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The Effect of P2P File Sharing on Music Markets: A Survival Analysis of Albums on Ranking Charts[1]

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Abstract

Recent technological and market forces have profoundly impacted the music industry. Emphasizing threats from peer-to-peer (P2P) technologies, the industry continues to seek sanctions against individuals who offer significant number of songs for others to copy. Yet there is little rigorous empirical analysis of the impacts of online sharing on the success of music products. Combining data on the performance of music albums on the Billboard charts with file sharing data from a popular network, we: 1) assess the impact of recent developments related to the music industry on survival of music albums on the charts, and 2) evaluate the specific impact of P2P sharing on an album's survival on the charts. In the post P2P era, we find significantly reduced chart survival. The second phase of our study isolates the impact of file sharing on album survival. We find that sharing does not seem to hurt the survival of albums.

Key words: peer-to-peer, digitized music, online file sharing, survival**.**

1. Introduction

Recent advances in information technologies have fundamentally altered business processes and systems in a number of domains. For example, as a result of Internet technologies, the stock market is now accessible to more investors, able to execute orders faster, and thwart simple arbitrage with widespread and near-instant information availability. The entertainment industry, in particular the music business, has been profoundly impacted by such technological changes. Music related technologies such as audio compression technologies and applications (MP3 players in 1998), peer-to-peer (P2P) file sharing networks like Napster (in 1999), and online music stores (in 2000) were introduced in a relatively short span of time, and gained rapid popularity. The consumers of music, in turn, have adapted rapidly to the new topical surroundings. Music, musicians and related terminology have consistently been among the top 10 searched items in major Internet search engines since at least 2000 (http://www.google.com/press/zeitgeist.html). This renders music and its related market a very effective choice to study the impact of technological change and other market forces on such goods.

The music industry and its legal arm, the Recording Industry Association of America (RIAA), have repeatedly claimed that emerging technologies, especially P2P networks, have negatively impacted their business. RIAA reports that music shipments, both in terms of units shipped and dollar value, have suddenly and sharply declined since 2000 (www.riaa.org). They attribute this dramatic reversal in revenues, coming in the heels of sustained long-term growth in the music business, directly to the free sharing of music on online P2P systems. This assertion has garnered immense attention, and has been the subject of numerous debates (Liebowitz 2004, King, 2000a, King 2000b, Mathews and Peers 2000, Peers and Gomes 2000, Evangelista 2000).

At the heart of the debate is whether sharing of music online leads to *piracy* or *sampling*. Proponents of the former argue that because of low marginal cost of reproduction of digital music and its quasi-public good characteristic, there is little loss in value and probably higher network externality in freely sharing music with others. P2P technologies lead to free-riders and undermine market efficiencies in the music industry with users obtaining music freely in lieu of legally purchasing it (Alexander 2002). Claiming that the impact of online music sharing on its business has been devastating, RIAA has aggressively pursued greater copyright enforcement and stronger regulations (Harmon 2003). Their initial legal strategy was aimed at Napster. RIAA succeeded in shutting down Napster, in large part due to the liability related to the centralized structure of Napster's file search technology. The so-called 'Sons of Napster' quickly emerged to fill the vacuum, and these networks escaped the legal wrath by deploying further de-centralized structures. In response RIAA has since altered its legal strategy by seeking sanctions against individuals "who offer significant number of songs for others to copy" (Ziedler 2003).

The opponents, on the other hand, argue that P2P systems significantly enhance the ability of users to sample and experience songs. Digital technologies have undoubtedly made information sharing and sampling easier[2] (Barua, et. al. 2001, Bakos et. al. 1999, Brynjolfsson and Smith 2000) and less costly (Cunningham, et. al. 2003, Gopal et. al. 2004) for individuals. It has been argued that consumers' increased exposure to music, which is made possible by P2P systems, can be beneficial to the music industry. An expert report to the court in the Napster case alludes to the possibility that such online sharing technologies provide sampling mechanisms that may subsequently lead to music album sales (Fader 2000). They further argue that the decline in the music industry is due to factors other than P2P enabled music sharing. Concomitant with the introduction and popularity of P2P systems, the music industry has also seen (a) a decrease in the

[2] Online fan clubs exist for numerous popular performers.

number of albums released, (b) increasing competition for consumer time and resources from non-music activities such as video games, DVDs, and online chat rooms (Mathews and Peers 2000, Mathews 2000a, Boston 2000), and (c) a downturn in the macroeconomic conditions (e.g. drop in GDP growth rates and employment figures since 2000, until 2004).

