

**Is iTunes Killing the Music Industry?
The Effect of Unbundled Track Sales on Music Industry Profits**

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Motivation and Research Question

The plight of the record industry is well known – sales of recorded music have fallen steadily since 2000 as the growth of digital sales has not been fast enough to compensate for the decline of physical cd sales. For example, in 2007 alone physical sales fell 13% to \$15.9 billion while digital sales grew by 34% to just \$2.9 billion, leading to an overall 8% decline in total global sales dollars. (New York Times 2008) While some of this decline may be explained by piracy (Liebowitz 2008, Robb and Waldfogel 2006) or perhaps a declining interest in music ownership, many industry experts and media sources cite album unbundling in digital stores as a major contributor to the decline in music revenues. (Wall Street Journal 2008, Elberse 2009). Specifically, the argument is that consumers who traditionally purchased CD albums when that was all that was available¹ have switched to cherry-picking only their favorite tracks digitally now that albums have been unbundled on stores like iTunes. By way of example, Nielsen Soundscan reports that combined digital and physical album sales dropped 15% in 2007 from the prior year while digital track sales grew 45% in the same year. (Nielsen 2007) Since digital albums are often sold at around 10 times the price of a digital track and physical albums are sold at 14-15 times the price of a digital track, it is no surprise that some labels and managers blame the shift toward digital tracks for lost industry revenues.

This still leaves unanswered several important questions. In a world where the market will unavoidably be dominated by digital music, are unbundled tracks profitable or unprofitable for the music industry? Record labels have little choice in the matter currently – the iTunes store dominates the digital market with 70% of all digital music sales (NPD 2009)² and Apple currently requires nearly all albums to be sold unbundled, with all tracks available for individual purchase at relatively low prices. It is not clear that Apple's policy is engineered to maximize music revenues - as the seller of the hardware most commonly used to play digital music (the iPod), Apple's iTunes policy may have the goal of generating large consumer surplus from music sales in order to generate hardware sales. What is the impact of this policy on music revenues and therefore labels, artists, and managers? What percent of digital track purchasers might instead purchase the digital album if tracks were not available individually and music labels were allowed to sell pure bundles (or set track prices discouragingly high)? Have consumers switched to digital tracks because the technology has changed their preferences between tracks and albums³, or because Apple enforces uniformly low pricing on tracks?

The literature on bundling indicates that under certain conditions common to information goods, a monopolist can increase profits significantly by bundling together large numbers of goods (Bakos and Brynjolfson 1999). This paper will contribute an empirical investigation to the literature, asking what effect unbundling and forced uniform track

¹ Some songs were sold as physical singles, usually the hit track of an album coupled with a significantly less popular track. However, most of the component tracks of the album were not available this way and the single that was available was sold at a discouragingly high price, typically four to five dollars.

² The second largest provider of digital music is Amazon, with only 8% of sales.

³ Physical singles may be undesirable because listening to them requires switching tapes/cd's in a player. Digital singles are not subject to this problem as users can create "playlists" of as many tracks as they choose.

pricing has had on the music industry and what digital album sales – and therefore profits - might look like in a world where pure bundling were permitted. Another contribution will be to ask whether consumers' substitution of tracks for albums (and vice versa) is moderated by underlying characteristics of the bundle, such as the relative desirability of each of the components or the overall desirability of the bundle. Finally, my analysis should provide some guidance to the industry, answering the question of whether labels can spur digital album sales by increasing track prices. As Apple has recently allowed labels to choose between three tiers of track prices (\$.69, \$.99, and \$1.29), understanding the cross price elasticity of album sales with respect to component track prices is critical to optimizing profits and this paper will help to quantify this.

Data

The dataset contains U.S. weekly iTunes sales volumes for the top 1000 selling digital albums of one major music label (which I will give the pseudonym “Music, Inc.”), as well as weekly sales volumes for the underlying tracks of these albums. It also contains the weekly price on iTunes for each of these tracks and albums. Various other album attributes are included in the dataset such as the release date, the musical genre, and the type of album (“best of,” studio album, live album, etc...) Tracks can be matched to their parent album through a unique album identifier variable. The data range from the beginning of December 2008 until the end of July 2009.

