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Master Thesis

Superstars and genre artists: spillover effects in the recorded music industry

Author:
Magnus Arén, 22359
Marcus Sebek, 50149

Supervisor:
Prof. Henrik Glimstedt

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"There are two kinds of artists left: those who endorse Pepsi and those who simply won't."

- Annie Lennox

STOCKHOLM SCHOOL OF ECONOMICS

Abstract

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by Magnus Arén, 22359 and Marcus Sebek, 50149

The superstars of the recorded music industry are not only some of the most well-known and admired people in the world, they are the strategic backbone of the industry. Research has mostly focused its attention on stars in isolation, or as the key component of a risk-minimizing portfolio of artists. Lesser-known genre artists are often viewed in the literature as tools of diversification and customer segmentation, and there is only inconclusive suggestions regarding the way these types of artists interact. In this thesis we set out to expand the view on the interaction in sales patterns between star artists and genre artists. We introduce the term intra-genre spillover to denote the effect that we set out to discover. Intra-genre spillover effects refer to the potential effect that a star artist could have on the sales of other artists in the same genre. Using event study techniques we estimate the intra-genre spillover effect caused by star artists' hit singles on the Billboard Top 40. We run four regressions estimating coefficients for 21 weeks surrounding the event, controlling for artist and time fixed effects. We find a positive, and statistically significant effect on genre artists streaming volumes in the weeks when a star artist from the genre enters the Billboard Top 40. The majority of the effect seems to reverse in the following week, and further conclusions about the length of the effect are uncertain. Further, the effect seems to be evenly distributed among genre artists of different sizes. We conclude that the existence of an intra-genre spillover effect could have implications for both theory and practice. Theory could benefit from expanding its view on the interaction in sales patterns between star artists and lesser-known genre artists. Managers and other stakeholders in the recorded music industry could more actively explore ways to create synergies between star artists and their vast roster of less successful artists.

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Stockholm, May 2015

Magnus Arén and Marcus Sebek

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Chapter 1

Introduction

We all know them. You probably hear them, or hear about them, everyday: Beyoncé, Justin Bieber, Kanye West, Miley Cyrus, and many more. These superstars are not only world class entertainers, they are also the backbone of the recorded music industry. In 1999, for example, 0.03 percent of releases represented a quarter of all music sales in the US (Alderman, 2008). The literature defines stars as the relatively small number of artists that dominate their field, and earn enormous amounts of money from it (Rosen, 1981). However, while star artists receive most of the attention of consumers, and most of the money, they only represent the tip of the iceberg of the music available; for each success there is a whole host of less successful artists. In the recorded music industry, and cultural industries in general, stars are the a key focus because they are seen as the main source of income. Stars are viewed as re-bounds for all those unprofitable, or less profitable artists (Bakker, 2012).

Cultural industries are often defined though the characteristics that distinguishes them from other industries. Consumption of music, and other cultural products, is highly volatile and unpredictable, and engaging in these businesses is very risky (Hesmondhalgh, 2013). The costs of production are very high, while costs of reproduction are extremely low. The amount of people willing to become artists also means that there is a constant oversupply of labor in cultural industries (Hirsch, 1972). These characteristics combine to shape many of the features of production, organization, and strategies commonly used in these industries. Building stars and defining genres are two of the strategies used to overcome the inherent uncertainty faced by labels in the recorded music industry (Hesmondhalgh, 2013, Ryan, 1992, e.g.). Stars and genres act as brands serving to stabilize sales patterns, and record labels collect a number of artists both in order to uncover the next star, but also to spread the risks of production. Theory suggests that stars allow record labels to economize on the learning costs of consumers, and that genres are used to associate products with particular uses and pleasures (Adler, 1985, Hesmondhalgh, 2013). Consumers act on the information of other consumers in order to minimize the search costs involved in finding new artists and songs (Adler, 1985).

In the last decade the recorded music industry has faced some radical technological changes in the movement from a physical to a digital marketplace (Gourvish and Tennent, 2010). Although older technologies are still available, all geographical markets are collectively moving towards the digital format in general, and on-demand streaming in particular (IFPI, 2013). This format gives users unlimited access to millions of songs in exchange for a subscription fee, or even for free (IFPI, 2013). The digital movement is not limited solely to the music industry. In fact, most segments of popular culture are becoming digitalized; books are increasingly sold as e-books, and movies are being consumed on streaming services such as Netflix. This service format, unlike purchasing physical products allows the customer to listen to anything they want without any additional charge; customers are given the freedom to explore the works of any artist without having to pay more. In terms of consumer learning, streaming has essentially driven the search costs involved in finding new music to zero. In the digital context, consumers should be more prone to explore and discover new artists. There might be cause for expanding the view traditionally held in the literature on the role of genre artists, and the interaction in the sales patterns between star artists and their less successful counterparts. The view of stars acting to absorb the losses incurred from other unprofitable artists, and genres as simply a means to diversify a product portfolio might be limited. The literature offers no real insight into the relationship in sales between star artists and the genre to which they belong. The possibility of exploring and discovering new artists for free could cause a spillover effect emanating from the success of star artist.

The purpose of this thesis is to explore this potential effect, which we chose to call an *intra-genre spillover effect*. Specifically, we investigate how star artists hit singles affects the streaming volumes of genre artists. We pose the question, *how do a potential intra-genre spillover effect from star artist hit singles impact the sales of other artists in the same genre?*

We examine a panel dataset of 504 artists across seven genres between the years 2010 and 2014. Using event study methodology we construct a quasi-experiment with the aim of uncovering any potential spillover effect caused by a star artist hit single. The event acts as the treatment, and all artists sharing the same genre as the star artist are considered the treatment group. The rest of the sample, all other genres, acts as the control group. We examine the impact of a star artist hit single on genre artists four weeks prior to the event, and sixteen weeks after. We find that the treated artists achieve significantly higher streaming volumes than the rest of the sample in the week when an artist from the genre enters the Billboard Top 40. However, the results do not allow us to draw conclusions on the length of this effect.

To further isolate the effect we examine the weekly growth in streaming volumes, in order to better determine if there is an actual boost for artists in the genre caused by the event. We find that there is a marked boost in growth, on average, in the week when an artist from the genre achieves a Billboard Top 40 single. Again, the length of this effect is hard to discern from our results. Most of the effect is reversed already in the first week after the event, suggesting that the effect is short-lived. In a final test we examine whether the size of the genre artists, measured as the deciles of yearly streams, causes an added effect to the growth in the week of the event. We find no evidence of an added effect caused by size.

Overall, we argue that we have identified and isolated an intra-genre spillover effect that seems to be caused by a star artist of the genre entering the Billboard Top 40. However, varying results causes us to be careful in drawing conclusions about the workings and dynamics of this effect. Since we cannot find a sustained period of time where the effect is significantly different from zero, we refrain from drawing too strong conclusions about the size and length effect. We conclude that the evidence can only support a very brief effect, almost completely reversed in the week following the event. Nonetheless, we argue that the findings suggest an intra-genre spillover effect exists, and that such an effect could have implications for both theory and practice. We bring insight into the interaction of sales patterns between star artists and genre artists, and also bring the study of stars and genres in the music industry into the context of streaming.

The remainder of the thesis is organized as follows: Chapter 2 presents a review of previous literature to introduce the concepts of the topic, and to develop a framework for the thesis. The first section of Chapter 2 introduces the field of cultural industries, and defines its borders and different research focuses. In the following section we review the literature on superstar economics. We introduce attempts at modeling the phenomenon of stars, and also present some empirical findings from cultural industries. Chapter 2 concludes by introducing strategic perspectives on stars and genres, and developing the framework of this study. In Chapter 3 we describe the data used to conduct this study. First by presenting the sources of the data, and in subsequent sections a description of the different types of data, and the collection process. Chapter 4 begins with a description of the research strategy and study design. We then develop the empirical model that is the backbone of this study. Chapter 4 concludes with a discussion on potential issues concerning the reliability and validity of the thesis, and a discussion regarding ethical considerations with respect to the methodology. In the subsequent chapter, the empirical findings are presented. First we present descriptive statistics of the sample, followed by estimation results. Chapter 5 ends with a discussion on the theoretical and practical implications of the findings. Finally, Chapter 6 concludes this thesis.

Chapter 2

Review of Literature

This section provides a review of previous literature on the subjects of cultural industries and the economics of superstars. These two fields of literature, through a strategic point of view, provide the theoretical framework from which we develop the research question posed in this paper. The section concludes with a development of the research question based the limited evidence on the interaction in sales between stars and genres.

2.1 The Cultural Industries

Any research in the field of cultural industries face the initial problem of defining its characteristics and borders. Problems of definition stem both from the inherent difficulty in defining *industry*, and the ambiguity inherent in the word *culture* and what actually constitute cultural goods (Throsby, 2001).

Williams (1981) suggests culture is a "'whole way of life' of a distinct people or social group" (p. 11). Similarly, Eliot (2010) suggests that "[culture] includes all the characteristic activities and interests of people" (p.14). With such broad definitions of culture, Hesmondhalgh (2013) notes, "it is possible to argue that all industries are cultural industries" (p. 16), and consequently that any good is a cultural good. These terms are usually used in a much narrower sense when used to refer to cultural goods and industries (Hesmondhalgh, 2013).

Hirsch (1972) defines cultural goods as "nonmaterial goods directed at a public of consumers, for whom they generally serve an esthetic or expressive, rather than a clearly utilitarian purpose" (p. 641). Hesmondhalgh (2013) builds on this definition, suggesting that defining texts[1] is a matter of "balance between its functional and communicative aspects" where texts are "heavy on signification and tend to be light on functionality and [are] created with communicative goals in mind" (p. 16). Throsby (2001) offers a more straightforward definition: "cultural goods and services involve creativity in their production, embody some degree of intellectual property and convey symbolic meaning" (p. 112).

Peltoniemi (2015) offers a good summary of the properties often associated with cultural goods, and of the industries that produce them in her definition: "[c]ultural industries are those that produce experience goods with considerable creative elements and aim these at the consumer market via mass distribution. The creative elements consist of stories and styles, and they serve the purposes of entertainment, identity-building and social display. Mass distribution refers to storage and delivery where economies of scale play an important role" (p. 1).

Given these definitions, the industries that are usually considered to be part of the field of cultural industries are film, music, book and magazine publishing, theatre and opera, TV and radio, and the fine arts (Peltoniemi, 2015). Depending of the definition of cultural industries, the boundaries of cultural industries can be quite wide. There are authors that include other industries, such as video gaming, photography, architecture, and even tourism in cultural industries (see DeFillippi et al., 2007, Hesmondhalgh, 2013, Towse, 2011, e.g.). The recorded music industry is by all accounts part of the cultural industries, and the literature on cultural industries offers a good lens through which the phenomenon of stars and genres can be viewed.

Cultural industries are distinguished from other forms of capitalist production in several ways. Engaging in business in cultural industries is very risky, even more so than other industries (Hesmondhalgh, 2013). Consumption of cultural goods is highly volatile and unpredictable. Garnham and Inglis (1990) suggest this is because cultural goods are often used by consumers to express the view that they are different from other people. As a result, fashionable artists and styles can suddenly become outdated, and other cultural goods can become unexpectedly successful (Hesmondhalgh, 2013). Simply put, there is extreme uncertainty regarding the success of specific products (Peltoniemi, 2015). Hesmondhalgh (2013) lists several telling statistics from the literature highlighting this uncertainty. For example, about 80% of the 50 000 books published per year in the U.S. in the 1980s were financial failures (Moran, 1997), and in the mid-1990s only around 10 films of the 350 or so films released each year in the USA were box office hits (Bettig, 1996). A telling example from the recorded music industry is provided by Wolf (2010)

[1]The term used by Hesmondhalgh (2013) as "a collective name for all the 'works' produced by cultural industries" (p. 3).

who found that from the nearly 30 000 albums released in the USA in 1998, less than 2% sold more than 50 000 copies.

