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PRODUCT LIFE-CYCLE: NEW PRODUCTS, QUALITY, SUBSTITUTES AND ADVERTISING IN THE THEATRICAL MOVIE MARKETS

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ABSTRACT

In the market for US theatrical movies, there are a set of products (movies), and over time, new products appear and existing products disappear. We develop and estimate a model of the product cycle for movies and the decay of products over time to examine the effect of product quality, production cost, advertising and substitutes on the movie life cycle. Intuitively, new products should have a strong negative effect on the probability of survival of existing movies. The effect, however, is heterogeneously present only for the substitutes from some types (genres). While it is expected that good-quality movies tend to survive longer in theatres and greater level of advertising also has a positive effect, our study finds that these variables slow down the rate of decay in the life cycle of movies, particularly towards the end of the product life cycle.

Keywords: *Product Life Cycle, Advertising, Product quality, Box office sales, movie demand, New Products*

1. INTRODUCTION

In most markets, new products are introduced routinely. Some are successful, while others are not. For example, some of the releases in the auto markets in 2017 included a sports utility vehicle from Jaguar, superior technology electric and hybrid cars from Chevrolet and the Model 3 from Tesla. New products and updates to existing products are a regular feature in this market (Vincent and Cherise, 2017 & Chitley, 2017). Similarly, in the cell phone market, there have been releases of the iPhone X by Apple, the Moto Z2 Force by Motorola, the Galaxy J7 and Galaxy S8 by Samsung: new products are introduced regularly. In the movie markets, new movies are introduced in theatres every week. Whether it is Wonder Woman or Blade Runner or Star Wars: The Last Jedi or Transformers: The Last Knight, there are some widely anticipated movies and there are others which please both critics and the audience alike.

Consumer interest in older movies in theatres decays over time. Eventually these movies are taken off the theatres. Both the entry and the exit of the products can and do have a significant effect on other products. The entry of an appealing new product that is similar in terms of quality to an existing product should cause a greater loss in consumer interest in the existing product. The markets for existing products typically decay after the introduction of the new products, but the effects may differ depending on the similarity the products introduced, the quality of the existing products and the level of advertising. Not only this, consumer appeal towards new products also plays a role in the extension of the existing product life cycle. Further, better quality and positive opinion of the early adopters toward the new products lead to a faster adoption.

In this study, we focus on the decay and exit of products using data that pertain to the movie market during the period 1985 to 1999. The movie market offers a significant opportunity to examine these effects because of the shortened life cycle of movies in theatres. Most often, right after the introduction of new movies, there is a rapid decay in movie sales. New products (movies) are routinely introduced. Each movie creates a different buzz (word-of-mouth, critique reviews and advertising) among its potential audience. Furthermore, there are different types (genres) of movies e.g., action, comedy, drama etc. Existing products decay with time i.e., a heavily advertised and touted movie often experiences the greatest attendance at the time of introduction and then decays with time. For example, according to the website "numbers.com", the movie Power Rangers (Lionsgate) with a production budget of $ 120 million

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started strong with the first week box office revenues of almost $ 51 million in March of 2017. The movie is about high school kids who must use extraordinary powers they have, to save the world. However, the sales of the movie dropped quickly to $ 18 million at the end of week 2 and $ 8.8 million at the end of week 3. The introduction of substitutes can increase this decay rate in sales. For the Power Rangers, substitutes were released consistently as it was screened in theatres. There were 2 substitutes released simultaneously, 2 in week 1, 3 in week 2, 2 in week 3, 5 in week 4 and so on. Moreover, there were some big movies already playing in the theatres such as Beauty and the Beast (Disney), The Lego Batman Movie (Warner Bros.) and Get Out (Universal).

Some movies are called good quality movies either because of good performance from actors such as Kramer vs. Kramer (1979, Dustin Hoffman and Meryl Streep) or a good plot in the story such as The Legends of the Fall (1994, Sony/ Columbia); Braveheart (1995, Paramount). Superior movie quality generates greater interest and a positive word of mouth. Generation of greater interest is expected to draw more audience even towards the end of the life cycle and consequently slow its decay in sales. Heavy advertising can also slow the decay in the box office performance. Advertising and film promotion through press releases and media, interviews with actors and producers, branding and merchandising creates familiarity, awareness and curiosity in the prospective audience. Higher advertising expenditures thus help create mass appeal for a movie.

The existing literature on product cycles predominantly cover products that last a few years. Levitt (1965) and Vernon (1966) discuss various stages of the product life cycle. These stages are: market development and growth; maturity and decline. For products with a short life cycle such as movies, most of the market development process occurs before a movie is released. This happens in the form of advertising and distribution. In addition, Einav and Ravid (2009) point to signaling of release dates typically occurring around holidays e.g., the 4th of July or Christmas. Some movies, especially those perceived as good quality movies experience some appreciation in sales in the weeks after their release, but most movies mature relatively quickly in just 2-3 weeks. Every week, the box office revenues of a new movie decrease as compared to the previous week. The first week of screening accounts for almost 30% of box office revenues. With non-existent price competition box office revenues represent the number of consumers watching movies in theatres (when we examined the ticket prices since 1980, in real terms, they are practically unchanged).

As of 2016, 718 new movies were introduced which grossed $ 11.4 billion up from 611 movies in 2007 (with box office gross of $ 9.6 billion. These data are according to the National Association of Theater Owners and the Motion Picture Association of America and not adjusted for inflation.

Good movie quality helps create a positive word of mouth through social learning and slower decay in box office sales as shown by Moretti (2011), Beck (2007) and Moul (2007). However, sales of a new movie rapidly decay reach maturity and decay until the movie is completely taken off the theatres. New products play a vital role in increasing the utility of consumers. However, their role in context of movies is relatively unknown. Nevo (2003) estimates utility function for individuals who consume products with changing product quality and to find welfare implications that exist for the consumer. Petrin (2002) estimates there are positive effects of new product introduction on consumer welfare. New products in the automobile market that successfully differentiate from the existing ones can yield large profits for the innovator and significantly increase the consumer surplus. Klepper (1996) discusses the evolution of the market structure in industries where there is innovation and technological progress in the product development. Product quality and innovation seem to be of paramount importance in the context of new products.

Entry and exit strategies also play a vital role in determining the product life cycle. Dunne et al. (2013) use a dynamic model to estimate the determinants of entry and exit in markets with imperfect competition. While these studies and the many models of Industrial Organization, such as the law of demand point to the negative influence of new products on existing products, the number of studies is scant in the context of movie life cycle. Research seems well organized around modeling the decay (Sawhney and Eliashberg (1996), Ainsle et al. (2005), McKenzie and Walls (2013)), or the influence of the determinants of the movie demand (Elberse and Eliashberg (2003), Elliott and Simmons (2008), Kim and Nora (2017) and Prieto-Rodriquez et al. (2015)).

