

# INFORMATION CASCADES IN THE ADOPTION OF NEW TECHNOLOGY

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With sincere apologies to the authors, I would like to note that the correct spelling is "Bikhchandani" and "Hirshleifer". If either of you are reading this. I am truly sorry.

## Abstract

*This work presents a theory of information cascades, based on the work of Bikhchandi, Hirschleifer, and Welch (1992), to explain fad-like behavior in the adoption of new technology. An information cascade occurs when an individual ignores his or her own private signal about the value of a technology and relies, instead, upon the observed actions of others. This can lead to serious problems if the observed actions in question are based on still other observed actions rather than private signals. The present research provides an operational model to assess information cascade theory and empirically tests the model in the context of the adoption of electronic commerce technologies. The results suggest that information cascades play a large role in the adoption of such technologies.*

## 1 INTRODUCTION

The adoption and diffusion of information technology (IS) is fraught with fad-like behavior, in which firms adopt new processes or technologies in rapid succession, seemingly for no other reason than the fact that other firms have adopted them. This type of behavior is a recurring theme in IS, having occurred to a greater or lesser extent in information technology (IT) outsourcing (Hu et al. 1997; Loh and Venkatraman 1992), enterprise resource planning system (ERP) implementation (Gumaer 1996), the formation of chief technology officer (CTO) positions (Adler and Ferdows 1990), and most recently in electronic commerce (EC) adoption (Kauffman and Walden 2001). This phenomenon is often explained by theories such as legitimacy (Deephouse 1996), which suggests that managers have a preference for conformity. However, while legitimacy may play an important role in fad-like adoption behavior, a theory based on the value of a technology rather than on the simple preferences of managers would be more useful. Preference theories fail to explain why managers frequently make the correct adoption choice when following a fad. Preference theories also fail to address the means of correcting an incorrect adoption fad. While managers display fad-like behaviors, there is a tendency for unprofitable fads to die out (e.g., many artificial intelligence areas and virtual reality). Thus, there exists a need for theory to explain why managers frequently follow profitable fads, why they might make systematic errors in choosing to follow a fad, and how unprofitable fads disappear.

This paper proposes information cascade theory (Bikhchandi et al. 1992) as an explanation of why managers rationally follow fads and why they occasionally make systematic errors. We then expand the basic information cascade model into an operational model and empirically test the hypotheses derived from the model. The tests fail to reject the information cascade model, leading to the conclusion that information cascades are a reasonable explanation of the fad-like behavior often associated with the adoption of new technology.

## 2 MODELS OF INFORMATION CASCADES

### 2.1 Basic Model

The basic model of information cascades, attributable to Bikhchandi et al. (1992), is presented here to familiarize the reader with the conceptual foundations of the theory. Assume that a technology has either a high value ( $H$ ) or a low value ( $L$ ), each with

probability  $\frac{1}{2}$ , and a cost  $c$  such that  $H > c > L$ . Thus, an individual should unambiguously adopt the technology if the value is  $H$  and should not adopt it if the value is  $L$ . Each individual receives a private signal about the value of the technology, drawn from a distribution that has a correct value with a probability  $p > 0.5$ , and an incorrect value with a probability  $1-p$ .<sup>1</sup> Assume for the purposes of the example that the true value is  $H$ . However, none of the individual decision makers knows this and must instead infer it from the signals they receive. In this context, a signal is a piece of information that indicates unambiguously the value of a technology as being  $H$  or  $L$ . Further, assume that each individual makes an adoption decision sequentially after observing a single private signal. The primary assumption is that each individual can observe only the choice of the individuals before him and not the actual signal. Thus, the signal must be inferred from the choice.

Consider what happens in the first three rounds of a choice situation. The first individual observes a private signal. Given that the probability of getting the correct signal,  $H$  in this case, is higher than the probability of getting the incorrect signal, the individual follows her private signal. In other words,

$$\Pr[\text{Truevalue} = \text{signal} \mid \text{signal}] = p > (1-p) = \Pr[\text{Truevalue} \neq \text{signal} \mid \text{signal}] \tag{1}$$

Note that this equation holds regardless of the signal, so there is a  $1-p$  probability that the first individual makes the wrong decision and a  $p$  probability of making the right decision.

