DOES MOVIE SOUNDTRACK MATTER? THE ROLE OF SOUNDTRACK IN PREDICTING MOVIE REVENUE

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Abstract

Music, as one of the essential elements in the filmmaking process, plays an important role in the success of a movie. Although prior studies have investigated several factors which influence movie revenue, there’s a lack of research examining the effect of search volume of movie soundtrack on the movie revenue. Therefore, we proposed the following research questions: (1) Is search volume of a movie soundtrack a predictor of the movie revenue in the opening week and the following weeks? (2) Does the effect of search volume of movie soundtrack on movie revenue differ between existing songs and new songs in different time periods? We investigated the effect of movie soundtrack search volume on the movie revenue in different time periods. Moreover, we also examined the moderating effect of existing songs vs. new songs on the relationship between search volume and movie revenue. Initial data collected from Google Trends and IMDb was used for the preliminary test of the research model. The initial results showed that online search volume of movie soundtrack has an effect on the movie revenue, and this effect in the pre-launch period is strengthened if existing songs are used in the movie soundtrack.

Keywords: movie, soundtrack, web search, revenue, pre-launch, opening week
INTRODUCTION

In the middle of 1920s, the development of technology enabled the systematical synchronization of sound and motion pictures (Hanssen 2002). As a result, the average revenue of a movie increased greatly with the emergence of sound. Music, as one of the essential elements in the filmmaking process, plays an important role in the success of a movie. The revenue yielded by music and songs accounts for about 5% of the total movie revenues (Doudpota and Guha 2011). Movie soundtrack comprises music and songs used in a movie. A movie soundtrack usually falls into three categories, including underscore (e.g. James Horner's score for the Titanic), pre-existing songs or original master recording (e.g. the Guess Who's "American Woman" in American Beauty), and the new songs specially composed for the movie (Brabec and Brabec 2007). Compared to the cost of using pre-existing songs, that of composing a new song is much higher, ranging from $20,000 for a lower-budget film to more than $1,000,000 for a big-budget studio release (Brabec and Brabec 2007). Therefore, for movie producers with small budgets, the use of pre-existing songs in the movie may be an optimal choice.

On the other hand, web search engines, such as Google, have become the first avenue that people turn up for news, information, solutions, and other purposes. As a market predictor, the web search volume has been used to predict markets in different domains. For example, Wu and Brynjolfsson (2009) used search query volume about real estate to predict the prices and quantities of housing purchase. Kulkarni et al. (2012) investigated the role of online search data in predicting new product (e.g., movie) sales. However, the relationship between web search trends of movie soundtrack and movie revenue is not yet clearly identified despite the heightened value of soundtrack to a movie.

Although prior studies have investigated several influencing factors of movie revenue, there’s a lack of research examining the effect of the search volume of the movie soundtrack on the movie revenue. It also remains unknown whether the use of pre-existing music used in a movie benefits its box office revenue. In order to address this gap, this paper aims to examine the following research questions: (1) Is search volume of a movie soundtrack a predictor of the movie revenue in the opening week and the following weeks? (2) Does the effect of search volume of movie soundtrack on movie revenue differ between existing songs and new songs in different time periods? We propose a model to investigate the effect of pre-launch search volume of movie soundtrack on the movie revenue in the opening week, as well as the effect of the movie soundtrack search volume in the opening week on the movie revenue in the following weeks. Further, we also test the moderating effect of existing songs vs. new songs on the relationship between search volume and movie revenue. Initial data collected from Google Trends and IMDb is used as a preliminary data to test the research model.

This study is expected to contribute to the existing IS literature on web search and it also identifies the role of soundtrack in predicting the movie revenue in the following weeks. In particular, it investigates the influence of online search of movie soundtrack in the prediction of movie revenue. To the best of our knowledge, it is the first study that takes the movie soundtrack into account and empirically examines the effects of movie soundtrack search volume on movie revenue. Besides, the effect of web search of the movie soundtrack using existing songs may differ in pre-launch and post-launch periods. This can also provide insights for movie producers to adopt varying online marketing strategies in different periods.

