Anita Elberse

Bye-Bye Bundles: The Unbundling of Music in Digital Channels

Fueled by digital distribution, unbundling is prevalent in many information and entertainment industries. What is the effect of this unbundling on sales, and what bundle characteristics drive this effect? The author empirically examines these questions in the context of the music industry, using data on weekly digital-track, digital-album, and physical-album sales from January 2005 to April 2007 for all titles released by a sample of more than 200 artists. The modeling framework, a system of an "album-sales" and a "song-sales" equation estimated with the seemingly unrelated regression method, explicitly accounts for the interaction between sales for the bundle and its components. The findings reveal that revenues decrease significantly as digital downloading becomes more prevalent, but the number of items included in a bundle (a measure of its "objective" value) is not a significant moderator of this effect. Instead, bundles with items that are more equal in their appeal and bundles offered by producers with a strong reputation suffer less from the negative impact of the shift to mixed bundling in online channels.

Keywords: unbundling, bundling, digital distribution, e-commerce, music industry, system-of-equations modeling

Facilitated by digital distribution, there is a trend toward unbundling in many information and entertainment industries. Because transaction costs are lower in online channels, the Internet enables companies to offer individual products that were previously only (or primarily) sold as part of bundles. For example, with the advent of online stores such as Apple's iTunes, music is now sold in the form of individual tracks instead of albums with a dozen or so songs, and consumers can download one episode of a television show at a time rather than pay for an entire season on DVD. Publishers have discussed plans to start selling access to some books a page or chapter at a time online (Fong 2008). Newspapers such as *The Economist* have unbundled their content online, selling individual articles to users for a small fee, and Web sites such as iStockphoto.com enable designers to purchase stock photos one-by-one, causing a shift away from the old practice of purchasing access to often hundreds of photos at once.

What is the effect of unbundling on sales, and what bundle characteristics moderate this effect? In this article, I examine these questions in the context of the music industry, in which the effects of digitization are arguably the most prominent and pressing. While the shift from offering albums to offering individual songs is widely believed to benefit consumers, a debate has emerged about the economic impact for producers and retailers, with some suggesting that unbundling negatively affects overall sales as people switch from buying albums to cherry-picking their favorite tracks on those albums and others contending that higher song sales will offset any decreases in bundle sales (e.g., Leeds 2006; Smith and Wingfield 2008). In addition, practitioners are wondering which mixed-bundle designs will best serve the industry going forward—for example, does the number of songs on an album matter, can hit songs continue to be counted on to stimulate album sales, and will superstar artists benefit from the trend toward unbundling? Though topical for the music industry, managers across a wide spectrum of entertainment and information industries will likely face the same kinds of questions as online channels make inroads in those sectors.

I investigate these issues using data on weekly digital-track, digital-album, and physical-album sales for all titles released by more than 200 artists. I analyze sales from January 2005 to April 2007—a period in which the share of unbundled units jumped from approximately one-third to two-thirds of total sales. The methodological approach is based on the realization that simply plotting the revenues per "mixed bundle," defined as the sum of sales for a bundle and its individual components, over time will not lead to conclusive insights into the revenue impact of unbundling. Several alternative forces could be at play at the same time, including a growth in illegal digital consumption and changes in the number and composition of titles on offer in the marketplace (if, for example, more titles of less commercially viable genres are released, mixed-bundle sales would also be expected to decrease). Therefore, I develop a model that relates the growth in (legal) digital consumption to temporal shifts in bundle sales but also controls for the most likely alternative explanations for those shifts.

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A complicating factor in modeling these phenomena is that sales of the bundle and its components are likely strongly intertwined: sales of the bundle can drive sales of one or more individual components, sales for one or more components may stimulate purchases of the bundle, and sales of the bundle and its components likely experience the same sales "shocks" over time. My modeling framework, tailored to the music industry but readily applicable to other industries in which sales of bundles are shifting to individual components (or vice versa), explicitly accounts for all three possible effects. I estimate a system of equations with one equation for the weekly sales of the individual components (songs) in a bundle and one for the weekly sales of associated bundled products (albums), allowing me to measure the drivers and interactions of bundled and unbundled sales. I estimate the model using the seemingly unrelated regression (SUR) method.

