THE AUDIENCE AS GATEKEEPER

Attention for unreleased techno music in online communities as indicators for post-release success

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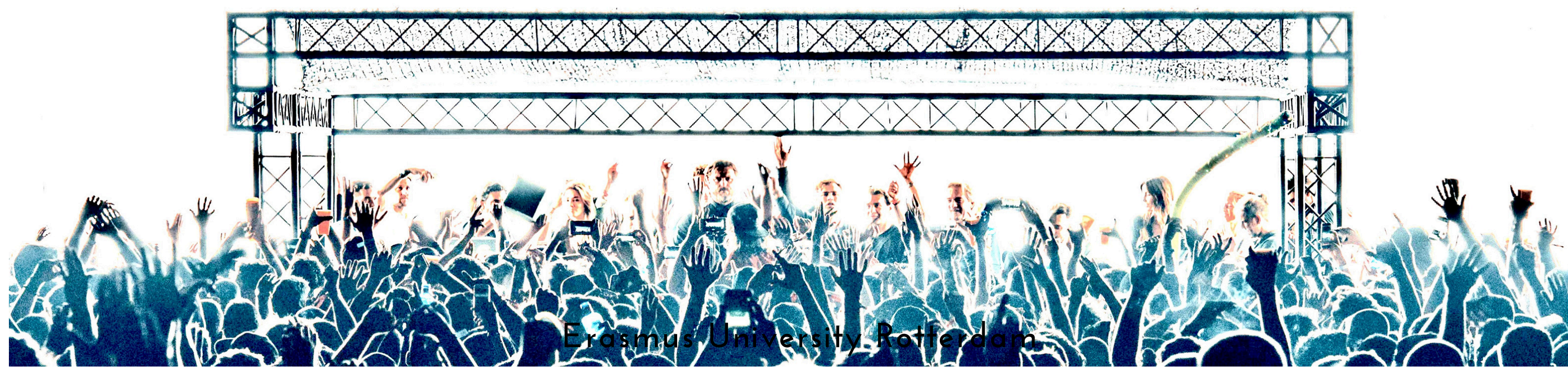

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Abstract

This thesis investigates to what extent pre-release attention for techno songs and popularity of artists in online communities can predict post-release success of songs on Spotify and Beatport. Before a song is released, it is difficult to estimate whether the audience will appreciate it or not. Gatekeepers and certifiers take a central role in the music industry because they decide whether the value of music is high enough to cover investment in the product. Since the digitization of music and emergence of social media, culture, and music in specific, is increasingly taking place online. This resulted in an enormous amount of data regarding preferences of the audience and popularity of artists. An extensive amount of these data is generated in online music communities and provides us with information about audience attention for songs before release. The focus of this thesis lies on the attention for unreleased techno songs in the online Facebook-community Raad de Plaat. In this community, recordings of unreleased songs at events are uploaded by members in order to identify the artist and title. The research question of this study is to what extent attention for songs in the online Facebook-community Raad de Plaat and the popularity of the artist on Facebook can predict success of songs after release. Success on Spotify is defined as number of plays per day. The success on Beatport is measured by a songs peak position in the charts and number of days in the charts. A quantitative content analysis is performed in which there is controlled for musical characteristics and the popularity of the DJ that plays the unreleased song. In the results, different models are presented in order to answer the research question. The research showed that attention for unreleased songs in Raad de Plaat significantly predicts the success on Spotify after release to some extent. When taking the popularity of the artist on Facebook into account, a majority of the success of songs can be predicted before release. For predicting success on Beatport, attention on Raad de Plaat is not a significant predictor when controlling for musical characteristics. The popularity of the artist on Facebook however, is in all models a significant predictor for success on Beatport and Spotify. When online communities enable the audience to collectively value songs before release, their practice is similar to the practice of certifiers and gatekeepers and this may have implications for the organization and structure of the music industry.

Keywords: *Electronic Music; Online Communities; Uncertainty; Gatekeepers; Economics of Attention*

Contents

Preface

There is a rave going on. At the bottom of the frontpage of this thesis, an audience full of energy is dancing, filming and throwing hands in the air ready to hear a new song. We see no faces, as they look to the DJ, craving for the techno beat to start. In the middle of the background, a DJ rises above everyone else. He is concentrated, while elegantly building up the tension he almost reached the point on which the beat of a new song, yet unreleased, starts kicking.

A square scaffolding marks the line between the DJ and the audience. As a gate through which the artist and the audience interact. Backstage, behind the DJ smiling faces appear, some are watching, some also raise their arm, but all with all they look more reposeful. This is the domain of managers, bookers event organizers. They are allowed to be here because they determine who can be here. As gatekeepers in the music industry they run the show. They decide what artists and what songs enter the domain of this culture and know what the audience want. You could envision them at both sides of the gate, but they are not. They are literally and figuratively at the background. At this moment, they do not play any role. The DJ is getting closer to dropping the new song, and the audience is craving for the beat to start. The interaction is clearly visible and many cameras and phones, including mine, captured it. According to the audience, the new song was a success.

As visitor of techno events, and from the perspective of cultural economics, I became increasingly interested in the culture around techno music. In every event, DJ's play new music and all visitors seem to be extremely interested in what variations in melody or percussion on the 4/4 beat are played. When a new song is played for the first time, it often takes months before the song is released. Meanwhile, the Dutch *Facebook*-community *Raad de Plaat* is fruitful solution for identifying this unreleased music. Within this community some songs become extremely popular before release and this buzz is promising for post-release popularity. As an artist producing techno music, finding and reaching an audience is a central activity. Artists and DJ's seem very interested in my music, but labels are often not easy to convince. Therefore, some numbers or validation regarding the value of music is necessary. However as soon as these numbers become impressive, it makes more sense to release it independently. From a cultural and economic point of view, I became interested in the role of online communities for artists to find and reach their audience.

1. Introduction

Before a song is released it is difficult to estimate whether the audience will appreciate it. This makes it very hard to determine the value of new music and artists before entering the market. As a result, record labels often choose to sign artists that already have proven to be successful (Lanham, 2006; Frank, Cook, 1995). This results in market concentration (Adler, 2006). For artists that lack economic capital, symbolic capital plays an essential role to present their music as subject of value towards record labels and bookers (Skeggs, 2004; Scott, 2012; Bourdieu, 1996). Symbolic capital denotes distinctions such as reputation, accumulated prestige and fame (Bourdieu, 1991, p. 230). It represents the artist's 'potential' as the unrealized capacity to be integrated systems of accumulation (Sennett, 2006). For artists, it is the most important form of capital besides economic capital, because as ''a veritable credit'' it can be converted into long term economic profits (Bourdieu 1996, p. 142). Scott (2012) states that field-specific symbolic capital is synonymous with 'buzz', which can be defined as the excitement and attention for an artist or song among cultural intermediaries. Within the scientific field of cultural economics, there are many theories and empirical researches established regarding the role of gatekeepers in the music industry. This thesis explores to what extent popularity of artists and attention for their songs before release by the audience can be an indicator for success after release. This is relevant because it can change the way in which the music industry is organized and structured.

Since every genre has its own logic, culture and economy it would be impossible to explain the ways in which symbolic capital are generated for the complete music industry. Therefore, in general this thesis focusses on the online record industry, and more specifically on techno music, a genre within the electronic music culture. Hesmondhalgh's states (1998, p. 234) that "the lack of a star system within dance music concentrates attention on 'the music itself', rather than on personality and 'image'". Furthermore, Hesmondhalgh (2006, p. 215) confirms the essential role of symbolic capital in the field of music production since the tension between low levels of economic capital and ''very high levels of field specific symbolic capital'' is a central concern in cultural entrepreneurship. Now that digitization diminished the costs of production and distribution, the importance of economic capital in determining the value of a song has decreased (Anderson, 2004, Epstein 2016) and research to the role of symbolic capital becomes increasingly relevant.

The digitization and online availability of music resulted in an enormous amount of data regarding characteristics and quantities that increase or decrease over time or take different values in different situations. An extensive amount of these data is generated in online music communities and can provide information about popularity of songs and artists (Waldron, 2018). The *Facebook*-group *Raad de Plaat* (*RdP*) is such an online community. Its purpose is to collectively track down the identity of techno songs that are played by DJ's at events. When attending events, members of *RDP* upload a video that presents a song of which the artist or the song title is unknown. The members in *RdP* react with a *Facebook 'like'* if they like the video and with a '*comment*' in order to stay updated about the identity of the song or to present the identity. In short, an enormous amount of potential symbolic capital is generated in this community. Similar groups are *The Identification of Music Group* (international version), *Melodic Diggers* (French version), and *Tune Drop* (Irish version). *RdP* has 38.385 Dutch speaking members that can be seen as representation of the audience for techno music in the Netherlands. To illustrate the size of this community, remember that the biggest electronic music events in the Netherlands, e.g. *DGTL* and *Awakenings Festival*, attract around 35.000 visitors. Based on the number of likes and comments, the videos uploaded in this community can be ranked from most to least popular. This popularity can be translated in variables that reflect attention for a song before release. Other forms of popularity generated within online communities is the number of likes on the *Facebook*-pages of artists and DJ's, which can be seen as reflection of their symbolic and cultural capital. To draw conclusions based on this kind of variables, they need to be clearly linked to the theoretical concepts to which they relate. These cultural, economic and musical concepts are explored in the literature review and connected to factors determining the structure and concentration of the music industry. The core of the theoretical framework in this thesis therefore is the relation between symbolic capital, defined as the attention for and popularity of unreleased songs, and concepts as quality uncertainty, information costs, herd behaviour, bandwagon effect, snowballing effect, the role of the gatekeeper, stardom and economics of attention.

In this research is defined to what extent attention for artists and their songs generated in online communities before release, can be associated with success of songs after release. The aim of this research is not to engage in some sort of sectoral forecasting. Rather it explores what elements regarding symbolic capital in the current music industry can be seen as determining for its structure and concentration. The purpose is to establish insights in the ways in which the value of music is created and to explore the relations between culture, economy, technology in the music industry in general. More specific, it investigates the possible implications of data generated in online music communities for the structure and organization of the online record industry. The research is designed to answer the following question:

Research question 1: To what extent can pre-release attention for techno songs and popularity of artists generated in online communities, signal prospective success on *Beatport* charts and *Spotify* after release?

The next two questions are formulated to control for the effect of stardom and popularity of the DJ playing the unreleased songs, and the effect of musical characteristics:

Research question 2: To what extent does popularity and reputation of the DJ that is playing the unreleased song influence the relation between the pre-release indicators and success after release?

Research question 3: To what extent do musical characteristics measured by *Spotify,* influence the relation between pre-release indicators and success after release?

2. Literature Review

2.1 The Value of Music

"There is no such thing as music" Small (1998, p.2) argues to point out that both aesthetic expressions as well as social conditions have to be taken into account in research about music. Small (2011) considers it not so much as a 'thing' but rather as a process which he refers to as 'musicking'. It emphasizes that the value of music lies not only in the musical works but also in the cultural and social world around it. The value of music, in this way, depends on the perspective someone looks from. Regarding techno music, Heller (2014, p. 1) describes that the definition of 'rave culture' is based on a genuine love for electronic dance music. She argues that being a raver is being part of an entire culture. Dan Sicko (2010) explored techno's original roots and how it became popular in Europe in the 1980s underground rave parties as the beginning of this performing art. He argues that techno initially developed in the city Detroit from a 'collective dreaming' about the future and became the first electronic music genre to touch an entire generation. This culture began in small, underground venues where people felt uninhibited and free to dance with everyone that visited the performance. Heller (p.4) states that the concept of PLUR, which stands for Peace, Love, Unity and Respect**,** central in this culture. DJ Frankie Knuckles, one of the pioneers in electronic music, coined the term in the early 1990's. These characteristics are reflected in a letter Obama wrote after Knuckles, passed away in 2014: "[Knuckles] Helped open minds and bring people together to […] ignite our imaginations". (Blistein, 2014). The collectiveness and focus on imagination and the future are central values techno culture.

From the perspective of the artist, Scott (2012, p. 243) states that there are two dominant poles in the field of music production. The first is the autonomous pole. It concerns the idea of 'art for arts sake' and the logic of the economic world does not apply to this pole, since songs that fail economically can still succeed culturally. According to Cowen (2008, p. 270) there is "a big shift towards free content […] not being backed by corporate financial power necessarily […] we're also seeing a huge shift toward fame seeking as a motive.". This could mean that direct social recognition of value would become more important than a financial representation of value. From a psychological perspective, social stimulation and recognition, which in its most extreme form is called 'fame', can influence the novelty generation process (Schweizer, 2004). The expectations and reactions of the audience can have a big influence on the creative process. To determine the value of songs, even the most independent creative artists need their music to be validated by others.

