IMPORTANT INDICATORS IN DETERMINING FUTURE ALBUM SALES SUCCESS

Designing a Model To Predict Future Album Sales

Supervision By Dr. Nanne Migchels
Secondary Examination by Dr. Herm Joosten

Meulen, M. van der (Marc)
S4265483

Contents

Important Indicators In Determining Future Album Sales Success

Designing a model to predict future album sales

Written By
Marc van der Meulen

Introduction

Would it not be a great help to people working as marketing managers, and interesting to management scholars from a theoretical standpoint, if the success of music albums could be predicted before the launch of the album? If looking at a series of metrics like Facebook likes, online word of mouth and website visits could tell you in advance how many albums you are going to sell, and ideally, how many extra albums will be sold for a rise in each of these metrics? If possible, it would grant an interesting insight into the extent to which certain marketing activities play a role in album success. Explicating the proportion of sales each metric explains would also help managers in practice to know what metrics to focus on in their marketing activities, and which not to.

The purpose of the current thesis is an attempt to answer the question 'Can (part of) the success of a new music album be predicted in advance by using a set of statistical measures?'. Also important is to explain the proportion of album sales each of these metrics accounts for and can be expected to predict. When answering this research question however, it is important to understand how it fits in and relates to current academic research in the field of marketing for two reasons. First it provides a backbone for the current research by explicating what is already known on the subject. By doing this, academics avoid wasting time answering questions that are already answered. Secondly it embeds the question in a broader framework, providing directions for future research and create the possibility to elaborate on the findings of this study.

As the broader framework in which this question fits is the launch of new products and the accompanying marketing strategy, looking into this research is a good starting point. So why is the launch of new products generally such a pressing issue in the field of study in marketing? Few things within the realm of business are as difficult and risky as launching new products. According to a recent article by USA Today (2017), chances of a new company with a new product surviving the first five years has been around 20% for many years now. Odds of new products by pre-existing companies being successful is not that much higher, being only about 25% according to Evanschitzky et. al (2012).

This is why a lot of research has already been done. A lot of factors seem to be important when trying to make a new product successful. According to the same study by Evanschitzky, recent academic literature points to several important and non-important predictors of whether a new product will be a success. A lot of this research is, however, unsuited to be the basis of the current study. This has to do with the distinction between hedonic and utilitaristic product qualities. Hedonic qualities focus on enjoyment of a product, utilitaristic on problem-solving. A hammer is, for most people, a utilitaristic product: a means to an end of solving a specific (set of) problem(s), not enjoy it as a hammer. This in contrast to for instance a movie, which usually is not watched to solve a specific problem but purely to enjoy.

Now turning back to our current research, launching a new album. Can the body of academic research help us to understand what might and might not work here? As previously mentioned, a problem one faces when searching for theoretical knowledge helpful in marketing for the music industry is the existence of a sharp distinction between utilitaristic products and hedonic products. According to Rozenkrants et. al (2017) for example, people dislike products that have a lot of negative reviews for utilitaristic products, but tend disregard negative reviews for hedonistic products. A rationale to explain this could be that a hammer that did not fix problem x for someone else online, has a good chance of not fixing problem x for you either. A movie that someone else does not enjoy might still be a great experience for you. In short, opinions of others about hedonistic products might just have a lower chance of predicting your enjoyment of them than utilitaristic products.

Why is this important? Because most of the current research on the marketing of new products is aimed at utilitaristic products. Take the meta-analysis of Evanschitzky et al. (2012) for instance. One of the strongest predictors they found for new product success is ‘product advantage’. This predictor is very difficult to translate to hedonic products. A new hammer might be said to solve a certain problem more efficient than its predecessors, but can the same be said for a painting? Furthermore, a lot of this research takes into account functional aspects of products, which is also incompatible with the way we use hedonic products. Few listeners of music will explicitly judge music and pick their favorites based on functional aspects like the guitar player using new strings, the amount of cymbals the drummer uses or the amount of notes a singer is able to sing.

The focus on utilitaristic products within the realm of marketing for new products combined with the questionable translatability of research focused on utilitaristic products to a hedonic product context creates a possible theoretical blind spot when it comes to launching new products in the latter category. This means a current lack of research that is useful for understanding the success factors of a successful launch of products within the music industry.

Besides the more specific aim of this paper to research metrics to predict album success, it also contributes to our theoretical understanding of launching hedonic, as opposed to utilitarian, products. Concretely, the research question is what metrics can be used to predict the success of a new album *before* it is launched. And by doing this, help better understand the launch of hedonic products in general as well. This is at the moment, not understood as well as the launch of utilitaristic products.

Surprisingly, despite the extensive amount of research on new product launch available, there is to the best of my knowledge no current research into marketing related directly to new product development of music using a specific set of metrics. There is however not a complete lack of academic research into hedonistic products in general. A very narrowly focused and mostly quite recent body of research has begun to get a lot of attention within the marketing literature, namely the research on success factors that might predict the success of a movie, prior to its release.

This body of research tries to uncover all kinds of factors and metrics that can predict the success a new movie will have. Examples of these factors include the amount of reviews, the valance of reviews, the amount of followers of the actors playing in a movie on social media, success of the previous movie, genre of the movie and many more (Sitaram Asur et. al, 2010); (M. Saraee, S. et. al, 2004); (W. Zhang, 2009); (Gemser, 2007). Together these metrics seem to point to the possibility of predicting whether a new movie will succeed before the first scene has been shot. A lot of similar research points out other situations that can help. For example, Rosenkrantz et. al (2017) discovered people like products with very polarizing reviews more if these are products that people use for self-expression. It would seem that a body of reviews that is very polarizing - people rating it either the lowest or highest score instead of everyone rating them generally average, - might have a positive influence on sales as well.

In the spirit of not reinventing the wheel, the research question of this paper is researched by taking this body of research as a basis. Looking whether these quite refined models of factors predicting movie success can be translated to success within the music industry. The expectation being that this body of research can be of help precisely because it is research on another clearly hedonic product.

There are however a few adjustments to be made before it becomes useable in the music industry context. When ‘success’ is discussed within this body of academic research on movie success, reference is made to box office success. This boils down to either the amount of tickets sold at the theatres or (more often) total box office revenue. In translating this for the music industry there are a few routes that can be taken to translate this to success in the music industry.

The most logical options to the best of my knowledge being either ticket sales at concerts or total album sales. In this thesis, album sales will be the measurement of success within the music industry. This factor was chosen over the other because of the focus of managers working within both industries. Where album sales would be closer to DVD sales and ticket sales to the theatre might be considered closer to concert tickets, they do not seem to be the same in the minds of management in the industries. Awards for movies are usually based on box office, where in the music industry this is album sales. Besides this it is really hard to link revenue of concert sales to a specific song or album, as bands generally keep playing songs from different works during concerts. So for both theoretical and practical considerations, this paper will take album sales to be the success factor in the music industry.

This means this thesis will be build up as follows. Starting out by a review of the research on success factors researched for the movie industry. The literature is examined, compared and as a result a set of important predictors of movie success will be selected. After that these factors are translated to the context of album sales, why they do and how they would work within the music industry. Then a few very similar factors that might be irrelevant or overlooked in the film industry research because they do not fit as well in that context are discussed and added. This will result in a set of factors that together form a model that can be expected to predict at least part of future album sales. This model is tested to see which of these factors do in fact correlate with album success, and will hopefully add to the theoretical and practical understanding of a set of important drivers that can explain and predict the success a new music album will have.

Literature Review

Most of the previous research into the topic of predicting box office success of films based on all kinds of metrics consists of papers building a model of a variety of factors to see which factors are important influencers, and how they relate to each other in strength. Though the topic has been researched for a while, it has become more researched in recent times, probably due to the availability of big data and the need for marketers to harness the potential of this new big data. Reviewing the literature provides us with an overview of factors that were researched. Shown in table 1a, 1b and 2 is an overview of these different factors and whether they turned out to be relevant predictors.

		Gemser et al. (2007)	Elliot C. et al. (2008)	Brewer (2009)	Korschat (2012)	Ho Kim et al. (2013)	Garcia et al. (2017)	Bagella (1999	Karniouchina (2010)
Star Power		No	Yes	no		No		Yes	
Distributor effect		No					Yes		
Release period		No	No	Yes		No			
Competing Films close to release			Yes						
Size and/or Number of Reviews	Professional	Yes		Yes		No			
	Consumer					Yes			Yes
Valence of Reviews	Professional	No	Yes***	Yes	Yes*	Yes**			
	Consumer				Yes	No			
Number of Screens		Yes			Yes	Yes			
Arthouse vs. Mainstream Movies		Yes							
Genre		Only Opening Weekend	Yes			No		Yes ****	
Remake			No						
Linked Television Show			No						
Popularity Director			No			No		Yes	
Awards Nominated				Yes			No		
Awards won			Yes				Yes		
Budget			Yes	Yes	Yes	Yes	Yes		
Popularity of predecessors				Yes					
Income Movie Goers				Yes*					
Profanity and Sex							Yes (-)		

Violence and Gore							Yes		
Price Ticket				no					

Table 1a: General Overview of Statistically Significant Predictors of Box Office Success
'*' = Effect was very small
'**' = Effect was very small and only present in the US
'***' = Reviewers were all UK based
'****' = Only for comedy

		Duan (2008)	Liu (2006)	Qin (2011)
Size and/or Number of Reviews	Professional			
	Consumer	Yes	Yes	Yes
Valence of Reviews	Professional			
	Consumer	No	No	No

Table 1b: Additional studies focused on review number and valence

		Asur (2010)	Rui (2011)	Beak et al. (2017)	Ding et al. (2017)	Oh et al. (2017)
Twitter	General Activity Amount			Yes**		Yes****
	amount of Posts	Yes	Yes			
	Valence of Posts	Yes*	Yes			
	Tweeting about purchase intention		Yes			
YouTube	General Activity Amount			Yes		
	Views					Yes
	Comments					Yes
Blogs	General Activity Amount			Yes		
Facebook	Likes				Yes	Yes
	Talk					Yes
Yahoo!Movies	General Activity Amount			Yes***		

Table 2: Overview of Social Media specific predictors of box office succes
'*' = Effect was very small
'**' = Especially in early stages of launch
'***' = Especially in later stages of launch
'****' = Only in isolation, insignificant in a model taking Facebook, Twitter and Youtube activity into account together.

Not all factors yield the same results, most of them showing to be significant in one research paper and insignificant in another. A general explanation of this could be found in the differing operalizations of the same metrics between papers. Though almost all of them are focused on box office revenue different papers use data from different countries, which could explain different outcomes. For instance, Bagella (1999) focused on box office success in Italy and is one of the few to find star power to be a significant predictor, and to find the genre comedy to be outperforming the other genres.
When analyzing all the different explanatory factors researched in previous papers it seems that a few underlying themes are important. These seem to be reputation, contextual factors, reviews, availability & accessibility and social media activity. First these themes and their corresponding predictive variables are discussed. For some themes a few factors are dismissed for reasons discussed below. After this it is possible to translate them to a setting that would work for album sales, making sure these themes discovered in box office success research are included in the current research as well.