This study makes two major contributions. First, as a substantive contribution, I quantify the effect of unbundling on revenues in the specific context of the music industry. Although existing research mostly emphasizes the benefits of a mixed-bundling strategy over a pure-bundling strategy (for comprehensive reviews, see Jedidi, Jagpal, and Manchanda 2003; Stremersch and Tellis 2002; Venkatesh and Mahajan 2009), I find that as the population of consumers buying music digitally increases, there is a sharp decrease in the revenues per mixed bundle. Although the demand for individual songs is growing at a faster rate than the demand for albums is declining, the dollar amounts gained through new song sales are not enough to offset the revenues lost due to lower albums sales. According to my estimations, a reduction of approximately one-third of the total weekly sales per mixed bundle is attributable to the increased digital-music-downloading activity over the course of the study period.

The shift to digital music buying offers an opportunity not only to study the substantive question of how much unbundling affects revenues but also, and more important, to test theoretical notions on what characteristics make mixed bundles more or less susceptible to such changes in demand. Therein lies this study's second contribution. As more people over time buy music through digital stores and thus expose themselves to mixed (instead of pure) bundles, it becomes possible to tease out the factors that accelerate or dampen the decrease in revenues. Building on the extant behavioral bundling literature (e.g., Gilbride, Guiltinan, and Urbany 2008; Johnson, Herrmann, and Bauer 1999; Soman and Gourville 2001), I test the moderating effect of three factors: the number of individual items in the bundle, the relative popularity of individual items in the bundle, and the reputation of the producer of (or the brand behind) the bundle. It might be expected that the higher the total dollar value of a bundle, expressed in terms of the number of (uniformly priced) items that are included, the more that bundle is insulated from the detrimental impact of unbundling, but I find no evidence of such a relationship. Rather, it appears that consumers evaluate mixed bundles in more complicated ways than simple economic models would predict. Consistent with assimilation and contrast theory, the results suggest that consumers evaluate a bundle more favorably if its items are more consistent in their appeal—bundles with a high concentration in popularity across individual components experience an even greater decrease in revenues over time. Highlighting the role of brands, the findings also show that a strong reputation of the producer helps curb the negative impact of unbundling. These findings have important and, in some ways, perhaps counterintuitive consequences for optimal bundling strategies. For example, the results indicate that the common strategy of bundling 1 highly appealing product (e.g., a hit song) and 11 relatively unappealing items may quickly become obsolete: In online channels, a seller may (all else being equal) be better off selling the 11 items as a mixed bundle and the high-appeal item separately.

These findings inform the growing literature on how firms should design, price, and promote bundles (e.g., Ansari, Siddarth, and Weinberg 1996; Hanson and Martin 1990; Mulhern and Leone 1991; Venkatesh and Kamakura 2003), particularly in the entertainment industry (Stigler 1963; Venkatesh and Chatterjee 2006; Venkatesh and Mahajan 1993). To date, the implications of a shift from a pure-bundling to a mixed-bundling strategy have been assessed only in analytical studies. In an industrial context, Wilson, Weiss, and John (1990) argue that the growth in the size of the market resulting from unbundling is a crucial determinant of the attractiveness of a mixed-bundling strategy. Focusing on the case of a magazine publisher, Venkatesh and Chatterjee (2006) theorize that offering individual products online as a complement to the offline offering is favorable when the market strongly prefers the offline good. The current study—the first "real-world" empirical examination in this area—offers meaningful new insights into how firms can best design and market mixed bundles.

The Impact of Unbundling

Motivating Example: Unbundling in the Music Industry

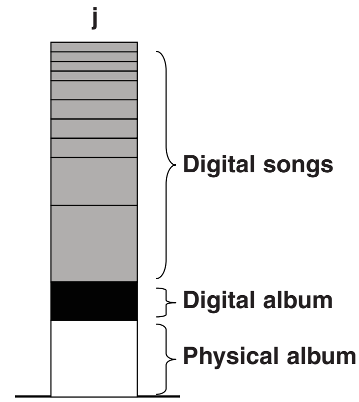
In December 2006, Interscope Records released pop star Gwen Stefani's second album, *The Sweet Escape*, with 12 new songs. Fans could buy Stefani's songs in three ways: They could purchase a traditional compact disc with the 12 songs for approximately $14, download the full album in a digital format from a store such as iTunes for $9.99, or choose whatever subset of downloadable songs on the album they liked most for $.99 per song. *The Sweet Escape* is no exception: Whereas recorded music has historically been sold in the form of albums, the lion's share of music in today's marketplace can be purchased both as an album or as an individual track.[1] Since the early 2000s, driven by the rise of digital channels, record labels have moved from what can be called a pure-bundling strategy, in which a firm sells only the bundle, to a mixed-bundling strategy, in which