Electronic music artists are known for mixing their repertoire with the songs of their colleagues in performances and remixes. Their practice entails both free and charged exchange of songs, even before release (Jordanous et al., 2014). This makes it an interesting sector from both a cultural and economic point of view. Where the value of traditional artists relies on their repertoire and songs known by the audience, the value of electronic music artists relies on their selection of songs and their ability to present new music, new styles and unreleased songs. Related to the social and symbolic value of music, Jordanous et al. stated that repeated plays of a commercially unreleased tracks in the right context can lead to a record deal, bookings and commercial release. 'Releasing' in this context refers to the economic release, to offering a song for sale on the market. It does not mean that unreleased music is not released culturally and socially. In contrary, sharing music before 'release' is the only way in which value is established before a song is offered for sale.

Key factors for the value of songs appear to be "(a) the DJ's decision to include a track within a live set (economy of scale regarding promotion), and (b) the audience's embodied responses to that decision." (Jordanous, p. 65). Online communities like *RdP* combine these factors by sharing videos of DJ's playing unreleased songs and by enabling its members to react on the videos. By monitoring the reaction of the audience on unreleased songs this community may also have implications for the artist. Csikzentmihalyi (1996) argues that many artists give up because it is just too excruciating to wait until critics take notice and pass judgement and successful creatives internalize judgements from outside. This illustrates another importance of the judgement of the audience regarding value of music before release. In general, these communities and digitization of music enabled artists to take part in networks and interact with the audience more extensively than ever before (Jordanous et al, 2014).

The second pole addressed by Scott (2012), is the heteronymous pole, which is structured by both cultural and economic logics like the star phenomenon, charts, sold-out performances, awards and previous hit songs. As mentioned, Bourdieu (1993, p. 38) defines previous success and reputation of artists as their symbolic capital, and these successes can be transformed into cultural and economic value (Scott, 2012). In the record industry, old hits are the golden age for game rules (Adorno, 2002, p.443). The most successful hits, styles and elements are imitated, and this results in a process in which certain standards are crystalized to be part of musical structures. Imitation also plays a central role in Simmel's (1975) definition of fashion. He argues that when something is imitated, not only the demand for the creative activity but also the responsibility for the creation itself is transferred from ourselves to another. As a result, artists that follow fashions free themselves from choosing and simply become a product of the group, "a vessel of the social contents" (p. 132). This also relates to the economic concept of herd-behaviour, in which a consumer or producer decreases uncertainty about the product by looking what others are consuming or producing (Caves, 2000). It is important to keep in mind that in music production, the line between those poles have been blurred. There are even scholars who claim that the artistic and commercial logic is now merged (Negus and Pickering, 2004). However, tt is exactly where those poles crossfade, that artists have to present their music as subject of value towards record labels and bookers that can provide access to the market. The entrepreneurial aspect of being an artist becomes clear by establish a reputation, attention and audience for their music without being financially backed up by record labels. A part of this practice is dealing with the intermediaries and gatekeepers, and decreasing uncertainty regarding their value, which will be discussed later.

Regarding the role of the audience in the creation of value, Csikzentmihalyi (1996, p. 6) reminds us that "creative ideas vanish unless there is a receptive audience". Following this logic, a receptive audience is essential for artists to become part of a culture and to make their songs valuable. In *Music and Identity*, Frith (1996, p109) states that the issue is not how a song reflects the listeners, "but how it produces them, how it creates and constructs an experience […] that we can only make sense of by *taking on* both a subjective and a collective identity**."** He emphasizes that the value of music describes not the quality of the song itself, but the experience of it. Music is the key to identity and values because it offers a sense of both the self and the others – the subjective and the collective. Frith concludes that compared to all other cultural forms, music is best able both to define places and identities; "in clubs, scenes, and raves […] we are only where the music takes us." (p.125). Music can even express values and identities for whole cultures and nations. Others argue that music is less autonomous and can also be used as instrument; culturally, to express one's identity, values and beliefs, and socially, for getting in contact with other people (Arnett, 1995; Behne, 1997; Larson, 1995)

Regarding the cultural value of popular music Adorno (2002) argues the listener feels connected with a culture only because he realizes that his apparently isolated, individual experience of a particular song is actually part of a collective experience. The recognized social value inherent to hit songs, relates to “the transfer of the gratification of ownership to the object which thus becomes ‘liked’." (p.455). This labeling process of what music is valuable, becomes a collective ownership process. The listener feels flattered because he too owns what everyone within this culture owns. By owning a widely appreciated hit, the listener gets the illusion of value. Whether it is an “illusion” or not, it shows that value, as a concept, is besides economical, very much a cultural concept. For music it closely relates to collective experience. Nowadays, the practice of ‘liking’ songs could not be better reflected than by the comments and likes of members of online communities like *RDP*.

2.2 The Music Industry

Since music can be recorded and amplified, the possibilities for an artist to supply the audience increased enormously. As a result, a mass market for music emerged and intermediaries like record labels and A&R managers emerged to match demand and supply. Adorno (2002) was the first to consider this as ‘the music industry’. In this context, Adler (2006) argues that since music can be recorded and reproduced, every consumer can inexpensively consume music. This increased the demand and resulted in the music industry as we know it. For record labels, generally, artists become interesting when their audience reaches the point on which it matches the minimum level of production. This may result in reinforced market concentration, since the availability of a product of artists with a large enough audience can have a multiplicative effect on their rewards, while artists that do not have sufficient audience size are not able to enter the market. (IK: eerst)

Intermediaries like record labels and especially A&R managers play a central role in the music industry and facilitate the relation between artists and their audience. Because major record labels dominate (IFPI, 2016), the music industry can be considered as an oligopoly. In such a situation product differentiation plays an important role for record companies to increase market share by supplying to certain segments (Caves, 2000). In economics there are two forms of differentiation. We speak of vertical differentiation when less quality is offered for a lower price. And horizontal differentiation means that different types of products are offered to different target groups. As Adler (1985, p.208) mentions: “Lesser talent is a poor substitute for greater talent” and therefore vertical product differentiation does not increase market share. Horizontal differentiation, however, is a way to supply the demands of different audiences and increase market share. In a low competitive music industry, dominated by major record labels, intermediaries are less likely to spot and contract new talent because the introduction of a new artist in the market results in a decrease of demand for other artists. Burke (2011) refers to this process as ‘cannibalization. For record labels that already can supply to their audience, introducing a new artist goes at the expense of the ones already contracted by the labels. Adorno (2002) reminds us that when marketing talent, record labels carefully differentiate popular music in production. The listener is presumed to be able to choose between them like a multiple-choice questionnaire. (p. 446). This labelling technique regarding music types, genres, artists etc. can be seen sociological since it happens outside the music production itself. By the presence of these types the audience, collectively, and the listener, individually, is encouraged to determine what it likes and dislikes. It provokes like-dislike patterns of behaviour that function as reflection of the consumer demand.

Besides in terms of differentiation, intermediaries play also an important role in the cultural conventions and standards within the music industry. As discussed, previous hits and successes can give birth to current day standards and conventions. On the one hand it shows how concentration in the music market dictates the structure of the market and songs of the future. On the other hand, it emphasizes the importance to understand what the hits of tomorrow will be. Record labels, and specifically A&R divisions, are central in socially enforcing these standards (Adorno, 2002). Record labels and A&R managers want songs that are fundamentally the same as all other hits and still fundamentally different. Songs need to have at least one feature by which it can be distinguished from the rest and yet possess all the conventions of other hit songs (Adorno, 2002). This makes the criteria quite paradoxical and the practice of intermediaries as understandable as catching a butterfly with bow and arrow. Becker (1982) described the rare power of artist to create value, but in this context, it seems more applicable to the intermediaries as gatekeepers of music industry, who are supposed to know what artists are talented or not. However, the gatekeeper does not produce anything. Instead, he magically knows how to deal with uncertainty and turbulence in the market. Nowadays, since costs to enter the market side of the domain are minimized, the economic capital that record labels – as gatekeepers to the market – have to offer to artists is getting less important and the social and cultural value is becoming increasingly important.

2.3 Dealing with Uncertainty: Gatekeepers and Certifiers

> *The old guy with the cigar, one day he goes: "I took a chance and sold a million units […] Let's get a hippie in here!" […] next thing you know […] he's got his feed on the desk and he's saying: "well, we can't take a chance on this. That's not what the kids really want. And I know."*
>
> – Frank Zappa (1987)

Record labels and the audience deal with uncertainty mainly by basing their decisions on data about previous sales as reflection of popularity. The success of artists in the traditional music market is administered after release by record companies, and in this way, there is excludability regarding information. Peterson and Berger (1971) described how record labels establish production-divisions to detect trends and adapt to turbulence and uncertainty in the market. The people doing this work, can be seen as gatekeepers for the market. Gatekeepers take a central role in the music industry because they decide whether the value of the artists and their music is high enough to cover the investment in the product before it can enter the market (Caves, 2000). It shows that, in the traditional music market, gatekeepers are essential for dealing with uncertainty. This results in limited ability for artists to directly interact with large audiences, and for record companies to deal with uncertainty regarding the value of new artists entering the market. Not every artist has access to production factors and market information. From the producers' perspective, releasing a new song or album therefore stays to some extent always a shot in the dark. Caves (2000, p.61) describes how agents traditionally help artists finding record labels. Their service is charged and not every artist has access to the expertise that is necessary to enter the market.

Regarding the economic and cultural success, besides the expertise of gatekeepers, charts and data about sales function as an important source for determining what is going on in the music market. For major record companies aiming for the mass market, charts reduce uncertainty about the value of artists. Furthermore, the commercial successful artists are essential to cover the costs of the less successful (Meige 1989, pp. 133-159). Caves (2000) argues that uncertainty is central in the selection process because selection is based on the chance and not the guarantee that an artist will be appreciated by the audience. Burke (2011) mentions a hit rate of only 19 percent in the top 100 charts, which means that there is a high concentration of attention. From the perspective of the record labels and artists, Caves (p. 61) states that roughly 80 percent of the single record sales fail to cover their costs, which makes the pay-out highly uncertain. We can speak of concentration in the music industry when a relatively small number of musicians earn a majority of the money and dominate the activity in which they engage (Rosen, 1981). According to the (WIN, 2015, p.32), this is the structure of the music industry nowadays because the music market is dominated by major record labels and independent labels take only 37.6% of the market.

The role of the talent of artists regarding uncertainty about their value is another issue in the record industry that has implications for market concentration. It is important to distinguish income share from market share since the online music market may have different implications for the concentration of respectively income and attention. Rosen (1981) argues that superstardom, as reflection of concentration, exists because of hierarchy in talent of artists and the reproducibility of creative goods. Regarding concentration of income in the traditional record industry, Adler (2006) argues that the existence of superstars is not due to differences in talent but is rather based on the part of consumers to consume the same art that others do. Macdonald (1988) argues that if every performing artist is capable of producing either a good or a bad performance, the difference in talent between artists is seen not in the quality of their good or bad performances, but in the probability that a particular performance will be good. This probability is lower for new performers than for well-known performers, and artists with a good track record can command higher ticket prices.

Dealing with uncertainty has cultural consequences. The production of popular music for a mass market necessarily results in standardization (Adorno, 2002). Adorno argues that standard schemes and tempo's, returning themes, range of tones and a certain number of bars can all be seen as essential elements in the structure of popular music in general. As a result, only variations of the standard and nothing fundamentally new will be produced. In general, he argues, that the hit songs that are the results of this industry, all lead back to the same familiar experience. Standardization is the most fundamental characteristic of popular music and "extends from the most general features to the most specific ones." (p. 437). This also applies to techno music that is known for a 4/4 beat scheme and clear tempo and structure within the artist is able to experiment. Adorno (1942) argues that since the melody, rhythm and lyric of popular music are constructed within a definite pattern or structural form, the listener is not completely free to interpret the meaning and feeling (p. 438). The reaction of the audience to the song does not lie in the experience of this concrete song, because its structure is pre-given and pre-accepted. It implies a value judgement before the actual experience of the song starts. As a result, the ear deals with uncertainty regarding the value of potentially new hit songs by applying the knowledge of the patterns (p.442). By producing songs in standard structures “the composition hears for the listener.” (p.442) To illustrate this, Adorno (p. 442) argues that how adventurous complicated rhythms and harmonies in popular music may appear, the listener still is capable of interpreting it as a variation to the standard scheme. In this way techno music has essential similarities with the characterization of popular music as described by Adorno. Popular music divests the listener of individual interpretations and promotes conditioned reflexes. For record labels and the audience standardization is a result of dealing with uncertainty regarding value. It provides a musical framework through which new music can be understood. The economic concentration among cartelized labels “institutionalized the standardization and made it imperative.” (p.446).

