Deterministic Adoption in Movie Industry

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Abstract

In this paper, we investigate the decision making process by movie goers. Under incomplete information environment, movie goers will have to learn the quality of the movie from the information relayed by predecessors. The hypothesis is formed by the movie goers when the movie is first released, and it is then compared to information received. In this environment, movie goers will constantly upgrade the belief system, or discard the weaker ones if found to be not consistent with the overall quality information received. Thus, positive news relayed in the initial stage will be magnified to greater importance; the movie becomes a hit. We model this deterministic adoption with first order difference equation. We find that the Hit movies exhibit higher deterministic adoption behavior and the relationship between current and previous adoptions can last longer, than if the movie is a flop. The time path or orbit of the dynamic growth also exhibits non-oscillatory behavior and converge to equilibrium level quickly; when the deterministic adoption mechanism loses its strength, the subsequent adoptions will eventually die off. In other words, the previous adoptions cannot determine the future adoptions. Although this behavior is present in both Hit and Non-hit movies, this diminishing mechanism is triggered in much earlier stage in Non-hit movies than it is in Hit movies.

Keywords: deterministic adoption, learning, movie, consumption behavior

JEL Classification: D01, L82

1 Introduction

In an environment when there is information flux, consumers are confronted with different information mix, which makes the consumers act on the belief which are not complete. This mix information can be modelled on ecosystem, in which the existing information source has to compete for survival with other information sources. Or a stream of information has to be combined with other information to become useful. Thus, what a consumer faces when there are many choices are myriad of information or belief interactions, congruence of different information sets and sometimes information is much diversified. When facing these situations, consumers will usually adopt strategies to learn, either from his predecessors or wait and see the development of the situation, in order to adopt the information which is most useful to him.

Although one may know the eventual goal is to pick the most optimal choice, due to the complex situation, one has to increment the belief system. Each set of information is benchmarked and tested with hypothesis formed in the early decision making process. If the information set is tested to be less credible, in this case the information may tell differently from the hypothesis, it maybe discarded or adopted. If the information is discarded, new information set is then adopted and tested with the existing hypothesis. If it is adopted, the hypothesis or belief system will be incremented. Consumer will constantly search for other source of information, thus, the belief system will then be tested further with other new information. This mechanism will go on until the consumer is fully convinced, or when a threshold value is reached, after which the consumer will adopt the good.

In this paper, we model this mechanism and apply it to the movie going behavior, particularly we intend to investigate the emergent behavior of the movie industry, the convergence of choices. Movie is experiential good as movie goers cannot know the quality of the movie before seeing it. They know only after seeing it. So it has no trial value. In search for most preferable movie among the choices, and since the movie is an experiential good, potential movie goers will adopt wait and see attitude, and constantly learn from different sources of information. We find that the presence of this learning mechanism renders the movie going activity to be deterministic; in which the positive information which is adopted by current movie goers is also adopted by subsequent movie goers. In other words, consumers are able to learn and pick the most optimal choice. The activity is deterministic is because the decision making is contagious; a piece of good news will be told and adopted by subsequent movie goers. The small early adopters will then be magnified into large followings in the later runs of a film. Therefore, the contagious effect, under this learning mechanism, is informative and the movie goers are motivated by credible news. Although the activity is deterministic, the future adoption is determined by current adoption, the movie goers are not herded. In the following sections, we apply this learning mechanism to movie industry and test its presence with empirical data.

Section two applies the mechanism to the movie industry, especially the misspecification of information, and how consumers handle the information flux which comes from many choices available in the market and the news provided from his predecessors. Section three models this mechanism with first order differential equation to see the deterministic adoptions. It especially addresses the question whether the movie going activity can be herded. Section four performs a statistical test on the autocorrelation to investigate the presence of this deterministic trend. It is to further prove the result in section three. Section five then concludes.