Reputation

A number of predictive measures from the literature review are measures that influence expectation based on track record. If a film is made by a filmmaker that has had a lot of success in the past, released by a studio that generally has a high standard of movies or features a lot of well known actors, it could drive sales. In the same way consumers prefer brands they have had positive experiences with in the past. It could be argued they prefer pieces of art featuring or that were released by people or companies they have had positive experiences with in the past. The following predictive factors are a part of this theme.

Star Power is used in a number of studies and is a measure of the popularity of the individual actors and actresses in a movie. This metric yields different results across studies, and is mostly found to not be a significant predictor of box office success. Looking at the differences between the papers we see the two outlier papers use data specifically of the UK (Elliot C. et al. 2008) and of Italy (Bagella. 1999), where the other papers use either data on box office in the Netherlands (Gemser. 2007) or the United States (Brewer. 2009, Ho Kim et. al 2013). Time could be factor to explain these differences but unfortunately this research is a bit recent to really see differences in time. The method of operationalisation could also play a factor, as this differs quite a lot between papers. Operationalisation for Star Power is done either based on box office success of the actor in previous movies (Brewer. 2009), as a yes or no variable based on film critics opinion on whether an actor is a star (Gemser. 2007, Bagella 1999), a yes or no variable based on whether an actor was considered a star in

Hollywood Reporter (Elliot C. 2008) or ‘whether a given movie includes a star actor who was cast in another movie which earned more than $50 million of the domestic revenues in the previous 5 years.’ (Ho Kim. et. al 2013). Interesting enough, the one time the same operationalisation was used by two studies it yielded different results, indicating that operationalisation might at least not be the only reason for the different outcomes. It is difficult to discard the possibility of star power being a relevant factor in predicting success of hedonic products, so it will be included in the current research model as well. However, literally translating the operationalisation to music could be redundant as it would probably overlap with general band popularity due to the fact that similar groups of musicians come together to produce another album way more often than the same group of actors do for a movie. This is why a slightly different operationalisation was chosen.

Distributor effect stands for the effect of a movie being released by a certain movie studio has on box office success. How much more will a movie make by being released by a certain studio as opposed to another. The differences in *Distributor effect* can probably be explained by radically different operationalisations. Gemser et. al (2007) operationalised this by including an either-or dummy variable in their model based on whether the film was distributed by a ‘large US distributor’ or not, not really explicating what exactly is meant by this and how a distinction between large and smaller distributors was made. Garcia et. al (2017) included dummy variables for each distributor in their sample. The latter method does not suffer from possible bias in selecting what a ‘large’ distributor is and truly looks at the effect for each individual distributor, which perhaps surprisingly led to a significant result as opposed to the former tactic. As explained by both papers, distributors can be expected to be an advantage because of the infrastructure they already have for new films, the contacts they have and the budget they can provide. In this regard, record labels can be considered very similar to these, which is why this metric will be included in the current model as the effect on album sales it has to be released by a certain record label over others.

Success of Predecessors is perhaps surprisingly only included in one model by Brewer et al. (2009). It seems likely that the existence of earlier movies that were successful is a good indicator of how sequels will perform, as they found in their research. Perhaps this is not taken into account in other studies because a minority of films was a sequel when most of this research was done. Despite the fact that this is rapidly changing as a continuously growing percentage of films are sequels according to an article on website Stephen Follows. In music however, it is way more likely that an album has at least one predecessor by the same band, and as the one study including this metric found it to be a significant indicator, it will be included in the current model as *previous album success*.

Both *Awards nominated* and *Awards won* seem interesting indicators, though very difficult to translate to the current context. Awards within music are awarded usually based on albums or singles sold. This means using this metric to determine albums sold would be redundant, as it would basically predict albums sold by the amount of albums sold. Which is why it will not be included in the model in this thesis.

The *Remake, Linked Television Show* and *Popularity of Director* metrics are very much movie specific. There is no series of music related to a record as there are movies related to series (series hinting at the movie in the story etc.) and a remake of a film is very different from its closest musical equivalent of a cover, as both are usually used for very different reasons. The role of a director is also quite difficult to translate to the music industry. A director is the person who usually utilizes and directs other people and their talents and combines them to create a movie. In music this is much more often than not done by the band or musician who also writes and performs. In short: these metrics do not seem relevant for our current purposes.

Contextual Factors

The next theme consists of factors that determine how the film relates to other films and to what other films it relates. If it is released in the winter, it can be expected to compete against other Christmas films. If it is released in a holiday, people might use the extra free time they have to visit the movie theater, driving sales for films released in that period, without it having anything to do with the movie itself. The same movie released as an action or as a horror movie can influence the type of consumers that will be interested and thus see the movie and its direct competition. These factors that determine the context or environment the film is placed and operates in will be discussed next.

Release Period is a measure expressing the time of the year when the movie was released. Does it matter for instance whether a movie is released in January or in August? For *Release Period* only Brewer (2009) finds it to be a significant predictor. Again, this might have to do with the operationalisation. In this research, a dummy variable is included to measure whether the movie is released in either of the popular times to visit the cinema, namely summer or during the Christmas holidays. Gemser et. al (2007), Elliot et. al (2008) and Ho Kim et. al (2013) all divide the year in parts of equal divisions of the year, and do not find significant results. This could be because for films, most release months are not significant predictors but these two especially busy months for cinema are (which makes sense). A big difference between album sales and movie tickets in this regard is availability. An album released six months before a busy period of buying records is still available during that hype, while movies are only available in theatres for a limited amount of time. However, it is not unthinkable that recall for albums when looking for gifts to buy someone is higher if the album and promotion for the album was done closer to such a period. This why, though expectation of significant results is low, a release period variable will be included in the current model. For comparison purposes and to be sure possible significance is in fact due to the holiday season, the release period is researched both by dividing albums into groups of equal periods of time and dividing them between released during or not during the holiday season. As significant results when only testing the latter might be due to a period effect that exists for albums in spite of holidays.

Despite its significance as a predictor, *competing films released in the same period* was only included by Elliot C. et al. (2008). The reasoning behind this might be the complexity of such a variable. In the operationalisation of this research it is taken to be a movie with a certain budget released within a certain time frame of the original movie. It could be asked though whether this automatically means it can be considered a competing film. A big budget drama released besides a big budget action movie does not necessarily compete for the same audience, and smaller films might turn out to be competition for a big movie when they attract similar viewers. Delving into the nature of competition for each film would require an amount time that would justify its own research paper, master thesis or perhaps even a book. Due to these practical considerations, this will not be included as a variable in our current model.

Art house vs. Mainstream Movies reflects whether a film is meant as an art film aimed at a very specific group of people or meant as a mainstream film intended to be enjoyed by the general public, and is one of the main indicators Gemser et al. (2007) wanted to test. Though already a bit difficult to distinguish within the movie industry, the distinction is even less obvious in other industries. In the music industry, this could translate to pop vs. non-pop music. Then again, a film is usually released as an art house film, whereas music usually turns out to be pop based on popularity and sales. Trying to explain sales based on the number of sales is a bit redundant, so it is not included in the current model. Making a specific distinction between art and non-art music is a discussion that could make or its own thesis, if not a larger work. All this does indicate that *genre* might be interesting to look at as a predictor variable, so it will be included in the current model.

Garcia et al. (2017) included both *Violence and Gore* and *Profanity and Sex* in their model. Though difficult to translate for our current purposes a similar measure of the presence of *Explicit Lyrics* could be included to see if this also has an effect for music album sales. However, a lot of albums if not all of them contain at least some explicit lyrics. A lot of albums are also released in both an explicit and a clean version, the latter being without explicit lyrics. Though a nice solution to serve all fans, it makes including such a metric almost impossible, as sources on album sales do not differentiate between sales of the explicit and clean versions of the album. This makes comparisons very difficult, and is why no such metric is included in the current model.

Movie Budget is found to be a significant indicator of box office revenue across all studies so would be interesting to take into account in the current model as well as budget set for the album. It is however excluded for the practical reason of availability as a metric. Where movie studios generally provide IMDB or similar sites with information about budget, this is a much better kept secret among record labels and artists. Reaching out to record labels for this information has made this abundantly clear. Even worse, smaller bands do not generally keep track of the amount of money spend on making an album. This would bias this metric in favor of better performing bands in case the information was made available and even then would be negatively influenced by too rough estimations by smaller artists. Making generalisability an issue.

Reviews

Another recurring and very interesting part of this research is the research into reviews as a predictive factor of box office success. It could be said that these are not strictly predictive measures, as most reviews appear only after the product has been released. This is especially the case for consumer reviews, which cannot be accessed beforehand. However, a number of marketing decisions can or sometimes have to be made before a product is released that influences both the valence and amount of reviews. Sending your product for review to all reviewers might increase the number of reviews, but lower the overall score and increase likelihood of negative reviews. Sending them only to reviewers that are likely to give positive feedback heightens the average score, but lowers the amount. With consumer panels the likelihood that consumers will write a review on a product can be estimated, and also what kind of scores can be expected. Knowing if reviews are a factor to be taken into consideration, and if so, what part of these reviews, is crucial to marketers in this field. The following factors are important.

The *size and number* of reviews, both those by professionals and consumers, are found to be a significant predictor of box office revenue except in the research of Ho Kim et al. (2013) who found the number of expert reviews to be an insignificant predictor. Looking at the data that was used in this research reveals that only reviews posted on Rotten Tomatoes were counted. The positive effect of the number of reviews in other studies is based around exposure a movie will get from having reviews. Whether ten or a thousand reviews were posted on Rotten Tomatoes, it is probably not going to increase exposure among non Rotten Tomatoes users. The other studies looked at reviews from various sources. This means that an extra review can point to another channel and thus another set of users that the review reaches. This explanation would explain the difference in results as well. It could be argued that this is a metric only known after the release of a movie or album. It is however something that can easily be influenced by marketing managers. The number of professional reviews is going to be impacted by the amount of reviewers you ask to write a review, and people could be incentivized to write a review about a movie. Whether this is a smart move is especially interesting in the light of results of the *valence of reviews*, which expresses the height of the scores given to the movies as an indication of quality.

Sometimes a marketer knows sending a product to one reviewer might have a higher or lower chance of a good review than with other reviewers. Asking a horror reviewer who loves a lot of gore to review your gore-free thriller might have a lower chance of resulting in a review full of praise than with others. If *valence of reviews* is more important than the *size and number of reviews* in predicting success, this might not be a good idea. If it is the other way around, a bad review might be better than no review at all. The same goes for incentivizing only certain types of movie-goers as opposed to all of them to write a review about your product. If only the number of reviews matter, considerations are different. It is also very interesting to research what is more important for album success in the music industry as based on previous research the amount of reviews seem to be a bit better predictor than valence when it comes to movies. Which is why these metrics will be included in the current model.

The interest this theme has sparked in the scientific community can be seen by the fact that there has been quite a bit of research into the impact of both the volume and valence of professional reviews and customer sentiment on box office revenue on its own. For instance, Liu (2006) finds that box office revenue is significantly impacted by the volume of electronic word of mouth, but that valence does not have such an impact. Qin (2011) finds similar results when looking at big movie blog sites. He finds there is a significant positive relationship between the amount of talk about a movie and the box office of a movie.

