The Effect of Digital Sharing Technologies on Music Markets: A Survival Analysis of Albums on Ranking Charts

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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: i) significantly reduced chart survival, except for those albums that debut high on the charts, ii) superstars and female artists continue to exhibit enhanced survival, and iii) a narrowing of the advantage held by major labels. The second phase of our study isolates the impact of file sharing on album survival. We find that, while sharing does not hurt the survival of top ranked albums, it does have a negative impact on low ranked albums. These results point to increased risk from rapid information sharing for all but the "cream of the crop".

1. Introduction

Recent advances in information technologies have fundamentally altered business processes and systems in a number of domains. 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 environment. In fact, music titles, names of musicians and music related technologies (e.g., MP3) 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).

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). RIAA attributes this dramatic reversal in revenues, coming on 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 wide 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 to sampling; that is, does sharing help or hurt the industry? Proponents of the former argue that because of low marginal cost of reproduction of digital music and the quasi-public good characteristic of music, there is little loss in value and likely higher network externality in freely sharing music with others. P2P technologies are viewed as leading to free-riders and undermining 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 the music business has been devastating, RIAA has aggressively pursued greater copyright enforcement and stronger regulations (Harmon 2003). Their initial legal strategy was aimed at Napster, which RIAA succeeded in shutting 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, attempting to escape 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).

But there is an opposing view arguing that P2P systems significantly enhance the ability of users to sample and experience songs. Digital technologies have undoubtedly made information sharing and sampling easier[1] (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. Consumers' increased exposure to music, made possible by P2P systems, also has potential benefits 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). The report argues that the decline in the music industry is due to factors other than P2P enabled music sharing. Concomitant with

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

the introduction and popularity of P2P systems, the music industry has also seen:

> (i) 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 2000, Boston 2000); and
>
> (ii) a downturn in the macroeconomic conditions (e.g. drop in GDP growth rates and employment figures since 2000).

While each of the conflicting views holds some intuitive and theoretical appeal, 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, and 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) that relates downloading activity on two P2P servers with sales of music albums. The authors' data set spans the final seventeen weeks of 2002, and was 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."

The purpose of our study is to complement such existing empirical work and add to the understanding of the impacts of file sharing on the music industry. Our study employs 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 twofold: (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 an album's 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 important economic implications and far reaching influence on awareness, perceptions, and profits of an album (Bradlow and

Fader 2001). Having an album featured in the charts is an important goal 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 top 100 chart before final drop off. This survival period on the chart 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).

Figure 1 illustrates the time frame of analysis for the initial phase of our study. The two-year span, mid-1998 to mid-2000, represents a watershed period in the music industry during which a number of significant events unfolded, including:

(i) introduction and rapid popularity of MP3 music format;

(ii) passing of the Digital Millennium Copyright Act;

(iii) introduction and rapid rise in the usage of Napster and P2P networks;

(iv) surge in the popularity of DVDs, online chat rooms and games; and

(v) the beginning of a downturn in the overall economy.

The first reported decline in music shipments occurred in 2001, suggesting the possibility that the influence of these events was beginning to be experienced by the music industry. The first phase of our study provides a comparative analysis of album survival before and after the mid-1988 to mid-2000 event window. As depicted in Figure 1, chart information was compiled for three time segments each before and after the event window, depicted as *pre*-TS1 to *pre*-TS3 and *post*-TS1 to *post*-TS3 respectively. In total, over 200 weeks of chart information, spanning the years 1995-2004, was collected for this phase of the study. Important explanatory variables of album survival are analyzed to assess any changes in impact between the *pre* and *post* time segments. The variables 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). To the best of our knowledge, this is the first study which explores the impact of gender on album popularity. Our decision to include this variable is based on the possibility that gender may indeed be relevant to music industry success.

