Abstract:

This work offers a theoretical explanation of the electronic commerce stock market bubble of 1999-2000. We propose that the bubble existed because a lack of good information about the potential value of electronic commerce led investors to rely on one another’s private valuations of electronic commerce. Because each investor relied on other investors, positive information early in the period was magnified and propagated through the market, leading to fad-like behavior. We test our theory empirically and find support for our propositions. Implications for theory and practice are discussed.
Technology is subject to fads—situations in which many agents adopt a technology with exaggerated zeal (Abrahamson 1991, Fichman 2000, Kauffman and Li 2003). We have witnessed the rise and decline of virtual reality, artificial intelligence, data marts, structured programming and a host of other technologies (Inmon 2002). While these technologies may not be gone, they have moved from being the next “killer app” to being just another technology. Currently, we are faced with blogging, peer-to-peer communication, open source software, voice over IP, and a myriad of other technologies. Some of them will surely become lasting trends, but just as surely many are over-hyped and will disappear from public awareness without any long term impacts.

Certainly other industries have fads, from bell bottom slacks to cabbage patch kids. But while bell bottoms and cabbage patch kids cost twenty dollars, many technologies cost twenty million dollars. Technology is a much more important decision, presumably undertaken by serious groups after careful deliberation. Why in such important decision situations do intelligent, rational individuals still join fads?

Individuals and organizations are prone to participating in technology fads because they have so little private information about the uses and benefits of a new technology that they believe they can actually make better decisions by simply joining fads than by careful analysis. Thus, technology fads are ways for independent agents to pool their limited information about a new technology to enhance their decision-making abilities. Because everyone acts based on the same pooled information, everyone’s decision is the same, thus creating a fad. Unfortunately, if the pooled information is still relatively incomplete, as we argue is the case with new technologies, then it may lead to the wrong decision for everyone.
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 price 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.

**LITERATURE REVIEW**

A variety of research has investigated why groups of agents choose to follow the same course of action. For example, legitimacy theory suggests that organizations try to be like other organizations to signal their legitimacy to stakeholders (Deephouse 1996, DiMaggio and Powell 1983). However, this theory suffers from three shortcomings in explaining technology fads. First, it does not consider the nature of technology specifically and hence sacrifices explanatory power. Second, it does not consider any rational basis for choosing the alternative that organizations collectively follow. In other words, it offers no discussion of the characteristics of the decision itself and instead focuses on how well the decision corresponds with other decisions. Third, technology decisions are often made before the legitimate structure has been solidified. Thus, legitimacy theory has difficulty explaining how the initial legitimate structure is formed.

A popular economic explanation of fad-like behavior is network externality theory (Brynjolfsson and Kemerer 1996, Economides and Himmelberg 1995, Gallaugher and Wang 1999, Kauffman, et al. 2000). 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 (Kauffman and Walden 2001, Liebowitz 2002, Liebowitz and Margolis 1994). 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
(Bikhchandani, et al. 1992, Bikhchandani, et al. 1998). Information cascade theory is based on
sequential decisions in an information poor environment. 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. This
allows them to make inferences about other decision makers’ private information. A rational
decision maker will then incorporate those inferences with his or her own private information to
increase the likelihood of making a correct decision.
For each individual decision maker it is rational 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—i.e., a fad.

Problems arise when, by chance, random errors propagate through the system to a greater
degree than they normally would. Even a very few early errors can put enough pressure on later
decision makers to make them ignore or severely discount their private information and join a
fad for a poor product or service.

THEORY

Information cascades have been validated in laboratory experiments (Anderson 2001,
Anderson and Holt 1996, Anderson and Holt 1997), and behaviors consistent with information
cascades have been observed in natural phenomena (Bikhchandani et al. 1998). Information
cascade theory claims that individuals infer information from the actions of other individuals and
then incorporate the inferred information with their private information to make decisions. This
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 decision maker $n$ has poor information that leads him to make an inappropriate
decision, then all future decision makers will infer that poor information and thereby incorporate
the poor information into their information set.

This type of sequential decision making has been studied as a string of individual decision
makers. In the present research, we extend this idea to explain how individuals infer the 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 can 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’ adoptions 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 stock prices of these
firms. Because the market responded well to these early events, investors inferred high values
for similar events, which they incorporated with 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.

This was possible because everyone’s private information was very poor. Even now, half a
decade later, all the dust has not settled. Investors still do not know how to value many internet
firms. At the time of the internet bubble, valuation methods were even more primitive, and
investors were thus forced to rely on the cumulative signals of the market.