Studies based on the demand estimation of movies focus on seasonality and release dates (Einav (2007), Gutierrez-Navratil et al. (2014), Chen et al. (2013)); role of critics (Zuckerman and Kim (2003), Ravid et al. (2006), Basuroy et al. (2003), Reinstein and Snyder (2005), Eliashberg and Shugan (1997) and Boatwright et al. (2007)); mathematical properties of box office revenues (DeVany and Walls (1999), Walls (2005), Collins et al. (2002)); word of mouth (Moul (2001 and 2007), McKenzie (2009), Liu (2006) and Duan et al. (2008)); Australian box office (McKenzie and Walls (2013)); effect of advertising and promotion (Basuroy et al. (2006), Zufryden (1996) and Zufryden (2000), Elberse and Anand (2007), Gopinath et al. (2013)); movie scripts (Eliashberg and Zhang (2014)); role of stars (Albert (1988), Ravid (1999), De Vany and Walls (1996) and Elberse (2007)); screen management (Swami et al. (1999)); policy makers for international films (Stokes and Jones (2017)) and online reviews and web based promotions (Dellarocas et al. (2007), Foutz and Jank (2010) and Liu (2006)). There are studies based on the indirect measure of quality such as reviewers (Ginsberg and Weyers (1999)), awards (Nelson et al. (2001), Deuchert at al. (2005) and Lee (2009)). The only study on effect of substitutes in related field appears to be in the field of movie theatres by Davis (2006), who finds that entry of new movie theatres leads to cannibalization of sales of incumbents and could cause exit of firms. While these studies may have focused on other aspects, the objective of our paper is to measure the effect of advertising, production cost, quality and the number of substitute movies both from the same genre as well as from other genres on the movie life cycle.

Our paper contributes to the existing literature in three ways. First, the data in this study include the box-office sale of wide release movies in the U.S. Besides working on the production cost and advertising expenditures of movies, as used by similar studies, this paper also utilizes the ratings of movies provided by viewers from Netflix as a measure of product quality. Second, we construct a new variable on substitutes, which measures the number of movies being played in theatres during a given week when a given movie is in theatres. We also look at substitutes from the same genre as a given movie in this study. Third, we also account for the decay effect of time of residence in theatres in this study.

We present three new empirical findings. First, there is significant impact of the introduction of new movies on the decay of existing movies. But, if broken down by genre, then the effect is relatively less significant. That is, the introduction of a children's movie does not have a significant influence on an existing children's movie, but the combined effect of all substitutes can be sizable. The effect also varies by the type of genre. Second, significant advertising expenditure and good movie quality help lower this decay especially in the later stage of the life cycle. Third, we find that with increasing time, the decay factor becomes more potent. The rest of the paper is organized as follows. In the next section, we present a model for movie life cycle that leads to the empirical framework in Section 2. Section 3 describes and discusses the sources of all data used. Section 4 contains the results, while Section 5 concludes.

2. MODEL

In our model of movies, we assume that consumers make a decision to go to movies and then choose a specific movie from a set of available movies playing in theatres at that time. Further, consumers react to signals from the market. Prices are an obvious factor but there is a surprising uniformity in prices for first run movies across theatres, and as such, are not useful modeling movie choices (when we use models described later with prices, we do not find evidence of a relationship between change in box office sales and ticket price). Instead, we assume that choices are made on the basis of market signals such as quality and advertising as well as how long the movie has been in the theatres. At a point in time, there is a set of movies **C**, and an individual chooses movie '*c*' if the utility from that movie exceeds that of alternatives. The utility is higher if movie quality is better or if the movie is relatively 'new' or if the movie is heavily publicized through relatively high advertising expenditures. From this framework, the demand model is as follows:

$$Q_c = f(A_c, R_c, \xi_c, w) \tag{1}$$

where Q_c is the box office sales for movie 'c' during week 'w'; R_c is the measure of quality of the movie; A_c is the advertising expenditure on movie *c*; ξ_c is a variable that captures other influencers of the utility, such as substitutes and production cost, and *w* is the week since the release of the movie. Major factors that lead to qualitative shift in demand is the number of substitutes released during a given week and season of the year in which the movie is released.

The central idea here is that as advertising and quality of movie '*c*' changes, there is change in attendance. In most cases, advertising and quality are determined prior to release, while in some these evolve with weeks since release. Naturally, as the length of time a movie has been in the theatres increases, viewers perceive lower utility from watching the movie in theatres and the probability of attending diminishes (decays).

There are a number of additional factors considered. First, agents may choose the genre i.e., the type of movie to attend and then the specific movie. Second, over time, the set of movies available for viewing changes as some existing movies are taken off theatres and some new movies are introduced. With it changes the choice set 'C'. Third, the week of the year in which a movie is released creates a difference in box office sales. It is well known that movie sales skyrocket during Independence Day (July 4) and Christmas (December 25) weeks (see Einav, 2007). Hence, blockbuster movies compete to receive greater audience eyeballs during these weeks through signaling much in advance of release (see Einav and Ravid, 2009).

Our data set contains total sales by movie and week for all first run movies which forms a part of the dependent variable in our empirical work. Control variables include advertising, quality, weeks in the theatre, a variable "sub" that captures the introduction of rival movies. Conventional life cycle studies are based on the Bass (1969) diffusion model which considers the probability of an individual adoption at time 't' given no previous purchases. As discussed previously, diffusion models have been applied for movies by Ainsle et al. (2005) and by Sawhney and Eliashberg (1996).

In the case of a movie, the role of a decision maker to watch a movie is based on the characteristics discussed above. However, unlike other new products, the simultaneous introduction of a (wide-release) movie, across many theatres nationally is dependent on capacity constraints (theatre screens), inter and intra-firm competition arising out of several movies from the same distributor and several distributors being represented at the same theatre and due to seasonality constraints (Einav, 2007 and Gil and Lafontaine, 2012).

To examine identify lifecycle effects, we consider a small change in demand for a representative movie 'j' during time 'dt'.

$$\frac{\partial(Q_{jt})}{Q_{jt}} = f_1(A_j, R_j, \xi_j)\ dt \tag{2}$$

where: Q_{jt} is the demand and is represented by box office sales for movie j at week t; R_j is the measure of quality of the movie; A_j is the advertising expenditure on movie j; and

ξ_j are the movie specific shifters such as substitutes released during week 't' and production cost for movie 'j'.

The assumption of the time independence of the factors that contribute to movie sales is relatively important. There are exceptions to this assumption. Some distributors stagger advertising expenditures. The audience's perception of product quality may be dynamic and evolve over the run of the movie in theatres. Some movies may postpone/ prepone their release date. Some others start out as limited release movies, being released in a handful of 'test' markets before being released as wide-release movies. While these factors are exceptions in the model, it is important to note this limitation of our model. Every movie becomes less attractive as more and more time elapses since its release. This causes degradation in movie sales. We can associate this with a decay parameter λ, and using equation 1 yields:

$$\frac{\partial Q_{jt}}{Q_{jt}} = f(A_j, R_j, \xi_j, \lambda)dt \tag{3}$$

If f(.) is independent of time, we rewrite (3) as:

$$\ln\left(\frac{Q_{jt}}{Q_{jt-1}}\right) = \left(a\xi_j + \alpha A_j + \rho R_j\right)\left(w_t - w_{(t-1)}\right) + \lambda_{t,t-1}\left(w_t - w_{(t-1)}\right) \tag{4}$$

where w_t is the number of weeks 't' since the introduction of the movie; and $Q_{j,t-1}$ is the box office revenues for movie j in week 't-1' from which the change is measured.