LITERATURE REVIEW

Predictive Performance of Web Search

Search volume has been used as an indicator to predict future outcomes and performance in various domains. For example, Wu and Brynjolfsson (2009) used Google search data to make predictions about prices and quantities of housing. They suggested that the index of housing search terms could forecast future housing prices and quantities. Choi and Varian (2009) predicted several economic metrics such as
unemployment, automobile demand, and vacation destinations by using Google Search Insights data. The search query time series data has also been employed to predict private consumptions of households (Schmidt and Vosen 2009).

In the context of our study, online search data has been used to predict movie revenue. For instance, Kulkarni et al. (2012) used online search data to forecast the sales of online product, i.e., movies. Particularly, they examined the effect of pre-release online search data of movies on the opening weekend movie revenue. They found that pre-release search data is a significant indicator of opening weekend box office revenues. Goel et al. (2010) investigated the predictive performance of search behavior on commercial success of cultural products (e.g., movies, music, video games). The volume of search query was used to predict opening weekend box office revenue of feature movies. They showed that search counts are highly predictive of box office revenue. Yet the influence of soundtrack search on movie revenue remains unclear.

2.2 Movie Soundtrack

The term soundtrack refers to the recorded music that is accompanied or synchronized to the images in movies, TV shows, books, and video games. A movie soundtrack could include pre-existing songs or original master recording, and the new songs specially composed for the movie (Brabec and Brabec 2007). As an important entertainment product, music has received attention from researchers. Beeman (1988) studied the difference between the East and West in using music in films. Later Hanssen (2002) found that the advent of sound fundamentally changed the inputs and revenues of movies. The silent films were replaced by films with a soundtrack or short sound. As a result, the average revenue per film increased with sound. Both these studies have shown the important role played by sound as well as music in movies. Despite the lack of research on the soundtrack, as an inseparable part of the movie, soundtrack should have a great impact on the consumers’ attitude towards the movie.

2.3 Movie Revenue

Several studies have been conducted to predict movie revenues. For example, Basuroy et al. (2003) investigated how critics affect the box office performance of films, as well as the moderating effects of stars and budgets. They showed that both positive and negative reviews are correlated with weekly box office revenue, indicating critics are able to influence box office revenue. A study by Moon et al. (2010) investigated how movie ratings from professional critics, amateur communities, and viewers themselves influence movie revenues and future movie ratings. They showed that high early movie revenues enhance subsequent movie ratings, and that high advertising spending on movies supported by high ratings maximizes the movie’s revenue. In addition, the effect of national online user reviews on the local geographic box office performance has been examined in prior studies (Chintagunta et al. 2010). The findings indicated that the valence matters at the local level but at the aggregate national level volume of review is the main driver of box office performance. While these findings indicate the influence of several factors including online search of the movie on its revenue, the impact of movie soundtrack search on movie revenue remains unclear.

3 RESEARCH MODEL AND HYPOTHESES

In this study, we divided the users’ search into two major periods, i.e., pre-launch period, and post-launch period. Within the post-launch period, we differentiate the opening week and the following weeks, because the first week after the movie release is the most important period for the movie’s revenue. Building on the previous literature, we propose a model to explain the relationship between pre-launch search volume of the movie soundtrack and the movie revenue in the opening week. Further, the impact of opening week search volume of the movie soundtrack on the movie revenue in the following weeks is also examined in our model. Additionally, we take into account the effect of the type of songs used in
movie soundtrack (i.e., existing music vs. new music). We expect that the type of the movie soundtrack will moderate the relationship between the search volume of the movie soundtrack and its revenue. The research model is shown in Figure 1.