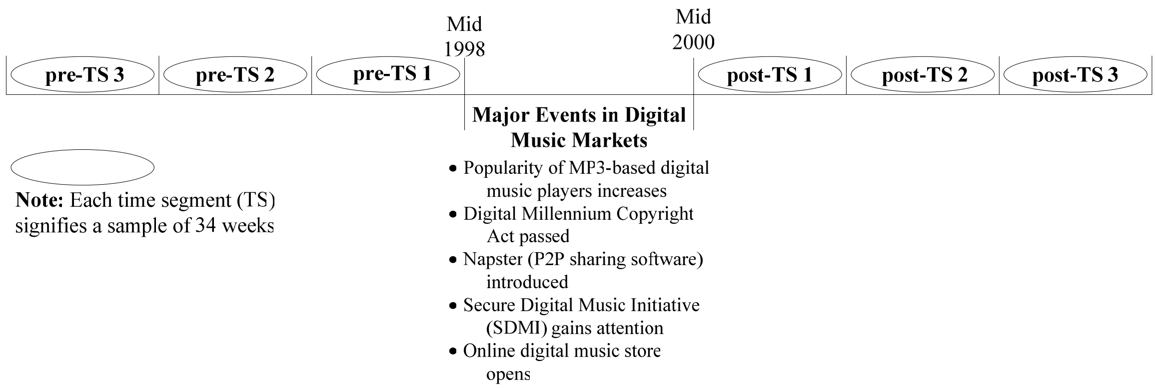

Figure 1: Survival Analysis Time Frame

While the first phase of our study considers 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. Our analysis utilizes: 1) data on sharing activity on WinMx for 300+ albums over a period of 60 weeks during 2002 and 2003, 2) corresponding Billboard chart information, and 3) relevant values for other variables detailed above. We note two important characteristics of our analysis. First, our analysis and findings relate only to those albums that appear on the charts. Over 30,000 albums are released each year, but only a small proportion of these appear on the charts. This small set of successful albums provides the lion's share of the profits for the record companies. Thus, our analysis centers on the impact of sharing for those albums that achieve at least a moderate level of success. Second, our analysis is on sharing that occurs after an album has made an appearance on the charts. Clearly, sharing does take place "*post*-release and *pre*-chart appearance". In fact, sharing can occur even before the album is officially released to the market (Bhattacharjee et. al. 2005). It is possible that sharing that takes place prior to chart appearance influences "if, when, and where" an album appears on the charts. But our analysis seeks to understand the impacts from sharing activity that occurs when an album debuts on the charts. The related research question we ask is: does the level of sharing influence survival time on the charts? Note that we not only explore the impact of sharing in the debut week but also the maximum level of sharing (see details in Section 4). Much of the initial sales of an album are to the so called committed fan base (Strobl and Tucker 2000). This core set of consumers are early adopters who have often completed their purchase by the time the album has appeared on the chart. Consequently, the number of weeks an album remains on the chart reflects its receptiveness by the non hard-core consumers.

Our work contributes to the growing understanding of digital information systems and their market effects. Our results show strong evidence that, overall, survival on the charts is significantly lower in the *post*-TS period (see Fig. 1). 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 a part our study provides results consistent with earlier research, our expanded analysis offers significant new insights. 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. However, a closer analysis reveals that the effect of sharing appears to differ across certain categories. Successful albums (albums that debut high on the chart), are not impacted by sharing, while online sharing has a low but statistically significant negative effect on survival for less successful (lower debut rank) albums. These results suggest a risk from rapid information sharing for all but the cream of the crop.

Section 2 discusses related literature that aids in the development of our empirical methodology. The model is presented in Section 3, followed by the details of the data collection in Section 4. Section 5 centers on model estimation. We conclude with discussion of key findings and their implications in Section 6, along with future research directions.

2. Related Literature

While we are only beginning to see the emergence of research on the *post* P2P music world, there does exist a rich body of earlier work in economics, marketing and information systems related to the markets for music and the music industry. Two characteristics of music products make their examination both interesting and challenging. First, music is an experience good, whose true value is revealed only after its consumption (Nelson 1970). Second, music is a hedonic product, whose evaluation is based primarily on personal experience and individual consumer tastes, rather than specific product attributes (Dhar and Wertenbroch 2000, Moe and Fader 2001). Music is also often alluded to as a fashion-oriented product, where the customer tastes and preferences change rapidly and where preference for a good can be influenced by other consumers that have purchased it. As a result of these characteristics, sampling and experiencing music prior to purchase, along with cues on how well a music item is perceived by other individuals, can be important components in consumer purchase decisions. However, sampling and learning about music items can require significant time and effort, especially given the large body of available recorded music. Major music labels (Sony-BMG, Universal, EMI and Warner Brothers) alone release about 30,000 albums annually (www.riaa.com, Goodley 2003). Only a tiny fraction of the albums released are profitable and achieve the success indicated by appearing in the top 100 charts (Seabrook 2003). In fact, of the albums released in 2002, the vast majority (over 25,000) sold less than 1000 copies each (Seabrook 2003). From the music labels' perspective, the fact that music is fashion-oriented adds a degree of complexity in assessing the likely success of the product (Bradlow and Fader 2001). Additionally, the introduction rate of new music albums and overall album sales vary across the year. Industry figures show that a large number of albums are released during the Christmas holiday period, suggesting that the success of music albums can also be impacted by their time of release (Montgomery and Moe 2000).

Even those albums that make it to the charts have numerous factors that can influence their lifecycle. Before detailing our model formulation and empirical approach, we briefly review prior research examining various factors that can influence the success of music albums. The phenomenon of superstardom in the music industry has been studied extensively (Rosen 1981, Hamlen 1991, MacDonald 1988, Towse 1992, Chung and Cox 1994, Ravid 1999, Crain and Tollison 2002). It has been suggested that the superstar effect results from consumer desire to minimize search and sampling costs by choosing the most popular artist (Adler 1985). The search for information is costly, especially for relatively unknown artists. In such cases, consumers must weigh their additional search costs for unknown artists or items of music with their existing knowledge of a known "popular" artist. MacDonald (1988) suggests that, in a statistical sense, consumers correlate past performance with future outcomes and try to minimize the variability in their expectations of individual performances. The superstar effect is augmented by the learning process, where a consumer's appreciation of a particular artist's output increases as their knowledge of the artist increases (Adler 1985). The music recording companies often exploit the resulting economies of scale by concentrating their efforts on a few stars that can cater to large audiences at lower cost.