The model developed in (4) is the log linear form similar to those used in Bass (1969) diffusion models. We can consolidate this equation across the 10 weeks of study for each movie 'j' as follows:

$$\ln\left(\frac{Q_{jt}}{Q_{jt-1}}\right) = \alpha_{t,t-1}A_j D_{t,t-1} + \rho_{t,t-1}R_j D_{t,t-1} + a_{t,t-1}\xi_j D_{t,t-1} + \lambda_{t,t-1}D_{t,t-1},\ \forall t = 2 \ldots 10 \tag{5}$$

If advertising expenditures and other shifters do not vary significantly across the weeks in theatres, then we can simplify equation (5) as

$$\ln\left(\frac{Q_{jt}}{Q_{jt-1}}\right) = \left(a_j\xi_j + \alpha_j A_j + \rho_j R_j\right) + \sum_{t=2}^{10}\lambda_{t,t-1}D_{t,t-1} + \varepsilon_j \tag{6}$$

In our model, the dependent variable is constructed from weekly box office sales classified per movie. However, it should be noted that this model does not exactly involve a demand function being observed. Since it is a change in box office sales, the representation is more about decay in sales being observed from a theatre's perspective on a macro level. Consequently, there are some assumptions involved here, which this research must make a note of, such as heterogeneity in weather, in cultural preferences of individuals evolving over periods of time in the study, that arises out of assuming the audience preference and tastes. However, we are not assuming perfect homogeneity, because we are still conditioning for preference for different genres. Moreover, the advertising expenditures of a movie, average customer rating for the movie, production cost of the movie and the number of substitutes are assumed to be exogeneous factors. Any residual audience heterogeneity is being captured by the error term, but applies to all wide release movies at the same point in time. Consequently, we can state that all the movies face the same audience heterogeneity, which leads us to make the assumption that the expected value of the error term will be zero. The validity of this assumption is based on the geographical and temporal dispersion of movies being considered in the model and would be more problematic had limited release movies also been included in the model. Another problem is of endogeneity, which we have considered in our model and this is discussed and explained in detail along with the discussion on empirical results.

The assumption that the chosen independent variables are exogeneous is intuitively reasonable. For example, the production cost of a movie is generally predetermined. The advertising budget is also set and the expenditures are determined before the launch of the movie, although sometimes the distributors may feel the desire to increase the advertising expenditures during the run in the theatres. The number of substitutes is predetermined due to the timing game. This study also assumes that consumers develop a perception of movie quality as soon as they watch the movie.

More specifically, we use the following regression model for empirical analysis:

$$\ln\left(\frac{Q_{jt}}{Q_{jt-1}}\right) = \alpha A_j + \rho R_j + a_1 PC_j + a_2 Sub_{tj} + \lambda_1 D_{2-1} + \lambda_2 D_{3-2} + \lambda_3 D_{4-3} + \lambda_4 D_{5-4} + \lambda_5 D_{6-5} + \lambda_6 D_{7-6} + \lambda_7 D_{8-7} + \lambda_8 D_{9-8} + \lambda_9 D_{10-9} + \varepsilon_j \tag{7}$$

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where Q_{jt} and Q_{jt-1} are respectively box office sales of movie j in week t and t-1; A_j is advertisement expenditure for movie j; R_j is the mean of consumer ratings for movie j; PC_j is the production cost incurred for movie j; D_{t-t-1} is the dummy for the week t over t-1, t going from 2 to 10; and Sub_{tj} is the number of new wide-release movies released in week t for movie j.

We consider only wide-release movies in this study. One limitation of the study is the lack of consideration of movies that used a limited release strategy before launching as wide release movies in order to test markets or to be eligible for consideration toward Academy Award. Examples of such movies include Wind River and Step (2017) and Lion (2016). The full theatrical run is not captured by our model in such a case. Furthermore, in an alternate specification to this model, the dummy for each week can be replaced by a linear time trend. However, that will violate the theoretical assumption of this specification of an exponential decay in box office sales. Similarly, other parametric specifications can be studied. However, these do not have a theoretical basis and support from the literature on life cycle of products.

In the analysis, there are five central hypotheses examined. These are:

- *Ceteris paribus*, higher production cost does not affect the change in box office revenues
  - $H_{1,0}: a_1 = 0 \ vs \ H_{1,a}: a_1 \neq 0$;
- *Ceteris paribus*, a change in advertising expenses do not affect the change in box office revenues
  - $H_{2,0}: \alpha = 0 \ vs \ H_{2,a}: \alpha \neq 0$;
- *Ceteris paribus*, a change in the quality of movies does not affect the change of box office sales
  - $H_{3,0}: \rho = 0 \ vs \ H_{3,a}: \rho \neq 0$;
- *Ceteris paribus*, each dummy captures the decay effect of time. (i.e. the effect of increasing time does not lead to a change in box office sales)
  - $H_{4,0}: D_{t,t-1} = 0 \ vs \ H_{4,a}: D_{t,t-1} \neq 0$;
- *Ceteris paribus*, the change in the number of substitutes released during the same week, does not have any effect on the change in box office sales.
  - $H_{5,0}: a_2 = 0 \ vs \ H_{5,a}: a_2 \neq 0$;

Negative and significant value of the "sub" variable will suggest that the introduction of a substitute movie has a deleterious effect on the box office revenues of the movie being analyzed, and makes the sales decay faster. As discussed before, we allow the effects to vary between movies of the same genre as well as from all genres.

We estimate 10 regression models to include the examination of the effect of substitutes on decay in box office sales. Model 1 is based upon the specification in equation 7 and does not distinguish a movie based on its genre. However, Model 2 includes the "sub" variable in Model 1 and considers the effect of release of all movies (irrespective of their genre) as substitutes. Models 3 – 6 take into account the genre of a movie. These genres considered are Action (Model 3), comedy (Model 4), drama (Model 5) and children (Model 6). Models 3 – 6 estimate equation 7 with the "sub" variable where "sub" is defined as the movies belonging to all genres. We also compare the effect of all movies as substitutes with movies from same genre as substitutes. Hence, in Models 7 – 10, the "sub" variable denotes the number of movies released during a given week that belong to the same genre. These effects are considered for action (Model 7), comedy (Model 8), drama (Model 9) and children's (Model 10) genre.

3. DATA AND DESCRIPTIVE STATISTICS

The movie data include 1535 wide release movies selected from a dataset of 2271 movies released between January 1, 1985 and December 31, 1999. First nine weeks of 1985 have not been considered because data on movies released in 1984 is not used. One opportunity to study movies from this time period is that due to the broad absence of the internet and online reviews being available to viewers during this period, the shifters under consideration were not affected by the online media. Viewers during this time depended more strongly on the early adopters, who went to watch the movie because of the perception being built from trailers, print media, television and most importantly from other viewers to determine movie quality. To these observations, the average of viewer ratings for each movie were matched up with data obtained from Netflix (www.netflixprize.com, accessed November 17, 2009). In 2009, Netflix had organized an open competition in which it made its user ratings public for a limited time. Average of Netflix ratings was 3.32 on a scale of 5, where a score of "1" indicates that a viewer "hated a movie" and "5" indicates that a viewer "loved it". Consequently, there are 13,358 weekly observations across movies of all genres. Any movie that reached 600 screens during a week in box office is defined as wide release movie. Any movie that reached 600 screens has been included in the data. Einav (2007) makes a similar judgment based on the fact that the peak of screens across movies follows a bimodal distribution with 600 screens falling between two modes.

