# MODELLING HETEROGENEOUS EFFECTS IN NETWORK CONTAGION: EVIDENCE FROM THE STEAM COMMUNITY

By

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## ABSTRACT

This study considers heterogeneous effects of reviews and social interactions on diffusion or contagion of new products in a networked setting, using a sample of interconnected public user profiles from the Steam Community. Ownership and reviews of two cult hit independent games – *The Binding of Isaac: Rebirth*, and *To the Moon* – are analyzed over a period of four years. This data was fit with a Hawkes Process Hazard Regression Model with exponential decay kernels for each game, yielding estimates of scale and duration of incremental heterogeneous actions within the network. This analysis finds strong, short term, additive, and marginally decreasing, social contagion effects from other users buying games, with much smaller, but also far more durable and highly significant, effects from review posting behavior in the network, independent of review quality. This seems to suggest that review influence, while still distinguishable from network homophily, is unlikely to lead to cascade effects.



**Keywords:** Information, Contagion, Cascades, Diffusion, Hawkes

# INTRODUCTION

Increasingly, online ratings and reviews are a driving force in consumers' decision processes. Whether considered as their own feature or a new form of the nebulous "word-of-mouth" marketing concept, ratings present complex mechanics and a unique challenge for researchers and marketers. Although many studies have been written on the topic of review lifecycles and effects, and some key results have been consistent across studies, others are still contradictory. A much smaller and more recent body of research has considered micro-level networked effects to explain heterogeneity in macro-level results. This paper's main goal is to offer a contribution to this group, using a rich data source and cutting-edge methods of social contagion research.

So far, research on product reviews has unearthed a few key results. First, we know that reviews are good predictors of product sales, even if not all studies agree that they drive sales. Second, we know that reviews exhibit consistent trends across product categories, although there are contradictory results for what causes those trends. Third, and perhaps most important, we know that reviews can be easily manipulated or moved by social contagion. To quote Sinan Aral (2014):

> "Digging deeper into the behavioral mechanisms explaining our results, we found that friends were quicker to herd on positive ratings and to come to their friends' rescue when those friends' ideas were poorly rated. This implies that the structure of social networks helps guide the structure of ratings bubbles."

In view of the vulnerability of aggregate reviews to network biases and external actors, it is in the interest of firms to learn more about the mechanisms behind product opinion diffusion, whether to prevent manipulation or to design more effective targeting strategies. However, that is not the end of the usefulness of the topic. The diffusion of reviews is essentially the diffusion of opinions, and much of the research behind the mechanisms of said diffusion can be generalized to propagation of false news, opinion-forming behavior in social media, thought bubbles, and permeability of networks to third-party influence.

As interesting as opinion contagion can be, many of its features remain understudied, such as heterogeneity in network effects. Although researchers have studied product diffusion in networks and opinion forming behavior in social media, those two areas have rarely come together. One of the main obstacles to this type of study is acquiring the right type of data. Another is choosing the theoretical framework with which to model it. Product sales data can portray the moment of purchase, and that information may be combined with either actual network data or network inference statistical models, but for most product categories the propagation of reviews itself is not observable. On the other hand, research using social media posts or community forum data can portray the behavior of the reviews themselves, but the moment of purchase remains unobserved. Thanks to this, for the most part opinions and sales remain separate in networks. There are a variety of jargons and popular models available for how to model these processes. Survival theory, marketing science, epidemiology, network theory, graph theory, control theory, neuroscience, and information economics, all offer different focuses, models, and methods when investigating information diffusion, contagion, or cascades.

This study attempts to bring some of those fields together with a uniquely rich dataset. It employs public data from a social network for gamers, sampling for two games: *The Binding of Isaac: Rebirth*, and *To the Moon.* For each user in the sample, variables include games owned, friends, reviews posted, and dates for first achievement earned in the two games as well as reviews postings. Models fit to this data at the individual user level estimate the scale and duration of effects from users buying and reviewing games on the buying behavior of surrounding users, which might not be discernible at the aggregate level. This granular approach allows the model to account for cascading effects and clustering behavior in dense areas of the network beyond baseline cumulative effects of diffusion. The key modelling assumption behind this analysis is that the behavior of users buying games in the immediate network may represent social contagion and serve as a proxy for homophily effects, that is, effects due to inherent similarities between users in the cluster, while effects of subsequent review-posting behavior are independent of any homophily captured in the first effect, and represent only social contagion. While games with larger marketing efforts might have any number of confounding unobservable effects behind user acquisition, *The Binding of Isaac: Rebirth* and *To the Moon* are small independent productions with little dedicated marketing that spread mainly through word-of-mouth and recommendations in the Steam platform itself. In these cases, any other external effects might be summarized under network homophily. Given these assumptions, this study finds comparable effects across games which go beyond those estimated by a more traditional proportional hazard (or logistic) regression.

A second motivation behind this study is to address a current practical concern in the platform from which the data was sampled. Valve Corporation's Steam is a crossbreed of store, media library and social network, and, as most social networks, it has recently come under scrutiny for thought bubbles and other forms of undesirable network clustering. Throughout 2017, Steam has had to deal with multiple illegal or undesirable practices being adopted by both consumers and game studios, such as users protesting practices of gaming companies by mass-publishing negative reviews which drown reviews that better represent the quality of the game itself, and with game developers banning and harassing users who publish truthful but negative reviews, or with some even using review bots to automatically publish dozens of positive reviews to embellish a game's store page. Although both the website and the app have received multiple updates and new features that attempt to discourage these behaviors, there are no publicly disclosed estimates of the extent of the consequences of such actions. The experiments used in this study are similar to those previously used in the study of cheating behavior (Blackburn et al. 2011), and could be extended to analyze other aspects of social contagion on Steam. Despite the heavily theoretical approach, this study hopes to offer insights that might be useful for buyers and sellers in the market, if not for the company itself.

**Literature Review**

The digital revolution introduced many new product diffusion channels in the business landscape, and the constantly evolving digital markets require unique marketing strategies and sales structures. User ratings are among the unique traits of digital commerce, and present distinct challenges that researchers have attempted to solve. In the last dozen years, a large body of research in marketing science, information technology, and information economics has formed around modelling the effects of ratings – or how ratings affect sales and product lifecycles – and modelling the social dynamics of ratings – or how ratings come into being in the first place.