Duan et al. (2008) also look at both the valence and number of online reviews to find out which of them - if any - are indicators for box office success. They also find only the number of reviews to be positive, significant indicators of box office success but the valence of those customer reviews not to have an impact on revenue. This is interesting especially because these findings contradict research by Brewer (2009), Elliot et al. (2008), Koschat (2012) and Ho Kim et al. (2013) mentioned above.

These seeming contradictions are not limited to movie success but exist for other products as well. For instance, Chen et al. (2004) find that the number of consumer reviews on books on Amazon had a significant impact on the number of sales. The valence of those same consumer reviews did not have a significant impact on sales. This finding was contradicted by a similar research paper by Chevalier and Mayzlin (2006) which finds that the most important metric to predict book sales is the valence of the consumer reviews, the number of reviews being significant as well but having a smaller effect.

Perhaps the results of a study by Vermeulen (2008) can shed some light on this. This research went into the impact of hotel reviews on consumer consideration for staying at that particular hotel. The findings indicate that having a review at all will improve consideration. Though negative reviews will damage the intention to stay at that hotel, this effect is compensated for smaller hotels by the exposure they get from even a bad review. This was partially confirmed by the results which indicate that, comparing lesser and better known hotels, bad reviews have a negative impact on intention to stay for lesser known hotels but is compensated by having a review at all. This was not the case for bigger hotels, for which the net effect was negligible.

As significant effects for at least some of these predictors on album success are to be expected, all four metrics (number of professional reviews, valence of professional reviews, number of consumer reviews and valence of consumer reviews) are included in the current model.

Availability & Accessibility

Availability and accessibility translate into the amount of places a product can be bought and the amount of people that have access to or can afford it. If a product is only available in a local store in India, it will probably sell worse in absolute numbers compared to when it is carried by a big multinational. If a product is cheaper, more people can afford it. These measures determine for how many people the product is accessible.

The number of screens stands for the total amount of cinemas the movie was shown at and was found to be a significant predictor of box office revenue across all studies. This is not very surprising as more screens means it is shown in more cinemas, which means it is available for purchase to more consumers. Roughly this points to the availability of the product. For this study it could be included in the current model as the number of stores the album is sold in.

The *income of movie goers* and *price of ticket* indicators were included by Brewer et al. (2009). They found the *income of movie goers* had a very small effect and *Price of ticket* had no significant effect at all. It is also the only research that took these measures into account. This is probably due to the practical difficulty of getting to know the income of movie goers and the fact that ticket prices (as do album prices) vary across different outlets.

However, metrics from this theme will not be included in the current model for very simple reasons of translatability to the current context. Due to the rise of online music stores, and the digital market, the number of stores is both immeasurable and redundant as a factor. Immeasurable because one could count every place with an internet connection as a possible store for albums. It is also redundant because it can be argued that another store does not add to the availability of the music. A store in Australia carrying the album will add an option to buy the music, but the same customer could have already bought it online. It makes sense to measure this for cinemas as a movie in the theatres can only be watched locally.

For a similar reason neither the income of movie goers and the price of ticket will be included. Because of the widespread availability across countries, it would move beyond the scope of almost any paper to research the income for the entirety of possible buyers for a music album. Because of online outlets and the amount of control they have on pricing, comparing prices is almost impossible because there is little consistency between stores on price of albums. Especially when taking Spotify into account, a platform through which consumers can listen to music without directly paying for a particular song, but rather through a monthly description.

Social Media Metrics

In even more recent times there also has been a lot of research into using social media metrics like those obtained on Facebook, YouTube, Twitter and the like to predict box office success. These are discussed in a similar way as the metrics above to see which metrics are suitable for the purpose of this research. Again, a summary of the findings can be found in table 2 above.

What becomes clear immediately is that, in contrast with the other metrics, the social media metrics are all significant predictors of box office success. Another advantage of these metrics is that they are relatively easy to translate to the current context and suit it very well. Oh et al. (2017) measure YouTube views by the amount of views a trailer video has, which in many respects is similar promotional footage to an album, as it is usually released prior to the album, only a part of it and meant to drive sales, not to be sold in itself. Blogs general activity is measured by Bleak et al. (2017) by looking at the amount of blog posts about a movie, which relates quite well to blog posts about albums. Facebook likes and talk as measured by Ding et al. (2017) and Oh et al. (2017) is all about frequency of mentions on Facebook which can be used in a very similar way as an indicator for album sales. Yahoo!Movies, though interesting, is very much movie specific, so will not be included in the current model. The amount of blog posts is measured by looking at the amount of professional reviews on Metacritic, and not looked at individually. This is done simply because finding all blog posts on all albums is practically impossible, and the amount of professional reviews on Metacritic already grants a good insight into how much is written on every album, especially proportionately and relative to each other.

Besides this, Oh et al. (2017) find that Twitter is one of the less explanatory indicators. They also find Twitter metrics to become insignificant when taken Facebook and YouTube metrics into account in the same model. According to their research, Twitter does not indicate any popularity that is not already indicated by YouTube and Facebook while the latter do indicate popularity that is not explained by other metrics. As this seems consistent with the other research that finds Twitter to be the weaker indicator of box office revenue, this will not be included in the current model. It also points to the possibility of some metrics making other obsolete in our context, which is something to keep in mind.

Original in their approach, Mestyán et al. (2013) look at a few Wikipedia metrics to try and predict box office success of movies. They looked at the number of users contributing to a movie page, the total number of edits, the number of edits by the same person and number of views of the movie wiki. They found these metrics to predict the degree of success of relatively successful movies quite well, but results became less and less accurate for less successful movies, the latter deviating from the predicted regression line more and more as they were less successful. This is an interesting finding especially because most research discussed used data on well performing movies. It also points to a possible limitation of those studies, along with the current one. Whatever the case, including Wikipedia data seems like a good choice, as expectation of its significance is high.

Model Extensions

Besides studies taking complete models into account, a lot of research has focused on expanding these models by researching one or a few predictors in depth rather than include them in an overarching model. For instance, Karniouchina (2010) finds that the amount of online chatter about a movie has a positive impact on box office revenues, and the amount of chatter about the actors only has a significant impact on revenue of the first week of the movie. So we could expect to find individual band member popularity to be an indicator especially early on for sales.

A later article by Treme et al. (2013) delves into the impact of the age and sex of lead actors, and the impact it has on box office revenue. Several interesting conclusions result from this research. First, it appears that having a male lead above the age of 42 significantly impacts box office revenue in a negative way, reducing revenue with at least $10.000.000. A similar effect for female leads was not found. Furthermore, the more media exposure male lead actors have, the higher the box office revenue of the movie is expected to be, while the reverse is true for female actresses, for which expected box office decreases when their media exposure increases. This indicates that it might be interesting to look at the media exposure of at least the front person of a band in combination with their sex. However, as it is expected to be measured by popularity of the front man or woman as well, this will not be researched on its own.

Missing Metrics

The final step is to consider whether any indicators are missing, perhaps because they are not relevant for movies. For practical reasons, this is limited to indicators that fit the themes found in previous research literature. A very obvious metric missing here is Spotify, which is a large player in the music industry, but obviously not in the film industry.

This brings us to the following set of predictors. The hypothesis of this paper being that all of these factors have a significant impact as independent variables on the dependent variable of total album sales. Despite having dismissed a number of factors, there remain predictors for four out of five themes discovered in the previous body of academic research, the fifth having too little relevance on our current research to be included.

Box Office Predictor	**Music Industry Predictor**
Reputation	
Star Power	Popularity musician(s)
Distributor Effect	Label effect
Popularity of predecessors	Popularity of previous albums
Contextual Factors	
Release Period	*Release Period*
Genre	*Genre*
Reviews	
Size and Number Reviews (professionals)	*Number of Reviews (professionals)*
Size and Number Reviews (consumers)	*Number of Reviews (consumers)*
Valence Reviews (professional)	*Valence of Reviews (professional)*
Valence Reviews (Consumer)	*Valence of Reviews (Consumer)*

Social Media Indicators	
YouTube (general)	*YouTube (general)*
YouTube # of Views	*YouTube # of Views*
YouTube # of Comments	*YouTube # of Comments*
Facebook # of Likes	*Facebook # of Likes*
Facebook amount of talk	*Facebook amount of talk about an upcoming album*
Wikipedia Activity	*Wikipedia Activity*
	Amount of Spotify Subscribers

Table 4: Final Indicators

Methodology

Chosen Statistical Methods

The point of this paper is to test whether the above mentioned variables are good predictors of album sales, which meant data had to be collected for each single predictor. After this it was to be tested whether the variance in each of these predictors accounted for a significant part of the variance in the related album sales, and if so how much. The expectation was a linear relationship between each of the almost all continuous independent variables and the continuous dependent variable ‘album sales’. This meant a regression analysis was appropriate for this particular study. In this study, the significance of variables is checked in three steps. First, it is checked whether a variable or a group of variables from the same source is a significant predictor on its own. After that, a model is made based on all predictor variables belonging to the same theme. This results in three different models. One model including only predictor variables which were significant in the model with all other predictor variables from the same theme. A second model including all predictor variables that were significant on their own. And finally a model including all predictor variables. Each time it is checked whether the new model is both significant and a significantly better fit to what can be expected in the real world. This should result in the most accurate model that explains real world situations best.

As a way to find out whether anything can be said about the way or structure in which this final set of predictors behave and interact with each other to predict album success, a partial least squares analysis is conducted for that final model.

Data Collection

Data was collected differently for almost all of the predictors. Below is an overview of these for each of the themes.

Reputation

Star power was measured by using the word search frequency tool in Adwords by Google. This is a tool designed by Google for business owners looking to advertise their company website or social media channel through Google. The tool estimates the search volume for each search term included in the advertising campaign. The advertising settings were set the same for each search word, to make a comparison possible. These were set to a worldwide scale, on a minimal budget, through all networks of advertising available to Google at the time.

For each band, all the names of members working on the album were entered in the tool. The search volume for the most popular band member is what is expressed through the metric star power in the current research. One remark has to be made here. In some bands nicknames were used that can obviously refer to other things with a much higher search volume. The name JB from a member of Got7 for instance, resulted in an unexpectedly high search volume. One Google search revealed that most searches for JB were probably not aimed at this particular person. In these cases birth names were used.

A number of sources could have been used to track popularity of an artist. However, Google was chosen because it is so widely used, and thus assumed to be representative for the search activity of the entire population. According to Smart Insights, 74,54% of all searches in 2017 were done through Google. Search engines are also a starting point when trying to find information on something or someone. This made Google search volume seem like a good indicator of artist popularity.

For the *popularity of the label* under which the albums were released categorical variables were used, each label being another category. Including dummy variables for each label. Because of the sheer amount of labels, a dummy variable was included only for labels appearing more than twice in the list. Different divisions of the same label (Sony Japan and Sony America for instance) were combined into one label. The other labels were combined into a ‘miscellaneous’ category which was used as the reference category.

The *popularity of predecessors* is a measure of the total amount of number top ten hits a band has had according to Billboard. Billboard was chosen because it made comparison easier, almost every band was featured on this website and album sales from previous albums were not widely available.