The second individual observes both his own private signal and the action of the first individual. The second individual can clearly infer the signal of the first individual from that person's actions and thus has two signals with which to form his evaluation. Either both of the signals will be the same, in which case the second individual will follow the signal, or the signals will be different. If the signals are different, then by Bayes' theorem,

$$\Pr[\text{Truevalue} = H \mid H, L] = \frac{p(1-p) \times \frac{1}{2}}{p(1-p)} = \frac{(1-p)p \times \frac{1}{2}}{p(1-p)} = \Pr[\text{Truevalue} = L \mid H, L] \tag{2}$$

and the second individual is indifferent between adopting and not adopting. For simplicity, assume that an individual always follows his own signal in the event of a tie.

The third individual faces two possible situations before observing her private signal. Either the prior actions were identical or they were different. In either case, the third individual can perfectly infer the signals of the first two people based on their actions. If the first two were different, then they cancel out and the third person is in the same situation as the first person and will follow her private signal.

However, if the first two signals were identical, then the third individual finds that

$$\begin{aligned} \Pr[\text{Truevalue} = H \mid H, H, L] &= \frac{p^2(1-p) \times \frac{1}{2}}{\frac{1}{2}p^2(1-p) + \frac{1}{2}p(1-p)^2} \\ &> \frac{p(1-p)^2 \times \frac{1}{2}}{\frac{1}{2}p^2(1-p) + \frac{1}{2}p(1-p)^2} = \Pr[\text{Truevalue} = L \mid H, H, L] \end{aligned} \tag{3}$$

This means that if the first two individuals choose to adopt the technology, the third individual will also adopt the technology, even if her private signal indicates that it is of low value. If the true value is indeed  $H$ , the third individual benefits from observing the actions of the first two and makes the right decision in spite of her own bad information. In this case, following the fad is beneficial and is the outcome of a rational decision process based on the value of the technology. This leads to a definition of an information cascade.

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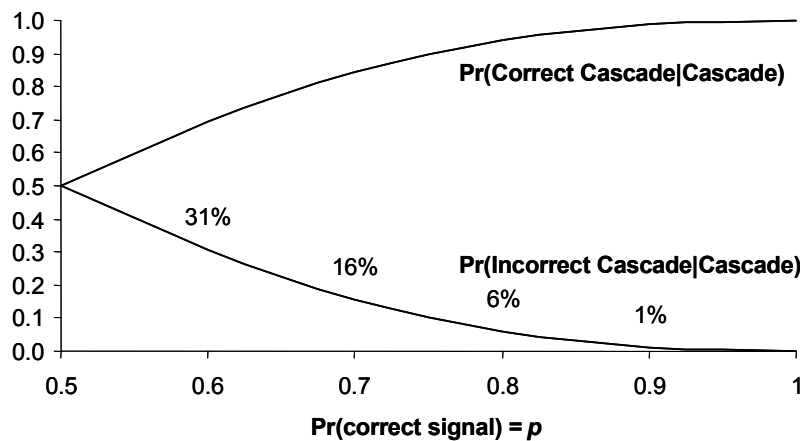
<sup>1</sup>Note that the value of a signal is symmetrical around  $p = 0.5$ , so that if the signal is correct with a probability less than 0.5 the decision maker simply does the opposite of what the signal suggests. In effect, a signal with probability less than 0.5 is converted into a signal with a probability of being correct of greater than 0.5. For example, a binary signal that is correct 75 percent of the time has identical value to a signal that is correct 25 percent of the time, because the decision maker can do the opposite of the signal and be correct 75 percent of the time. Thus, the assumption that  $p > 0.5$  is only made for conceptual clarity and has no effect on the outcome of the model.

**Definition:** An information cascade occurs when an individual takes action contrary to his or her private signal based on the actions of others.

Several interesting implications follow from this analysis. If the first two individuals choose to adopt, the third will, too. However, the third individual’s signal cannot be inferred from her action and consequently has no information content. As a result, the fourth individual faces the same information set as the third and will behave in the same way. By induction, once a cascade has begun, if no further information enters the system, then all subsequent individuals will behave in the same way. Hence, fad-like behavior will result.

