The Economics of Internet Companies

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Abstract

In this paper, we analyze the effects of brand loyalty and network effects on the fortunes of Internet companies in an agent-based model. We find that brand loyalty and network effects produce interesting dynamics when included together in a simulated Internet which are very different from the dynamics observed when only one or neither of these effects are present. If both brand loyalty and social communication are high, a loyal user can be convinced to switch web sites, thus causing large and traumatic changes in the fortunes of the Internet companies.

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1 Introduction

The growth of the Internet is one of the outstanding cultural, social, political, and financial events of our time. The Internet has transformed many business, economic, and financial relationships in ways that are not satisfactorily captured by textbook economic and financial theory. The ability to adjust prices instantly, to analyze the micro-behavior of consumers, and to dynamically modify the product are novel characteristics and little is known about how to exploit them.

In this paper we describe an agent-based model of Internet markets that sheds light on how consumers navigate through the space of web pages, how social interaction influences the choices that consumers make, and how Internet markets develop. The field of agent-based modeling draws on ideas from artificial intelligence, simulation, sociology, and anthropology , among others. Agent-based simulations have been used to model telephone markets, predict the sales of hit movies, and trade the financial markets (Palmer *et al.* 1994) .

Agent-based simulations are particularly well-suited to the problem of understanding how Internet markets develop because they support the implementation of models that have many heterogeneous agents with rich internal state and complicated relations with other agents. In contrast, traditional economic and financial models typically contain a small number of representative agents which have little internal state and do not interact in complicated ways with other agents.

This paper is organized into six sections. The second section of the paper explains why building models of Internet markets is of interest to academics, venture capital firms, and entrepreneurs; the third section shows how this research is related to other work in this field; the fourth section defines and explains our Internet market model; the fifth section describes the agent-based simulation of this model and the results of several experiments we performed with this simulation; and the sixth section summarizes our conclusions.

2 Motivation

Understanding how Internet markets develop, grow, and change is of interest to academicians, entrepreneurs, and venture capitalists. Because the Internet phenomenon is so new, little work - empirical and theoretical - has been done in this field.

From an academic standpoint, Internet markets bring together many subfields of standard theory including research on auction mechanisms, game theory, and pricing. Not surprisingly, there is a growing body of work that adapts these models to Internet markets (Varian & MacKie-Mason 1995; 1994). However, as suggested in the introduction, these models do not incorporate all of the new information, such as the micro-movements of consumer's mouse, that the Internet makes available for analysis. As such, there is room for substantial improvement in our understanding of how Internet markets work.

While academics are interested in technical features of Internet markets, entrepreneurs are interested in practical questions such as:

- What drives users to a particular Internet site?
- How can web sites be promoted?

- How can competitive advantages be sustained?

Currently, entrepreneurs solve these questions via trial and error. Witness, for example, the very frequent changes in web site layouts. Given the high valuations of companies in the Internet space, a more formal model which permits the testing of multiple hypothesis is clearly needed.

The venture capitalists who fund entrepreneurs would like to know which markets make for the best investments, what are the critical factors that determine the success of Internet businesses, and how they should be valued. To answer these questions, venture capitalists rely on rules of thumb, along with some traditional analytical models, that capture their past experiences investing in Internet firms.

The work that we describe in this paper is a small step towards a theory of how Internet markets work and, as such, may be helpful in addressing some of these questions.

3 Related Work

Most of the the research on web-browsing behavior has had a marketing focus. Graphics, Visualization, & Usability (GVU) Center at the Georgia Institute of Technology have conducted nine on-line surveys on Web usage since January 1994, approximately once every six months. The earlier surveys represented young computer-savvy users. Their share in respondents has steadily declined over the span of the surveys. The average age of the respondents have been quite steady, about 33, but age distribution has changed dramatically as more and more people at the tails of the distribution have started using the Internet. There seems to be a fairly steady stream of new users to the Internet as indicated by the percentage of users who have been on less than twelve months which has been about 45 to 50 percent. For a description of the surveys and a summary of results see (Kehoe & Pitkow 1996) and (Pitkow & Kehoe 1996).

Raman (Raman 1997) observes eight users as they browse the Web at a laboratory and interviews them afterwards. Users are found to browse through pages that don't interest them very quickly. They usually start from a familiar page and through its links browse other pages. McMellon et al. (McMellon & Sherman 1997) look at the behavior of cyberseniors on the Internet and conclude that personality characteristics explain a lot about their on-line behavior. Rheingold (Rheingold 1993) suggests that two personality types gravitate towards the Internet: those whose professional background is a good fit for on-line activities and those curious about the Internet as a technological phenomenon.