The average cumulative box office revenue for non-wide release movies is $3.75 million, and the average production cost is $ 5.57 million. It is noted that production costs are determined prior to the movie release, and as such can be thought of as pre-determined sunk costs. While these variables are at an aggregated level and a wide dispersion in the nature of the movies makes it intuitively tougher to account for movie fixed effects, understanding the inherent movie heterogeneity and classifying it according to a specific genre makes the analysis a bit more comprehensive. Average cumulative box office revenue for wide release movies is $ 43.61 million and average production cost is $ 26.23 million for the included wide-release movies. Wide release movies account for 96% of total box office sales in the original sample. Hence, we assume that wide release movies are a better representation of movie life cycle analysis. The average number of weeks in theatres is 8.7, and most of the revenues, 90 percent, are realized in the first ten weeks. Almost 71% of wide-release movies did not complete 10 weeks in theatres. Most movies, about 85%, are released on Fridays. To account for movies not released on Friday, box office sales until the same Friday were considered to belong to week 0. This could be a potential source of measurement error in our empirical model and results. Weekly revenues of wide release movies are as in figure 1. Another reason why we limit our discussion to wide-release movies is that the decay of sales for limited release movies could be negative (representing growth in movie sales). This growth may be purely due to expansion in extent of their release on an account of relaunch as wide release movie. We therefore limit our discussion to wide-release movies, to avoid this difference in the product diffusion characteristics of box office revenues. The analysis of life cycle of limited release movies can be the topic of discussion of an altogether new study as an extension of this study.

4. RESULTS

Table 2 presents results from regression Models 1 - 10. In Model 1, we consider the empirical specification of equation 7, without the 'sub' variable. The coefficient of production cost (a_1) is not significantly different from zero at 10 percent level, suggesting that production cost does not matter in determining the change in the movie sales. This could be due to the fact that production cost is a sunk cost. But there is a chance that "advertising" and "movie quality" are endogenous variables. These may be a function of the production cost. When the total cost of movies is being allocated, there are instances that the advertising budget may also be determined as a percentage of the overall budget. Similarly, viewers may construe superior production cost as a signal for higher quality, which may also attract higher advertising expenditures. We test for the endogeneity of movie quality and advertising cost. We use production cost as an instrument for advertising cost and movie quality. We perform 2-stage least squares regressions using production cost as instrument in all models (1 - 10). While, we find no evidence of endogeneity in our base model (Model 1), we do find evidence in the model when the "sub" variable is introduced. We also perform Hausman's Test for finding evidence of specification bias. The statistic is not significant at 10 percent in the base model, but does show significance when the "sub" variable is introduced. Hence there is some evidence that IV is the appropriate estimator. However, the numerical estimates of OLS and IV are very similar, and, in no case, are the primary findings of the paper affected by the choice of estimation technique. Moreover, significance of Hausman's statistic is not evident in all models. Only the models of children's movie (Models 6 and 10) reject the hypothesis that parameters in name consistent (IV) and name efficient (OLS) models are significantly different from each other at 1 percent significance. Since the coefficient of production cost is not significantly different from zero at 10% level, we fail to reject the hypothesis $H_{1,0}$.

From model 1 in table 2, the coefficient of advertising expenditure, α, is positive and significant at 1 percent. This seems to suggest that strongly advertised movies are likely to attract greater audiences and face slower decay in sales, all else constant. However, there is also some support in the argument that good quality movies will be allocated greater advertising budgets creating endogeneity in the advertising variable. However, from the findings of model 2 we reject the null hypothesis $H_{2,0}$.

Moreover, from model 1, we find that ρ, the coefficient of product quality is positive and significant at 1%. This implies that the null hypothesis $H_{3,0}$ is rejected at 1%. Superior quality prevents the decay of product revenues. Looking at the decay effects of time, the coefficients of dummy variables (λ_1 – λ_9) are all negative and significant at 1 percent, thus demonstrating the importance that the effect of time has on product life cycle. Moreover, there is evidence of increasing decay effect of time on change in box office sales, as evidenced by the coefficients λ_1, λ_2, λ_3, λ_5, λ_7 and λ_8. This enables us to reject the null hypothesis $H_{4,0}$.

In Model 2, the "sub" variable represents number of substitute movies released during a given week. The coefficient of "sub" variable is negative and significant at 1 percent. This confirms the intuition of a strong negative effect exerted by substitutes on product life-cycle of movies during the week of their release. The audience tends to gravitate toward what is "new". The key finding obtained by comparing Models 1 and 2 is that every new substitute movie launched during a given week will lead to faster decay in movie sales. Thus, we reject the null hypothesis $H_{5,0}$.

We also examine the effects of the introduction of a substitute in the same genre. We compare the introduction of a substitute in the same genre with that of the introduction of movie from any genre. These effects are captured in Models 3 – 10. In general, the results indicate strong substitution effects for movies of certain genres due to introduction of movies from all other genres. Results also indicate weak substitution effects for movies of specific genres due to introduction of movies in the same genre. Specifically, the introduction of a new movie from any genre leads to faster decay in life of Action and Comedy movies (Models 3 and 4). This could be because action and comedy movies draw more general audiences than drama and children's movies. We fail to reject $H_{5,0}$ when we look at a_2 in models 5 and 6. Furthermore, our results are also not conclusive for introduction of new movies from the same genre (i.e. Comedy and Children's movies in Models 8 and 10). For action and drama genres, the introduction of new movies also do not have statistically significant effects at 10% level. Hence, we fail to reject the hypothesis $H_{5,0}$ when substitutes from the same genre are introduced (Models 7 – 10).

To measure the effect of each control variable during different week, we run the same regression as specified in tables 2 and 3, but we interact each control variable with weekly dummies. This enables us to capture the effect of the controls partially each week. This empirical specification is seen in equation 5. These results are shown in table 4 for all movies and movies of specific genres but with the effect of all new substitutes. In table 5 regressions for models 17 – 20 consider models 13 – 16 but only with the effect of substitutes of the same genre.

From table 4, Models 11 – 12, we find that initially there is no effect of the movie quality on product life cycle. Positive effects begin to play a more meaningful role in preventing the decay beyond 4 weeks. This makes sense intuitively as the word of mouth catches up, the movie does not decay as rapidly as a movie that does not generate a strongly positive word of mouth. This is seen from the coefficients $\rho_{t,t-1}$, when we reject the null hypothesis $H_{3,0}$ for almost all the weeks after week 4. The parameters of the production cost variable remain indistinguishable from zero at 10% significance. This is observed in the coefficients $a_{1\ t,\ t\text{-}1}$. The coefficients of the sub variable are negative in model 12, with the exception of $a_{2\ 3,2}$. Furthermore, these coefficients are significant at 1% for weeks 8, 9 and 10. Substitutes accelerate the decay of movie life particularly toward the end. The magnitudes of these three coefficients are relatively larger and significant at 1 percent. We can conclude that exit of a product is exacerbated by introduction of substitutes. A plot of coefficients of the "sub" variable interacted with the weekly dummy variables is shown in figure 2. This plot demonstrates the increased effect of the release of substitute movies from all genres during last three weeks of movies in theatres. Thus, $H_{5,0}$ is rejected strongly during the last three weeks. The coefficients of advertising expenses are positive and significant across all weeks indicating the high correlation of movie life cycle with strongly advertised movies.

When we look at models 13 – 16 in table 4, these models represent the effect of different variables on movie life cycle if broken down by genre. Model 13 is for action movies, 14 for Comedy, 15 for Drama and 16 for children's movies. The results are somewhat similar to models 11 and 12. The estimates for movie quality are positive and significant but do not begin to accrue until week 4. The coefficients of production cost are generally not significant at 10%. The coefficients of "sub" variable ($a_{2\,t,\,t\text{-}1}$) are negative but are not as significant as in model 12. The coefficients of advertising continue to show strong positive and significant effects especially after week 4 (Model 14, 15) and week 5 (Model 13, 16).

