Rational fads in investor reactions to electronic commerce announcements: An explanation of the Internet bubble

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Received 7 April 2006; received in revised form 29 September 2006; accepted 29 September 2006

Abstract
This work proposes that information cascade theory can help to explain the formation of the Internet bubble. We propose that the bubble existed because a lack of good information about the potential value of electronic commerce led investors to rely on other investors’ private valuations of electronic commerce. We use the event study methodology to estimate returns to company announcements of electronic commerce initiatives in 1999 and 2000. We find that after controlling for network externalities and time trends, investors’ valuations of the returns to electronic commerce initiatives were significantly influenced by the market return from prior periods. Moreover, the relative weight placed on prior periods’ returns decreased as the variance of the prior periods’ returns increased. Both of the results are consistent with the behavior predicted by information cascade theory.

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Keywords: DotCom bubble; Electronic commerce; Empirical research; Event study; Information cascade theory; Investor psychology; Rational fads; Stock market

1. Introduction
Technology is subject to fads – situations in which many agents adopt a technology with exaggerated zeal [1–3]. Recently, we witnessed an impressive technology fad – the Internet bubble. From 1998 to 2000 the popular press hailed the beginning of a new economy, and investments in electronic commerce activities were believed to be the best use of one’s money. Then, by 2002, we returned to the old economy and electronic commerce investment was no longer seen as being particularly better or worse than any other kind of business investment. Businesses certainly needed the electronic channel, but they also needed many other things. During this time the chosen vehicle for investing in electronic commerce was the stock market.

For example, in the 24 months from January 1998 to January 2000, the AMEX Internet stock index increased nearly 600%. However, by January 2002 it had returned to its 1998 level. Even today, in 2006, it is only about 50% higher than its 1998 level.

Why did investors believe that the returns on electronic commerce initiatives should be so large? Mills [4] cites four key reasons given to explain the Internet bubble: It was an accident, it was engineered by the incentive structures of financial services firms, it was due to inexperienced investors entering the market, and it was an example of “the madness of crowds”. To this list we add another reason. This work proposes that investors’ estimates of electronic commerce returns were the best guess of rationally-motivated individuals making decisions with great uncertainty.

Specifically, we argue that each individual was very uncertain about how large returns on e-commerce investments should have been, and therefore supplemented his or her own information by relying on information contained in the investment behavior of others. Although there were clearly other causes of the bubble, our data suggest that as much as 25% of the value investors placed in an electronic commerce investment was based on the value others placed on prior electronic commerce investments.

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In this paper, we investigate empirically the idea that technology fads are a consequence of agents inferring information about the benefits of a technology from the observable actions of other agents. We use stock return data from the “DotCom” era to investigate this question.

In particular, we investigate agents’ willingness to pay for technology based on other agents’ willingness to pay for similar technologies.

The paper proceeds as follows. In the next section we review literature explaining technology fads. We then develop a theoretical explanation of fads as information processes. We then describe the data and conduct our analyses. We conclude with implications of our findings for research and practice.

2. Background literature and relevant theory

In the present research we develop an explanation of the development of the DotCom bubble using a rational explanation of fad-like behavior. The most popular rational explanation of fad-like behavior is network externality theory [5–8]. Communication networks often have the characteristic that their value increases as the number of agents on the network increases. Thus, as more agents join a network, the value of the network increases, causing more agents to want to join the network. This positive feedback loop leads to rapid growth. However, this theory also suffers from three shortcomings in the present context. First, not all technologies are characterized by network effects [9–11]. Thus, network externality theory is not general enough to explain the full range of technology decisions. Second, network externality theory does not consider the information available to decision makers, and thus misses an important aspect of the decision maker’s environment. Third, network externality theory does not offer a good explanation of failed or mistaken fads. Agents always choose the most popular technology, even though it may not be the most advanced, because the size of the network outweighs the benefits of advanced features.

To overcome these difficulties, we take the perspective of information cascade theory [12,13]. Information cascade theory is based on sequential decisions in an information-poor environment. In this context, decision makers are faced with several courses of action and must make the best choice. Unfortunately, no single decision maker has complete information; rather, each has some imperfect private information. Decision makers can observe the actions, but not the private information, of prior decision makers. Observing the actions allows them to make inferences about the prior decision makers’ private information. A rational decision maker then incorporates those inferences with his or her own private information to increase the likelihood of making a correct decision, which is a reasonable response to an information-poor environment. However, because decisions occur in a sequence, a mistake made by a particular decision maker propagates to all future decision makers. If a decision maker has poor information that leads him to make an inappropriate decision, then all future decision makers will incorporate that poor information into their information set. It is rational for each individual decision maker to make use of the information implicit in the actions of others. However, as more individuals make the same decision, there is increasing pressure for other decision makers to make the same decision, regardless of their private information. Thus, we experience a situation in which everyone begins making similar decisions and a fad for a poor product or service is begun. Information cascades have been validated in laboratory experiments [14–16], and behaviors consistent with information cascades have been observed in natural phenomena [13].