Another distinguishing feature of the cultural industries are the high costs of production relative to the low costs of reproduction. This feature is clearly not exclusive to the cultural industries, but it is the extreme ratio of these costs that distinguishes these industries (Hesmondhalgh, 2013). Producing a cultural good, a studio album or a feature film for example, is a lengthy process and carries very large upfront costs, but once the product is finished the cost of each new copy is negligible. In the case of the music industry, the digitization of music sales has essentially pushed the cost of reproduction to zero in recent years, and once a track is distributed to digital music services, it is instantly available to all potential consumers. This extreme ratio of costs means that big hits are extremely profitable, and can compensate for the large number of failures that result from the uncertain demand (Hesmondhalgh, 2013).

Further, there is a constant oversupply of labor in these industries. There are many more aspiring artists than the market can support, and cultural industries employ gatekeeping functions to restrict access to these industries (Hirsch, 1972). The record labels themselves are gatekeepers, and they employ several gatekeeping functions within their organizations, most notably the Artists & Repertoire function. Combined with the low cost of reproduction, the oversupply of labor allows corporations of culture to overflow the market looking for the next success. These features combine to form a system of cultural production, and to shape the strategies corporations of culture employ to manage and organize the production of cultural goods (Hesmondhalgh, 2013, Peltoniemi, 2015).

Research in the field of cultural industries can either focus on the industry level, the organizational level, or the product level (Peltoniemi, 2015). At the product level the objective of research in the field is to explain why certain products reach the consumer market, and others do not, and also to explain the differential sales of those that do reach the market (Peltoniemi, 2015). The former objective focuses on the selection process in which an artist's product is selected for release to the public. The focus of this paper, however, is investigating the latter; a key feature of the differential sales in cultural industries, certainly in the recorded music industry, is the phenomenon of the superstar, the focus of the next subsection.

2.2 Economics of Superstars

Stardom refers to the phenomenon where a relatively small number of people dominate the field in which they are engaged, and earn enormous amounts of money from it

(Rosen, 1981). Marshall (1920) who was the first to describe the phenomenon argued that stars could be observed in a range of fields and industries, but not in the music field due to the lack of reproduction capabilities.

In his seminal work, Rosen (1981) builds on the ideas of Marshall (1920), wherein small differences in talent translate into large differences in the level of success, adding that technological advances in the field of music had now enabled its reproductive capabilities and hence qualified it as a superstar economy. This has led to the music industry becoming a testing ground for the predicted superstar phenomenon (Crain and Tollison, 2002). Consequently, several theoretical models on the phenomenon followed in the years and decades since Rosen (1981) suggested the recorded music industry is a star economy.

Borghans and Groot (1998) build on the Marshall-Rosen form of stardom, in which high incomes are the result of talent alone. They find that two conditions must be met for an artist to achieve superstar incomes. First, an artist who is known to be the best is strongly preferred by consumers over other artists. This gives the artist certain monopolistic power. To exploit this power talent is necessary, since the chance of reaching the number one spot, and exerting monopolistic power will attract many aspiring stars. If talent were not a factor, everybody would have an equal chance of becoming number one, and the investments required to improve their chances would outweigh the benefits of potential superstardom.

Adler (1985) suggests that the skewness of remunerations does not have to be the product of talent or quality, suggesting that familiarity with an artist increases the satisfaction of the consumer. Before a consumer purchases an artist's product they need to become aware of the artist. Consumers do this by discussing the music with other consumers, and by listening to the music in record stores or on the radio. Adler (1985) views these activities as search costs, and by choosing the works of popular artists these search costs can be minimized. In the view of Adler (1985) "[s]tardom is a market device to economize on learning costs in activities where 'the more you know the more you enjoy'" (pp. 208-209). Popularity, then, is self-reinforcing and this reinforcement produces stars.

MacDonald (1988) focuses rather on how stars emerge in the first place. In his view, numerous young performers enter the market and earn income well below their alternative. Success is rare, but on the other hand highly rewarded. Success is dependent on the probability that an artist performance will be good. Since entrants are numerous, and poor performers exit the market, known artists are more likely to deliver good performances. Artists whose performances are good over time will be able to attract higher prices and reach larger audiences. This is not dissimilar to the concept of learning costs from Adler (1985), in that known artists accumulates an advantage as they grow ever more popular.

In addition to model proposals, there are plenty of empirical papers, some attempting to validate theoretical models of superstardom, others investigating superstar effects in a range of cultural industries. Hamlen (1991) offers early empirical tests of the Marshall-Rosen form of superstardom. Using measures of voice quality to proxy for talent he test the model, but does not find enough evidence to support the Marshall-Rosen superstar model. While he finds some support for the notion that greater talents reap greater rewards, the relationship is not proportional. Chung and Cox (1994) models music sales using a Yule distribution (Yule, 1924) and find evidence that initial success better determine success than differences in talent, lending some support to the model suggested by Adler (1985). However, Giles (2006) finds that the model suggested by Chung and Cox (1994) does not provide a good description of the superstar phenomenon.

Pitt (2010) finds strong evidence of superstar effects in his study of performance rights payments in the music industry. In his study he found that a very small number of artists with blockbuster hits earned a large share of the total royalties paid out. Connolly and Krueger (2006) find the same phenomenon in the distribution of concert revenue among artists. Strobl and Tucker (2000) find that success on the music charts in the UK between the years 1980 and 1993 is substantially skewed to the right, indicating a top-heavy distribution of sales. Another telling example of the star phenomenon, and a very top-heavy sales distribution is provided by Alderman (2008) who notes that in 1999 in the US 0.03 percent of releases accounted for a quarter of total record sales.

Evidence from other industries suggests the phenomenon is commonplace in most cultural industries. Star authors and artists in fine arts, blockbuster films, and television all show superstar effects. Peltier and Moreau (2012) examines sales of comic books in France and finds that the bestsellers receive smaller market shares online, than offline. They also find that the sales are shifting from the top of the distribution towards the tail both for offline and online sales of comic books. Walls (2013) finds that a small proportion of blockbuster movies earn a disproportionate amount of box-office revenue in the motion pictures industry, while Elberse and Oberholzer-Gee (2006) finds the same effect for video sales. They also find evidence that "an ever-smaller number of titles accounts for the bulk of sales" (p. 18), suggesting that the effect is becoming more pronounced, contrary to the findings by Peltier and Moreau (2012) from the comic books market.

There is ample empirical evidence for the existence of the star phenomenon in cultural industries, in which sales are heavily skewed towards a select few individuals. The literature also provides several suggestions as to what might cause this skewness: artist ability, consumer learning, luck or any of the other explanations attempted. Each of these variables likely provides part of the explanation to why some performers are dominating the fields they are in. However, we find the literature does not provide sufficient insight into the interaction between star artists, whether they are recording artists or other cultural performers, and the vast majority of less successful artists. In the literature on the economics of superstar, the star performer is viewed in isolation, and the focus is rather on how stars interact with the market as a whole, examining sales distributions and varying demand.

2.3 Stars and Genres as Strategy

Ryan (1992) suggests another view, in which stars and genres (*styles* using the terminology of Ryan (1992)) are viewed as strategies that companies of culture employ to overcome the inherent difficulties of cultural industries. The processes of making stars and styles are similar to what other industries might refer to as product differentiation and customer segmentation (Ryan, 1992). These strategies are used to compensate for the unpredictability of demand and risks involved in cultural industries by spreading the high fixed costs involved in production, and reaping the rewards from the low reproduction costs (Hesmondhalgh, 2013). Ryan (1992) notes, “stars and styles come to function in the market like ’brands’, serving to order demand and stabilise sales patterns, allowing the corporations of culture to engage in a degree of planning” (p. 186).

Negus (1998) extends the argument by suggesting that stars and genres are key components in the portfolio management strategies of corporations of culture. He suggests that the star-system is part of a larger portfolio-management strategy used by multinational cultural corporations to distribute risk. From these product portfolios stars arise and functions as re-bounds for the other unprofitable product investments (Bakker, 2012). These views combine to portray record labels, and other cultural corporations, as custodians of a collection of brands with the purpose of offsetting losses, and stabilizing sales patterns (Ryan, 1992) . The strategic view offers a perspective in which stars and genres are not viewed in isolation. Ryan (1992) argues that there is a systematic relationship between stars and genres, wherein stars can transform into styles. Successful artists influence other contemporary artists, and through imitation the personal style of the star can develop into a public style, or a genre (Ryan, 1992). Examples of this transformation given by Ryan (1992) are how country rock grew out of the success of artists like Bob Dylan, and The Band, and soft rock grew out of successful artists such as Simon & Garfunkel, the Mamas and the Papas, and Buffalo Springfield. This view of the interaction between stars and genres, however, does not provide any insight into the interaction in terms of sales patterns. The portfolio management view, likewise, offers no real insight into differential sales other than that genre artists are simply a way to spread the losses incurred in search of the next superstar, or as a tool of portfolio diversification and customer segmentation. The strategic view certainly carries some weight, and the view that record labels manages a portfolio of artists in order to maximizes profits in an uncertain environment is certainly true to a large extent. Minimizing risk is crucial in cultural industries, and adopting a portfolio management view provides an explanation to how corporations of culture can efficiently satisfy an unpredictable demand.

However, we find the knowledge on the extent and dynamics of the interaction between stars and genre artists is incomplete. The field of superstar economics provides good explanations, and empirical validation, of the superstar phenomenon in a range of industries, but the phenomenon is studied in isolation. The strategic view, which incorporates both stars and genres and views them as brands that compose a risk minimizing portfolio, offers no insight into any potential interaction other than the risk minimization and diversification effect of genre artists.

There is some literature that has touched upon the interaction between stars and genre artists. Sorensen (2007), in examining the impact of bestseller lists on the sales of hardcover books, finds some suggestions that a bestseller appearing on such lists actually might spill over to the genre the bestseller is labeled as. He concludes that his results "offer indirect evidence that for hardcover fiction, bestsellers and non-bestsellers within the same genre may in fact be complements: weeks in which books of a particular genre first appear on the bestseller list tend to be strong-selling weeks for non-bestsellers of the same genre. Although too indirect to be conclusive, this result suggests that market expansion effects dominate any business stealing associated with bestseller lists, so that bestseller lists may in fact increase the number of books published in equilibrium" (Sorensen, 2007, p. 738).

Garthwaite (2014) examines demand spillovers from celebrity endorsements in the publishing industry. He examines the effect that being endorsed by Oprah Winfrey's book club has on the sales of the book itself, but also investigates the effect it has on other titles by the endorsed author. Unsurprisingly, he finds a clear effect on the endorsed title, but he also finds a spillover effect onto the author's unendorsed titles. These results are in line with the findings of Hendricks and Sorensen (2009) who find a spillover effect from an artist's album release onto the artist's catalogue. When examining the market expansion effect hinted at by Sorensen (2007), however, Garthwaite (2014) finds that celebrity endorsement causes more business stealing than market expansion effects; suggesting large aggregated sales declines in genres disproportionally favored by consumers likely to respond to club endorsement.

2.4 The Research Question

We set out to answer whether the information provided to consumers by a star artist's hit single result in intra-genre spillover effects onto other related artists. Specifically, we ask: *how do a potential intra-genre spillover effect from star artist hit singles impact the sales of other artists in the same genre?*

Hendricks and Sorensen (2009) and Garthwaite (2014) both find evidence for spillovers onto the artist's, or author's previous unendorsed titles, suggesting an information effect influences consumers' buying behavior. Sorensen (2007) finds hints of a potential spillover effect onto the genre in the book publishing industry, but finds the results to be inconclusive. Further, if as Adler (1985) suggests, success in the recorded music industry is a function of learning, this could extend beyond the star artists themselves. The advent of music streaming services has essentially driven the search costs down to zero, potentially making discovery easier.

We hope to bridge a gap in the literature on the differential sales within the music industry by providing an insight into any potential intra-genre spillover effect, and the dynamics in sales patterns between superstar artists and their less successful colleagues.

Chapter 3

Data

3.1 Panel Data

The dataset consists of an unbalanced panel of 504 artists from 7 genres across a weekly time series between quarter three of 2010 and the end of 2014. Quarter three of 2010 was the earliest date for which streaming data was available. Each artist is coupled with streaming data, leaving the dataset with approximately 600 000 streaming days in total. The days were summed to weekly streams to overcome weekly streaming patterns. The panel is unbalanced because of the varying length of the data available for each artist. Some artists are present throughout the sample, having released music since the beginning of the sample period, while other artists are present for shorter periods. We have cleared the dataset from all artists with less than six months of data available.