Wendy Moe and Michael Trusov's own literature review (2011) summarizes well the key findings by the group of researchers studying the lifecycles and effects of ratings:

> "The majority of research in this area has identified three metrics of online word of mouth: valence, variance, and volume (…) Valence is represented most frequently by an average rating measure (…) The variance in ratings has also been measured in a variety of ways, ranging from a statistical variance (…) to entropy (…), and volume is represented most commonly by the number of postings."

Although this basic theoretical model has been stable, studies have commonly found conflicting evidence in their experiments. While all agree that ratings are strongly correlated with sales, some studies suggest that volume is the most impactful metric for sales (Liu 2006; Duan, Gu, and Whinston 2008), but others claim that valence and variance are more meaningful for growth rates (Clemons, Gao, and Hitt 2006). Furthermore, studies have not been able to indisputably distinguish if higher ratings cause higher sales, or if they are indeed caused by superior product quality – which could drive sales by itself. This last distinction would inform the most important practical question of ratings: how marketers and platforms should monitor and seek to affect or protect ratings. If ratings are irrelevant in light of a product's quality, they serve as little more than predictors of sales. On the other hand, if digital impressions drive sales to any extent, platforms and producers should be aware of potential tampering and third-party negative campaigns in ratings and reviews.

Research in this group uses somewhat similar experiments with richer and richer datasets to attempt to explain confounding effects. Their data ranges from movies (Liu 2006) to craft beer (Clemons, Gao, and Hitt 2006). One of the challenges addressed by some researchers is whether those product categories are truly equivalent. Zhu and Zhang (2010), for instance, compared ratings and sales across video-games and concluded that the importance of valence versus volume versus variance depended on the size of other marketing campaigns and existing expectation ahead of launch, with results remaining constant within groups after controlling for that. Similar studies have not been conducted for most product categories used in other experiments.

One of the key results that remains constant across studies is that the lifecycle of ratings follows a pattern: ratings get worse over time (Li and Hitt 2008). There is still no consensus over whether this is caused by consumers changing their expectations based on previous ratings (Godes and Silva 2012) or by the consumer pool itself changing as time goes on (Liu and Hitt 2008). This result is one of the first to suggest the existence of systematic bias in reviews and ratings. Schlosser (2005) and Amabile (1983) had already examined how negative opinions spread, and suggested that consumers' opinions at large would be driven down by negative opinions of a few early users, but these later studies generalized that result for reviews of any valence. Social influences are the main topic of Moe and Trusov (2011) as well as Moe and Schweidel (2012), and remain a heated topic for marketing research in digital channels. Table 1 is a reproduction of exhibit 1 in Wendy Moe and Michael Trusov's "The Value of Social Dynamics in Online Product Ratings Forums," summarizing key previous studies in the macro analysis of review effects.

Table 1
LITERATURE REVIEW

| *Article* | *Product Category* | *Dependent Variable* | *Significant Word-of-Mouth Effects* |
|---|---|---|---|
| Liu (2006) | Movies | Sales | Number of posts |
| Duan, Gu, and Whinston (2008) | Movies | Sales | Number of posts |
| Dellarocas, Zhang, and Awad (2007) | Movies | Sales diffusion parameters | Average rating, number of ratings |
| Clemons, Gao, and Hitt (2006) | Beer | Sales growth rate | Average rating, standard deviation of ratings |
| Godes and Mayzlin (2004) | Television shows | Television-viewership ratings | Entropy of posts, number of posts |
| Chevalier and Mayzlin (2006) | Books | Sales rank | Average rating, number of ratings |
| Current study | Bath, fragrance, and beauty products | Cross-product temporal variation in ratings and sales | Static and dynamic effects of ratings |

Micro-level analysis of reviews has a considerably smaller body of research. Among those studies, a key topic is heterogeneity due to network effects, that is the idea that networked dynamics behind ratings and opinions may help explain why macro-level studies often get conflicting results. Spearheaded by Sinan Aral, this group focuses on studying what form the previous results take when examined as a network, not an aggregate, of opinions. Aral's own research can be found on all levels of this, from data collection and experiments (Aral 2016), to methodological frameworks (Aral 2009, 2012), to results and caveats (Aral 2011, 2014). Data for this type of research is much harder to come by, with very few platforms being able to accurately report their users’ connections and many unwilling to do so, which might explain the smaller amount of papers published so far. Nonetheless, these frameworks can be useful in explaining multiple forms of information propagation, generalizing beyond reviews and ratings to also explain thought bubbles and clustering of online communities (Chu and Manchanda 2016). The tools of micro-level, networked, analysis can differ greatly from those of macro-level studies. Many theoretical works in this field are concerned with adapting tools from Survival, Graph and Control Theory to a market context (Dhillon 2013, Gomez-Rodriguez et al 2013, Li et al 2013, Valera and Gomez-Rodriguez 2015). The applicability of these methods to multiple contexts has attracted to the discussion researchers of many areas previously unrelated to digital ratings. Perhaps the most characteristic trait of this body of research is its recency, with even key papers being less than ten years old, also meaning that it has not been long enough for more than a few papers to get published. It is this subfield, small and recent as it is, that is of most interest to this study. In estimating the size of networked shocks, this paper will build upon the work of Gomez-Rodriguez et al (2013) and White et al (2016), using a Hawkes-Process-Based Diffusion Model, a popular framework for survival theory and modelling pandemics. Furthermore, in considering the source of the data, the Steam Community, this study draws inspiration from Blackburn’s “Cheaters in the Steam Community Gaming Social Network” (2011), which analyzed social contagion of cheating behavior in the Community. Although some research has been done independently by websites such as Sergey Galyonkin’s SteamSpy, the Community remains a relatively unused source of network data for academic research.

# METHODOLOGY

## Data

This study draws data from public profiles in Valve Corporation's Steam, a hybrid digital store, media platform, and social media for digital games. Using this platform, gamers can buy games, manage their collections, publish reviews, share their in-game progress and join multiplayer queues with friends. As of January 2017, Steam had a total of 15,624 games in its store, with more than 5,000 others added since. In late 2015, Steam had 125 million yearly active users. Valve has not reported the same metric since, although it is fair to assume it has grown. On the other hand, they have publicly disclosed that in 2017 there were 67 million monthly active users on average. Steam collects data on many interactions that would not be observable elsewhere, two of which are crucial to this study. First, the Steam Store page for each game offers the complete list of reviews for that game, which user published them, at what time, and how many users found those reviews useful. Second, all public user pages in the Steam Community show that user's games collection, friend list, and in-game achievements list.