2 Misspecification and Consumption Behavior

In a process of decision making whether to see a movie or not, movie goers usually face with myriad of complex situations in which the information are incomplete. In view of the many choices available, short shelf life, and the nature of the good (movie is experiential good), it is costly to postpone decision or to experience the good. However, one may adopt wait and see attitude; learning from other movie goers of the true quality of the movie. This strategy enables the movie goers to learn the current statistics and will decide to see the movie based on this statistics. This argument has been widely studied in the literature about the role of word of mouth advertisement among movie goers about a particular movie. Among the few are Dodson and Muller (1982), Ellison and Fudenberg (1995), and Goldenberg et al. (2001).

However, one also has to look into the misspecification of information when making decision. Although word of mouth advertisement will help to facilitate decision making process, preferences exhibited by each human being are different and the decision made by others may not be utility maximizing for other audiences. Furthermore, when we look into the decision making process which based on the past statistics to fathom the overall consumption behavior, one may think that the subsequent consumption decisions are quantity induced rather than quality motivated. Therefore, learning to adopt has to be something that involves more factors or multidimensional such as personal preferences, information revealed by past statistics, and we propose in this paper, that audiences learn the quality of a good through inductive learning (Arthur; 1994).

When face with choices that are complicated and ill-defined, audiences will learn from others about the quality of a movie and based on this information, will form simplifying patterns and hypothesis. These patterns and hypothesis will then be tested with the current environment. As new information arrives, these patterns will be strengthened or weakened, and weaker ones will be discarded, the stronger hypothesis will then be tested in the future interactions. The process, hence, will play a role in filtering information received, and the means to do exactly that is through interactions. In the world of complexity, hypothesis will be strengthened if the feedback from the interactions is credible and consistent; when audiences receive constant information of a particular movie many times, and it contains more or less similar information, the hypothesis formed earlier will be made stronger.

However, the hypothesis forming is not smooth and homogeneous but it requires different preferences among the audiences. The hypothesis is formed when the movie is advertised; movie distributor and exhibitor will advertise before the movie is released to create "lock on" effect. Different preferences will help vary the hypothesis formed among the potential movie goers; some may benchmark against other movies seen in the past, some may think highly about the movie, and some are difficult to be convinced. This diversity is important to facilitate the convergence of opinions among audiences. This hypothesis formed will then be compared with the overall information received from their predecessors during their interactions and information exchanges.

If the information received talks highly about a movie, the hypothesis about the movie will be strengthened and movie goers will compare it with other information again. If the subsequent information is continuously positive, movie goers will upgrade the belief system, and know that he is in the right trend. If the information is negative, the hypothesis will be discarded or its strength discounted. And if the information is mixed, audiences will exhibit many hypotheses. Each audience possesses a threshold level, which if it is exceeded by belief system during information exchanged; he will go to see the movie. Until it is reached, audiences will "ask" and exchange information with others.

This learning mechanism employed by the audiences will seal the faith of a movie; the constant positive information exchanged in the earlier interactions will exceed the threshold value of movie goers, and propel the film to become a hit. However, if the information does not strengthen the hypothesis and upgrade the belief system, the film will die very fast. This is usually exhibited by the exhibition market, in which if the film is successfully opened and able to garner large early followings, the subsequent information exchanged will propel the film (De Vany, 2004).

If one were to model this characteristic, the overall decision is to be determined by the initial value of a movie. If the initial opening is successful, and create large positive remarks of the film, the subsequent interactions among audiences will convince more movie goers. However, this mechanism is not always successful; the large opening made by heavy advertisements does not determine the success of a film if the early followings distribute negative news about the movie. In this latter case, the hypothesis formed will be changed and the belief systems are weakened by the mix information. Therefore, the threshold value is never reached, and the movie is not watch-worthy.

Thus, we may differentiate the Hit from the Flop by analyzing the initial adoption behavior; if the early adoptions are able to propel the movie, then the earnings in current period is strongly determined by immediate past, and this determination will last longer than when the movie is a flop. In the latter case, the life of this mechanism is short, and movie will quickly reach its peak and die off very fast. We test this mechanism in the following sections.