Past research has studied this type of sequential decision making in strings of individual decision makers. In the present research, we extend this idea to explain how individuals infer group-level information in prior periods. We posit that the members of a group of decision makers individually infer information about the group by examining other group members’ prior decisions. Specifically, we propose that stock markets react simultaneously to events, but that when another similar event occurs, individual investors infer information about the value of the event by the market’s cumulative reaction to prior, similar events.

The context for our investigation is firms’ adoption of electronic commerce technologies during the Internet stock bubble. We argue that the Internet stock bubble was, to some degree, a rational response by investors to the early success of Internet firms. However, this response was made in an environment with poor information about the true costs and benefits of electronic commerce. A few early apparent successes (e.g., Amazon, eBay, Dell) caused informed investors to value electronic commerce very highly, which drove up the returns of electronic commerce initiatives [17]. Because the market responded well to these early events, investors inferred high values for similar events, which they incorporated into their own private valuations. This caused investors to value the events higher than if they had relied solely on their own private information. The cumulative effect thereby drove valuations even higher, and the abnormal valuations of early events propagated through future events.

It could be argued that the observed behavior indicating the rise of DotCom stocks is just a variation on the “hot-hand phenomenon” (we thank an anonymous reviewer for this excellent point; see also [18]). The “hot hand” refers to the belief among many people that “streaks” that occur (such as a basketball player who has made many baskets consecutively) are likely to continue (and thus other players should pass the basketball to him so he can take additional shots). Although most associated with sports activities, the belief applies to many superstitious behaviors (such as people saying to a person who has had several good outcomes recently that he should take a trip to Las Vegas). (See [19] for a detailed explanation of this phenomenon.)
Similarly, it could be argued that the fall of DotCom stocks is due to a behavioral phenomenon known as the “gambler’s fallacy” [18]. The gambler’s fallacy refers to the belief that relatively short sequences of events should be representative of the event’s overall distribution. For example, if a coin is flipped five times and lands on “heads” every time, most people will be willing to bet that a sixth flip will land on “tails”. This reflects the belief that six flips should be roughly representative of the overall event distribution (50% each for heads and tails). However, the likelihood of the sixth flip landing on tails is only .50, and it is thus irrational to bet more on tails than on heads for that flip. In the context of the DotCom crash, it could be argued that people simply began to believe that too many “heads” (i.e., too many rising technology stocks) had occurred in a row and quit buying stocks (i.e., bet in the other direction).

However, there are several key differences between situations in which the hot hand and gambler’s fallacy explanations prevail and the current context. In contexts such as “hot” shooters in basketball games, the information environment is arguably quite rich. People observe the behavior directly and draw inferences based on their direct observations. Second, in such situations, there is a lack of apparent causal explanations for the occurrences (e.g., a player making six baskets in a row or red occurring on eight consecutive spins of a roulette wheel). Thus, people invent causal explanations such as the hot hand, when in fact statistical analyses reveal that the occurrences are simply random occurrences in known data distributions [20]. Decision errors occur due to the hot hand belief and gambler’s fallacy because the sequences are truly random and no information about the future can be gained from the past.

In contrast, in the context of investing in e-commerce companies, the environment was information-poor because investors were not able to observe technological innovations directly. Thus, they had to base their inferences about the value of innovations and e-commerce companies selling them on (at best) secondary information. Second, investors were aware of many possible explanations for the value of e-commerce stocks, but they had no good basis for determining causation (i.e., no good methods for performing valuations) because of the scarcity of information available to them. Thus, because investors’ private information was poor and the resulting ability to make inferences about causation (valuation methods for e-commerce stocks) was also poor, our thesis is that investors chose to follow the behaviors of other investors who (they assumed) had better knowledge. Finally, prior realized values of e-commerce initiatives were the consensus estimates of many knowledgeable individuals, each of whom had some private information. Thus, information about the future could be gained from the past.

3. Theory

We now turn to developing a new model of information cascades appropriate to investor decision making. First, we introduce our assumptions and discuss their impact. Next, we define the individual and market perceptions of value. Then, we add the effects of information cascades on perceptions of value. Finally, we add network externalities and time as control variables.

We make several assumptions to help formalize our model. First, we assume that financial markets quickly incorporate the information contained in an event into the price of the stock (a standard assumption in much stock market research). Second, we assume that all investors have access to the same public information (e.g., analyst recommendations, media reports, economic indicators). These assumptions together allow us to control for the effects of public information, which is interesting but well studied. The release of public information is an event, and if it is quickly incorporated into the price of a stock, then when we observe the effects of events the price of the stock will have already been adjusted for the information.

