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Preprint

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Version: June 16th, 2016

Previous version published in

Mehrafshan, N. (2013). Essays on Value Creation in Marketing Management. Unpublished dissertation. University of Hamburg.

Abstract

We conduct an event study to (1) analyze whether investors revise their expectations about a music album's success when new chart information is published and (2) estimate how these revised expectations affect the value of a music label. We find that expectations about the success of an album are formed with respect to the performance of the promotional singles and that failure to meet these expectations leads to negative stock returns. However, unexpectedly high chart positions do not lead to significantly higher valuations of labels. The initial album success is anticipated at a very early stage when single charts are released one week prior to the release of the initial album charts.

1 Introduction

In many product categories – ranging from perfumes to computer software – firms offer product samples to support the upcoming market entry of innovations. The samples provide consumers with a product experience that potentially triggers purchases and creates favorable word of mouth for the subsequently released main product (Heiman et al. 2001). Such product sampling strategies are well known in the music industry. Music labels release singles as pre-album samples to promote high-margin albums that are released a few weeks later (Yanbin et al. 2011).

Considering the relevance of innovations for firm value (Sorescu and Spanjol 2008), we argue that the market success of a product sample (e.g., the single) may serve as a valuable information source for investors regarding the upcoming release of the main product (i.e., the full album). Because information about new products is often rare, presentations of samples or prototypes attract the attention of capital markets (e.g., Apple's Macworld presentations). Capital market theory suggests that investors update their expectations regarding new products when relevant new information becomes available. If a new piece of information changes the expectations of investors about the future cash flows of a company, they immediately engage in stock transactions correcting the valuation of the firm and rendering the stock market "efficient" (Fama et al. 1969). An illustrative example from the music industry was the 16% plunge in the share price of EMI after its management announced the delay of two new album releases by Coldplay and Gorillaz to the next fiscal year, because this delay presumably signaled management issues with the bands (Goodway 2005). We argue that the success of a single may form music label investors' expectations with respect to the performance of the album. Especially, *unexpected* sales deviations of sequentially released products (e.g., albums) may cause investors to alter their expectations and therefore reevaluate a record label's stocks. For example, our data show that the surprising second chart rank of Mariah Carey's album "The Emancipation Of Mimi" after her rather disappointing single 'It's Like That' (peaking at chart rank 16) was followed by an *abnormal positive stock return* of her label Universal-Vivendi of approximately 2%.

The objective of this study is to gain insight regarding the relevance of product samples in the product introduction process of music and when and how investors update their expectations with regard to a new product to be introduced. We conduct an event study to analyze how the unexpected billboard chart success or failure of a new album influences firm value. Grounding on a unique sample of music albums we model investors' expectations of the chart success of a new album and compare predicted with observed chart success. We find that expectations about the success of an album are formed with respect to the chart performance of the promotional singles and that a failure to meet these expectations leads to negative stock returns. However, unexpectedly high chart positions do not lead to significantly higher valuations of labels. Our findings further reveal that the initial album success is anticipated by investors at a very early stage using single charts one week prior to the release of the initial album charts.

With this study, we contribute to the field of media economics in different ways. Although the effects of new product (pre-) announcements on firm value have been studied previously (e.g., Hendricks and Singhal 1997; Sorescu et al. 2007), little is known about the effects of product samples on firm value when the samples are introduced to the market prior to the main product. By employing the event study methodology within a time period covering the most crucial phase of the introduction process surrounding the album release, we are able to determine when investors react to new information and thus update their evaluation of the stock and how the reactions of investors move stock prices depending on market expectations. For managers both inside and outside of the music industry, this knowledge is valuable because the strategic management of expectations can lead to higher stock prices and, more importantly, may prevent stock price drops if expectations are not met.

We continue with an overview of related literature and provide our hypotheses. We then discuss our methodological approach, our data and the results of the event study. The paper closes with conclusions and implications of our empirical study.

2 Product Introduction Events

2.1 Product Introductions in the Music Industry

The evaluation of future market success is generally a difficult but crucial task for producers and investors. Consumer feedback regarding product samples may serve as an important indicator of the demand for new experience goods (Chellappa and Shivendu 2005; Hirschman and Holbrook 1982). Most music labels follow a standardized product introduction process to reduce consumers' uncertainty with respect to the quality of the product. Promotional singles are distributed several weeks prior to the release of an album; these singles are partly even free of charge through (Internet) radio airplay or music videos to create media awareness and to enable consumers to evaluate the songs.[1] Thus, due to the hedonic nature of the product, labels regularly release singles to support the sales of the subsequent album.

The music industry has several advantages for studying the influence of product samples on firm value using event studies. First, information regarding product success is transparent and publicly available in the music industry via chart rankings that are published in short intervals (e.g., by *Billboard* magazine, Bradlow and Fader 2001). Second, there is a large number of product releases each week, and each release has the character of a venture with a high risk of not recovering its initial investment (production and especially marketing) and a slight chance of becoming a big hit and thus covering the losses of many flops (Krasilovsky and Shemel 2007). Third, a few large stock exchange listed companies (major labels), some of which are parts of technology (e.g., Sony Music) or media (e.g., UMG/Vivendi) conglomerates, domi-

[1] Although the single is regaining importance as a product itself due to growing single-download sales, albums are still generating the majority of music sales (Elberse 2010). In 2012, albums worth US$ 3.86 bn, and singles worth US$ 1.63 bn were sold in the US (both including downloads, Source: RIAA).

nate a large number of small and medium-sized firms (independent labels) that partially distribute their products through the infrastructure of the major labels or other service companies. According to Nielsen Soundscan, the major labels account for about 67% of the value of the U.S. music industry (or even 88% if calculated by distribution ownership;(Billboard 2013). Forth, although the music industry has experienced massive structural changes, the basic mechanisms of product introductions in the music industry, including large marketing investments in the weeks before an album release using promotional singles, have not been affected. Most notably, these changes include the efficient digitalization of music records, which enabled music to be distributed through the internet, but also facilitated illegal reproduction replacing a supposedly substantial proportion of global music sales (Rob and Waldfogel, 2006). As a reaction, music labels introduced so called '360 deals', which include participation in live performances and merchandise, to benefit from a wider range of musicians income streams, partly induced by their marketing investments (Leeds 2007). On the other hand, technological advances reduced the cost of music production, marketing and distribution, leading some artists to abandon major record deals (Graham 2009).