Finally, in table 5 we consider equation 5 with substitution effects of movies from the same genre. The results of coefficients of movie quality, advertising, production cost and the weekly dummies remain largely similar to those in table 4. There is a slight difference in the effect of substitutes on movie life cycle. The coefficient of the "sub" variable remains negative for Action movies from weeks 7 – 10. However, the parameter estimate loses statistical significance, indicating that new movies affect action movies negatively during the later part of the life cycle. However, the effect is not as pronounced if the substitutes are from the Action genre. Similar results are observed for the "comedy" and "drama" genres but the exception is the children's genre. Substitutes of movies in this genre are negatively affected by movies from the same (Children's) genre during weeks 6 and 10, which is different from the effect of all movies on the movies in this genre (Model 16 vs Model 20).

5. CONCLUDING REMARKS

Movies in theatres are quick to perish and provide an opportunity to study life cycle for products with a short shelf-life. From our results, we observe that the audience appreciates a good quality movie. Consequently, the decay effects are less pronounced for such movies especially after weeks 4 and 5 since release, when the word-of-mouth effects start building up. Similarly, it is also observed that increased advertising expenditures are linked with the slower decay effects. Both quality and advertising are an important tool at the disposal of the producers. However, production cost does not seem to affect the product life cycle. Generally, substitutes shorten the product life cycle, particularly toward the end. However, in case of differentiated products, depending on the nature of the product, substitutes effect product life cycle differently. The effect of substitutes is more significant in case of action and comedy movies but is the least effective in case of drama movies. Children's movies are less significantly affected by movies from the other genres as they are from other children's movies.

This paper has four main conclusions. First, the introduction of substitutes is an important reason that causes a product to decay faster. Second, good quality products survive significantly longer than the average. Consumers tend to reward superior movie quality with slower decay rates. Third, as with any differentiated product, the effect of substitutes is different for products of different types. The effect of the same genre substitute movies is less than the overall effect of substitutes except in the case of highly focused children's movies. Fourth, good quality products with the strong support from advertising tend to be more successful. This shows producer confidence and the audience tends to be more convinced about the product than their poorly advertised counterparts. Our empirical work supports the Economic theory that good product quality and strong advertising support the product life cycle while increasing competition from substitutes hurts the product life.

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Table 1: Descriptive Statistics of Wide Release Movies

Variable	Description	N	Mean	Std. Dev.	Min	Max
R	Average of Ratings obtained from Netflix	1535	3.32	0.36	2.10	4.46
pc	Production cost ($ million)	1535	31.41	23.28	1.01	208.68
Q_{21}	log of ratio of revenue in current week to revenue in the previous week	1535	-37.65	189.95	-1000	2.40
A	Advertising expenditures ($ million)	1535	8.79	6.01	0.01	42.48
Sub	Number of new substitute released during the week	13815	1.83	1.55	0.00	9.00

Table 2: Regression Results for Models 1 – 6

Genre	Model 1 All	Model 2 All	Model 3 Action	Model 4 Comedy	Model 5 Drama	Model 6 Children
ρ	27.894^{a}	28.088^{a}	27.226^{a}	29.527^{a}	38.034^{a}	15.895
	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.278)
a_1	-0.057	-0.061	0.159	0.061	-0.238	-0.182
	(0.517)	(0.490)	(0.284)	(0.795)	(0.181)	(0.465)
α	3.292^{a}	3.496^{a}	3.463^{a}	3.260^{a}	3.490^{a}	2.883^{a}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ_1	-123.700^{a}	-118.237^{a}	-119.666^{a}	-117.491^{a}	-155.246^{a}	-82.579
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.122)
λ_2	-133.117^{a}	-127.396^{a}	-132.691^{a}	-123.108^{a}	-159.528^{a}	-99.302^{c}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.062)
λ_3	-154.210^{a}	-148.563^{a}	-154.453^{a}	-152.984^{a}	-178.583^{a}	-90.322^{c}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.090)
λ_4	-153.419^{a}	-148.073^{a}	-168.938^{a}	-133.627^{a}	-182.200^{a}	-99.737^{c}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.061)
λ_5	-165.083^{a}	-159.416^{a}	-157.005^{a}	-160.137^{a}	-191.784^{a}	-144.467^{a}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)
λ_6	-162.733^{a}	-157.761^{a}	-162.599^{a}	-154.653^{a}	-198.224^{a}	-108.577^{b}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.042)
λ_7	-172.060^{a}	-167.482^{a}	-179.020^{a}	-159.961^{a}	-201.914^{a}	-125.177^{b}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)
λ_8	-174.383^{a}	-170.078^{a}	-201.614^{a}	-163.857^{a}	-173.159^{a}	-133.735^{b}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.012)
λ_9	-168.110^{a}	-163.999^{a}	-165.925^{a}	-157.800^{a}	-205.231^{a}	-133.876^{b}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.012)
a_2		-4.068^{a}	-4.620^{b}	-5.831^{a}	-3.520	2.280
		(0.000)	(0.030)	(0.002)	(0.101)	(0.515)
N	11538	11538	3762	3960	2790	1026

p-value in parenthesis, ^{c} p<0.10, ^{b} p<0.05, ^{a} p<0.01

Table 3: Regression Results for Substitute Movies Released in the Same Genre

	Model 7	**Model 8**	**Model 9**	**Model 10**
Genre	Action	Comedy	Drama	Childrens
ρ	27.486[a]	29.317[a]	37.794[a]	15.902
	(0.004)	(0.000)	(0.000)	(0.277)
a_1	0.153	0.075	-0.218	-0.187
	(0.305)	(0.750)	(0.218)	(0.452)
α	3.189[a]	2.963[a]	3.288[a]	3.001[a]
	(0.000)	(0.000)	(0.000)	(0.000)
λ_1	-127.012[a]	-124.202[a]	-162.609[a]	-76.954
	(0.000)	(0.000)	(0.000)	(0.147)
λ_2	-142.191[a]	-130.724[a]	-165.493[a]	-94.873[c]
	(0.000)	(0.000)	(0.000)	(0.074)
λ_3	-163.845[a]	-160.362[a]	-185.116[a]	-86.507
	(0.000)	(0.000)	(0.000)	(0.103)
λ_4	-178.249[a]	-139.915[a]	-188.245[a]	-94.926[c]
	(0.000)	(0.000)	(0.000)	(0.073)
λ_5	-166.152[a]	-167.174[a]	-197.966[a]	-138.618[a]
	(0.000)	(0.000)	(0.000)	(0.009)
λ_6	-170.836[a]	-160.427[a]	-204.385[a]	-103.568[c]
	(0.000)	(0.000)	(0.000)	(0.051)
λ_7	-187.663[a]	-165.001[a]	-207.595[a]	-121.148[b]
	(0.000)	(0.000)	(0.000)	(0.022)
λ_8	-209.174[a]	-169.339[a]	-178.641[a]	-129.847[b]
	(0.000)	(0.000)	(0.000)	(0.014)
λ_9	-173.188[a]	-162.515[a]	-210.764[a]	-130.025[b]
	(0.000)	(0.000)	(0.000)	(0.014)
a_2	3.405	-2.075	2.980	-6.730
	(0.462)	(0.534)	(0.493)	(0.545)
N	3762	3960	2790	1026

p-value in parenthesis, [c] $p<0.10$, [b] $p<0.05$, [a] $p<0.01$

Table 4: Regression Results with Interacted Weekly Dummy for All movies (Model 11), with effect of substitutes (Model 12) and for Movies in Different Genres (Models 13 – 16)