In the first place this shows that knowledge of the music is necessary to interpret it. The consumer uses it to perceive and give meaning to the song he is hearing. By doing this, one could argue that knowledge is a both a resource in production and in consumption of music. This makes the listener a producer of meaning as well (Frith, 1996). It shows that standard elements and patterns play an important role in evoking conditioned reactions by the audience. This is not different for techno music. Secondly, since the knowledge about the standards is shared listening to music is a collective instead of an individual experience and shows that music is a collective and shared good.

From the perspective of the artist, however, Adorno (2002) argues that the production of music still remains in a handicraft stage. While it is highly centralized in its economic organization, he argues that from the perspective of artists, dealing with uncertainty is still an individualistic and social practice. The production of music can only be called industrial in terms of its promotion and distribution. Scott (2012, p.423) argues that the ‘cultural entrepreneurship’ is necessary for artists to produce and deal with uncertainty. The creation of new songs requires a nuanced understanding the conventions and trends in current culture. This can be linked to Csikzentmihalyi (1996, p. 7) who mentions that “It would be inconceivable without prior knowledge, without intellectual and social network that stimulated their thinking and without the social mechanisms that recognized and spread their innovations.” Someone is creative for and by virtue of others. Amabile (1983) pointed out that appropriate judges are necessary to determine what creative products are accepted as part of a culture and what are not. Artists can lower uncertainty regarding the value of their music by finding gatekeepers, intermediaries, fellow artist and other certifiers who guarantee the value of their music. Caves (2000) defines certifiers as people who present themselves as experienced and independent valuators of creative goods. It is important to understand that the value and quality of music does not exist on itself but is generated socially and culturally. In the research of this thesis, it is explored to what extent members of online music communities collectively, can function as appropriate observers or certifiers for the value of music.

And how does the audience deal with uncertainty? From an economic perspective the audience can be defined as the consumers. According to Caves (2000) cultural products can be seen as experience goods. For music, this means that past experiences tend to influence the current preferences, so in general a consumer will prefer a well-known author or a familiar genre to the ones he know nothing about. In short, consuming music takes time and searching for information, costs effort and requires expertise (Adler, 2006). In economic terms, this is referred to as consumption- and information-costs. Adler focusses further on the consumers perspective by arguing that concentration in the music market is caused by "the need on the part of consumers to consume the same art that others do" (p. 897). He argues that concentration of income and attention among artists is because of initial attention, which, on its turn, reinforces more attention. He refers to this process as the snowballing-effect. Besides empirical data Adler substantiates his vision by the fact that consumption of culture is a dynamic process and not a momentary experience. Although addresses ideas like "the more you know, the more you enjoy" (p. 897) and 'enjoyment of encounter' (p. 898) with both the product and other consumers, the definition of this process is left somewhat vague. For a better understanding of concentration of attention, determining this process is essential. Therefore, it is useful to distinguish the concepts he mentioned respectively in experience goods or consumption capital and bandwagon or network effects. Leibenstein (1950, p. 184) describes the bandwagon effect as an "interpersonal aspect of utility and demand", which is also very relevant for music. This relates to the process in which consumers' demand for a product increases with the number of people that consume the same product.

As mentioned, for consumers the validation of music relies on previous experience, consumption capital and bandwagon or network effects. From the consumers point of view, excludability regarding information relates to product differentiation in terms of access to information about music. The availability of information may reduce consumption costs and increase value of new music. Also for consumers, charts are an important source for information about new music and developments. Besides that, reviews, in magazines, media and online provide information to the consumers to certify the value of music and decrease uncertaint. This effect is further driven by online platforms like *Spotify,* that advice consumers on what music to listen to. Waelbroeck (2013) describes the mass market of consumers; people that follow the charts and take them for granted. He justly puts this in contrast with the growing number of younger consumers that streams songs and is attracted to a greater diversity of music, included electronic music. From the consumers' perspective, the demand increased because the digitization of music resulted in lower prices to distribute and produce. Furthermore, the increase of supply does not lead to loss of quality. The amount of music that can be produced and distributed is independent of the costs and so the potential output becomes limitless. In relation to consumer costs and economics of attention, the audience can be overexposed. This decreases the utility of music that is produced, which will result in less demand (Rosen, 1981). In this context, the main limiting factor for supply is demand because the consumers' attention for certain music is not inexhaustible. Therefore, economics of attention will play a decisive role for artists in reaching their audience.

2.4 The Economics of Attention

Music is everybody's business. It's only the publishers who think people own it.

— John Lennon (1975)

The powerful cultural role of the intermediary in current music industry once again becomes clear when Scott (2012) argues that to sustain career aspirations the artists convert different forms of capital into the cultural intermediary interest. Based on this information, the intermediary knows what new artists and songs are marketable and good enough. Scott states that besides music, artists have to produce an identity, attention and social trajectory for themselves as a 'new taste maker'. He links this to symbolic capital as defined by Bourdieu (1984). Scott argues that artists entering the market are entrepreneurs because they have to find innovative ways of doing so without sufficient economic capital. Artists have find alternative resources and capitals as defined by Bourdieu (1997) to generate the attention to the field in which they operate. These features in the practice of artists is in alignment with Lanham's (2006) theory about the economics of attention. Following Lanham (2006), a successful artist creates two products: the music itself and the attention for this music. This can be associated with Frith (1996) who argued that the value of a song does not rely on the music itself but on the experience of it. Lanham argued that economics of attention resulted in a centripetal gaze, a flow of energy from the margins of society to its centre of attention, which functions as a natural creator for the winner-take-all society (2006, p.52). So, if we assume all economic conditions sufficient, constant and equal among all producers of to supply the whole world with good music, he argues that ability to produce attention for music is the decisive factor in explaining market concentration. A minority of artists with the ability or means to attract attention increase their audience and receive most of the income and attention. Lanham refers to this process as the economics of attention, and this can be linked to Merton's (1957) St. Matthew's effect, described by Frank and Cook (1995) as the process in which success breeds further success.

Regarding economics of attention, as described by Lanham (2006), the online music market increases possibilities for artists to produce attention for their product (WIN, 2015). According to Epstein (2016), the online music market enabled millions of people around the world to use the internet in their way to find stardom. Acquiring followers and likes for their product and being visible on online platforms are just a few examples in which the internet can facilitate the self-perpetuation of attention. Compared to the physical music market, the diversity of online supply is much greater because the barriers to enter the market minimized. It has resulted in growing markets for niche music and specific genres since the cumulative market for those artists worldwide is increasing, which is defined by Anderson (2004) as the long tail economy. He argues that in a long tail economy, it is more expensive to evaluate than to release (Anderson, 2004) and therefore differentiation of music is likely to be dictated by the audience. Yet, digital dissemination did not result in a lower market share for the mainstream (WIN, 2015). So, a greater diversity does not necessarily imply less concentration (Epstein, 2016). Now the barriers to enter the market are minimized, a main question for artists entering the market is how to increase attention for their product and get rewards for supplying their audience. As mentioned, besides financial rewards, the online music market can also provide enormous amounts of symbolical, social and cultural rewards.

2.5 The Online Music Industry

> *Many of our assumptions about popular taste are actually artefacts of poor supply-and-demand matching – a market response to inefficient distribution*
>
> - Anderson, 2004)

The technology of the online market makes huge amounts of data available in real-time, which potentially enables artist to interact directly with their audience. The more people that use these platforms, the more valuable they become. Network effects can be seen in relation to the bandwagon effect, because the benefit of a good increases with the number of users using the same good (Handke, 2010). If we relate this to online platforms that facilitate the music market, network effects – in which the more people use a platform, the more people will use it – can be associated with economies of scale. A platform like *Spotify* is achieving a central position in the music industry by monitoring demand, attention and musical characteristics. When a platform is able to supply information more efficiently than if there were competition between several smaller suppliers, this may lead to a natural monopoly (Handke, 2010). Besides traditional intermediaries like record labels, data and AI play generated in these platforms are becoming increasingly important in the record industry. Furthermore, platforms like *Spotify* use it to increase their value towards all stakeholders in the music industry. With algorithms following the preferences of users, online platforms for music can guide consumers through the music market which lowers the consumption costs. Recommendation services and charts can be customized to the consumers preferences, resulting in a growing audience for less known artists (Anderson, 2004). Furthermore, for artists and record labels, these platforms provide insight in how to find their audience. Epstein (2016) reminds us that the market share of mainstream producers did not decrease, because the availability of mainstream music on platforms is necessary to attract consumers (Anderson, 2004). The centralized control by platforms, who have means to focus consumers' attention, now becomes one of the most important factors that influences the concentration of attention and income.

An important remark regarding digitization of the record industry, therefore, is that the facilitation of 'attention flows' in this market, and the rewards resulting from it, are mainly concentrated on big platforms (WIN, 2015). Epstein (2016) emphasizes that major media companies take advantage and subsequently most of the revenue in this online market does not go to the artists. He argues that, rather than less concentration among artists, the main concern for those platforms is the minutes of attention that consumers spend on their digital applications. If the most popular artists attract the main attention for platforms, this will not result in less concentration. Also Gordon (2012) is sceptical about the implications of new technology and states that the era of computers replacing human labour is largely over (p.13). Whether this is true or not, artificial intelligence (AI) and data about preferences can provide a more complete picture about what is going on within a culture and may be more objective than knowledge and value judgement of traditional gatekeepers and certifiers. Major record labels already invest in and trust on AI and big data to improve the selection process of new talent (MBW, 2018). Platforms like *Spotify* and *Beatport*, and online communities like *RdP* collect an enormous amount of information about the market. When platforms commercialize their ability to monitor and strive for a monopoly in this way, the excludability of information goods becomes a crucial factor increasing the concentration of income and attention.

Schumpeter stated that it is meaningless to “accept the data of the momentary situation as if there were no past or future” (p. 84). The relevant problem for creativity and the economy is how structures are created and destroyed. These structures, whether an oligopolistic market or a creative environment, are collectively made within a culture. This is in alignment with Amabile (1983) who argued that for a better understanding of these developments “criteria for creativity require an historically bound social context” (p.34). Online communities may shape and display these structures criteria. From this perspective, the emergence of online music communities may have increasingly decisive role in the way the culture and market is structured and concentrated. This would change the cultural economy since it enhances the role of symbolical capital – in this thesis defined as reputation of the artist and attention for unreleased music – because financial capital is becoming less decisive since production and distribution costs are diminished (Anderson, 2004).

2.6 Culture and Technology

The new generation's music […] might rely heavily on electronics.
[…] I could envision one person with a lot of machines, tapes, electronic setups.
- Jim Morrison (1969)

Cultural and social needs are essential factors driving technological innovations, and innovations and technological changes, on their turn, are the most important factor to determine long-term social and economic growth and structures (Schumpeter, 1942). The cultural and social needs of audiences and listeners to interact, to communicate and to establish a collective experience resulted in innovations like the internet, mobile phones and livestreams. These needs are also important features of rave culture, which from its beginning, embraced technological innovations and would not exist without it. It is not without a reason that this genre is called techno. Collective experiences, technology as drum computers and sharing of music are determined as important factors of this culture (Jordanous, 2014; Olaveson, 2004). For a better understanding, the technologies on which techno culture is based, needs to be seen in relation to the social and cultural needs that has driven them.

In the first place, technology has implications for culture around music. Techno music, raves and the activity of sharing experiences online can be seen as an epitome of collective application of technology within this electronic music culture. Olaveson (2004) proposes that technology is at the roots of electronic music culture because turntables, mixers, samplers, drum machines, and bass machines are necessary to produce a rave. This application of technology guided the creative energy and vibe among dancers at raves, but also resulted in a change within this culture. Heller (2014) argues that new media had an enormous influence on the rave culture. The increased and persistent use of technology in rave culture appears to be a reason for its shift from a participatory activity to a spectator model. Nowadays, the vast majority of electronic music event attendees bring smartphones in order to record and share the event, changing the original rave concept of the sharing experience of 'living in the moment' into the activity of sharing videos and experiences online. As a result, fewer people are dancing, and more people are recording videos at events. This shifts the experience of techno culture from solely a dance experience to an one in which the value of artists and the culture as a whole is to a great extent collectively defined online. It also resulted in another product within this culture: videos and livestreams. Rushkoff (2013) proposes that because we have 24/7 access to the online digital world, consumers spend a lot of time in the digital world and less in the physical world. Streaming services like *be-at.tv* attract many people interested in electronic music or that are not able to attend these performances. Another example is *Cercle,* a *YouTube*-channel that films techno events on extra-ordinary locations without the possibility for an audience to attend – e.g. on the Eiffel tower, in a cave and on a boat in the Pacific Ocean. As mentioned, from the perspective of the audience, Adorno (2002) argues that the listener is encouraged by the inexorable presence of these types to choose what he dislikes and likes. This is exactly what happens in online communities like *RdP,* in which every member can 'like' the song in a video, or not. They also comment in order to receive notifications about the identity and release-date of unknown songs. (IK: einde link naar musical characteristics)

Secondly, as a result, technology has also implications regarding the value of music itself. The entanglement of techno music and technology resulted not only in a collective experience but also in enormous availability of electronic songs online. In 2016 and 2016 a total of 234.300 techno songs were released on *Beatport*. All songs are categorized on tone and musical characteristics like beats per minute (*bpm*). The availability of digital music online combined and innovations in technology changed the way in which value of music is generated. Automatic playlist suggestions, searchable music collections, and music recognition systems can be seen as response to the needs of listeners to be advised in what to listen to and to the need of record labels to understand the audience. These applications are not able without technologies to retrieve information from music (Casey et al., 2008). It resulted in the emergence of the field of Music Information Retrieval, which is a multidisciplinary domain that gets an increasing amount of attention and is concerned with retrieving and analysing multifaceted information from large music databases (Herremans et al., 2014; Pachet, 2012).