However, rather than reversing economic relationships, these changes have intensified prevalent patterns, such as the superstar phenomenon and the use of (free) samples (Hamlen 1994; Bhattacharjee et al. 2007; Elberse 2008 and 2010). Finally, similar to the movie industry, in which cinematic box office success determines the expected revenues from DVD sales and television licensing (Hennig-Thurau et al. 2007), the chart success of new songs indicates the total monetary success in downstream markets (e.g., the sale of recorded media, concert tickets, merchandising, and music licensing). Thus, album sales are not only an important driver of record label profits but they also serve as an indicator for future revenues. Album releases mark highly important milestones in a musician's life cycle.

2.2 Prior Research on Product Introduction Events

The actual market entry is a highly sensitive stage in any product's life cycle. Hendricks and Singhal (1997) analyze the detrimental effects of delaying the release of a product, which illustrates how negative information during this crucial phase may affect firm value. However, there is little prior research on the direct effects of new information regarding the actual process of product *introductions* (as opposed to product introduction announcements) on the financial value of firms, especially concerning product samples as primary information sources. Table 1 provides an overview of the most relevant literature on product introductions and firm value. If not stated otherwise, we extracted the average abnormal return (AAR) on the event day (-0,+0) and listed significant moderators with an indication of their direction.

Most prior studies have investigated the announcements or pre-announcements of new products as opposed to the success of introductions of the actual products or product samples. Chaney et al. (1991) were the first to analyze the stock market reactions to new product announcements, and showed that returns to new products are more pronounced for technology firms and for original products as opposed to mere remakes of existing products. They also find that stock returns are larger when detailed information is provided in an announcement.

Sorescu et al. (2007) extend these findings by differentiating short and long term effects, showing that capital markets react more sustainably if information provided in new product preannouncements are reliable and if capital markets are continuously being updated about the progress of the product introduction. Their research suggests that there are several events (preannouncements and follow ups) in the introductory process of new products that lead to reactions by investors. In this context, product samples may be a very reliable source of information because investors and consumers can to some extent examine and test a product prior to its market introduction. However, experimental studies have shown that product samples, as opposed to other consumer promotions, may have negative long-term effects on sales and lead to the cannibalization of the main products (Bawa and Shoemaker 2004). It is thus unclear how the success of product samples influences stock market expectations with respect to the overall firm's performance. [2]

Sood and Tellis (2009) analyzed different types of events in the initiation, development and commercialization phases of innovation processes and found that the total average stock returns for an innovation project are 13 times the average returns for a single innovation event ($49 m). By contrast, Kelm et al. (1995) find that returns for events in commercialization phases are lower than for events in other phases. This result may have arisen because market expectations toward a project have already been formed by the time the product is launched; thus, it is crucial to incorporate expectations into the analysis to ensure accurate valuations.

Joshi and Hanssens (2009) applied an expectation model to address this problem. They analyzed new product introductions in the movie industry and found that unexpected box office successes or failures (difference between expectations and actual revenue and absolute profit) explain abnormal returns after movie releases. We extend their research by focusing on the

[2] We assume in this paper that a music single serves as a product sample of the music album. However, due to increased unbundling in the digital world (Elberse 2010) it can be argued that singles and albums are not necessarily complements. While this trend is likely to continue, we argue that higher single sales will also lead to publicity for the corresponding album resulting in additional sales of either the full album or unbundled parts of the album.

analysis of (music) product samples and examining how the success of samples are used as

Table 1: Event Studies on New Products and Innovations

Authors	Event	Effect on Firm Value	
		AAR (0,0)	Moderators
Chaney et al. 1991	Product introductions	+.22%	Technology intensity in the industry (+), degree of innovation (+)
Kelm et al. 1995	Product developments	+.96%[1]	*Pre-announcement*: Technology strength (+) *Announcement*: R&D intensity of the industry (-), concentration within industry (+), firm size (u-shaped)
Hendricks and Singhal 1997	Delays of product introductions	-3.25%[2]	Competition in industry (-), diversification (+), provision of estimate of delay (+)
Kalaignanam et al. 2007	Product development alliances	not reported (+)	Development alliances[3]: Extension of alliance (+), cooperation experience (+), innovativeness of partner (+)
Sorescu et al. 2007	Announcements of new products	n. s.[1]	*Short term*[4]: Information depth of pre-announcement (+), reliability of information (+); *Long term*[4]: Follow-up information (+), reliability of information (+)
Joshi and Hanssens 2009	Theatrical movie release	+.42%[6]	Expectation shock[5] (+), movie profit (+), ad intensity (+)
Fosfuri and Giarratana 2009	Rival's new product announcements	not reported (-)	None
Sood and Tellis 2009	8 innovation event type announcements	+.40%	Firm size
Ransbotham and Mitra 2010	Technology acquisition announcements	-1.26%[7]	Target age (-), recent patents (+), privately held company (+)

[1] CAR (-1,0)
[2] The negative AAR results from the announcement of a product's introduction delay
[3] Effects are asymmetrically distributed depending on the size of the partner.
[4] Short term: Daily return; Long term: One-year return
[5] Difference between estimated and actual open week gross
[6] Difference between above and below average advertising CAR (-2,+2), i.e. the cumulated AARs starting two days prior to and ending two days after the event
[7] Difference of AAR between above and below median age target companies

highly relevant informational resources for estimating the success of later released products (i.e., albums). Further, Joshi and Hannssens (2009) focus on the motion picture industry in which expectations are formed in a different way, as there are no full samples provided to consumers (except movie trailers). Joshi and Hannssens (2009) do not include the "quality" or demand of trailers in their expectation model due to data limitations in the motion picture industry. However, in the music industry labels typically release the “best” single prior to album release for free on radio in order to advertise the new album. Thus, the music industry is a well suited industry for studying the influence of product samples on firm value.