[1]Record labels have historically released "singles"—discs typically containing what was deemed to be the most commercially viable song by an artist on a new album (on the "A" side) as well as a more unusual choice (on the "B" side). However, digital channels now enable customers to choose from the full range of songs on most albums.

a firm sells both the bundle and (all) the products separately (e.g., Stigler 1963).[2]

In general terms, the combined sales at any given time for an album can be represented graphically as in Figure 1: the sum of the sales generated by the physical album (the white bar), the digital album (the black bar), and each of the songs (the gray bars). The sum of sales for each of these components (i.e., the total represented by the vertical bar) is the total sales for a mixed bundle, denoted here as j. What will the shift to mixed bundling online do to sales over time, and to what extent do characteristics of the bundle moderate this effect?

FIGURE 1
Schematic of a Mixed Bundle



Hypotheses

Drawing on the extant marketing and economics literature on bundling (and unbundling) and industry-specific considerations, I formulate one substantive hypothesis on the likely revenue impact of the shift to mixed bundling in online channels. In addition, building on more general behavioral theories, such as assimilation and contrast theory, to help understand how consumers decide between competing offerings, I formulate three hypotheses on bundle characteristics that possibly determine the magnitude of that impact; the idea is that an understanding of how consumers evaluate bundles should help predict which mixed bundles benefit more (or suffer less) from the shift to mixed bundling online.[3]

H_1: the revenue impact of mixed bundling. The large body of work on bundling in economics and quantitative marketing has traditionally emphasized one critical determinant of the payoff of a bundling strategy: the variance in reservation prices across and within consumers. According to Schmalensee (1984, p. 228), (pure) bundling "operates by reducing the effective dispersion in buyers' tastes," which will "enhance profits by permitting more efficient capture of consumers' surplus" as long as people's reservation prices are not perfectly positively correlated. Mixed bundling, he argues (p. 229), enables a seller to "reduce effective heterogeneity among buyers with high reservation prices" for two (or more) of the bundled items "while still selling at a high markup to those buyers willing to pay a high price for only one of the goods." Thus, mixed bundling can work as a tool of price discrimination: When reservation prices vary, a bundle can be designed to appeal (and more profitably sell) to consumers who would otherwise buy only one or a few items at prices below their reservation prices (e.g., Adams and Yellen 1976; Guiltinan 1987; Jedidi, Jagpal, and Manchanda 2003; Schmalensee 1984; Stigler 1963; Wilson, Weiss, and John 1990).

Most of this literature assumes that there is a monopoly seller seeking to bundle two products. In such a context, a mixed-bundling strategy is, at the very least, never strictly dominated by other forms of bundling. Whether (pure versus mixed) bundling or unbundling is optimal in more competitive environments remains unclear; studies on duopoly situations do not paint a consistent picture (e.g., Anderson and Leruth 1993; Economides 1993; Kopalle, Krishna, and Assunção 1999). Recently, quantitative marketers and economists have begun to consider other factors that might drive a preference for one particular bundling strategy, including the degree of complementarity or substitutability of the components and cost considerations, and have considered bundles with a larger number of products. As Venkatesh and Mahajan (2009) conclude in their review, in all likelihood, no one form of bundling is always the best—the context matters.

Myriad factors could play a role in the focal context of the music industry, but three factors conceivably make the shift to mixed bundling in online channels less than ideal. First, several forces in the music industry collectively may dampen the variation in reservation prices, thus decreasing the consumer surplus that mixed bundling is designed to capture. The uniform pricing for recorded music—record labels set prices for music regardless of the production costs or some measure of product quality—may serve as a cognitive reference point and has come to affect customers' reservation prices (e.g., Thaler 1985; Winer 1986). Janiszewski and Cunha (2004) demonstrate the role of reference prices in the perceived value of bundles. Though an arbitrary price point for a song, the ubiquitous price of $.99 for a digital track may also lower people's perceptions of what music is worth; that consumers can readily see the prices of bundle components in online stores may further undercut the effectiveness of a mixed-bundling strategy (Stremersch and Tellis 2002). In addition, the widespread availability of "free" music on the radio, through new online distribution mechanisms, such as Pandora, as well as in illegal forms, may put

[2]The form of bundling considered here is that of price rather than product bundling. Stremersch and Tellis (2002) define the former as "the sale of two or more separate products as a package at a discount, without any integration of the products" (p. 56) (other examples are a luggage set or a variety pack of cereal) and the latter as "the integration and sale of two or more separate products at any price" (p. 57) (examples are a multimedia personal computer or a sound system).