![Research Model Diagram]

**Figure 1. Research Model**

### 3.1 Search Volume of Movie Soundtrack and Movie Revenue

#### 3.1.1 Search in Pre-launch Period

Before the release of a movie, consumers have few channels to get to know the information about the movie except movie trailers and pre-launch marketing campaigns. Many movies release their soundtrack before the official release of the movie. For example, the soundtrack of *Twilight* sequel *New Moon* was released more than one month before the movie’s release. In the pre-launch period, since neither experienced quality nor evaluated quality is available, consumers’ primary perception towards the movie is derived from its available product characteristics (Kim 2013). Therefore, as one of the important attributes of the movie, soundtrack becomes a source for consumers to know the movie before its release. Consumers’ interest in the movie may lead them to search for the related information about the movie, such as features, press releases (Kulkarni et al. 2012). Consumers’ pre-launch search for the movie soundtrack can serve as an indication of their interests in the movie. Ceteris paribus, the high volume of pre-launch search of movie soundtrack indicates more interest to watch the movie once it is released. Thus, we argue that,

**H1**: The pre-launch search volume of the movie soundtrack is positively related to the movie revenue in the opening week.

#### 3.1.2 Search in the Opening Week

We divide post-launch period into two time periods, i.e., opening week, and weeks after it. In the post-launch period, consumers have chances to experience the movie by themselves. Moreover, the online review information about movies is also available to consumers at this stage. Therefore, they can search the information online to update their initial evaluation of the movie. The consumption experience of consumers and their reviews in the opening week are crucial for movie’s revenue. For potential movie consumers, searching the user reviews online is an effective approach to make a consumption decision (Chintagunta et al. 2010). As one of the important attributes of movies, consumers’ feedback on consumption experience of the soundtrack could be an information source for potential consumers’ decision on watching the movie. The search of soundtrack related information in the opening week may
thus reflect potential consumers’ interest and intention towards watching the movie in the upcoming weeks. Thus we hypothesize,

**H2:** The search volume of the movie soundtrack in the opening week is positively related to the movie revenue in the following weeks.

### 3.2 Moderating Effect of Existing Songs in Soundtrack

We argue that the presence of existing songs in the soundtrack moderates the relationship between the search volume of movie soundtrack and movie revenue in the upcoming time periods. Not all movie producers choose to make investments towards composing new songs for a movie. Therefore, using existing songs in the soundtrack is a common choice for movies. A highly rated soundtrack could be a bonus point for the movie. Hargreaves (1988) found that people give higher ratings to familiar music compared to unfamiliar music. Therefore for an existing song, there has a greater likelihood to have better reviews and ratings.

If existing songs are used in the movie soundtrack, because existing songs are released long before the movie, their ratings and reviews will be already available for consumers in the pre-launch period. People who are interested in these existing songs may search them before the launch of the movie, and go to see the movie in the opening week. Therefore, there is a strong relationship between movie soundtrack search volume in the pre-launch period and movie revenue in the opening week if existing songs are used. On the contrary, if new songs are used in the movie soundtrack, because people are not familiar with these new songs before the launch of the movie, they will focus on the movie itself but not its soundtrack. Therefore, the relationship between the search volume of movie soundtrack in the pre-launch period and movie revenue in the opening week is much weaker under such circumstance. Thus we hypothesize,

**H3:** The use of existing songs in the movie soundtrack moderates the relationship between pre-launch search volume of the movie soundtrack and the opening week movie revenue, such that this relationship is stronger when existing songs are used in the movie soundtrack than when new songs are used in the movie soundtrack.

After the launch of a movie, consumers’ online search not only reflects the interest in the movie itself, but also the interest in other consumption information such as show time, cinema venue, and reviews (Kulkarni et al. 2012). More information of the movie is available to consumers after the release of the movie. The focus of consumers’ search activities shifts from the limited information available in pre-launch period to other information (e.g., ratings, consumer reviews) facilitating their decision on watching the movie in the future.

If existing songs are used in the movie soundtrack, because consumers’ attention is switched from the existing music to other information of the movie after it is launched, the predictive power of soundtrack search volume on movie revenue in the following weeks is much weaker. On the contrary, if new songs are used in the movie soundtrack, because people only know these new songs after the launch of the movie, more people may be interested in them compared to the pre-launch period. Therefore, those people who search for these new songs in the opening week will probably go to watch the movie in the following weeks. Hence, the relationship between search volume of movie soundtrack in the opening week and movie revenue in the following weeks is much stronger when new songs are used in the movie. Thus we hypothesize,