3.1.1 Data Sources

In our analysis we look at data from Spotify, one of the leading services for digital on-demand streaming of music. Today, the service provides streamed music to over 50 million active users, accounting for approximately 37% of all on-demand streams of music worldwide (IFPI, 2015). The streams that occur on the platform are monitored and stored as numerical data and further used to provide a better service for both end-customers and various business partners such as artists and record labels. In our analysis we look at some of this data in order answer our research question.

Using streaming data from Spotify was the predominant choice because of their global presence, and their dominance of the on-demand streaming market. The size and popularity of Spotify adds legitimacy to our final results given that the service is one of those that best embodies this contemporary way of consuming music. It is important to mention that the format of on-demand streaming is not the dominant way of consuming music today. Geographical areas differ tremendously in the way music is consumed. In Germany, physical distribution and sales of CDs has a major presence still. Scandinavia by contrast, has adopted on-demand streaming much faster and is today pioneers of this type of music consumption. The overall pattern in every one of these countries indicates strong growth of on-demand streaming (IFPI, 2010, 2014). Customers are rapidly adopting on-demand services as their predominant choice of consuming music. Another reason to why we look at data from Spotify is the way the user interface is structured. Spotify is provides recommendations by linking similar artists to every artist page. This function works as a catalyst to the behavior that we are researching.

In order to carry out our analysis, data for two 'types' of artists were collected. The first type of artists are the star artists. These are the artists that have had a single entering the Billboard Top 40. The second type of artist is referred to as genre artists. These are artists that did not achieve a single on the Billboard Top 40 list in the sample period. For the genre artists we collect global daily streaming data. This numerical value accounts for all the streams that have occurred on the platform for a given artist a particular day. In total we look at daily streaming data for 504 genre artists for all days between the third quarter in 2010 and the end of 2014. This time interval was set by the fact that data was unavailable further back in time. In total, the accumulated streaming days for these artists accounts for approximately 600 000 unique observations. For star-artist we simply look at the date where their single entered the Billboard Top 40. The entry date marks the event date in our study. All Spotify data used for the paper is solely granted to rights holders that distribute music through the service. Because of the sensitivity of the data to the rights holders we have agreed upon not disclosing any information that could tie the companies to the further presented research.

3.1.2 Description of Genres

An important characteristic of our analysis is that we assess the effects of star artists and other artists within certain genres. Star artists within hip hop will only generate events that affect other artists within the genre hip hop. It was important to identify genres that did not overlap in terms its artists. The potential overlapping of artists belonging to two or more genres was something that we to took into account when choosing what genres to include in our analysis. Another important aspect of selecting the genres was the need for star artists. Every genre would need at least one star artist in order to provide event windows to analyze. Any genre that did not have any hit single within our time period was removed. The genre also needed a rigid statistical sample of other artists, which was determined by the accessibility we had through our partner companies.

The selected genres that we use for our analysis were: (1) Boyband, (2) Hip Hop, (3) Indie Folk, (4) Indie Rock, (5) Progressive House, (6) R&B and (7) Teen Pop. These fairly popular genres have at least one artist reaching the Billboard Top 40 within the time period we are testing.

The first genre that was added to our data set was (1) Boyband. This genre is characterized by a group of male vocalists often coupled with highly choreographed dance movements. Members within this type of group seldom play any instruments. Typical boybands are Backstreet Boys and N'Sync. The second genre is (2) Hip Hop, a distinct movement in music in the early 1970s. Characteristics of this genre include incorporating new musical techniques such as turntables, beat-boxing, and scratching. Typical Hip hop artists are Kendrick Lamar and Drake. Genre (3) Indie Folk, originates from the 1980s and early 1990s and is a movement that developed from Indie Rock. Characteristics of this genre include touches of acoustic folk and country. Within this genre you find bands such as Bon Iver and Fleet Foxes. The fourth genre that was added was (4) Indie Rock. This style of music has its roots in the UK and grew in popularity in the 1980s. The word "indie" originally referred to independent — not being associated to a major label. Another genre that was used was (5) Progressive House. This genre is a further development of trance and emerged from the UK in the early 1990s. The sound image is characterized by melodic synthesizers that progress throughout the song. Another genre that we used was (6) R&B, often referred to as rhythm and blues. Traditionally a genre used by record labels to create a distinction to popular Afro-American music. Contemporary R&B mixes elements of rap and soul. The last genre that we included in our sample was Teen Pop (7). This genre is characterized by its lyrics that aim at fulfilling an emotional craving among teenagers. The genre borrows its sound image from other popular genres such as pop and hip hop. Within Teen pop you find artists such as Katy Perry and Justin Bieber.

Table 3.1 is a compilation of the number of unique artists we looked at for each genre. The table also provides a split between star artists and other remaining artists per genre. In the upcoming section we present an overview and further description of these artists.

NUMBER OF ARTISTS BY GENRE AND YEAR						
Year	2010	2011	2012	2013	2014	Total
Genre artists in the sample						
Boyband	35	38	43	45	45	**45**
Hiphop	39	44	67	70	70	**79**
Indie folk	24	43	61	68	71	**76**
Indie rock	56	64	66	72	74	**78**
Progressive house	29	56	81	94	94	**95**
R&B	49	53	63	73	74	**74**
Teen pop	26	35	49	56	57	**57**
Total	**258**	**333**	**430**	**478**	**485**	**504**
Star artists not in sample						
Boyband	2	3	4	4	4	**4**
Hiphop	5	9	20	20	18	**21**
Indie folk	1	2	2	2	2	**2**
Indie rock	N/A	N/A	2	2	2	**2**
Progressive house	4	4	4	4	4	**4**
R&B	9	12	18	18	18	**18**
Teen pop	11	17	22	23	23	**23**
Total	**32**	**47**	**72**	**73**	**71**	**74**

Table 3.1: Number of artists by genre and year

3.1.3 Description of Artist Data

Within this chapter we have so far described the two types of artists that we use for our analysis. We have also described the seven genres we look at when comparing these artists. In this section we provide some additional information regarding the complete artist dataset that we use. By looking at the country of origin we find that artists within our sample come from countries all over the world. Apart from the dominant presence of the United States, the difference between these countries is for the most part quite small. Table 3.2, shows the distribution between our 74 star artists. This table is not limited to any right holder agreements as we are able to include any artists that had entered the Billboard Top 40, and account for all defined events. Table 3.3 shows

Country of Origin: Star artists	
Country	Per cent
United States	64,6
United Kingdom	16,2
Canada	3,8
Barbados	2,4
Sweden	2,3
Germany	1,9
Ireland	1,9
Australia	1,6
Iceland	0,5
Netherlands	0,5

Table 3.2: Country of origin: Star artists

Country of Origin: Genre artists			
Country	Per cent	Country	Per cent
United States	64,6	Estonia	0,2
United Kingdom	16,2	Finland	0,2
Netherlands	3,8	France	0,2
Canada	2,4	Haiti	0,2
Sweden	2,3	Iceland	0,2
Australia	1,9	Iran	0,2
Germany	1,9	Israel	0,2
Ireland	1,6	Mexico	0,2
Italy	0,5	Norway	0,2
Switzerland	0,5	Philippines	0,2
Barbados	0,4	Puerto Rico	0,2
Brazil	0,4	Russia	0,2
Denmark	0,4	Spain	0,2
Japan	0,4	Taiwan	0,2
Belgium	0,2	Turkey	0,2

TABLE 3.3: Country of origin: Genre artists

the distribution between the remaining 556 artists. This table takes into account those artists that where provided to us by our partner companies.

3.2 Data Collection Process

The data collection period consists of multiple phases, which are all coupled with some limitations or other implications. Within this section we try to provide a rigid overview over all implications and phases we went through in order to collect the data that we used for the final analysis.

We want to start this section by introducing The Echo Nest, a company that Spotify acquired in March 2014 (Echonest, 2014). This company is a support function for Spotify and deals with back-end analysis and storage of large quantities of Spotify data. The Echo Nest supports the Spotify user interface by structuring artists in different genres and further organizing these artists by various metrics. We relied on metrics from The Echo Nest API[1] to guide our data collection process.

Before collecting artist data from Spotify, we spent a long time figuring out what artists to actually use. By modulating callbacks from the Echo Nest API we were able to retrieve 300 artists per chosen genre, in descending order, based on the artists familiarity score. The familiarity score is an algorithm that calculates a score ranging from 0 to 1 for every

[1]The Echonest API (Application Programming Interface) is open, and available to the public upon registration.

artist available on Spotify. More specifically, the score accounts for the total volume of streams per artist, coupled with the volume of recent streams. This mixture balances and captures two important elements; the established artist familiarity of all time and the peeking familiarity of contemporary artists.

We started of the collection process by collecting 300 artists for 10 genres. The lists of artists were in a second stage matched with the availability of artists provided by our partner companies. We wanted to make sure we had enough artists for running a statistically viable analysis. When we found a genre that matched well with our data availability we went on to a third stage. In this stage we took this same sample of genre artists and cross-referenced it with the all Billboard Top 40 singles between 2010 and 2014. We wanted to make sure that the genre had at least one artist that had been on this top list. If this was not the case we removed the entire genre, as it would not provide any instances to estimate the desired cause and effect used in our analysis. A forth consideration was the overlapping of artists across multiple genres. In order to provide viable results that could tell us something about the effect within a genre, no major overlapping could be allowed in the data set. All genres where cross-referenced between each other in order to test the occurrence of overlapping artists. Although very few, some artists did indeed overlap between multiple genres. All overlapping artists were removed from the sample. All genres which passed this four stage process were added to our data set. The sample was the cleared from artists with streaming data available for less than six months. In the end we had collected usable data for a total of 578 unique stars and genre artists across 7 different genres.

Chapter 4

Methodology

The following section will introduce the methodology and methods used to conduct the empirical study. We describe the research strategy guiding this paper, the study design and methods used to answer the research question set out in Chapter 2. We also discuss potential limitations of the methods by considering issues of reliability and validity related to the data collection process, and the empirical modeling. The chapter concludes with a discussion on ethical considerations with regards to developing the methodology.

4.1 Study Design

In developing the design of this thesis we have followed the research design typology laid out in The Palgrave Handbook of Research Design in Business and Management (Strang, 2015). The typology is presented - in true management fashion - as a four-layer process-oriented model: beginning with the research ideology, followed by the research strategy, the methods, and finally the techniques used to answer the research question.

Strang (2015) presents research ideologies on a continuum ranging from the positivist-, to the constructivist stance, where positivist refers to a purely evidence driven ideology, and constructivist in which the construction of reality is the participant's. The term ideology is equivalent to other terms, such as the term *worldview* from Creswell (2002), *design strategy* from Patton (1990), or the term *paradigm* from Lincoln et al. (2011), among many others (Strang, 2015). Pure positivism is rare, and fact-driven research more often adopt a post-positivist stance, in which the difficulties in uncovering factual truths is recognized. It is about admitting that the analysis is limited to what can be identified and controlled, instead of attempting to quantify uncertainties and unknowns

(Strang, 2015). Although labeling oneself as subscribing to one ideology or the other seem to serve little purpose in and of itself, and the continuous nature of these ideologies suggest most papers would fall somewhere in between, we find post-positivism to closest approximate our own ideologies.

The research strategy is the formulation of the goals, research questions, or hypotheses of the study. Strang (2015) suggests these should be determined through defining the unit of analysis, the level of analysis, and generalization goals. Once these factors are decided upon, the research question or hypotheses can be formulated.

The unit of analysis refers to the "factor, variable, process, relationship, tacit phenomena, or plural combination thereof, which is the focus of the study" (Strang, 2015, p. 34). An important decision when deciding the unit of analysis is whether the focus should be examining differences within or between-groups. In our study, a between-group unit of analysis was necessary since this type of unit of analysis refers to "comparing independent individuals or groups in the sample" (Strang, 2015, p. 36). The unit of analysis in this paper is the relationship between star artists and genre artists. More specifically, the unit of analysis is the potential intra-genre spillover effect emanating from star artists.