[3]A growing body of research in marketing draws on behavioral decision theories to explain how consumers evaluate (mixed) bundles. Recent work on "price partitioning" (e.g., Morwitz, Greenleaf, and Johnson 1998) has also offered relevant insights. However, because price partitioning essentially involves the division of prices of single products, whereas bundling is the collective pricing of distinct products, I focus less on this literature.

an overall downward pressure on and decrease variation in reservation prices.

Second, actual prices for individual components ($.99) in the music industry seem relatively low compared with the prices for bundles (upward of $9.99), which might not yield enough revenues on component sales. As Schmalensee's (1984) description of the rationale behind bundling highlights, choosing prices that generate a high enough markup on individual components is essential to making the mixed-bundling strategy work. In this context, it is unclear whether the price of $.99 per song satisfies that requirement: Record labels will need to sell more than 10 songs to make up for the loss of one digital album sale and 15 to make up for the loss of one physical album sale.[4]

Third, in markets for entertainment products, people's tastes tend to converge on a select few blockbuster products rather than be dispersed across the assortment of available offerings. Even the most successful albums rarely generate more than one or two hit songs (Smith and Wingfield 2008). Ample evidence suggests that a strong concentration in sales is a common characteristic of markets for cultural products, in which producers focus marketing efforts on a select group of likely winners (e.g., Elberse 2008) and social influence (e.g., Salganik, Dodds, and Watts 2006) and success-breeds-success trends (e.g., Elberse and Eliashberg 2003) play a critical role in generating hits. These forces exacerbate the problems stemming from the relatively low price point for individual components, in that people's preferences may concentrate on one or a select few songs on the album. Furthermore, the focus on winners possibly reduces people's willingness to buy a bundle even if their reservation prices for the components collectively exceed the bundle's actual price, in that it may encourage people to cherry-pick higher-valued hit songs across several albums. Such a scenario is particularly likely in online channels, in which people can now choose from a vast assortment of goods, though people's budgets have not kept pace with the increased supply. As a result, while record labels may have relied on their ability to sell albums based on the strength of a select few songs in an offline pure-bundling setting, this strategy may be less suitable for an online context, in which consumers are also able to choose individual songs. Therefore, I formulate my first hypothesis as follows:

> H_1: As music becomes increasingly consumed digitally, the sum of the dollar sales across all components in a mixed bundle decreases over time.

This hypothesis can be split into three subhypotheses:

a. The sum of the sales for the album in a mixed bundle decreases as digital music consumption increases.
b. The sum of the sales for the individual songs in a mixed bundle increases as digital music consumption increases.
c. The increase in the sum of the sales for the individual songs in a mixed bundle is not enough to offset the losses due to decreasing sales of the albums in that mixed bundle.

[4]A contributing factor here is that leading digital music retailer Apple may not be trying to maximize revenues or profits on music but instead may view music as a catalyst for (more profitable) hardware sales of iPods and iPhones.

H_2: the moderating impact of the number of individual items. As an initial hypothesis on bundle characteristics that moderate the impact of unbundling on sales, I consider the role of the number of components in a bundle. Compared with most existing research settings, the entertainment industry stands out for having relatively many items as part of a bundle—the average music album contains 12 songs, while the average DVD box set may contain 20 or so television episodes. What is also unusual here is that the components and bundles are mostly uniformly priced, meaning that the actual savings per bundle are almost a direct function of the number of items in that bundle.

A large body of literature suggests that consumers' overall assessments of the value of a good are based on their perceptions of what is received versus what is given up (e.g., Hamilton and Srivastava 2008). Perceived value is positively influenced by benefits and negatively influenced by price (e.g., Dodds, Monroe, and Grewal 1991). There is some evidence that most consumers follow a relatively straightforward economic choice model in deciding whether to purchase the bundle (Gilbride, Guiltinan, and Urbany 2008). In perhaps its simplest form, this implies that consumers adhere to an additive model in which, for example, a bundle with 14 components constitutes a "better deal" than one with 10—that is, all else being equal, the more items a bundle contains, the higher is its perceived benefit relative to its price. The second hypothesis expresses the idea that bundles with a higher "additive" dollar value will be less at risk from the shift to mixed bundling:

> H_2: As music becomes increasingly consumed digitally, the sum of the dollar sales across all components in a mixed bundle decreases (increases) over time, but less so (and more so) the higher the number of individual components in a mixed bundle.