The results of the surveys are useful in tracking the evolution of the web population. So far, survey results show that most of web usage is for entertainment. However, recently the types of businesses that are conducted on the Internet have exploded, with convenient on-line banking services, affordable on-line trading and even paying your taxes on-line.

In this paper, we investigate the web-browsing behavior of users of the Internet. In investigating the user's behavior, we incorporate the network of the user's to understand the process behind popular web sites.

4 An Agent-based Model of Web-surfing

We analyze how agents allocate their time between web-surfing and other activities. Web-surfing is modeled as time spent on visiting different web pages. The duration of agent i's visit to the nth web page is w_n^i such that $\tau_w^i = \sum_{n=1}^{N} w_n^i$ where N is the total number of web pages on the Internet. Throughout the paper, subscripts will be used to index web pages and superscripts will be used to index the agents. The utility the agent derives from consuming w_n of the nth web page is $u(w_n)$. Time spent on other activities will be denoted by c, and the utility derived from these activities will be denoted by $u(c)$.

We assume that consumers maximize an additively separable utility function subject to a time constraint. Agents don't know exactly how much utility they are going to derive from a web page before they visit it, so they maximize expected utility. An agent's expectations are formed by her own experience and the experiences of the other agents she communicates with. Ψ^i will denote the network of agent i. Agents exchange information about web pages they have visited within their network. This information set will be denoted by $I(\Psi)$. Agents also rely on their personal experience which we will denote by β. Agent i solves the following time allocation problem:

$$\begin{aligned} \max u^i(c^i, w_1^i, w_2^i, ...w_N^i) &= u^i(c^i) + \sum_{n=1}^{N} E(u^i(w_n^i)|I(\Psi^i), \beta^i) \qquad (1) \\ s.t. \quad \tau &= \tau_c^i + \tau_w^i \end{aligned}$$

$u(.)$ is a quadratic utility function such that $u(x) = bx - x^2$.

$$E(u^i(w_n^i)|I(\Psi^i)) = w_n^i \sum_{j\in\Psi} b_n^j \alpha_i^j - (w_n^j)^2 \tag{2}$$

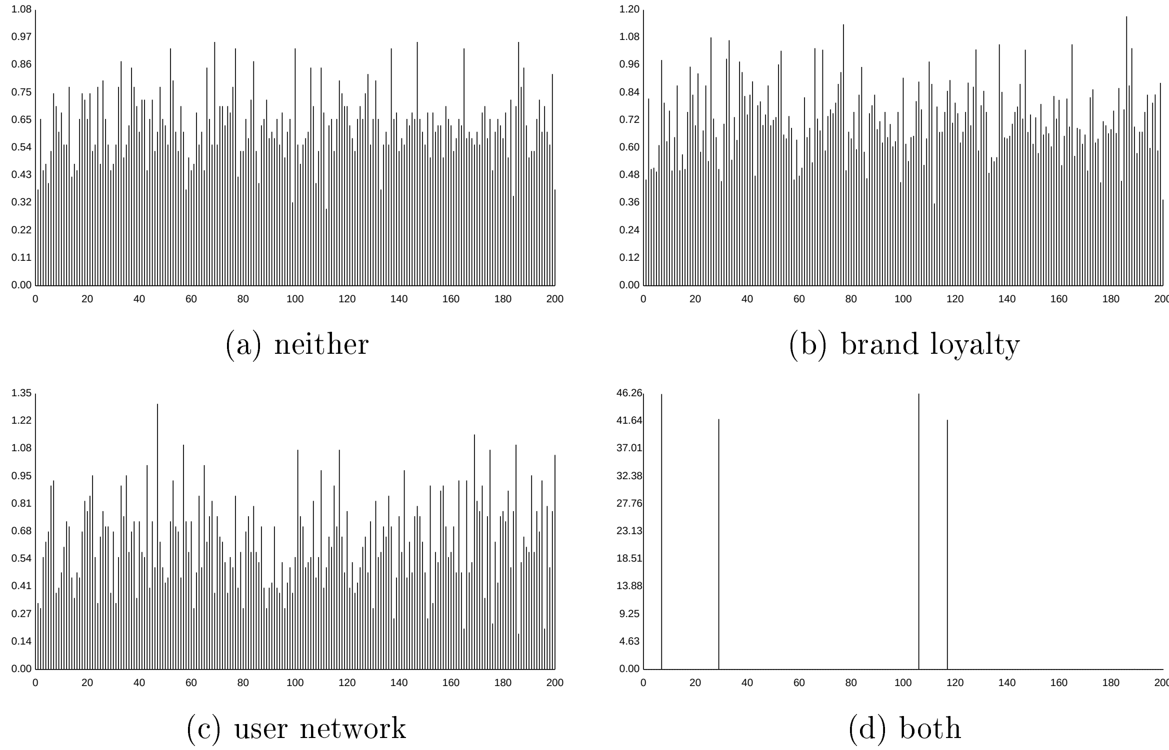
α_i^j are the weights agent i gives to the agent j in her network. Own experience overrides any other information, so once the agent has visited a particular web page, the network can only have an indirect effect on the agent's use of this web pages which works through the information provided on the web pages she has not yet visited.