Context

Release period was included my using a dummy variable for each quarter of the year within the dataset, with September until November as the reference category, to check whether any significant differences could be found between the months an album was released. The data on album release was taken from Mediatraffic.

The *genre* of the music was added to the regression analysis as a series of dummy variables for each genre with rock as the reference category, in a similar way as the release period. As different sites report different genres, the indication by Google Play was used. Mainly for comparability across cases, as almost all albums were available through this store.

Reviews

For *the number of professional reviews* and *valence of professional reviews* data from the website Metacritic was used. This was done for a simple reason. In the existing body of research, a distinction is made between professional and consumer reviews. From a theoretical standpoint this is a difficult distinction to make or maintain, especially since the rise of the internet. What exactly is a professional? There are a lot of writers reviewing musical albums in their blogs, on their websites and even in YouTube videos. When does a consumer review become a professional one? Does it take a specific amount of followers? Is it important to be an academic scholar of music? The choice for Metacritic was made to circumvent this discussion, which could be the subject of a master thesis in its own right. This website maintains a list of professional music review websites and accumulates those reviews and averages scores to come to a number and average valence score for each album featured. Of course, it can always be argued that this website should have included or excluded a number of reviewers from being a professional. Because the list of reviewers used on this website is constantly updated according to these considerations this is a widely accepted list in this regard, which is as close as one can get to a list of professional reviewers, precisely because it remains a matter of judgment.

To conclude: these metrics express the average scores and number of professional reviews found on this website.

Data on the *number of consumer reviews* were calculated by adding together the amount of review scores on a particular album given on Amazon and Google Play, as the latter also accumulates consumer scores. Because of the sheer amount of websites it is practically impossible to add up every review each consumer has written. Besides this, the question of what constitutes a consumer review also plays a role here. Is a YouTube comment a consumer review? Does it have to include a valence score? Adding up the consumer reviews for these same two sites for every album gives a good picture of the proportions of consumer reviews for each album compared to the others, which is what is interesting in light of this research. Both Amazon and Google Play carry almost every album in the currently used dataset, making biases based on availability of reviews less likely.

The valence of consumer reviews was calculated by taking the average of all scores given on each album on these three sites. As all three use the same scale for ratings, scores did not have to be transformed and could be used as found on these websites. This circumvents discussion about whether a six on a scale of ten is the same as a three on a scale of five. Data from both is collected from the time an album was released.

Social Media Metrics

Finally the social media metrics are included. *Wikipedia Activity1* is a measure of the total amount of views of Wikipedia page of a band one month before the album release. *Wikipedia Activity2* is a similar measure but of the amount of views of the Wikipedia page of the specific album in the same time period. Data for this is taken from Wikimedia Labs. *YouTube Activity1* is a measure of the total amount of subscribers the YouTube account of the band has at the time an album is released, *YouTube Activity2* stands for the amount of views a channel has at the moment of an album release. Both were collected from YouTube itself. *YouTube views* and *YouTube Comments* express the amount of views and comments the first music video in support of the album has at the moment of the album release. *Facebook Likes* and *Facebook Talk* were taken from Fblikecheck.com. These were also retrieved at the time of an albums release. *Spotify subscribers* is a measure of the amount of monthly listeners a band has according to their Spotify profile.

Finally, the data for the dependent variable ‘album sales’ were retrieved from MediaTraffic.de. This is a German website that gathers data on global album sales. This measure expresses the amount of albums sold in the first week of the release. The reason for choosing the record sales of the first week is because what is important is the effect the above mentioned metrics have on album sales. These can be supposed to be strongest for the initial sales of the album, as a lot of other factors come into play when considering album sales after that, like positive offline word of mouth or eventually the next album by the same band. Also, a lot of these metrics like *Facebook Talk* measure hype generated for the album, which can be expected to generate most sales immediately when the album comes out or in presales. As the purpose of this study is to confirm whether these metrics predict music album success as well, the point at which the strongest effect can be expected is the point chosen to measure.

Method

As previously mentioned, to get as much insight out of the data previously collected a number of regression analyses were conducted. To start out, a regression analysis was conducted for each set of predictors from the same source. Than a model was made using only the predictors from the same theme, and finally a model was made including all independent variables. This way, it is possible to get insight into whether independent variables are significant predictors of album sales on their own, together with other predictors and whether they remain significant when other variables are included.

This way was inspired by the research and conclusion of Oh et. al. (2017). Again, they found Twitter activity to be a significant predictor of box office success, but found it to be insignificant when including Facebook and YouTube into the model as predictors of box office success as well. As will become evident, the same phenomenon occurs in the current research. This gives managers insight about whether a certain platform can be used as a predictor and which platforms predict album sales better than others.

This can be important when the most significant or important predictor values are not available. If Spotify metrics for example would turn out to be significant on their own, but insignificant when Facebook is taken into account as well, it would help management of acts that do not have a Facebook account to not incorrectly assume Spotify metrics cannot be used. From a theoretical standpoint it also grants us a more complete perspective on the workings and interactions of different metrics and stimulate directions for further research

Furthermore, including only a final model would dismiss albums by bands that do not have all data available. For instance, not every band has its own YouTube page, not every band is on Facebook. The final model will inevitably exclude acts that do not have a complete online presence. It is possible that this would bias the results. Keeping up social media is very time consuming. Bands and acts signed by big labels have enough manpower to be active on all these platforms. Bands that have less of a budget might have to be more selective due to time constraints or budgetary constraints of not being able to hire people to maintain profiles for them. As this research strives for conclusions that are as broadly applicable as possible, these steps were chosen.

Of course these acts will still be excluded in the final model. However, the aim is that this method will at least be able to detect this bias and take this into account in the discussion of the results.

Results

This brings us to the results of the current study. As previously mentioned this will be done by looking at the predictors in small groups that share a common source, by looking at them in connection to their assigned themes and finally in an overall global model. This is done to get as much insight from the data as possible, which has proven worthwhile in examining the results of this chapter.

In this section, a lot of regression analyses are performed, meaning assumptions required to be able to do and interpret such an analysis have to be met. In order to avoid redundancy a few words on these assumptions. With regression analysis a low Skewness and Kurtosis is preferable. In quite a few cases below they were not strictly met. However, because of the sample size of 102 cases this is usually not a problem, unless mentioned otherwise. Transformations carry with them problems in interpretation of the results in themselves. Due to these considerations, it was decided not to transform data based on these violations.

The other requirements, of linearity, constant variance of error terms, independence of error terms and normality of the error term distribution are usually met. Instances that deviate from this are mentioned, and solutions are explained.

Reputation

First it was checked whether the popularity of the most popular musician alone impacts album sales by running a regression analysis with the popularity of musician as the only independent variable. When checking the assumptions for linear regression however it became clear that the assumption for linearity was not met. The scatter plot showed a clear pattern and the added polynomial terms were both significant. Following Field (2016, pp 309 & 203) the independent variable was transformed using a log transformation, after which the assumptions for linear regression were met. There was no longer a visible pattern in the scatter plot, the standardized predicted values were .000 for the mean and 1.000 for the standard deviation, and the error distribution seemed to approach normality. The relatively minor problem of skewness and kurtosis was also fixed by this transformation, changing from 17,427 and 0,474 to 3,852 and 0,239 respectively. Which means the results could be interpreted.
This model was found to be significant at a significance level of 0,05 with a positive effect. The explanatory power however was quite small, with an R square of 0,072. Meaning 7,2% of the variance in album sales can be explained based on the search volume.

Secondly the impact of the popularity of previous albums as a predictor of album sales was tested. Though less obvious as with the prior variable, again a transformation was required to meet the assumption of linearity. After which no patterns were obvious in the scatter plot, the variance of error terms seemed constant and the error term distribution was still constant (as before the transformation). This model was significant at a significance level of 0,000 and reported an R Square of 0,197. Meaning 19,7% of variation in album sales could be explained by the popularity of previous albums.

Thirdly it was checked whether the label an album was released by had any significant impact on album sales. To start out, an Analysis of Variance was conducted to check whether there is indeed a significant difference between the different labels. A few assumptions have to be met doing an ANOVA. First, the different categories have to be mutually exclusive. This was the case, as labels and albums in the used set do not overlap. Secondly, the error term should be normally distributed, which was the case. Third and finally, there should be equal variance across groups, which was the case (Levene's test null hypothesis could not be rejected at a significance level of 0,652). The null hypothesis that the average value of the dependent variable is the same for all groups could not be rejected, with a significance of 0,930. This means that there is no reason to expect there to be a difference in average album sales between labels. Because there is no significant difference between the different groups, this variable was also not included in the final model

Lastly, a regression analysis was performed to check for the remaining variables for this theme. For this the log transformations of the predictor variables were used to account for the fact that the assumption for linearity is not met otherwise. This results in a significant model with an adjusted R square of 0,165. Taken together, the popularity of musicians is no longer a significant predictor of album sales at a significance level of 0,932, while the success of previous albums remains a significant predictor at the level of 0,002.

Taken Alone	R Square	Adjusted R Square	Model Significance	Predictor Significance	Unst. B	Std. Error	Std. B
Popularity Musician*	0,072	0,063	0,007*	0,007	42659,339	15532,823	0,269
Popularity Previous Albums*	0,197	0,183	0,000*	0,000	266168,517	71077,442	0,444
Label Effect			0,930				
Complete Model							

Popularity Musician	0,195	0,165	0,003	0,476	177-3,996	24681,728	0,091
Popularity Previous Albums*	0,195	0,165	0,003	0,002	245492,927	75263,160	0,413
Label Effect (excluded)							

Table 5: Results for Reputation.

*=significant at 0,05

Contextual Factors

The second theme identified consists of predictors that are contextual factors. In this case, when the album was released and which genre it was assigned. Starting with the former, an analysis of variance was conducted to check whether there is indeed a significant difference in album sales between albums from different release periods. This was however not the case. With an F-ratio of 0,219 and a significance of 0,804, the null hypothesis stating there to be no significant difference in values of album sales between groups could not be rejected. It was however suggested and tested by Brewer (2009) that difference in release period might be caused by holiday seasons or Christmas when a lot of gifts were given. This is why a second analysis of variance was conducted with two groups, one to represent December and the other to represent the rest of the year. Despite a lower significance level of 0,731 the null hypothesis stating there to be no difference between groups could still not be rejected.

The second predictor of genre was also initially researched by conducting an analysis of variance. This time to see whether the genre an album is assigned influences its sales. In this case as well as the case of release period, the null hypothesis of there being no difference between groups of albums of the same genre could not be rejected at a significance level of 0,526. However a note has to be made here. The sample of albums used in this study is not a random selection of albums. These concern albums that have appeared in the top ten best selling albums for at least one week. Looking at the frequencies of genres appearing, there is a small indication that hip hop and pop albums are around two to three times as likely to make it onto this list, appearing 29 and 23 times respectively.

Just to be sure, a regression analysis was conducted with dummified versions of both predictor variables to check whether this might yield significant results. This model was highly insignificant as expected based on the analyses of variance conducted previously at a significance level of 0,812.