3 Hypotheses

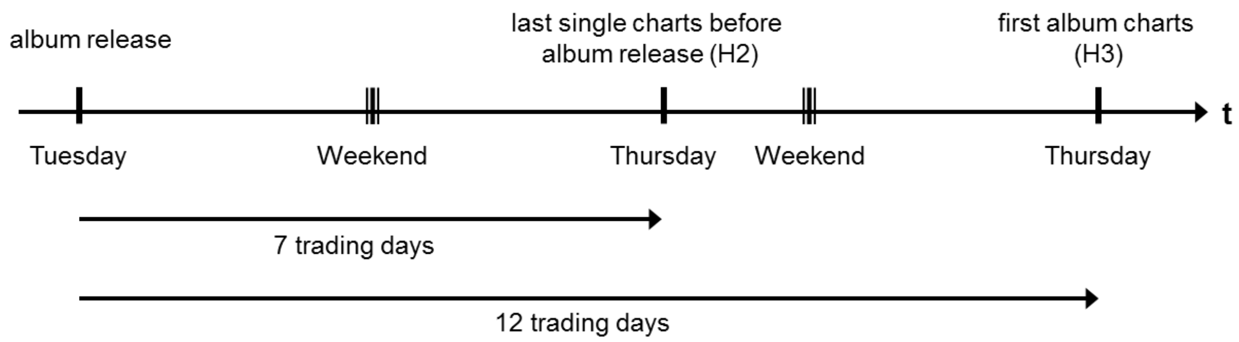
A number of sources provide public information regarding the success of music singles and albums. Shortly after the release of a song as a single, the first charts reflect the actual demand of consumers for the product. This occurs several weeks prior to the release of the album. Airplay, DJ, and sales charts are published and provide information about the success of new releases. We argue that, at least for typical pop records, the promotional singles act as product samples for consumers and can thus be used as indicators of the future success of the main products (i.e., the albums). Thus, single charts prior to album release already contain considerably reliable information about probable chart ranks and can influence the expectations of investors. However, only *new* information will lead to adjustments of investors’ evaluations. Investors form expectations with respect to a new release based on market data. Therefore, they will expect a new single of a super star to enter the charts at a high position indicating a bestselling forthcoming album. Consequently, the capital market will only react if the success of the new album is either *unexpectedly* high or low. If the expectations are simply met, capital market theory predicts no changes due to the absence of new information.

Unexpected rankings: Previous research grounding on prospect theory has shown that investors are usually more sensitive towards negative news due to loss aversion. This sensitivity is sometimes referred to as the negativity bias (Akhtar 2012; Kahneman and Tversky 1979; Sood and Tellis 2009; Tellis and Johnson 2007). Therefore, we expect stronger capital market reactions for flops than for hits. We use “hits” and “flops” to refer to unexpectedly high-/low-ranking records. According to this definition, a flop may be a profitable title, but may not meet the (estimated) expectations. Analogously, a hit may be a title that did not rank very highly in the charts, but has exceeded its (low) expectations (see method section). Referring to the theoretical framework of prospect theory, we assume that stocks of labels facing unexpectedly low-ranked albums will suffer more than stocks associated with unexpectedly high-ranked albums will gain, leading to hypotheses 1:

<u>H1</u>: The magnitude of negative cumulative abnormal returns will be higher for unexpectedly low-ranked albums compared to the positive cumulative abnormal returns of unexpectedly high-ranked albums.

Timing: We formulate two hypotheses regarding the timing of new chart information. In the U.S., singles and albums are typically released on Tuesdays, and the corresponding first week charts are published on Thursdays of the week after the following week (i.e., 16 days later).[3] Figure 1 shows the context of album release, i.e. relevant single chart, and album chart publications.

Fig. 1: Timeline of relevant charts releases



Higher initial chart rankings (i.e., strong demand of early adopters) correspond to higher levels of acceptance of the song by followers (Strobl and Tucker 2000). Furthermore, high chart positions reflect higher demand which leads to herding behavior of consumers (Salganik, Dodds, and Watts 2006). Therefore, labels attempt to optimize the initial chart ranks of their artists using advertising and promotion measures (e.g., by encouraging airplay). Labels thus rely on daily trend chart information provided by market research services (e.g., Nielsen SoundScan), which approximates the official chart positions. Official chart movements are also available to investors of music labels and can be used to estimate future cash flows from an album and related products. Album success may also affect the artist's brand value and thereby the cash flow of their future releases. Thus, if singles act as product samples and the album is a milestone in the process of artist brand value building, the ranking of a single may change the expectations about the performance of the album, which will be reflected in share prices in an efficient market. Hence, a rational investor will use the most recent information about a product sample (i.e., single charts) to gauge the future success of the main product. We expect that an album's sales expectations are updated one week before the release of the

[3] The week after the release week is referred to as the *first chart week*.

album charts, when the *last single chart ranks* (prior to the first album charts) publicly indicate the potential success of the album. Hence, we hypothesize:

<u>H2</u>: Positive (negative) abnormal returns will be observed on the Thursday on which the last single charts are made available prior to the album release for unexpectedly high- (low-) ranked albums.

The expectations for an album increase with the performance of a single release. Of course, there can still be surprising discrepancies between single and album chart performance that will cause investors to re-evaluate the stock. If these discrepancies are sufficiently high to change the expectations of the investors regarding the financial contribution of the album, the re-evaluation should instantly be reflected in the share price. Therefore, we also expect to observe abnormal returns for the *first album charts* (week 3) if the chart rank of the album does not correspond to the investors' expectations that are formed based on the single chart performance and other album characteristics.

<u>H3a</u>: Positive (negative) abnormal returns will be observed on the Thursday on which the first album charts are made available for unexpectedly high- (low-) ranked albums.

However, because the majority of the expectation revisions have already been made after the release of the single charts (week 2), the ARs surrounding the album chart release will be smaller.

H3b: The magnitude of these abnormal returns will be smaller than those of the single charts released a week earlier (H2).

4 Expectation model

4.1 Relevance of Expectations in Event Studies

According to the theory of efficient capital markets, new information will lead to an immediate reaction in stock prices, reflecting changes in market expectations (Fama et al. 1969). We use the well-established event study methodology to obtain firm-specific returns (abnormal returns or ARs) related to events (new chart information). Because the expected positive and negative returns would simply mutually be cancelled out when calculating average abnormal returns (AARs), we divided our sample into a group of albums that outperformed (hits) and a group that underperformed (flops) in comparison with the *expectations* of the market. According to the theory of efficient capital markets, these expectations are based on all relevant market information available to investors, including the past successes of the artists, the marketing abilities of the labels and, most importantly, the performance of product samples (i.e., single releases). We model these expectations ex post using an econometric model of album chart ranks. Predictions of this model approximate market expectations of chart ranks based on the included variables. Positive or negative differences between predictions and actual chart positions indicate the extent to which an actual chart rank is a positive or negative surprise with respect to prior expectations.

The event study methodology quantifies the effects these surprises have on the firm value of the stock listed labels, by examining the statistical significance of daily abnormal stock returns averaged over as many occurrences of the respective event (e.g., chart releases) as can be obtained. Other influences not correlated with the event, which may affect abnormal returns, represent 'noise' in the statistical sense and are mutually cancelled out. To further reduce this noise, it is common practice to exclude observations where so called 'confounding events' occur, i.e., new information unrelated to the event under study, but likely to affect abnormal returns. It is thereby possible to include stocks of conglomerates (such as Sony Music/Sony BMG, Universal Music Group/Vivendi) in the analysis that generate only a fraction of their cash flows with music.