The sample in this study is based on the first 1000 user reviews from public profiles for each game, out of a random sample of 23,890 reviews for *The Binding of Isaac: Rebirth*, and 16,649 reviews for *To the Moon.* A web-scraping crawler then collected data from these 2000 users and propagated the sample outwards through the public profiles in their friend lists up to four degrees of separation, totaling a sample of 409,000 users. Data on each user included whether they owned the games, their public friend list, whether they had posted reviews, and the date of posting. A first limitation of this analysis is that the date when a user acquired a game is not publicly available. On the other hand, achievement lists are readily available. In the context of Steam, an "achievement" is a digital trophy given to the user for in-game progression.

Normally, any user has to play very little to unlock a game's first achievement, so as long as the interval between a user buying a game and playing it for the first time is not too large, the date of unlocking the first achievement may serve as a good proxy for acquisition time. *To the Moon* may challenge this assumption as it only gives one achievement, which is awarded for completing the game, but its short length (2 to 3 hours) suggests that most users would complete the game in a single play session, which would still make the assumption viable. Out of the full network sample, more than little more than 15000 owned *To the Moon* and had a dated achievement, while just over 20000 owned *The Binding of Isaac: Rebirth* and had a dated achievement. In other words, this data fully portrays the date of inception of a review, the network immediately around it, and any purchases made in that network from then to the present. The earliest activity in the sample is in early 2014, while the last one is in early 2018, giving four years of activity to analysis.

**Model Building**

One of the oldest and still most commonly used model for studying aggregate sales is the Bass Diffusion Model. Developed by Frank Bass in the late 1960s, the key idea behind the Bass Model is that individual hazard in product adoption is proportional to the population's cumulative adoption of that product. In general for survival theory, the instantaneous hazard function, $\lambda(t_i)$, also called the "intensity function," is given by

$$\lambda(t_i) = \frac{f(t)}{1 - F(t)}$$

In simple terms, $\lambda(t_i)$ is the probability of an event happening at time $t_i$ given that it has not happened yet. In the Bass Model, this can be fully written as

$$\lambda(t_i) = \frac{f(t)}{1 - F(t)} = p + qF(t)$$

where $p$ is a baseline value that stays constant over time, commonly called the "innovation coefficient," and $q$ is a constant being multiplied by the CDF, informally known as the "imitation coefficient." This leads to a CDF of the form

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}$$

The shape of this function is quasi-sigmoidal. The common intuitive explanation for this is that initial adoptions are driven by innovation, with imitation gaining momentum as the total number of adopters increases. The graphs for hazard and PDF over time can be seen in Figure 1.

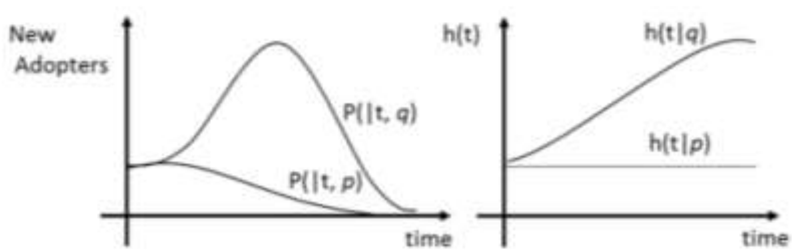



**FIGURE 1:** PDF AND HAZARD GRAPHS FOR THE BASS MODEL, WITH DIFFERENT CURVES REPRESENTING THE EFFECTS OF Q AND P OVER TIME

In general, the Bass Model can characterize aggregate sales sufficiently well, but many are skeptical of its inherent biases (Bulte and Lilien 1997, Kumar et al. 2015). Furthermore, while the Bass Model is easy to estimate, it is not robust or flexible enough to model individual-level granular data.  Many models can be constructed for that purpose by combining the baseline Bass with covariates and heterogeneous $p$ and $q$. Hawkes Processes form one family of such models.

Hawkes Processes are a broad class of self-stimulating heterogeneous stochastic process, roughly defined by hazard functions of the form

$$\lambda(t_i) = A(t_i) + \sum_{j:j<i} B(t_i - t_j)$$

Where $A(t_i)$ is a baseline function and $B(t_i - t_j)$ is any time-dependent function that portrays a hazard shock. A variety of functions may be used in each slot, which leads to Hawkes Processes being a broad and unequally studied family of models. Model in this class are similar to a Bass Model in that they include two layers of hazard, but instead of having a static baseline, theirs may suffer endogenous self-stimulating effects and vary over time, and instead of having a momentum term conditional on the CDF, they sum external triggering events individually. Besides being a superior tool for modelling heterogeneity, the Hawkes-Process framework makes for models that are better at capturing multimodal or hyperdispersed processes, where processes either cluster around a few points in time or are spread far apart. Although Hawkes-Process-Based Models are very popular in survival theory, they are not as present in marketing or economics, despite the efforts of some scholars (Valera and Gomez- Rodriguez 2015, Gomez-Rodriguez, Leskovec & Schölkopf 2013, Li et al 2013).

