broker’s profit is maximized for a small number of categories ($J = 1$ and $J = 2$, respectively). For $P_C = P_T = 0.23$, however, profit increases monotonically with $J$. We may call this the “spam” regime, in which the extrinsic costs of computation and transportation are so low that the broker can always make more profit by offering more categories.

As Fig. 3 shows, for each setting of extrinsic costs costs $P_C$ and $P_T$, there is an optimal number $J^*$ of categories that maximizes broker profit. Fig. 4 shows a contour plot of $J^*$ as a function of $P_T$ and $P_C$, again for $V = 1$. Note that, for $P_C + P_T > 1$, $J^* = 0$. In this region, it is impossible to simultaneously satisfy the consumers’ and broker’s conflicting desires as indicated in Eq. 4. Even for a maximally interested consumer ($\tau_i = 1$), $S_i = 0$ for all positive prices $P$.

Again assuming that articles are published uniformly in all active categories ($\alpha_j = 1/J$ for all $j$), we again found an analytic solution for $J^*$ as a function of $P_C$ and $P_T$. Figs. 5 and 6 show contour plots of the optimal number of categories $J^*$, for the two bias values $\nu = 0.5$ and $\nu = 0.1$, respectively. One thing to note in Fig. 5 is the small “jump” in the contours at $P_C \approx 0.5$, $P_T \approx 0.1$. This does not appear to be an artifact, though we do not at this time have an interpretation of it. In general, though most of the contours are nearly parallel, they are not exactly so.

In Fig. 6, the bias $\nu = 0.1$ has caused the spam regime to be much reduced in area, with a similar shift in all the other contours. This is due to the overall reduction in the number of articles a typical consumer would buy, caused by the change in bias. This bias value, which corresponds to the average consumer being very interested in 10% of the categories and not at all interested in the remaining 90%, is perhaps not an unreasonable distribution for an information filtering context.

The shape of the contours differs only in detail from the uniform distribution of Fig. 4. In all cases, there is a large region of $(P_C, P_T)$ space in which a broker prefers to specialize to a small number of categories, even though it has a monopoly over any category it chooses to offer. The fact that such dissimilar distributions of consumer interests give rise to qualitatively similar result suggests that contours like Figs. 4, 5 and 6 would be found for a wide class of consumer interest profiles. And as we will see in the next section, the optimal single-broker $J^*$ plays a central role in the behavior of multi-broker systems.

### 3.2 All-or-nothing interest profiles

Let us perform the same analysis for the all-or-nothing distribution, in which a consumer’s interest in a category is either $\gamma_{cj} = 1$ or $\gamma_{cj} = 0$, with probability $Pr(\gamma_{cj} = 1) = \nu$. How can we understand these contours? In the region where $J^* = 0$, as we have already noted, the extrinsic costs are too high to permit any value of price $P$ that simultaneously gives profit to the broker and positive net value to the consumers. But why should there be large regions for which $J^*$ is nonzero but small?

Consider for the moment the interest profile distribution that gives rise to Fig. 6. As the number of categories offered by the broker grows, the likelihood of any given consumer being interested in all categories decreases as $\nu^J$. In general, for the typical consumer, additional categories means additional junk. This means there is an overall decrease in

![Graph](image-url)

**Figure 3:** $I(J, P^*)$ vs. $J$ for $P_T = P_C = 0.23$, $P_T = P_C = 0.29$ and $P_T = P_C = 0.35$ $V = 1$ for all three curves.

![Graph](image-url)

**Figure 4:** The optimal number of categories $J^*$ for the broker to offer as a function of $P_C$ and $P_T$, for the uniform distribution of consumer interests. As before, $V = 1$.

![Graph](image-url)

**Figure 5:** The optimal number of categories $J^*$ for the broker to offer as a function of $P_C$ and $P_T$, for the all-or-nothing distribution of consumer interests with $\nu = 0.5$. As before, $V = 1$.

How can we understand these contours? In the region where $J^* = 0$, as we have already noted, the extrinsic costs are too high to permit any value of price $P$ that simultaneously gives profit to the broker and positive net value to the consumers. But why should there be large regions for which $J^*$ is nonzero but small?
the percentage of articles each consumer pays for, regardless of the price $P$. Since the broker has to pay $P_T$ for each article it sends, there comes a point at which the transportation costs outweigh the expected revenue from sales to consumers. Similarly, each consumer has to pay $P_C$ to evaluate whether it is interested in an article. At some point, the percentage of positive evaluations becomes so low that it fails to overcome the cost of evaluating. Reducing $P_T$ and $P_C$ reduces the disvalue of sending (and receiving) junk, pushing out the threshold at which the cost of junk outweighs the value of good information, and thereby increasing $J^*$. As the extrinsic costs are further reduced, they become so low that the broker is assured of a profit on every additional category it offers, and the system finds itself in the spam regime where $J^* \to \infty$.