Another implication is that cascades are common. In fact, it is easy to verify that at any point at which a given action has been taken two more times than the other action, a cascade will occur. A full proof is omitted for space considerations, but the logic is simple. The decision maker always chooses the action for which the most signals exist. If, for example  $\#H = \#L + 2$ , then  $H$  is chosen even if the individual receives an  $L$  signal because the single  $L$  cannot outweigh the two-signal lead of the  $H$ s. As the number of individuals approaches infinity, the probability that at some point one of the signal categories will exceed the other by two approaches unity. Again, formal proofs are not offered, but see Bikhchandi et al. for a full discussion.

All of the examples thus far have talked about adopting a technology when it is the correct choice, but the model clearly shows that there is a possibility of an incorrect cascade. Specifically, in the first two decisions, the proper cascade will occur with probability  $p^2$ , and an incorrect cascade will occur with probability  $(1-p)^2$ . The chart below, adapted from Bikhchandi et al., illustrates the probability of being in a correct or incorrect cascade after two individuals have made choices given that a cascade occurs. The reader should note that  $p$  is a measure of the certainty in the system. Values of  $p$  close to 0.5 indicate high uncertainty while values close to one indicate great certainty. In other words, if an individual has a 100 percent chance of receiving the correct private signal, then there is no uncertainty, but if the individual has a 50 percent chance of receiving either private signal, then system entropy is maximized.



**Figure 1. Probability of Being in a Correct or Incorrect Cascade Given a Cascade**

The chart presented in Figure 1 shows that the chance of being in an incorrect cascade is not trivial, even when the probability of a correct signal is high. When considering the adoption of a new technology, the environment is likely to be quite uncertain and, accordingly, managers are likely to experience an incorrect information cascade with disturbing regularity. This helps to explain why technology adoption in particular seems to be more prone to unprofitable fads.

The last implication of information cascade theory that this paper addresses is that cascades tend to be fragile. This occurs because once a cascade has started, an individual’s actions are not informative and thus the certainty with which decisions are made never exceeds the minimum level necessary to start a cascade. Thus, new public information can reverse a cascade. Consider that a cascade occurs whenever  $\#H = \#L + 2$ , using  $H$  as the cascade value. Combined with the fact that no actions are informative after the cascade has begun, this means that regardless of the behavior after the cascade, an individual will only be able to rationally believe that there are two more  $H$ s than  $L$ s. If a signal from new research, a news report, or even an earnings report, becomes publicly available that suggests the true value is  $L$ , then the next individual will believe there is only one more

$H$  than  $L$  signal. If he receives  $L$  as his private signal, he will choose  $L$  and break the cascade. Again, space considerations rule out a full proof. Moreover, there are additional interesting comparative statics and generalizations that we are prevented from pursuing here due to space limitations, but see Bikhchandani et al.

The information cascade model offers a useful explanation for how rational decision makers can exhibit fad-like behavior with no particular preference for conformity. Moreover, it explains why individuals can make systematic errors in following a fad, particularly in high uncertainty environments. In addition, it offers an explanation of fad-like behavior that is fragile, so that incorrect information cascades can be identified and corrected. Finally, it has been well documented in experimental conditions that individuals behave as the theory predicts by discounting their own private information and joining the information cascade, particularly when they are rewarded for making correct decisions (Anderson 2001; Anderson and Holt 1996, 1997).

## 2.2 Operational Model

Unfortunately, non-laboratory research on information cascade theory is problematic for two reasons. First, in real world settings, people do not commonly make binary choices and receive binary signals. More often, individuals attempt to assign a valuation to a course of action. Rather than using broad categories such as high and low, real world decision makers try to determine the actual value of some action. The second problem for a researcher is the same as that faced by the individuals in a cascade. There is no way to observe a private signal. Thus, empirical research into information cascades must proceed by developing an operational model based on observable variables. This section develops such an operational model.

Assume a market of  $n$  agents. Each agent  $i$  receives a private signal about the value of a technology initiative at time  $t$  of the form

$$s_{i,t} = v + \varepsilon_{i,t}, \text{ where } E[\varepsilon_{i,t}] = 0 \text{ and } \text{VAR}[\varepsilon_{i,t}] = \sigma^2 \text{ for all } i \text{ and } t \quad (4)$$

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 and, in fact, many equities are handled by market makers whose job it is to insure that all of the trades that can be made are made. Moreover, some exchanges, like the Arizona Stock Exchange, behave in exactly this manner, soliciting bids in discrete time and then setting the price to maximize the transaction volume. Thus, 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

$$p_t = p_t(s_t) = v + \text{median}(\varepsilon_t), \text{ where } E[p_t] = v \quad (5)$$

Here  $p_t$  is a function of the vector  $s_t = \{s_{1,t}, s_{2,t} \dots s_{n,t}\}$  and *median* is a function of the vector  $\varepsilon_t = \{\varepsilon_{1,t}, \varepsilon_{2,t} \dots \varepsilon_{n,t}\}$ .