4.2 Data

In order to estimate the expectation model, we combine chart data with individual information regarding 853 albums in the sample collected from multiple sources (RIAA [riaa.com], allmusic.com, grammy.com). We use Billboard Top 200 album chart ranks, Billboard Hot 100 single chart ranks from January 2004 to February 2006, which are derived from the physical (i.e., CDs, Vinyl records, etc.) and as of February 2005 also digital (e.g., iTunes and Napster downloads) album and single sales, respectively.

To compare the ARs of unexpectedly under- and outperforming albums, we estimate a model to reconstruct the expectations of the capital markets regarding potential chart success prior to the release of the album chart. The dependent variable is the first Billboard Top 200 album chart rank after the release, which we have coded as an ordinal variable with five chart categories ($Charts_l^{album}$, where l denotes the album, see table 2) to account for the non-linear relationship between sales and chart ranks (Chevalier and Goolsbee 2003). Higher chart ranks represent disproportionally higher sales per release than lower ranks due to the specific supply and demand characteristics of artistic markets; this situation is generally referred to as the superstar phenomenon (Adler 1985; Giles 2006; Hamlen 1994; Rosen 1981). This situation may be problematic when sales charts are used directly as a measure of financial success in this study setting. By relying on these charts, we (and likewise the capital markets) have limited information on the exact levels of sales and only know their order. Therefore, we cannot derive the functional relationship between chart ranks and sales. Thus, we account for the underlying skewed distribution of record sales by categorizing the chart positions. This categorization also accounts for possible jumps or breaches between different chart slots. For example, climbing one chart rank and reaching a higher slot (e.g., rank 11 to 10) may have a greater effect than simply a one-rank increase (e.g., rank 8 to 7) because the release becomes available in media and retail stores that cover or promote the higher slot (e.g., radio top 10 countdowns), and this promotion and coverage may lead to higher product awareness and availability (Connolly et al. 2006). Hence, we formed our chart categories to represent common chart rankings in the music industry (e.g., top 5, top 10, top 20, top 40 and top 200 for album charts and, similarly, the top 10, top 40, and top 100 for singles[4]). This scale also solves the problem of how to treat unranked titles: Releases that are not ranked form the (lowest) base categories of the ordinal charts variables.

Table 2: Coding of chart variables

Variable	Highest album chart rank $Charts_l^{album}$			Highest single chart rank $Charts_{lj}^{single}$		
Categories	Top 200 album	k	n_k	Hot 100 Singles	j	n_j
	Ranks 1-5	5	187	Ranks 1-10	3	35
	Ranks 6-10	4	80			
	Ranks 11-20	3	125	Ranks 11-40	2	77
	Ranks 21-40	2	150			
	Ranks 41-200	1	150	Ranks 41-100	1	143
	No Rank	base	161	No Rank	base	598
		$\sum$	853		$\sum$	853

To predict album chart ranks, we use single chart information and control for a range of artist- and album-related measures (see table 3 for descriptive statistics and the correlation matrix of the data): The independent variables $Charts_{lj}^{single}$ take the value 1 for the respective peak chart rank category j of the highest-ranking single in the Billboard Hot 100 Singles from the considered album l prior to the release of the album chart (table 2).[5] The variable *Amazonstars*

[4] This configuration is modeled along the typical chart categories used by Billboard. It resembles the thresholds the analysts are confronted with when assessing chart success of either singles or albums.

[5] Since in the sample only 23 albums had two singles and only two albums had three singles released prior to the album release, we only included the best performing single peak rank as an explanatory variable.

(mean=4.1, s. d.=.57) represents the mean of the customer ratings of an album on Amazon.com as a measure of perceived product quality. We also included a squared *Amazonstars* variable (mean=16.7, s. d.=4.1) to account for non-linear quality effects.[6] *ln(Prior_albums)* (mean=1.4, s. d.=1.3) is the natural log of the number of albums an artist formation has released prior to the release of the respective album. We include two variables that measure prior success and star power as the performance of an established band might be of more interest than of a band that barely entered the Billboard Top 200 once: $ln(Gold\_platinum)$ (mean=-14.0, s. d.=14.8) is the natural log of the number of gold and platinum records a formation has been awarded prior to an album release (platinum records receive a double weight because they represent sales of 1 m records as opposed to 500 k for gold records).[7] *Grammys* (mean=.7, s. d.=2.0) is the number of Grammy awards a formation has received prior to the release of an album. *Pop* (31%), *Rock* (28%), and *Rap* (15%) are dummy variables reflecting the genre of an album; these variables take the value 1 for the respective genre (pop, rock/heavy metal, and rap/hip-hop) and 0 otherwise (26%). We control for the distribution power of major labels by including dummy variables for the major labels. *Warner* (18%), *EMI* (11%), and *Conglomerate* (55%) are dummy variables taking the value 1 if an album has been released by Warner Music/WMG, EMI Music, or by one of the two major labels that were owned by conglomerates during the study (Sony Music/Sony BMG, Universal Music Group/Vivendi).[8] The base category are independent labels (16%). Finally, $Foreign\_country$ (13%) takes the value 1 if an artist or formation is not from an English-speaking country (U.S., Canada, U.K., Australia) and 0 otherwise.

[6] We note that the relation of chart positions and the ranking of an album at Amazon might be subject to endogeneity. However, the primary model objective is a prediction task (and not obtaining consistent parameter estimates). Hence, we follow Ebbes, Papies and van Heerde (2011) who recommend refraining from correcting for endogeneity with IV estimation when prediction is the main modeling objective.

[7] We used the natural logs of *Prior_albums* and *Gold_platinum* to account for the diminishing returns that we found to be prevalent in the data. With an increasing number of albums (awards), the amount to which each additional album (award) contributes to the probability of higher or lower chart ranks is assumed to decrease.

[8] We have combined Sony Music and UMG into one variable, because according to a Chow test, coefficients on separate dummy variables have shown to be indifferent from one another in the model (p=.77). This combination is plausible because albums from these conglomerates seem to have similar characteristics with respect to chart success, whereas the more specialized and less integrated major labels Warner and EMI have distinctive properties.