Four recording labels (Sony-BMG, Universal, EMI and Warner Brothers) dominate the music industry and are often referred to as the 'major labels.' These major labels account for over 75% of music sales (Spellman 2003). They exert significant control in recording, distributing, and promoting of music albums, and posses the financial resources to gain access to large customer bases. The minor labels are hampered by the lack of resources to reach wider audiences, and tend to operate in niche segments of the market (Spellman 2003). The albums released by the major labels are promoted more and have a wider audience exposure, and consequently last longer on the charts (Strobl and Tucker 2000).

Previous research suggests that one of the most important characteristics in guaranteeing survival on the charts is the initial debut rank (Strobl and Tucker 2000). This relationship may be due to what has been termed the "bandwagon effect" in the demand for music (Towse 1992, Strobl and Tucker 2000). The bandwagon effect arises from the process of "acquiring tastes" in which preferences for a good increase because other agents have purchased it (Leibenstein 1970, Bell 2002). When market demand increases, an individual's demand for the product also increases. In the context of music markets, the initial debut rank has a significant influence on the success (i.e. survival time) of an album on the charts (Strobl and Tucker 2000). The initial debut rank reflects an album's acceptance by early adopters, which can create a snowballing of further demand from remaining consumers (Yamada and Kato 2002). With relatively lower knowledge levels than the committed fans, the less committed fans take their cue from the core fan base. Thus we include debut rank as a key explanatory variable of survival.

All these factors – superstar effect, major label promotion effect, and the debut rank influence –

reflect consumers' unwillingness to incur additional search and sampling costs to identify unknown music of potentially high value (Adler 1985, Rosen 1981, Leibenstein 1970). P2P technologies have significantly lowered these consumer costs to sample and experience music, acquire and enhance their knowledge on artists, and to interact with other individuals. The question of how such sharing technologies impact the relationship between the key variables and success on the charts has received little attention in the literature. Gopal et al. (2004) suggest that sharing technologies enable consumers to be more discerning on their purchases from products by superstars. Armed with an ability to easily experience music, individual purchase behavior will be driven more by the value attached to the album and less by the reputation of the artist. Gopal et al. (2004) predict that sharing technologies will lead to a dilution in the superstar effect together with the appearance of more new artists on the charts.

The work presented here is distinguished from earlier work by a combination of the following: (a) we examine for shifts in the influences of the key explanatory variables since the advent of sharing technologies; (b) we analyze gender effects on album survival; and (c) we isolate the impacts of sharing on album survival on the charts. We turn now to presentation of our formal models followed by details of data gathering and analytic results.

3. Model of album survival

Survival models are quite popular in the literature (see Keifer 1988 for details). The "survival" we model here is the length of time or duration that an album remains on the charts before it drops off. The "hazard" we estimate for any period is the hazard of an album leaving the charts. Left or right data censoring issues (i.e. inability to identify birth or death times of some data entities) often occur in survival analysis. Such concerns do not arise in our analysis, however, as we track each album from its debut (birth) till its final drop off (death) from the charts.

Existing survival model literature commonly employs a non-parametric Cox proportional hazard model. When there are no censoring issues, employing ordinary least squares (OLS) regression using logarithmic transformation of the dependent variable yields results that closely approximate those from hazard models. In each of the cases detailed below, we estimated both OLS and hazard models to validate our approach, and found the results to be consistent (in sign and interpretation). For brevity, we report only one set of model formulation and estimation results, choosing the simplicity and robustness of linear models and OLS estimation.[2]

3.1. Album Survival

The first part of our analysis focuses on the shifts in album survival since the major events related to the music industry. The initial model to be 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. The effect of an artist's gender on album survival is also explored here. $Debut\ post\text{-}TS_i$ is an indicator that signifies an album's debut period (see Fig. 1); it is 1 if the album debuted in the *post* period (2000-02) and 0 otherwise. The estimate of δ is of significant interest here, as it indicates how survival has changed over the *pre*- and *post*-TS periods. However, the change in survival may not be linear and may be moderated by album characteristics. For example, top ranked albums (numerically lower ranks) may be more affected across *pre*- and *post*-TS periods. Similarly, minor (or major) record labels may have benefited more (or less) after the popularity of file sharing networks. To test this, we interact album specific characteristics with $debut\ post\text{-}TS_i$ and estimate the following model:

$$\text{Log}(Survival_i) = X_i\ \beta + Debut\ post\text{-}TS_i\,\delta + (X_i \times Debut\ post\text{-}TS_i)\,\xi + \mu_i \qquad (2)$$

where ξ is the vector of parameters to be estimated, along with β and δ.

3.2. Impact of Sharing on Survival

The second part of the analysis examines the specific impact of file sharing on an album's survival. As discussed later in Section 4, we observe the number of files being shared for each album in time segment *post*-TS 3. We use this information to understand how the intensity of file sharing affects an album's survival. The model estimated is

[2] Estimation results for the hazard models are available upon request.

$$\text{Log}(Survival_i) = X_i\beta + \text{Log}(Shares_i)\lambda + \mu_i \quad (3)$$

where, as before, X_i is a vector of album specific control variables, and $Shares_i$ denotes the number of files being shared for a given album. We use a logarithmic transformation for shares to account for high variance and skewness in the sharing levels across albums. The estimate of λ is of key interest here as it indicates the impact of sharing levels on an album's continued survival.