While both arguments hold intuitive and theoretical appeal, clearly the question is inherently empirical. However, extant literature on rigorous empirical evaluation of the impacts of sharing on the success of music products is sparse. Much of the existing work is anecdotal or survey-based. Issues such as self-reporting bias, sample selection problems, lack of suitable data to draw the appropriate conclusions have led to contradictory findings. A notable exception is the recent work by Oberholzer and Strumpf (2004) which relates the downloading activity on two P2P servers with the sales of music albums. Their data set spans the final seventeen weeks of the year 2002. The data is obtained from OpenNap, a relatively small P2P network with a centralized structure as in Napster. The significant finding of the study is that the effect of downloads on the sales is "statistically indistinguishable from zero."

Our study complements existing empirical works and adds to the growing understanding of the impacts of file sharing on the music industry. We employ micro-data on the performance of music albums on the Billboard Top 100 weekly charts, and the daily file sharing activity of these albums on WinMx, one of the most popular file sharing P2P networks. The objectives of our study are two fold: (1) assess the impact of recent market and technological developments related to the music industry on the survival of music albums on the top 100 charts, and (2) evaluate the specific impact of P2P sharing on the album's subsequent survival on the chart. Since 1913, Billboard magazine has provided chart information based on sales of music recordings (Gopal et. al. 2004). The chart information for the weekly Top 100 albums is based on "…a national sample of retail store sales reports collected, compiled and provided by Neilsen Soundscan" (www.billboard.com). Appearance and continued presence on the chart has staggering economic implications and has far reaching influence on awareness, perceptions and profits (Bradlow and Fader 2001). Having an album featured in the charts is the primary goad of most popular music artists and their record labels (Strobl and Tucker 2000). Our focus here is on the *survival* of albums as measured by the number of weeks an album appears on the charts before the final drop off. This survival on the charts captures the "popular life" of an album, and has been the object of analysis in a number of studies related to music (Strobl and Tucker 2000; Bradlow and Fader 2001).

The first phase of our study provides a comparative analysis of album survival before and after the event window, where the event window is year 1998-99. P2P networks, MP3 players, etc. gained immense popularity from this period onward. In total, over 200 weeks of chart information, spanning the years 1995-2004, is utilized in this phase of the study. Important covariates of album survival are analyzed to assess any changes in their impact between the *pre* (mid 1995–mid 1998) and *post* (mid 2000–mid 2003) time segments (henceforth referred to as *pre*-TS and *post*-TS respectively). The covariates utilized in the study include: debut rank of the album, reputation of the artist (as captured by the superstar status), record label that promotes and distributes the album, and artist descriptors (solo female/solo male/group).

Our results show strong evidence that, overall, survival on the charts is significantly lower in the *post*-TS period. Interestingly, albums that debut high on the charts did not experience a significant decline in the *post*-TS period while those albums that debut low on the charts did suffer a statistically significant decline in survival in *post*-TS.

While the first phase of the study provides the cumulative effect of technology and other factors on chart survival, the second phase of the study attempts to isolate the impacts of file sharing on chart success. Data on sharing activity is collected for over 300 albums over a period of 60 weeks on WinMx (a very popular file sharing application), and is analyzed along with the associated chart information and other covariates. We find that since the occurrence of the significant events outlined above (in the mid-1998 to mid-2000 time frame), the effect of debut rank on chart success has risen while the effect of major labels has fallen. In addition, solo female artists perform better than either solo male artists or groups across the periods. Importantly, we find that sharing has no statistically significant effect on survival.