This study starts with a more traditional Hawkes Process formulation, where $A(t_i)$ is a static baseline diffusion probability $\mu$, and $B(t_i - t_j)$ is an exponential decay function, but opts to parametrize B by a scale parameter $\alpha$ and a duration parameter $\beta$ independently, where many formulations in the family define a single parameter to facilitate estimation. Furthermore, the parameters for external shocks are independent for the first 20 game acquisitions by surrounding users as well as the first 10 reviews among those users, and no shocks for the entire network are considered. That is, for this Hawkes-Process-Based Contagion model (HPC), the hazard rate of an event happening at time $t_i$ for a user who has witnessed d events at times $t_j$ $\{0 < j < i\}$ in the immediate vicinity of his network, is:

$$\lambda(t_i) = \mu + \sum_{j:j<i}^{d} \alpha_j e^{-\beta_j(t_i - t_j)}$$

In other words, each user's probability of buying the game in each day is a combination of the baseline process (each user's isolated adoption probability) with external shocks from friends purchasing the game or posting reviews. To estimate the parameters $\mu, \alpha_i, \beta_i$ $\{i \leq 30\}$, one may use maximum log-likelihood. A simple survival analysis log-likelihood equation is

$$l = logL = \log\big(\lambda(t_n)\big) - \Lambda(t_n) = \log\big(\lambda(t_n)\big) - \int_0^{t_n} \lambda(u)du$$

For each user who bought the game, where $t_n$ is the time in which the purchase took place. If $\delta_i$ is an indicator for whether the ith user bought the game, and substituting for the specific hazard function of the HPC yields

$$l = \sum_{i:\delta_i=1} \log\left(\mu + \sum_{j:j<i}^{d} \alpha_j e^{-\beta_j(t_i - t_j)}\right) - \sum_{i:\delta_i=1} \int_0^{t_i} \left[\mu + \sum_{j:j<i}^{d} \alpha_j e^{-\beta_j(u - t_j)}\right] du$$

$$= \sum_{i:\delta_i=1} \log\left(\mu + \sum_{j:j<i}^{d} \alpha_j e^{-\beta_j(t_i - t_j)}\right) - \sum_{i:\delta_i=1} \left[\mu t_i + \sum_{j:j<i}^{d} \left(\frac{\alpha_j}{\beta_j}\left(1 - e^{-\beta_j(t_i - t_j)}\right)\right)\right]$$

This equation presents a complex and flat decision surface, quickly degenerates when $\beta<\alpha$ , and has a total of 61 parameters for its 30 dimensions, leading to slow and computationally expensive estimation, as is the case for many Hawkes Process models. Nonetheless, over multiple iterations of a Nelder-Mead simplex solver, it is possible to estimate recurring maximum estimations. The seminal paper on the theory of Hawkes MLE is T. Ozaki's (1979), but many other theoretical investigations of the complexities and alternatives in estimating the parameters of Multivariate Hawkes Processes were described by authors since, such as Liniger (2009), Laub et al (2015), Etesami et al (2016), Guo and Luk (2013). To simplify estimation in this case, a preliminary aggregate level model was used for feature selection. The bass model reduced to a logistic distribution when *p=0*, so a logistic regression was fit to verify the significance of the jth friend buying a game or posting a review for predicting whether users acquire the game by the last moment observed.

## Model Results

First, graphs for the probabilities of a user owning *The Binding of Isaac: Rebirth*, or *To the Moon*, conditional on the number of friends who own the game and have posted reviews, are given in Figures 2 to 5.

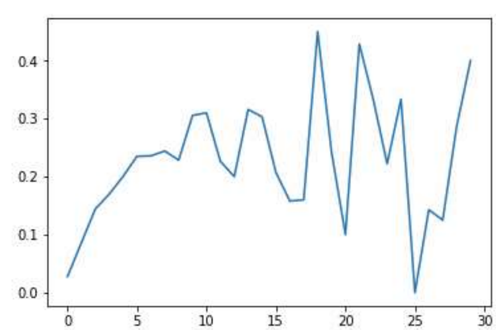


**FIGURE 2:** THE BINDING OF ISAAC, P(OWNING GAME| NUMBER OF FRIENDS WHO OWN THE GAME) BY NUMBER OF FRIEND WHO OWN GAME

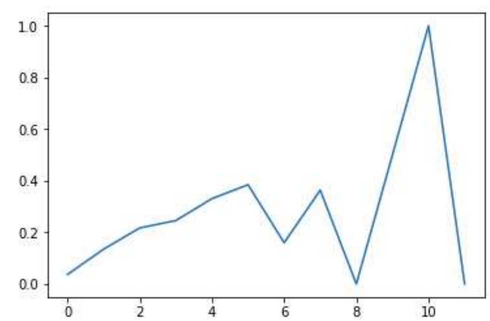
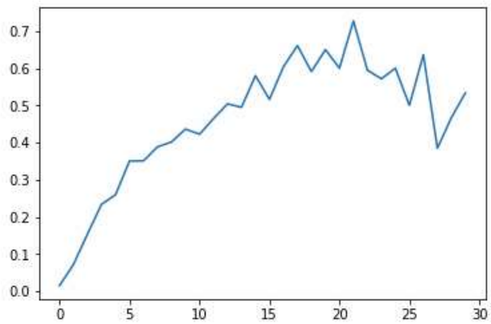


**FIGURE 3:** THE BINDING OF ISAAC, P(OWNING GAME| NUMBER OF FRIENDS WHO HAVE REVIEWED THE GAME) BY NUMBER OF FRIENDS WHO HAVE REVIEWED THE GAME



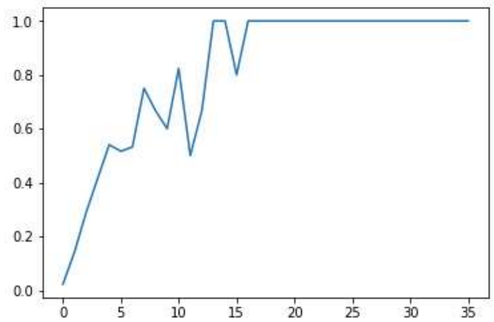


**FIGURE 4:** TO THE MOON, P(OWNING GAME| NUMBER OF FRIENDS WHO OWN THE GAME) BY NUMBER OF FRIEND WHO OWN GAME

**FIGURE 5:** TO THE MOON, P(OWNING GAME| NUMBER OF FRIENDS WHO HAVE REVIEWED THE GAME) BY NUMBER OF FRIENDS WHO HAVE REVIEWED THE GAME

These graphs suggest roughly decreasing additive increments for both variables on both games, with more volatility for higher values of the variables – probably due to the small numbers of users with those network characteristics. For modelling, users with more than 20 friends who own the game and 10 friends who have posted reviews are considered outliers, and only increments up to that size are considered. To justify this threshold, data was modelled in aggregate using logistic regressions. Tables 2 and 3 give model estimates for both games with linear increments for both variables. Effects for friends' acquisitions and reviews are positive and highly significant, with larger effects for reviews.