H_3: the moderating impact of the relative popularity of individual items. There is considerable evidence, albeit primarily from laboratory experiments and for a small set of bundled items, that suggests that consumers' evaluations of bundles work in more complicated ways (e.g., Yadav 1994). A critical factor may be the ease with which consumers can choose what to buy—that is, whether to buy one or more individual items (and, if so, how many) or to buy the bundle. In contexts with (mixed) bundles consisting of a relatively large set of components (as in music albums), assimilation and contrast theory (Sherif and Hovland 1961) may offer a particularly useful framework. The theory prescribes that some evaluations are contrastive in nature, in that they are displaced away from a comparison standard, whereas others are assimilative in nature, in that they are pulled toward a comparison standard (Markman et al. 2007). Assimilation can be thought of as a kind of magnetic attraction toward and contrast as a kind of repulsion from a context or standard (Suls and Wheeler 2007). Thus, how the set of to-be-evaluated items is distributed on a relevant metric is critical. Assimilation and contrast theory has been applied to a wide range of (social-) psychological phenomena, such as perceptions, affect, mood, and behavior (Suls and Wheeler 2007). In marketing, it has formed the basis for research on pricing. For example, as Mazumdar, Raj, and

Sinha (2005) describe in their review of reference price research, marketing researchers have used assimilation and contrast theory to study how consumers integrate external information into their reference price (e.g., Lichtenstein and Bearden 1989). The theory suggests that for a given quality level, a consumer has a distribution of prices that are considered acceptable. New price information is assimilated only if the observed price is judged as belonging to that distribution (Mazumdar, Raj, and Sinha 2005).

How would the theory come into play in the evaluations of bundles? Consider a mixed bundle, j_A, consisting of 2 highly appealing items (e.g., 2 hit songs) and 10 unappealing items, and compare that with another mixed bundle, j_B, consisting of 1 highly appealing item and 11 moderately appealing items. Assimilation and contrast theory would predict that consumers are more likely to treat the items in the second bundle, j_B, as belonging to the same underlying "quality" or "appeal" distribution, leading the 11 moderately appealing items to be evaluated better than they would be by themselves—in other words, assimilation occurs.[5] In turn, this would make it more likely that consumers opt for the full bundle. In the case of the first bundle, the sharp differences between the highly appealing and the unappealing items make it more probable that consumers view the items as belonging to different categories, causing the 10 unappealing items to be evaluated worse than they might be if they were evaluated by themselves—in other words, a contrast effect. In turn, this would make it more likely that consumers opt only for the two highly appealing items rather than the bundle. In other words, in deciding how many items are worth buying, sharp differences in the attractiveness of items make it easier for consumers to choose which subset of items to purchase, while a relatively even distribution in attractiveness across items makes it more difficult to decide where to "draw the line," thus stimulating bundle purchases.

The argument is one of relative (rather than absolute) differences. Consider the two graphs in Figure 2 (which I describe in more detail subsequently) that depict the relative popularity of songs on albums by artists Gwen Stefani (top) and Jack Johnson (bottom). The argument I put forth here is that music consumers will be more likely to opt for the bundle if the appeal of songs is distributed in a pattern akin to that of Johnson's album than if the distribution of popularity across songs is more concentrated as it is on Stefani's album, regardless of the absolute sales levels. Consumers will have an easier time deciding that, for example, only Stefani's top two songs are worth purchasing; the choice is far less obvious for Johnson's album, which, I argue, makes full bundle purchases more likely.[6]