The last critical assumption is that investors have some private information that allows them to generate a private valuation for an event. Every investor has private information simply by virtue of his unique experience. For example, the event of a firm developing a new type of laser will have different meanings for an optics engineer, a financial analyst, and an attorney. The optics engineer may be aware of a need for that type of laser for a new technology, or may be aware of an even better laser that is about to be announced. A financial analyst may know a great deal of financial information about the firm. An attorney may be aware of a lawsuit about to be filed by someone who was blinded by a laser. Every individual is unique in the knowledge he uses to make sense of an event, and, hence, uses to form an estimate of the value of the event. This means that when investors observe an electronic commerce event they will all form different perceptions of its worth. Damodaran captures this notion perfectly when he says, “I have no doubt that you will disagree with me on some of the inputs I have used, and the values that you assign these firms will be different from mine” [21, p. xvi].

Stock market reactions to events yield a unique opportunity to observe willingness-to-pay for IT implementations. When a firm makes an announcement of an event, each individual in the market must evaluate her own willingness-to-pay to be part of that event. If the event in question is an IT implementation, then investors must form an opinion about how much that implementation will increase the value of a firm, and hence how much more (or less) they would be willing to pay for it.
are willing to pay to own the stock in question. The individual then rapidly buy and sell until the price reaches a new equilibrium. The difference between the old price and the new price represents the return to the electronic commerce initiative. Thus, we are able to observe the consensus opinion about the information content of an event, which is backed by investors’ real money and represents the potential for real gain or loss. This is unique because investors must commit resources to the point of equilibrium.

Thus, they are motivated to make use of all the information available to them, even if it is sparse.

To operationalize the theory, assume there is a market of $x$ risk-neutral agents. Each agent $i$ receives a private signal $s_{i,t}$ about the value of a technology initiative at time $t$ of the form

$$s_{i,t} = v + e_{i,t},$$

where $E[e_{i,t}] = 0$ and

$$\text{VAR}[e_{i,t}] = \sigma^2$$

for all $i$ and $t$. (1)

The variable $v$ represents the true value of the technology and $e$ is an independent, mean-zero error term with constant variance across time and individuals.

Each agent evaluates his own private signal and submits a bid for participation in the technology to a market maker whose goal is to maximize transaction volume. This simplification allows us to model the daily behavior of equity markets without having to consider the dynamic trading considerations. The market is set up to maximize transaction volume (this is a reasonable assumption, since many equities are handled by market makers whose job it is to ensure that all of the trades that can be made are made).

The market clears at $v$ plus the median of the distribution of $e$, because the median is the point at which exactly half the people are willing to sell and half the people are willing to buy. For simplicity, assume the expected value of the median to be zero. The expected market-clearing return, then, is $\bar{v}$. This can be written as

$$R_t = R(s_t) = v + \text{median}(e_t), \quad \text{where } \bar{E}[R_t] = \bar{v}. \quad (2)$$

Here $R_t$ is a function of the vector $s_t = \{s_{1,t}, s_{2,t}, \ldots, s_{n,t}\}$ and the median is a function of the vector $e_t = \{e_{1,t}, e_{2,t}, \ldots, e_{n,t}\}$.

For each technology initiative, the expected market-clearing return is the value of the technology. While there will be variations because of the stochastic nature of the private signals, there will be no consistent biases over time.

### 3.1. Adding information cascades to the operational model

The model above assumes that agents ignore the information contained in the realized market-clearing return of prior initiatives. In general, for well-behaved distributions on $e$, the market-clearing return will have lower variance than the individual private signals and thus be quite informative. From a human psychology perspective, most people know they do not know everything and realize that a group of independent decision makers can make better estimates than an individual [22]. We assume that agents cannot observe other agents’ private signals, but can observe the market-clearing return in prior periods.

We also assume that only one prior period is informative. There are at least three reasons why this is a reasonable assumption. First, and most importantly, there is no compelling theoretical reason to believe that the return from two periods prior would have a direct effect on the return in the current period. Note that the return at time $t - 2$ does have an effect on the return in time $t$ through its effect on the return at time $t - 1$. To include two periods would give the return at $t - 2$ both a direct effect and an indirect effect, and this is not theoretically reasonable. Second, using two periods complicates the model considerably by making it a polynomial in the lags. Thus, parsimony suggests using only one lag. Third, when a second lag is included and the model is estimated, the coefficient on the first lag is unchanged and the coefficient on the second lag is non-significant. Thus, theoretically and empirically, it does not seem that a second lag is needed. Therefore, we consider only one lag.