The level of analysis is the level where the analysis of the data is performed. There is of course a close relationship between the unit- and the level of analysis, since the level of analysis defines where the unit of analysis originates. It also defines the intended level of generalization of the findings, given that they are reliable and significant (Strang, 2015). As such, it is very much intertwined with both the generalization goal, and the unit of analysis. A generalization goal consists of two parts: a deductive or inductive goal, and the generalization target population (Strang, 2015). Our research goal is deductive, rather than inductive. Although we set out to potentially introduce a new concept to the study of stars and cultural economics, that of a potential intra-genre spillover effect, our idea is to make use of a priori theories and concepts such as spillover effects and stars, and extend the concept. The goal is to take theoretical arguments from the fields of superstar economics and cultural industries to introduce an extension of the strategic view on stars and genres.

The intended target population, and consequently the level of analysis for this study is the recorded music industry, in particular popular music. The extensive dataset, the broad range of artist sizes, and the global streaming volumes was gathered in order to not only examine the existence of intra-genre spillover effect for a single genre, or for a select group of artists, but with the aim of uncovering a potential effect for the market for popular music as a whole.

Methods of research tend to be in line with ideology and strategy, and particularly the unit of analysis (Strang, 2015). Recall that we intend to study the unit of analysis with a between-group focus. In positivist leaning research, between-group studies are usually done through experimental methods, either through true experiments or through quasi experiments (Strang, 2015). In these methods subjects are assigned to either a treatment group, or to a control group (Gray, 2013). In a true experiment, the assignment into groups is random, and the method is considered to be the most robust and positivistic of all methods (Strang, 2015). However, this method is not feasible in this setting. In a quasi-experiment the treatment group is not drawn from a random sample, but assigned (Gray, 2013). This is necessary, since even if the treatment group is assigned through an external criterion – a hit single on the Billboard Top 40 – it is a criterion decided upon by us. The fourth and final layer of the Strang (2015) typology is the research technique. These are the scientific procedures and tools used to carry out the method. These include everything from data collection, to the tools used to analyze the data. The sample composition, and the data collecting procedure were described in Chapter 3. The technique we are intending to employ to perform the experiment is described in detail in the next subsection.

4.1.1 Empirical Model: Event Study

First introduced by Fama et al. (1969), event studies are commonplace in financial economics literature to study the effect of chocks or unforeseen events on markets. Since then the method has had an enormous impact on capital markets research (Corrado, 2011). It is commonly used to examine the behavior of security prices around certain events, such as earnings announcements, regulation changes, merger announcements, and a host of other types of events (Binder, 1998). The event study method have also migrated to fields outside of accounting and finance, and is now used in other disciplines such as economics, history, law, management, marketing and political science (Corrado, 2011). The goal of an event study is to measure whether a particular event influences some outcome (Wooldridge, 2012). Its application allows one to observe abnormal returns, whether stock market returns or otherwise, caused by a certain event.

The original event study method models abnormal returns using market model equations (Binder, 1998). However, another approach allows estimations of abnormal returns in a regression framework, which allows examining the dynamics of the periods around the event (Sandler and Sandler, 2014). The regression equation typically used in these types of studies is:

$$y_{i,t} = \alpha_0 + \sum_{k=-K,k\neq-1}^{K} 1(t - e^i = k)\beta_k + \gamma_i + \nu_t + \varepsilon_{i,t} \qquad (1)$$

The independent variables in the regression are a series of dummy variables that indicate one if t is k weeks from the event, and 0 otherwise. Individuals that are not affected by the events acts as the control group for the individuals treated with the event. Panel fixed effects estimators are often used, and γ_i and ν_t controls for individual and time specific fixed effects (Sandler and Sandler, 2014).

This regression equation has been used in literature related to this paper. Hendricks and Sorensen (2009) and Garthwaite (2014) use a variant of this model to estimate spillover effects in the music and publishing industry, respectively. Both also include period dummies to control for seasonality of sales, leaving the equation:

$$y_{i,t} = \alpha_0 + \sum_{k=-K}^{K} \beta_k I_{i,t}^k + \sum_{m=1}^{M} \delta_m D_{i,t}^m + \gamma_i + \nu_t + \varepsilon_{i,t} \qquad (2)$$

In their setting y is the natural logarithm sales of individual i at time t, and $I_{i,t}^k$ is a set of indicator variables equaling one if the individual has been treated k weeks ago, and zero otherwise. β_k, then, measures the percentage sales impact of the event for each of the weeks tested. $D_{i,t}^m$ is the period dummies controlling for seasonal effects of sales. $\varepsilon_{i,t}$ is the error term.

The standard event study model assumes only one chock or unexpected event per individual. That is, there is only one event for each individual affecting the outcome variable (Sandler and Sandler, 2014). In the studies performed by Hendricks and Sorensen (2009) and Garthwaite (2014) of spillover effects in cultural industries, each considers one such event. Hendricks and Sorensen (2009) consider an album release and its impact on an artist's previous releases. Since album releases are usually several years apart and the intention is to estimate the effect on the previous albums by the same artist, multiple events in the event window is not likely to be an issue unless some artists released several albums within the event period. Similarly, Garthwaite (2014) estimates the impact of endorsement by Oprah Winfrey's book club on the sales of other books on the market. Each of the 25 endorsed books in his sample was only endorsed once. In this study, however, the event we consider is not as clearly defined. Star artist singles within the same genre can, and often will, enter the Billboard Top 40 multiple times in the space of an event window. Consider, for example, that Star A of a particular genre achieves a hit single in early June of 2012, and Star B of the same genre does the same in late August the same year. In such cases we would be left with indicator variables denoting one in two instances of the same event window for each non-star artist in the same genre. The outcome variable would be associated with events months apart, and the estimation results would provide dubious estimates that does not isolate any potential spillover effect correctly. The standard event study methodology, then, is not fully applicable in this setting.

Sandler and Sandler (2014) examine different methods to overcome problems caused by multiple events. First they consider the option of simply ignoring the events subsequent to the first. A second option is to treat the event as the unit of observation, duplicating observations and instead of having one observation per individual and time period there is one observation per individual, time period and event. Sandler and Sandler (2014) refers to the third option as the *Multiple dummies on method*, which means multiple dummies can have non-zero values, but instead of denoting one the variable takes on the value of the total number of events prior to each week.

Through Monte Carlo simulations of the different methods, they find that the multiple dummies on approach consistently produces unbiased estimates. Just like in the standard model they let t denote calendar time, and i denote individuals. However, they also let J_i denote the number of events that occur for each individual i and then let e_i^j denote the time when individual i experiences j:th the event, such that the dummy variables of the standard model now can take on values 1 to J when an event occurs, and zero otherwise. This leaves the multiple events model:

$$y_{i,t} = \alpha_0 + \sum_{j}^{J_i} \sum_{k=-K}^{K} 1(t - e_i^j = k)\beta_k + \gamma_i + \nu_t + \varepsilon_{i,t} \tag{3}$$

In this paper we apply the multiple events model of Sandler and Sandler (2014), and add controls for seasonality following Hendricks and Sorensen (2009) and Garthwaite (2014). This leaves us with the multiple events variant of equation (1), and the main equation used in this paper:

$$y_{i,t} = \alpha_0 + \sum_{j}^{J_i} \sum_{k=-4}^{16} \beta_k I_{i,t}^k + \sum_{m=2}^{12} \delta_m D_{i,t}^m + \gamma_i + \nu_t + \varepsilon_{i,t} \tag{4}$$

In this equation $y_{i,t}$ is the natural logarithm of streams of artist i at time t, and $I_{i,t}^k$ is a set of indicator variables equaling j if a star artist entered the Billboard Top 40 k weeks ago, and zero otherwise. The coefficient β_k, then, measures the percentage impact of a star hit single on non-star artists sales k weeks from its Billboard entry. The term γ_i is the artist fixed effects, and ν_t are year dummies controlling time fixed effects. We control for seasonal effects of yearly music sales through a set of month of the year dummies, denoted $D^m_{i,t}$. $\varepsilon_{i,t}$ is the error term.

Further, we also follow Hendricks and Sorensen (2009) and consider a model in which the dependent variable is first differenced, instead indicating the growth in streaming volumes from week to week:

$$\Delta y_{i,t} = \alpha_0 + \sum_{j}^{J_i} \sum_{k=-4}^{16} \beta_k I^k_{i,t} + \sum_{m=2}^{12} \delta_m D^m_{i,t} + \gamma_i + \nu_t + \varepsilon_{i,t} \tag{5}$$

The model estimates the impact of star artist hit singles on the percentage rate of change of the weekly streaming volumes of genre artists. The fixed effects estimators, and the month of the year dummies remain the same in this specification. However, the fixed effects transformation in this case eliminates the trends in streaming that are time consistent.

Fixed effects transformation removes effects that are unobserved from the equation prior to the estimation (Wooldridge, 2012). In the case of artist fixed effects, the transformation removes unobserved effects that are consistent over time. For time fixed effects the opposite is true, unobserved effects that are consistent across artists are removed. In this study, the main artist consistent effect we wish to control for is the growth of music streaming over the sample period. The fixed effects transformation should eliminate omitted variable bias, which would almost certainly be present in the model without it; there are of course a number of unobserved factors that influence the streaming volumes of an artist that are omitted from the regression, the most clear example of which would be an artist's talent. If talent were a key explanatory variable of an artist's streams, the effect would remain consistent over time for each artist. By removing the mean value on both sides of the regression equation, any time constant unobserved effect is removed (Wooldridge, 2012). The omitted variables no longer introduce a bias into the estimation.

Fixed effects estimators are efficient when the error terms are serially uncorrelated and homoscedastic[1] (Wooldridge, 2012). This means that we must adjust the standard errors for serial correlation and heteroskedasticity. In addition, a test for correlation in the cross-section showed an average absolute average correlation in the sample of 0.306, and the test could not reject the null hypothesis that standard errors are uncorrelated across artists. Consequently, in the estimations of Equations (4) and (5) we use Driscoll-Kaay standard errors. Driscoll-Kaay standard errors are robust to both heteroskedasticity and serial correlation (Hoyos and Sarafidis, 2006). The choice of Driscoll-Kaay standard

[1] For an overview of heteroskedasticity and serial correlation see Wooldridge (2012) (pp. 432-436).

errors was used since they are robust to correlation in the cross-section as well (Hoechle, 2007, Hoyos and Sarafidis, 2006). The results from the specifications presented in this section are presented in more detail in Chapter 5.

4.2 Potential Limitations

4.2.1 Reliability

The notion of reliability in social research means that the results of a study should be repeatable, and that measures are consistent and stable (Bryman, 2012, Ghauri and Grønhaug, 2005). The data used in the study are the weekly streaming volumes of artists as the dependent variable, and the independent variables consist of indicator variables that represent dates when star artists enter the Billboard Top 40. These values are, for each point in time of the observation, consistent and stable. For any given historical week, these volumes or dates will not change. Great care was taken in the construction of the indicator variables, and in making sure the dates from the two original datasets – one containing Billboard chart data and the other Spotify streaming data – properly matched. We find no reason to believe that the data, or any of the instruments, would have an impact on the reliability of the results presented throughout the remainder of this paper; the collected data we use to conduct our analysis today, will yield the same results tomorrow (Creswell, 2002).

Another feature associated with the reliability of the study is the repeatability, or replicability of the instruments and the study (Strang, 2015). There could be some potential problems in replicating this study, since the data containing streaming volumes are provided to us under an agreement of confidentiality. They are confidential due to their strategic importance of the labels providing them. An anonymous dataset could be provided after approval from the labels involved. Issues of confidentiality are further expanded on in Section 4.3.

Another area that could potentially have implications on the repeatability is that the Echo Nest familiarity score is not static, but subject to change over time. It is likely that the top 300 artists within a genre may not be the same at different points in time. As such, the list of artists within the genre may slightly differ if extracted from The Echo Nest at another time. The extent to which this would affect the results is not consequential, but small differences could theoretically exist. However, the results should be the same no matter who the artist occupying a certain spot at any given time is. The distribution of streams across the range of artist sizes in the sample should be the same, or very similar, no matter whom is the tenth most popular artist at a given time, for example. The issue is not a concern in terms of star artists as these represent dates, and not an aggregated variable of popularity.

4.2.2 Validity

Validity of the data refers to whether the measures are truly capturing what they are supposed to be capturing. Measurements can often contain some errors, and the observed measurement may to varying degrees reflect the true value, but could also contain some other factors as well (Ghauri and Grønhaug, 2005).