3. Methods

3.1 Choice of Method

In this thesis the research question will be answered by a quantitative content analysis. In the first place, this type of research enables to look for relations between the amount of attention unreleased songs get in the online community *RdP* and the success of a song in terms of streams on *Spotify* and chart position and points on *Beatport*. In the second place it enables to explore the relation between the popularity of artists and DJ's before release, in terms of number of likes on their Facebook-page, and the success after release.

In general, statistics offer several methods to determine correlations and relations between the variables. In this research, the analysis is performed in two steps. First, a bivariate analysis is conducted to determine how the different variables are associations to each other, in order to get a preliminary indication of which variables are most closely associated. In general, this type of analysis only shows that the variables are associated to each other and cannot determine any causality. Regarding variables that are not static and prone to change, such as *Spotify plays per day* and *Beatport points,* causal conclusions can not be drawn yet, since in reality many factors can influence the popularity of a song at the same time. Pearson's *R* is used to find the associations between interval and ratio scaled variables. Spearman's *rho* is used to find relationships between ordinal variables and between ordinal and interval or ratio variables.

Secondly, staged regression analyses are presented in order to specify the relationship between the variables before and after release. A regression analysis is used to show that two or more independent variables can explain the dependent variable. Different models are presented in which pre-release variables, as independent variables, are predictors for post-release success. To establish a clear understanding of the different predictors, this analysis is staged. This means that first, the most important independent variables, related to attention for a song in *RdP* are entered in the models to predict success after release. Secondly, the variables related to popularity of the artist are entered into the model. When these models are explored there is a third and fourth model presented in which is controlled for other variables. These will be described more specifically later. Controlling for variables gives a more complete explanation because it quantifies the relationships and avoids spurious results from other influences that affect the main predictors. The purpose of staged regression is that it becomes clear how the model changes when adding other variables. In this way a better understanding of the various predictors for success can be established. Important in these analyses is the adjusted R^2, which indicates how much of the variance in the dependent post-release variables is explained by the independent variables about popularity of the artist and attention for the song before release.

3.1 Data Collection & Sampling

The units of observation in this research are unreleased songs presented in videos that are uploaded in *RdP*. In total there are 40.000 videos uploaded this community between June 2011, when it was founded, and May 2018, when the data from *RdP* was collected. In this research I will focus on the most popular videos in 2016 and 2017. In this period a total of 28.936 videos was uploaded. The videos are ranked based on their popularity. This is a composed variable that consists out of the combined number of likes and comments and is only used to determine the 120 most popular unreleased songs in *RdP*. Based on a total of 350.779 comments and 612.938 likes, I used a comment/like ratio of 1:1.747. This means a 'comment' weights more than a 'like' because members are less likely to comment. To compose the variable popularity, on which the ranking is based, for each unit the number of comments on each video is multiplied by 1.747 and added to the number of likes. Out of the ranking that resulted out of this, the sample of the 120 most popular videos that contain unreleased songs, was taken.

In order to determine a correlation between the popularity of songs before and after release, it is necessary that songs that were not released at the moment the videos were posted, are released on both *Spotify* and *Beatport* before the moment the data was collected. Videos containing songs that are not released at the moment the data was collected, cannot be included. The date on which the data was collected was 9^{h} of May 2018. Because I did not know how many videos contained unreleased songs at the moment they were uploaded, I started coding until I reached 120 videos containing unreleased songs at the moment the video was taken. This resulted in a total number of 600 coded videos, of which 120 contained unreleased songs. The other 480 videos contain music that was already released at the moment the video was taken, that was not released yet or that never will be released because it was for example performed live. Some videos were taken at the exact same moment from a different point of view and as a result some videos contained the same unreleased song. In the dataset videos that contain the same unreleased song are combined under the name of this song. This means that the variables of all videos containing song X are combined in the case of the most popular video. To illustrate this, if song X was uploaded in three different video's and video 1 had a popularity of 1700, video 2 a popularity of 192 and video 3 a popularity of 400, the numbers of 192 and 400 are added to 1700 to reach a total of 2292. In this way, the sample contains a total of 120 coded unreleased songs that give information about the popularity of songs before release.

A second step in the data collection was adding information about the popularity after release to each case. For every song, therefore, the peak position on *Beatport* and the *Beatport* points were added using information of *beatstats.com*. *Beatport points* are calculated daily on a song's position in the Beatport top 100 charts. If a track is at position 1, it gets 100 points, if it is in position 100, it gets 1 point per day in the charts. Songs that did not reach the charts get a '0'. Thirdly, the dataset was supplemented with variables that showed the plays per day on *Spotify.* This is calculated at total plays divided by the number of days between the release of the song and the day I collected this data, the 9th of May 2018. Furthermore, *Spotify* not only uses data about the musical characteristics in their algorithm to recommend music to its users, it also enables them to access these data. The songs are added to a playlist* in order to access information about musical characteristics. For every song the musical characteristics are also added as variables. Lastly, based on literature, it is possible that the attention for a song in *RdP* is influenced by the popularity of the DJ that is playing it. To explore this correlation, the position of the DJ in the *Resident Advisor* (*RA)* Top 100 is added as variable representing the reputation. The position of the DJ in the top 100 is subtracted from 101. As a result, the number 1 DJ gets the value '100' and the number 100 DJ gets the value '1'. Besides that, regarding the popularity of the DJ playing the unreleased song, the DJ's number of *Facebook*-page likes is recorded for every song on the day before release of the song using www.sociograph.io.

*https://open.spotify.com/user/bgunst/playlist/4PlAIysBXk3bda51nV1Iwk?si=XnqGC0sMS Hun1AtBGmoOEA

3.2 Operationalization of the Concepts into Variables

In the literature review it became clear that from a cultural perspective, the artist and audience together create the value of songs before and after release. In short, it showed that value can be expressed in cultural, social, symbolic and economic terms. Furthermore, intermediaries and gatekeepers take a central role in the music industry and facilitate the interaction between the artist and the audience. In the research conducted in this thesis, the popularity of artists and the attention for songs before release, are central concept in order to explore their association with success after release. The concept of attention for the unreleased song is reflected by the variables *number of RdP-likes* and *number of RdP-comments*. Popularity of the artist is represented by the variable *artist's number of Facebook-page likes*.

From the economic perspective, the literature review showed that previous economic success of artists function as important factor to deal with quality uncertainty. It can result in bandwagon effects, herd behaviour and market concentration. With the costs of production and distribution being diminished, economics of attention become central. A main question for artists is how to find their audience. For all actors in the music industry, charts play an essential role in determining previous success of an artist. Furthermore, central online platforms like *Spotify* and *Beatport*, administer the popularity of artists and songs after release and use it to advice the audience both implicitly and explicitly. The concept success after release is in this research represented by three variables. The first is *Spotify plays per day*, which shows how often songs are streamed. The second is *Beatport peak positon,* which is a reflection of the popularity on *Beatport* based on how much the songs are bought after release. The third variable related to the concept success after release is *Beatport-points* which is based on the peak position and the number of days in the *Beatport* charts.

The relation between technology and music, was explored in the last part of the literature review. It pointed out that new technologies are able to administer both the popularity of artists and musical characteristics of songs. Following Lanham (2006) and Frith (1996) not only the music itself but also the attention for the music but also are both relevant factors for the value of a song. In order to include the role of the music itself in this research, the musical characteristics of the songs, as recorded by *Spotify*, will be introduced as control variables. In the research it is explored to what degree musical characteristics, as control variable representing the music itself, influence the relation between attention for unreleased songs, popularity of the artist before release and success of the songs after release. The variables *DJ's number of Facebook-page likes* and *DJ's Top 100 position,* relate to concept of stardom, and are also treated as control variables. Note that *DJ's number of Facebook-page* *likes* is different from the *artist's number of Facebook-page likes,* since the latter represents popularity of the artist of the song, as independent variable and the first represents popularity of the DJ playing the song, as control variable. Table 1 presents an overview of the variables, their type, source and scaling and the theoretical concepts to which they are associated.

Table 1

Overview Concepts Variables

Theoretical Concept	**Variable**	**Variable type**	**Source**	**Scale**
Success (post-release)	*Spotify* plays per day	Dependent	(Total plays on *Spotify**) / (days between *Spotify** release date and 8-5-2018)	Ratio
	Beatport peak position	Dependent	*Beatstats***	Ratio
	Beatport-points	Dependent	*Beatstats***	Interval
Attention for the song (pre-release)	Number of *RdP*-comments	Independent	Number of comments per video in *Raad de Plaat******	Ratio
	Number of *RdP*-likes	Independent	Number of comments per video in *Raad de Plaat******	Ratio
Artist's popularity (pre-release)	Artist's number of *Facebook*-page likes	Independent	*Facebook*-page likes of artist on day before release via *Sociograph****	Ratio
DJ's popularity (pre-release)	DJ's number of *Facebook*-page likes	Control	*Facebook*-page likes of DJ on day before release via *Sociograph****	Ratio
	DJ's *Top 100* position	Control	Position in top 100 2016 via *Resident Advisor*****	Interval
Musical Characteristics (pre-release)	Bpm	Control	*Spotify**	Ratio
	Energy	Control	*Spotify**	Interval
	Danceability	Control	*Spotify**	Interval
	Liveliness	Control	*Spotify**	Interval
	Valence	Control	*Spotify**	Interval
	Acousticness	Control	*Spotify**	Interval
	Speechiness	Control	*Spotify**	Interval

*http://organizeyourmusic.playlistmachinery.com/, **www.beatstats.com, ***https://sociograph.io/my.html , ****www.residentadvisor.net/features/2857 , *****www.facebook.com/groups/raaddeplaat/

3.3 Variables and Descriptive Statistics

The purpose of this research is to explore to what extent variables before release can indicate success after release. In the table 1, there are three variables presented that relate to success after release: (1) *Spotify plays per day*; (2) *Beatport-points*; and (3) *Beatport peak position*. These are the dependent variables in this research. Then, the independent variables in this research are the indicators before release because they are expected to explain the success after release. The indicators before release relate to the concepts attention for the song before release and symbolic capital of the artist and of the DJ. The independent variables therefore are: (4) *the number of RdP-likes;* (5) *the number of RdP-comments*; and (6) *the artist's number of Facebook-page likes*. The control variables are (7) *DJ's position in Top 100*; (8) *DJ's number of Facebook-page likes*; and (9) *musical characteristics*. The strengths, weaknesses and descriptive statistics of each of the variables mentioned above will be discussed separately in the paragraphs below.

As mentioned, the dependent variables relate to the concept success after release and the independent variables relate to attention for a song and popularity of the artist before release. Rosen (1986) argues based on his superstar theory that there is an uneven distribution of rewards among artists. Also, based on other stardom theories (Adler, 2006, Macdonnald, 1988) and economics of attention (Lanham, 2006), it can be expected that popular songs and popular artists receive exponentially more attention than artists that are less well known. Only a minority of released songs become hits (Burke, 2011). This means that it can be expected variables *Spotify plays per day*, *Beatport peak position* and *Beatport-points* are not normally distributed and that hit songs are extreme outliers per se. This may also apply to the attention for songs before release, since the more popular a song becomes the more attention it will get. When testing the dependent variables on normality the Kolmogorov-Smirnov test confirmed this. For analysing the relations between variables normality is assumed and therefore the data needed to be transformed. In such a situation a logarithmic transformation is useful in order to meet the assumption of normality (Field, 2013). Furthermore, a logarithmic transformation is theoretically justified because, based on the stardom theory and economics of attention some songs and artists get exponentially more attention than others. In this research the independent and dependent variables, except for *Beatport peak position,* are log-transformed. Below, the variables are described and the descriptive statistics of the original, so not log-transformed, data are presented.