On the other hand, such direct estimation may not be appropriate since sharing may be closely correlated with unobservable (or not directly measurable) album characteristics (perhaps "popularity" of a particular artist). While debut rank should control for some of this, such a correlation would bias the estimate for λ, as $Shares_i$ would be correlated with the error term μ_i, thus violating the assumptions of the general linear model. One strategy is to find an instrument which is correlated with sharing but not with survival. We would then estimate:

$$\text{Log}(Shares_i) = Z_i\,\alpha + X_i\,\beta + v_i \quad (4)$$

Where Z_i is a vector of instruments uncorrelated with μ_i. A general strategy is to substitute the predicted values of sharing into the first stage (equation (3) above) and re-estimate the first stage. With Z_i uncorrelated with μ_i the resulting estimators are unbiased. We use an instrument based on a natural experiment that occurred during our data collection period. As described below, the instrument had direct implications on sharing but not on survival.

Analysis using Instrument

In June 25, 2003 RIAA announced that it would start legal actions against individuals sharing files on P2P networks, an announcement extensively disseminated through various print and broadcast media on June 26. Unless RIAA was mistaken, this event should have a direct impact on users sharing these files on the network. But, since the event would likely be uncorrelated with the error term, we use this event as an instrument shifting the intensity of sharing. 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 October 2002 to June 2003, and from July 2003 to December 2003. The sharing statistics before (October 2002-June 2003) and after (July-Dec 2003) the event suggest that the intensity of sharing fell considerably after the event, from a mean of 345.1 to 61.9, while survival increased slightly from 7.17 weeks to 8.34 weeks. To avoid a temporal effect or other exogenous variables which may have an impact on survival, we chose a relatively short window of four months before and after the RIAA announcement. We include only those albums that debut between Feb-May 2003 and Jul-Oct 2003 (Figure 2). We also tried to control for factors like overall economic indicators by incorporating the S&P 500 market index[3]. Using the sample described above and the June 2003 event as the instrument, we estimate equations (3) and (4) using 2-stage least squares.

Finally, similar to album survival analysis before and after major market and other events (Section 3.1), we study interactions between *Shares* and other variables in X_i to understand if the impact of sharing is moderated by these variables. Thus we estimate

$$\text{Log}(Survival_i) = X_i\ \beta + \text{Log}(Shares_i)\ \lambda + (X_i \times \text{Log}(Shares_i))\ \theta + \mu_i \qquad (5)$$

As before, we use $Z_i \times X_i$ as a potential instrument for the interaction term $X_i \times \text{Log}(Shares_i)$. As in the previous case, the vector of parameters θ needs to be estimated along with β and λ.

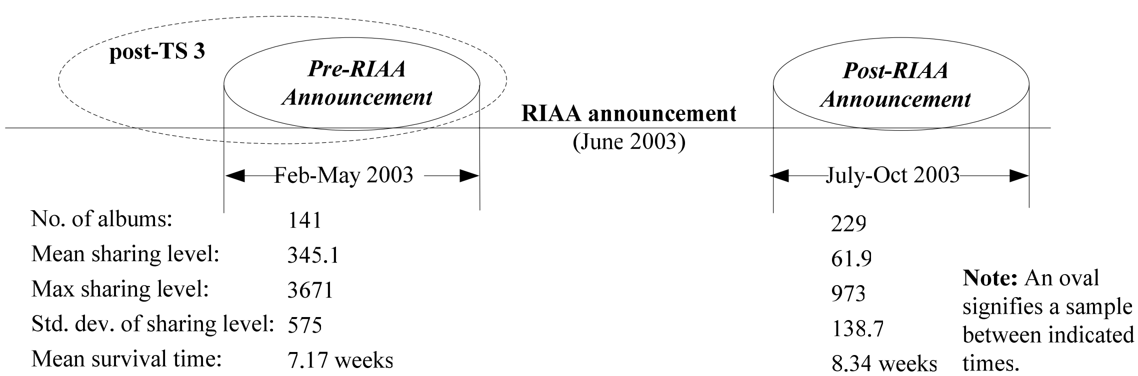

Figure 2: Time Frame for Sharing Analysis with Instrument

[3] For example, it may be that economic outlook is substantially different over these periods, thus affecting buyers' purchasing behaviors systematically. We tested with various dummy variables indicating the month of album debut. All lead to insignificant results.

4. Data

4.1. Data Set One

The first part of the data set required for our initial models is the weekly rankings of albums on the Billboard top 100 charts. For each time segment, 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

We collected data on the survival model explanatory variables (X_i*'s)* which we operationalize 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 that debut in *pre*-TS and 1 for *post*-TS;

Albums released: 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 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 charts 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); and,

Holiday_month Debut: To control for the holiday effect (or "Christmas effect"), we include an indicator variables for December, which is 1 if album debuted in that month and 0 otherwise.

Table 2 presents descriptive statistics of the first data set. The average survival has decreased between the two periods, from about 14 to 10 weeks, indicating that, on average, albums do not last as long on the charts in the *post* period. Conversely, average debut rank has improved from 49 to less than 40 on average, indicating that albums tend to debut at a better position but drop more steeply in the *post* period, while the number of albums released has stayed roughly the same or increased marginally[4]. The number of superstars appearing on the chart decreased marginally for the *post* period, while the percent of male and female artists have registered a small increase at the expense of groups. Finally, albums from minor labels show a substantial jump on the chart during the *post* period.