The concept of measurement validity – sometimes also referred to as construct validity – is the notion that a measure should truly represent the concepts they are supposed to be denoting; that they are the correct theoretical measures (Bryman, 2012, Strang, 2015). The effect we are attempting to observe is a potential information effect emanating from star artists, and to what extent it results in a spillover effect onto genre artists. In the classic event study an assumption about the event is that the event is unexpected and not known to the market a priori. An artist's entry onto the Billboard Top 40 can be preceded by weeks climbing the charts, and weeks of promotion. However, of the feasible alternatives considered the chosen event was the closest estimation of new information reaching consumers. Album releases, for example, is generally preceded by even more promotion, not to mention one or more singles being released in the months leading up to the album release. The release date of the first single of an album, or a press release announcing it, would likely have been a more distinctly defined event, but would bring other problems: first, a problem of data collection, but more importantly, both alternatives would require defining star artists beforehand. Defining star artists beforehand, through identifying top selling artists in the sample for example, would make it impossible to account for all events in the period, since the data is only from a select few rights owners.

We believe it is a reasonable assumption that for most hit singles, certainly by established star artists, entry onto the Billboard Top 40 is almost instantaneous, and a good approximation for new information reaching the consumer. This approach is also similar to Sorensen (2007) who estimated the effect of entering the New York Times bestseller list on book sales.

Internal validity is concerned with issues of causality, whether it truly is the independent variable causing a potential change in the dependent variable, and not some other effect (Bryman, 2012), and whether statistical inference can be made that there exists a causal relationship between a set of variables (Ghauri and Grønhaug, 2005). Factors such as violations of the underlying assumptions of the statistical test used, and the existence of bias in the data could make statistical inference dubious (Ghauri and Grønhaug, 2005, Strang, 2015). We have, to the best of our ability, taken steps to ensure model assumptions are met and potential biases accounted for (see Wooldridge (2012), (pp. 503-504) for the assumptions underlying fixed effects estimations). Return to section 4.1.1. for further detail into the development of the method, and the steps taken to ensure instruments and measures are exogenous and unbiased.

External validity is concerned with the extent to which the findings can be generalized beyond the study; whether the instruments chosen, and the unit of analysis of the study, are sufficiently able to generalize to other situations and outside the context of the study (Strang, 2015). External validity is of course related to the other forms of validity previously discussed; a robust model, and valid instruments and data increases the likelihood that the findings can be generalized.

One issue that might affect the ability to generalize the results in this paper is concerned with the approach to defining star artists. The definition is the same as the event, that is, that the definition we use to define a star is an artist that has had a Billboard Top 40 hit in the sample period. This means that all genres in the sample necessarily need to be established and popular genres, since they produce hit singles. Questions could be raised about the extent the results are applicable for smaller and more niche genres, although most likely with a different definition of star artists. Results from this study should be generalizable to the extent of popular music, and the intra-genre effect of star artist hit singles.

To conclude, Strang (2015) argues the importance of illustrating that the findings are accurate, credible, and statistically significant. A lot of time and effort has been put into to developing a fair and honest model that to our best capability mirrors that of the real world. The method we have developed is, to the best of our ability, an attempt to reliably and validly reflect the true relation between stars and genre artists. We have taken measures to control for endogeneity and bias in the dataset, we have also run tests of our standard errors (Pesaran, 2007) and adjusted the method accordingly. In Chapter 5 we present and discuss the results of the empirical model presented in this chapter. The next subsection discusses ethical considerations regarding the study design.

4.3 Ethical Considerations

This section will discuss the ethical considerations that authors may face when conducting research. It is of the research community's interest to keep research ethically and morally legitimate in terms of how data is used and presented. Ghauri and Grønhaug

(2005), explains that “[r]esearchers have a moral responsibility to explain and find answers to their research questions honestly and accurately” (p. 20). Ghauri and Grønhaug (2005) further explains that there is often a cognitive dissonance towards ethical issues as they are often ”difficult, time consuming or does not fit into [the] research plans” (p. 20). We have throughout the process of conducting this research paper considered two main areas of ethical considerations as proposed by Ghauri and Grønhaug (2005): the researcher-participant (subject) relationship and the researcher’s moral responsibilities.

Ghauri and Grønhaug (2005) explains that “the researcher-participant (subject) relationship is the most sensitive one in the process of research in business studies” (p. 21). Ethical considerations may differ greatly given the format of the conducted research given the nature of the collected information. In our research we have preserved all anonymity of the participants both in terms of how the data was used and presented. We decided from the very start of our research process that our analysis must be of such a character that no additional value would be added by disclosing any personal references or names of the partner companies or artists in the sample. Another ethical consideration was the transparency towards partner companies about the goal of our research. It was important to us to not involve any participants without their full consent. Further considerations are the use of deception, coercion or the depriving of the participants rights in order to get additional data. These considerations are to be taken very seriously but are difficult to apply to this research paper as suggested by the data we use. On a last note we want to affirm that this paper was reviewed by all involved participants before it was made public. In addition, all involved participants where provided with a final copy.

The second area of ethical considerations is the researchers’ moral responsibilities. Ghauri and Grønhaug (2005) explains, “[t]he moral responsibility of the researchers deals with social guidelines and constrains upon research techniques and measurements” (p. 22). He further presents five areas of considerations: Public Interests, Company Interests, Government Rules, Researchers Interest, and Peer Pressure. For the purpose of this paper we consider the company interests and the researcher interests as these areas are of considerable relevance to us. The conducted research presented in this study is not of a sensitive character and has not been to any extent influenced by the involved partner companies. In addition, the interest from our side has been to conduct an analysis that to our best capability explains the truth. We put a lot of emphasis on this in our methodology.

Chapter 5

Empirical Results

The empirical analysis begins with a presentation, and analysis of descriptive sample statistics in the first subsection. We try to discern any clear patterns in the data, and provide a glimpse into the sample and its diverse collection of artists. In the subsequent subsection we test the event study model outlined in Section 4.1.1. We run four specifications of the model to attempt to capture a potential intra-genre spillover effect. A discussion of the findings, and their potential theoretical and practical implications concludes this section.

5.1 Descriptive Statistics

In this section we present sample statistics that might give a first indication of a potential intra-genre spillover effect. Table 5.1 shows summary statistics of the weekly streaming volumes for each of the years in the sample. The table is divided into weeks when a star single enters the Billboard Top 40, and all weeks when there were no entry into the charts by an artist belonging to one of the seven genres.

Table 5.1 clearly indicates some effect in weeks when star artists enter the Billboard Top 40. The sample is cleared from the star artists themselves, so the mean weekly streaming volumes in the table refer only to the remaining artists in the sample. It seems that a hit single markedly boosts streaming volumes of other artists, on average. Mean weekly streaming volumes are substantially higher in weeks where a star artist enters the Billboard Top 40. In percentage terms the difference is largest in 2010 at approximately 60.5% larger volumes in weeks when there is an artist entering the Billboard Top 40. The smallest difference is found in 2011, where the difference is around 14%. In the subsequent years the difference grows to 21% in 2012, 23% in 2013, and in 2014 the

SAMPLE STATISTICS BY YEAR AND EVENT						
Year	2010	2011	2012	2013	2014	Total
Top 40 Single						
Mean	47 594	29 946	55 183	107 116	174 027	93 031
Max	725 035	395 967	783 831	1 978 124	3 081 832	3 081 832
Min	1	1	1	1	1	1
Standard deviation	102 343	63 620	123 464	225 468	400 133	246 936
Count	159	277	352	405	399	1 592
No hit single						
Mean	29 648	26 302	45 721	86 829	133 955	72 717
Max	501 482	404 655	635 014	1 310 286	2 406 437	2 406 437
Min	1	1	1	1	1	1
Standard deviation	70 527	57 136	100 281	182 590	313 203	194 591
Count	257	333	434	488	512	2 024

TABLE 5.1: The table presents summary statistics for the sample. The values are divided into weeks in which a star artist from the genre entered the Billboard Top 40, and weeks with no such event.

difference is around 30%. These findings seem to suggest that, on average, there seem to be some spillover onto other artists when a star artist is succeeding on the charts. Comparing instead the maximum streaming volumes in weeks with and without a star hit single shows another indication of a potential spillover effect. For all years the maximum weekly streaming volumes are higher in weeks where the genre has an entry onto the Top 40, than for weeks where there is none. These figures represent the largest artists in the sample that has not achieved a hit-single in the five-year sample period. Again, there is an indication of some effect in weeks of a chart entry. However, these values can only offer a glimpse of any potential spillover effect, since they only reflect the weekly average, or maximum values of a given year, they do not compare artists at the same point in time. For example, the maximum values in 2014 in both the event of a hit single and no hit single could be values from the same artist, but months apart, and the difference could be down to the rising popularity of the artist herself.

There are other noticeable features of Table 5.1. First, the growth of music streaming and Spotify since 2012 is markedly evident in the average streaming volumes of artists. For the average artist weekly streaming volumes almost tripled between 2012 and 2014. The same trend is evident from the maximum weekly streaming volumes; from relatively stable levels between 2010 and 2012, the largest artists accumulated more than four times as many streams in 2014 than they did in 2012. Second, the minimum values of average weekly streams show the breadth of the sample, ranging from artists accumulating millions of streams in a week to artists barely anyone listens to. The size of the smallest artist might differ slightly by genre, but the sample covers a very broad spectrum of artists.

MEAN STREAMING VOLUMES BY YEAR AND GENRE					
Year	2010	2011	2012	2013	2014
Boyband					
Star Top 40 Hit	N/A	29 763	101 691	118 174	191 769
No new hit	56 974	38 466	59 304	100 892	167 641
Hiphop					
Star Top 40 Hit	35 751	32 806	61 037	144 736	239 268
No new hit	24 355	28 994	46 727	112 078	182 379
Indie folk					
Star Top 40 Hit	N/A	N/A	48 639	77 472	136 688
No new hit	26 655	23 133	43 317	62 953	93 282
Indie rock					
Star Top 40 Hit	63 666	32 371	N/A	N/A	N/A
No new hit	22 895	32 219	57 539	108 961	138 047
Progressive house					
Star Top 40 Hit	N/A	12 962	17 133	48 250	120 334
No new hit	5 217	8 731	13 804	45 667	95 713
R&B					
Star Top 40 Hit	30 397	32 799	82 188	178 697	225 239
No new hit	27 755	29 341	69 541	125 834	185 996
Teen pop					
Star Top 40 Hit	69 949	42 211	44 100	90 139	142 838
No new hit	49 818	26 294	41 551	64 617	100 458

TABLE 5.2: The table depicts the mean weekly streaming for artists in the respective genres. The mean values are divided into weeks in which a star artist from the genre entered the Billboard Top 40, and weeks with no such event.

To gain further insight into the results presented in Table 5.1, we turn our attention to Table 5.2 and the genre specific mean weekly values. We first note that there are not hit singles for all genres in all years. Hip hop, R&B and Teen Pop have all had hit singles in each of the years, Boyband and Progressive House have had hits in each year apart from 2010. Indie folk has only had hit singles in three of the years, while Indie rock only in two. The potential spillover effect can be observed for most of the years when examining the mean weekly streaming volumes. For most of the years where a genre artist achieved a hit single, the trend for the overall sample is similar; streaming volumes are higher for most of the genres in weeks where a star artist achieves a Top 40 single. The only exceptions are found for Boyband in 2011 where streaming volumes was quite substantially lower in weeks with a chart entry, and for Indie Rock in the same year where the positive difference was negligible.

Although unrelated to the questions posed in this paper, we find it interesting that the indie genres had all their hits at different times, with indie rock being more successful in the charts in 2010-2011, and indie folk in 2012-2014. There seems to have been a shift among consumers towards a "folkier" sound of music labeled as indie. Another interesting observation shown in Table 5.2 is the incredible growth of Progressive House since 2010. It seems to have been only a niche genre with a very narrow fan base in 2010, with artists averaging streams of only 5 217 per week. Today, although still the smallest genre in the sample, it averages somewhere around 107 000 streams per week – an increase of almost 2000% – and has clearly moved into the mainstream. On the surface, this explosive growth of the genre seems to have been driven by superstar artists such as Avicii, Calvin Harris or Deadmau5. Early results seem to indicate hit singles in a genre has a positive impact on smaller artists in the genre, and in the next subsection we perform a series of regressions, using the event study methodology developed in Section 4.1.1 to further explore this effect.