3 Deterministic Adoption

The simplest way to look at the deterministic growth is the first order differential equation (Li and Yorke, 1975), and the definitive analysis of the equation can be seen in Hoppensteadt and Hyman (1977). The phenomena can be described by the current number of adoptions, x_t is estimated purely as a function of the number of adoptions in the previous year, x_{t-1}. Formerly, it is written as:

$$x_t = F\left(x_{t-1}\right)$$

where F maps an interval into itself. The relationship of adoption between time t and lagged t is formed when perception of the movie at time *t-1* influences the perception at time t. The process goes like this: there is a perception on the quality of the movie formed in time *t-1*, and the movie goers in time t will adopt this perception prevalent at that time. Thus, the relationship is positive. Assume that x_t is functioned to some parameter B of pervious number of adoptions, x_{t-1}, where B can be considered as the influence of x_{t-1} on

x_t, then B becomes positive. However, since movie is a non-repeat good, there is a saturation level, after which the influence of x_{t-1} is diminishing, where B approaches 1 or $x_t = x_{t-1}$.

The strength of this relationship can happen either in the early life of a movie, after the movie is released or end of a movie's life. If the strength occurs in the early life, the initial adoption is said to be able to propel further adoptions; success breeds more success. If the strength occurs in the second case, the initial adoption is less effective. We call these both cases deterministic; the initial adoption determines the future adoptions. The adoption becomes inderterministic when the adoptions are periodic (see for example, Hoppensteadt and Hyman, 1977).

To illustrate the deterministic adoption, we assume that $0<B<3$[1]. We model the saturation factor through renormalisation process, namely, x_{t-1}/K where K is the maximum capacity of a movie. The deterministic growth model can then be written as:

$$x_t = Bx_{t-1}\left(1-\frac{x_{t-1}}{K}\right).$$

This is the quadratic logistic equation investigated by Lorenz (1963). The logistic equation represents the concave relationship between the current and previous adoptions. We analyze the logistic equation to determine the deterministic growth of adoption behavior of movie. We iterate the function

$x_t = f\left(x_{t-1}\right) = Bx_{t-1}\left(1-\frac{x_{t-1}}{K}\right)$, t = 2, 3, 4, ..., or $f^t = f(f^{t-1})$ to gain $x_{t+1}=f(x_t)$, $f^2(x_t) = f(f(x_t))$, ..., $f^{t+1}=f(f^t(x_t))$.

[Insert Figure 1 and 2 here]

To illustrate the deterministic force we show in Figure 1 the concave relationship between x_{t-1} and x_t, and the time path of adoption growth when B = 2.9. The concave curve intersects the 45^o line at $x_t = x_{t-1}$. The converging time path to the stable point is illustrated in Figure 2. The oscillations in the figures are non-converging in the initial runs of the film; the time path does not change direction and rising steadily (see Figure 1). Thus, if the relationship is $x_t = ax_{t-1}$, then $a > 0$. However, towards the rightward end of the diagram (figure 2), the relationship approaching a = 1. At the equilibrium point, when $x_t = x_{t-1}$, the previous adoptions are no more able to determine the subsequent adoptions. After this level, the adoptions will taper off and the movie will die.

This approximation allows us to determine the deterministic growth of adoptions throughout the film's run. If the opening is strong and able to garner large lock on effect, the subsequent adoptions are determined by initial effect. And for this reason the earlier adoptions will propel the subsequent adoptions to higher level along the curve; in other words, the life of the film will be longer due to the influence from earlier adoptions.

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[1] When B > 3, it becomes chaos, see Li and Yorke, 1975.

[Insert Figure 3 and 4 here]

Figure 3 illustrates the deterministic growth of three hit movies with total Box Office more than USD300 million. In the figure, the deterministic growth is monotonic and the patterns are similar; the previous adoptions determine the current adoptions. However, when we compare the time path to those of flop movies in Figure 4, the deterministic time path of flop movies are shorter and the relationship between previous and current adoptions is short-lived. Furthermore, the slopes for flop movies are less steep compare to Hit movies; reflecting the relationships are quickly tapered off in a short period of time.