	Model 11 All	Model 12 All	Model 13 Action	Model 14 Comedy	Model 15 Drama	Model 16 Children
$\rho_{2,1}$	-5.267	-5.407	0.171	-9.874	-6.109	0.288
	(0.712)	(0.705)	(0.995)	(0.688)	(0.834)	(0.995)
$\rho_{3,2}$	15.083	15.211	-4.080	2.682	43.837	62.968
	(0.291)	(0.287)	(0.886)	(0.913)	(0.131)	(0.152)
$\rho_{4,3}$	62.510[a]	62.377[a]	63.766[b]	81.987[a]	54.095[c]	-18.515
	(0.000)	(0.000)	(0.024)	(0.001)	(0.063)	(0.682)
$\rho_{5,4}$	13.629	13.758	38.098	15.457	-6.335	-19.626
	(0.340)	(0.335)	(0.177)	(0.530)	(0.827)	(0.658)
$\rho_{6,5}$	40.647[a]	40.765[a]	30.335	13.956	53.175[c]	170.601[a]
	(0.004)	(0.004)	(0.282)	(0.570)	(0.067)	(0.000)
$\rho_{7,6}$	49.863[a]	50.323[a]	38.004	52.540[b]	98.723[a]	5.902
	(0.000)	(0.000)	(0.178)	(0.032)	(0.001)	(0.893)
$\rho_{8,7}$	19.042	21.700	6.784	31.052	45.219	7.701
	(0.183)	(0.129)	(0.810)	(0.207)	(0.120)	(0.860)
$\rho_{9,8}$	32.329[b]	33.356[b]	35.800	57.812[b]	35.729	-110.362[b]
	(0.024)	(0.020)	(0.204)	(0.019)	(0.222)	(0.012)
$\rho_{10,9}$	23.209	25.146[c]	41.861	21.131	22.764	50.561
	(0.104)	(0.078)	(0.138)	(0.391)	(0.433)	(0.249)
$a_{1\ 2,1}$	0.000	-0.004	-0.001	0.111	-0.104	0.001
	(0.999)	(0.989)	(0.999)	(0.874)	(0.846)	(0.999)
$a_{1\ 3,2}$	0.010	0.009	-0.082	0.058	0.059	0.553
	(0.971)	(0.972)	(0.853)	(0.934)	(0.912)	(0.460)
$a_{1\ 4,3}$	-0.125	-0.129	0.487	-0.528	-1.166[b]	-0.161
	(0.637)	(0.628)	(0.275)	(0.453)	(0.030)	(0.829)
$a_{1\ 5,4}$	-0.359	-0.367	0.650	-0.338	-1.360[b]	-1.460[c]
	(0.176)	(0.167)	(0.144)	(0.630)	(0.011)	(0.052)
$a_{1\ 6,5}$	0.393	0.400	0.381	0.301	0.682	0.706
	(0.139)	(0.132)	(0.396)	(0.669)	(0.199)	(0.344)
$a_{1\ 7,6}$	0.145	0.144	0.485	-0.331	-0.050	0.323
	(0.585)	(0.588)	(0.275)	(0.638)	(0.925)	(0.664)
$a_{1\ 8,7}$	-0.336	-0.330	-0.296	-0.243	-0.480	0.093
	(0.205)	(0.213)	(0.506)	(0.729)	(0.368)	(0.900)
$a_{1\ 9,8}$	-0.414	-0.446[c]	-0.767[c]	0.752	0.266	-1.505[b]
	(0.119)	(0.093)	(0.085)	(0.286)	(0.619)	(0.043)
$a_{1\ 10,9}$	0.171	0.163	0.591	0.742	-0.046	-0.114
	(0.520)	(0.540)	(0.185)	(0.291)	(0.932)	(0.878)

p-value in parenthesis, [c] $p<0.10$, [b] $p<0.05$, [a] $p<0.01$

Table 4 continued...

	Model 11 All	Model 12 All	Model 13 Action	Model 14 Comedy	Model 15 Drama	Model 16 Children
$a_{2\,2,1}$		-1.736	0.009	-2.795	-2.484	0.012
		(0.631)	(0.999)	(0.655)	(0.711)	(0.999)
$a_{2\,3,2}$		0.584	1.801	-0.393	0.137	-1.697
		(0.861)	(0.785)	(0.942)	(0.983)	(0.863)
$a_{2\,4,3}$		-1.244	2.761	-9.210	-1.881	2.465
		(0.715)	(0.670)	(0.100)	(0.774)	(0.848)
$a_{2\,5,4}$		-2.419	-0.191	-5.824	-3.416	0.170
		(0.480)	(0.976)	(0.324)	(0.605)	(0.988)
$a_{2\,6,5}$		-1.922	7.406	-8.345	-4.719	-5.894
		(0.550)	(0.233)	(0.115)	(0.459)	(0.546)
$a_{2\,7,6}$		-3.026	-5.552	-3.052	-2.440	2.154
		(0.365)	(0.407)	(0.574)	(0.697)	(0.839)
$a_{2\,8,7}$		-10.459^{a}	-12.793^{b}	-11.167^{c}	-14.587^{b}	10.333
		(0.002)	(0.044)	(0.053)	(0.018)	(0.303)
$a_{2\,9,8}$		-8.860^{a}	-16.930^{a}	-7.992	-1.550	-6.537
		(0.007)	(0.007)	(0.140)	(0.810)	(0.525)
$a_{2\,10,9}$		-9.611^{a}	-18.912^{a}	-6.433	-3.340	1.317
		(0.004)	(0.001)	(0.268)	(0.617)	(0.911)
$\alpha_{2,1}$	0.189	0.241	0.002	0.139	0.724	0.013
	(0.853)	(0.815)	(0.999)	(0.944)	(0.720)	(0.996)
$\alpha_{3,2}$	1.868^{c}	1.851^{c}	2.729	1.829	1.195	0.707
	(0.069)	(0.072)	(0.180)	(0.351)	(0.554)	(0.770)
$\alpha_{4,3}$	4.408^{a}	4.443^{a}	3.268	5.196^{a}	7.425^{a}	0.953
	(0.000)	(0.000)	(0.106)	(0.008)	(0.000)	(0.693)
$\alpha_{5,4}$	4.839^{a}	4.934^{a}	3.744^{c}	2.624	7.841^{a}	5.107^{b}
	(0.000)	(0.000)	(0.064)	(0.182)	(0.000)	(0.038)
$\alpha_{6,5}$	3.673^{a}	3.754^{a}	2.176	5.932^{a}	4.111^{b}	3.864
	(0.000)	(0.000)	(0.280)	(0.003)	(0.044)	(0.117)
$\alpha_{7,6}$	3.404^{a}	3.615^{a}	3.555^{c}	4.349^{b}	3.140	1.931
	(0.001)	(0.001)	(0.089)	(0.028)	(0.126)	(0.448)
$\alpha_{8,7}$	4.179^{a}	4.747^{a}	6.292^{a}	4.451^{b}	3.557^{c}	3.202
	(0.000)	(0.000)	(0.002)	(0.025)	(0.087)	(0.186)
$\alpha_{9,8}$	4.613^{a}	5.278^{a}	9.873^{a}	1.717	-0.292	7.970^{a}
	(0.000)	(0.000)	(0.000)	(0.397)	(0.888)	(0.001)
$\alpha_{10,9}$	2.459^{b}	3.250^{a}	1.104	3.496^{c}	4.285^{b}	3.104
	(0.017)	(0.002)	(0.593)	(0.080)	(0.047)	(0.212)