| Variable | β | SE | p-value |
|---|---|---|---|
| Intercept | -3.281673 | 0.008472 | <2e-16 |
| Acquisitions | 0.267584 | 0.00498 | <2e-16 |
| Reviews | 0.467534 | 0.017543 | <2e-16 |
| AIC | 138718 | | |

**TABLE 2 :** THE BINDING OF ISAAC, LOGISTIC REGRESSION WITH LINEAR INCREMENTS

| Variable | β | SE | p-value |
|---|---|---|---|
| Intercept | -3.781663 | 0.010557 | <2e-16 |
| Acquisitions | 0.363608 | 0.005131 | <2e-16 |
| Reviews | 0.62378 | 0.020717 | <2e-16 |
| AIC | 97785 | | |

**TABLE 3:** TO THE MOON, LOGISTIC REGRESSION WITH LINEAR INCREMENTS

As an alternative, both models are refit considering nonlinear additive effects. Results for these models are given in Tables 4 and 5.

| Variable | β | SE | p-value |
|---|---|---|---|
| Intercept | -3.5834 | 0.01054 | <2e-16 |
| Acquisition1 | 1.13594 | 0.01931 | <2e-16 |
| Acquisition2 | 1.66655 | 0.02857 | <2e-16 |
| Acquisition3 | 1.82595 | 0.04253 | <2e-16 |
| Acquisition4 | 1.98809 | 0.0583 | <2e-16 |
| Acquisition5 | 2.1631 | 0.07579 | <2e-16 |
| Acquisition6 | 2.19016 | 0.09741 | <2e-16 |
| Acquisition7 | 2.16288 | 0.11643 | <2e-16 |
| Acquisition8 | 2.04868 | 0.14705 | <2e-16 |
| Acquisition9 | 2.46644 | 0.15646 | <2e-16 |
| Acquisition10 | 2.41693 | 0.18714 | <2e-16 |
| Acquisition11 | 1.95729 | 0.23698 | <2e-16 |
| Acquisition12 | 1.87964 | 0.2617 | 6.85E-13 |
| Acquisition13 | 2.40756 | 0.29199 | <2e-16 |
| Acquisition14 | 2.3311 | 0.38825 | 1.92E-09 |
| Acquisition15 | 1.72333 | 0.46732 | 0.000226 |
| Acquisition16 | 1.46708 | 0.45415 | 0.001236 |
| Acquisition17 | 1.58724 | 0.55417 | 0.004181 |
| Acquisition18 | 3.05711 | 0.46071 | 3.23E-11 |
| Acquisition19 | 1.93221 | 0.41567 | 3.35E-06 |
| Acquisition20 | 1.98538 | 0.20748 | < 2e-16 |
| Review1 | 0.84699 | 0.02961 | < 2e-16 |
| Review2 | 1.08985 | 0.06458 | < 2e-16 |
| Review3 | 0.70471 | 0.13541 | 1.95E-07 |
| Review4 | 0.38113 | 0.21411 | 0.075069 |
| Review5 | 0.93617 | 0.27908 | 0.000795 |
| Review6 | 0.6955 | 0.41508 | 0.093817 |
| Review7 | 1.14835 | 0.45198 | 0.011063 |
| Review8 | 1.29033 | 0.51131 | 0.011617 |
| Review9 | -0.7443 | 1.04555 | 0.476546 |
| Review10 | 1.11076 | 0.49055 | 0.023556 |
| AIC | 133577 | | |

**TABLE 4 :** THE BINDING OF ISAAC, LOGISTIC REGRESSION WITH NONLINEAR INCREMENTS

| Variable | β | SE | p-value |
|---|---|---|---|
| Intercept | -4.23395 | 0.01405 | < 2e-16 |
| Acquisition1 | 1.59636 | 0.02447 | < 2e-16 |
| Acquisition2 | 2.39548 | 0.03398 | < 2e-16 |
| Acquisition3 | 2.86675 | 0.04561 | < 2e-16 |
| Acquisition4 | 2.98193 | 0.0602 | < 2e-16 |
| Acquisition5 | 3.36055 | 0.07172 | < 2e-16 |
| Acquisition6 | 3.32888 | 0.08673 | < 2e-16 |
| Acquisition7 | 3.42372 | 0.1016 | < 2e-16 |
| Acquisition8 | 3.49832 | 0.1243 | < 2e-16 |
| Acquisition9 | 3.67289 | 0.12772 | < 2e-16 |
| Acquisition10 | 3.56437 | 0.15612 | < 2e-16 |
| Acquisition11 | 3.69469 | 0.16762 | < 2e-16 |
| Acquisition12 | 3.8923 | 0.18744 | < 2e-16 |
| Acquisition13 | 3.80754 | 0.21344 | < 2e-16 |
| Acquisition14 | 4.12263 | 0.25201 | < 2e-16 |
| Acquisition15 | 3.88596 | 0.26298 | < 2e-16 |
| Acquisition16 | 4.13261 | 0.28965 | < 2e-16 |
| Acquisition17 | 4.44898 | 0.2905 | < 2e-16 |
| Acquisition18 | 4.38915 | 0.31196 | < 2e-16 |
| Acquisition19 | 4.23699 | 0.34442 | < 2e-16 |
| Acquisition20 | 4.1496 | 0.11995 | < 2e-16 |
| Review1 | 0.78279 | 0.03415 | < 2e-16 |
| Review2 | 0.87319 | 0.07044 | < 2e-16 |
| Review3 | 0.90275 | 0.12785 | 1.65E-12 |
| Review4 | 1.0065 | 0.17625 | 1.12E-08 |
| Review5 | 1.07829 | 0.26366 | 4.32E-05 |
| Review6 | 1.55839 | 0.39737 | 8.79E-05 |
| Review7 | 1.03628 | 0.4412 | 0.018835 |
| Review8 | 1.2821 | 0.58995 | 0.029761 |
| Review9 | 2.36941 | 0.77906 | 0.002355 |
| Review10 | 2.68669 | 0.7927 | 0.000701 |
| AIC | 90658 | | |