Agents learn to make more use of web pages they frequently visit, and as a result can increase the utility they can derive from them. So for pages already visited, b_n^i is a function of the number of visits to page n such that $\frac{\partial\alpha}{\partial v} \geq 0$.

We assume that the providers of web pages make money on advertisements as well as conducting business through the web pages. So the number of people who visit a web page and the time time they spend there, is a measure of the page's success. The company's revenues, hence expected revenues and the company's worth, are an increasing function of w^i. Let company n's revenues be $R_n(w_n) = \sum_i w_n^i$.

5 Simulations

In the simulations below, there are 1000 users and a 200 web pages. User parameters that determine their enthusiasm for random browsing, b_R, and the intrinsic quality of all web pages, b_n are set to 0.5 for all users. The users' liking for other activities, b_c, are set to 2.2.



(a) neither

(b) brand loyalty

(c) user network

(d) both

Figure 1: Network Effects versus Brand Loyalty

5.1 Network Effects versus Brand Loyalty

These simulations are designed to explore the relative importance of network effects and brand loyalty. Figure 1 shows the distribution of time spent on each company's web page at the end of the 100th period. Time spent is measured on the vertical axes, and web sites are indexed from 1 through 200 on the horizontal axes. We see that in the absence of network effects and brand loyalty, even though all web pages have the same quality, some web pages are visited more than others (see Figure 1(a)). When brand loyalty is introduced, the distribution of time spent on web pages is not affected but time spent on the Internet increases as brand loyalty works to increase the user's appreciation of the web pages visited often (see Figure 1(b)). Introducing communication among users without brand loyalty affects distribution of time spent on different web sites (see Figure 1(c)). The most successful web sites in this simulation attract users who spend in total more time on these web sites when compared with the previous two cases. When we introduce both brand loyalty and communication among users, we observe that a few companies eventually capture the attention of all users, driving all other web sites to obscurity (see Figure 1(d)). We would again like remind the reader that all web sites have the same quality initially, and all users have the same utility function. What distinguishes one user from another is only which web pages she happened to visit first, and when there are network effects, which users she communicates with. When these simulations are run with web pages of different quality, there is a bias toward better quality web pages. In the presence of both user network and brand loyalty, the companies that make it big are the best quality ones. In the other cases, better quality web pages also attract more users although the best does not necessarily attract the most users.

5.2 Dynamics with Network Effects and Brand Loyalty

Figure 2 shows the distribution of time spent on each company's web page over time. Time spent is measured on the vertical axes, and web sites are indexed from 1 through 200 on the horizontal axes. Each user communicates with 5 other users selected uniformly over all users.

In the first period, users randomly select the web sites they want to visit so the distribution is quite flat over web sites. By the 10th period, some sites have started to become popular but all web sites still have users. By the 20th period, some web sites are failing to attract any users, while the more popular sites are increasing their user base. Drastic changes continue to occur, and by the 100th period, four web sites have captured the attention of all users, and have driven all others out of business.