The optimal number of categories $J^*$ for the broker to offer as a function of $P_C$ and $P_T$, for the all-or-nothing distribution of consumer interests with $\nu = 0.1$. As before, $V = 1$.

4 Competitive webs

As noted in the last section, broker $b$ deactivates category $j$—so far as it is concerned, at least—by setting the corresponding interest level $\beta_{b,j}$ to 0. In the multi-broker system, brokers are still free to select any set of categories they wish, so they may in general have different interest vectors, thereby offering different selections of categories. Specialization then becomes a co-evolutionary phenomenon, as brokers move themselves into or out of direct competition with each other.

When a broker offers more than one category, it may find itself in competition with a different set of brokers in each category. Since each of its competitors is in the same situation, what emerges is a competitive web of brokers linked by partially overlapping category selections. Two brokers may offer disjoint sets of categories, but may still be in indirect competition with each other because of a third broker in partial competition with each.

In this section, we will experimentally study the evolution of a system with multiple brokers. An exact solution of the type discussed in section 3 is not accessible due to the dimensionality of the state space: each broker contributes $J + 1$ dimensions, making calculations prohibitively difficult. Therefore, it becomes necessary for brokers to have some sort of dynamical algorithm to help them set prices and select categories.

For the experiments reported here, we choose one broker at random in each time step and, holding all other brokers fixed, allow it to attempt to optimize its profitability by making a fixed number of hypothetical changes to its price and interest vector. Hypotheses are generated in two ways, neither of which uses information about any of the consumers or other brokers, by incremental changes to current parameter values, and (less frequently) by choosing values at random. For each hypothesis, the broker’s profitability is accurately determined under the assumption that the other brokers do not change. The broker then sets its parameters to match the hypothesis that gave the best profit. The profitability calculation, described in ref. [7], is feasible because only one broker’s parameters are being set. We might think of the evaluation of a few hypotheses as a form of market research. Note, however, that the change actually made by the broker depends crucially on the hypotheses it generated, and that the profitability calculation assumes (false) that the other brokers do not change; thus the results of the market research are neither complete nor completely accurate.

We consider an information filtering economy with $B = 5$ brokers, $J = 5$ categories in all, and $C = 1000$ consumers in the “all-or-nothing” distribution with $\nu = 0.1$, for which the single-broker category contour plot is shown in Fig. 6. We will take 3 points in that figure corresponding to optimal number of active categories $J^* = \{1, 2, \infty\}$ and measure the category coverage of each broker as a function of time.

The category coverage is the quantity that most closely corresponds to the number of active categories in the single-broker system ($J^*$).

Fig. 7 shows $N_J(b; t)$ for each of the five brokers $b$ in the system. The costs are $P_C = P_T = 0.40$, $V = 1$, corresponding to a point in the $J^* = 2$ region of the single-broker system. Each broker starts out offering all five categories, but all but one quickly specialize to a single category by time $t \approx 2000$. The last broker continues to offer all five categories until $t \approx 7500$, when it suddenly specializes as well.

A detailed examination of the timeseries shows that the late-specializing broker, though offering all articles in all categories, was in fact not selling any of them in any category, not even the category in which it held a monopoly. It could not find any customers that were sufficiently interested in all five categories. The broker was behaving as if it were in the spam regime, with disastrous consequences. Nevertheless, it was eventually able to stumble into the one niche not filled by any other broker, at which time its profitability rose from 0 to the same value maintained by the other brokers. Fig. 8 shows the profit of all five brokers vs. time. The late-specializing broker is the one whose profit curve rises abruptly from 0 at $t \approx 7500$. Also note the initial wild fluctuations in broker profit, with attendant fluctuations in category coverage. These are caused by a sorting-out period in which brokers are collectively forming, breaking, and re-forming price- and category wars of the type reported in ref. [7].