**TABLE 5:** TO THE MOON, LOGISTIC REGRESSION WITH NONLINEAR INCREMENTS.

These models are superior than the previous at modelling the data as suggested by AIC. Under the nonlinear assumption, review effects are smaller than acquisitions. Similar to the conditional probabilities, the sequential effects look almost negative quadratic, with the added insight that review effects are still significant after the model has accounted for acquisitions. Nonetheless, it is easy to see that even after restricting review effects to the tenth occurrence, estimates for the eighth effect onwards have large standard errors and smaller levels of significance. Differentiating these effects between positive and negative reviews yielded no AIC gains, and weakened estimates. With these results verified, the HCM is fit to *The Binding of Isaac: Rebirth* users using at most 20 acquisitions and 10 reviews, with reviews pooled independent of their positivity/negativity. Results for the model with only acquisition data are given in Table 6, and for the model with review and acquisition data in Table 7.

| | | |
|---|---|---|
| LL | 1.56E+15 | |
| Intercept | 1.00E-06 | |
| Variable | α | β |
| Acquisition1 | 2.09E-03 | 1.41E-02 |
| Acquisition2 | 4.00E-02 | 3.96E-01 |
| Acquisition3 | 1.00E-06 | 4.35E-06 |
| Acquisition4 | 5.45E-04 | 5.50E-04 |
| Acquisition5 | 2.19E-02 | 5.29E-01 |
| Acquisition6 | 4.52E-05 | 4.00E-03 |
| Acquisition7 | 4.85E-02 | 1.03E-01 |
| Acquisition8 | 4.87E-04 | 5.86E-04 |
| Acquisition9 | 4.71E-04 | 8.02E-03 |
| Acquisition10 | 6.40E-06 | 9.81E-05 |
| Acquisition11 | 4.31E-06 | 8.56E-05 |
| Acquisition12 | 4.01E-03 | 4.27E-02 |
| Acquisition13 | 6.42E-04 | 3.30E-03 |
| Acquisition14 | 1.12E-03 | 2.09E-03 |
| Acquisition15 | 9.38E-06 | 1.50E-05 |
| Acquisition16 | 4.99E-02 | 2.46E-01 |
| Acquisition17 | 2.58E-06 | 2.95E-06 |
| Acquisition18 | 1.00E-06 | 2.80E-01 |
| Acquisition19 | 1.97E+00 | 2.67E+00 |
| Acquisition20 | 2.37E-03 | 2.45E-02 |

**TABLE 6:** THE BINDING OF ISAAC, MODEL ESTIMATE FOR THE HCM WITHOUT REVIEW EFFECTS

| | | |
|---|---|---|
| LL | 5.08E+15 | |
| Intercept | 1.00E-06 | |
| Variable | α | β |
| Acquisition1 | 7.90E-02 | 7.90E-02 |
| Acquisition2 | 1.27E-02 | 1.27E-02 |
| Acquisition3 | 2.80E-06 | 1.36E-01 |
| Acquisition4 | 1.10E-06 | 1.10E-06 |
| Acquisition5 | 4.65E-02 | 4.65E-02 |
| Acquisition6 | 6.38E-01 | 6.38E-01 |
| Acquisition7 | 7.06E-02 | 7.06E-02 |
| Acquisition8 | 1.02E-06 | 7.90E-06 |
| Acquisition9 | 1.11E-01 | 1.11E-01 |
| Acquisition10 | 1.79E-01 | 1.79E-01 |
| Acquisition11 | 1.57E-05 | 6.03E-03 |
| Acquisition12 | 1.35E-01 | 1.35E-01 |
| Acquisition13 | 3.19E-06 | 4.05E-05 |
| Acquisition14 | 1.16E-06 | 1.45E-04 |
| Acquisition15 | 1.28E-06 | 3.74E-05 |
| Acquisition16 | 1.41E-03 | 5.26E-01 |
| Acquisition17 | 1.19E-06 | 2.50E-06 |
| Acquisition18 | 2.50E-03 | 1.08E-02 |
| Acquisition19 | 4.10E-06 | 4.10E-06 |
| Acquisition20 | 2.68E-06 | 9.76E-06 |
| Review1 | 1.46E-02 | 1.65E-02 |
| Review2 | 1.00E-06 | 5.48E-01 |
| Review3 | 1.04E-06 | 1.28E-06 |
| Review4 | 4.00E-03 | 2.38E-01 |
| Review5 | 3.76E-02 | 3.76E-02 |
| Review6 | 6.00E-04 | 1.08E-03 |
| Review7 | 4.69E-05 | 2.48E-04 |
| Review8 | 1.00E-06 | 1.12E-05 |
| Review9 | 2.90E-03 | 2.90E-03 |
| Review10 | 7.64E-03 | 2.01E-01 |

**TABLE 7:** THE BIDNING OF ISAAC, MODEL ESTIMATE FOR THE HCM WITH REVIEW EFFECTS

A likelihood ratio test confirms a significant improvement by the addition of the 20 parameters for reviews. Figure 6 displays the decaying effects of the first 20 acquisitions (colors in descending order on the right) over a period of 90 days according to the complete model. Figure 7 shows the range of the 20 acquisition effects and 10 review effects, with the average effects of each category in bold lines. The main result in these is that acquisition effects have larger scale in the short run, but quickly decrease through the first month, while review effects are smaller but decay much slower. The acquisition effects fall below those of reviews around the 27th day. Next, the HCM is fit to *To the Moon*, with model summaries in Tables 8 and 9.

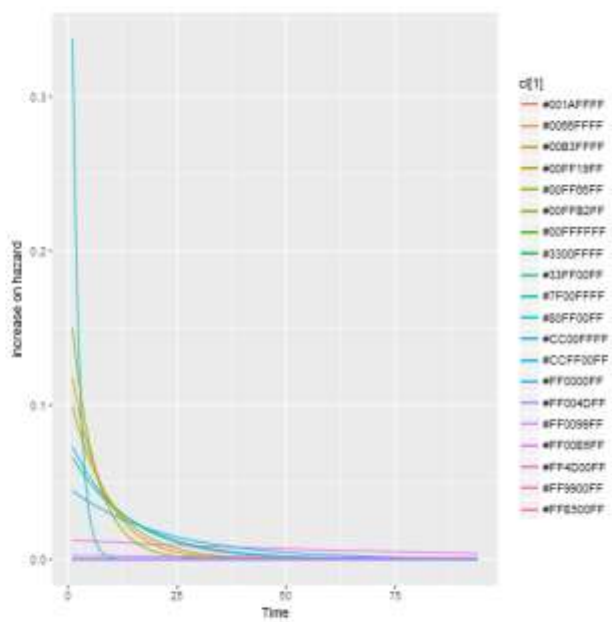



**FIGURE 6:** THE BINDING OF ISAAC, MODEL ESTIMATES FOR THE DECAYING EFFECTS OF THE FIRST 20 GAME ACQUISITIONS BY FRIENDS ON A USER'S HAZARD RATE OVER THE PERIOD OF A YEAR