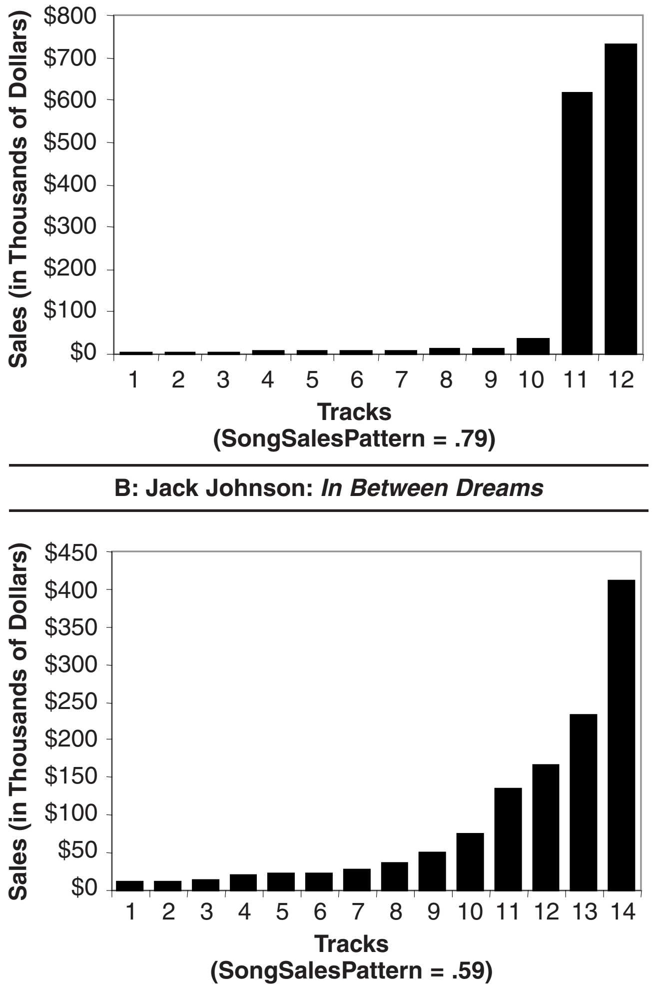
[5]I use the terms "appeal," "attractiveness," "popularity," and "quality" (with the latter referring to popular appeal, not critical acclaim) interchangeably. There is strong empirical evidence for a positive relationship between an entertainment product's popularity and people's appreciation of the product (e.g., Elberse 2008).

[6]These interpretations are consistent with Kahneman and Tversky's (1979) prospect theory, if the (reasonable) assumption is made that consumers compare the other songs on the album with one or more hit songs with which they are most familiar. A central organizing principle in behavioral decision theory is that of gains and losses relative to a set of benchmarks and the idea that losses are considered more detrimental than corresponding gains.

These considerations suggest that providing consistent levels of quality in a (mixed) bundle is paramount to stimulating full bundle sales. All else being equal, having a set of songs that are relatively even in their appeal may lead to a higher overall willingness to pay for the bundle. The larger the share of products that reach a certain level of relative attractiveness, the more people will revert to buying the bundle instead of buying only the most attractive individual components. The third hypothesis expresses this idea:

FIGURE 2
Illustrations of the Concentration Measure

A: Gwen Stefani: *The Sweet Escape*



Notes: The top graph represents the distribution of cumulative sales across the 12 digital tracks on Gwen Stefani's album *The Sweet Escape* up to its 12th week of release (i.e., up to the week of February 25, 2007). The top two tracks, *Wind It Up* and *The Sweet Escape*, together account for 92% of the total cumulative sales. The bottom graph represents the distribution of cumulative sales across the 14 digital tracks on Jack Johnson's album *In Between Dreams*, also up to the week of February 25, 2007. Here, the top two tracks, *Sitting, Waiting, Wishing* and *Better Together*, account for only slightly more than half the total cumulative sales. The sales distribution is more concentrated for Gwen Stefani's album than for Jack Johnson's album in this particular week; thus, Stefani's SongSalesPattern score for the corresponding week is closer to 1 than Johnson's.

H_3: As music becomes increasingly consumed digitally, the sum of the dollar sales for the bundle in a mixed bundle decreases (increases) over time, but less so (and more so) the more equal the relative appeal of individual components in a mixed bundle.

H_4: the moderating impact of the brand strength of the producer. Entertainment products are experience goods: People cannot reliably judge product quality or appeal before consumption. This elevates the importance of brands, defined by the providers of the goods (or, in the context of music, artists and bands), as signals of quality. Those who have established a reputation for making products that "caught on" in the past may receive more favorable overall bundle evaluations, leading to a higher overall willingness to pay for the set of components. This could work because creators with past successes may indeed be more capable of producing solid bundles in the future (as also captured in H_3) or because they may be perceived as such.

This reasoning fits Simonin and Ruth's (1995) research about the role of prior attitudes toward (component) brands in people's bundle evaluations: These researchers find that such attitudes significantly affect the evaluation of the bundle, which in turn mediates the influence of these prior attitudes on consumer reservation prices for the bundle itself and for the component products. More generally, the ideas are also in line with extant research that has established a link between a consumer's perceptions of the benefits of a product or component and both his or her willingness to pay (e.g., Zeithaml 1988) and price sensitivity for the component (Hamilton and Srivastava 2008).