Finally, in addition to the current private signal and the prior period’s observed return, we define a weighting term $x$ that measures the relative weight the decision maker places on these two variables. Each agent’s private valuation of the technology becomes $f(s_{i,t}, R_{t-1}, x)$, where $f$ is increasing in both $s_{i,t}$ and $R_{t-1}$. This indicates that errors in the market-clearing return of the prior initiative would tend to continue into the current period. Thus, if for some reason the market overvalued (undervalued) a technology in the earlier period, it would tend to stay overvalued (undervalued) in the current period.

Without loss of generality, we can normalize such that $0 \leq x \leq 1$, where $x = 1 \Rightarrow f = f(s_{i,t})$ and $x = 0 \Rightarrow f = f(R_{t-1})$. The optimal (i.e., variance minimizing) value of $x$ will depend upon the relative information contained in $s$ and $R_{t-1}$, or, in other words, on the inverse of the relative standard error of $s$ and $p_{t-1}$. Define $\sigma_s$ and $\sigma_p$ as the standard error of $s$ and $p_{t-1}$, respectively. The weighting term can be defined as $\alpha = \alpha(\sigma_s, \sigma_p)$, where $\alpha$ is decreasing in $\sigma_s$ and increasing in $\sigma_p$. Thus, as the variance of the current period’s private signal increases, the weight assigned to the current period’s private signal decreases, and as the variance of the prior period’s return increases, the weight assigned to the current period’s private signal increases.

To make the example concrete, assume that $f(s_{i,t}, R_{t-1}, x)$ is a convex combination of $s_{i,t}$ and $R_{t-1}$. Thus, agents are rational in the sense that they update their beliefs in a Bayesian manner. Then each agent’s valuation of the technology is

$$f(s_{i,t}, R_{t-1}) = \alpha s_{i,t} + (1 - \alpha) R_{t-1}$$

$$= \alpha v + (1 - \alpha) R_{t-1} + \alpha e_{i,t}, \quad (3)$$

where $0 \leq \alpha \leq 1$.

To form a measure for estimation, it is necessary to determine the overall market return, which is observable.
The market realization is the median of all individual valuations,

$$ R_t = v + (1 - a)R_{t-1} + \text{median}(x_{i,t}). $$

(4)

This can be rewritten as

$$ R_t = \beta_0 + \beta_1 R_{t-1} + \xi_t. $$

(5)

The reader will recognize Eq. (5) as the standard form of an autoregressive process. Such a process can be estimated by ordinary least squares. Note that the model uses only one lag because the latest estimate of value is contained solely in that lag. There is, however, carryover from earlier lags because the value estimate in any period $t - 1$ is a function of the value in period $t - 2$. Thus, the behavior of prior periods is accounted for in the model although we only estimate the direct impact of one lag.

This discussion leads to a new definition of an information cascade for the continuous version of the theory presented here.

**Information Cascade:** An information cascade occurs, under the preceding assumptions, when a market’s valuation of the current period’s adoption decision is significantly dependent upon the market’s valuation of the prior period’s adoption decision.

Thus, to test for the presence of an information cascade, $\beta_1$ from Eq. (5) is estimated. An information cascade indicates that individual market participants are not simply applying their own private signals about the value of a technology, but are also applying public information about other participants’ valuations as inferred from the emergent market return in prior periods. Thus, a positive coefficient for $\beta_1$ indicates information cascade behavior.

3.2. Including the possibility of changing technology value

We have assumed that the true underlying value, $v$, of the technology is constant. However, this may not be the case. As noted above, in e-commerce research network externalities [5,7,8,23,24] have been invoked to help explain adoption of e-commerce technologies. For example, the more users on the Internet, the more value to any potential adopter because more users leads to a greater potential range of information available to additional users. However, while the Internet as a communication medium is certainly characterized by network externalities, it does not necessarily follow that the Internet as a business environment is characterized by those same externalities. This is an empirical question, and one that must be addressed given the operationalization of our model of information cascades.

To incorporate the possibility of network externalities, we redefine $v$ as $v(n)$, to recognize that value is a function of the number of participants in the network. This model will occur when

$$ v(n) = k_1 + \delta n, $$

(6)

where $k_1$ is some inherent value of being on the network, $n$ is the number of other firms on the network, and $\delta$ is a constant to be estimated. As a proxy for $n$ we use the cumulative number of adoptions in our data set at each point in time. This implicitly assumes that our observation of the level of adoption is proportional to the actual level of adoption. It also assumes that the rate of change of value is linear. Research in rational expectations supports this proxy. The notion is that “... due to network externalities, it is in the best interest of each firm within a sub-group sharing similar characteristics andlor serving similar markets to adopt simultaneously” [25, p. 5]. Thus, it does not necessarily matter whether the participants are using the network to communicate with one another. Even if the firms are only building a network that others will use, they should still adopt together.