Table 3: Descriptive statistics and correlation matrix of expectation model data

	Variables	N	Mean	S. d.	Correlations												
					1.	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**	**10.**	**11.**	**12.**	**13.**
1.	Top 200 album	692	34.025	46.338	1												
2.	Hot 100 singles	255	48.267	29.149	.217	1											
3.	Amazonstars	853	4.067	.550	.119	.264	1										
4.	Prior_albums	853	8.461	9.682	-.063	.006	-.014	1									
5.	Gold	853	3.566	5.605	-.086	.051	.000	.361	1								
6.	Platinum	853	2.882	6.549	-.048	.012	.002	.255	.812	1							
7.	Grammys	853	.686	1.697	-.117	-.003	-.022	.373	.353	.303	1						
8.	Pop	853	.309	.463	-.001	-.158	.012	.070	.161	.052	.137	1					
9.	Rock	853	.285	.357	.051	.140	.039	.050	-.029	-.002	-.021	-.423	1				
10.	Rap	853	.149	.460	-.109	-.100	-.233	-.132	-.098	-.068	-.079	-.280	-.264	1			
11.	Warner	853	.179	.375	-.039	-.008	.028	-.046	-.051	-.036	.029	-.075	.125	-.024	1		
12.	EMI	853	.107	.298	.087	.124	-.034	.079	.108	.030	.042	.122	-.041	-.059	-.162	1	
13.	Conglomerate	853	.549	.466	-.106	-.089	-.029	-.005	.075	.099	.030	.042	-.117	.088	-.515	-.381	1
14.	Foreign_country	853	.131	.228	.127	-.046	.082	-.019	-.095	-.106	-.105	.055	.008	-.153	-.019	.068	-.136

4.3 Model estimation

To estimate the expectation model, we use ordinal regression with a complementary log-log link function from the class of generalized linear models (GLM) because the largest category of the dependent variable is the highest rank category in our data:

$$\begin{aligned}
&\eta_{lk} = \log(-\log(1-\gamma_{lk})) = \\
&\theta_k - [\textstyle\sum_{j=1}^{3}\beta_j(Charts_{lj}^{single}) + \beta_4(Amazonstars_l) + \beta_5(Amazonstars_l^2) + \beta_6 ln(Prior_albums_l) + \\
&+\beta_7 ln(Gold_platinum_l) + \beta_8(Grammys_l) + \beta_9(Pop_l) + \beta_{10}(Rock_l) + \beta_{11}(Rap_l) + \beta_{12}(Warner_l) + \\
&+\beta_{13}(EMI_l) + \beta_{14}(Conglomerate_l) + \beta_{15}(Foreign_country_l)]
\end{aligned} \tag{1}$$

with $\gamma_{lk} = \Pr ob\left(Charts_l^{album} \le k \mid \mathbf{x}_l\right)$ for $k = 1,\ldots,5$

Table 4 shows the estimation results.

According to the LR test, the joint model is highly significant, and the pseudo R^2 values suggest a reasonably good model fit. Multicollinearity among independent variables does not seem to be a severe problem in modeling the expectations. The correlation between *Amazonstars* and $Amazonstars^2$ is naturally high (r=.975, VIF=21.4 and 21.1). However, since both coefficients are significant, collinearity is not detrimental. Apart from that, the highest correlations are between $ln(Gold\_platinum)$ and $ln(Prior\_albums)$ (r=.441) and between $ln(Gold\_platinum)$ and *Grammys* (r=.306). However, apart from the quality variables (*Amazonstars* and $Amazonstars^2$) there are no VIFs higher than 1.60. Finally, we conducted an out-of-sample hold-out prediction test to verify that the model serves as a reasonable approximation of market expectations. We re-estimated the model using a sub-sample of 700 randomly selected observations. Using this model, we predicted the chart categories for the 153 observations of the hold-out sample. The model coefficients did not significantly differ from our final model, which utilizes all available observations. The out-of-sample hit rate of the predicted categories was 42.5%.

Table 4: Ordinal regression results of the dependent variable Charts^{album} (complementary log-log link function)

Independent variables	Parameter estimate	Standard error	Wald coefficient
$Charts^{single}_{Top41-100}$	.758***	.122	38.382
$Charts^{single}_{Top11-40}$	1.129***	.185	37.218
$Charts^{single}_{Top1-10}$	1.374***	.304	20.408
Amazonstars	.936**	.303	9.564
Amazonstars-squared	-.182***	.043	18.142
$\ln(Prior\_albums)$	-.122**	.039	9.916
$\ln(Gold\_platinum)$	.018***	.003	31.314
Grammys	.104***	.027	15.210
Pop	.128	.108	1.411
Rock	.145	.106	1.858
Rap	.429**	.149	8.258
Warner	.556***	.133	17.393
EMI	.236	.150	2.470
Conglomerate	.920***	.114	65.276
$Foreign\_country$	-.977***	.120	66.337
** p < .01, *** p < .001 (n=853)			
LRT Chi-square (15)			562.4 (p<.001)
Pearson Chi-square (3,825)			4,402.0 (p<.001)
Cox and Snell / McFadden R^2			.483 / .187

For a better understanding of the influence the single chart rank has on the expectations with regards to the subsequent album chart rank, we conduct an analysis of the marginal effects of the single chart rank. We use the expectation model to predict the probabilities for each outcome of Charts^{album} for each level of Charts^{single} (holding all other variables at their means). The following results in table 5 hold for an average album in the dataset.

Table 5: Predicted probabilities for each category of $Charts^{album}$ by levels of $Charts^{single}$

	k		Charts^{single}			
			No Rank	Ranks 41-100	Ranks 11-40	Ranks 1-10
Charts^{album}	5	Ranks 1-5	.141	.329	.435	.503
	4	Ranks 6-10	.085	.106	.103	.098
	3	Ranks 11-20	.148	.148	.134	.122
	2	Ranks 21-40	.190	.154	.130	.114
	1	Ranks 41-200	.211	.142	.111	.093
	base	No Rank	.226	.122	.087	.070

Calculating the album chart slot expectation for each level of Charts^{single} through:

$$E(Charts_l^{album}) = \sum\nolimits_{k=0}^{5} [\hat{\gamma}_{lk} \cdot Charts_l^{album}] \tag{2}$$

results in table 6:

Table 6: Marginal effects of $Charts^{single}$ on $Charts^{album}$

	Charts^{single}			
	No Rank	Ranks 41-100	Ranks 11-40	Ranks 1-10
$E(Charts_l^{album})$	2.078	2.962	3.359	3.594
Marginal effect	-	.884	.397	.235

An average single peaking in 'ranks 41-100' compared to 'no Top 100 ranking' increases the expected album chart slot from 21-40 ($E(Charts_l^{album})$ =2.1) to 11-20 ($E(Charts_l^{album})$ =3.0). Going from single chart ranks 41-100 to ranks 11-40 does not result in an increase to a higher album chart slot. Moving from single chart ranks 11-40 to Top 10 increases the expected album chart slot from 11-20 to 6-10.