Empirical Strategy

Traditionally, while Apple has allowed labels flexibility in setting the prices of their albums, they have required all tracks to be priced uniformly at \$.99 per track. In April of 2009 Apple changed this policy, opening up both \$.69 and \$1.29 as potential track prices for labels. Labels quickly began experimenting, and while few tracks have been priced at \$.69 many have been increased in price to \$1.29. Music Inc. followed a very specific strategy to experiment with track pricing – on April 20 they increased the prices of their top 200 selling digital tracks to \$1.29. Then, two weeks later they increased the prices of tracks 201-400 to \$1.29 and a week after that, they increased the price on the top 401-600 track (and so on). In one sense, this is not an ideal experiment as the tracks selected for price increases were not random. However, given the rule used, the selection of tracks was random from a longitudinal perspective – that is to say, the selection was made without any thought as to whether the track's sales were expected to increase or decrease. Thus, there is an experiment that may be random (and this is testable) through time. As price on some tracks increases, sales on those tracks will decrease some (with respect to tracks that remain at \$.99). But there is no reason to believe that sales of the parent albums of treated tracks should be changing any differently than the parent albums of untreated tracks. Thus the track price serves as an instrument for track sales when asking the question “are track sales cannibalizing album sales?” Specifically, the general form of my analysis will have two stages. In stage one, I will show that increasing track prices lowers sales of those tracks. In stage two, I will ask if albums with treated tracks (price increased to \$1.29) experience increased sales, relative to albums with no treated tracks. With this methodology, I can calculate how many of the potential customers who did not buy the track due to increased price chose instead to purchase the album. If one is further willing to accept the assumption that consumers who chose not to purchase the track due

to the 30% price increase are similar to other consumers (with respect to their valuation of the album), one can then generalize these results to determine how much album sales would increase if tracks could no longer be purchased individually at all. This would make possible a comparison of what Music Inc's revenues would be in a world where they were able to sell pure bundles versus what their revenues are today given Apple's policy.

Preliminary Results

Clearly there are many forces interacting in this problem and a very careful, thorough analysis is required. I will build a theoretical framework that will motivate my empirical tests, and the paper will contain many summary statistics and exploratory work. However, here are the results of several simple reduced form models indicating that this study looks promising in terms of delivering interesting results. These are meant to spark interest, not as final answers.

Stage 1

First it is very important to show that the instrument in this experiment is not weak – that is to say, there is only an experiment here if increasing track prices does indeed decrease sales of those tracks. One basic way to do this is with a regression model aimed at computing the own price elasticity of tracks. Although only the high selling tracks have price increases, we have data on the tracks both before and after the price change and can therefore include track-specific fixed effects in our model to account for the relative popularity of each track. As well, sales are changing over time (for example, track sales spike around Christmas), so we include time fixed effects in the model as well in the form of a dummy variable for each week of sales.

$$\text{Log}(sales_{it}) = \beta_0 + \beta_1 * \text{log}(price_{it}) + \beta_2 * \theta_t + \beta_3 * \Phi_i + e_{it} \quad (1)$$

In equation (1), $sales_{it}$ represents the sales of track i in week t , $price_{it}$ is the price of track i in week t , θ_t is a vector of week-specific fixed effects, and Φ_i is a vector of track specific fixed effects. Thus, while accounting for overall market time/season trends, this model asks within each track how a change in price affects the weekly sales of that track. The coefficient of interest is β_1 , as it represents our estimate of the average own price elasticity of the tracks in the dataset that had their prices raised to \$1.29. If this coefficient is negative, then increasing the price of the track is associated with decreased sales of that track.

β_1 is estimated as -0.34, providing some evidence that there is a viable experiment here as a 1% increase in track price leads to a .34% decrease in track sales. This implies that when the price on tracks was increased by 30% to \$1.29, sales of those tracks fell by just over 10%, providing us with a reasonably strong instrument for track sales.