Another possibility is that the value does not depend on the number of adopters but still changes over time. For example, if technology improves over time, it is reasonable to assume that the value of adopting that technology will increase. This leads to a reformulation of value as a function of time. This model is defined when

$$ v = v(t) = k_2 + \lambda t, $$

(7)

where $k_2$ is the value of the technology at the beginning of the sample time frame, $t$ is the time since the beginning of the sample period, and $\lambda$ is a constant to be estimated. Again, this assumes that the change over time is linear.

Lastly, it is possible that both effects occur simultaneously, so that $v$ is a function, $v(n,t)$, of both time and the number of other participants in the market. It is defined as

$$ v = v(n,t) = k_3 + \delta n + \lambda t. $$

(8)

Given these models, Eq. (4) becomes

$$ R_t = x(k + \delta n + \lambda t) + (1 - a)R_{t-1} + \text{median}(x_{i,t}). $$

(9)

This can be rewritten as

$$ R_t = \gamma_0 + \gamma_1 R_{t-1} + \gamma_2 n + \gamma_3 t + \xi_t, $$

(10)

where $\gamma_2 = 0$ if $j = 2$ and $\gamma_3 = 0$ if $j = 1$.

3.3. Including the possibility of changes in the relative weighting

As discussed above, the optimal weighting is a function of the noise in the private signal and the noise in the prior period’s return so that $x = x(\sigma_n^2, \sigma_{R_{t-1}}^2)$. While it is conceptually difficult to measure the noise in the private signal for the same reasons it is difficult to measure the private signal itself, it is possible to estimate the noise in the prior period’s return. The estimate of the noise in the prior period’s return is given by

$$ \hat{\sigma}_{R_{t-1}}^2 = (\hat{\xi}_{t-1})^2, $$

(11)
where $\xi_{t-1}$ is the error term from the prior period, and the
\[ x \] indicates an estimate. Thus, the prior period's estimated
variance depends on the distance from the predicted value
to the last period's return.

This implies that the weighting scheme changes over
time in response to the noise in the market so that
\[ x_t = \alpha(\xi_{t-1}^2)^2 \] and $\alpha$ is increasing in $[\xi_{t-1}^2]$. This means
that, as suggested earlier, the weight applied to the private
signal increases as the noise in the prior period's return
increases and that the weight applied to the prior period's return
decreases as the noise in the prior period's return
increases. At a high level, this means that investors rely less
on the prior period's return when it is further away from its
expected value.

To operationalize this, let
\[ x_t = x_1 + x_2 (\xi_{t-1}^2)^2. \] (12)

This allows $x_t$ to be a linear function of $[\xi_{t-1}^2]$. Eq. (4) can
then be rewritten as
\[ R_t = \left[ x_1 + x_2 (\xi_{t-1}^2) \right] R_{t-1} + \xi_t. \] (13)

This can, in turn, be rewritten as
\[ R_t = \phi_0 + \phi_1 (\xi_{t-1}^2) + \phi_2 R_{t-1} + \phi_3 (\xi_{t-1}^2) R_{t-1} + \xi_t. \] (14)

Given the specification of the model, we would expect
$\phi_2 > 0$ and $\phi_3 < 0$.

3.4. Combining all models

To derive the fullest estimate we can combine Eqs. (8)
and (13) as
\[ R_t = \left[ x_1 + x_2 (\xi_{t-1}^2) \right] \left[ k_3 + \delta_3 t + \lambda_3 t \right] + \left( 1 - \left[ x_1 + x_2 (\xi_{t-1}^2) \right] \right) R_{t-1} + \xi_t. \] (15)

This can be rewritten as
\[ R_t = \omega_0 + \omega_1 n + \omega_2 t + \omega_3 (\xi_{t-1}^2) + \omega_4 n (\xi_{t-1}^2) \]
\[ + \omega_5 t (\xi_{t-1}^2) + \omega_6 R_{t-1} + \omega_7 (\xi_{t-1}^2) R_{t-1} + \xi_t. \] (16)

We can now propose hypotheses based on this equation.
The first hypothesis is simply that investors rely on the
information contained in prior realizations of electronic
commerce returns when formulating their current evaluation
of an electronic commerce return. This suggests that
the coefficient on return should be positive and significant.
Thus, our first hypothesis is:

Hypothesis 1 (Information Cascades hypothesis): The
effect of prior returns on the current return is positive
and significant.