4 Empirical Tests

We further examine the present of deterministic adoption with the relationship of Box Office revenues throughout the course of a film's run. We obtain the data from the *Variety's* international Box Office sample and the data ranges from 1st Jan 1985 to 25th Dec 2003 inclusive. Each film is tracked based on its inception and until its death (drop from the 150th chart). We categorize the data set to Hit Movies with total revenues exceed USD50 million and non-hit movies with revenues lower than USD50 million. Both categories of movies have life which is longer than 10 weeks. The equation is written as:

$$\sum_{t=t+1}^{\infty} revenue_t = \beta_0 + \beta_t \sum_{t=1}^{t} revenue_t + \varepsilon_t \,,$$

where revenue is the weekly revenue of a movie. For immediate past to impact on the cumulative revenue (which means the presence of deterministic adoption), the β_t should be statistically large. The results of the regression analysis are depicted in Table 1 and 2.

[Insert Table 1 and 2 here]

For both tables, the coefficients explain the impact of immediate past to the cumulative revenues immediate after the week. The effect is stronger in hit movie category than in the non-hit category. The immediate effect on the cumulative revenue is stronger from fourth week onwards for hit than for non-hit. The effect is 4.9015 for fourth week, 5.8386 for fifth week and 6.225 for tenth week for Hit category. The strength of the immediate past statistically implies that the cumulative revenue can be predicted by immediate past for Hit category. And we may claim the presence of stronger deterministic adoption in Hit than in Non-hit, as the perception prevalent in the immediate past is assumed to the present.

[Insert Figure 5 here]

Figure 5 illustrates the strength of the diagonal elements (immediate past) for both hit and non-hit categories. It shows that both categories of movies begin at the almost similar trend; for the first three periods, the immediate future revenues can be determined by the immediate past. However, they begin to bifurcate when both runs to the fourth week. The impact of immediate past on immediate future remains strong or increasing for hit movies, whereas, the impact decays for non-hit movies. Overall, the empirical evidences correspond to the results of logistic equation that the presence of stronger deterministic adoption in hit than in non-hit. This is due to the learning process exhibited by movie goers; without sufficient information of the quality of the movie, movie goers will adopt wait and see strategy and learn from the predecessors. If the learnt information is positive, more movie goers will adopt.

The presence of strong positive relationship between past revenues and future revenues in hit movies in the beginning of the run illustrates that the positive information is carried forward to the subsequent runs to convince potential movie goers. In this case, the paths of the future earnings are deterministic by the immediate past. Although this behavior finally diminishes, as shown in Figure 5 that the effect decays after week 8, the life of this mechanism is longer compare to non-hit movies (the deterministic adoption for non-hit runs out its strength in week 4).

5 Conclusions

In the paper, we model the decision making of movie goers. We emphasize on learning by the movie goers in the environment when information is not complete. When the movie goers face with choices, they form their own belief system and preferences. The degree of belief on one particular movie is constantly strengthened or weakened by information spread among them. Under this process, audiences are learning to choose with incremental pace. Therefore, if the film is able to encourage positive news, subsequent potential audiences will follow, whereas if the remarks are negative, the strength of the film will die off easily.

We model this deterministic adoption with first order difference equation, and find that the mechanism is present both in hit and non-hit categories of movies. The immediate past or previous earnings follow closely the subsequent earnings when the word of mouth advertisement is strong; in which the positive news are magnified to convert more potential movie goers. However, the strength is credible only when the movie is first released. We also observe that although this strength diminishes for both categories, it lasts longer in hit category.

The observation of deterministic adoption rules out the idea that movie goers can be herded. Although the subsequent movie goers follow the existing trend when choosing movie, the decision is quality motivated, or rather it is informative cascade that encourages movie going. Each decision is constantly fine tuned and checked with benchmark and threshold value before it is made. The overall convergence of opinions can only be explained by *the success breeds more success* in the industry, or deterministic pattern in consumption behavior.