At this setting of extrinsic costs, a single-broker system prefers to offer only one category. In the multi-broker sys-

![Figure 6: The optimal number of categories $J^*$ for the broker to offer as a function of $P_C$ and $P_T$, for the all-or-nothing distribution of consumer interests with $\nu = 0.1$. As before, $V = 1$.](image-url)
unprofitable state of affairs ends when all brokers specialize. Instead of wild fluctuations, each broker’s profit is pegged at a maximal value.

Finally, let us look at $P_C = P_T = 0.05$, for which $J^* = \infty$ in the single-broker system. The time evolution of the each broker’s category coverage is shown in Fig. 11. This is well into the spam regime, where an isolated broker prefers to offer all five categories. The brokers did not specialize. They remained locked in a competitive struggle through time $t = 10000$, when the simulation was stopped. There is no reason to expect that the system would ever have settled down. As Fig. 11 shows, however, competition did cause the brokers to give up some of their categories, leading to a time-averaged coverage of about 2.1 categories per broker.

In the experiments reported in this section, we found that under the proper circumstances our simple model system was able to achieve spontaneous specialization. This is despite the fact that none of the brokers was “aware” of even the notion of specialization, let alone of its potential benefit. Specialization was brought about solely by market forces as they made themselves felt through each broker’s profitability. For the first experiment, $P_T = P_C = 0.40$, specialization is attributable to the preference of offering a single category
even without competition. In this case, the most notable observation is that, despite the simplicity of their dynamics, the brokers succeeded in finding the niches at all. In the second experiment, \( P_T = P_C = 0.17 \), for which \( J^* = 2 \) in the single-broker system, a single-broker system would not have specialized fully; it was only due to added disvalue of competition in price wars that brokers found it preferable to offer one category instead of two. Finally, when the extrinsic costs were well into the "spam" regime, \( (P_T = P_C = 0.05) \), the disvalue of competition forced the brokers' time-averaged category coverages from \( J^* = 5 \) down to about 2; but the residual competition was still enough to prevent brokers' category selections from stabilizing.

Another avenue of further enquiry would test the realism of the model's economic features. For example, no provision is made for the cost incurred by a broker when it changes its price category offerings. In any real situation, there is likely to be a nonzero cost of adding or dropping a category—e.g., capital outlays for additional bandwidth, storage, or processing power. Probably there will be a cost associated with deciding which categories to add or drop and what new price to offer—i.e., doing market research. The observed rapid fluctuations in category offerings crucially depended on brokers being able to freely switch categories in pursuit of maximum profit. Some early investigations into the effects of switching costs show that they can sometimes quench the fluctuations, depending on the relationship between the magnitude of the switching cost and the various choices of interest vectors. Note, however, that an excessive switching cost can also prevent brokers from moving into a potentially profitable niche.

As noted at the end of section 2, many improvements are possible to the informational aspects of the model as well. We expect these will lead to novel and interesting behavior as the agents are made more sophisticated and the details of article selection by brokers and consumers change. The nature, and number, of potential niches is likely to change radically, and may itself become an emergent property. Even so, we expect that the overall dependence of specialization on extrinsic cost and cost of competition will be qualitatively similar to what we have found here.

5 Conclusions and open questions

In this paper, we investigated the economic conditions governing the spontaneous development of specialized market niches in a population of competing information brokers. We found that the emergence of niches is sensitively dependent on the extrinsic costs of doing business. Further, the stability of the specialization process may be understood in terms of the preferred number of categories offered by a single broker without competition. We found several distinct regimes. When the extrinsic costs are such that a single broker prefers to specialize, the multi-broker system does as well. When the single-broker system would prefer to offer multiple categories, brokers in the multi-broker system find themselves in an ever-changing competitive web of partially overlapping categories. Even so, competition functions like an effective cost, causing brokers to offer fewer categories than in the single-broker case; if the extrinsic costs are not too low, the system may still specialize fully. If the extrinsic costs are sufficiently low, however, the perceived advantages of offering multiple categories overcome the disadvantages of competition, pushing the brokers into the "spam" regime of complex and disastrous price-and-category wars, with no stable niches emerging.

The experimental results reported here raise a number of interesting questions. For example, what are the factors governing the timescale of the transient sorting-out period? How can we best quantify the cost of competition, and how does it depend on the system parameters? And what are the conditions leading to the seemingly abrupt collapse from price wars to full specialization?

Figure 11: Category coverage \( N_j(b; t) \) vs. time \( t \) for brokers \( b = \{1, 2, 3, 4, 5\} \) when extrinsic costs are \( P_C = P_T = 0.05 \).

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