5.2 Event Study Estimations

In this section we present and discuss the results from regressions using Equations (4) and (5) laid out in Chapter 4. Because the regressions are performed on such a large number of variables, the coefficients of the regressions are presented in graphical form here. The results are presented in their entirety in the Appendix.

Figure 1 shows the coefficients from the first regression, using the logarithm of weekly streams as the dependent variable, together with its associated confidence intervals calculated using Driscoll and Kaay standard errors. The full results from Regression (1) are found in Table A.1 in the Appendix.

As Figure 1 show, the four weeks leading up to the week of entry show a mixture of positive and negative coefficients. However, none of the coefficients from the pre-event period are distinguishable from zero at any level of significance. In the week of entry into the Top 40 of a star artist in the genre there is a significant and marked difference for the treated genre artists compared to the rest of the sample. As Halvorsen and Palmquist (1980) first pointed out, the log-linear relation in the model means the relative effect of the coefficient $\hat{\beta}_k$ is:

$$100 \cdot (e^{\hat{\beta}_k} - 1)$$

That is, the coefficient of 0.080 indicates approximately 8.3% higher streaming figures for the artists in the same genre compared to other artists. The coefficients in the 16 weeks following the release are continuously positive, but with varying levels of significance. In weeks 1, 2, 6, 8 and 13 after a star artist single enters the Billboard Top 40 the coefficients are not significant at any level. For the remaining 10 weeks the results show small positive effects on genre artists, significant at levels ranging from 0.1 to 0.01.

Regression (1) was performed on 80 885 observations across 504 artists with an R^2 of 0.284.

The lack of significant results in the pre-treatment period lends some support to the model and its ability to isolate the effect of the star event; the streams from artists in the genre are statistically indistinguishable from other artists in the sample in the four weeks leading up to the event, and significantly larger in the week of the event and most weeks thereafter. It is however problematic that the estimated coefficients drop in and out of significance in the post-treatment period. If the information effect from an artist achieving a hit single has spillovers onto the genre associated with the star, the effect should be measurable in a single period of an unknown number of weeks. This is not the case. The question, then, is to what extent the model actually isolates the spillover from the star artist.

In an attempt to better understand what might cause the information effect to seemingly disappear randomly, we examine whether the definition of a star hit single is too loose in Regression (1). In Regression (2) we restrict the list of star artist hit singles to those that have remained at least eight weeks on the Top 40. The argument is that short-lived singles that only make a brief stint at the Top 40 perhaps do not qualify to be actual hit singles, and the performers stardom might be overstated. If the disappearing

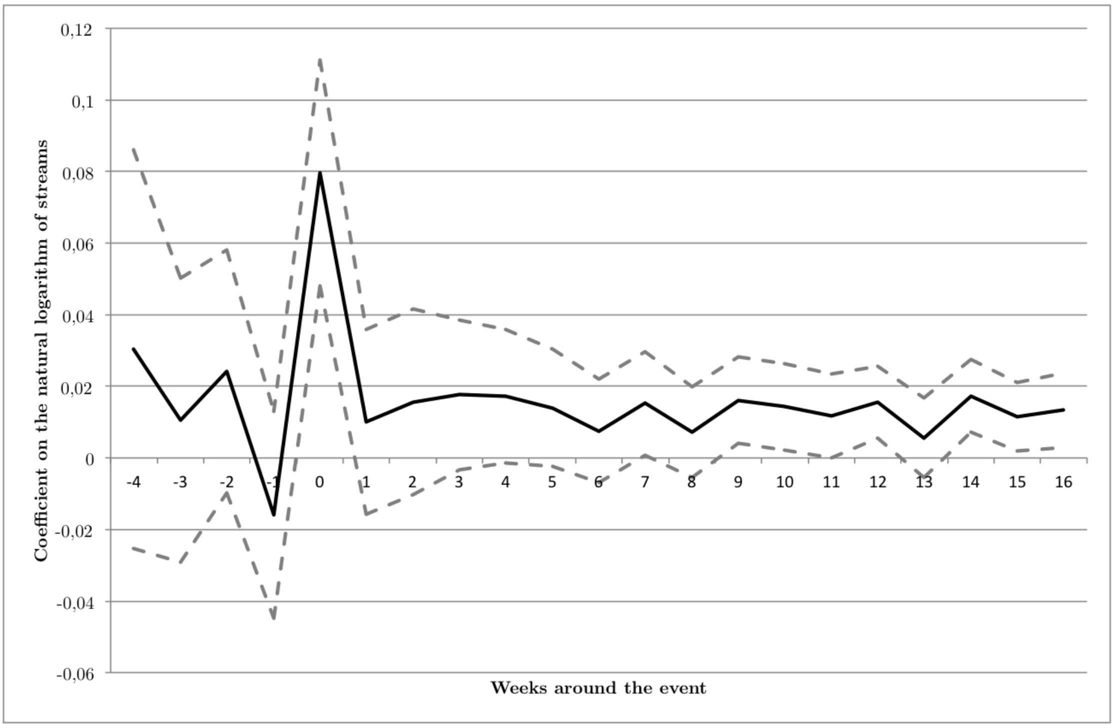

FIGURE 5.1: The Figure shows the coefficients on the natural logarithm of streams from Regression (1) for each week of the event window. The coefficients are presented together with the 95% confidence interval. The full regression results are found in Table A.1 in the Appendix.

information effect that the results from Regression (1) suggests is caused by short lived hit singles, the estimates should show a consistent significant effect until any potential information effect wanes out and streams of genre artists return to pre-treatment levels.

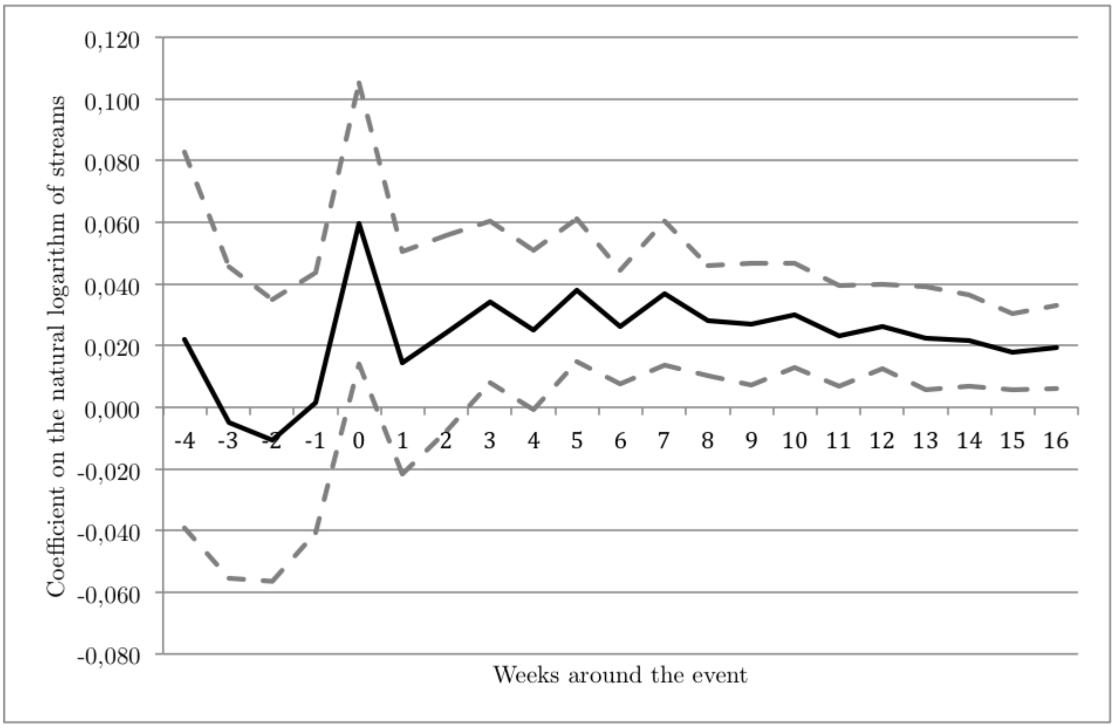

FIGURE 5.2: The Figure shows the coefficients on the natural logarithm of streams from Regrssion (2), performed with a restricted definition of star artist, for each week of the event window. The coefficients are presented together with the 95% confidence interval. The full regression results are found in Table A.1 in the Appendix.

The results of Regression (2) still suggest that the model to some extent capture a potential information effect that transfers from the star hit single to genre artists, with pre-event estimates not distinguishable from zero and a positive and significant effect the event week. The coefficient on the event week is lower at 0.060, or 6.2% higher streaming figures than non-treated artist in other genres. The post-event results do show more consistent estimates, with 14 out of the 16 post-even weeks significantly different from zero at levels of significance ranging from 0.1 to 0.01. This Regression was performed over 82 627 observations across 514 artists, with an R^2 of 0.285.

The result suggests that restricting the definition of a star hit single, and allowing only those that have achieved a prolonged stay in the charts seem to account for some of the peculiar results on the coefficients in Regression (1). We also test whether the accumulated coefficients sum to zero, which is rejected at the 99.9% level, suggesting that the cumulative positive effect for treated genre artists suggested by Regression (2) is statistically distinguishable from zero. Figure 5.3 provides the cumulative effect over the sample period, together with the accumulated confidence interval of the regression.

It clearly shows the lack of any effect in the pre-event period, and the continuously positive effect throughout the period. Although the size of the accumulated effect can vary greatly, as indicated by the large confidence interval at week 16, the post-estimation tests indicates that there is an effect that is larger than zero for the entire estimation window accumulated.

However, the loss of significance in the two weeks immediately following the event week remains. This could suggest that any potential spillover caused by a star artist hit single is very brief; the information effect that the model attempts to capture seem to last only for the week of the event, and then disappears. A significant and positive effect reappears in the third week, and remains throughout the event window, but this effect cannot be simply assumed to derive from the same information that caused the initial positive effect. The estimation seems to capture some other effect in addition to the intra-genre spillover immediately created by a star single becoming a hit, or some effect not swept away by the fixed effects transformation. For example, the observed effect in the weeks after it first seems to disappear could be caused by genres that produce more hit singles than others being more popular, and its artists are simply larger for most weeks than most other genres in the sample.

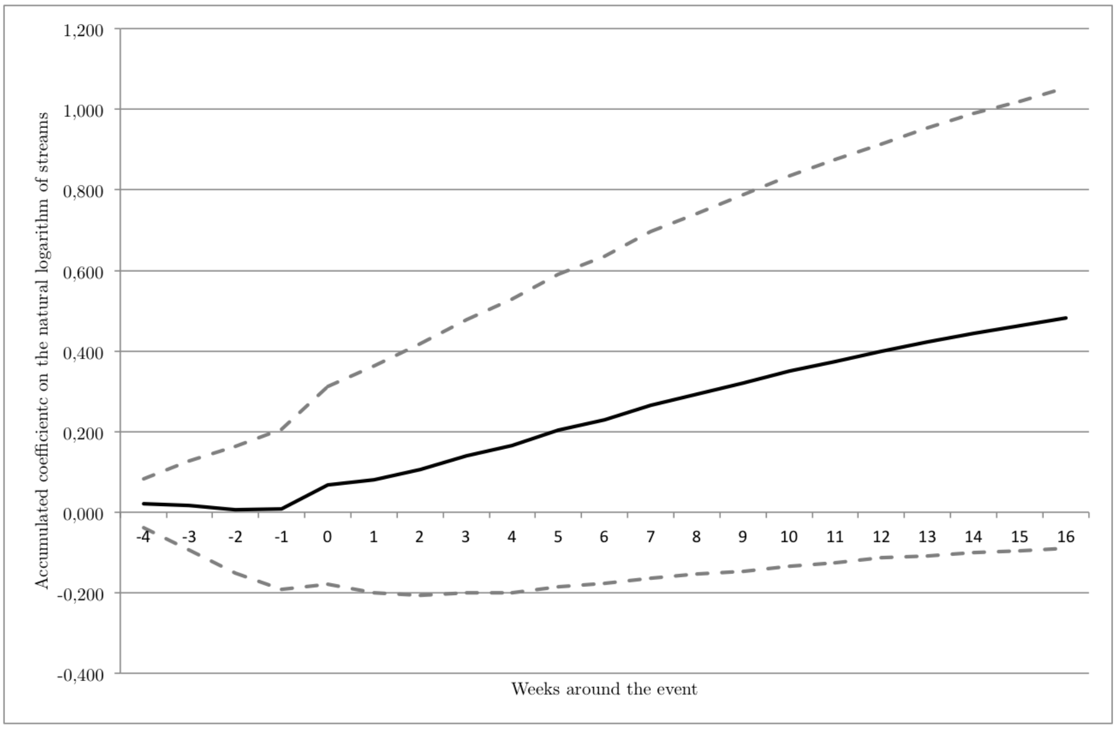

FIGURE 5.3: The Figure shows the cumulative coefficients on the natural logarithm of streams from Regression (2) from four weeks prior, and sixteen weeks after the event. The coefficients are presented together with the 95% confidence interval, also accumulated.