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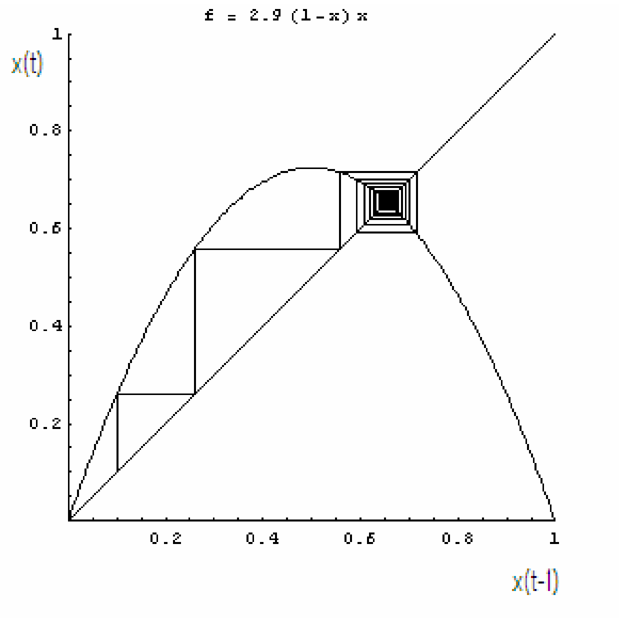

Figure 1:
The initial adoption is increasing monotonically determined by previous values. It is illustrated by the growing time path, it goes up steadily. The relationship losses its steam when the immediate past value cannot determine the future value. This is when the time path becomes oscillatory. The relationship then becomes more stable when the equilibrium level is reached, in which the previous values are not able to determine subsequent adoptions, and the whole system (the time path) converges to the equilibrium point.

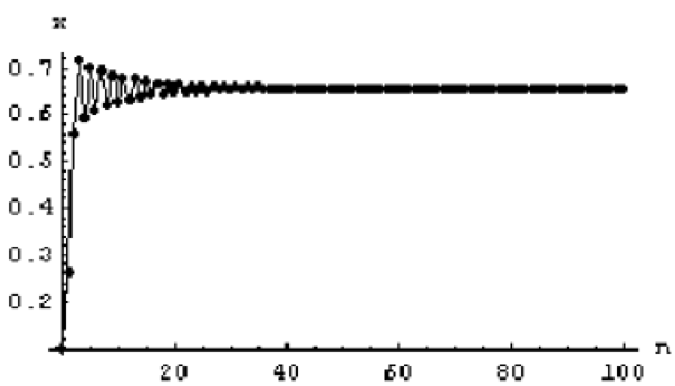

Figure 2:
The time path of the system begins with the value 0.1 with 100 iterations in a two dimensional from. The deterministic adoptions are evident in the beginning of the run, after which the orbit fluctuates in a limit set. The oscillation occurs when the previous value starts to lose its strength and finally it goes into the equilibrium level.