4.4 Discussion

All coefficients have the expected signs. The coefficients of the dummies of the single charts increase with each category, but the increases diminish. Thus, the probability for a strong album chart rank is higher for albums with chart-listed singles. The probability increases if the single chart rank is higher (categories 2 and 3), but the increase is less than the probability increase associated with being listed in the single charts, at all. We find an inverted U-shaped non-linear relationship for *Amazonstars*, suggesting higher rankings for albums which have neither very poor nor exceptionally good average quality ratings. This finding might be due to possibly higher variance in the reviews. Sun (2012) reports that niche products that some consumers love and others hate are often associated with a high variance of ratings. Based on the informational content of reviews, a higher variance of reviews $Amazonstars$ may in turn lead to a higher subsequent demand, because it spurs curiosity and may lead to customer and media controversy.

The star power and quality-related variables $\ln(Gold\_platinum)$ and $Grammys$ capture the effect of prior successes and have a strong positive effect. The negative sign of $\ln(Prior\_albums)$ may indicate that (holding prior success constant) younger (more trendy) musicians have higher average chart rankings than older bands that may already have completed the growth stage of their 'artist life cycles'.[9] Moreover, domestic rap albums from major labels have the highest probability for high album chart entries. With the exception of EMI, we find a significant impact of the major label's dummy variables *Warner* and *Conglomerate* (Sony and Universal Music) on the album's chart success. Finally, we find a significant disadvantage with respect to the album's chart success if the album is not from an English-speaking country.

The model results are used to calculate the deviations of the expected from the observed chart position and to assign unexpected hits and unexpected flops to the respective group for the event study. If the prediction error is greater than zero ($\hat{\varepsilon}_l > 0$), which indicates that the true or realized chart category is higher than expected, the album is allocated to the group of unexpected hits, and vice versa for unexpected flops. We define the prediction error as follows:

$$\hat{\varepsilon}_l = \underbrace{Charts_l^{album}}_{actual\,category} - \underbrace{\sum\nolimits_{k=0}^{5}[\hat{\gamma}_{lk} \cdot Charts_l^{album}]}_{\text{category expectation}}. \tag{3}$$

5 Event Study

5.1 Event study methodology

In most event studies, the market model, which is a simple regression of the return of a firm on a market index return, is used to predict abnormal returns (McWilliams and Siegel 1997):

$$AR_{it} = \hat{e}_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i r_{Mt} \tag{4}$$

- R_{it} is the actual return of stock i on trading day t
- $\hat{\alpha}_i$ is the autonomous return of stock i
- $\hat{\beta}_i$ is the systematic (market) risk factor of stock i
- r_{Mt} is the return of the market portfolio M on trading day t.

[9] In our dataset, the 395 albums of bands that have released more than 4 albums (median) have a mean initial chart category of 2.3 compared with 2.6 for the 458 albums that have released 4 or fewer albums (p<.001).

To draw inferences regarding the hypotheses, the abnormal returns (AR) must be aggregated over all firms in the sample to test their statistical significance. The simplest method is to consider average abnormal returns (AAR) and conduct ordinary cross-sectional t-tests.

$$AAR_t = \frac{1}{I}\sum_{i=1}^{I} AR_{it} \tag{5}$$

The t-statistics can be obtained following Boehmer et al. (1991):

$$T_1 = \frac{AAR_t}{\sqrt{\frac{s^2}{I-1}}} \tag{6}$$

with $s^2 = \frac{1}{I}\sum_{i=1}^{I}(AR_{it} - AAR_t)^2$

To unveil the effects that manifest over several trading days, the AARs are cumulated over the event window (L_2) to obtain cumulated average abnormal returns (CAR).

$$CAR_{t_2,t_3} = \sum_{t=t_2}^{t_3} AAR_t \tag{7}$$

The respective t-distributed test statistic is as follows (Hendricks and Singhal 1997):

$$T_2 = \frac{CAR_{t_2,t_3}}{\sqrt{\sum_{t=t_2}^{t_3} S^2_{AAR_t}}} \tag{8}$$

To control for heteroscedastic ARs on the event day and to prevent highly volatile stocks from dominating the tests, standardized abnormal returns (SAR) are calculated following the method by Dodd and Warner (1983):

$$SAR_{it} = \frac{AR_{it}}{SD_{it}} \tag{9}$$

SD_{it} is the estimated forecast standard deviation of the abnormal returns.

$$SD_{it} = \sqrt{\left(s_{it}^2\left(1 + \frac{1}{L_1} \cdot \frac{(r_{Mt} - \overline{r}_{Mt})^2}{\sum_{\tau=t_0}^{t_1}(r_{M\tau} - \overline{r}_{Mt_1})^2}\right)\right)} \tag{10}$$

with $s_{it}^2 = \frac{1}{L_1} \sum_{\tau=t_o}^{t_1} (AR_{i\tau})^2$

The accumulation of the SARs to obtain standardized average abnormal returns (SAAR) is analogous to equation (4):

$$SAAR_t = \frac{1}{I} \sum_{i=1}^{I} SAR_{it} \tag{11}$$

The corresponding test statistic is formed with the now constant standard deviation $[(L_1 - 2)/(L_1 - 4)]^{0,5}$ of the SAR:

$$Z = \frac{SAAR_t}{[(L_1 - 2)/(L_1 - 4)]^{0,5}} \cdot \sqrt{I} \tag{12}$$

This test statistic follows a t-distribution, as well (Dodd and Warner 1983).

Both significance tests require that the ARs are not correlated. The test statistic for the SAARs underlies the implicit assumption that the event-induced variance is insignificant.

5.2 Data

We use the event study to control for economy- or industry-wide price movements to obtain firm-specific returns. To calibrate the AR model, we choose a prediction window of 250 trading days (L_1) ending 20 trading days before the event (the day of the initial album chart release). By defining the event window (L_2) from seven trading days before the event to three trading days after the event, we are able to capture all effects that occur from the last pre-album single chart release to the album chart release. We chose the DJ Stoxx Media 1800 as the market index and collected share prices and index return data from *Datastream*.

Since stock returns can only be retrieved for stock exchange listed companies only those 712 albums from major labels could be considered in the event study. Because record labels release multiple albums on one day, the sign of the errors from the expectations model may differ across the albums released by one company on one Tuesday. In these cases and in case the event windows overlap, the abnormal returns of the respective music labels have been eliminated from the sample, which decreases the sample size. Moreover, confounding events have been eliminated from the sample for each individual trading day. The following types of confounding events have been searched for: (1) financial results (e.g., company reports, earnings warnings), (2) co-operations and significant contracts, (3) changes in management, (4) changes in analyst recommendations, (5) mergers and acquisitions activity, (6) other (e.g., purchase of licenses, other contracts, investigations against the company, court decisions, restructuring announcements), (7) financing measures (e.g., issuance of shares or bonds), and (8) outliers (absolute returns that are larger than 3 times their standard deviation).[10] Therefore, the sample sizes vary for each day, ranging between 145 and 159 albums.