The secondary hypothesis of interest concerns the relative
weighting of private information and information contained
in the prior period's return. This is captured by the
coefficient $\omega_6$. The weight investors apply to the prior period's
return should decrease as the prior period's return
becomes noisier. Thus, $\omega_7$ should be negative and significant
if investors are placing less weight on the prior period's
return as the variance of the prior period's return
increases. This leads to our second hypothesis:

Hypothesis 2 (Relative Weighting hypothesis): Increasing
the variance of the prior period's return decreases
the effect of prior returns on the current return.

We also include network externalities and time as control
variables. We offer no hypotheses about these variables,
but they both provide alternative explanations of the market's
behavior that could, in the absence of control, generate
similar behavior. For example, if the value of an
electronic commerce initiative increases as the number of
adopters increases, then we will see value increasing consistently
over time. Each new electronic commerce initiative
will increase the value of future electronic commerce events.
If we do not provide this control, then even in the absence of
the process we described there will be a significant effect
of prior period returns on current period returns. Similarly,
if the return to electronic commerce were simply rising over
time due to a wealth effect of investors or improving tech-
nology or some other factor, we would expect prior returns
to predict current returns. Thus, we control for the number of
prior adoptions and a linear time trend.

4. Data

The data for this study come from firms' adoptions of
electronic commerce technologies. This is a particularly
good environment for consideration because e-commerce
is characterized by both high uncertainty and poor observ-
ability of private signals. Each data point is a firm's public
announcement of an e-commerce initiative in the media.
We collected the data from a full text search of company
announcements related to e-commerce in the period
between January 1, 1999 and December 31, 2000, using
two leading news sources: PR Newswire and Business
Wire. Following prior literature [26,27], we searched
Lexis/Nexis for announcements containing the words
\textit{launch} or \textit{announce} within the same sentence as the words
\textit{online or commerce and .com and NYSE, NASDAQ, or
AMEX}. The search yielded 4744 potential announcements

Please cite this article in press as: E. Walden, G.J. Browne, Rational fads in investor reactions to electronic ..., Electron. Comm. Res.
We use Subramani and Walden’s definition of an event:

“The criteria we used to identify an announcement as an event was that the news item be an announcement of a new electronic commerce-related initiative or the expansion of an existing initiative. Miscellaneous announcements such as estimates of expected earnings, news about personnel changes, and site traffic volumes, etc. were discarded” [27, p. 141]. Electronic commerce is an activity related to the trading of goods and services facilitated by Internet technologies.

To insure the consistency and accuracy of the coding, two coders – one of the authors and a graduate student unfamiliar with the hypotheses of the study – worked independently. Each coder performed his own analysis of the data. The data were then matched, and one of the coders reconsidered any disagreements. In this phase, the coder could change his and only his original coding if on the second examination he agreed with the other coder. If the coder did not agree, he wrote his own comments as to why he believed his original coding was correct. The data were then given to the other coder, who had a chance to change his original coding based on the first coder’s comments. Any disagreements that could not be resolved by this two-step process were then decided in a face-to-face meeting between the two coders.

To focus attention on the task at hand, we excluded several different types of announcements from the coding. Coders excluded marketing announcements or news of customer acquisition and minor, temporary promotions such as Christmas or Super Bowl specials. Coders also removed earnings announcements and management changes by firms. Coders eliminated announcements of minor Web site redesign, unless the redesign developed new capabilities. Coders also dropped announcements pertaining to mergers and acquisitions. To eliminate the bias introduced by thinly-traded stocks that might be illiquid and low-value stocks that are not representative of the broad market, we removed firms with an average share price of less than one dollar and firms with an average trading volume of less than 50,000 shares per day. This procedure is consistent with prior literature [27]. Of the 4744 potential announcements, 2097 were coded as announcements of e-commerce with prior literature [27]. Of the 4744 potential announcements, 2097 were coded as announcements of e-commerce.

Average abnormal return on electronic commerce initiatives in the year period.

We use four variables in our estimation. These are described in Table 2.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R_t )</td>
<td>Average abnormal return on electronic commerce initiatives on day ( t )</td>
</tr>
<tr>
<td>Time</td>
<td>The number of days since December 31, 1998</td>
</tr>
<tr>
<td>( N )</td>
<td>The cumulative number of electronic commerce events</td>
</tr>
</tbody>
</table>
| \( \sigma_{t-1}^2 \) | The square of the estimated error of \( R_t \) in time \( t-1 \), that is, \( (\text{actual } R_{t-1} - \text{predicted } R_{t-1})^2 \)

The results are shown in detail in Table 3.

5. Results

To correct for overall market movements, it is necessary to calculate an abnormal return according to the following formula.

\[
AR = R_{t,s} - (\delta_s + \alpha_{s,Rs} R_{t,1}).
\]

The term in parentheses is the expected return on the stock, where \( \delta \) and \( \gamma \) are estimates from day 251 to day 2 before the announcement (see [28] for detailed description of the technique). \( R_t \) terms are returns, with the subscript \( t \) denoting time, the subscript \( s \) referring to a specific stock, and the subscript \( m \) referring to the market return, in this case the return on the S&P 500.