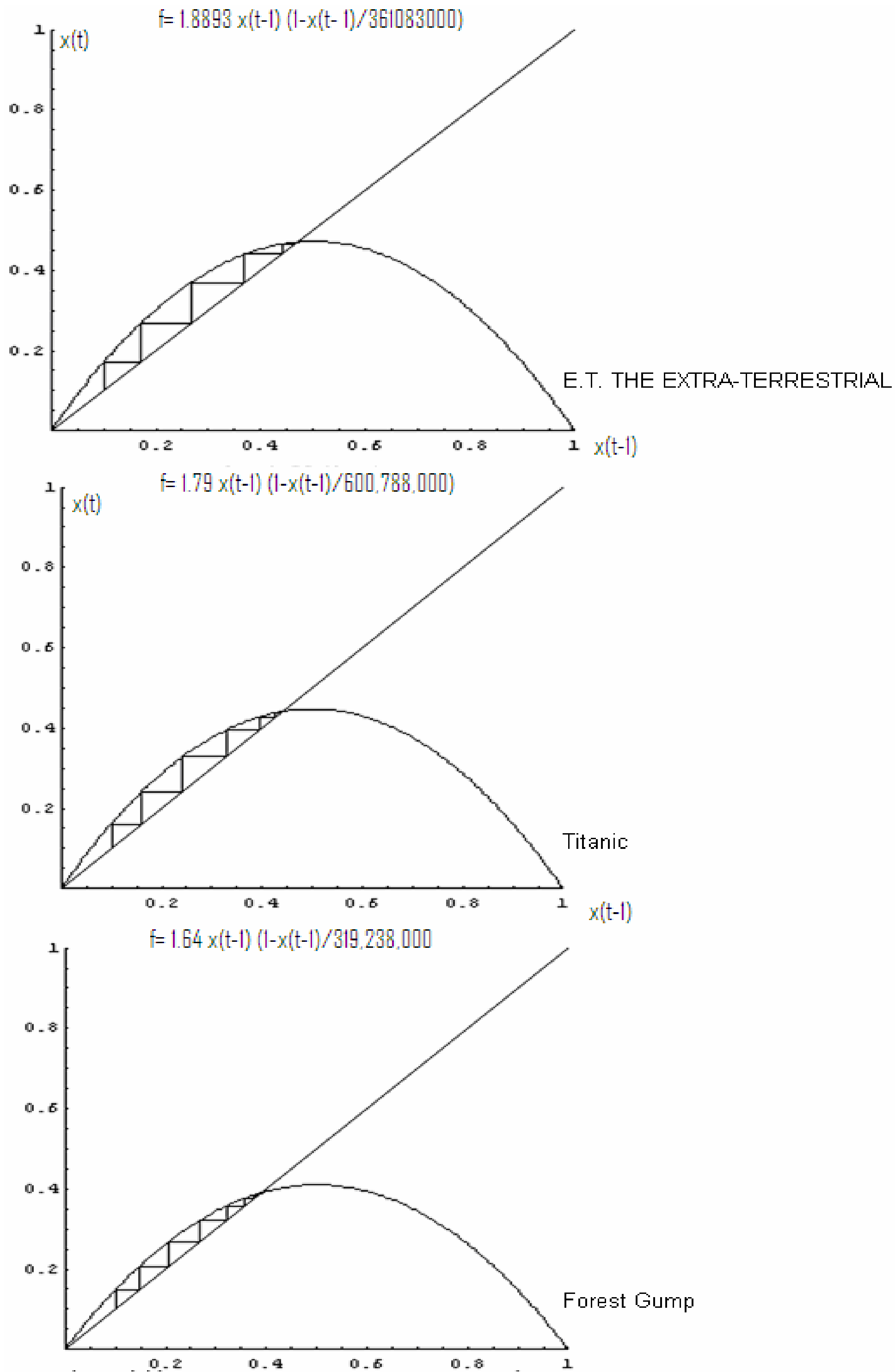

Figure 3:
The time paths of three hit movies exhibit a similar pattern; in which the deterministic growths are monotonic and converging to stable point. The previous adoptions follow closely the current adoptions.