Model of album survival

Our aim is to analyze the impact of various factors on an album's survival. Survival models are quite popular in literature (See Keifer 1988 for details) and it is well known that if the data is right or left censored then OLS (ordinary least square) leads to biased estimates (hence many survival models use a proportional hazard model). However, we face no left or right censoring in our data and hence logarithmic transformation of the dependent variable (survival) yields to OLS analysis. We also use an instrumental variable approach when analyzing the sharing data, and again, log transformation of survival yields to robust and widely used 2-stage least square analysis (See Abowd and Kang 2002 for similar analysis in different context). Therefore, we use log transformation of survival as our dependent variable and use OLS for future analysis.

Album survival trend

The first part of our analysis aims to understand the overall trend of album survival namely between and pre-TS and post-TS. The model estimated is

$$\text{Log}(Survival_i) = X_i\,\beta + Debut\ post\text{-}TS_i\,\delta + \mu_i \qquad (1)$$

where i is the album specific subscript, X_i is a vector of album specific control variables: debut rank, superstar status, distributing label (major/minor) and debut month (from extant literature). The effect of an artist's gender on album survival, not tested earlier, is also explored here. *Debut post-TS* is an indicator that signifies whether an album debuted on the charts in the *post* period, which is 1 if the album debuted in the post period (2000-02) and 0 otherwise. The estimate δ is of significant interest here, as it indicates how survival has changed over the *pre* and *post* periods.

Impact of sharing on survival

The second part of the analysis examines the specific impact of file sharing on an individual album's survival. We observe the number of files being shared for each album in time segment *post*-TS 3 (described in Table 2 below). We use this information to understand how the intensity of file sharing affects an album's survival. The model estimated is

$$Log(Survival_i) = X_i \beta + Log(Shares_i)\lambda + \mu_i \qquad (2)$$

where, as before, X_i is a vector of album specific control variables discussed above, and *Shares* denotes the number of files being shared for a given album during its debut week. We use a logarithmic transformation for shares to account for high variance and skewness in the sharing levels across albums. The estimate λ is of key interest here, which denotes the impact of initial sharing levels on an album's continued survival.

Unfortunately, this direct estimation may not be appropriate as sharing is probably correlated with some unobservable album characteristics which also affect survival (say popularity of a particular artist). While debut rank should control for some of this, such a correlation will bias the estimate for λ, as *Shares* will be correlated with error term μ_i (violating OLS assumptions). One strategy then is to find an instrument which is correlated with sharing but not with survival. Thus one would estimate

$$Log(Shares_i) = \boldsymbol{Z_i \alpha} + X_i \beta + v_i \quad (3)$$

Where $\boldsymbol{Z_i}$ is a vector of instruments which are uncorrelated with μ_i. A general strategy is to substitute the predicted values of sharing into the first stage (eqn. 2) and re-estimate the first stage. This ensures that the estimates are unbiased. We use an instrument based on a natural experiment that occurred during our data collection period. This had direct implications on sharing but not on survival. We describe it below.

In June 25, 2003 RIAA announced that it would start legal actions against individuals who are sharing files on P2P networks, which was extensively disseminated through various print and broadcast media on June 26. This event had a direct impact on users sharing these files on the network. This event can be used as an instrument as it shifted the intensity of sharing but would be uncorrelated with the error term. Thus Z_i is 1 for data after June 2003 and 0 otherwise.

To use this event as an instrument we collected sharing data from July 2003 to December 2003. We include only those albums that debut between Feb-May 2003 and Jul-Oct 2003. Using the sample described above and the event in June 2003 as the instrument, we can estimate equations (2) and (3) using 2-stage least squares.

Data

The data set for the first analysis consists of weekly rankings of albums on the Billboard top 100 charts. For each year, the data consists of albums that debut during 34 consecutive weeks of observation. The exact start date for each year is shown in Table 1. Our data collection captures both the traditional holiday sales period, when new releases and sales volume are the highest, as well as the more tranquil first and second quarters.

Table 1: Billboard Top 100 Data Collection

Time Segment	**Start Date**
Pre-TS3	27 October 1995
Pre-TS2	25 October 1996
Pre-TS1	24 October 1997
Post-TS1	27 October 2000
Post-TS2	26 October 2001
Post-TS3	25 October 2002

The survival model parameters are defined as follows.