Table 2: Mean statistics for key variables

Variables	**pre-TS3 (n = 218)**	**pre-TS2 (n = 224)**	**pre-TS1 (n = 234)**		**post-TS1 (n = 248)**	**post-TS2 (n = 261)**	**post-TS3 (n = 307)**
Survival	14.2 wks	14.6 wks	15.3 wks	(Mid-1998 to mid-2000)	11.3 wks	9.5 wks	9.6 wks
Debut rank	49.9	49.15	49		42.9	39.5	34.5
Albums released	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%

4.2. Data Set Two

The second data set used in our analysis relates to album-level sharing activity. We captured sharing information from WinMX for the 34 week period corresponding to the time segment *post*-TS 3. We also collected additional data from July-Dec 2003 for our analysis using the instrumental variable to

[4] 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.

assess the impact of sharing on album survival. 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 show on any given search result. Using KaZaA could thus result in significant understatement of the level of sharing activity due to this hard upper limit imposed by the KaZaA search option.

The WinMX data was collected 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 was randomly sorted into the order in which the search was conducted each day. The daily results were 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 were highly correlated (e.g. a correlation coefficient of 0.93 between sharing levels in the debut week and week after). We find the mean number of copies available for sharing in our sample to be approximately 802, with a minimum of 1 and a maximum of 6620. In addition to the explanatory variables (X_i's) defined above, the second phase of our analysis includes two alternative measures of sharing, defined as follows:

Shares_debut: average number of copies of an album available on the network during the debut week;[5] and,

Shares_max: maximum available copies of a file over a 4-week period or until the album drops off the charts (whichever is less).

Because it is possible that the daily search method may not find all sharers on the network during the debut week, we also capture the maximum available copies of a file. As reported in Section 5, we find that both measures yield consistent results.

[5] 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 formulations produced similar and consistent results.

Note that we are not measuring the impact of downloading on an album's survival. Rather, we use "shares" as an indication of an album's availability on the network. Our approach corresponds to the modus operandi of RIAA, which has sued significant file sharers and not significant downloaders. The use of "availability" of a file also has certain advantages and does not suffer from potential bias associated with "download" data. First, availability of a file on a user's computer indicates that the user has archived the file and is offering it for sharing. On the other hand, using downloading activity would include files sampled but discarded. Second, search results for the number of available copies of a file returns information from a large number of nodes on the network. On the other hand, collecting downloading information requires monitoring "super nodes" through which control information is routed. Oberholzer and Strumpf (2004) use download data from only two servers in their analysis[6]. Finally, we suggest that higher availability (more copies) of a music item available on a network increases the ease and opportunity of finding and downloading.

5. Results

We now present the estimation results for each of the two parts of our analysis. In the first part, we estimate how album survival has changed over time (from *pre*-TS to *post*-TS), first examining the main effects of each of the explanatory variables and then the interaction effects (with *debut post-TS*) (models (1) and (2)). In the second part of the estimation, we filter out the temporal effects of market and other forces that have affected survival and focus on the impact of online file sharing on album survival using two alternative measures.

5.1. Analysis of Album Survival

Table 3 presents the estimation results for both the main and interaction effects models of the first part of our analysis. We include only *Solo Male* and *Group* in our analysis, with *Solo Female* as the base category. We first discuss results without interaction terms, followed by those with interaction terms.

[6] 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 bias.

Table 3: Album Survival Estimation Results

Parameter	Without interactions (equation 1)		With interactions (equation 2)	
Constant	0.45	(0.1)	-0.62	(0.1)
Debut rank	-0.02**	(24.0)	-0.014**	(12.4)
Debut post-TS	-0.54**	(8.3)	-0.20	(1.2)
Albums released	0.27	(0.47)	0.35	(0.7)
Superstar	0.30**	(4.8)	0.30**	(3.4)
Minor label	-0.26**	(3.8)	-0.43**	(3.9)
Solo Male	-0.36**	(4.2)	-0.41**	(3.1)
Group	-0.42**	(5.1)	-0.45**	(3.6)
Holiday_month Debut	0.21**	(2.9)	0.19**	(2.6)
Debut rank × Debut post-TS			-0.01**	(6.6)
Minor label × Debut post-TS			0.28*	(2.0)
Superstar × Debut post-TS			0.02	(0.2)
Solo Male × Debut post-TS			0.11	(0.7)
Group × Debut post-TS			0.09	(0.5)
R^2	0.345		0.366	
Adjusted R^2	0.342		0.360	

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

In the model without interactions, 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% [7]. This significant shift in the survival pattern is consistent with our summary data in Table 2, 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. In particular, a unit change in rank is estimated to reduce survival time by approximately 1.98%. An album debuting at rank 25 (out of 100) survives 38.1% less than one debuting at the top of the charts, and another debuting at 50 demonstrates an estimated relative drop in survival of 62.5%. This suggests the continued existence of the bandwagon effect in the music business (Towse 1992, Strobl and Tucker 2000).

[7] 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.

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[8]. 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). Overall, the regression model is highly significant with *F*-value significant at 1% and a fit (R^2) of approximately 35%.