Finally, to allow for announcements that occurred before the market opened or after the market closed, the three-day cumulative abnormal return was used. This return measure is the summation of abnormal returns starting on the day before the event and ending on the day after the event [29,30]. The models in Eqs. (10), (14) and (16) were then estimated using the cumulative abnormal return data. The results are shown in detail in Table 3.

As the table shows, the empirical testing supported the information cascade hypothesis in all specifications. In fact, in all specifications, the \( t \)-statistic for the effect of the prior period’s return was the greatest. Moreover, the coefficient was not sensitive to the inclusion of the cumulative number of adoptions or the time of adoption.

The Relative Weighting hypothesis (H2) was supported in the absence of a control for time and network effects. While it has the correct sign in the full model, it fails to achieve significance. Thus, support is mixed for the hypothesis that investors reduce their reliance on prior period returns when those returns are more extreme.

When the information content of the prior period was included in the form of the estimated standard error from the prior period, the influence of the prior period increased, as suggested by information cascade theory. The coefficient on the interaction between prior period return and prior period information content was negative, as predicted, and this coefficient was significantly negative in the data.

The data are presented in Table 1, where price and volume are the average price and volume of the stock over the two-year period.

Table 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Event</td>
<td>Cumulative abnormal return by day</td>
</tr>
</tbody>
</table>

The data demographics are described in Table 2.
Table 3: Autoregressive results (t-statistics on bottom)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>AR(1)</th>
<th>AR(1) + time</th>
<th>AR(1) + N</th>
<th>AR(1) + time + N</th>
<th>AR(1) + variance interaction</th>
<th>Full model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>4.88E-03</td>
<td>0.01</td>
<td>8.89E-03</td>
<td>0.04**</td>
<td>2.03E-03</td>
<td>0.11</td>
</tr>
<tr>
<td>N</td>
<td>0.14***</td>
<td>0.13***</td>
<td>0.13***</td>
<td>0.12**</td>
<td>0.26</td>
<td>0.24</td>
</tr>
<tr>
<td>R²</td>
<td>0.018</td>
<td>0.016</td>
<td>0.024</td>
<td>0.005***</td>
<td>0.024</td>
<td>0.007***</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.458</td>
<td>0.438</td>
<td>0.423</td>
<td>0.406</td>
<td>0.392</td>
<td>0.396</td>
</tr>
<tr>
<td>White's heteroskedasticity test (p-value)</td>
<td>0.458</td>
<td>0.003***</td>
<td>0.007***</td>
<td>0.003***</td>
<td>0.861</td>
<td>0.241</td>
</tr>
</tbody>
</table>

* At the 0.10 level. ** At the 0.05 level. *** Indicates significance at the 0.01 level.
The impact of lagged values is robust. Nor does the lagged-value-only model, which suggests that the full model does not have heteroskedasticity problems, determinant of current values across all models. Moreover, the results. Lagged values are still the most important of the results. Lagged values are still the most important determinant of current values across all models. Moreover, the full model does not have heteroskedasticity problems, nor does the lagged-value-only model, which suggests that the impact of lagged values is robust.

Another point to note is that the $R^2$ for each model is lower than we usually see. This is typical of event analysis because the variance of returns is very high. $R^2$ measures the ratio of explanation to noise, and the stock market is very noisy. Every day millions of things occur that move stock prices. As can be seen from Table 1, the mean return in this study was 0.06%, while the standard error was 8.62%, which is more than 100 times larger. The return on an electronic commerce initiative depends on a huge number of variables, including factors about the initiative, who is undertaking the initiative, and the environment in which it occurs. There are certainly other systematic effects that we have not captured, but our goal is to explain the causal mechanisms of one effect that has significant impact.

6. Conclusion

6.1. Contribution

We have proposed a theoretical explanation of the Dot-Com fad of 1999–2000. Specifically, we posited that the willingness of investors to commit capital to successive electronic commerce initiatives stemmed from the lack of information in the environment. To supplement their own limited information investors used the pooled information present in the market’s previous reactions to e-commerce initiatives. Each successive positive market reaction modified investor perceptions of electronic commerce in a positive manner, and each successive negative reaction modified investor perceptions in a negative manner, thus creating reinforcing effects that caused a rapid rise, then fall, in perceptions of electronic commerce value. The primary implication of this research is that IT will continue to be characterized by fads. IT is complex and requires complementary organizational changes to realize value. This means that the real benefits of IT are not known until firms have to make decisions about them. One mechanism rational individuals can use to help them value novel IT is to observe how others value the same lead to fads. These fads can move in both directions, with adopters overvaluing IT or undervaluing IT. Therefore, both researchers and organizations must be careful in evaluating new IT. This means that decision makers should collect as much private information about the value of IT as possible before incorporating the behaviors of others. However, the behavior of others should be incorporated because it does lead to better decisions, but it should be discounted appropriately.