p-value in parenthesis, ^{c} $p<0.10$, ^{b} $p<0.05$, ^{a} $p<0.01$

Table 4 continued…

	Model 11 All	Model 12 All	Model 13 Action	Model 14 Comedy	Model 15 Drama	Model 16 Children
λ_1	13.335	16.793	-0.771	30.914	16.603	-1.221
	(0.776)	(0.723)	(0.993)	(0.700)	(0.869)	(0.994)
λ_2	-79.517[c]	-80.951[c]	-26.633	-34.718	-174.586[c]	-256.746[c]
	(0.090)	(0.088)	(0.776)	(0.663)	(0.080)	(0.096)
λ_3	-277.531[a]	-274.848[a]	-300.096[a]	-318.997[a]	-244.721[b]	45.765
	(0.000)	(0.000)	(0.001)	(0.000)	(0.014)	(0.780)
λ_4	-110.632[b]	-107.085[b]	-234.293[b]	-72.677	-33.906	49.717
	(0.018)	(0.023)	(0.010)	(0.366)	(0.734)	(0.743)
λ_5	-225.163[a]	-222.728[a]	-186.952[b]	-134.100[c]	-276.390[a]	-694.068[a]
	(0.000)	(0.000)	(0.040)	(0.092)	(0.006)	(0.000)
λ_6	-243.244[a]	-241.185[a]	-209.544[b]	-234.191[a]	-412.924[a]	-83.259
	(0.000)	(0.000)	(0.021)	(0.003)	(0.000)	(0.587)
λ_7	-141.968[a]	-138.274[a]	-105.595	-159.445[b]	-200.222[b]	-124.157
	(0.002)	(0.003)	(0.246)	(0.044)	(0.044)	(0.418)
λ_8	-190.052[a]	-183.958[a]	-234.535[b]	-255.156[a]	-149.319	305.244[b]
	(0.000)	(0.000)	(0.010)	(0.001)	(0.132)	(0.046)
λ_9	-152.043[a]	-150.109[a]	-186.996[b]	-148.299[c]	-166.041[c]	-254.999[c]
	(0.001)	(0.001)	(0.040)	(0.061)	(0.094)	(0.093)
N	11538	11538	3762	3960	2790	1026

p-value in parenthesis, [c] $p<0.10$, [b] $p<0.05$, [a] $p<0.01$

Table 5: Regression Results for Substitute Movies Released in the Same Genre with Interacted Weekly Dummy Variables

	Model 17 Action	Model 18 Comedy	Model 19 Drama	Model 20 Children
$\rho_{2,1}$	0.168	-9.805	-5.146	0.295
	(0.995)	(0.691)	(0.859)	(0.995)
$\rho_{3,2}$	-2.317	2.467	43.783	64.968
	(0.935)	(0.920)	(0.132)	(0.138)
$\rho_{4,3}$	64.060[b]	83.024[a]	53.985[c]	-19.914
	(0.023)	(0.001)	(0.064)	(0.651)
$\rho_{5,4}$	38.618	17.078	-6.029	-20.534
	(0.172)	(0.487)	(0.836)	(0.641)
$\rho_{6,5}$	33.556	11.401	57.305[b]	167.665[a]
	(0.236)	(0.644)	(0.050)	(0.000)
$\rho_{7,6}$	37.194	51.963[b]	97.701[a]	3.881
	(0.188)	(0.035)	(0.001)	(0.929)
$\rho_{8,7}$	3.758	27.407	45.379	0.657
	(0.894)	(0.265)	(0.119)	(0.988)
$\rho_{9,8}$	37.155	57.229[b]	34.994	-108.936[b]
	(0.189)	(0.020)	(0.229)	(0.013)
$\rho_{10,9}$	39.824	21.731	23.701	50.995
	(0.159)	(0.381)	(0.415)	(0.242)
$a_{1\ 2,1}$	-0.001	0.119	-0.086	0.001
	(0.999)	(0.866)	(0.872)	(0.999)
$a_{1\ 3,2}$	-0.060	0.059	0.056	0.534
	(0.894)	(0.933)	(0.917)	(0.471)
$a_{1\ 4,3}$	0.486	-0.439	-1.146[b]	-0.169
	(0.276)	(0.533)	(0.032)	(0.820)
$a_{1\ 5,4}$	0.679	-0.339	-1.342[b]	-1.454[c]
	(0.130)	(0.631)	(0.012)	(0.050)
$a_{1\ 6,5}$	0.444	0.384	0.742	0.649
	(0.319)	(0.587)	(0.164)	(0.381)
$a_{1\ 7,6}$	0.483	-0.331	-0.047	0.353
	(0.278)	(0.638)	(0.929)	(0.635)
$a_{1\ 8,7}$	-0.334	-0.195	-0.399	0.030
	(0.454)	(0.782)	(0.454)	(0.968)
$a_{1\ 9,8}$	-0.824[c]	0.812	0.274	-1.493[b]
	(0.065)	(0.250)	(0.607)	(0.045)
$a_{1\ 10,9}$	0.494	0.735	0.063	-0.167
	(0.269)	(0.296)	(0.906)	(0.822)

p-value in parenthesis, [c] $p<0.10$, [b] $p<0.05$, [a] $p<0.01$

Table 5 continued…

		Model 17 Action	Model 18 Comedy	Model 19 Drama	Model 20 Children
$a_{2\,2,1}$		0.015	-1.676	-7.030	-0.040
		(0.999)	(0.881)	(0.535)	(0.999)
$a_{2\,3,2}$	12.779	2.771	0.696	13.252	
		(0.369)	(0.773)	(0.958)	(0.696)
$a_{2\,4,3}$	9.580	2.217	-1.013	4.865	
		(0.485)	(0.824)	(0.941)	(0.909)
$a_{2\,5,4}$		7.333	-1.841	-4.092	5.982
		(0.580)	(0.849)	(0.794)	(0.869)
$a_{2\,6,5}$	11.866	-19.479^{b}	18.839	-62.600^{c}	
		(0.396)	(0.044)	(0.174)	(0.086)
$a_{2\,7,6}$		-5.868	-2.574	-6.667	-22.877
		(0.665)	(0.791)	(0.623)	(0.543)
$a_{2\,8,7}$	-10.562	-4.264	7.763	49.730	
		(0.450)	(0.696)	(0.504)	(0.191)
$a_{2\,9,8}$	20.389	-5.095	-0.778	-2.833	
		(0.130)	(0.603)	(0.950)	(0.914)
$a_{2\,10,9}$	-19.894	7.357	18.454	-80.462^{b}	
		(0.138)	(0.472)	(0.197)	(0.024)
$\alpha_{2,1}$		0.002	0.054	0.554	0.013
		(0.999)	(0.978)	(0.785)	(0.996)
$\alpha_{3,2}$		2.664	1.795	1.198	0.562
		(0.188)	(0.358)	(0.553)	(0.817)
$\alpha_{4,3}$		3.319^{c}	4.839^{b}	7.359^{a}	0.932
		(0.100)	(0.013)	(0.000)	(0.701)
$\alpha_{5,4}$		3.599^{c}	2.415	7.754^{a}	5.038^{b}
		(0.077)	(0.219)	(0.000)	(0.040)
$\alpha_{6,5}$		2.072	5.690^{a}	3.683^{c}	4.814^{c}
		(0.306)	(0.004)	(0.069)	(0.056)
$\alpha_{7,6}$		3.214	4.212^{b}	3.028	2.127
		(0.115)	(0.032)	(0.134)	(0.377)
$\alpha_{8,7}$		5.567^{a}	3.846^{c}	2.499	3.426
		(0.006)	(0.051)	(0.217)	(0.155)
$\alpha_{9,8}$		8.501^{a}	1.060	-0.397	7.670^{a}
		(0.000)	(0.591)	(0.845)	(0.002)
$\alpha_{10,9}$		-0.133	2.898	3.723^{c}	3.116
		(0.948)	(0.139)	(0.066)	(0.196)