- *Survival*: number of weeks an album appears on the Billboard top 100 charts. On occasion, an album may drop off for some weeks and reappear again on the chart. Each album is continuously tracked till its final drop-off. Note that the drop-off may occur well beyond the 34 weeks of each time segment.
- *Debut rank*: the rank at which an album debuts on the Billboard top 100 chart. Numerically higher ranked albums are less popular.
- *Debut post-TS*: This is an indicator variable which is 0 for albums in *pre* time segments and 1 for *post*.
- *No of albums*: The number of albums released during each year of the study period. This is used as a control variable since more albums released in a given year may signify increased competition amongst albums and reduce their survival.

- *Superstar*: a binary variable denoting the reputation of the artist. If a given album's artist has previously appeared on the Billboard top 100 Chart for at least 100 weeks (on or after January 1, 1991) prior to the current album's debut then the variable is set to 1, otherwise 0.
- *Minor label*: a binary variable that is set to 0 if the distributing label for a given album is one of {Universal Music, EMI, Warner, SONY-BMG}. A value of 1 denotes independent and smaller music labels.
- *Solo Male*: a binary variable that denotes if an album's artist is a solo male (e.g. Eric Clapton).
- *Solo Female*: a binary variable that denotes if an album's artist is a solo female (e.g. Britney Spears).
- *Group*: a binary variable that denotes if an album's artist is a group (male or female) (e.g. U2, The Bangles).
- *Holiday_month Debut*: To control for the holiday effect (or "Christmas effect"), we include indicator variables for albums debuting in December month, which is 1 if album debuted in that month and 0 otherwise.

Table 2 presents descriptive statistics of the data. The average *survival* has decreased between the two periods, from about 14 to 10 weeks, suggesting that albums do not last as long on the charts in the *post* period. Conversely, *debut rank* has improved from 49 to less than 40 on average, indicating that albums debut at a better position but drop more steeply in *post* period, while the number of albums released has essentially stayed the same or increased marginally. This may indicate that album sales may be concentrated upfront in this period, however lack of publicly available sales data precludes us from investigating this phenomenon. There is also a physical limit to the size of upfront sales in consecutive weeks, which is primarily constrained by logistics, distribution and retailer shelf space. Retail distribution is the major sales channel, accounting for more than 98% of sales. The number of superstars appearing on the chart has decreased marginally in *post* period, while male and female artists have registered a small increase at the expense of groups. Finally, albums from minor labels show a significant jump on the chart during *post* period.

Table 2: Mean statistics for key covariates

Variables	***pre*-TS3** (N = 218)	***pre*-TS2** (N = 224)	***pre*-TS1** (N = 234)	(Mid-1998 to mid-2000)	***post*-TS1** (N = 248)	***post*-TS2** (N = 261)	***post*-TS3** (N = 307)
Survival	14.2 wks	14.6 wks	15.3 wks		11.3 wks	9.5 wks	9.6 wks
Debut rank	49.9	49.15	49		42.9	39.5	34.5
No of albums	30200	30200	33700		35516	31734	33443
Superstar	31.6%	28.5%	27.8%		26.6%	23.3%	15.6%
Minor label	13.7%	16%	13.2%		22.9%	25.6%	24.7%
Solo Male	29.8%	33%	31.6%		29.7%	34.8%	34.5%
Solo Female	11.5%	9.4%	12.3%		12.5%	15.3%	14%
Group	58.7%	57.6%	55.9%		57.6%	49.8%	51.5%

The second data set used in the analysis relates to the album-level sharing activity. Sharing information is captured from WinMX for the 34 week period corresponding to the time segment *post*-TS3. We also collected additional data from July-Dec 2003 to be able to use as an instrument when examining the impact of sharing on album survival, as discussed in §3. Although a number of file sharing applications were available, we conducted our data gathering on WinMX for two primary reasons: (1) During the data collection period, WinMX was the second most widely used P2P network (Schatz 2003); and (2) KaZaA, the most popular P2P network at the time, places a fixed limit on how many files can shown on any given search result. Using KaZaA results in significant understatement of the level of sharing activity, due to this hard upper limit imposed by the application.