In estimating the model with interaction effects, we found only two statistically significant interaction effects. The interaction effects of *debut post-TS* with *debut rank* and *minor label* were statistically significant, while the main effect coefficient of *debut post-TS* was now statistically insignificant. Note that the main effect needs to be interpreted differently when an interaction term is present. With the interactions included, the main effect measures the impact of *debut post-TS* for the album debuting at top rank (or more precisely rank 0). This is in contrast to the results without interaction terms (equation 1), where the impact of *debut post-TS* is measured at the mean value of *debut rank*. There does not appear to be a uniform shift in album survival in the *post*-TS period. There are, however, significant shifts in the survival environment – shifts that are linked to only two album characteristics, *debut rank* and *minor label*.

The interaction *Debut rank* × *Debut post-TS* suggests that the top ranked albums have not suffered in the *post*-TS period. In the *post*-TS period, the survival climate is increasingly hazardous for higher debut ranks. Although the survival time for albums has decreased overall in the *post* period, this decrease is sharper for less popular albums (numerically higher debut rank). That is, in the *post*-TS period, the estimated survival time diminishes more rapidly as debut rank increases. This is graphically illustrated in Figure 3, where predicted survival is plotted with respect to debut rank keeping other

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

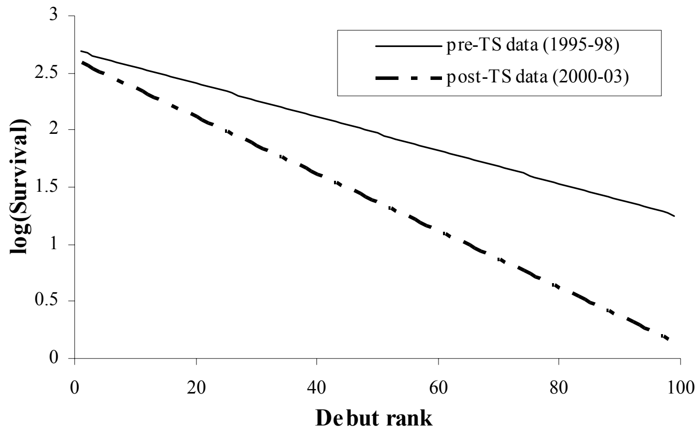

Fig 3: Impact of Market and Other Factors on Album Survival

variables at their mean values, for both *pre*- and *post*-TS periods. The figure highlights the increasingly hazardous environment as an album debuts at higher (numerical) ranks.

The interaction *Minor label* × *Debut post-TS* suggests that minor labels have benefited considerably in the *post* period, and are now surviving longer than before. However, the main effect of minor label is still negative and significant, suggesting that major labels continue to survive longer but the difference is narrowing. This is consistent with a variety of anecdotal evidence (Spellman 2003, Green 2004) suggesting that minor labels have adapted better to technological and market changes, and have in fact utilized file sharing networks and other non-traditional methods to popularize their albums. There is no significant interaction effect with superstar, indicating that the superstar status has not significantly shifted in the *post* period. Similarly, the effect of gender has remained invariant across the time segments.

5.2. 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.

Table 4 presents the estimation results without the instrumental variable. The impact of sharing is positive but insignificant with *Shares_debut* but significant at a 5% level with *Shares_max*. 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 with Log(*Shares_debut*)**	**Model estimates with Log(*Shares_max*)**
Constant	2.54** (14.6)	2.37** (13.4)
Debut rank	-0.03** (17.0)	-0.03** (16.7)
Log(*Shares_debut*)	0.015 (0.8)	
Log(*Shares_max*)		0.036* (2.01)
Superstar	0.235 (1.9)	0.25* (2.02)
Minor label	0.10 (0.9)	0.11 (1.1)
Solo Male	-0.04 (0.3)	-0.03 (0.2)
Group	-0.19 (1.4)	-0.17 (1.3)
Holiday_month Debut	0.55** (3.7)	0.53** (3.6)
R^2	0.58	0.59
Adj R^2	0.57	0.58

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

Estimation using Instrument

We use an instrumental variable to complete a two stage least squares estimation of models (3) and (4). In the first stage we estimate (4), and in the second stage we estimate (3) with the predicted values from (4). 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). Independent of the event, it is possible that the July-Oct 2003 album sample is inherently different from the Feb-May 2003 sample. Table 5 provides the average survival times for albums that debut between Feb-May and July-Oct for the similar period in the previous two years. The results of the t-tests suggest that overall survival across these two periods is quite similar. Hence we utilize the corresponding periods in 2003 for analysis.

Table 5: Average Survival Times (number of weeks)

Year	**Feb-May**	**July-Oct**	**t-test of difference between means**
2001	10.81	10.36	$p > 0.71$
2002	8.01	8.60	$p > 0.64$

Table 6 reports the estimation results with the instrument. We confine our discussion on the results with average sharing as they are consistent with those using maximum sharing. 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 6: Overall Impact of Sharing on Survival using Instrument