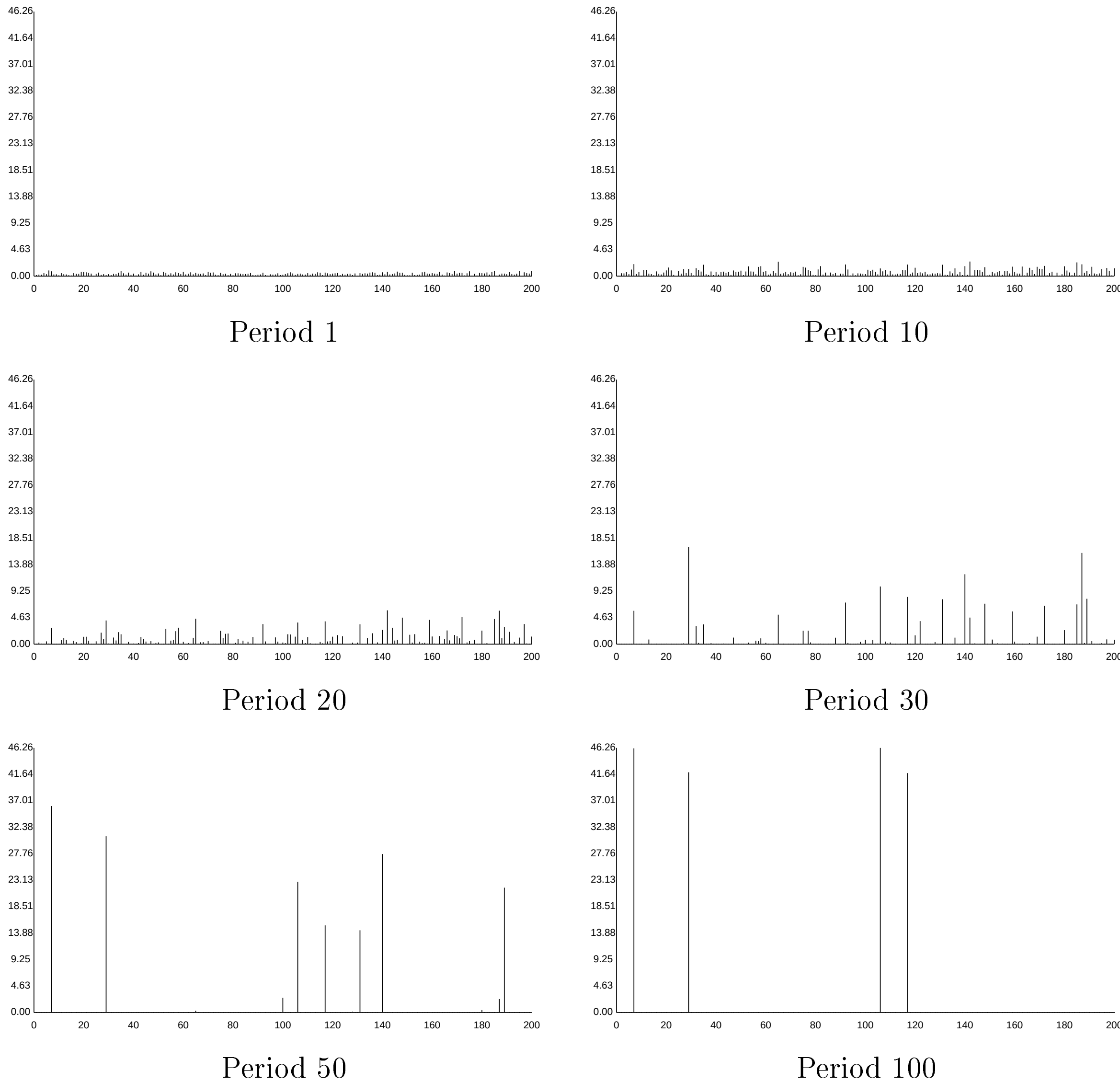


Figure 2: Dynamics with Network Effects and Brand Loyalty

5.3 Internet Company Revenues

Figure 3 shows the revenues of selected companies over time. Time spent is measured on the vertical axes as before, but the horizontal axes indexes time. Even though all pages started