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.

## 2.3 Adding Information Cascades to the Operational Model

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 hence be quite informative. Assume that agents cannot observe other agents' private signals, but can observe the market-clearing price in prior periods. For simplicity at this point, also assume that only one prior period is informative. Each agent's private valuation of the technology becomes  $f_{i,t} = f(s_{i,t}, p_{t-1})$ , 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 prior period, it would tend to stay overvalued in the current period.

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

$$f(s_{i,t}, p_{t-1}) = \alpha s_{i,t} + (1 - \alpha) p_{t-1} = \alpha v + (1 - \alpha) p_{t-1} + \alpha \varepsilon_{i,t} \quad (6)$$

where  $0 \leq \varepsilon \leq 1$ .

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,

$$p_t = \alpha v + (1 - \alpha) p_{t-1} + \text{median}(\alpha \varepsilon_{i,t}) \quad (7)$$

This can be rewritten as

$$p_t = \beta_0 + \beta_1 p_{t-1} + \xi_t \quad (8)$$

The reader will recognize equation (8) 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 estimates in any period  $t-1$  are 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. From this equation, we can form two hypotheses using market data.

First, to test for the presence of an information cascade,  $\beta_1$  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 the prior period. Thus, a positive coefficient for  $\beta_1$  indicates information cascade behavior, and yields hypothesis 1.

**Hypothesis 1:** *The market valuation of a technology in the current period will be a positive function of the market valuation in the prior period.*

The second hypothesis concerns the influx of information over time. Information cascades differ from other fad-like behavior because they are fragile (Bikhchandi et al. 1992). Fragility means that the strength of the prior belief can only rise to the point where it marginally outweighs any single private signal. After such a point, new adoption decisions are no longer informative. Thus, at any time that new information (news) becomes available that weakens the decision maker's confidence in the prior, it is possible to break the cascade. From the example above, we see that after two adoption decisions, in the absence of news, each subsequent decision will be to adopt, but all of those decisions will do nothing to strengthen the belief in the prior. Compare this to a situation in which the signal, rather than the action, is observed. Each positive signal will serve to increase the strength of the prior, so that many positive signals will be hard to reverse. When only the action is observable, the first two actions have the same information content, and hence are as easy to reverse as any number of prior actions because it is known that adopters three through  $n$  were part of a cascade.

Fragility is present because new information entering the system is used by decision makers to reevaluate their estimates. In this case, information concerning the viability of a technology, such as earnings news from early adopters or analysts' reports on the success of the technology, becomes available between periods. Thus, some part of each individual's private signal will consist of information that was unavailable in the prior period, which will tend to make the private signal more reliable than the previous period's public signal. This would, of course, increase the weight that individuals applied to their private signals.

If markets contain a large number of participants, then the private signal would be extremely noisy compared to the public signal. If there is no new information entering the system, this would mean that the weight applied to the last period's public signal should be much greater than that applied to the noisy private signal. As the market size approaches infinity, as it does in financial markets, the weight given to the private signal will approach zero. Thus, in a large market with no new information, the  $\beta_1$  coefficient should equal unity.

If new information does enter the system, then the  $\beta_1$  should be less than unity. As information cascades are presumed fragile due to new information entering the system, hypothesis 2 is as follows:

**Hypothesis 2:** *The weight placed on the market valuation of the prior period is less than unity.*

### 3 DATA

The data for this study come from firms' adoption of EC technologies. This is a particularly good environment for consideration because EC is characterized by both high uncertainty and poor observability of private signals. Each data point is a firm's public announcement of an EC initiative in the media. We collected the data from a full text search of company announcements related to EC 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*.<sup>2</sup> The search yielded 4,744 potential announcements—2,170 in 1999 and 2,574 in 2000.