Parameter	**Model estimates with Log(*Shares_debut*)**		**Model estimates with Log(*Shares_max*)**	
	First Stage	**Second Stage**	**First Stage**	**Second Stage**
Constant	6.00** (19.5)	2.7** (8.2)	6.86** (20.7)	2.79** (6.5)
Debut rank	-0.029** (8.9)	-0.027** (11.0)	-0.032** (9.01)	-0.028** (10.3)
Log(*Shares_debut*)		-0.054 (0.9)		
Log(*Shares_max*)				-0.056 (0.89)
Superstar	-1.12* (2.8)	0.12 (0.9)	-1.37** (5.2)	0.11 (0.7)
Minor label	-0.11 (0.5)	0.06 (0.6)	-0.29 (1.1)	0.05 (0.5)
Solo Male	-0.33 (1.05)	-0.03 (0.2)	-0.41 (1.2)	-0.04 (0.25)
Group	-0.79** (2.6)	-0.28 (1.9)	-1.07** (3.3)	-0.30 (1.9)
RIAA announcement indicator (*instrument*)	-1.61** (7.4)		-1.52** (7.0)	
R^2	0.38	0.48	0.40	0.48
Adj R^2	0.37	0.47	0.39	0.47

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

Recall that the overall survival estimation (Section 5.1) shows that survival of less popular albums has declined significantly in the *post*-TS period, while there was no significant change in the survival of more popular albums. Since we find that overall file sharing does not affect album survival, we now consider whether such a differential decline in survival might be attributable to file sharing. To operationalize this, we estimate model (5) by interacting Log(*Shares*) with *debut rank*. With two endogenous variables, Log(*Shares*) and Log(*Shares*)×*debut rank*, we run two first stage regressions: Log(*Shares*) with *RIAA announcement indicator* as instrument, followed by Log(*Shares*)×*debut rank* with

RIAA announcement indicator×*debut rank* as instrument. As before, our results are consistent with both average sharing in debut week and maximum sharing, and consequently we report only the former in Table 7.

Table 7: Impact of Sharing on Survival: Interaction Effects[#]

Parameter	**First Stage**		**Second Stage**
	Log(*Shares_debut*)	**Log(*Shares_debut*) × *debut rank***	**Log(*Survival*)**
Constant	6.4** (18.6)	47.0** (2.7)	2.1** (5.4)
Debut rank	-0.04** (7.7)	2.14** (8.1)	-0.012* (1.8)
Log(*Shares_debut*)			0.12 (1.5)
Log(*Shares_debut*)×*Debut*			-0.006** (2.3)
rank	-1.16** (4.6)	-49.2** (4.0)	0.008 (0.1)
Superstar	-0.11 (0.5)	-5.25 (0.5)	0.05 (0.4)
Minor label	-0.34 (1.1)	1.65 (0.1)	0.03 (0.2)
Solo Male	-0.76** (2.5)	-11.5 (0.8)	-0.21 (1.3)
Group			
	-2.23** (7.1)	-16.3 (1.1)	
RIAA announcement indicator			
(*instrument*)	0.018** (2.7)	-0.75** (2.3)	
RIAA announcement indicator			
(*instrument*)×*Debut rank*			
R^2	0.40	0.30	0.40
Adj R^2	0.38	0.29	0.39

[#] Results are consistent with average sharing and maximum sharing. We report figures for average sharing here.
* $p < 0.05$, ** $p < 0.01$; t-statistics in parenthesis; n=370

A key outcome in both the first stage regressions (Table 7) is that the coefficient on the respective instrument is highly significant, suggesting that sharing has decreased after the RIAA announcement in June 2003. The fit of the first two regressions is 37% and 30%, respectively. In the second stage regression, we find that the main effect of sharing, though estimated to be positive, is not significant. This result again suggests that top albums are not adversely affected by sharing. The interaction term Log(*Shares*)×*debut rank* is negative and significant. Hence the estimated effect of sharing is more negative for numerically higher ranked albums. In other words, less popular albums suffer more from increased sharing while top albums experience no significant deleterious impact on survival. This is illustrated in Figure 4, which depicts the relationship between survival time and debut rank for three levels of sharing. The mean of Log(*Shares*) is 3.12, and the three values of Log(*Shares*) are set as: low (=

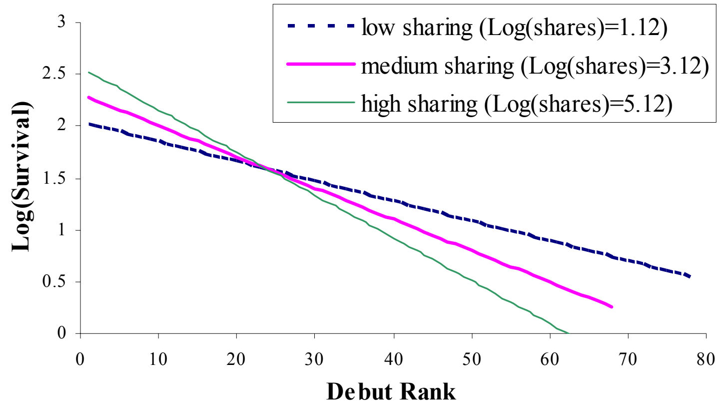

Fig 4: Impact of Sharing on Survival

1.12), medium (= 3.12) and high (=5.12).