5.3 Results

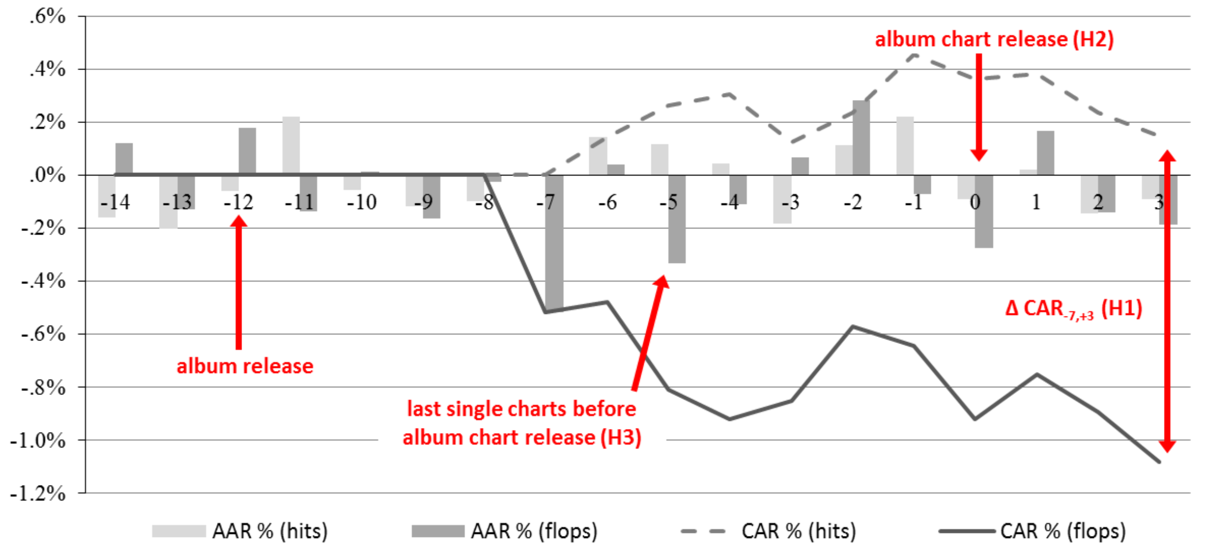
Table 4 shows the event study results within the two groups of the unexpected hits and flops for the period beginning two trading weeks prior to the album chart release and ending three trading days after the release of the album chart.

Figure 2 presents a visual representation of the results. We observe that the cumulative average abnormal returns (CARs) within the flops group are (with the exception of trading day -2) significantly negative beginning seven trading days before the album chart release. Within the event window the CARs (–7; +3) for the flops group accrue to 1.08% ($p<.05$). The CARs are significant (at least at the 10% significance level) throughout this period, with the exception of the Tuesday of the first chart week, where a positive AAR of .28% ($p<.10$) may represent a slight reversal effect. On the contrary, during the event period the CARs of the hits group are all insignificantly different from zero. The differences (ΔCAR) between the CARs of the hits and flops groups are statistically significant over the whole event window ($p<.10$), with two exceptions: the Tuesday of the first chart week (-2) and the Monday after the album release (2). The t-values of the respective tests are lower due to the high standard errors of the insignificant CARs of the hits group.[11] These differences peak on the Thursday of the third week when the album charts are released (0).

[10] Sources used for confounding events identification: IR news on the corporate websites of major labels and press releases from a broad range of publications via the press database LexisNexis; for U.S.-listed companies: releases of SEC forms 10-K (annual report), 10-Q (quarterly report), and 8-K (current report filing) from the EDGAR database (www.sec.gov/edgar). Album announcements themselves were not eliminated as they are not identifiable. Information on upcoming albums usually diffuse into the market over time (as opposed to dedicated product announcements in the technology sector). Any piece of information adds marginally to the set of information for the investors. This also applies to single releases.

[11] We used t-tests assuming unequal variances and sample sizes for the difference tests. We used the Welch–Satterthwaite equation for calculating the degrees of freedom.

Figure 2: AARs and CARs over the event period (t=trading days)



Thus our data supports H1 of asymmetric reactions of investors toward positive and negative information, as suggested by prospect theory and previously observed for movies (Kahneman and Tversky 1979; Joshi and Hanssens 2008), because we observe significant negative effects for unexpectedly low chart ranks, whereas unexpectedly high chart ranks are not rewarded with significant positive AARs.

During the week of the album release (week 1) there is only one significantly positive AAR of .23% ($p<.10$) in the hits group on the Wednesday one day after the album release (-11). Other than that there are no significant AARs in the hits group. We find a significant negative AAR of -.33% ($p<.05$) in the group of underperforming albums one week after the album has been released (week 2) on the day of the single charts release (-5) providing support for the "negative side" of H2. Interestingly, however, the largest one day AAR of -.52% ($p<.001$) can be observed two days earlier (-7). As a robustness test we also calculated standardized average abnormal returns (SAAR) that account for heteroscedastic ARs and conducted non-parametric sign tests (as indicated by the N+/N- columns in table 7), which substantially confirmed the results obtained by ordinary tests of AARs. This result is further evidence for the "negative side" of H2 and indicates that negative ARs will be observed at (or near) the Thursday on which the last single charts are made available prior to the album release, though only for unexpectedly low ranked albums. Interestingly, the market seems to partly anticipate the new information provided by the single charts, which suggests insider information that may be based on trend charts provided by market research companies.

In week 3, on the day of the album chart release (0), the average abnormal return for the flops group is -.28% (p<.05), providing support for the hypothesis that unexpected album charts provide new information leading to abnormal returns (H3a). However, the cumulative abnormal returns (the sum of the AARs over the respective days) for the single chart release week (CAR(-7,-3)=-.85, S.E.=.10) is significantly larger in magnitude than those of the album chart week (CAR(-2,+2)=-.04, S.E.=.09, diff.=-.81, p<.10); this result is in accordance with the hypothesis that most of the information regarding the success of the album is already included in the single charts in week 2 (H3b).[12]

Thus, the results suggest that there are two main points in time at which relevant information becomes available. In week 2, single charts indicate the success of product samples and provide the basis for estimating the success of albums (H3a). The effect of the album charts is much lower; this result suggests that a product sample has provided most of the information needed for updating expectations on product introduction success (H3b).

[12] As a standard procedure we also conducted an event window sensitivity analysis. Therefore, we test three alternative event windows with -1;+1, -2;+2, and -3;+3 trading days around the event (0). The CAARs for all these event windows are insignificant. Table 8 shows the results in detail. These findings further support the hypotheses.