3.3.1 Dependent Variables

<u>After release: *Beatport-points* and *Beatport peak position*</u>

Beatport is the most important marketplace for electronic music online (Jordanous et al. 2014). Every year, more than a million songs are released and sold here. In this way, the *Beatport*-charts provide a fruitful overview of the what songs are most successful in economic terms. This can be linked to the concepts of fame and popularity as mentioned in the literature review. These concepts are closely related to the stardom theories, bandwagon effect and herd behaviour. Furthermore, network effects relate to the central role of this platform but does not directly relate to the variables measured in this research. Because *Beatport* only administers the songs that are released on this platform, the chart position presented here is not based on sales and streams on platforms such as *Spotify*. Furthermore, *Beatport* gives information about popularity based on how many times a song is sold and not based on how many times it is played. Therefore, this type of popularity is different from the popularity monitored by *Spotify*.

In this research, two variables relate to success on *Beatport* after release. The first is *Beatport* points and the second is *Beatport* peak position. The peak position of a song is different from the *Beatport* points since it only shows the peak in demand and popularity and does not take the duration of the popularity into account. To illustrate this, a song that reaches the number one position in the charts for a week is not necessarily more popular than a song that reaches the number thirty and stays in the charts for a few months. The peak position only shows that the demand for a song was very high during a certain period of time. If a song leaves the charts soon after a high peak position, it means that the demand for a song was very concentrated timewise. In this context the concept of overexposure of the audience can be related to the peak position because the audience's attention for song that is very popular can decrease as soon as the song is played too often. Songs with high *Beatport-points* but a low peak position can stay interesting for the audience because they are played by less DJ's or less often, while the demand for a song with a high peak position can decline because the audience have heard enough of it. In short, the overall demand for a song with a high peak position is not necessarily higher than for a song with a low peak position. While *Beatport* peak position represents the highest popularity a song reached, *Beatport*-points tell us more about the overall demand for a song.

Table 2

Descriptive Statistics Beatport Variables

	Mean	Median	Mode	St. Dev.	Min.	Max
Beatport **Peak Position**	50	66	0	42	0	100
***Beatport*-Points**	3346.54	745	0	8170.95	0	74192

N =120

<u>After release: *Spotify Plays per Day*</u>

Spotify is the most important platform for streaming music (WIN, 2015). It exactly administers how much a song is played and, in this way, gives an accurate and insight in how popular a song is. One could argue that it is a more 'pure' indicator of how popular a song is than sales numbers are. Furthermore, it administers the popularity of songs among different segments of the audience. *Spotify* uses this information together with musical characteristics in algorithms to advise its users what to listen to (Epstein, 2016). Artists earn about $4,- per 1000 plays (www.royaltycalc.com) and therefore also this variable relates to the general concept of economic capital and success. In this research *Spotify plays per day* are treated as variable representing success after release. This variable is calculated based on the total plays on the date on which this data was collected, the 9th of May 2018. This value is divided by the number of days between the release date and the 9th of May. An important remark is that the plays per day are average values between those dates and therewithal can change after the date this data was collected. A song that is barely played can still become popular after this research and songs that are played very often at this moment can become less popular in the future. Nevertheless, popularity is never an absolute value that can be perfectly measured. Just as with the abovementioned *Beatport* variables popularity of artists and songs is often self-reinforcing (Rosen, 1981; Adler, 2006; Epstein, 2016) and as a result, popular songs get exponentially more attention, while it is harder for less popular songs to get more attention. Below the descriptive statistics of the original data.

Table 3

Descriptive Statistics Spotify Plays Per Day

	Mean	Median	Mode	St. Dev.	Min.	Max
Spotify **plays per day**	1001	175	25	3941	2	41582

N =120

3.3.2 Independent Variables

<u>Pre-release: Attention for song in *Raad de Plaat*</u>

The first independent variables represent the attention of the audience for the unreleased songs. It can be linked to the concept of attention and symbolic capital, as discussed in the literature review, because it is part of the buzz around a song before it is released. Within *RdP,* two variables represent the buzz before release: the number of likes and the number of comments on unreleased music videos. Because *RdP* attention was not normally distributed, the variables were log-transformed. Below the original descriptive variables are presented.

Table 4

Descriptive Statistics RdP-Comments & RdP-Likes

	Mean	Median	Mode	St. Dev.	Min.	Max.
Number of RdP-Comments	121,73	90	58	86.70	30	581
***Number of RdP*-Likes**	257.90	191.50	96	214.05	81	1701

N =120

<u>Pre-release: *Artist's number of Facebook-page likes*</u>

The third pre-release variable is the *artist's number of Facebook-page likes* and relates to the concept of stardom and popularity before release. This variable represents the overall popularity of the artist and the potential size of the audience for an unreleased song. Therefore, this variable can also be linked to the theoretical concept of symbolic capital of the artist. For each song the *artist's number of Facebook-page likes,* was recorded on the day before release of the song, using www.sociograph.io. Below the descriptive statistics are presented. Because a small part of the artists get most of the attention, this variable is not normally distributed. For this reason also this variable is log transformed. In Table 5, the descriptive statistics of the original data are presented.

Table 5

Descriptive Statistics Artist's Facebook-Page Likes

	Mean	Median	Mode	St. Dev.	Min.	Max.
Artist's number of Facebook-page likes	148,514	32,370	9,526	290,340	0	1,656,295

N =120

3.3.3 Control Variables

Pre-release: *DJ's position in Top 100* and *DJ's number of Facebook-page likes*

The DJ top 100 was an annual chart based on a poll that was taken by *Resident Advisor* (*RA*) from the audience. *RA* plays a central role in reporting developments in electronic music culture. The position of the DJ can therefore be seen as indicator of the popularity of the DJ, generated by the audience. Since the DJ's reputation is increases when getting a position in *RA* Top 100, this variable also relates to the concepts of symbolic capital, stardom and fame. The *DJ's number of Facebook-page likes* relates to the concept of stardom and popularity before release. This variable represents the overall popularity of the DJ playing the unreleased song. Therefore, this variable can also be linked to the theoretical concept of symbolic capital of the DJ.

Table 6

Descriptive Statistics Resident Advisor Top 100 Position

	Mean	Median	Mode	St. Dev.	Min.	Max.
***RA* DJ Top 100**	52	61	0	40	0	100

N =120

Table 7

Descriptive Statistics DJ's Facebook-Page Likes

	Mean	Median	Mode	St. Dev.	Min.	Max.
Artist's number of Facebook-page likes	474,554	346,224	995,237	444,907	0	1,886,419

N =120

Pre-release: Musical Characteristics

The next variables relate to the concept musical characteristics. This concept itself can be linked to the concepts of cultural capital and standardization, since these characteristics may enable measurement of conventions and standards, as discussed in the literature. Secondly, these musical characteristics can be seen in relation to the technology that made it possible to record these characteristics and that may have implications to understand the preferences of the audience (Herremans, et al. 2014). Bpm measures the tempo of a song based on beats per minute. The higher the bpm, the faster the tempo of a song.. Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0 is least danceable and 100 is most danceable. Valence is a measure from 1 to 100 describing the musical positiveness of a song. Songs with high valence sound more positive, while tracks with low valence sound more negative. Energy is a measure from 1 to 100 and represents a perceptual measure of intensity and activity. Energetic tracks feel fast, loud, and noisy. Acousticness is a confidence measure from 1 to 100 to determine whether the track is acoustic, so techno songs, as electronic music, will score lower than a classical concert. Liveness detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 80 provides strong likelihood that the track is live. Speechiness detects the presence of spoken words in a track, and measures on a scale from 0 to 100 the attribute value. Tracks that are probably made entirely of spoken words typically get a value above 66. Values between 33 and 66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 33 are likely to represent non-speech-like tracks, but still may contain some speech elements.

Table 8

Descriptive Statistics Musical Characteristics

	Mean	Median	Mode	St. Dev.	Min.	Max.
Bpm	126.57	126	125	4.53	118	140
Energy	77.80	80.50	86	14.05	43	100
Danceability	73.10	75.00	80	9.44	46	93
Liveliness	12.96	10.50	11	10.05	4	63
Valence	22.35	16.00	4	18.68	3	82
Acousticness	3.52	0.00	0	9.02	0	53
Speechiness	6.00	6.00	5	3.09	3	26

N =120

4. Results

In this chapter the variables are analysed according to the methods discussed in the previous chapter. To answer the research question, first the bivariate analyses between the variables will be explored to see what independent variables are associated with each other and with the dependent variables. Secondly, multivariate regression analyses are presented to determine how the correlations are influenced when control variables are introduced. For every dependent variable – *Spotify plays per day, Beatport points* and *Beatport peak position* – four models are presented.

4.1 Correlations

4.1.1 Correlations between Pre- and Post-Release-Variables

4.1.1.1 *RdP* Attention and Post-Release Success on *Beatport* and *Spotify*

The central question in this thesis is to what extent audience attention before the release of a song can signal the success of the song after release. Before defining models, it is useful to first look to what extent the attention for unreleased songs and popularity of the artist can be associated with success on *Beatport* and *Spotify* after release. In this paragraph, the correlations between audience attention in *RdP,* popularity of the artist on *Facebook* and success after release are explored. When these are determined the same correlations will be investigated when controlling for musical characteristics, DJ's top 100 position and DJ's number of likes on the *Facebook*-page.

Based on the findings in the table 9, the following correlations are determined. The number of comments before release and the plays per day on *Spotify* after release*,* got a significant positive correlation (r=.420, p<.001). Furthermore, the number of comments is also significantly associated with *Beatport*-points (r=.270, p < .01). To determine to what degree comments can be associated with the rank of the song in the *Beatport* Top 100 determining a parametric correlation analysis like Pearson's R is not appropriate, and a this is a Spearman *rho* correlation. This shows that the ranking the number of comments is positively and significantly related to *Beatport* peak position in Top 100 after release (r=.308, p<.001). This indicates that the number of comments before release may function as predictor of popularity of songs after release. When controlling for musical characteristics, *DJ's Top 100 position* and *DJ's number of Facebook-page likes,* the associations slightly change. The association between *Spotify plays per day* and *the number of RdP-comments* (r = 0.362, p <

0.001) stay significant but becomes less strong. This is also the case for *the number of RdP-likes* (r = 0.345, p < 0.001). For *Beatport-points*, both the significance and the strength of the association with *number of RdP-comments* (r = 0.217, p < 0.05) and *RdP-likes* (r = 0.187, p < 0.05) decrease. The control variables have a similar influence on the association between *Beatport Peak Position* and *number of RdP-comments* (r = 0.220, p < 0.05) and *number of RdP-likes* (r = 0.180, p < 0.1). This indicates that the attention in *RdP* can better be associated with *Spotify plays per day*, as platform where the audience streams music, than with success on *Beatport,* as online market where songs are bought. The control variables seem to have a bigger influence on the success on *Beatport*. Nevertheless, when controlling for *musical characteristics, DJ's Top 100 positin* and *DJ's number of Facebook-page likes,* these findings show that attention for a song in *RdP* before release, especially the *number of RdP-comments*, can be associated with success after release.

Table 9

Correlations RdP-Comments and - Likes and Success after Release

	Spotify plays per day	***Beatport points***	***Beatport Peak Position* Spearman's *Rho***
Number of	.420****	.270***	.308***
RdP-Comments	(.000)	(.003)	.001
Number of	.362****	.278***	.182**
RdP-Likes	(.000)	(.002)	(.048)
Controlling for *musical characteristics*, *DJ's Top 100 position*, *DJ's number of Facebook-page likes*			
Number of	.362****	.217**	.220**
RdP-Comments	(.000)	(.022)	(.020)
Number of	.345****	.187**	.180*
RdP-Likes	(.000)	(.049)	(.059)

**p<0.1, **p<0.05, ***p<0.01, ****p<0.001*

4.1.1.2 *Artist's number of Facebook-Page* Likes and Post-Release Success

As mentioned the *artist's number of Facebook-page likes* – so, not of the DJ playing the song – is a variable in this research that represents of the concept popularity of the artist among the audience before release of a new song. This research explores to what degree this indicator before release tells something about how much a song will be played after release. Table 10 shows that *the artist's number of Facebook-page likes* is strongly related to the *Spotify plays per day* after release (*r*=.575, p<0.001). Since it can be expected that the potential audience for a song is bigger for artists with a bigger audience, this may not seem so surprisingly. However, to establish a clear understanding of how determine indicators of success before release, it is essential to include this factor in regressions analyses. The *artist's number of Facebook-page likes* can also significantly associated with *Beatport points* ($r = 0.324$, $p < 0.001$), but this association is less strong. The association between *Beatport peak position* and *artist's number of Facebook*-page likes, is again determined based on Spearman's correlation, which also shows a positive significant relation (*r*=.417, p<.001).