Figure 4 suggests that for albums that debut at a rank worse than about 20, sharing hurts survival (negative interaction term), and the effect increases progressively as debut rank worsens. Moreover this effect appears more pronounced as sharing increases. Thus, a higher sharing of albums which are not very popular initially is linked to an adverse impact on the survivability of those albums. On the other hand, albums that debut near the top ranks do not appear to be adversely affected by sharing. Table 8 reports the mean survival times of albums before and after the RIAA announcement. Survival of albums that debut high on the charts has not dramatically altered since the RIAA announcement (which reduced sharing); however survival of worse ranked albums have shown an increase from 2.92 to 4.7 weeks. This again illustrates that sharing had an adverse impact on the survival of numerically higher ranked albums.

Table 8: Mean Survival Time

	Debut Rank <= 20	Debut Rank > 20
Feb-May 2003	13.11 weeks	2.92 weeks
July-Oct 2003	13.65 weeks	4.70 weeks

6. Discussions and Conclusion

We began by noting that the music industry has faced profound changes, including peer-to-peer (P2P) file sharing networks. The music industry and its legal arm, RIAA, have repeatedly and vigorously opposed P2P networks, and have begun legal suits against individuals "who offer significant number of songs for others to copy" (Ziedler 2003). Others have argued that P2P systems significantly enhance the ability of users to sample and experience music.

Our analysis focused on the survival of albums as measured by the number of weeks an album appears on the Billboard 100 charts before the final drop off. The two-year span, mid-1998 to mid-2000, represents a watershed period for the music industry during which a number of significant events unfolded, including: (i) introduction and rapid popularity of MP3 music format; (ii) introduction and rapid rise in the usage of Napster; (iii) passing of the Digital Millennium Copyright Act; (iv) surge in the popularity of DVDs, online chat rooms and games; and, (v) the beginning of a downturn in the overall economy.

The first phase of our study was a comparative analysis of album survival before and after this event "window" (mid-1998 to mid-2000). Our analysis included the following explanatory variables of album survival: debut rank of the album, reputation of the artist (as captured by the superstar status), major or minor label promoting and distributing the album, artist descriptors (solo female/solo male/group), and holiday month debut.

While this first phase considered the cumulative effect of technology and other factors on chart survival, our second phase attempted to isolate the impacts of file sharing on chart success. The additional data piece necessary for the second phase was sharing activity which we captured from WinMX over a period of 34 weeks. We also utilized an instrumental variable approach in this phase. The instrument was tied to the June 25, 2003 RIAA announcement that it would start legal actions against individuals sharing files on P2P networks, an announcement extensively disseminated through various print and broadcast media on June 26. Thus, the instrument, Z_i, is 1 for data after June 2003, and 0 otherwise. This event would be expected to have a direct impact on user file sharing. But, since the event would likely be uncorrelated with the error term, we use this event as an instrument shifting the intensity of sharing. Our results suggest that the intensity of sharing fell considerably after the RIAA announcement. To avoid a temporal effect or the effects of other exogenous variables which may have an impact on survival, we chose a relatively short window of four months before and after the announcement.

The key findings of the first part of our analysis include:

i) debut rank is highly significant with a negative impact on survival; in the *post*-TS period, this effect is even more pronounced for albums debuting lower on the charts, (i.e. less popular albums);

ii) survival time on the chart has decreased by 42% after controlling for other variables. However closer inspection reveals that albums that debut at the top of charts have not suffered. It is the less popular albums whose survival has reduced dramatically in *post*-TS period;

iii) albums by a superstar performer survive approximately 35% more on the charts even after controlling for other variables; further, this did not change in the *post*-TS period;

iv) neither solo male artists nor groups survive as long as female artists on the top 100 chart; and,

v) in both *pre*- and *post*-TS periods, albums promoted by major labels tend to last more than those promoted by minor labels. But our results indicate that minor label albums have experienced a significant beneficial shift in the *post*-TS period and are surviving longer than before.

In the second part of our analysis that incorporated sharing, our initial finding was that sharing is beneficial with more sharing linked to longer survival. However, as discussed in detail in the model specification section, these estimation results may be spurious and we thus utilized an instrumental variable approach. The resulting analysis provided the following key insights:

i) the instrument is highly significant suggesting a decrease in sharing after the RIAA announcement in June 2003; and

ii) the estimated effect of sharing is more negative for numerically higher ranked albums, i.e., less popular albums suffer more from increased sharing while top albums experience no significant impact.

To summarize, our key finding suggests that sharing does not appear to aid survival. While it does not hurt the survival of top ranked albums, sharing does have a negative impact on low ranked albums. This is also consistent with our first analysis where we find that there was no significant shift in the survival time for albums that debut at the "top" of the charts (low numerical ratings), but lower ranked albums have suffered. Further, the superstar effect appears to be alive and well. With other variables taken into account, albums from solo female artists continue to survive longer than albums from solo male artists or from groups. But there have been shifts in survival, some negative and some positive. Albums debuting at higher ranks (less popular) on the chart now face a "shorter life". While the chart albums from major labels still tend to fare better than those from minor labels, the gap has narrowed. A variety of anecdotal evidence (Spellman 2003, Green 20004) suggests minor labels have adapted better to technological and market changes and have utilized file sharing networks and other non-traditional methods to increase the popularity their albums.

As noted earlier, our analysis comes with a qualification that we consider sharing that occurs after the album has made an appearance on the charts. File sharing may take place *pre*-chart appearance, and such sharing could influence "if, when and where" an album appears on the charts. Our current research is directed at investigating the impact of early sharing.

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