Further, we regressed the CAR_i(-7,3) on the residuals from the expectation model in order to test whether we find a linear relationship. However, the result is an insignificant model (F=0.03) and an insignificant coefficient of the expectation error (t=- 0.18).

Table 7: Event study results

		Unexpectedly high chart ranks						Unexpectedly low chart ranks						Difference	
t	**Week day**	**AAR %**	**S. E.**	**CAR %**	**S. E.**	**N**	**N+**	**AAR %**	**S. E.**	**CAR %**	**S. E.**	**N**	**N-**	**ΔCAR%**	**S. E.**
Week 1: Release of the album (Tuesday)															
-14	Friday	-.153	(.210)			43	18	.117	(.197)			60	32		
-13	Monday	-.189	(.222)			45	18	-.135	(.151)			59	35*		
-12	Tuesday	-.050	(.178)			45	23	.172	(.175)			56	23		
-11	Wednesday	.234*	(.178)			43	26*	-.154	(.200)			55	33*		
-10	Thursday	-.054	(.210)			43	21	.014	(.192)			55	26		
-9	Friday	-.108	(.189)			44	18	-.166	(.163)			57	31		
Week 2: Release of last single charts before album charts (Thursday)															
-8	Monday	-.098	(.166)			41	20	-.025	(.166)			60	30		
-7	Tuesday	.000	(.233)	.000	(.233)	46	24	-.516***	(.186)	-.516***	(.186)	58	36**	.516**	(.298)
-6	Wednesday	.145	(.212)	.145	(.317)	45	23	.038	(.196)	-.478**	(.269)	59	29	.622*	(.416)
-5	Thursday	.116	(.177)	.261	(.376)	41	21	-.332**	(.180)	-.809***	(.321)	60	32	1.071**	(.495)
-4	Friday	.043	(.237)	.304	(.430)	45	23	-.109	(.193)	-.919***	(.377)	59	32	1.223**	(.572)
-3	Monday	-.181	(.162)	.123	(.464)	44	17	.067	(.182)	-.852**	(.422)	58	30	.975*	(.627)
Week 3: Release of first album charts (Thursday)															
-2	Tuesday	.111	(.220)	.234	(.519)	43	22	.282*	(.191)	-.570	(.450)	62	31	.804	(.687)
-1	Wednesday	.220	(.247)	.454	(.598)	39	19	-.073	(.176)	-.643*	(.494)	59	28	1.097*	(.776)
0	Thursday	-.090	(.215)	.364	(.608)	43	24	-.276**	(.158)	-.919**	(.527)	57	37**	1.283*	(.805)
1	Friday	.019	(.193)	.383	(.625)	45	23	.168	(.189)	-.751*	(.547)	60	31	1.134*	(.831)
2	Monday	-.145	(.212)	.238	(.654)	46	18	-.141	(.152)	-.892*	(.591)	55	32	1.129	(.881)
3	Tuesday	-.092	(.182)	.146	(.693)	44	21	-.188	(.155)	-1.080**	(.596)	58	30	1.226*	(.914)

* p < .10, ** p < .05, *** p < .01, one-sided tests
t = Number of trading days counted from album release

6 Conclusion

We extend prior research on how new information regarding product introductions affects firm value by focusing on product samples as primary information sources. In the music industry, singles serve as a major promotional tool to initiate the demand for later released music albums. We have reconstructed capital market expectations regarding the chart success of the albums using an expectation model that incorporated the performance of promotional singles and analyzed the effects of deviations from these expectations on the stock valuation of the labels. Our hypotheses were largely supported by the data. In particular, we found that labels that introduce outperforming albums gain considerable firm value over companies that introduce underperforming albums. This effect is significant for a period of eleven trading days (with one exception). As hypothesized, we find that the magnitude of the abnormal returns is greater for negative expectation revisions than for positive expectation revisions (H1). We only found significant abnormal returns during the chart release weeks (weeks 2 and 3) for the group of disappointing albums; this result clearly supports this hypothesis.

With respect to the timing of the effects, we find that labels introducing underperforming albums significantly lose firm value near the days of the chart release. Most of these negative abnormal returns are observed in the week before the album charts are released when the single charts are made publish (H2). The loss of firm value on the day of the release of the album charts is smaller (H3).

These findings help us to understand the process of firm value generation during the introduction phase of new products. Our results provide specific insight regarding the role of product samples, which clearly formed the basis for expectations with regard to the success of the main product. Firm value will be affected only when the main product substantially fails to meet the expectations that were formed in the market when the success of the product sample was evaluated. In accordance with prospect theory, investors in the capital market tend to react more strongly to negative news, i.e., when the main product (the album) misses the expectations built by the product sample (the single), as opposed to main products that exceed expectations.

This study has important implications for managing the introduction process of new products. Companies may be tempted to raise expectations before a product is introduced to the market. If the product sample is successful, product awareness is raised and creates publicity. However, there is a severe risk that a company may fail to meet these expectations. Our event study provided evidence that product introductions that fail to confirm expectations may lead to a considerable decrease in firm value. Therefore, new products should meet the expectations that were formed on the basis of promotional tools. Product samples can be used to decrease perceived consumption risks and preference uncertainty but should be chosen as sustainable representations of the main products.

Music managers should be aware of the fact that their actions are under the scrutiny of the capital market and that they influence market expectations of album success by manipulating chart success of respective promotional singles. Our results show that disappointments of expectations with album success, which were raised by single success may decrease firm value or at least create stock price volatility due to the alternating raises and falls of capital market expectations. For value orientated managers two strategies to avoid stock price volatility and firm value destruction come to mind. First, to avoid disappointments with album success, managers should concentrate marketing investments on albums that had the most successful singles prior to album release. And second, they should avoid investing too much of their marketing budget in promotional singles that are extracted from albums, which they do not expect to match the expectations raised by the promoted singles.

However, these considerations have to be made, of course, in light of expected cash flows from single and album sales, as well as effects on the brands of the artists. If a large fraction of the prospected future profits of an artist are expected to be generated by single record sales, management of album success expectations should not be the main focus. If, on the other hand, an artist is expected to make much of their money with album sales and other subsequent products the label participates in (e. g., royalites, live performances, merchandise), managing capital market expectations may be vital. Our results prompt further research questions. As noted above, product trials are particularly important for experience goods, such as music, to enable consumers to “experience” and evaluate products before making a purchase. Moreover, information regarding the demand for sample products is readily available in the music industry via single chart rankings. Thus, further studies in the field of media economics should ascertain whether the results are generalizable to other experience or non-experience goods and identify additional indicators of product sample demand, such as downloads of movie trailers or software trials.

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