The data was collected from WinMX daily. Each day, we began with the list of albums that appeared on the Billboard top 100 chart since October 25, 2002 until the current week. The list of albums is sorted in a random order, and search is initiated for each album. The daily results are averaged to produce weekly information on sharing for that album. While we have data on the sharing activity for every week after an album makes its first appearance on the chart, our analysis focuses on the sharing levels of an album during its debut week. Inclusion of sharing levels in subsequent weeks did not add qualitatively to the results, as the sharing levels across the initial few weeks are highly correlated. We find the mean number of copies in our sample to be approximately 802, with a minimum of 1 and maximum of 6620. We introduce the final model parameter:

- *Shares*: average number of copies of an album available on the network during the debut week.[3]

Note that our focus is not on measuring the direct impact of piracy (due to downloads) on an album's survival. Rather, we use "shares" as an indication of an album's availability on the network. The use of "availability" of a file has several advantages, and does not suffer from potential sampling bias associated with "download" data. First, availability of a file on a user's computer is a greater indication of the file's archival value to the user than his/her downloading

[3] Various other formulations of *shares* were considered, including the proportion of tracks from an album that are available, and the number of unique users sharing a particular album; all produced consistent results.

activity, which may result in the file being listened to and discarded. Second, search results for the number of available copies of a file returns information from a significant number of users on the network, and it is more accurate which reduces sampling bias. However, collecting downloading information requires monitoring "super nodes" through which control information is routed. Oberholzer and Strumpf (2004), for example, use download data from two servers. However, one is unlikely to measure true number of downloads and it is not clear whether such a sampling methodology reduces bias, given the hybrid nature of the network[4]. Finally, a higher availability of a file on the network increases the ease and opportunity of finding and downloading it. Thus higher availability signifies the popularity and is probably highly correlated with actual downloads. This has also been the modus operandi of RIAA, which has sued significant file *sharers*, and not significant *downloaders*.

Estimation Results

Analysis of Album Survival

Table 3 presents the estimation results for the first part of our analysis (equation 1). We include only *Solo Male* and *Group* in our analysis, with *Solo Female* as the base category. Coefficients on all variables, except *albums released*, were significant (0.01 level). Of the variables, *superstar* and *Holiday_month debut* enhance album survival, while the other variables display a deleterious impact. In particular, we note that survival in the *post*-TS period, *ceteris paribus*, is estimated to have declined by approximately 42% [5]. This significant shift in the

[4] Several nodes are connected to a super node, which monitors the activity of the connected nodes. Hence it is possible that the downloading information may be biased by the types of users connected to the monitored super node. Availability information, as collected and used in this paper as "shares", usually is gathered by contacting several super nodes for the information if it is not available with the nearest super node, which reduces the bias.
[5] This result follows since the dependent variable is in logarithmic form while the explanatory variable is not. Comparing the *pre*- and *post*-TS periods yields a difference of 1- $e^{-0.54}$, which equates to a 42% decline.

survival pattern is consistent with our summary data in Table 1, where the mean survival time shows a sharp decrease. Albums that debut at higher numerical rank (hence less popular) tend to survive less on the Billboard top 100 chart.

Table 3: Album Survival Estimation Results

Parameter	**Model Estimates**
Constant	0.45 (0.1)
Debut rank	-0.02** (24.0)
Debut post-TS	-0.54** (8.3)
Albums released	0.27 (0.47)
Superstar	0.30** (4.8)
Minor label	-0.26** (3.8)
Solo Male	-0.36** (4.2)
Group	-0.42** (5.1)
Holiday_month Debut	0.21** (2.9)
R^2	0.345
Adjusted R^2	0.342

* p < 0.05, ** p < 0.01; t-statistics in parenthesis; n = 1484

The estimation results also highlight the reliance of the music business on an artist's superstar status for chart success is still viable. The estimate of 0.30 suggests that an album by a superstar survives 35% more on the charts, *ceteris paribus*. Further, albums promoted by major labels tend to last longer than those promoted by minor labels. Those from minor labels survive

23% fewer weeks on average than albums from major labels. Turning to the gender effect, it is interesting to note that neither solo male artists nor groups survive as long as female artists on the top 100 chart[6]. In fact, groups tend to survive the shortest time. Albums that are released in December are estimated to survive 23% more weeks than albums released at other times, reflecting the holiday effect (Montgomery and Moe 2000).