When controlling for *musical characteristics*, *DJ Top 100 position and DJ's number of Facebook-page likes*, the strength of the association between *artist's number of Facebook-page likes* and both *Spotify plays per day* ($r = 0.613$, $p < 0.001$) and *Beatport-points* increases. For *Beatport peak position*, however, it slightly decreases. This indicates that *musical characteristics*, *DJ's Top 100 position* and *DJ's number of Facebook-page likes* do influence the relation between popularity of the artist before release and success of the song after release. A regression analysis may give more insight in which of these control variables influence the relation between *artist's number of Facebook-page likes* and the success after release and in what way. In short, the findings so far indicate that *the number of Facebook-page likes* – as representation of artist's popularity – can significantly be associated with success on *Beatport* and *Spotify* after release

Table 10

Correlations Artist's Facebook-Page Likes and Success after Release

Success after release			
	Spotify plays per day	***Beatport points***	***Beatport Peak Position*** **(Spearman's Rho)**
Artist's number of likes on Facebook-pag	.575**** (.000)	.324**** (.000)	.417**** (.000)
Controlling for *musical characteristics*, *DJ's Top 100 position*, *DJ's number of Facebook-page likes*			
Artist's number of Facebook-page likes	.613**** (.000)	.384**** (.000)	.383**** (.000)

**p<0.1, **p<0.05, ***p<0.01, ****p<0.001*

4.1.2 Post-Release Correlations

Before defining models with regression analyses, the relations between the dependent variables, regarding success on *Beatport* and *Spotify* after release, are explored. Table 11 shows that *Spotify plays per day* are strongly and significantly associated with both *Beatport Points* (r = 0.516, p < 0.001) and *Beatport Peak Position* (r = 0.620, p < 0.001). Because *Beatport Points* are based on position in the *Beatport* charts times the days on this position, there is a strong association with *Beatport Peak Position*. It indicates that songs that reach a high position in the *Beatport* charts also get more *Beatport Points.* It does not necessarily mean that songs with a high peak position also stay in the charts for a longer period of time.

Table 11

Correlations between Post-Release Variables

	Success after release		
	***Spotify* Plays per Day**	***Beatport* Points**	***Beatport* Peak Position (Spearman's *Rho*)**
***Spotify* Plays per day**	-	. 516**** (.000)	620**** (.000)
***Beatport* Points**	. 516**** (.000)	-	.881**** (.000)
***Beatport* Peak Position (Spearman's *Rho*)**	.620**** (.000)	.881**** (.000)	-

**p<0.1, **p<0.05, ***p<0.01, ****p<0.001*

4.1.3 Pre-Release Correlations

4.1.1.2 *RdP* Attention and Musical Characteristics

An important remark regarding the musical characteristics is that they only apply to the most popular songs in the *RdP*-community and therefore cannot be generalized for the relation between these characteristics and the popularity of techno songs in general. In short, this only provides insight in the characteristics of the most popular songs within this community and this is useful to understand what songs get most of the attention within this community before release. There is a significant negative correlation found (r= -.220, p < 0.05) between *bpm* and the number of comments. This indicates that, within the 120 most popular unreleased music videos in *RdP*, more people are reacting to slower songs than to faster songs. A regression analysis may give more inside in how and to what degree *bpm* can be associated with the members' decision to react. Another musical characteristic that is significantly associated with the number of comments is *valence* (r=.192, p < .05). This relation is positive, which indicates that the number of comments are higher for songs that got a higher valence. Another positive relation is found between *acousticness* and the number of comments (r=.217, p<.05). This could mean that electronic songs with more acoustic elements get more comments than songs that are determined less acoustic. Furthermore, the only musical characteristic that is associated with the number of likes is *liveliness* (r=.198, p<.05). This indicates that videos presenting songs that appear to have more live elements, get more likes from the community members. However, it must be noted that it is hard for *RDP*-members to hear live elements of songs via videos that are recorded live at a performance. Although these associations are not relevant for answering the research question it shows that online communities like *RdP* may have implications for artists and DJ to better understand the musical preferences of their audience.

Table 12

Correlations Musical Characteristics and Reactions on Video

	Musical Characteristics						
	bpm	energy	danceability	liveliness	valence	acousticness	speechiness
N° of comments on video	-.220**	-.179	.006	.034	.192**	.217**	-.089
	(.016)	(.050)	(.947)	(.712)	(.035)	(.017)	(.336)
N° of likes on video	-.018	.029	-.147	.198**	.076	.079	-.048
	(.846)	(.756)	(.110)	(.031)	(.407)	(.392)	.605

**p<0.1, **p<0.05*

4.1.1.1 *RdP* Attention and DJ Popularity

To understand how the audience reacts to a song before release, it is also interesting to explore what factors can be associated with their decision to react on a video. A bivariate analysis between both *DJ's number of Facebook-page likes* and *DJ's Top 100 position* – representing the concept popularity of the DJ playing the song – and *number of RdP-likes* and *number of RdP- comments* can give more insight. It also provides an indication of the extent to which stardom theories of Rosen (1981) and Adler (2006) are applicable to the attention unreleased songs get within this online community. First of all, there is also no correlation found between the *DJ's number of Facebook-page likes* and the *DJ's Top 100 position* (p=.683). This is interesting because it shows that popularity measured by the variable *DJ's Top 100 position* is different from the popularity measured by *DJ's number of Facebook-page likes.* While the top 100 is facilitated by *Resident Advisor* and aims to provides an overview of the best DJ's in this culture, the DJ's *Facebook-page* reflects popularity in terms of audience size. A top 100 position can be seen as popularity that resulted in a reputation, while number of *Facebook*-page likes is just a measurement of popularity.

Besides that, the table 13 shows that there is no correlation found between the *DJ's position in Top 100* and *number of RdP-comments* ($p = 0.243$) nor *number of RdP-likes*. Furthermore, the position of the *DJ's Top 100 position* and the *DJ's number of Facebook-page likes* are both not associated with *the number of RdP-comments*. This means that the attention of members of *RdP* for a song before release, is not influenced by the popularity of the DJ that plays the song. This is interesting because it indicates that economics of attention and stardom theories (Adler, 2006; Rosen, 1981) do not necessarily apply to the influence of the DJ's popularity on the audience's attention for a song before release. However, this does not say anything about the influence of stardom and economics of attention on the success of a song after release. The regression analyses may provide more insight in this context.

Table 13

Correlations DJ's Popularity and RdP Attention

	DJ's *RA* Top 100 Position	DJ's *Facebook*-page likes
N° of *RdP*-comments on video	.108	.038
	(.243)	(.638)
N° of *RdP*-likes on video	.005	.166*
	(.959)	(.071)

**p<0.1*

4.2 Regression Analyses

In the following paragraphs the regression analyses are presented in order to answer the research questions more precisely. In these regressions, variables that indicate the success of a song after release – the plays per day on *Spotify, Beatport*-points and *Beatport* peak position – are the dependent variables. For each of the dependent variables three models are discussed. The first model introduces the number of *RdP*-likes and the number of *RdP*-comments on the unreleased music videos as the main independent variables in this research. The goal of this model is to explore to what extent the interest in a song in online communities like *RdP* before release, can predict the success of a song after release. The second model introduces the number of likes on the *Facebook*-page of the artist as extra independent variable in order to determine its influence on the success after release. This variable represents the interest in the artist of the unreleased song and can be linked to the symbolic capital of the artist. In agreement with dr. Christian Handke, supervisor of this thesis, the third model controls for *bpm* as most determining musical characteristics influencing the predictive power of pre-release variables for post release success. Lastly, the fourth model is controlling for all *musical characteristics*, *DJ Top 100 position* and *DJ's number of Facebook-page likes.* In all the models there is checked for multicollinearity, which means that the predictors do not correlate with each other in a regression model (Field, 2013). In all models there is no evidence found for multicollinearity, as the tolerance values were much higher than 0.2, which is the minimum to assume no potential problem (Field, 2013) The average VIF is presented below each model.

4.2.1 Pre-release Variables as Predictor for *Spotify Plays per Day*

In table 14, the relations between variables before release and the plays per day on *Spotify* after release, are further investigated. Model 1 contains the number of *RdP* comments and the number of *RdP* likes as main predictors for plays per day on *Spotify* after release. This model is highly significant (F (2; 117) = 13.440, $p<0.001$), which means that it is suitable to say something about the number of plays per day after release. The number of comments and the number of likes together explain 17.3% of the variance of the dependent variable. While the number of comments on the video are significant and moderately correlated with the number of plays per day (b^* = 0.324, t = 2.835 , p < 0.005), the number of likes are not a significantly correlated (p =0.224). This means that the number of comments is a good predictor for plays per day on *Spotify,* while the number of likes is not. An explanation for this finding is that within this community, commenting and liking are acts with different intentions. Commenting on a video that contains unreleased music is an act by which people want to stay updated about the name and artist of the song. Liking can be seen as an expression of appreciation of the video or the song, and members that like a video do not necessarily want to stay updated

Table 14
Regressions with 'Spotify Plays per Day' as Dependent Variable

	Model 1	**Model 2**	**Model 3**	**Model 4**
RdP-Comments (log)	.324***	.396****	.315****	.237***
	(0.005)	(0.000)	(0.001)	(0.010)
RdP-Likes (log)	.140	-018	032	.114
	(0.224)	(0.846)	(0.724)	(0.253)
Artist's FB-page Likes (log)		.571****	.582****	.585****
		(0.000)	(0.000)	(0.000)
DJ FB-page likes (log)				-.092
				(0.266)
DJ Top 100 Position				.011
				(0.901)
Musical characteristics				
Bpm			-.212***	-.169**
			(0.003)	(0.047)
Acousticness				.015
				(0.826)
Valence				.069
				(0.314)
Energy				-.091
				(0.223)
Danceability				-.011
				(0.872)
Liveliness				-.089
				(0.194)
Speechiness				-.119**
				(0.05)
Observations	120	120	120	120
R^2	.187	.498	.539	.575
Adjusted R^2	.173	.485	.523	.527
F Statistic	13.440****	38.394****	33.663****	12.048****
	(df = 2; 117)	(df= 3; 116)	(df= 4; 115)	(df= 12; 107)
$\overline{VIF}$	1.883	1.637	1.557	1.547

*Notes: *p<0.1, **p<0.05, ***p<0.01, ****p<0.001* about the identity of the song it presents.

In model 2 the number of likes on the artist's *Facebook*-page are introduced as variable that represents the audience size of the artist of the song, and in this context can be linked to the concept of symbolic capital of the artist before release. This model is significant (F (3; 116) = 38.394, p<0.001) and able to explain quite a big amount of the variance 48.5%. Furthermore, within this model the number of likes on the *Facebook*-page of the artist is strongly correlated with the number of plays per day ($b* = 0.571$, $t = 8.485$, $p < 0.001$). The remarkable increase of the R^2 – which shows the percentage of the variance of plays on *Spotify* that is explained when this predictor is added to the model – must be seen in perspective. As mentioned, the artist's number of *Facebook*-page likes can be thought of as a reflection of the overall audience attention for an artist before the song is released. Furthermore, the *Facebook*-page is also a medium through which the artist communicates with his or her audience. The song of an artist with a big audience is more likely to be played often than songs of artists with a smaller audience. Off course, this does not indicate that a song of a famous artist that does not appeal to the audience will be played more than a song of a small artist that is very interesting to the audience. However, this model does tell us that the reach of an artist increases when his audience size does, and that, as a result, a new song of an artist with a big audience is likely to be played more often. Therefore, the number of *Facebook*-page likes is an appropriate indicator of the overall interest of the audience in the artist and the music he or she releases. Within this model, the addition of the number of *Facebook*-page likes also has a positive effect on the correlation between the number of *RdP*-comments and plays per day ($b* = 0.396$, $t = 4.374$, $p < 0.001$). This indicates that, when taking the audience size of an artist into account, the interest in the song before release is a better predictor for the number of plays per day on *Spotify*, than when the number of *Facebook*-page likes are not taken into account. The number of *RdP*-likes still remains not a significant predictor, which confirms that the intention of liking fundamentally differs from the intention of commenting on a video.