Alone (ANOVA)	F-ratio	Significance
Release Period (quarter periods)	0,219	0,804
Release Period (december vs. rest of the year)	0,119	0,731
Genre	0,879	0,526
Together (Regression)	F-ratio	Significance
Release Period and Genre	0,578	0,812

Table 6: Results for Contextual Factors.

Reviews

This brings us to the third overarching theme to be researched, being the review metrics. First, a regression analysis was conducted to check whether there is a causal link between the amount of professional reviews found online and album sales. At a significance level of 0,054 it is close but still not possible to reject the null hypothesis that there is no such causal link. Had this paper adopted a less strict ninety percent confidence level however, this would have been a significant effect.

The question whether the valence of these professional reviews impact album sales is a different story. At a significance level of 0,770, it seems very unlikely that there exists a causal link here. Combining these two predictor variables to try and explain album sales results in a model with a 0,067 significance level. Again, had this paper adopted the less strict ninety percent confidence interval the model would have been significant. Not only that, in that case the number of professional reviews would have been a significant predictor at a significance level of 0,029, where the valence of professional reviews would not have been at a significance level of 0,190. Of course, neither is significant, but it is worth mentioning.

Next a regression analysis was conducted to test whether there is a link between the amount of consumer reviews and album sales, starting with those found on Amazon. At a significance level of 0,000 the amount of Amazon reviews on its own is a significant predictor of album sales. The reviews found on Google tell a similar story, at the same significance level the amount of consumer reviews found of Google Play is also a significant predictor of album sales. A model taking both of these metrics as predictor variables is also significant at a significance level of 0,000. However, in this model only the amount of Google play consumer reviews is significant at a significance level of 0,000, Amazon changes a bit to be significant at 0,002. Also interesting to note is the coefficients. One extra Google Play consumer review is in this model expected to account for about 58 albums sold, while Amazon reviews account for about 413. The average amount of reviews on Google Play is however almost ten times higher than on Amazon, making the effects of both sites relatively equal.

The valence of consumer reviews and its impact on album sales was tested next. First again the valence of Amazon consumer reviews, which did not yield a significant model at a significance level of 0,633. Though a bit closer to significance the valence of Google Play consumer reviews also cannot be assumed to significantly impact album sales at a significance level of 0,322. A model containing both predictor variables is also insignificant at a significance level of 0,586.

Finally, a model was made containing all predictor variables previously mentioned. This resulted in a significant model at a significance level of 0,000, and an adjusted R Square of 0,541. In this model, only the two predictors representing the amount of consumer reviews were significant at a significance level of 0,000 for the amount of Amazon reviews and 0,002 for the amount of Google Play reviews. Another model was conducted including data from Metacritic regarding consumer reviews as well, to check whether this would grant any additional insights. When including the amount and valence of consumer reviews according to Metacritic we get a new model with a significant F change at a significance level of 0,001. The only difference being that the amount of Google Play reviews is no longer a significant indicator of album sales and the amount of Metacritic consumer reviews has seemingly taken its place. The valence of consumer reviews on Metacritic was also insignificant.

Taken Alone	R Square	Adjusted R Square	Model Significance	Predictor Significance	Unst. B	Std. Error	Std. B
Number of Professional Reviews	0,071	0,053	0,054	0,054	7790,502	3947,781	0,266
Valence of Professional Reviews	0,002	-0,018	0,770	0,770	-762,219	2590,740	-0,041
Number of Consumer Reviews: Amazon*	0,492	0,242	0,000	0,000	708,185	130,649	0,492
Number of Consumer Reviews: Google Play*	0,590	0,348	0,341	0,000	74,493	10,631	0,590

Valence of Consumer Reviews: Amazon	0,002	-0,008	0,633	0,633	91,304	190,775	0,050
Valence of Consumer Reviews: Google Play	0,011	0,000	0,322	0,322	45,300	45,462	0,103

Table 7: Results for Reviews Individually.

*=significant at 0,05

Taken Together	R Square	Adjusted R Square	Model Significance	Predictor Significance	Unst. B	Std. Error	Std. B
Number of Professional Reviews	0,596	0,541	0,000	0,072	5920,180	3216,265	0,200
Valence of Professional Reviews	0,596	0,541	0,000	0,060	-5660,088	2933,271	-0,218
Number of Consumer Reviews: Amazon*	0,596	0,541	0,000	0,000	802,402	210,902	0,427
Number of Consumer Reviews: Google Play*	0,596	0,541	0,000	0,002	45,729	14,017	0,361
Valence of Consumer Reviews: Amazon	0,596	0,541	0,000	0,695	270,892	686,440	0,050
Valence of Consumer Reviews: Google Play	0,596	0,541	0,000	0,359	121,920	131,397	0,112

Table 8a: Results for Reviews together.

*=significant at 0,05

Taken Together With Metacritic Consumer Data	R Square	Adjusted R Square	Model Significance	Predictor Significance	Unst. B	Std. Error	Std. B
Number of Professional	0,706	0,650	0,001	0,270	3232,295	2893,726	0,109

Reviews							
Valence of Professional Reviews	0,706	0,650	0,001	0,240	-3759,551	3154,000	-0,145
Number of Consumer Reviews: Amazon*	0,706	0,650	0,001	0,000	713,949	188,147	0,380
Number of Consumer Reviews: Google Play	0,706	0,650	0,001	0,882	-2,745	18,366	-0,22
Valence of Consumer Reviews: Amazon	0,706	0,650	0,001	0,364	554,478	604,046	0,101
Valence of Consumer Reviews: Google Play	0,706	0,650	0,001	0,213	149,531	118,202	0,137
Number of Consumer Reviews: Metacritic*	0,706	0,650	0,001	0,001	385,483	104,029	0,549
Valence of Consumer Reviews: Metacritic	0,706	0,650	0,001	0,139	-3935,303	2607,717	-,186

Table 8a: Results for Reviews together Including Metacritic.

*=significant at 0,05

Social Media Activity

The fourth theme for research is social media activity. This concerns online stats for social media or closely related websites for bands or albums. The first platform for which metrics were taken was for music perhaps the most obvious one, namely Spotify. Despite a low R square of 0,141 and a very low b coefficient of 0,007 the amount of monthly listeners on Spotify is, on its own, a significant predictor of album sales at a significance of 0,000. This low b coefficient could however be caused by the relatively high average amount of Spotify listeners of 859600.

Next a regression analysis was conducted to check whether the amount of Facebook likes a band has, and the amount of Facebook word of mouth there is significantly impacts album sales taken on its own. With a relatively high Adjusted R square of 0,516 this was a significant model at a significance level of 0,000. The difference between the effect sizes of the two predictor variables is however very noticeable. While both of these where significant, the effect size of the more active Facebook Talk approached to be 200 times bigger than Facebook likes. Making it that it would seem more important for a band to have a lot of people talking about them on Facebook at the moment than once having liked them.

Next, YouTube statistics where tested to look for a causal relationship between them and album sales. In this research four YouTube metrics were tested together. The amount of subscribers the official band page has, the total amount of views it has, the amount of views the first music video for the album has and the amount of user comments that could be found for that music video. This model taken on its own was found to be a significant predictor of album sales with a significance level of 0,000 and an adjusted R squared of 0,284. Of the predictor variables only the amount of YouTube subscribers and the amount of YouTube total channel views were found to be a significant predictor of album sales. The former at a significance level of 0,000 and the latter at 0,042. Pointing to channel statistics being more relevant than music video statistics.

Finally a regression analysis was conducted taking only Wikipedia statistics into account. Both the amount of views of the band’s wiki and the wiki for the album were taken into account, adding together all views one month prior to the album release. As with the other individual models for social media activity, this model was significant at a level of significance of 0,000. The adjusted R square is 0,263. However, only the activity for the album wiki, not of the band wiki, was found to be a significant predictor of album sales.

Finally, a model was made with all the social media predictor variables to see how they behave as predictors of album sales as a whole. The regression analysis yielded a significant model at a level of significance of 0,002 and an adjusted R square of 0,228. Interestingly, when all these predictor variables are taken together, only the amount of views of the Wikipedia album Wiki remained a significant predictor of album sales.

Taken Alone	R Square	Adjusted R Square	Model Significance	Predictor Significance	Unst. B	Std. Error	Std. B
Spotify Monthly Listeners*	0,141	0,132	0,000	0,000	0,007	0,002	0,375
Facebook Likes*	0,526	0,516	0,000	0,000	0,005	0,001	0,376
Facebook Talk*	0,526	0,516	0,000	0,000	0,891	0,156	0,458
YouTube	0,319	0,284	0,000	0,000	0,042	0,007	0,737

Subscribers*							
YouTube Views*	0,319	0,284	0,000	0,042	-6,064E-005	0,000	-0,219
YouTube Clip Views	0,319	0,284	0,000	0,106	0,000	0,000	-0,242
YouTube Clip Comments	0,319	0,284	0,000	0,694	0,102	0,259	0,050
Wikipedia Bandpage Activity	0,282	0,263	0,000	0,197	2,262	1,736	0,142
Wikipedia Album Wiki Activity*	0,282	0,263	0,000	0,000	21,586	5,234	0,451

Table 9: Results for Social Media Indicators Alone.

*=significant at 0,05

All Combined	R Square	Adjusted R Square	Model Significance	Predictor Significance	Unst. B	Std. Error	Std. B
Spotify Monthly Listeners	0,326	0,228	0,002	0,794	-0,001	0,003	-0,051
Facebook Likes	0,326	0,228	0,002	0,473	-0,001	0,002	-0,108
Facebook Talk	0,326	0,228	0,002	0,273	0,362	0,327	0,165
YouTube Subscribers	0,326	0,228	0,002	0,647	0,003	0,007	0,095
YouTube Views	0,326	0,228	0,002	0,663	-1,409E-005	0,000	-0,050
YouTube Clip Views	0,326	0,228	0,002	0,838	5,901E-005	0,000	0,039
YouTube Clip Comments	0,326	0,228	0,002	0,833	-0,067	0,315	-0,032
Wikipedia Bandpage Activity	0,326	0,228	0,002	0,427	2,006	2,508	0,120
Wikipedia Album Wiki Activity*	0,326	0,228	0,002	0,002	22,005	6,904	0,455

Table 10: Results for Social Media Indicators Alone.

*=significant at 0,05

Full Model

Having finished researching the thematic parts individually, the full model can be made. The regression analysis for the full model is conducted with three successive blocks with more elaborate models, each time checking whether there is a significant F change, or in other words, whether the more elaborate model significantly describes the real world situation better than the previous model. In the first model, only indicators that were significant within the full set of predictors of their respective themes are included. In the second model, all indicators that were significant predictors on their own were included. And in the third model the indicators that were not significant were included in the model as well. This with the exception of *Genre, label* and *release period* as ANOVA revealed there to be no significant difference between groups there is little sense in interpreting their effects in a regression analysis as dummy variables. Had the third model been a better fit than the second model, this would have been a consideration for making a fourth model. But as including the other insignificant variables into the second model to create the third did not provide a better fitting model, there is even less of an expectation that including these three predictor variables as well would provide a better fitting model.

All three models are significant at a significance level of 0,000. However, as mentioned above, not all models are a significant improvement on the previous one. The second model, including indicators that were significant individually as predictors of album sales, was a significant improvement on the first model at a significance of 0,011. The third model however was not, at a significance level of 0,081.