Analysis of Sharing on Survival

The previous analysis indicated that album survival has suffered in the *post* period – a period characterized by the presence of P2P sharing networks. To analyze whether this drop in survival might be attributable to sharing, we now focus on how intensity of sharing affects survival on the charts (equation 2).

Table 4 presents the estimation results without the instrumental variable. The impact of sharing is positive but insignificant with *Shares_debut*. This suggests that sharing is beneficial with more sharing leads to longer survival. However, as noted earlier in the model discussion, this estimate may be spurious and we now incorporate an instrumental variable for more robust analysis.

Table 4: Overall Impact of Sharing on Survival (without instrument)

Parameter	**Model estimates**
Constant	2.54** (14.6)
Debut rank	-0.03** (17.0)
Log(*Shares_debut*)	0.015 (0.8)
Superstar	0.235 (1.9)

[6] *Solo female* is the reference category.

Minor label	0.10 (0.9)
Solo Male	-0.04 (0.3)
Group	-0.19 (1.4)
Holiday_month Debut	0.55** (3.7)
R^2	0.58
Adj R^2	0.57

* $p < 0.05$, ** $p < 0.01$; t-statistics in parenthesis; n = 299

Estimation using Instrument

We use an instrumental variable to complete a two stage least squares estimation of models (2) and (3). In the first stage we estimate (3), and in the second stage we estimate (2) with the predicted values from (3). We estimate this model with the 4-month prior and *post* samples around the RIAA announcement event described in Section 3 (Feb-May 2003 and July-Oct 2003).

Table 5 reports the estimation results with the instrument. In the first stage regression, the instrument *RIAA announcement indicator* is highly significant and negative. The estimated sharing decrease linked to the RIAA announcement (threat to sue file sharers) is approximately 80%. Debut rank is also highly significant and negative, indicating that less popular albums (which debut at higher numerical rank) have significantly less sharing opportunities available. The first stage results also indicate that albums from superstars and those released by groups are shared less. The fit of the first stage model is approximately 38%. The second stage analysis indicates that, overall, sharing does not significantly affect survival (the sign is negative, but insignificant). The fit of the second stage model is 48%.

Table 5: Overall Impact of Sharing on Survival using Instrument

Parameter	Model estimates with Log(*Shares_debut*)	
	First Stage	**Second Stage**
Constant	6.00** (19.5)	2.7** (8.2)
Debut rank	-0.029** (8.9)	-0.027** (11.0)
Log(*Shares_debut*)		-0.054 (0.9)
Superstar	-1.12* (2.8)	
Minor label	-0.11 (0.5)	0.12 (0.9)
Solo Male	-0.33 (1.05)	0.06 (0.6)
Group	-0.79** (2.6)	-0.03 (0.2)
RIAA announcement indicator (*instrument*)	-1.61** (7.4)	-0.28 (1.9)
R^2	0.38	0.48
Adj R^2	0.37	0.47

* $p < 0.05$, ** $p < 0.01$; t-statistics in parenthesis; n=370

Conclusion

Our modeling approach, and the extensive data set at our disposal in particular, provides a rigorous analysis and insight of an extremely important topical question: the effect of free information sharing networks on mostly copyrighted goods, and its related impact on intellectual property rights. Key findings include:

i) debut rank is highly significant with a negative impact on survival;

ii) the superstar effect appears to be alive and well;

iii) albums from minor labels are increasingly narrowing the gap with those from major labels;

iv) sharing does not appear to impact survival.

The results would be of significant interest to P2P network designers, intellectual property researchers, economists, policy makers, and music industry executives.

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