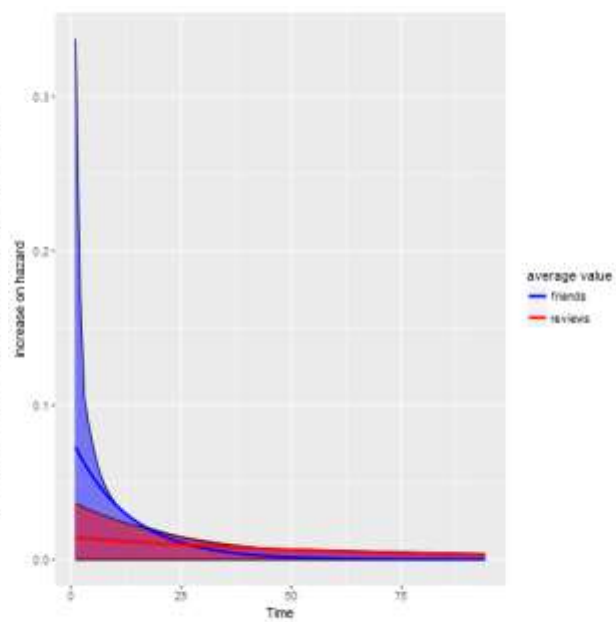



**FIGURE 7:** THE BINDING OF ISAAC, RANGES AND AVERAGE EFFECTS FOR ACQUISITIONS AND REVIEWS OVER A PERIOD OF A YEAR

| LL | -19460617.3 | |
|---|---|---|
| Intercept | 1.00E-06 | |
| Variable | α | β |
| Acquisition1 | 1.32E-03 | 0.0013257 |
| Acquisition2 | 1.64E-03 | 0.001648 |
| Acquisition3 | 3.86E-05 | 0.0343016 |
| Acquisition4 | 1.54E-04 | 0.034108 |
| Acquisition5 | 4.46E-04 | 0.0280738 |
| Acquisition6 | 7.75E-05 | 0.0209972 |
| Acquisition7 | 1.75E-04 | 0.0150106 |
| Acquisition8 | 1.88E-05 | 0.0020885 |
| Acquisition9 | 1.42E-04 | 0.0114327 |
| Acquisition10 | 5.25E-04 | 0.0006966 |
| Acquisition11 | 4.92E-04 | 0.0033265 |
| Acquisition12 | 3.17E-04 | 0.0207132 |
| Acquisition13 | 2.15E-04 | 0.0017017 |
| Acquisition14 | 8.17E-04 | 0.0045966 |
| Acquisition15 | 1.86E-04 | 0.0117099 |
| Acquisition16 | 4.20E-04 | 0.0090356 |
| Acquisition17 | 2.03E-04 | 0.0128332 |
| Acquisition18 | 2.02E-04 | 0.0005363 |
| Acquisition19 | 1.75E-04 | 0.0197339 |
| Acquisition20 | 2.01E-04 | 0.0092251 |

**TABLE 8:** TO THE MOON, MODEL ESTIMATE FOR THE HCM WITHOUT REVIEW EFFECTS

| LL | -19452197.56 | |
|---|---|---|
| Intercept | 1.00E-06 | |
| Variable | α | β |
| Acquisition1 | 1.36E-03 | 0.0013666 |
| Acquisition2 | 1.53E-03 | 0.0015651 |
| Acquisition3 | 4.80E-05 | 0.0356417 |
| Acquisition4 | 1.65E-04 | 0.0362547 |
| Acquisition5 | 4.71E-04 | 0.027908 |
| Acquisition6 | 7.60E-05 | 0.0201698 |
| Acquisition7 | 1.44E-04 | 0.0179117 |
| Acquisition8 | 1.87E-05 | 0.0020917 |
| Acquisition9 | 1.38E-04 | 0.0118442 |
| Acquisition10 | 5.70E-04 | 0.0006582 |
| Acquisition11 | 5.34E-04 | 0.0032265 |
| Acquisition12 | 2.98E-04 | 0.0207383 |
| Acquisition13 | 2.27E-04 | 0.0018192 |
| Acquisition14 | 8.62E-04 | 0.0045375 |
| Acquisition15 | 1.90E-04 | 0.0117709 |
| Acquisition16 | 4.10E-04 | 0.0090788 |
| Acquisition17 | 2.04E-04 | 0.013448 |
| Acquisition18 | 2.12E-04 | 0.000535 |
| Acquisition19 | 1.81E-04 | 0.0205966 |
| Acquisition20 | 2.14E-04 | 0.0085154 |
| Review1 | 1.01E-04 | 0.0001008 |
| Review2 | 2.26E-04 | 0.0004335 |
| Review3 | 1.22E-04 | 0.018974 |
| Review4 | 1.42E-04 | 0.0092549 |
| Review5 | 1.74E-04 | 0.0055553 |
| Review6 | 5.16E-05 | 0.0104224 |
| Review7 | 1.09E-04 | 0.0133017 |
| Review8 | 1.01E-04 | 0.01051 |
| Review9 | 1.31E-04 | 0.005883 |
| Review10 | 8.24E-05 | 0.0105595 |

**TABLE 9:** TO THE MOON, MODEL ESTIMATE FOR THE HCM WITH REVIEW EFFECTS

For *To the Moon*, results are similar to the previous. The Likelihood Ratio test suggests that the improvement in log likelihood by the addition of the ten review variables is significant. Figure 8 displays the decaying effects of the first 20 acquisitions over a period of a year according to the complete model. Figure 9 shows the range of the 20 acquisition effects and 10 review effects, with the average effects of each category in bold lines. Overall, the effect estimates for *To the Moon* are smaller and last for longer than for *The Binding of Isaac.* Nonetheless, they show a similarity with previous estimates: the acquisition effects show larger scale at their inception with quick decays, while review effects are much smaller but last for longer.