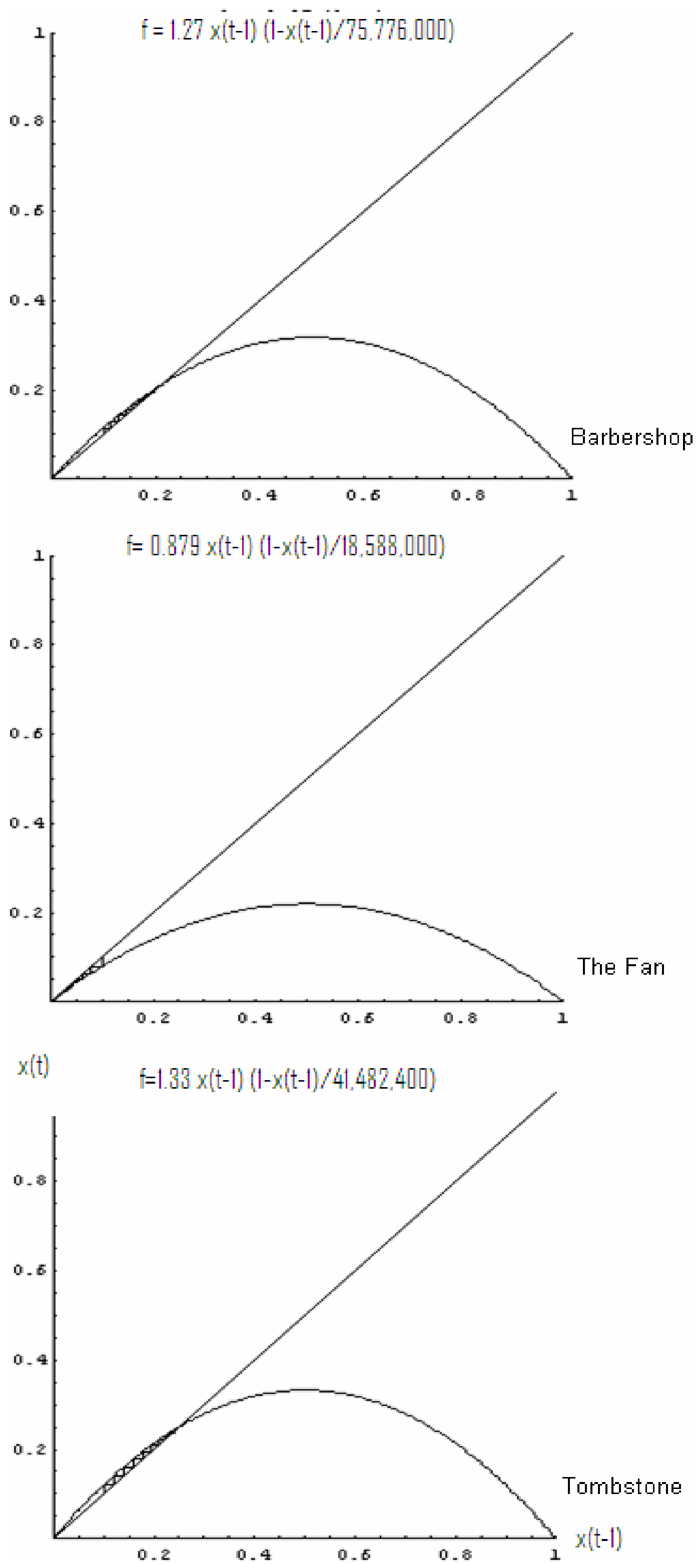

Figure 4:
The time paths of three non-hit movies exhibit a shorter life; the previous adoptions are not able to propel the subsequent adoptions.

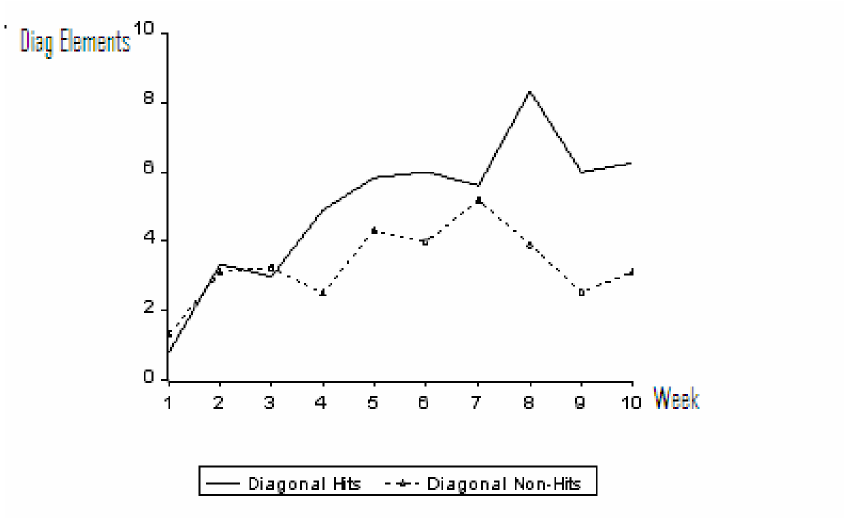

Figure 5:
Marginal Impact of Prior Revenue on Subsequent Revenue Streams throughout the run