According to the second model, only the Wikipedia Album Wiki activity and the number of Google Play consumer reviews are significant predictors of album sales, while according to the third model, besides these the number of Metacritic consumer reviews, the number of professional reviews and the amount of views for the YouTube music video are also significant predictors.

Models compared	R Square	Adjusted R Square	R Square Change	F Change	Significance of F Change
1	0,477	0,423	0,477	8,879	0,000
2	0,656	0,565	0,179	3,538	0,011
3	0,812	0,663	0,156	1,991	0,081

Table 11: Models in Three Blocks.

Model 1	R Square	Adjusted R Square	Model Significance	Predictor Significance	Unst. B	Std. Error	Std. B
Popularity of Predecessors	0,477	0,423	0,000	0,190	8236,980	6175,693	0,196
Number of Consumer Reviews: Amazon	0,477	0,423	0,000	0,316	196,571	193,530	0,142
Number of Consumer Reviews: Metacritic	0,477	0,423	0,000	0,223	-154,661	127,726	-0,160
Wikipedia Album Wiki Activity*	0,477	0,423	0,000	0,000	34,235	8,370	0,563

Table 12a: Results Final Model: Block 1.

*=significant at 0,05

Model 2	R Square	Adjusted R Square	Model Significance	Predictor Significance	Unst. B	Std. Error	Std. B
Popularity of Predecessors	0,656	0,565	0,000	0,220	8852,317	7088,433	0,211
Number of Consumer Reviews: Amazon	0,656	0,565	0,000	0,150	299,688	203,730	0,217
Number of Consumer Reviews: Metacritic	0,656	0,565	0,000	0,103	-272,751	162,600	-0,282
Wikipedia Album Wiki Activity*	0,656	0,565	0,000	0,001	27,764	7,894	0,456
Popularity of Musician	0,656	0,565	0,000	0,672	0,010	0,025	0,053
Number of Consumer Reviews: Google Play*	0,656	0,565	0,000	0,010	66,914	24,643	0,394
Facebook Likes	0,656	0,565	0,000	0,282	-0,003	0,003	-0,237
Facebook	0,656	0,565	0,000	0,318	0,341	0,337	0,146

Talk							
YouTube Subscribers	0,656	0,565	0,000	0,673	0,003	0,006	0,067

Table 12b: Results Final Model: Block 2.

*=significant at 0,05

Model 3	R Square	Adjusted R Square	Model Significance	Predictor Significance	Unst. B	Std. Error	Std. B
Popularity of Predecessors	0,812	0,663	0,000	0,512	4575,910	6874,910	0,109
Number of Consumer Reviews: Amazon	0,812	0,663	0,000	0,616	124,172	244,376	0,090
Number of Consumer Reviews: Metacritic*	0,812	0,663	0,000	0,049	-353,763	170,488	-0,365
Wikipedia Album Wiki Activity*	0,812	0,663	0,000	0,040	23,234	10,723	0,382
Popularity of Musician	0,812	0,663	0,000	0,757	0,007	0,023	0,036
Number of Consumer Reviews: Google Play*	0,812	0,663	0,000	0,004	96,277	30,006	0,566
Facebook Likes	0,812	0,663	0,000	0,474	-0,002	0,003	-0,163
Facebook Talk	0,812	0,663	0,000	0,104	0,774	0,457	0,330
YouTube Subscribers	0,812	0,663	0,000	0,169	-0,013	0,009	-0,327
Spotify Subscribers				0,169	0,005	0,003	0,330
Professional Reviews: Valence	0,812	0,663	0,000	0,086	-4659,435	2604,661	-0,283
Professional Reviews: Number*	0,812	0,663	0,000	0,030	5390,925	2315,570	0,159
Consumer Review	0,812	0,663	0,000	0,406	1956,503	2315,570	0,159

Valence: Metacritic							
Consumer Review Valence: Amazon	0,812	0,663	0,000	0,651	235,319	514,235	0,070
Consumer Review Valence: Google Play	0,812	0,663	0,000	0,850	17,445	91,013	0,028
Wikipedia Bandpage Activity	0,812	0,663	0,000	0,334	-3,273	3,317	-0,164
YouTube Total Views	0,812	0,663	0,000	0,186	-4562E-005	0,000	-0,168
YouTube Music Video Views*	0,812	0,663	0,000	0,029	0,001	0,001	0,557

Table 12c: Results Final Model: Block 3.

*=significant at 0,05

A PLS Model

Unfortunately, SPSS can only inform us about whether a set of indicators have a relationship with the dependent variable as a group. It does not grant us insight in how exactly these indicators work amongst each other. To try and explain this, a series of PLS analyses were ran with the indicators of our second, most significant, model. The first model had all variables individually correlate with album sales. The second model had all insignificant variables correlate with both Wikipedia Album Wiki Activity and Number of Google Play Consumer Reviews and these variables in turn interact directly with album sales. The third model had both the Wikipedia Album Wiki Activity and Number of Google Play Consumer Reviews correlate with all of the insignificant variables individually and only those insignificant variables interact with Albums Sales directly. Model 4 was identical to the second model but included the direct relation between the insignificant predictors and Album Sales. Model 5 was identical to the third model but included the direct relation between both Wikipedia Album Wiki Activity and Number of Google Play Consumer Reviews and Album Sales.

Both the third and fifth model had a SRMR value above 0,08, meaning they are not a good fit to what can be expected to go on in the real world. Of the remaining three models, the first model, resembling the SPSS model, had the best fit. (0,0000 vs. 0,0443 for the second and 0,0067 for the fourth model). Models including only Wikipedia Album Wiki Activity (model 6) or including the five significant predictor variables from the first SPSS model (model 7) had the same model fit as the first model but a lower R squared (0,592 for model 6 and 0,666 for model 7 against 0,741 for model 1).

Discussion

Reputation

The first predictor variable measured individually is the popularity of the musicians involved. The body of literature used as a basis for this study does not provide a clear prediction as to whether having popular actors in your film will have a positive significant effect on box office. By doing the analysis in the current fashion, both looking at a comparable indicator in the music industry alone and together with other indicators, it might be possible to shed some light on why this happened.

As we see, the popularity of the musician (which had to be log transformed because of problems with linearity) taken alone has a significant impact on album sales. As soon as it is combined into a model with popularity of previous albums, it becomes insignificant as a predictor. This might be a possible explanation for this discrepancy in the previous research. For instance, all papers finding star power to be insignificant measured the amount of professional reviews, and none of the papers finding it to be a significant predictor did. The one paper measuring both previous movie success and star power also found it to be an insignificant predictor. This seems to mean that by itself, it could be an adequate way to get a slight indication of album success, but other metrics will be able to tell you much more.

The popularity of previous albums was also found to be a significant predictor of album sales by itself. Interestingly, combined with the popularity of musicians, it remains a significant predictor. Taken together, these predictor can account for 16,5 percent of the total difference between bands in the amount of albums sold. However, because of the necessary transformations of both these metrics it is difficult to translate the obtained coefficients into practice, because they do not indicate exactly the amount of albums you can expect to sell more for a specific increase in popularity of previous albums. However the track record of a band in terms of how well previous albums performed does seem to give an indication of how well a new album will perform, and does so better than relying on statistics into how popular the most popular musician in the group is.

Finally in this theme, the difference in labels was taken into account. However before checking what the difference is between labels it was checked whether there is a significant difference between groups. There is a very clear indication that there was no such difference. This could however have to do with the sample, and because it was collected in a similar way as data on movies in the previous research, it could explain why results differed in those papers as well. The cases were collected from a site used to generate a weekly top ten in album sales, the sample consists almost solely of successful albums. This means that labels that have a low success rate, but similarly high sales when an album is successful will appear to be equally profitable in this sample. The same goes for the studies on box office success used as a basis for the current research. Their data collection was mostly from top grossing films. Which is fine for most metrics, but here biases the sample and might have caused the insignificant effect in our current study.

Secondly, because the sample consists only of popular albums it might be expected that only popular labels were represented. It remains a question whether it really does not make a difference, but for now it must be concluded that the current study does not yield any reason to assume there is a significant effect of record label on eventual album sales.

Contextual Factors

The contextual factors that were taken into account in this research are the release date of the album and the genre. The first one to be checked was whether the release period had an effect on album sales on its own. An analysis of variance revealed there to be no significant difference between groups when albums were grouped according to their release period. To be sure about whether there was an effect or not two different divisions were tested using ANOVA.

The rationale for the first grouping - splitting all possible months evenly across three groups - was to look for a general effect of the period of release. Perhaps weather conditions influenced album sales, or the amount of outdoor festivals held which is not evenly divided across the year. This rationale however was more exploratory than the second rationale that did have a clear reasoning behind it. It might be that the last month of the year, in which generally a lot of gifts are bought through Christmas and similar festivities, yields extra sales. Both divisions clearly did not have a significant effect on album sales, though the second rationale had a slightly lower, but still undoubtedly insignificant, significance score. This was however to be expected, as three out of the four studies that researched release period as an indicator of box office success for films found no significant difference either. Brewer (2009) did find such an effect but tested primarily according to our second rationale, splitting the films according to being released during a holiday season. This discrepancy might be explained by the fact that, as stated in that research, people go to the movies more often during those periods. It would seem that a season of gift giving does not necessarily help albums that were just released along. There might be a spike in sales on the long run for albums in total, but in the current sample of albums and their short term income does not yield significant results.

Secondly it was tested whether genre had a significant impact on album sales. Before delving into the ANOVA, one point should be noted. When looking at the average of how many times each genre appears in the current sample of records, it becomes clear that both hip hop and pop music are present almost three and two times as much as the other albums respectively. The data and the cases are taken from a website with data on the top ten sold albums of the week. There seems to be an indication that it is more likely to end up in such a list, and thus have a better performing album, when you make hip hop or pop music.

Delving into the analysis of variance to see whether there exists a significant difference between groups of albums divided according to genre however does not yield significant results. For now, there is no reason to assume that the genre of music impacts the album sales. This is in line with the previous research on the effect of movie genre to box office. Only one in four studies found very definite results here.

Reviews

Taking the valence and number of professional and consumer reviews and testing whether they impact album sales yielded some very interesting results. First, it was tested whether the amount of professional reviews has a significant impact on album sales. The resulting regression analysis showed it is very close to being a significant indicator of album sales. Had this study taken the less stringent ninety percent confidence interval instead of the ninety five percent confidence interval, it would easily have been. The reason that this is interesting is because the valence of professional reviews on the other does, taken alone as the only predictor of album sales, not come close to being significant. When taken together the overall significance of the model lowers to a significance of 0,067, the predictor variable of the number of album reviews does become significant. Of course, this has to be taken with a grain of salt due to the confidence interval chosen in this paper. But it has to be at least mentioned for the following reason.

It could be said that the reason the amount of reviews an album has impacts album sales is because of the publicity. Clearly, when your product is unknown it is better for your sales if people come to know it through a bad review than to not come to know it at all. In this case however, the albums concerned are all brought out by already popular artists. The exposure effect of bad reviews is not expected to be present in this situation. It seems to point to the fact that, as already theorized within the academic literature on marketing and previously mentioned in this paper, the valence of reviews does indeed matter less or at the very least work differently for hedonic products.