In the context of entertainment markets, there are strong indications of the enduring appeal of top performers, likely triggering higher reservation prices among some consumers (and thus creating more consumer surplus that bundling can capture). Two key factors cause the emergence of a "superstar" phenomenon—when relatively small numbers of people dominate the activities in which they engage: First, lesser talent is a poor substitute for greater talent, and second, because people enjoy discussing their consumption experiences with others, they prefer to patronize the same artists as others do (Rosen 1981). Empirical research by Chung and Cox (1994) confirms that the superstar phenomenon exists in the popular music industry. Bhattacharjee and colleagues (2007b) find a significant, negative impact of peer-to-peer file-sharing technologies on the chart survival of albums, but not for albums by superstar artists (see also Gopal, Bhattacharjee, and Sanders 2006).

These considerations lead to the expectation that, keeping the number and relative popularity of bundle items constant, bundles provided by a superstar with a reputation for hit products will suffer less from the shift to mixed bundling online than those without such brand equity. Thus:

H_4: As music becomes increasingly consumed digitally, the sum of the dollar sales across all components in a mixed bundle decreases (increases) over time, but less so (and more so) the stronger the reputation of the provider of the bundle.

Data and Measures

Nielsen SoundScan Data

Nielsen SoundScan, the leading source of information on recorded music sales in North America, provided the main data used in this study. Nielsen captures all albums and tracks sold through 14,000 retail, mass-merchant, and online outlets in the United States and Canada, including all major recorded music bricks-and-mortar retailers and the largest online stores. Nielsen publishes the popular *Billboard* Top 200 for albums and the *Billboard* Hot 100 for singles, named after *Billboard Magazine*, which prints the charts every week. The *Billboard* charts reflect sales of physical products, airplay, and, since 2005, sales of digital albums and tracks. Nielsen also compiles charts for specific categories, including the top new albums ("Heatseekers") and the "Hot R&B Bubbling Under," as well as charts for specific genres, including blues, classical, jazz, Latin, rap, reggae, rock, and world music.

Sample. To compile a sample for this study, I randomly selected 250 artists from a list of all artists appearing at least once on any of Nielsen SoundScan's charts between January 1, 2005, and December 31, 2006. While an artist's presence on a chart indicates at least some level of sales success, the focus on the full range of charts guarantees the inclusion of a wide spectrum of artists, ranging from some of the biggest bands and individual performers (e.g., Justin Timberlake, Maroon 5, Mary J. Blige, and Rascal Flatts, each of whom sold millions of units) to more niche artists who have only scored a modest hit in a genre-specific chart. After the data were cleaned—for example, by filtering out compilation albums—224 artists remained.

Measures. For all available titles (i.e., those released before and during the sample period) for each of the 224 artists, Nielsen provided weekly unit sales data from January 1, 2005, to March 31, 2007 (i.e., nine quarters, or 117 weeks). The data cover 2333 unique physical albums, 2018 unique digital albums, and 14,962 unique digital tracks. Together, the artists sold more than 326 million units in the study period. I obtained dollar sales information by multiplying the unit sales with average prices published by the Recording Industry Association of America (RIAA) in its yearly statistics report (RIAA 2006, 2007)—namely, \$.99 for each track; \$9.99 for each digital album; and \$14.91 for physical albums in 2005, \$14.90 in 2006, and \$14.88 in 2007.

Because Nielsen could not disclose which digital tracks appeared on which album, two coders subsequently matched songs to albums using the iTunes store and other publicly available music databases. This resulted in 2549 bundles—an average of just over 11 per artist. The weekly dollar sales for a mixed bundle were calculated as the sum of the dollar sales for an album (the variable AlbumSales) and its associated individual tracks (SongSales). The coders further counted the songs in a bundle (NumberOfSongs) and scored each album and set of songs on their availability on iTunes (AlbumsNotOniTunes and SongsNotOniTunes), the dominant online music retailer, with an estimated share of 90% of the digital music market (Smith and Wingfield 2008).

Using publicly available music chart information published weekly by Nielsen SoundScan, I compiled a rolling-window, four-year *Billboard* charting history for each of the 224 artists and bands. I constructed two metrics for each artist's reputation: the number of albums that appeared in the *Billboard* Top 200 Albums chart (ArtistAlbumHistory) and the number of singles that appeared in the *Billboard* Hot 100 Singles chart (ArtistSongHistory) in the previous four years. The latter measure is similar to the "artist-history" metric that Bradlow and Fader (2001) use and is highly correlated with the "artist-reputation" metrics that Gopal, Bhattacharjee, and Sanders (2006) and Bhattacharjee and colleagues (2007b) employ, as well as the counts of the number of gold and platinum albums that Lee, Boatwright, and Kamakura (2003) use.