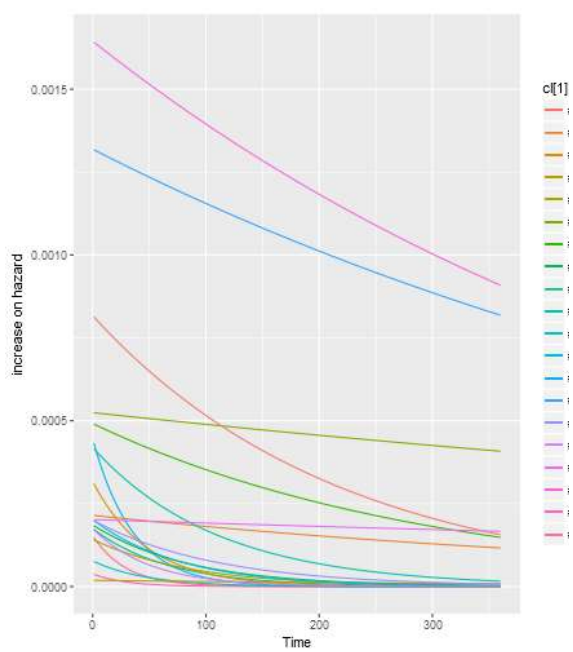



**FIGURE 8:** TO THE MOON, MODEL ESTIMATES FOR THE DECAYING EFFECTS OF THE FIRST 20 GAME ACQUISITIONS BY FRIENDS ON A USER'S HAZARD RATE OVER THE PERIOD OF A YEAR

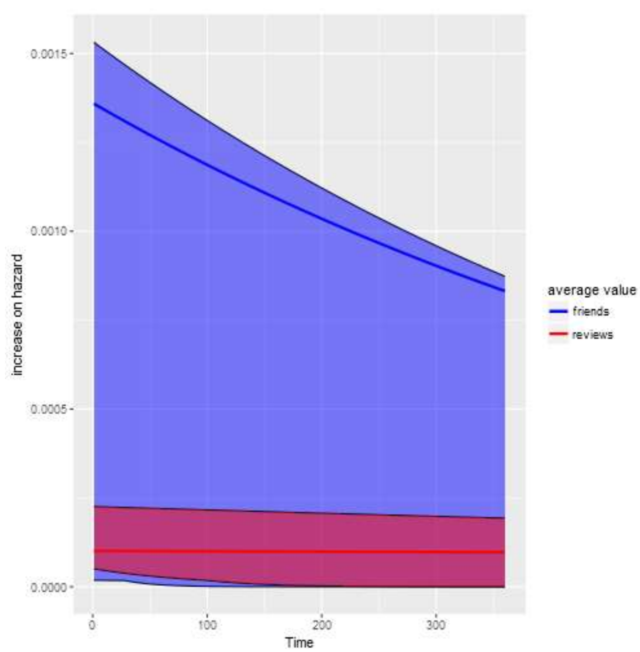



**FIGURE 9:** TO THE MOON, RANGES AND AVERAGE EFFECTS FOR ACQUISITIONS AND REVIEWS OVER A PERIOD OF A YEAR

# CONCLUSION

There are incremental effects of friends buying games and posting reviews in the immediate network. *The Binding of Isaac: Rebirth* exhibits larger effects with faster decays, characteristic of contagion-based spread, while *To the Moon* exhibits longer term but smaller effects, suggesting a prevalence of endogenous forces on diffusion. These differences are likely due to the inherent characteristics of the games: *The Binding of Isaac: Rebirth* has the benefit of a large streaming and speedrunning community, while *To the Moon* is a one-man project with no marketing efforts put into it, produced in a rudimentary game engine. On the other hand, the relative sizes of review and acquisition effects are consistent across games: acquisition effects are larger and shorter-lived, suggesting that most contagion and homophily-based diffusion is captured in those interactions, while review effects are smaller bur far more enduring. This suggests that review effects, after accounting for natural network evolution or social contagion, are negligible in the short run, but relevant over a long stretch of time, and are more connected to a user's awareness of a game than social imitation. If these results were to hold over a variety of games, they would suggest that manipulation of reviews in the short run (whether review bombings or inflations) should not by itself strongly affect sales or lead to network-wide cascading effects. On the other hand, network behavior of social imitation is proven to be highly contagious, and possibly more dangerous, in the short run, leading to cascading effects.

## Limitations and further research

A logistic regression does well enough predicting the relevance of these effects on a single user's tendency to acquire the game and finds that review data has an incremental effect past any network/homophily/diffusion/contagion portrayed by the friends' data alone. Modelling the temporal behavior of *The Binding of Isaac: Rebirth* and *To the Moon* players in the network using a survival analysis framework gives estimates of the differences in magnitude and duration of both friend and review effects. The added detail of these model estimates shows once more that Hawkes-Process-based models are powerful tools for modelling social behavior over time. However, the computational difficulties of a Hawkes Process approach make a study such as this impractical for recurring estimates or larger-scale applications. Before similar studies can gather more popularity, further improvements in Hawkes estimation are sorely needed.

A few other caveats of this study require future research. The first is whether the results can be generalized to other games. While the two games chosen proved to have different enough scales of diffusion and contagion, they are similarly independent productions. If another study were to consider higher-budget games with dedicated marketing efforts, the proportional relationship between friends' acquisitions and reviews might not hold, and shocks external to the network, such as negative reviews by popular game reporters or internet personalities, might become confounding factors. The second is that by the nature of the model, it is likely that for cases in which a user acquires a game, then shortly afterwards posts a review, but where neighboring users take a long time to acquire the game, the model would overestimate the duration of review effects. Overvaluing the last shock is common for all attribution models. This is offset by the nature of a Hawkes Process: the model will only overemphasize the duration of one such effect, but not its scale (which would drive likelihood down). The third is that while this study comfortably amalgamates contagion and homophily-driven diffusion under the *acquisition* variable, further studies concerned with the negative potential of cascading contagion effects should first differentiate between pure homophily and contagion due to friends' acquisitions.

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