We make several assumptions to help us model this formally. We assume that the internet
bubble was actually an instance of fad-like behavior and that the true underlying values of the
stocks were not the same as their prices. Second, 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). Third, we assume that all investors have access to
the same public information (e.g., analyst recommendations, media reports, economic
indicators). Assumptions two and three 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. The private information can consist of secret knowledge or can be
expertise in the form of, e.g., mental models or financial models of valuation. 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 a professional dancer. These different meanings result in
different investors having different valuations for the same event, which we represent as a
random term.

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 are
willing to pay to own the stock in question. The individuals then rapidly buy and sell until the
price reaches a new equilibrium that is the market’s willingness-to-pay. 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. It is different than a survey, in
which there is no penalty for guessing wrong, and it is different than observing the actual prices
firms pay for implementation, which are less than their willingness-to-pay.
To operationalize the theory, assume there is a market of \( n \) risk-neutral agents. Each agent \( i \) receives a private signal about the value of a technology initiative at time \( t \) of the form

\[
s_{i,t} = v + \varepsilon_{i,t}, \quad \text{where } E[\varepsilon_{i,t}] = 0 \text{ and } \text{VAR}[\varepsilon_{i,t}] = \sigma^2 \text{ for all } i \text{ and } t. \tag{1}
\]

The variable \( v \) represents the true value of the technology and \( \varepsilon \) 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.\(^1\) The market clears at \( v \) plus the median of the distribution of \( \varepsilon \). For simplicity, assume the expected value of the median to be zero. The expected market-clearing price, then, is \( v \). This can be written as

\[
p_t = p_t(s) = v + \text{median}(\varepsilon), \quad \text{where } E[p_t] = v. \tag{2}
\]

Here \( p_t \) is a function of the vector \( s_t = \{s_{1,t}, s_{2,t} \ldots s_{n,t}\} \) and \( \text{median} \) is a function of the vector \( \varepsilon_t = \{\varepsilon_{1,t}, \varepsilon_{2,t} \ldots \varepsilon_{n,t}\} \).

For each technology initiative, the expected market-clearing price 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.

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\(^1\) This is a reasonable assumption, since many equities are handled by market makers whose job it is to insure that all of the trades that can be made are made. Some exchanges, such as the Arizona Stock Exchange, behave in exactly this manner, soliciting bids in discrete time and then setting the price to maximize the transaction volume.
The model above assumes that agents ignore the information contained in the realized market-clearing price of prior initiatives. In general, for well-behaved distributions on $\varepsilon$, the market-clearing price will have lower variance than the individual private signals and thus be quite informative. Assume that agents cannot observe other agents’ private signals, but can observe the market-clearing price 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 price two periods prior would have a direct effect on the price in the current period. Note that the price at time $t-2$ does have an effect on the price in time $t$ through its effect on the price at time $t-1$. To include two periods would give the price at $t-2$ both a direct effect and an indirect effect, and this is not theoretically reasonable. Second, considering two periods considerably complicates the model 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 price, we define a weighting term $\alpha$ that measures the relative weight the decision maker places on these two variables. Each agent’s private valuation of the technology becomes $f_{i,t} = f(s_{i,t}, p_{t-1}, \alpha)$, where $f$ is increasing in both $s_{i,t}$ and $p_{t-1}$. This indicates that errors in the market-clearing price of the prior initiative would tend to continue into the current period. Thus, if for some reason the market overvalued a technology in the earlier period, it would tend to stay overvalued in the current period.
Without loss of generality, we can normalize such that $0 \leq \alpha \leq 1$, where $\alpha = 1 \Rightarrow f = f(s_i,t)$ and $\alpha = 0 \Rightarrow f = f(p_{t-1})$. The optimal (i.e., variance minimizing) value of $\alpha$ will depend upon the relative information contained in $s$ and $p_{t-1}$, 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 price increases, the weight assigned to the current period’s private signal increases.

To make the example concrete, assume that $f(s_{i,t}, p_{t-1}, \alpha)$ is a convex combination of $s_{i,t}$ and $p_{t-1}$. Then each agent’s valuation of the technology is

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

(3)

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

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

$$p_t = \alpha v + (1-\alpha) p_{t-1} + \text{median}(\alpha \epsilon_{i,t}).$$

(4)

This can be rewritten as

$$p_t = \beta_0 + \beta_1 p_{t-1} + \xi_t.$$

(5)

The reader will recognize equation (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.

**Definition:** 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 equation (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 price in prior periods. Thus, a positive coefficient for $\beta_1$ indicates information cascade behavior.

**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. In e-commerce research, network externalities (Brynjolfsson and Kemerer 1996, Gallaugher and Wang 1999, Kauffman et al. 2000, Li 2004, Riggins et al. 1994) 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,

$$v(n) = k_1 + \delta_1 n,$$ (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.