In order to distinguish the immediate effect on artists, we run a regression with the percentage change from one week to another as the dependent variable, instead of the absolute value of streams for each week. That is, we run a regression with the first difference of the natural logarithm of streams as the dependent variable, using Equation (5). The fixed effects estimator in this setting absorbs unobserved patterns in the artist's weekly growth rate.

The first differenced regression (3) produces a different set of estimates, measuring instead the weekly percentage change for treated artists compared to non-treated artists. The results show a different pattern to regressions (1) and (2) insofar that there is some significance in the weeks leading up the event. It still estimates a marked effect in the week of the event. The coefficient of 0.067 for the event week is estimated at a level of significance of 0.01, and indicates the growth in streaming for genre artists from the week prior to the event is approximately 6.7% higher than for untreated other artists. More interesting, however, are the results for the subsequent weeks of the event window. The results suggest that most of the increase that occurs when a star artist achieves a hit single is reversed the following week. The coefficient for the first week is -0.054, also at a level of significance of 0.01. The following week there is no distinguishable growth for genre artists; the same is true for weeks 9, 10 and 15.

Figure 5.4 shows the cumulative estimated coefficients, together with the accumulated confidence intervals. The full result of this regression is presented in Table A.2 in the Appendix.

The same post-estimation test was performed on this regression, this time indicating that the accumulated value of the coefficient is not distinguishable from zero. However, as Figure 5.4 shows, this should be expected, since the accumulated coefficients sum to zero around the 15th week. It indicates an almost immediate, but very short period of intra-genre spillover, followed by steady decline over the following weeks until the accumulated growth is back to zero. The effect of the first week is reversed by around 80% by the subsequent week. The rate of growth in the week of the event for genre artists is similar in size to the difference between genre artists and the rest of the sample estimated in regressions (1) and (2). This suggests that most of the difference found in these estimations for the event week were indeed the result of an increase in streams for treated artists, rather than a combination of any potential spillover effect and the unobserved effect that seem to affect the rest of the event window. Further, the estimated effect is not caused by consumers' discovery of the star artist herself causing spillover onto the star artist's catalogue, an effect identified by Hendricks and Sorensen (2009), since each star artist is removed entirely from the sample. It seems, then, that when a hit single reaches the consumer it triggers an interest in discovering similar artists to the star behind it. This effect is brief, and the sales growth of genre artists is almost entirely reversed in the first week following the single achieving hit status. The remaining growth seems to decline steadily in the weeks after the event until the effect entirely disappears.

In the last regression (4) we run a variant of regression (3), but focusing solely on the week of the event. We add interaction variables of the event week variable and a set of dummy variables that denote 1 if an artist is in a certain decile of yearly genre streams. The interaction variable measures any potential added effect from being in a particular decile of the genre, in order to gauge whether the spillover effect in the event week is equally distributed across all genre artists. The dependent variable is the streaming growth from the week before the event to the event week. The results are found in Table A.3 in the Appendix.

The results show no significant added effect for any of the deciles of genre artists. The coefficient on the event week is higher in this regression, at 0.119 at a significance level of 0.05. It seems, then, that there is no distinguishable difference related to the popularity of the genre artist in the sales growth in the event week. The estimated effect seems to be distributed across the genre, and small artist gain, on average, the same relative boost in streams as the top genre artists in the sample.

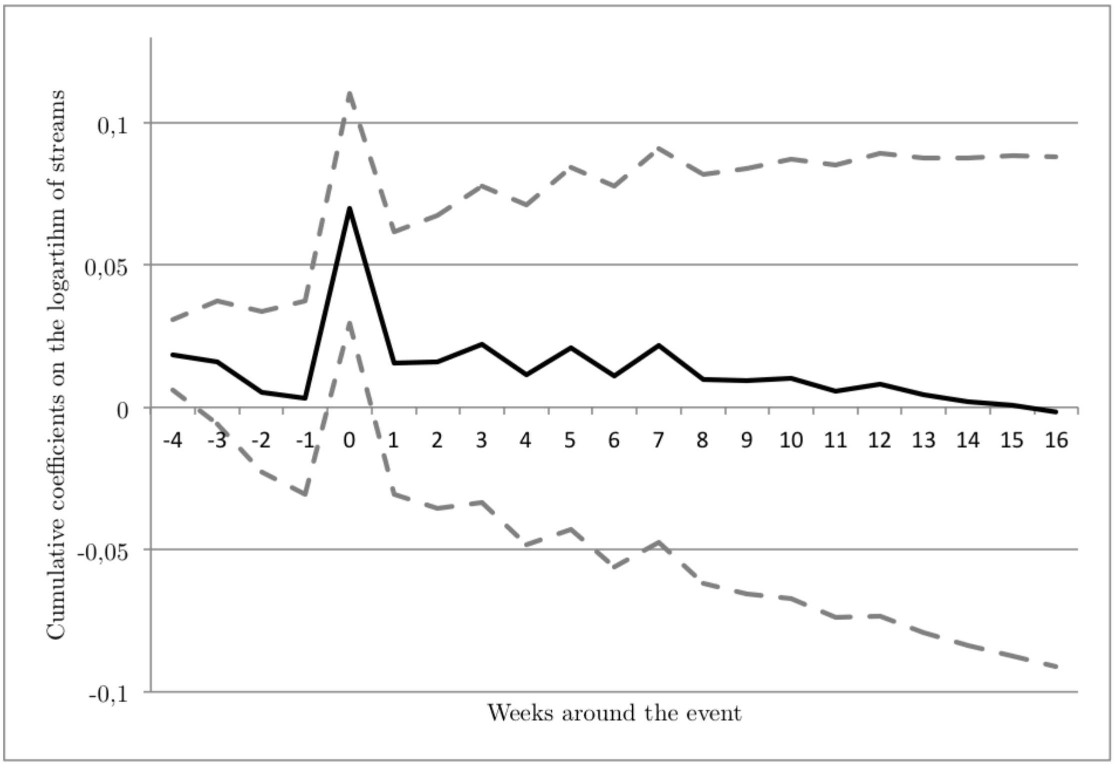

Figure 5.4: The Figure shows the cumulative coefficients on weekly growth in streams from Regression (3) from four weeks prior, and sixteen weeks after the event. The coefficients are presented together with the 95% confidence interval, also accumulated.

5.3 Discussion

Results from Regressions (1) through (4) are somewhat conflicting. Although there are mostly significant results, the loss of significance several times in the event window throughout all estimations suggests the model do not sufficiently isolate the intra-genre spillover effect. Since the significance returns, there could very well be several other unknown events that influence the streaming volumes for artists in the sample. However, the results in the week of the event are consistently positive and significantly different from zero. The coefficients are similar in size through all specifications. We believe this shows that the success of star artists can cause spillover effects onto similar artists, at least in the short term. The length of this spillover effect is difficult to discern from the results presented above. Regression (3) gives the best indication of the length of the effect, showing that most of the increase in the week of the event is reversed the following week, also offering an explanation to the lack of distinguishable difference in that week in the previous estimations. Although Regression (3) suggests it takes several weeks, even months, until the effect is entirely reversed, the coefficients for these weeks are very small, and drop in and out of significance. We are therefore careful in drawing any conclusions about the dynamics of the effect we have observed. We do however believe that there is an effect, certainly for the week of the event. The length of the effect is difficult to infer from our results, and we refrain from suggesting the effect lasts beyond the week of the event. The lack of significance in the first few weeks after the event found in regressions (1) and (2), and the significant decrease found in regression (3) suggests that most of the effect is reversed in a short period of time.

We also find, somewhat surprisingly, that the effect is similar for artists of all sizes of artists in the release week; we could find no significant added effect caused by the size of the artist. This finding suggests that no genre artist is disproportionally more affected by the spillover effect in the week of the event.

5.3.1 Implications for Theory

This paper is similar in its method and subject to the research of Hendricks and Sorensen (2009) and Garthwaite (2014). The results are to some extent similar to those found in their papers as well. However, the effect of the event in this study is not only less pronounced, it is also not as long lasting as the effects previously hinted at. The findings of Hendricks and Sorensen (2009) and Garthwaite (2014) suggested sales increases on previous releases and unendorsed titles at levels ranging from around 30% to 70% in the peak weeks. These estimates are also consistently significant and remain so for the entirety of their respective estimation windows, suggesting that the effect is sustained for months after the event. This is to be expected; both Hendricks and Sorensen (2009) and Garthwaite (2014) examine the effect of an event related to the individual of observation. Hendricks and Sorensen (2009), for example, examine the effect of a new album release of an artist on the same artist's previous releases. We let the event affect a group of individuals that is labeled to be similar in style, in order to see the average intra-genre spillover effect on artists in the genre. It is logical that the effect is less pronounced in this setting, as the connection is not as obvious to the consumer. The link between a new album by an artist and the artist's catalogue albums is really clear; the artist is the identifier in both cases. In our case the genre is the common factor, but consumers will still identify the tracks they enjoy by the artists. The link between a hit song of a certain genre, and the genre itself is not as clear, meaning that the effect should be less pronounced.

Hendricks and Sorensen (2009) further develop a model of album discovery, based on their findings. With slight changes in the set up of the model, an artist discovery model could be developed based on the finding that genre artists benefit by star artists' success. Instead of the three albums and three periods-model developed by Hendricks and Sorensen (2009), we consider two artists and two time periods. Let 1 denote a non-star artist, and 2 denote a star artist, and let $t = 1$ denote a period with no hit singles from star artists in the genre, and $t = 2$ a period with a star artist hit single. We then use Hendricks and Sorensen (2009) reasoning, and apply it to the setting of this paper, in the context of streaming instead of purchases, and with spillover across artists instead of albums.

Consumers are divided into three groups (Hendricks and Sorensen, 2009). Applied to this setting, the first group consists of those that discovered the artist in a previous period, and has continued to listen to the artist in the following period. The second group consists of those that has discovered the artist, but has not continued to listen to it in the subsequent period. The assumption is that the consumer does not care for the artist, and therefore did not continue listening. Finally, those who have yet to discover the artist belong in the third group. Hendricks and Sorensen (2009) denotes the first two groups "informed" and the last group "uninformed".

Given these assumptions, the size of the intra-genre spillover from the star artist hit single is determined by (1) the number of uninformed consumers, (2) the proportion of the uninformed consumers who discovers the genre artist as a result of the star hit single, and (3) the proportion of these consumers who like the artist enough to continue to listen to her. The model is based on the simple logic that for a consumer to stream an artist, they must know about the artist. The probability that the consumers continue to stream an artist is then based on two probabilities: the probability that they discover the artist, and the probability that they like the artists they discover (Hendricks and Sorensen, 2009). Hendricks and Sorensen (2009) goes on to develop these probabilities into the model of album discovery, and estimate the unknown parameters. We will not develop and test an artist discovery model in this paper. However, using the same logic as Hendricks and Sorensen (2009), we have with some simple changes in the setup shown that their model can be applicable in a cross-artist setting as well. Our findings suggest that there is a group (2) that upon learning of a hit single of a particular genre set out to discover artist similar to the artist they enjoy.