**H4:** The use of existing songs in the movie soundtrack moderates the relationship between the opening week search volume of the movie soundtrack and the movie revenue in following weeks, such that this relationship is weaker when existing songs are used in the movie soundtrack than when new songs are used in the movie soundtrack.
4 METHODOLOGY

4.1 Data Collection

Data used to test the model was collected from two sources, i.e., Internet Movie Database (IMDb) and Google Trends. Film related information, such as film name, release date, gross revenue, budget, ratings, and soundtracks, was collected from IMDb. The web search volumes of movie soundtracks were collected from Google Trends. Our data spans from 2004 (when the Google Trends data was first available) to 2012. Within this period of time, we scraped the weekly Google trend scores of movie soundtrack for each movie that has been released in IMDb.

4.2 Operationalization

The dependent variable in this study is the movie revenue i.e., Revenue, which is measured by the gross revenue of the movie. Specifically, the weekly movie gross revenue (WeeklyRevenue) derived from IMDb is used. For the analysis of pre-launch period, the dependent variable is movie revenue in the opening week. In the post-launch period, the dependent variable consists of the weekly revenue of each week after the first week of movie release.

We operationalized the search volume of the movie soundtrack as the Google Trend score of songs used in the movie for that week, i.e., music_trdscore. The trend score of a term is derived from the analyses of how many searches have been done for the term, which is related to the total number of searches done on Google over that week. The trend score in Google trends is normalized, which means that the sets of data have been divided by a common variable to countermand the variable’s effect on the data. The data is presented on a scale from 0 to 100. During normalization, each point on the result graph will be divided by the highest value and then multiplied by 100. Music_existing is a dummy variable used to indicate whether a song used in the movie is a pre-existing one. It equals 0 if the theme song is specifically composed for the movie, and 1 if the song already exists before the movie.

We also include control variables that may contribute to the movie revenue. One of the control variables is Budget, which is the estimated cost in making the movie. In order to make it distributed normally, we use the log transformation form of budget, i.e., ln(Budget) in our analysis. The second control variable is the movie_score, which is the rating for each movie. It is determined by the rating scores from IMDb. The rating scores vary from 1 to 10.

4.3 Model Specification

We use log transformation for movie weekly revenue and budget in the regression to make these two variables normally distributed. Therefore, we propose the econometric model as follows:

\[ \ln(WeeklyRevenue_{i,t}) = \theta_i + \beta_1 Music\_trdscore_{i,t-1} + \beta_2 Music\_existing_i + \beta_3 Music\_trdscore_{i,t-1} \times Music\_existing_i + \beta_4 \ln(Budget_i) + \beta_5 Movie\_score_i + \epsilon_{i,t} \]

In this equation, \(i\) denotes the movie, \(t\) denotes the time period, \(\theta_i\) is the movie-specific fixed effect. \(\epsilon_{i,t}\) is the residual error term. We used \(Music\_trdscore_{i,t-1}\) in previous week \((t-1)\) in the equation to deal with simultaneity issues and allowed for lagged effects of search volume on the movie revenue.

5 DATA ANALYSIS AND RESULTS

The analysis of this study comprises of two stages. The first stage focuses on the pre-launch period, measuring the effect of movie soundtrack search in previous week on the opening week movie revenue. Using a random selection of 390 movies from IMDb from 2004 to 2012, a liner regression model was
analyzed in the first stage. The second stage focuses on the post-launch period. Through a panel regression model, we examined the effect of preceding search of movie soundtrack on the movie revenue in the following week (the movie revenue starts from the second week after the release date). Out of the 390 movies, there are 230 movies that used pre-existing songs while 160 movies composed new theme songs. Table 1 presents the descriptive statistics and variable correlations.