The specification in model 3 (F (4; 115) = 33.663, p<0.001) tests the same predictors as in model 2, while controlling for *bpm.* This model explains 52.3% of the variance in *Spotify plays per day*. It shows that *bpm* has an effect on the predictors *RdP-comments* ($b* = 0.315$, $t = 3.469$, $p = 0.001$), and the *number of likes on the Facebook-page* ($b* = 0.582$, $t = 8.976$, $p < 0.001$), but they both stay significant. Model 4 controls for all *musical characteristics*, *the number of DJ's Facebook-page likes* and *DJ's top 100 position*. The model is completely significant (*F* (10; 109) = 14.340, p<0.001) and has a strong explanatory power before release, it accounts for more than half of the variance in plays per day, 52.7%. Within this model, the number of *RdP*-comments still is a significant moderate predictor (b^* =0.237, t = 2.441 p = 0.010), and also the artist's *Facebook*-page likes still got a significant strong explanatory power (b^* = 0.585, t = 8.759, p = 0.000). Of all the musical characteristics, *bpm* is most significant predictor for plays per day on *Spotify*. The negative and weak coefficient (b^* = -0.169, t = -2.010 p = 0.047) indicates that faster songs are less likely to be played often than slower songs. Also, *speechiness* is significant predictor for plays per day on *Spotify* (b^* = -0.119, t = -1.802, p = 0.50). The weak negative coefficient shows indicates that songs that contain more spoken word are played less per day than songs that are completely free of spoken word. The other musical characteristics, *acousticness*, *valence*, *energy*, *danceability* and *liveliness,* are not significant predictors within this model and therefore cannot explain how often songs are played per day on *Spotify*.

4.2.2 Pre-Release Variables as Predictor for *Beatport Points*

In table 15, the regression analyses between the variables before release and *Beatport*-points, as dependent variable after release, are presented. Model 1 shows the number of *RdP*-comments and the number of *RdP*-likes as main predictors for *Beatport*-points. The model is significant (F (2; 117) = 4.645, $p < 0.05$), but does not explain more than 5,8% of the variance of the dependent variable. Just as in the model that explains plays per day on *Spotify,* the number of *RdP*-comments is a significant predictor for *Beatport*-points (b^* = 0.239, t = 1.956, $p < 0.05$), while the number of *RdP*-likes is not (p = 0.716). It underscores that within this community the act of commenting tells something about the interest in a song and the act of liking does not. As mentioned, the motivation of a community member to like a video that contains an unreleased song, is different from the motivation to comment.

In model 2 the number of likes on the *Facebook*-page of the artist is introduced as predictor. The model is significant (F (3; 116) = 9.751, $p < 0.001$). The coefficient of the number of the artist's *Facebook*-page likes is significant and moderately associated with *Beatport*-points (b^* = 0.366, t = 4.309, $p < 0.001$). Compared to the model in which *Spotify* plays per day are predicted this is a weaker association. As a whole, the model explains 18.1% of the variance in *Beatport*-points after release. This is a remarkably lower R^2 than in the model in table 14, in which the same independent variables explain the variance of the dependent variable *Spotify plays per day*. A reason for this can be that *Spotify* is a streaming platform and *Beatport* is a platform in which songs are bought and downloaded. While streaming allows people to just listen to music, downloading on *Beatport* enables the audience to own a song. For DJ's this is necessary if a song needs to be mixed in a set. They need to download the songs to play in their performances and therefore they are more likely to use *Beatport* than the audience that just streams the music. Furthermore, DJ's select a song based on its ability to fit their performance and entertain the audience (Jordanous, 2014). People downloading on *Beatport,* may have different music selection criteria than people streaming on *Spotify* and in this context, it is interesting to explore what the model looks like when it controls for musical characteristics.

Table 15

Regressions with 'Beatport Points' as Dependent Variable

	Model 1	Model 2	Model 3	Model 4
RDP Comments (log)	.239**	.285**	.112	.166
	(0.05)	(0.014)	(0.289)	(0.153)
RDP Likes (log)	.045	-.057	.050	.012
	(0.716)	(0.628)	(0.633)	(0.917)
Artist's FB-page Likes (log)		.366****	.389****	.375****
		(0.000)	(0.000)	(0.000)
DJ FB-page likes (log)				.044
				(0.652)
DJ Top 100 Position				-.015
				(0.883)
Musical Characteristics				
Bpm			-.452****	-.438****
			(0.000)	(0.000)
Acousticness				-.089
				(0.275)
Valence				-.104
				(0.196)
Energy				-.041
				(0.639)
Danceability				.045
				(0.587)
Liveliness				.076
				(0.345)
Speechiness				-.007
				(0.924
Observations	120	120	120	120
R^2	.074	.201	.389	.409
Adjusted R^2	.058	.181	.367	.343
F Statistic	4.645***	9.751****	18.268****	6.179****
	(df = 2; 117)	(df = 3; 116)	(df = 4; 115)	(df = 12; 107)
$\overline{VIF}$	1.883	1.637	1.557	1.547

*Notes: *p<0.1, **p<0.05, ***p<0.01, ****p<0.001*

Model 3 (F (4; 115) = 18.268, p<0.001) controls for *bpm* and by adding this variable to the model, *number of RdP-comments* is not a significant predictor anymore (p = 0.289). This model is able to control 36.7% of the variance in *Beatport-points,* which is much lower than the model in which *Spotify plays per day* are predicted. The number of likes on the *Facebook*-page of the artist, however is still a moderate and significant predictor (b^* = .389, t = 5.212, p < 0.001). Model 4 gives more insight in the influence of popularity of the DJ and the music itself on success after release, by controlling for all *musical characteristics, DJ's Top 100 position* and *DJ's number of Facebook-page likes,* First of all, the model is significant (F (10; 109) = 7.516, p<0.001) and shows that, when controlling for musical characteristics, the number of *RdP*-comments is not a significant predictor for *Beatport*-points (p = 0.153). This is in contrast with the model in which *Spotify* plays per day are predicted and confirms that the interest of the audience streaming music is different from the interest of the audience that buys the music. Also, in this model, the number of *RdP*-likes again is not a significant predictor of *Beatport*-points (p = 0.917). The *artist's number of Facebook-page likes* is a significant predictor for *Beatport-points* and shows a moderate positive relation (b^* = 0.375, t = 4.760, p < 0.001). Regarding musical characteristics, however, the model shines more light on the selection criteria of the audience buying on *Beatport*. First of all, *bpm* is a very significant predictor for *Beatport*-points. (b^* = -0.438, t = -4.411, p < 0.001). Because the coefficient is quite strongly negative it indicates that the higher a *bpm* of a song, the lower the *Beatport*-points after release will be. In short this means that faster songs are less popular to be bought. However, the findings regarding musical characteristics as control variables only say something about the most popular songs within this community. For a good understanding it is necessary to put this in perspective. Based on the descriptive statistics presented in the previous chapter, most songs got a tempo around 125 *bpm,* which shows a certain standard within this type of music. Within this sample, there are no songs present with a *bpm* lower than 118, which makes clear that songs that are slower are also not popular within this online community. In this context, it is necessary to remark that this sample does not show whether songs slower than 118 *bpm* are played on events. For example, in theory it is possible that DJ's play slower songs very often, but the audience does not like it enough to record this type of songs and share it in order to find the identity. Nevertheless, the model makes clear that DJ's play songs with a tempo around 125*bpm* and songs that are faster than that are less popular on *Beatport*.

4.2.3 Pre-Release Variables as Predictor for *Beatport* Peak Position

In table 16, *Beatport peak position* is presented as dependent variable in 3 models. In this table the relation between pre-release independent variables and *Beatport* peak position after release is investigated. In model 1, solely the *number of RdP-comments* and *-likes* are entered as predictive variables. The model is significant (F (2; 117) = 4.479, $p < 0.05$), but explains a very small percentage, 5.5%, of the variance of the dependent variable. Just like in the previous models, the *number of RdP-likes* are not significant to explain the variance in peak positions of the songs after release (p=0.900). However, without taking the other variables into account, the number of *RdP-comments* again is a useful predictor for peak position on *Beatport* (b^* =0.256, t = 2.093, $p < 0.05$). The coefficient shows a moderate positive correlation with the peak position in these charts. This means that the higher the number of comments on an unreleased music video before release, the higher the peak position of this song will be in the charts.

The number of *Facebook*-page likes of the artist are added as predictor in model 2. Although it does not explain more than 17.2% variance in *Beatport* peak position this model is significant (F (3; 116) = 9.243, $p < 0.001$). The model shows that also for the peak position in the *Beatport* charts, the *number of Facebook-page likes* is a significant moderate predictor (b^*= 0.357, t = 4.184, p<0.001). This means that interest in and the audience size of an artist before release is a useful factor in predicting the popularity of a song on *Beatport* after release. Regarding the *RdP-comments* and *-likes*, the findings within this model are similar to the same models in which *Beatport*-points and plays per day on *Spotify* are predicted. *The number of comments* is a moderate and significant predictor for the *Beatport*-peak position (b^*= 0.301, t= 2.619, $p < 0.01$). *The number of RdP-likes* remain, also for predicting *Beatport* peak position in the charts, not significant (p =0.478).

Model 3 shows that, when controlling for *bpm, the number RdP-comments* is, just as for *Beatport-points,* not significant for predicting success on *Beatport peak position* (p = 0.257). The model as a whole is significant (F (4; 115) = 19.277, $p < 0.001$). The number of *Facebook*-page likes, stays a significant predictor. Model 4 is also significant (F (12; 107) = 7.005, $p < 0.001$) and shows that, when adding all musical characteristics, *the DJ's Top 100 position* and *DJ's number of Facebook-page likes* to the model, the number of *RdP*-comments is not a significant predictor for *Beatport* peak position anymore (p= 0.110). This is in accordance to the same model with *Beatport*-points as dependent variable. Also, just like in all the other models *the number of RdP-likes* is not a significant predictor (p = 0.920). When taking the findings of model 4 for predicting *Beatport*-points into account, this confirms that *musical characteristics* are a better pre-release predictor for popularity on *Beatport* than the interest for a song in the *RdP*-community is. Therefore, we can assume that musical characteristics have a more important role for the audience that buys on *Beatport* than for the audience that streams techno music on *Spotify.* In particular, *bpm* is the most decisive factor for popularity. The quite strong negative coefficient (b^*= -0.451, t = -5.153, $p < 0.001$) illustrates that songs around 125 *bpm* – based on the descriptive statistics in the previous chapter – reach higher peak positions in *Beatport* charts than songs with a faster tempo. This is in alignment with the models in which *Beatport*-points and plays per day on *Spotify* are explained. However, this model shows another musical characteristic that was not found to be indicative for popularity in the previous models. *Acousticness* has a negative correlation with peak position in the charts. Although, the correlation is not very significant (b^* = -0.140, t = -1.774, p = 0.079), the negative coefficient indicates that within the electronic genre, songs with acoustic elements are less appreciated by buyers on *Beatport* than songs that are completely electronic. Because this was not found in the model in which plays per day on *Spotify* are predicted, it underscores that the decision to buy a song is based on different motivation that the decision to stream a song. To illustrate this, think about a DJ that likes acoustic music a lot but also loves to perform at techno events. When not performing, he or she can stream acoustic music on *Spotify* and does not have to buy it on *Beatport*. However, while preparing for a techno performance this DJ needs to buy techno music and is likely to visit *Beatport*. The negative coefficient seems to be in line with the conventions and standards of the electronic genre of techno music. It indicates that DJ's rather select completely electronic songs than songs with an acoustic character for a performance.

Table 16

Regressions with 'Beatport Peak Position' as Dependent Variable

	Model 1	**Model 2**	**Model 3**	**Model 4**
RDP Comments (log)	.256**	.301***	.118	.181
	(0.039)	(0.010)	(0.257)	(0.110)
RDP Likes (log)	.015	-.083	.029	-.011
	(0.900)	(0.478)	(0.382)	(0.920)
Artist's FB-page Likes (log)		.357****	.382****	.360****
		(0.000)	(0.000)	(0.000)
DJ FB-page likes (log)				.050
				(0.595)
DJ Top 100 Position				.012
				(0.905)
Musical Characteristics				
Bpm			-.477****	-.435****
			(0.000)	(0.000)
Acousticness				-.140*
				(0.079)
Valence				-.118
				(0.134)
Energy				-.080
				(0.350)
Danceability				.060
				(0.459)
Liveliness				.097
				(0.217)
Speechiness				-.035
				(0.647)
Observations	120	120	120	120
R^2	.071	.193	.401	.440
Adjusted R^2	.055	.172	.381	.377
F Statistic	4.479**	9.243****	19.277****	7.005****
	(df = 2; 117)	(df = 3; 116)	(df = 4; 115)	(df = 12; 107)
$\overline{VIF}$	1.883	1.637	1.557	1.547

*Notes: *p<0.1, **p<0.05, ***p<0.01, ****p<0.001*

5. Conclusion and Discussion

Hence the many are better judges than a single man of music

- Aristotle, Politics III

First of all, this research showed that the number of comments on unreleased music videos in the online community *Raad de Plaat,* is a significant moderate predictor for plays per day on *Spotify.* This means that the attention of the audience for a song before release can partly explain the success of this song on *Spotify* after release. In this context, this confirms Jordanous et al. (2014) who stated that the audience's embodied responses to a song, play a role in the production of value of music. In this context, this research showed that the experience of a songs by the audience before release can be an indicator of the audience's experience and value of songs after release on *Spotify*. This is alignment with Frith (1996) who stated that value of music does not just rely on the music itself but rather on the experience of it. When online communities enable the audience to collectively value songs before release, their practice is similar to the practice of certifiers and gatekeepers as defined by Caves (2000) and this may have implications for the organization and structure of the music industry. In relation to the economics of attention as defined by Lanham (2006) online communities may enable artists to monitor the attention for songs before release and find the right audience for them. In this way they can better align future releases and anticipate on demand. This can be related to Adler (1985) who described a snowballing effect in which initial attention reinforces more attention. However, because *RdP* is mainly a Dutch online community and the market and audience for techno songs is worldwide, it is not likely that initial attention of *RdP* caused a snowballing effect. Rather, the experience of the unreleased song by *RdP* members can predict the experience of the song by the overall audience.