To insure the consistency and accuracy of the coding, two coders—one of the authors and a graduate student—worked independently. Each coder performed his own analysis of the data. The data were then matched, and one of the coders revisited any disagreements. In this phase, the coder could change his and only his original coding if a second examination agreed with the other coder. If the coder did not agree, he wrote his own comments on 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 by 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 Superbowl 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 insure that the sample contained stocks representative of the broad market, coders removed penny stocks and thinly traded stocks. 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). Out of the 4,744 potential announcements, 2,097 were coded as announcements of EC initiatives.

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

$$AR = R_{s,t} - (\delta_s + \gamma_s R_{m,t}) \quad (9)$$

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.

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<sup>2</sup>The terms NYSE, NASDAQ, or AMEX are added to filter non-public companies. This works because the newswire articles list the ticket and trading symbol for the firms that they discuss. Thus, a typical announcement may read something like this: *Today the Microsoft Corporation (NASDAQ: MSFT) announced...*

Finally, to allow for announcements that occur before the market opens or after the market closes, 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. 2000).

The model in (8) was then estimated using the return data. When there were multiple announcements in a single trading day, the average return was used. Because the underlying value of EC technology adoption may change over time, two alternative specifications were used. First, a time trend was included in the estimation to capture any linear changes over time. Further, because some research suggests that the change in EC value over time is not linear (Subramani and Walden 2002), a squared time trend was included. The results are shown in detail in Table 1.

**Table 1. Autoregressive Results**

	Equation Estimated		
	$\beta_0 + \beta_1 p_{t-1}$	$\beta_0 + \beta_1 p_{t-1} + \beta_2 t$	$\beta_0 + \beta_1 p_{t-1} + \beta_2 t + \beta_3 t^2$
$\beta_0$	0.0003	0.0108	0.0159
StdErr	0.0043	0.0086	0.0130
$\beta_1$	0.1366	0.1305	0.1297
StdErr	0.0496	0.0497	0.0498
$\beta_2$		-5.19E <sup>-05</sup>	-1.27E <sup>-04</sup>
StdErr		3.70E <sup>-05</sup>	1.49E <sup>-04</sup>
$\beta_3$			1.87E <sup>-07</sup>
StdErr			3.56E <sup>-07</sup>
1 - $\beta_1$	0.8634	0.8695	0.8703
T-stat	17.4217	17.4979	17.4931
F-stat	7.600	4.790	3.280
Prob F	0.006	0.009	0.021
R <sup>2</sup>	0.019	0.024	0.024
R <sup>2</sup> adjusted	0.016	0.019	0.017
df	399	398	397

As the table shows, the empirical testing failed to reject the hypothesis of information cascades in all specifications. The hypothesis that market participants used the prior period's observed valuation to form their current period valuation cannot be rejected at the 1 percent confidence level even when controlling for underlying EC value and temporal effects. Furthermore, the hypothesis that new information enters the market between periods, making information cascades fragile, cannot be rejected at the 1 percent level, also when controlling for underlying EC value and temporal effects. Moreover, the only variables that achieve significance at standard levels in any of the specifications are the two being tested. While the R<sup>2</sup> is low, the F-statistics strongly indicate the presence of a regression.

## 5 CONCLUSIONS

The adoption of information technology seems to be particularly susceptible to fad and fashion, resulting in herd-like behavior by firms. However, these fads are distinctive both because they often result in firms adopting a beneficial technology and because detrimental fads are fragile. Prior theory has often attributed such behavior to a managerial preference for conformity. This paper proposes information cascade theory as an alternative and shows fad-like behavior to be a rational response to decision processes in a highly uncertain environment.

Information cascade theory suggests that firms may follow the lead of other adopters in spite of private information. This results in firms making better decisions overall, but may occasionally give rise to an incorrect cascade, wherein all firms follow the wrong course of action. However, as more public information about the outcomes of actions enters the system, incorrect cascades will tend to die out.

This paper contributes to the technology adoption literature by creating an operational model of information cascades and offering the first non-laboratory empirical test of information cascade theory. The results provide support for the operational model of information cascades in the adoption of EC technology. Both the hypothesis that prior period information is being incorporated in the current period and the hypothesis that cascades are fragile are borne out in all specifications tested.