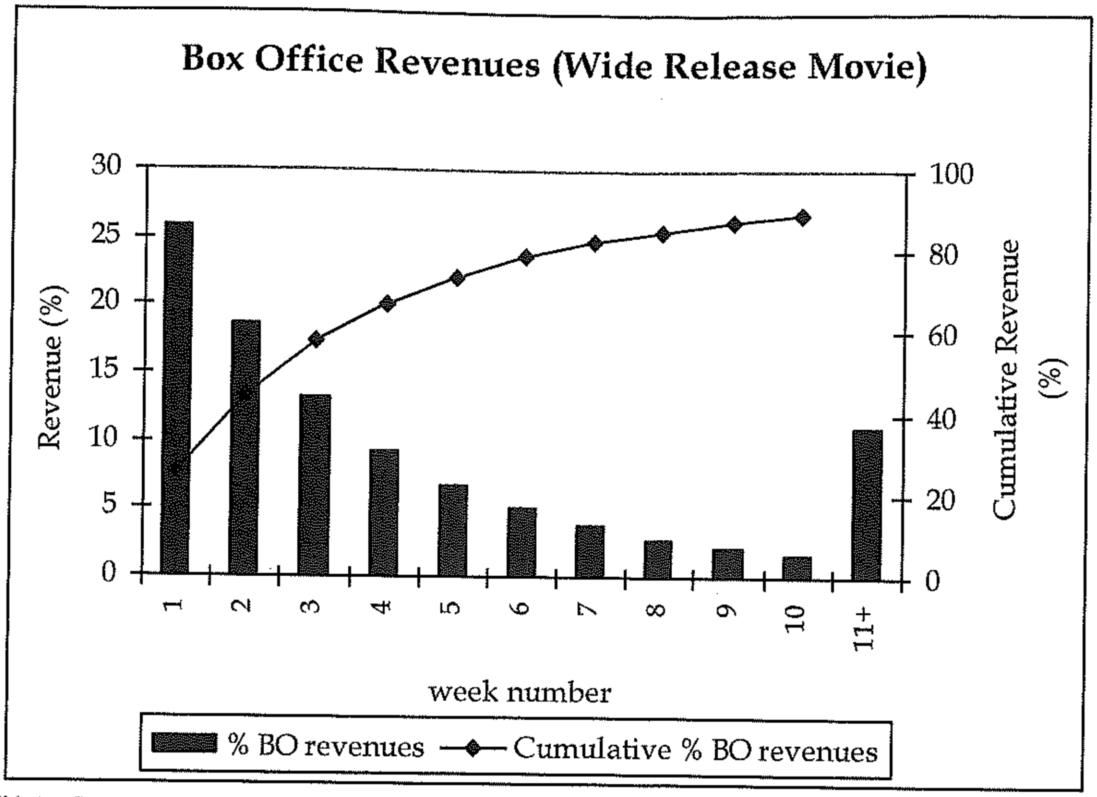
p-value in parenthesis, ^{c} p<0.10, ^{b} p<0.05, ^{a} p<0.01

Table 5 continued...

	Model 17 Action	Model 18 Comedy	Model 19 Drama	Model 20 Children
λ_1	-0.755	27.033	13.087	-1.210
	(0.993)	(0.736)	(0.895)	(0.994)
λ_2	-36.693	-36.730	-174.410^{c}	-267.080^{c}
	(0.693)	(0.643)	(0.079)	(0.079)
λ_3	-302.106^{a}	-341.771^{a}	-247.562^{b}	54.530
	(0.001)	(0.000)	(0.013)	(0.722)
λ_4	-240.933^{a}	-85.477	-39.171	52.500
	(0.009)	(0.282)	(0.693)	(0.730)
λ_5	-192.125^{b}	-128.166	-307.344^{a}	-692.932^{a}
	(0.037)	(0.108)	(0.002)	(0.000)
λ_6	-209.870^{b}	-234.674^{a}	-409.688^{a}	-70.323
	(0.022)	(0.003)	(0.000)	(0.643)
λ_7	-103.963	-158.568^{b}	-223.401^{b}	-93.272
	(0.254)	(0.047)	(0.025)	(0.537)
λ_8	-264.018^{a}	-258.790^{a}	-148.268	293.549^{c}
	(0.004)	(0.001)	(0.136)	(0.053)
λ_9	-181.849^{b}	-160.368^{b}	-182.853^{c}	-237.688
	(0.047)	(0.048)	(0.067)	(0.116)
N	3762	3960	2790	1026

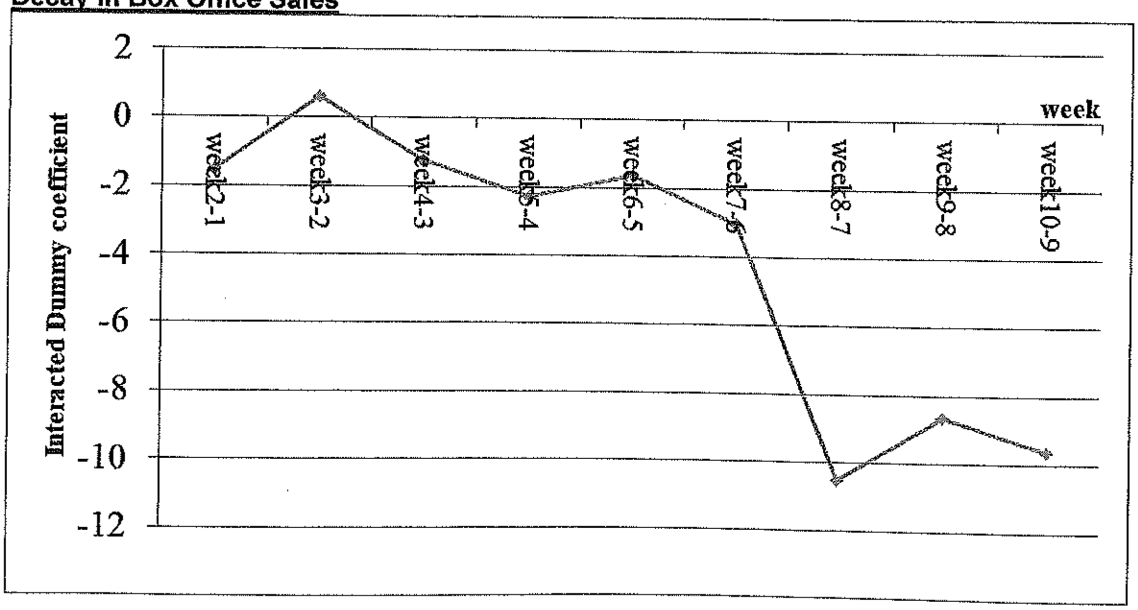
p-value in parenthesis, ^{c} $p<0.10$, ^{b} $p<0.05$, ^{a} $p<0.01$

Figure 1: Box Office (BO) Revenues by Week and Cumulative Revenues by Week for Wide Release Movies



(Note: Revenues are a Percent of Total Revenues and BO : Box Office)

Figure 2: Effect of Weekly Dummy Variable Interacted with the Number of Substitutes on the Decay in Box Office Sales



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