The setup above could also help explain the brevity of the effect that our findings suggest. In the streaming context, group (3) could explain the length of the effect; if a number of consumers discovers new artists through looking for similar music as the star hit single they enjoy, but the genre artist is not to their taste, they will not continue to stream the newly found artist. Our finding that indicated an average growth in streams of around 7% in the week of the event, and the reversal of around 80% of that effect in the subsequent week could be because a majority of the consumers simply was not satisfied with what they discovered. There seem to be several consumers that belong to group (2) and attempts to find similar music to the hits they hear on the radio or elsewhere, but only some 20% seem to find what they are looking for and make their way into group (3).

By adopting and modifying the album discovery model to the context of streaming and intra-genre spillovers, we have shown that an artist discovery model could be developed with the model of album discovery from Hendricks and Sorensen (2009) as its foundation.

In Chapter 2 we suggested there exists a theoretical gap in terms of the literature on stars in the field of cultural industries. We found that although there is plenty of research on the phenomenon of the superstar, both theoretical and empirical, there was a lack of insight into how stars' sales interact with other artists. The interaction is often limited to their interaction with the market as a whole, examining the distribution of sales, and concluding that stars receive a lion's share of them. From the strategic view of Ryan (1992) and Negus (1998), stars and genres are found to interact, but again we found the view of this interaction to be limited; stars are viewed as just absorbing the losses incurred by lesser-known genre artists, and genre artists in turn are seen as a means to spread the risks and diversifying a product portfolio.

We believe this paper is a first step in exploring the dynamics of the interaction between star artists and the genres to which they belong. Our findings suggest that star artist has an effect on genre artists that goes beyond dominating lesser-known artists or absorbing losses, they can actually act as knowledge enhancers for the genre as a whole, and consumers seem to set out to discover similar artists upon hearing a hit song they enjoy.

Smaller artists in the genre seem to benefit from the success of the few artists who make it all the way to the top, albeit for a short period of time. In the next subsection we discuss the implications of these findings for the recorded music industry.

5.3.2 Implications for the Recorded Music Industry

Although the intra-genre spillover effect identified in Chapter 5 seems to be short lived, singles reaching the Top 40 positions of the Billboard charts appear to have a positive effect on artists in the entire genre. With some precaution, our findings suggest that star artists are of value for other artists in the genre, at least for a brief moment. We herein provide some managerial implications with regards to our findings, while being cautious about claiming that we have any factual answers for predicting success or generating enhanced financial results. Our results simply imply a tendency in genre streaming with regards to an isolated event; an event that will not cease to reoccur any time soon.

There are multiple stakeholders within the music industry that may be interested in our findings. Both major and independent recorded music labels may want to consider possible ways of extending the period of genre exposure in connection to projected major hit releases. A label that owns vast amounts of music within a certain genre may want to consider resurrecting catalogue or pushing front-line releases during this window. In some sense, it could be described as strategic reputation parasitism or opportunistic exploitation aimed at maximizing profit. As single releases are seldom secret, rather marketed beforehand, labels may cease an opportunity here with regards to all major releases – whether they are by artist in their own roster, or competitors' star artists.

Another implication for the record labels is the thought of genres and stars as a strategy. Given our findings, labels may to some degree consider that all owned repertoire within a genre might be of short-time value during periods with major releases by the genre's superstars. The star artist is in this context not only responsible for the success of herself but can also act as an aggregator for the genre as a whole. The implications of a successful star artist could be more important than previously thought. Given that the price is right, a label may want to acquire repertoire and use it as a statistical leverage with regards to this event window.

Our results also provide some potential value to the artist or artist management. This is especially true for smaller or mid-sized artists. Given that the genre as a whole increases by the events of a star artists within that same genre, artists may want to consider this time window as an opportunity to gain streams. The release of a very successful star-product may have previously been considered as something that overshadows other similar and less popular artists. Given our findings this way of thinking may not be completely accurate. Artists that are about to release music may want to consider this event-window as a good date of releasing music given the opportunity to gain streams.

Stakeholders such as major streaming services may also want to consider our findings. As our results suggest that there is short enhanced interest in the genre in the week around the event, services like this should consider developing better recommendations. It could be argued that this rather short-lived peak is due to recommendations from the service itself that are not in line with what the consumers are looking for. We do not provide any evidence that the event window increases the overall streaming on the platform. However, as the interest seems to be there, meeting this customer behavior by better recommendations of artists within the genre may increase customer satisfaction of the service and increase the intra-genre spillover effect.

Chapter 6

Concluding Remarks

In this paper we have examined intra-genre spillover effects from star artist hit singles. Through event study methods, following similar studies by Hendricks and Sorensen (2009) and Garthwaite (2014), we have shown there is a marked increase in the average streaming volumes for genre artists in the week of a star hit single entering the Billboard Top 40. Through four specifications we examine the effect, and attempt to investigate its length and distribution among genre artists. We find a clear effect on the streams of genre artists in the week a star artist enter the Billboard Top 40. This result is consistent across all specifications. Evidence of the effect in the weeks following the release is inconclusive. Further, we find no evidence that differences in size of the genre artists affects the distribution of the spillover.

Although the results were too inconclusive to make inference about the length and dynamics of the effect, we argue that the consistent results on the week of entry suggest there is a spillover effect present. We show that artists in a genre with a hit single in a certain week show larger streaming volumes than other artists. We also show this effect is caused by growth in streaming volumes, and not just caused by larger genres having more hit singles, skewing the results.

This paper is greatly inspired by earlier research on spillover effects within cultural industries by Hendricks and Sorensen (2009) and Garthwaite (2014), however as far as we are aware this is the first paper that have explicitly examined a spillover effect from one artist to another. We set out to bridge the gap of the interaction between the sales patterns of star artists and lesser-known genre artists, and believe that our findings give a first indication of this interaction. We argue that the finding that genre artists benefit, at least in the short term, from the success of star artists can have implications for both theory and for the recorded music industry. In terms of theory we argue that the findings could shed some light on how consumers discover music, and that the view of stars and genres perhaps should be as complements, rather than as just risk minimizing parts of a portfolio. In terms of implications for the industry, we suggest the results could have strategic importance in terms of planning releases and looking to find synergies between smaller artists and superstars.

Some caveats should be kept in mind when interpreting the results, and their implications. As mentioned in Chapter 4 issues regarding the validity of the results could be raised, particularly issues regarding construct validity. The definition of the event was identified as a potential issue early on. Finding an event in the recorded music industry that is completely isolated is difficult, and we suggested that the chosen event was a good approximation for previously unknown information. The results suggest that it was a good approximation, with no significant results prior to the week of the event, and a clear effect in the event week. However, the effect found in the weeks subsequent to the event dropped in and out of significance, suggesting that some endogenous chocks could impact on the results.

We are also careful in generalizing these findings beyond the recorded music industry, and popular music in particular. The construction of the study included only some of the largest genres in recent years out of the necessity to include artists with hit singles in each genre.

Overall we believe our results show an indication that there are spillover effects between star artists and lesser-known genre artists from charting hit singles. But further insight is necessary to draw definite conclusions about the intra-genre spillover effect, and of its length and dynamics. Further research could dive deeper into the vast amount of musical genres to examine whether the largest artists in less popular genres have a similar effect. Such studies would require a different definition of star artists, but would offer more insight into how sales of large artists and smaller artists interact. Further, and as mentioned above, we do not generalize these findings to include the whole field of cultural industries. Studying the phenomenon in related industries such as the book publishing industry, or the feature film industry could be an avenue for further research.

Another avenue for future research could be building on the album discovery model developed by Hendricks and Sorensen (2009) to a model of artist discovery. We showed that with small modifications, the logic of his model is applicable to our findings. However, we lack sufficient knowledge in economic modeling ourselves to attempt to provide such a model in this paper.

We hope the findings in this thesis might expand the view of both star artists and genres. While stars will likely continue to dominate their respective genres, and keep collecting the majority of earnings, in doing so they seem to spur consumers to discover other similar artists. This paints a more complex picture of the interaction between the sales of stars and genre artists. Both star artists and genre artists could prove to be of more strategic importance than previously thought.

Appendix A

Appendix

Event study regression results

The table provides the coefficients. Driscoll-Kaay standard errors. and significance levels of Regressions (1) and (2). The dependent variable is the natural logarithm of weekly streaming volumes. Regression (2) is performed on a sample with restrictions on the definition of stars. Control variables for year and month are excluded from the table for the purpose of space.

Variable	(1)	(2)
Week		
-4	0.030	0.022
	(0.028)	(0.031)
-3	0.011	-0.005
	(0.020)	(0.026)
-2	0.024	-0.011
	(0.017)	(0.023)
-1	-0.016	0.001
	(0.015)	(0.021)
Event	0.080***	0.060**
	(0.016)	(0.023)
1	0.010	0.014
	(0.013)	(0.018)
2	0.016	0.024
	(0.013)	(0.016)
3	0.018*	0.034**
	(0.011)	(0.013)
4	0.017*	0.025*
	(0.010)	(0.013)
5	0.014*	0.038***
	(0.008)	(0.012)
6	0.008	0.026***
	(0.007)	(0.009)
7	0.015**	0.037***
	(0.007)	(0.012)
8	0.007	0.028***
	(0.006)	(0.009)
9	0.016***	0.027***
	(0.006)	(0.010)
10	0.014**	0.030***
	(0.006)	(0.009)
11	0.012**	0.023***
	(0.006)	(0.008)
12	0.016**	0.026***
	(0.005)	(0.007)
13	0.006	0.022***
	(0.006)	(0.008)
14	0.017***	0.022***
	(0.005)	(0.007)
15	0.012**	0.018***
	(0.005)	(0.006)
16	0.013**	0.020***
	(0.005)	(0.007)
Constant	5.997***	6.061***
	(0.220)	(0.221)
Observations	80 885	82 627
Number of artists	504	514
R^2	0.284	0.285

Table A.1: Event study results from Regressions (1) and (2). Significance levels are: * p<0.1, ** p<0.05, *** p<0.01

Event study regression results

This table provides the coefficients, standard errors, and significance levels of Regression (3). The dependent variable is the percentage change in weekly streaming volumes. Control variables for year and month are excluded from the table for the purpose of space.

Variable	(3)
Week	
-4	0.018***
	(0.006)
-3	-0.003
	(0.005)
-2	-0.011***
	(0.003)
-1	-0.002
	(0.003)
Event	0.067***
	(0.003)
1	-0.054***
	(0.003)
2	0.001
	(0.003)
3	0.006***
	(0.002)
4	-0.011***
	(0.002)
5	0.009***
	(0.002)
6	-0.010***
	(0.002)
7	0.011***
	(0.001)
8	-0.012***
	(0.001)
9	-0.001
	(0.002)
10	0.001
	(0.001)
11	-0.005***
	(0.001)
12	0.003**
	(0.001)
13	-0.004***
	(0.001)
14	-0.002**
	(0.001)
15	-0.001
	(0.001)
16	-0.002**
	(0.001)
Constant	0.133***
	(0.009)
Observations	81 337
Number of artists	514
R^2	0.016

TABLE A.2: Event study results from Regression (3). Significance levels are: * p<0.1, ** p<0.05, *** p<0.01

Fixed effects regression results on deciles of artist sizes

This table provides the coefficients, standard errors, and significance levels of Regression (4). The dependent variable is the percentage change in weekly streaming volumes. The independent variables are interaction terms for percentiles of artists and the week of the event. Control variables for year and month are excluded from the table for the purpose of space.

Variable	(4)
Event	0.119**
	(0.057)
90th percentile * Event	0.000
	(0.028)
80th percentile * Event	-0.002
	(0.028)
70th percentile * Event	0.010
	(0.026)
60th percentile * Event	0.008
	(0.026)
50th percentile * Event	0.011
	(0.027)
40th percentile * Event	0.004
	(0.030)
30th percentile * Event	0.006
	(0.028)
20th percentile * Event	-0.004
	(0.028)
10th percentile * Event	0.006
	(0.026)
Constant	-0.051
	(0.038)
Observations	81 337
Number of artists	514
R^2	0.010

Table A.3: Fixed effects regression results on deciles of artist sizes, Regression (4). Significance levels are: * p<0.1, ** p<0.05, *** p<0.01

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