Some important remarks need to be stated regarding the reliability of the valuation of music by the audience before release within this community. The number of likes was not found to be a significant predictor for plays per day on *Spotify* and this indicates that liking and commenting are based on different motivations. Also, when controlling for musical characteristics, and especially *bpm*, the predictive power of the number of *RdP* comments for plays per day on *Spotify* decreased. For success on *Beatport,* the number of comments in *RdP* was only found to be a significant but weak predictor when not controlling for musical characteristics. When musical characteristics were entered to the model the relation between the number of *RdP*-comments and both *Beatport* peak position and points, was effected to such an extent that the number *RdP*-comments was not a significant predictor anymore.

This difference between the predictive power of pre-release attention for success on *Beatport* on the one hand and *Spotify* on the other, shows that platforms enabling to stream and platforms enabling to buy serve different submarkets. *Beatport* is a platform in which music can be bought, and *Spotify* is a service in which the audience can stream music. The difference between predictive power of pre-release attention for success on *Spotify* and for success on *Beatport,* can be explained in two ways. In the first place, for DJ's, streaming songs is not an option because they need to mix songs in a set. As a result, they need to buy the music and are likely to do it at *Beatport*, since it is the biggest market place for electronic music. The selection of songs of *Beatport* users, therefore, may rely on different criteria than of *Spotify* users. *Beatport* users know what to buy and for what occasion, while the audience using *Spotify,* can just explore music. In the second place, the users of *Spotify*, when paying for this service, can freely and limitless stream music while having access to an enormous collection of songs. This variety offered by *Spotify* also have implications for the music its users explore, discover and listen to. It also attracts a part of the audience that prefers this way of listening to music. In short, the difference between the two submarkets for streaming and buying music is reflected by the finding that the number of *RdP* comments is a significant predictor for *Spotify* but not for *Beatport*.

Secondly, the number of likes on the *Facebook*-page of the artist was a significant and strong predictor in all models. This means that the bigger the audience size and popularity of the artist before release, the more successful a song will be on *Spotify* and *Beatport*, after release. Artists with a big audience get more plays per day on *Spotify,* reach higher *Beatport* peak position and get more *Beatport points.* This confirms the snowballing-effect as defined by Adler (1985), in which a concentration of attention among artists is explained by initial attention, which, on its turn, reinforces more attention. It shows a self-perpetuation of attention and also confirms stardom theories of Macdonnald (1988), who argued that that the audience assumes that probability of good quality is lower for new performers than for well-known artists. Therefore, most people tend to choose for well-known artists. In general economic terms, it confirms the bandwagon effect as described by Leibenstein (1950, p. 184) as the "interpersonal aspect of utility and demand". This means that the consumers' demand for a product increases with the number of people that consume the same product.

In this context it is interesting that the administration of demand for artists and their popularity in the current record industry are still mainly based on economic success. Charts and the audience size of an artist are based on digital and physical sales of albums and songs. The number of *Facebook*-page likes of an artist, however, is not based on sales. In this way likes on a *Facebook*-page can be seen as a social currency instead of economic currency of attention for the artist. This can also be linked to symbolic capital as defined by Bourdieu (1996) as the reputation of the artists. He argued that it is the most important form of capital besides economic capital because it can be converted into long term economic profits. This research confirms this theory, because it showed that the number of *Facebook*-likes is a significant predictor for the sales and streams of artist before release and therefore can be linked to economic success. In this context, this indicates that gatekeeping decisions can be made based on the attention for artists, reflected by *Facebook*-page likes, instead of basing them on previous sales of artists. Furthermore, regarding the theory of Amabile (1983) it has possible implications for what actors in the music industry can be seen as an appropriate judge for accepting creative products as part of a cultural domain or not. In relation to Csikzentmihalyi (1996) who argued that any creative product need to have a receptive audience in order to be successful, online communities also have the possibilities regarding the reception of creativity. It is clear that attention of the audience in online communities and especially the number of *Facebook*-page likes, potentially enable that artist to find their audience. Besides that, it also works the other way around, since the purpose of communities like *RdP* is to enable the audience to define what is going on within their culture.

Thirdly, regarding the control variables, this research showed that musical characteristics of a song influence the relation between pre-release indicators – attention for the song in *RdP* and popularity of the artist on *Facebook* – and success on *Beatport* and *Spotify* after release. *Bpm* is found to be the most decisive characteristic to influence the relation between pre-release indicators for success and the success after release. Furthermore, the musical characteristics are more strongly related to sales on *Beatport* than to streams on *Spotify* which confirms that the audience that buys on *Beatport* select music in a different way than the audience that streams on *Spotify.* In this context the findings are not relevant to answer the research question, but the they do indicate that online communities like *RdP* may have implications for artists and DJ to better understand the musical preferences of their audience. It is important to keep in mind that musical characteristics not only show what songs are popular or not. They may also indicate whether there are certain standards, conventions or preferences within a certain community. In this way, the measurement of musical characteristics and their potential implications for differentiation and creation of music can have implications for Adorno's (2002) ideas about standardization in pop music. There are weak but significant relations found between certain characteristics and the number of comments within this group. Within the 120 most popular songs in this community, the average tempo of a techno song is 126 *bpm,* and songs that are faster are less popular in terms of both downloading and streaming. The correlations showed that *valence* of songs is positively associated with number of comments in *RdP*. Within the online community of *RdP* acoustic elements are positively associated with the number of comments by its members, but in a regression analysis it shows a negative coefficient as predictor *Beatport* peak position. Because these findings only apply to the 120 most popular songs before release within this community, they cannot be generalized. Further research, discussed below, may give more insight in how musical characteristics influence the success of songs after release. As mentioned in the literature review, this is a new field of research that receives attention increasingly.

Furthermore, regarding the control variables, the popularity of the DJ's playing unreleased songs – measured by their position in the top 100 and the number of likes on their *Facebook*-page – did not influence the success of the songs after release. There was also no association found between the popularity of the DJ and the attention for a song in *RdP* before release. Regarding stardom theories, this means that the popularity and reputation of the DJ playing does not influence the amount of attention for a song before release or the success of the song after release.

There are a few suggestions for further research. Because the artist's *Facebook*-page likes was such a strong and significant predictor for success after release on *Beatport* and *Spotify,* it can be useful for further research to investigate where the number of likes is based on. Relevant questions can be to what extent the number of performances, the number of cooperations with other artists, and the number of songs released can be associated with the number of *Facebook*-page likes as representation of the audience size. Furthermore, research regarding the way in which musical characteristics can be used by artist to better understand the preferences of their audience can be interesting as well. It can also be interesting to explore the way in which their audience listens to music based on musical characteristics. Another focus of further research could be the extent to which we can speak of standardization in the music industry based on musical characteristics. In this context, it can also provide insights in how DJ's and artist select songs to release, perform or play in relation to musical characteristics.

Regarding the data of this research, an important limitation is that although the unreleased songs in this research are selected by the audience at techno events, there is still a selection by the performing DJ's on these events. In this way there is a pre-selection and the community does not provide information about the popularity of unreleased songs that are not played by DJ's. However, songs selected by DJ's do not necessarily have to be selected by the *RdP* members to record and upload within this community. A second important limitation in this research is that it only focusses on the most popular songs from the 28.000 videos that are uploaded in 2016 and 2017. Therefore, the conclusions only relate to the most popular songs and are not applicable to the complete collection of videos in this group. For example, the most popular unreleased songs are not compared to the least popular. Although the findings therefore cannot be generalized to the population as a whole, it is important to underscore that it still gives a better insight in what makes songs popular.

Popularity of music is always relative because it depends on the audience that values it. From a cultural perspective it means that researching the popularity of music means finding what audiences is receptive for what type of music. From the most basic economic perspective relates to matching supply and demand. Because hit songs are very important in the music industry and are able to set the tone in the complete market, it is a main concern for gatekeepers in the current music industry. In this way popular music is often associated with commercial thinking. However, when thinking about popularity in terms of the right audience finds the right artists, online communities may have an important role culturally as well. They potentially enable interaction between the artist and the audience and self-organization of culture independent of intermediaries. Since the digitization of music and emergence of social media, culture, and music in specific, is increasingly taking place online. This research showed that the data about audience attention and popularity of the artists can provide fruitful insights in where value of techno music is based on. When online communities enable the audience to collectively value artists and songs before release, their practice is similar to the practice of gatekeepers and this may have implications for the organization and structure of the music industry. In general, the fact that this research could take place, based on data that is generated by the audience, shows that online communities make it possible to establish a better understanding of mechanisms and preferences within cultures. Within this research analysing the data even resulted in strong and significant correlations and models that describe the ways in which audience attention and success after release are related. Furthermore, it showed that it can provide insights in the ways in which the audience, artists and intermediaries engage regarding the creation of value. This can be every useful for not only the scientific field of cultural economics, but also for artists, the audience and intermediaries within a cultural domain in general.

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Appendix

Coding Scheme

Variable	Explanation	Coded	Source
Dependent			
Spotify Plays per Day	Number of plays per day on *Spotify* after release	Total plays / (Number of days between release-date and the 9th of May 2018)	Spotify*
Beatport Points	If a track is at position 1, it gets 100 points, if it is in position 100, it gets 1 point per day in the charts	Number of *Beatport* points of the song on 9th of May 2018	*Beatstats***
Beatport Peak Position	Peak position of a song after release in the *Beatport* charts	For songs not in *Beatport* Top 100 a '0' is recorded. Otherwise, 101 - (Position of the DJ in Top 100)	*Beatstats***
Independent			
Number of RdP-Comments	Number of comments on the song in *RdP*	Number of comments on the video presenting the song in *RdP,* before release-date.	*Raad de Plaat******
Number of RdP-Likes	Number of likes on the song in *RdP*	Number of likes on the video presenting the song in *RdP,* before release-date	*Raad de Plaat******
Artist's Number of Facebook-page likes	Number of likes on the *Facebook*-page of the artist on the day before the release of a song	Number of likes on the *Facebook*-page of the artist, defined by the variable *artist*, on day before release.	Sociograph***
Control			
DJ's number of Facebook-Page Likes	Number of likes on the *Facebook*-page of the DJ on the day before the release of a song	Number of likes on the *Facebook*-page of the DJ based on the information on the	*Sociograph****

		description of the video in Raad de Plaat.	
DJ's Top 100 Position	Position of the DJ in the *Resident Advisor Top 100* of December 2016	For DJ's not in top 100 a '0' is recorded. Otherwise, 101 – (Position of the DJ in Top 100) = score between 0 and 100.	*Resident Advisor*****
Bpm	Bpm measures the tempo of a song based on beats per minute	Number of beats per minute measured by *Spotify* (above 0)	*Spotify**
Acousticness	Acousticness is a confidence measure to determine whether the track is acoustic.	Score between 1-100	*Spotify**
Valence	Valence describes the musical positiveness of a song.	Score between 1-100	*Spotify**
Energy	Energy represents a perceptual measure of intensity and activity.	Score between 1-100	*Spotify**
Danceability	Danceability describes how suitable a track is for dancing.	Score between 1-100	*Spotify**
Liveliness	Liveness detects the presence of an audience in the recording	Score between 1-100	*Spotify**
Speechiness	Speechiness detects the presence of spoken words.	Score between 1-100	*Spotify**
For Sampling (not directly used in research)			
Song Artist	Artist of the song. For a remix, artist of the remix.	Artist – Title + (if relevant remixer)	*Raad de Plaat****** (one of the last comments under the video of the song) If not present in comments,

			Shazam was used to define the identity
Song Title	Title of the song		
Song Release Date	The date a song is released on *Spotify.*	yy-mm-dd	*Spotify**
RdP-Popularity	Popularity based on the combined number of comments and likes on a video.	(Number of likes) + (number of comments x 1.747)	*Raad de Plaat******

*http://organizeyourmusic.playlistmachinery.com/, **www.beatstats.com, ***https://sociograph.io/my.html , ****www.residentadvisor.net/features/2857 , *****www.facebook.com/groups/raaddeplaat/