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

\[
v = v(t) = k_2 + \lambda_2 t, \quad (7)
\]

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

\[
v = v(n,t) = k_3 + \delta_3 n + \lambda_3 t. \quad (8)
\]

Given these models, equation (4) becomes

\[
p_t = \alpha(k_j + \delta_j n + \lambda_j t) + (1 - \alpha)p_{t-1} + median(\alpha \epsilon_{i,t}). \quad (9)
\]

where \( \lambda_j = \delta_j = 0 \) and \( j \in \{1,2,3\} \). This can be rewritten as

\[
p_t = \gamma_0 + \gamma_1 p_{t-1} + \gamma_2 n + \gamma_3 t + \xi_t. \quad (10)
\]

where \( \gamma_2 = 0 \) if \( j = 2 \) and \( \gamma_3 = 0 \) if \( j = 1 \).
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 price so that \( \alpha = \alpha(\sigma_s^2, \sigma_p^2) \). 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 price. The estimate of the noise in the prior period’s price is given by

\[
\hat{\sigma}_{p,t-1}^2 = \left( \hat{\xi}_{t-1} \right)^2.
\]  

(11)

where \( \hat{\xi}_{t-1} \) is the error term from the prior period, and the \(^\hat{\phantom{0}}\) indicates an estimate. Thus, the prior period’s estimated variance depends on the distance from the predicted value to the last period’s price.

This implies that the weighting scheme changes over time in response to the noise in the market so that \( \alpha_t = \alpha([\hat{\xi}_{t-1}]^2) \) and \( \alpha \) is decreasing in \([\hat{\xi}_{t-1}]^2\). Therefore, as noted earlier, this means that the weight applied to the private signal increases as the noise in the prior period’s price increases and that the weight applied to the prior period’s price decreases as the noise in the prior period’s price increases.

To operationalize this, let

\[
\alpha_t = \alpha_1 + \alpha_2 \left( \hat{\xi}_{t-1} \right)^2.
\]  

(12)

This allows \( \alpha_t \) to be a linear function of \([\hat{\xi}_{t-1}]^2\). Equation (4) can then be rewritten as

\[
p_t = \left[ \alpha_1 + \alpha_2 \left( \hat{\xi}_{t-1} \right)^2 \right] p_{t-1} + \left[ 1 - \alpha_1 - \alpha_2 \right] \hat{\xi}_{t-1} + \hat{\xi}_t.
\]  

(13)

This can, in turn, be rewritten as

\[
p_t = \varphi_0 + \varphi_1 \left( \hat{\xi}_{t-1} \right)^2 + \varphi_2 p_{t-1} + \varphi_3 \left( \hat{\xi}_{t-1} \right)^2 p_{t-1} + \hat{\xi}_t.
\]  

(14)

Given the specification of the model, we would expect \( \varphi_2 > 0 \) and \( \varphi_3 < 0 \).
COMBINING ALL MODELS

To derive the fullest estimate we can combine (8) and (13) as

\[ p_t = \left[ \alpha_1 + \alpha_2 \left( \hat{\xi}_{t-1} \right)^2 \right] \left[ k_3 + \delta_3 n + \lambda_3 t \right] + \left( 1 - \left[ \alpha_1 + \alpha_2 \left( \hat{\xi}_{t-1} \right)^2 \right] \right) p_{t-1} + \xi_t. \]  

(15)

This can be rewritten as

\[ p_t = \omega_0 + \omega_1 n + \omega_2 t + \omega_3 \left( \hat{\xi}_{t-1} \right)^2 + \omega_4 \left( \hat{\xi}_{t-1} \right)^2 + \omega_5 \left( \hat{\xi}_{t-1} \right)^2 \]
\[ + \omega_6 p_{t-1} + \omega_7 \left( \hat{\xi}_{t-1} \right)^2 p_{t-1} + \xi_t. \]  

(16)

If information cascades explain the valuation of the technology by the market, then \( \omega_6 \) should be positive and \( \omega_7 \) should be negative. The presence of network externalities implies that \( \omega_7 \) should be positive.

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 observability 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 to December 31, 2000, using two leading news sources: PR Newswire and Business Wire. Following prior literature, (Dardan and Stylianou 2001, Subramani and Walden 2001) we searched Lexis/Nexis for announcements containing the words launch or announce within the same sentence as the words online or commerce and .com and NYSE, NASDAQ, or AMEX. The search yielded 4744 potential announcements—2170 in 1999 and 2574 in 2000.