It is important to point out that, although our hypotheses were both supported, we have not proven that information cascade theory applies in this context. We are unable to test information cascade theory directly because the signals, which are unobservable to the market participants, are also unobservable to the researchers. Thus, hypothesis 1 does not directly test our definition of an information cascade, because we cannot know if market participants are ignoring their private signals, due to the unobservability of those signals. Rather, we have tested a necessary condition that is predicted by the theory.

This research is an introductory exploration, and thus is subject to several limitations. The first concerns the assumption that the underlying value of adoption is constant across time. It may be the case that as competition increases, the value to a firm of adopting EC technology decreases, and thus is not stable across time.

At the same time, the theory of network externalities suggests that the value of adopting may increase. Addressing network externalities in this context is quite important, because it is widely held to be one of the driving forces of EC and the information economy in general. Network externalities arise when the value of a network increases as the number of members in the network increases (for a detailed review, see Economides 1996). While this is a powerful explanation of adoption of the Internet by consumers, it is less satisfying as an explanation of the adoption of EC technologies by firms, for three reasons. The first reason is that the network effects are not directly related to the number of other firms, but rather indirectly related to the number of customers. This is what Kauffman and Walden (2001) term *second order externalities*. The second reason, as mentioned above, is that more firm participants in the EC environment leads to greater competition in that environment, which directly reduces the value of adopting. The third reason is simply the fact that firm value has not grown exponentially then leveled out at this new high value. If network externalities were the driving force, then the value of adopting the technology would rise consistently as the number of other adopters increased. However, it is well known that in mid-2000, the value attributed to EC dropped considerably in what is termed the bursting of the Internet bubble, while the number of adopters continued to increase. If network externalities had been at the root of the value, then there would have been no bubble and EC adoption now would generate more value than it did in 1999. However, this is clearly not the case.

Nevertheless, information cascade theory does not in any way contradict network externality theory. Information cascade theory assumes that adopters receive a private signal, but does not specify the nature of that signal. Clearly, there is no conflict if that private signal arises through an evaluation of network benefits. In this sense, information cascade theory provides a decision theoretic model of the adoption choice, while network externality theory offers an economic model of value drivers. As a theory of the adoption decision in EC, network externality theory lacks face validity because it requires potential adopters of an unknown technology to have perfect knowledge of the value functions arising from that technology. This is obviously a poor assumption in the EC context, as even now there is no strong consensus on how to profit from EC. Information cascade theory, on the other hand, assumes that decision makers have imperfect knowledge of the true value and thus depend on the actions of other adopters to supplement their limited domain knowledge.

Another point to consider is the time frame and nature of the data. Specifically, this investigation uses data from 1999 and 2000, during a time that has been characterized as the "dotcom frenzy." However, this is not as problematic as it seems on the surface. While we do not argue for the lack of frenzy, we do propose an explanation for this frenzy. Specifically, we believe markets were in a state of information cascade due to the limited information available to participants for objective valuations. Thus, overreaction due to good news in one period carried over to the next, was present in this time period. However, information cascade theory argues that this type of behavior is rational in highly uncertain markets, such as EC during 1999 and 2000. This theory is an attempt to explain the complex rise and fall of EC valuations during this period by explicitly modeling investor decision making.

Finally, we note that this work does not discriminate between different types of EC technology adoptions. It may be the case that different types of technologies have different effects. Some may be competitive necessities, while others may be strategic differentiators, and still others may have significant network effects. We leave this investigation for future research.

This research indicates that information cascade theory may offer a good description of new technology adoption, which has several implications for practice. First, practitioners should be sensitive to the possibility that other firms' adoption decisions are the result of an information cascade rather than due to a positive private signal. In the strongest form, the theory suggests that, regardless of whether two previous firms have adopted a technology or 2,000 previous firms have adopted it, the same information content is presented to later potential adopters. In a weaker form, such as that tested here, the theory illustrates that, while current period investors should consider the evaluations of prior periods investors, they should realize that evaluations of many previous firms might be built into any single firm's current adoption decision.

Information cascade theory provides a useful explanation of the underlying mechanism used by managers in making adoption decisions. The theory has now been supported in laboratory settings and in real world settings. In addition to its theoretical value, it offers practical suggestions for managers and is worthy of additional exploration.

## 6 REFERENCES

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