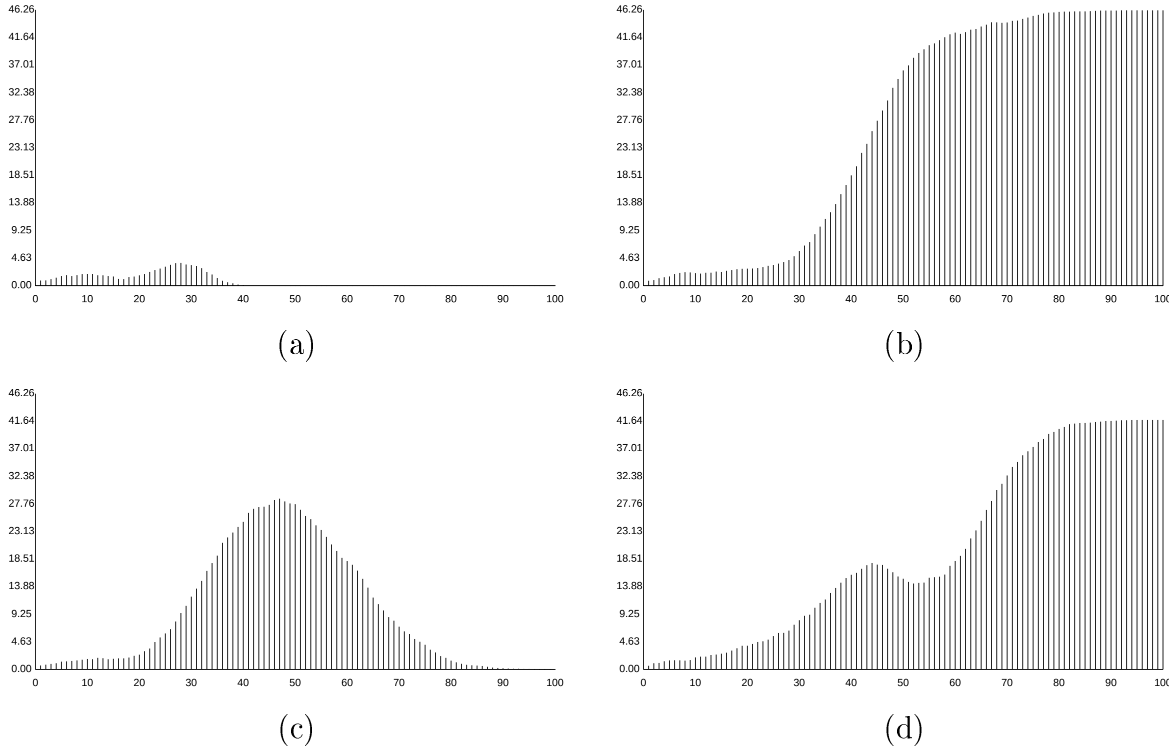


Figure 3: Comparison of Internet Company Revenues

out as the same, brand loyalty gets transferred through network effects to shift users to a select few companies. Figure 3(a) is typical company that is driven out of business earlier on. Figure 3(b) shows the revenues and hence the user base of a company that is one of the few that eventually captures the attention of all users. There is nothing to distinguish it from the company that failed to make it in (a) for the first 30 periods but then on it steadily builds on its user base. (c) and (d) are interesting because they show the unexpected dynamics of this simulated Internet. In (c), we have a company that steadily builds a loyal user base but gradually loses all its users, demonstrating that even loyal users can be convinced to shift their loyalty through network effects. In (d), we have a company that is able recapture the users that it loses.

5.4 Network Size and Network Effects

For the following simulation, we introduced heterogeneity in the users and the web pages to explore the effect of network size on Internet usage. Table 1 shows how the size of the user population affects Internet usage with and without user communication after 10 periods. When users do not communicate with each other, Internet usage increases linearly with the number of users. When users communicate with each other, the growth in Internet usage is larger and faster. Communication increases the users' ability to discover higher quality pages.

Table 1: The Effect of Network Size on Internet Usage

	Time Spent on the Internet by All Users	
Users	Communication On	Communication Off
10	1.70	1.63
15	3.80	2.52
20	4.81	3.39

6 Conclusion

In this paper, we investigated the effects of brand loyalty and communication among users in a simulated Internet. In the context of an Internet where all web sites have the same quality for all the users, we established that a few companies would make it big through network effects and brand loyalty, although neither of these effects would produce this result alone. Although this simulated Internet, at its present form too simple to capture all the dynamics of the Internet as it exists, it nevertheless provides useful insights into the dynamics that are at work. We believe brand loyalty is an important factor for web users, and communication does affect exposure to certain sites on the Internet. Internet companies can take appropriate measures to ensure that these dynamics work for them rather than against them. We believe that investing in advertising and in quality improvement will be most effective if undertaken together, the optimal balance remains to be determined in a more realistic simulation.

In future work, we will explore the choices the Internet companies can make to increase their user base. The companies can advertise in different ways both through the Internet and through more conventional media. They can choose to link their pages to other quality web pages that serve a similar user base and increase their exposure in this way. Again, the right number of links, the direction of the links remains to be determined.

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