Stage 2

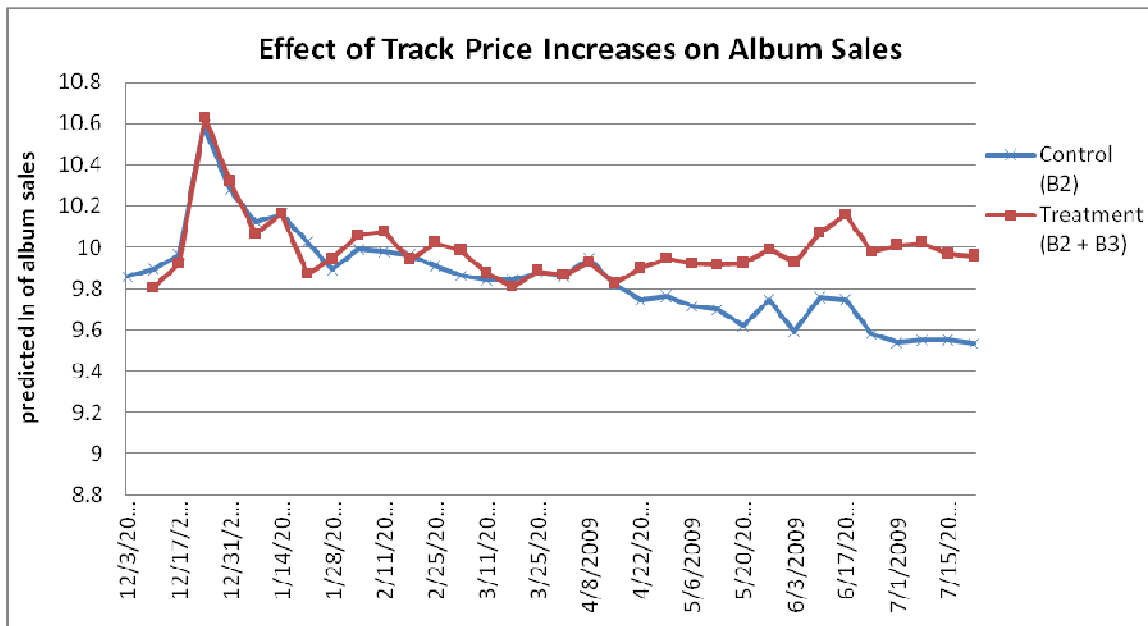
In stage 2, I must establish first that treatment albums (those that contained at least one track that would be increased in price) trended similarly over time as control albums (those that would not receive a track price increase) before the date of the track price

increases.⁴ Then, I can ask if treatment albums experience increased sales, relative to control albums, after track prices were increased. To this end, I estimate the following model.

$$\text{Log}(\text{sales}_{it}) = \beta_0 + \beta_1 * \text{log}(\text{price}_{it}) + \beta_2 * \theta_t + \beta_3 * \theta_t * \text{treatment}_i + \beta_4 * \Phi_i + e_{it} \quad (2)$$

sales_{it} indicates the unit sales volume of album i for week t , while price_{it} indicates the price of that album during that week. θ_t is a vector of dummy variables for each week of the data and θ_i is a vector of album specific fixed effects. Finally, treatment_i is a dummy variable equal to 1 if the album is one that had a track price increase on the treatment date. (for this analysis, any albums that had a track price increase on a later date are removed, thus the control group is all albums with 99 cent uniform pricing for all tracks on all dates).

The β_2 vector of coefficients indicate the effect of being each particular week on sales of the control group of albums (essentially, the mean log sales for each week), while β_3 indicates the difference between the treatment and the control group sales for each week. Because we have included a vector of album fixed effects which should subsume the average differences across albums, we expect β_3 to be 0 for all weeks before the treatment date if changes in control group sales are truly a good predictor for changes in treatment group sales. Then, for all weeks after the treatment date, β_3 indicates the degree to which track price increases have causally changed sales of the treatment albums. For brevity in this abstract, rather than reporting the estimates produced by this model, I will simply plot the predicted log sales each week for the control group and for the treatment group in a graph below.



⁴ It is reasonable to think this would be so since treatment albums were selected solely as a result of their cumulative sales at a given point in time.

As is evidence from this graph, the control albums seem to very closely mirror the treatment albums every week until the date of treatment on April 22, 2009 (even at the Christmas spike in late December) implying that the control group provides a good counterfactual for what treatment album sales would have been in the absence of the track price increases. However, after April 22, 2009, sales of the treatment albums begin to rise significantly above sales of the control albums, with the implication that track price increases on these albums have caused album sales to increase.⁵ Thus we have some evidence that indeed some track purchases are cannibalizing album purchases – consistent with what theory would predict.

Further Work

Much more analysis is necessary before any conclusions can be drawn, but the goal of this paper will be to determine how many track purchases cannibalize one album sale and to then to compare what pure bundling profits would look like as compared to the current unbundled policy. This is motivated in part by the theoretical literature on bundling of information goods but also by the question of what effect Apple's iTunes pricing policy is having on the music industry.

⁵ I suspect the reason that the gap between treatment and control increases over time is because some of the treatment albums had additional track prices increased (beyond the first most popular one) on dates following April 22. This will be tested in the paper and indeed could provide further support of the hypothesis.