We define electronic commerce very broadly, but consistently with prior literature, because we are investigating the internet bubble, rather than the “portal bubble” or the “auction bubble” or the “retail bubble.” The behavior we are investigating is with respect to the entire class of internet technologies, because that is how investors and observers defined the scope. The
theoretical prediction is that investors lacked information about the class of internet technologies, which led them to depend upon the market’s aggregate valuation about these technologies, which led to persistent shocks when these valuations changed. In other words, investors did not have a good idea of how useful internet technologies were to different firms under different conditions. Thus, some of the hype surrounding an electronic commerce event at, e.g., eBay, would be carried over into the valuation of an electronic commerce event at, e.g., Kmart.

One might argue that the true valuation of a specific event at an online portal, for example, would be most affected by identical events at other portals. This is probably true, but our unit of analysis is not value but willingness-to-pay. We seek to explain why willingness-to-pay for IT implementations was able to drift so far from the true value. At the time, the unit of analysis for willingness-to-pay was internet technologies. We recognize that defining electronic commerce so broadly might result in a less powerful test, but for our investigation that is the appropriate level of analysis. We are investigating how investors might infer information about internet technologies from the market.

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 website 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 (Subramani and Walden 2001). Of the 4744 potential announcements, 2097 were coded as announcements of e-commerce initiatives, and 1273 contained enough data to estimate abnormal returns. When there were multiple announcements in a single trading day the average return was used, resulting in a total of 402 data points. The demographics of 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>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Std Err</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>$ 29.96</td>
<td>$ 24.56</td>
<td>$ 23.79</td>
<td>$ 1.02</td>
<td>$ 158.57</td>
</tr>
<tr>
<td>Volume</td>
<td>3,021,852</td>
<td>591,744</td>
<td>6,412,472</td>
<td>50,256</td>
<td>33,475,710</td>
</tr>
<tr>
<td>Average Cumulative Abnormal Return By Day</td>
<td>0.06%</td>
<td>0.05%</td>
<td>8.62%</td>
<td>-35.48%</td>
<td>65.47%</td>
</tr>
</tbody>
</table>

Table 1: Data Demographics

RESULTS

To standardize the measure of value for estimation, it is necessary to use the return on the stock rather than the price of the stock. Using returns rather than prices corrects for autocorrelation in the price of an individual stock by using first differences and reduces
heteroskedasticity by dividing by the price of the stock. This produces a percentage measure.

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

\[
AR = R_{s,t} - (\delta_s + \gamma_s R_{m,t}).
\]  

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. The \(R\) 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 (Chatterjee et al. 2001, Rajgopal et al. 2001). The models in (10), (14) and (16) were then estimated using the cumulative abnormal return data. The results are shown in detail in Table 2.
Table 2: Autoregressive results (t-statistics on bottom)

*** indicates significance at the 0.01 level, ** at the 0.05 level and * at the 0.10 level

As the table shows, the empirical testing supported the existence of information cascades 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.

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 price and prior period information content was negative, as predicted, and this coefficient was significantly negative in the price-only model. Introducing network externalities (as measured by cumulative adoption) and time did not affect the coefficient of prior period price, but did render the interaction coefficient non-significant. This pattern is indicative of information cascades.
DISCUSSION

We have proposed a theoretical explanation of the electronic commerce 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.

Interestingly, the coefficients of network externalities and time were not significant individually, but were significant in different directions when included together. Specifically, the coefficient of network externalities was marginally positive and the coefficient of time was negative. A potential explanation for this result can be found in prior network externalities literature examining the fax machine market (Economides and Himmelberg 1995). The fax machine market was characterized by both network externalities and a technology whose price was falling over time, leading to complementary adoption effects. The results in the present research suggest network externalities in a market in which the price of the technology was rising over time, leading to different effects than in the fax machine market.

The primary implication of this research is that IT will continue to be plagued by fads. IT is complex and requires complementary organizational changes to realize value. This means that the real benefits of IT are not known when firms have to make decisions about them. One mechanism rational individuals can use to help them value novel IT is to look to how others value the same IT. While this helps each decision maker individually, it leads 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 to use more theory when valuing IT. Theory that bases its arguments on well tested logic can facilitate realistic valuations of IT. For example, while the general perceptions of the internet were that it was a new economy with new rules, and firms like eToys and Pets.com would replace firms like Toys R Us and Petsmart, Subramani and Walden 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” (Subramani and Walden 1999 p. 195). The point of theory is that it is (sometimes painfully) rigorous, which makes it less susceptible to hype. It is extremely important to make use of some stable and logical theory in a domain like IT, in which the artifacts being studied change frequently.

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 (Kauffman and Walden 2001, Subramani and Walden 2000, Weill and Vitale 2001). Future research could examine which categories of electronic commerce activities were 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 is investors, but firm behavior is likely to be somewhat 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 adoption and diffusion of technology. 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 Surowieki in suggesting that people make use of the wisdom of crowds (Surowiecki 2004). 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 technology adoption and diffusion contexts involving potential information cascades are warranted.

REFERENCES