When delving into the results of the amount of consumer reviews as a predictor variable a similar pattern as with professional reviews becomes apparent. Taken alone, both the amount of consumer reviews found on Google Play and Amazon significantly impact album sales. When taken together, a model with both the number of Google Play and Amazon reviews is also significant. However the valence of Amazon reviews or of Google reviews are insignificant predictors of album sales, both together and taken individually. This seems to point towards the idea that the amount of word of mouth about an album is more important than whether it is positive or negative.

These results are largely in line with what was found in previously done research on box office success. The almost significant result of the amount of professional reviews lines up well with two out of three studies finding significant results here. The clearly significant result of the amount of consumer reviews corresponds well with all studies finding a positive link between high box office and a large amount of consumer reviews. However in previous studies the valence of professional reviews was by most studies (four out of five) found to have a small yet significant effect. In two out of these cases, the effect was only present or measured in a specific country however, where the reach of the current study is worldwide. This was also the case in the study finding there to be no significant effect of valence. Consumer valence was in one study found to be a significant predictor, and in one not to be. As the latter study was the only one to include the number of consumer reviews as a predictor of box office success as well, the current results seem to be in line with the previous literature and thus expectations as well.

Social Media Metrics

A number of social media metrics were also tested to see whether there is reason to believe they impact album sales. The expectation is for all of these to be significant at least on their own, as previous research has found all of these social metrics to be significant indicators of box office success with movies.

First, a regression analysis was conducted to check whether the number of Spotify monthly listeners significantly impacts album sales. Though the effect for each extra monthly listener was very small, there is definitely reason to believe there is an impact. The small number of extra albums sold for each extra listener might be due to the high average amount of listeners acts in the current sample had, which was 859.600. Whatever the case, Spotify is a solid predictor of album sales though the variance in album sales explained by Spotify alone is quite small.

There were two metrics from Facebook taken into account in this research. Namely the amount of likes a band has on their band page, and the amount of chatter there is about the band around or on the date the album was released. As we found, both are a significant predictor of album sales. However, the effect size of Facebook talk or chatter is nearing to be two hundred times as big as that of Facebook likes. Not only is this in line with research by Oh et al. (2017), but it is also to be expected when considering the findings regarding reviews. The results of the impact of reviews indicate that the amount of talk about an album is a good predictor of album success. Here the amount of talk about a band is in a way also a measurement of the amount of talk about a band surrounding album release. Secondly, a like on Facebook can be a very passive way of liking a band. A like could be given years ago, while the band has been long forgotten. Talk is much more actual, it means people are currently thinking and talking about it. Taking this into account, it is not surprising that this is a much more explanatory indicator of album success.

Next it was considered whether data found on YouTube could help predicting album sales. This regression analysis had differing results. Though the model with only YouTube metrics was significant overall, only the data on the YouTube channel was significant, and not the data on the music video accompanying the album release. There are a number of reasons for this insignificant result.

First, not every band releases music videos, making comparison quite difficult sometimes. Lyrics videos are on the rise, possibly due to lower cost of production. Also, a lot of bands do not host any of their official music videos on their own page, but instead choose to host them on the channel of their record label or other music group. This is great for their statistics because they benefit from the popularity of their host. However, this does make it a bad indicator for album sales as this is a better representative of how the host channel is doing than how popular the band itself is. Besides that it makes comparison between different bands, as this research does, much more difficult. Also very hard to explain are the negative correlations between album sales and views on both the clip and the channel. More views seem to result in less album sales. One reason for this might be that the more listeners a band has that listens music through YouTube, the less likely someone is to buy their music, as it is available freely online. However, one would in that case expect negative correlations for Spotify as well. It could also be caused by the current trend of buying views. Though at this point this is speculative, it could be that bands that do really well in album sales or on YouTube feel less of a need to buy views than other bands. In this way, views could become an indicator of for instance insecurity of the band, or expectation of low popularity. We can however conclude that looking at YouTube subscribers is an adequate way to assess how well an album will perform.

Wikipedia activity is a really interesting predictor variable to look at for a related reason to what was said about YouTube statistics. Unlike on YouTube, buying Wikipedia views is not a trend. One could expect these metrics to be a bit more representative and better indicators of album success based on this. The two predictors tested where the amount of visits on the wiki of both the band, and the album. Though the model is significant, only the amount of views on the band wiki was a significant predictor of album success. It is to be expected that the number of visits on an album page represents album popularity better than visits on a band page because it is a direct search for the product itself.

Taking all of the social media metrics together and combining them into one model shows a very interesting result. Only the amount of visits the Wikipedia page for the album has had is a significant predictor. It is, for the reason mentioned above however not completely unexpected and in line with previous research on box office success. Previous research by Beak et al. (2017) already indicated Twitter activity becoming irrelevant as an indicator of box office success when YouTube and Facebook are taken into account. Also, none of the previous research included Wikipedia activity into a model with other social media metrics. It could for instance be that Wikipedia activity is the only indicator left not manipulated by record labels or bands themselves. This in turn could make it a more honest indicator of hype for an album. Whatever the case, it seems that from all metrics tested for this theme Wikipedia activity on the album wiki is the most reliable indicator of album sales.

Full Model

Finally a series of regression analysis was conducted to come to a complete model of predictors for future album success. This was done by running a regression analysis of three blocks. The first with only predictors significant in the full models of their theme, the second only with predictors significant on their own, and a third with all other predictors as well. This was done to see whether each step of additions of predictors made for a better model, which was not the case. All models are a significant model of predicting album sales, though the third model was not a significant improvement on the second. What becomes apparent is that the structure or way of building up to a final model was validated here. Immediately adding together all predictors, without the steps taken in between in this paper, would have not resulted in the best fitting model.

The second model seems to be the best model to predict future album sales. Significant indicators here are the number of consumer reviews on Google play and Wikipedia album Wiki activity. The third model, which also includes the number of consumers on Metacritic, the number of professional reviews and the number of views of the accompanying YouTube music video as significant indicators, was in and of itself also a significant model. Though the latter is not a significant improvement compared to model two. The second model explains 56,5% of the variance in album sales.

A PLS Model

Running the PLS models as well did grant us some insight into how these different predictor variables interact, even though the model of all variables interacting with album sales equally remained the best model fit for the real world. First, these models confirm that in every context, the Wikipedia Album Wiki Activity indicator variable has the biggest effect on album sales. Secondly, it showed that all things being equal, models that show the effect of the insignificant variables to influence album sales at least in part indirectly through Wikipedia Album Wiki Activity and Number of Google Play Consumer Reviews have a much better model fit than models that assume this to be the other way around. For the effect of Wikipedia Album Wiki Activity and Number of Google Play Consumer Reviews on album sales to run at least partly through the insignificant predictors. Though again, in spite of this, the classic SPSS model remained the best fitting model with the highest R square explained.

Conclusion, Limitations and Future Research

Conclusion

The goal of the current study was to research whether it is possible to predict album sales based on a number of metrics similar to those used in previous research to predict box office success of movies. Research on those metrics for box office success was reviewed. Looking both for a set of variables predicting album sales and a few overarching themes around which these metrics seemed to revolve. Finally these metrics were translated to the current context with their themes, to make sure each relevant theme was adequately researched in the current context as well. As it turned out, quite a few of these metrics did in fact, at least on their own, give an indication of album sales, or at least part thereof. It also provided insight on a hierarchy between metrics. For example, the popularity of musician can be used to indicate album sales, but looking at the success of previous albums is a more reliable metric to use to predict album sales and explains a bigger portion of variance. Besides these insights on hierarchy between variables a model was found combining the different metrics in a way to best predict album sales together. To find this model, three consecutive models were formulated and tested to be both significant and better fits to what can be expected in the real world than the previous model. The first model including only predictor variables that were significant predictors within a regression model with other predictors from their theme. The second model including each variable that was significant on its own as a predictor of album sales. And a third model including other insignificant predictor variables as well. It turns out all three models were significant, but the third model was not a better fit than the second model, indicating the second model to be best describing real world effects.

The most important and interesting take away from this research is that it does in fact seem possible to predict album sales based on a set of indicators as used in this research quite well. Looking at the R square for the second, best fitting, model, it seems 56,5% in variance amongst album sales can be explained based on the factors in that model.

A lot of other interesting insights came out of this research. First and foremost, the results of this study seem to indicate that Wikipedia Album Wiki Activity is by far the most reliable indicator of album sales. This is very interesting precisely because the amount of Wikipedia Album Wikis made at least one month prior to the album coming out was far from all of them, while measuring this would be the most reliable way to predict how an album will do.

The results also indicate that the amount an album is talked about really does matter. Taken alone, the amount of talk on Facebook about the band around the time of album release is a much better indicator of album sales than the more passive band page likes. Taking the review metrics alone it also becomes apparent that the amount of reviews is an important indicator of album sales, while the valence scores given by both professionals and consumers seems much less significant as a predictor.

This is interesting because it is an indication that there is, in this regard, a crucial difference between hedonistic products and utilitaristic products. It is very hard to imagine a refrigerator getting a massive amount of bad online reviews stating it breaks down within a week will continue to sell well, while the same effect seems to be absent with the hedonistic music albums.

Looking especially at the social media indicators, it is an interesting outcome that the one indicator least likely to be manipulated by boosting through money investment is also the most reliable and significant predictor. Facebook likes can be bought indirectly (through sponsored posts) or directly through third parties, as is the case with all social media metrics. Numbers on this are of course hard to obtain, as the whole point of buying views and likes is for your audience to think these heightened numbers represent numbers generated naturally and by activity from their peers, not so called ‘click-farms’ somewhere in third world countries. It does raise the question of whether manipulating these numbers really helps album sales, as the numbers that can reasonably be expected to be manipulated the most (YouTube clip views and comments, Facebook likes) are also the least trustworthy in album sales. The heightened number of views or likes does not seem to persuade people to buy the album, at least there is no indication for such an effect in this research. Perhaps they do influence concert visits or other possible goals that bands might have for the better, it might also work great for smaller bands or bands in general up to a certain point. Whatever the case, these possibly manipulated metrics should not be used to predict album sales.

Managerial Implications

There are a number of clear and possibly very obvious managerial takeaways for marketing managers working in the music industry. A remark has to be made before mentioning these. They are insights for management focusing on album sales. Whether the same effects occur when the goal is to get more shows or sell other merchandise than albums remains to be researched. These insights are also meant for bands that perform relatively well, and their fruitfulness for smaller less well performing acts has yet to be established.

First, management of bands should make it common practice to make sure there is a Wikipedia Wiki for the upcoming album as soon as possible, at least a month in advance. This will give an indication of the album sales so marketing managers can act accordingly, and monitor interest in the album in advance. It is also advised to make use of Wikipedia statistics tool to monitor activity, as it turns out to be a solid indicator of album sales.

Secondly, there is strong indication that the amount of reviews, both by professionals and consumers, is more important than the scores given. When planning which reviewers to send a message or give an album to for review, it does not seem necessary, or even beneficial, to select only those reviewers likely to give a high rating. It seems more important to gather as much reviews as possible, as having more reviews seems more important than having only good ones.