<table>
<thead>
<tr>
<th>No</th>
<th>Variable</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ln(Revenue)</td>
<td>12.44</td>
<td>2.48</td>
<td>3.47</td>
<td>18.90</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Music_trdscore</td>
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<td>4.89</td>
<td>0</td>
<td>74</td>
<td>0.08</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>3</td>
<td>Music_existing</td>
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<td>0.49</td>
<td>0</td>
<td>1</td>
<td>-0.04</td>
<td>-0.09</td>
<td>1.00</td>
<td></td>
<td></td>
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<td>4</td>
<td>ln(Budget)</td>
<td>15.96</td>
<td>2.48</td>
<td>5.01</td>
<td>19.34</td>
<td>0.31</td>
<td>0.06</td>
<td>-0.06</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Movie_score</td>
<td>6.60</td>
<td>1.05</td>
<td>2.5</td>
<td>9.4</td>
<td>-0.05</td>
<td>-0.05</td>
<td>-0.00</td>
<td>0.01</td>
<td>-0.07</td>
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</table>

Table 1. Correlation Table of Pre-launch Period (N=390)

5.1 Pre-launch Period

Table 2 provides the results for the pre-launch period with this initial sample. Model 1 is the baseline model including only control variables. Results show a significant and positive relationship between revenue and budget (β = 0.511; p<0.01). Interestingly, the relationship between movie score and movie revenue shows a significant while negative effect (β = 0.263; p<0.05). Second, Model 2 tests the impact of music trend score one week prior to movie release on opening week revenue. Music_trdscore shows a significant positive effect (β = 0.060; p<0.01), indicating empirical support for Hypothesis 1. Model 3 is the full model, examining the moderating effect of existing songs on the relationship between music_trdscore and Ln(Revenue). As shown in Table 2, the interaction term music_trdscore×music_exist is positively related to Ln(Revenue) (β = 0.122; p<0.05). This result provides support for Hypothesis 3. The model is statistically significant with a R² of 0.225.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1 Control Ln(Revenue)</th>
<th>Model 2 Main Ln(Revenue)</th>
<th>Model 3 Full Ln(Revenue)</th>
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<tr>
<td>Music_trdscore</td>
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<td></td>
<td></td>
<td>0.060*** (0.020)</td>
<td>0.038* (0.023)</td>
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<td>Music_existing</td>
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<td></td>
<td></td>
<td>-0.110 (0.262)</td>
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</tr>
<tr>
<td>Music_trdscore×Music_exist</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.122** (0.053)</td>
</tr>
<tr>
<td>ln(Budget)</td>
<td>0.511*** (0.049)</td>
<td>0.502*** (0.049)</td>
<td>0.495*** (0.048)</td>
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<tr>
<td>Movie_score</td>
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<td>-0.249** (0.114)</td>
<td>-0.281** (0.114)</td>
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<td>Intercept</td>
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<td>7.594*** (1.068)</td>
<td>7.867*** (1.078)</td>
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<tr>
<td>R²</td>
<td>0.225</td>
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<td>0.246</td>
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<td>390</td>
<td>390</td>
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</tbody>
</table>

Note: Standard errors in parentheses. * p<0.1; ** p<0.05; *** p<0.01

Table 2. Data Analyses Results of Pre-launch Period

5.2 Post-launch Period

Table 3 presents the results of the post-launch period. Model 1 is the base model including the control variables that predict movie revenue in the post-launch period. Model 1 shows that ln(budget) has a positive effect on the movie revenue. Then other variables were incrementally added in the following models. In the Model 2, the effect of music_trdscore in the opening week on the movie revenue in the
following weeks is positive and statistically significant ($\beta = 0.04$; $p<0.01$). The result of the random effects model (i.e. Model 3) shows that $\text{music_trdscore}$ in the opening week has a positive and a significant effect on the movie revenue in the following weeks ($\beta = 0.037$; $p<0.01$). This result provides statistical support for Hypothesis 2. Model 4 provides the result of the full fixed effects model. It indicates that besides the positive and significant effect of $\text{music_trdscore}$ ($\beta = 0.031$; $p<0.05$), the effect of the interaction term $\text{music_trdscore} \times \text{music_exist}$ is also positive and statistically significant ($\beta = 0.090$; $p<0.01$). However, in Model 5, the results of random effects full model showed that the moderating effect of existing songs has no effect on the relationship between search volume of the movie soundtrack in the opening week and the movie revenue in the following weeks ($\beta = 0.015$; $p=0.598$). Thus, Hypothesis 4 is partially supported by our analyses.