Table 1: Impact of past revenue on future revenues for hit movies

	Dependent Variable: Cumulative Revenues after week#									
	1	2	3	4	5	6	7	8	9	10
Weekly Revenues										
1	0.8195	-1.3480	-0.9941	-0.7609	-0.3595	-0.1592	-0.0973	-0.0544	0.0125	-0.0476
	(0.0635)	(0.126)	(0.1205)	(0.1042)	(0.0919)	(0.0787)	(0.0675)	(0.0546)	(0.049)	(0.0461)
2		3.3453	0.7461	0.6782	-0.1403	-0.4006	-0.2296	0.0672	-0.1266	0.0065
		(0.2203)	(0.303)	(0.2592)	(0.2256)	(0.1915)	(0.1643)	(0.1336)	(0.1203)	(0.1129)
3			2.9915	-1.1418	-0.0399	0.0441	-0.2308	-0.0768	0.0077	0.0227
			(0.3489)	(0.4041)	(0.3492)	(0.2954)	(0.2536)	(0.2051)	(0.183)	(0.1705)
4				4.9015	-0.7502	-0.4066	-0.3943	-0.7074	-0.4473	-0.1712
				(0.369)	(0.4674)	(0.4126)	(0.3534)	(0.2861)	(0.2559)	(0.2401)
5					5.8386	0.0090	1.1631	-0.2276	-0.3683	-0.4274
					(0.4347)	(0.5213)	(0.4527)	(0.3738)	(0.3334)	(0.3107)
6						5.0090	-0.0340	0.0201	-0.0340	0.3002
						(0.4431)	(0.5801)	(0.4702)	(0.4193)	(0.3923)
7							5.6184	-0.9680	-0.1051	-0.6977
							(0.4385)	(0.5066)	(0.4568)	(0.43)
8								8.3321	1.3928	0.0551
								(0.513)	(0.7129)	(0.6784)
9									5.9898	1.4841
									(0.5509)	(0.691)
10										6.2551
										(0.7448)
R-squared	0.1331	0.289	0.2906	0.3828	0.4707	0.543	0.5902	0.6747	0.6845	0.6707

Table 2: Impact of past revenue on future revenues for non hit movies

	Dependent Variable: Cumulative Revenues after week#									
	1	2	3	4	5	6	7	8	9	10
Weekly Revenues										
1	1.3323	-1.1271	-0.4809	-0.2648	-0.0899	-0.0358	-0.0046	-0.0315	-0.0356	-0.0284
	(0.0328)	(0.0731)	(0.0599)	(0.052)	(0.0448)	(0.0394)	(0.0345)	(0.0311)	(0.0294)	(0.0279)
2		3.1061	-0.4623	-0.2922	-0.1501	-0.0474	-0.0623	0.0557	0.0606	0.0358
		(0.1136)	(0.1266)	(0.1092)	(0.0933)	(0.082)	(0.0719)	(0.065)	(0.0614)	(0.0583)
3			3.2572	0.3600	0.1259	0.0098	0.0789	-0.0138	-0.0600	-0.0878
			(0.1068)	(0.133)	(0.1138)	(0.1)	(0.0877)	(0.0791)	(0.0748)	(0.071)
4				2.5144	-1.1651	-0.5504	-0.2268	-0.1678	-0.1294	-0.0004
				(0.1165)	(0.1544)	(0.1374)	(0.121)	(0.1091)	(0.103)	(0.0982)
5					4.3096	-0.2017	-0.3522	-0.1926	-0.1361	-0.1666
					(0.1705)	(0.2207)	(0.1935)	(0.1745)	(0.1648)	(0.1566)
6						4.0026	-0.8412	-0.9282	-0.3658	-0.4768
						(0.1798)	(0.2341)	(0.2109)	(0.2016)	(0.1917)
7							5.1931	1.2901	0.4703	1.0740
							(0.2212)	(0.2549)	(0.2451)	(0.2356)
8								3.9004	1.3250	-0.4572
								(0.1995)	(0.2374)	(0.2493)
9									2.5432	0.8819
									(0.1988)	(0.2133)
10										3.1147
										(0.2453)
R-squared	0.3881	0.3652	0.4218	0.3968	0.4157	0.4134	0.4302	0.4232	0.3715	0.3294