An important implication for practitioners is that theory should be used when valuing IT. Theory that bases its arguments on well-tested logic can facilitate realistic evaluations of IT. For example, while a common perception at the time of the DotCom bubble in the popular press was that the Internet was a new economy with new rules, and that firms like eToys and Pets.com would replace firms like Toys R Us and Petsmart, researchers used the resource-based view of the firm to argue, “…the initial disadvantages of non-net firms from being on the learning curve with respect to Internet technologies and the novel e-commerce context are likely to be largely offset by the considerable advantages derived from the migration of existing firm competencies to e-commerce operations” [33, p. 195]. Use of theory provides a foundation for decision making, which can lead to the avoidance of irrational fads. This is particularly important in domains such as IT, in which the artifacts being evaluated change frequently.

6.2. Limitations

As with any research effort, there are certain limitations to the work performed in this paper. A central limitation of the study is the period examined. Undoubtedly, the time period under consideration was not a typical period in stock market history. We chose it specifically to examine behavior in fad-like conditions. Therefore, it is not clear that we can generalize the results to other periods. On the other hand, information cascade theory suggests that some fads are rational specifically because relying on the behavior of others improves one’s chance of making a good decision. In fact, information cascade theory shows that people will, on average, do better by relying on the signals of others. The theory mainly focuses on what happens when things go awry because that is more interesting, but following the model we suggest does in fact result in better estimates over time than relying on personal information alone. Thus, the results may be generalizable, with this period simply representing an extreme outcome.

There are also several statistical limitations that are worth noting. First, on many days there were multiple announcements, and we used the average abnormal return to all announcements on a day. However, this is only one way to deal with the problem that many firms may pursue a particular course of action on a given day. We chose to look at day-to-day changes rather than event-to-event.
changes. Also, we do not allow for information decay. That is, we only count periods as days that electronic commerce initiatives were announced. Several days may actually elapse between periods, particularly on weekends. It is not clear whether it makes sense to discount the effects of a Friday event on a Monday return more than the effects of a Tuesday event on a Wednesday return. Finally, it is important to note that not all events are created equal.

Some electronic commerce announcements may be profound while others may be trivial. We do not classify events into different types. In general, this would tend to increase the error of measure, and thus reduce the power of the tests, so the fact that the tests are significant is even more surprising. However, it is possible that our theory holds for some subsets of electronic commerce initiatives and not others. In particular, it seems reasonable to argue that those for which there is a great deal of information would be less susceptible to the behavior of others, while those that are particularly novel would be more susceptible to the processes we describe.

6.3. Future research

An area for future research is a consideration of the scope of e-commerce initiatives that lead to fads. Our unit of analysis is e-commerce initiatives generally, but other researchers have delineated different categories of e-commerce initiatives [9,31,32]. Future research could examine which categories of electronic commerce activities are most subject to fads and what sorts of spillovers one category has on another. For example, consumer portal investors may react more strongly to market information than online travel services investors. Similarly, content provider investors may react more strongly to the information contained in the market’s reaction to initiatives by online retailers than to the information contained in market reactions to business-to-business exchanges. Elucidating theory about who receives information from whom about the value of IT initiatives has great potential value.

Another area for future research is the decision processes of the electronic commerce firms themselves. In this case, our unit of analysis was investors, but firm behavior is likely to be dependent upon investor perceptions and upon other firms’ behavior. However, the dependencies are likely to be different, largely because firms have a great deal of time and resources to devote to their decisions, whereas individual investors in modern markets must often react very quickly to information without access to such resources. Moreover, firm decisions are much more complicated than simply deciding on a price. Of course, firms exercise direct control over the execution of the decision and can choose to modify their decisions in complicated ways over time. Taken together, the firm decision is likely to be different than the decisions of investors.

In sum, this research offers a promising new direction for research on technological fads. Our results indicate that investors put significant weight on prior market sentiment about the value of technology when they make their own decisions about the value of similar technology. We propose that this occurs because the market is a means of aggregating the scarce information available about the potential benefits of new technologies. Thus, we follow Surowiecki in suggesting that people make use of the wisdom of crowds [22]. Moreover, people should make use of such wisdom, as it often leads to better individual decisions. However, it can also lead to pathological outcomes, such as electronic commerce bubbles and busts, for the system as a whole. Thus, further investigations into the behavior of individuals in valuing technological innovations in contexts involving potential information cascades are warranted.

References