<table>
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<tr>
<th>Variables</th>
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<td>Full RE</td>
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<td></td>
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<tr>
<td>$\text{Music_trdscore}$</td>
<td>$0.040^{***}$</td>
<td>$0.037^{**}$</td>
<td>$0.031^{**}$</td>
<td>$0.033^{**}$</td>
<td>$0.033^{**}$</td>
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<td></td>
<td>(0.015)</td>
<td>(0.012)</td>
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<tr>
<td>$\text{Music_existing}$</td>
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<td>(0.048)</td>
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<td>(0.028)</td>
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<tr>
<td>$\text{Music_trdscore}$ × $\text{Music_exist}$</td>
<td>$0.305^{***}$</td>
<td>$0.300^{***}$</td>
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<td>(0.035)</td>
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<td>$\text{Ln(Budget)}$</td>
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Note: Standard errors in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table 3.  Data Analyses Results of Post-launch Period

6 DISCUSSION

In this study, we examined the relationship between search volume of movie soundtrack and movie revenue. Our results found that soundtrack search volume during the pre-launch period has a significant and positive effect on movie revenue in the opening week. The results also show that the presence of existing songs in the movie soundtrack strengthens the relationship between search volume of movie soundtrack and movie revenue. In the post-launch period, search volume of movie soundtrack in the previous week has a positive and a significant impact on the following week’s movie revenue. However, different from the pre-launch period, the movie soundtrack using existing songs had no effect on the relationship between search volume of movie soundtrack and its revenue.

6.1 Implications

An important theoretical implication of this study and for its follow-up would be that it can enrich our understanding of web search and its role in predicting the revenue of a forthcoming product (e.g. movie). The initial results showed that online search volume of movie soundtrack indeed has an effect on the movie revenue. The findings can contribute to the literature and provide empirical evidence for the predictive validity of the online search in this context. Additionally, other than antecedents investigated in previous studies such as review, rating, and budgets, we take the movie soundtrack into account and empirically examine its effect on movie revenue. Movie soundtrack, as one of the important components in a movie, hasn’t been paid adequate research attention. This study attempts to address this issue and
provide insights for future work in this domain. Further, our preliminary findings suggest that the interaction effect of different types of movie soundtrack differs in pre-launch and post-launch periods. When existing songs are used in a movie, in the pre-launch period the search volume has a stronger effect on opening week’s movie revenue. However, this effect does not continue into the post-launch period. This may be due to the distraction effects of other factors such as audience reviews, ratings and word-of-mouth available after the movie release.

Based on the findings, several practical implications could be suggested. First, for movie producers, this study highlights the important role of the movie soundtrack on the revenue of the movie. The movie soundtrack can be utilized as an approach for drawing customers’ attention. Further, due to the different effects of web search of the movie soundtrack using existing versus new songs on movie revenue in different periods, it seems appropriate for movie producers to adopt varying advertising strategies in the pre-launch and post-launch period. For example, the existing songs used in the movie could be emphasized in the pre-launch period. The preliminary findings indicate that the type of songs used in movie soundtrack alone has no effect on movie revenue. This needs to be further validated, but adds to the low cost advantage of employing pre-existing songs for low-budget movies.

6.2 Limitations and Future Work

However, this study needs further validation. First, our study explains 25% of the variance in movie revenue. This implies that there are opportunities for inclusion of other explanatory factors. For instance, the genre of movies and its moderating effect on the relationship between movie soundtrack search volume and movie revenue. Another limitation lies in the potential endogeneity problem. In order to minimize this, we have used the search volume of the movie soundtrack in the previous week to predict the following week’s movie revenue. Besides, we have also examined the effects of online search of movie soundtrack separately in the pre-launch and post-launch periods. Third, the small sample size of this study is also a limitation. More movies will be included in the future analysis. Finally, due to the constraints of the dataset, only two control variables have been used in this study. Other factors such as the reviews and star power may also impact the movie revenue. In the follow-up work, we intend to take into account additional control variables in the analysis. Nevertheless, this study serves as an initial step to increase our understanding of the relationship between movie soundtrack and movie revenue.

References