Also, there is indication that social media that generally enjoy a lot of investment by bands and record labels to boost statistics are worse predictors of album sales than when this is done less. This makes it possible that investing money into social media might not be as effective as seems to be thought. It is thus a recommendation to managers to monitor the effects of social media spend closely to see whether it does indeed help attain the set goals. Closely related to this marketers in the music industry should be careful when recruiting bands for their record labels by looking at YouTube or Facebook, as these turn out to not always be a great indication of album sales.

Limitations and Future Research

As with any research, the question remains how broadly it describes processes as they occur in the real world and how broadly they are described by it. Any research comes with limitations, boundaries of what it does and does not describe and with what precautions results should be interpreted. The first Limitation of the current research is that the dependent variable Album Sales was, due to limited availability, taken from a website meant to unveil the best selling albums for each week. This means that the data set for this research consists of relatively high performing bands in terms of album sales only. Though this does limit the applicability of the research, it is also in this context inevitable, as information on album sales is scarcely available. Similarly, as the sales numbers are of album sales close to release, it is not obviously applicable to long term sales as well. Some results might differ if focus had been on long term sales, which is definitely an avenue future research could delve into.

Smaller, lower performing bands tend to keep track of their album sales very poorly, at least in my own experience. Online sales are rarely monitored, albums are given away as a much needed promotional effort, traded with other bands for their albums or given to friends and family for heavily reduced prices. It is difficult to track what counts as an album sale in these cases. Using a database such as Mediatraffic allows for a fair comparison, as in the very least, all album sales were measured equally by a professional and dedicated team. However, this possibly limits these results to predicting the album sales for high performing bands. Though the outcomes might be very similar for less well performing bands, this is something that remains to be researched to be certain, and would be a great direction for future research.

Further, it might explain some predictor variables to be insignificant while we would expect there to be a small effect in the very least. Record labels vary in the budget they have to promote albums they release, the contacts they have and so on. In this research however, no significant difference between labels was found. This could be because firstly, only popular labels were included because of the data set, and secondly failing albums of those labels were not taken into account. If for example Sony has a hundred unsuccessful albums for each successful album, where Interscope has one unsuccessful album for each successful album, they would through this data collection method appear equally successful in album sales. Because averages did indicate some labels to be present more often than others, it could be an interesting avenue for further research whether there is indeed a significant difference between labels.

The same holds for difference between genres. The current data set focuses on success stories. Hip hop was present in our data sample a lot more than other genres, but maybe hip hop has a very low success rate, but a very high payoff when it does appear to be a success. It could also be that chances of reaching the top ten with each genre are similar, but hip hop is just made a lot more often than other genres. Research focusing on genres alone taking equal samples for each genre not biased as our data set was might reveal there to be significant differences after all.

This research has also focused on the possibility of predicting rather than influencing album sales, which should not be confused with each other. The fact that the amount of activity on a Wikipedia Album Wiki indicates the amount of albums sold does not automatically mean that trying to increase this activity will also impact album sales. On the contrary, as it was both the strongest predictor of album sales and the one that can be expected to have been manipulated the least. This might be the very reason it represents hype the most honestly and in turn makes it the best indicator for album sales. This would make research into possibilities of ways to manipulate album sales a very interesting avenue of further research.

It also became clear that not all bands regard social media presence on the platforms measured in this study equally important. Especially Asian bands had a habit of not seeming to maintain their online presence very well for the exception of the presence on Spotify. As people of Russia tend to favor VK over Facebook, some countries, like those in Asia, might prefer social media sites not taken into account in this research, leaving blind spots. Further research could delve into different ways bands choose to communicate with their fans, popular social media platforms for bands across countries and whether prediction of album sales is possible based on data on these communication methods and platforms.

It should also be noted that in this research, the link was between a bunch of metrics and album sales. However, not every act has selling as many albums as possible as its primary goal. Some bands might try and make money off of merchandise like t-shirts, some may try and make money by doing shows, others might have their eyes set on getting as many streams through Spotify as possible and along with this a large number of goals are thinkable. It is not necessarily true that actions influencing album sales for the better will also influence these goals in the same direction. Maybe a high Wikipedia Album Wiki Activity is also an indication of a low probability to visit concerts or buy merchandise. This would make similar research into actions to predict likelihood to visit concerts, buy merchandise and other possible goals, or even comparing effects on different goals at the same time an interesting avenue for future research as well.

Furthermore, the current study was based on record sales close to the album release and was no long term study. It is very much possible that the effects show different results when looking at long term sales for an album. However, that would also make the model a lot more complicated, and unfit for a study of the current size. The impact of new releases would, for instance, come into play as well. Research on long term effects would be an interesting direction for future research, though would probably have to be limited to one or a few of the metrics used in the current study to be practical due to time and other restrictions.

The biggest and most relevant avenue for further research following the current research is finding models with metrics that fit even better. As with any set of indicators, expectation is that a model will never be complete. Further research could focus on finding the missing indicators, or finding a set of indicators predicting a bigger variance in album sales.

References

Asur, S., Huberman, B. A. (2010). Predicting The Future with Social Media. Proceedings of the 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology. 492–499.

Baek, H. et. al (2017). Electronic word-of-mouth, box office revenue and social media. Elsevier, 22, 13 - 23.

Bagella M., Becchetti L. (1999) The determinants of motion picture box office performance: Evidence from movies produced in Italy. Journal of Cultural Economics 23: 237–256.

Brewer, S. M., Kelley, J. M. Jozefowicz, J. J. (2009). A blueprint for success in the US film industry. Applied Economics, 41:5, 589-606.

Chen, P.Y., Wu, S., Yoon, J., (2004). The impact of online recommendations and consumer feedback on sales. Proceedings of the 25th International Conference on Information Systems. AIS, Washington, DC, USA.

Chevalier, J. A., Mayzlin, D. (2006) The Effect of Word of Mouth on Sales: Online Book Reviews. Journal of Marketing Research, 43:3, 345-354.

Duan W., Gu, B., Whinston, A. B. (2008) Do Online Reviews Matter?: An Empirical Investigation of Panel Data. Elsevier, 45:4, 1007 - 1016.

Ding, Chao et al. (2017) The Power of the Like Button: The Impact of Social Media on Box Office. Elsevier 94, 7-84.

Elliott, C., Simmons, R. (2008). Determinants of UK Box Office Success: The Impact of Quality Signals. Review of Industrial Organization, 33: 93.

Evanschitzky, H., Eisend, M., Calantone, R. J. and Jiang, Y. (2012). Success Factors of Product Innovation: An Updated Meta-Analysis. Journal of Product Innovation Management, 29, 21–37.

Field, A. (2016). Discovering Statistics Using IBM SPSS Statistics. California, USA: Sage Publications.

Garcia-del-Barrio, P., Zarco, H. (2017). Do movie contents influence box-office revenues?. Applied Economics, 49:17 1679-1688.

Gemser, G., Van Oostrum, M. & Leenders, M.A.A.M (2007) The impact of film reviews on the box office performance of art house versus mainstream motion pictures. Journal of Cultural Economics, 31:1, pp 43- 63.

Ho Kim, S., Park, N., Park, S. H. (2013). Exploring the Effects of Online Word of Mouth and Expert Reviews on Theatrical Movies' Box Office Success. Journal of Media Economics, 26:2, 98-114.

Karniouchina, E.V. (2010). Impact of star and movie buzz on motion picture distribution and box office revenue. International Journal of Research Marketing 28:1, 62–74.

Koschat, M. A. (2012). The Impact of Movie Reviews on Box Office: Media Portfolios and the Intermediation of Genre. Journal of Media Economics, 25:1, 35-53.

Krushikanth, R. A., Merin, J., Supreme, M., Chien-Chung, C., Kathy, L., Frederico, G. (2013). Prediction of movies box office performance using social media. Conference: Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining. 1209-1214.

Lilien et al. (2002). Performance Assessment of the Lead User Idea-Generation Process for New Product Development. Management of Science 48: 8, 1042-1059.

Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. Journal of Marketing 70 (3), 74–89.

Mestya´n, M., Yasseri, T., Kerte´sz, J. (2013). Early Prediction of Movie Box Office Success Based on Wikipedia Activity Big Data. PLoS ONE 8 : 71226.

Mukherjee, A. and Yun Lee, S. (2016) Scarcity Appeals in Advertising: The Moderating Role of Expectation of Scarcity. Journal of Advertising 45, 2, 256-268.

Oh, C et al. (2017). Beyond Likes and Tweets: Consumer Engagement Behaviour and Movie Box office in Social Media. Elsevier, 54:1, 25 - 37.

Rozenkrants, B., Wheeler C. S., Shiv, B. (2017) Self-Expression Cues in Product Rating Distributions: When People Prefer Polarizing Products. Journal of Consumer Research, 44:4, 759–777.

Rui, H., Liu, Y., Whinston, A., (2011). Whose and What Chatter Matters?. The Impact of Tweets on Movie Sales Framework, Working Papers. University of Texas at Austin, 1 - 29.

Salehan, M., Kim, D. J. (2016). Predicting the performance of online consumer reviews: A sentiment mining approach to big data analytics. Elsevier, 81, 30 - 40.

Saraee, M., White, S., Eccleston, J. (2004). A data mining approach to analysis and prediction of movie ratings. The Fifth International Conference on Data Mining, Text Mining and their Business Applications, 15-17, 344-352.

Treme, J., Craig, L. A. (2013) Celebrity star power: Do age and gender effects influence box office performance?. Applied Economics Letters. 20:5, 440-445.

Treme, J. (2010). Effects of Celebrity Media Exposure on Box-Office Performance, Journal of Media Economics, 23:1, 5-16.

Vermeulen, I. E., Seegers, D. (2008). Tried and tested: The impact of online hotels on consumer consideration. Tourism Management, 30:1, 123-127.

Qin, L., (2011). Word-of-mouth for movies: a predictor and an outcome of box office revenue?. Journal of Electronic Commerce Research. 12:3, 187–198.

Zhang, W., Skiena, S. (2009). Improving Movie Gross Prediction Through News Analysis. IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology, pp. 301 – 304.

Websites

- Billboard:https://www.billboard.com/
- New York Times: https://www.nytimes.com/2016/03/25/business/media/music-sales-remain-steady-but-lucrative-cd-sales-decline.html
- Stephen Follows: https://stephenfollows.com/hollywood-sequels-by-the-numbers/
- USA Today: https://www.usatoday.com/story/money/business/small-business-central/2017/05/21/what-percentage-of-businesses-fail-in-their-first-year/101260716/
- Smart Insights: https://www.smartinsights.com/search-engine-marketing/search-engine-statistics/
- Setlist fm:https://www.setlist.fm
- NPD:https://www.npd.com/wps/portal/npd/us/news/press-releases/itunes-continues-to-dominate-music-retailing-but-nearly-60-percent-of-itunes-music-buyers-also-use-pandora/
- Wikimedia Labs:https://tools.wmflabs.org/pageviews/
- Zephoria:https://zephoria.com/top-15-valuable-facebook-statistics/
- Style of Sound:https://styleofsound.com/top-100-influential-music-blogs/