In addition, I constructed other artist, title, and market descriptors. Of the 20 genre classifications Nielsen employs, I used the 8 genres that belong to at least 5% of titles in the sample: alternative, Christian, country, metal, pop, rap, R&B, and rock (GenreAlternative–GenreRock). Nielsen also identifies whether the album was released by a major or an independent label (MajorLabel). Finally, I calculated two time-varying variables: how many weeks had lapsed since the album's release date (WeeksSinceRelease) and the number of albums and songs on the market each week (CompetingAlbums and CompetingSongs).

NPD Group Data

I turned to the NPD Group's MusicWatch Digital study for the monthly percentage of U.S. households downloading music files from paid (legal) digital music download services (DigitalBuying) and, as a control variable, the monthly percentage of U.S. households downloading music files from (illegal) peer-to-peer services (DigitalSharing). The NPD MusicWatch data are collected continuously from the Windows PCs of 40,000 online panelists balanced to represent the online population of U.S. Internet-enabled PC households. The two measures represent the penetration of paid and peer-to-peer services used to download at least one music file; they do not include video, games, or other types of files that might also be shared or sold. The data show that legal music downloading increased steadily from 2.5% in January 2005 to 9% at the end of the study period; illegal music downloading is more stable and fluctuates mostly between 9% and 12% of the population. There is some overlap: For example, in the first quarter of 2005, 12% of peer-to-peer users also purchased at least one song from a legal service (The NPD Group 2005). Table 1 briefly explains each measure and provides descriptive statistics.

Reflections on the Nielsen SoundScan Data

Although there are several studies in marketing, management, and related fields that use Nielsen SoundScan charts (e.g., Bradlow and Fader 2001; Lee, Boatwright, and Kamakura 2003; Moe and Fader 2001), no previous study has split sales by format, let alone matched album sales to associated song sales. This is a critical void in the research, given the surge of digital channels that facilitate unbundling.

Ideally, a study such as this one, which examines the revenue impact of unbundling, will cover the beginning of the transition from a fully bundled market to one in which unbundled products are increasingly available. That is not the case here: Nielsen SoundScan was not able to provide sales breakdowns for the period before 2005. Therefore, the study period begins well beyond the digital unbundling of music (e.g., Apple iTunes was launched in April 2003). Fortunately, the study covers a time of rapid growth in the market for paid digital downloads. In early 2005, just over 10 million units had been sold of Apple's popular music player, the iPod, which enables users to play iTunes songs; by the end of the first quarter of 2007, the installed base had increased with close to another 89 million iPods (Apple Inc. 2007a). Digital recorded music sales followed suit: In late January 2005, Apple had sold a quarter of a billion songs worldwide; by April 2007, that total had risen to more than 2.5 billion songs (Apple Inc. 2007b).

General unit sales statistics provided by Nielsen SoundScan for a wider set of more than 3300 randomly sampled artists (with the sample frame again being defined by one or more appearances on a *Billboard* chart) confirm the effect of the growth in digital distribution on the sales of music recordings (see Figure 3). The figure expresses three important trends. First, although there is considerable seasonal variation—sales jump significantly in the fourth (holiday) quarter—physical album sales display a strong downward trend, decreasing from approximately 105 million units in the first quarter of 2005 to just over 80 million units in the first quarter of 2007. Second, the number of units sold in a digital format trends upward, with digital albums and tracks increasing from a combined 54 million units in the first quarter of 2005 to more than 151 million units exactly two years later. Third, and arguably most prominent, the growth in digital units comes predominantly in the form of unbundled units (which make up 96% of digital units sold in both quarters): The share of digital tracks jumps from 33% of the total unit sales in the first quarter of 2005 to approximately 62% in the first quarter of 2007. In other words, in the period covered in this study, the share of recordings sold in an unbundled form increases from roughly one-third to almost two-thirds of total units sold, thus providing excellent conditions to examine the drivers and consequences of unbundling.

Although it may be tempting to take these overall figures as evidence that unbundling indeed goes hand in hand with lower overall revenues, it is important to account for interactions between album and song sales and to exclude alternative explanations for a decrease in revenues. Not doing so could lead to incorrect conclusions about the true impact and moderators of unbundling.

Modeling Approach

Several considerations underlie the model specification. First, because record labels' product development and marketing investment decisions are primarily made at the level of the mixed bundle, I analyze sales at that level.

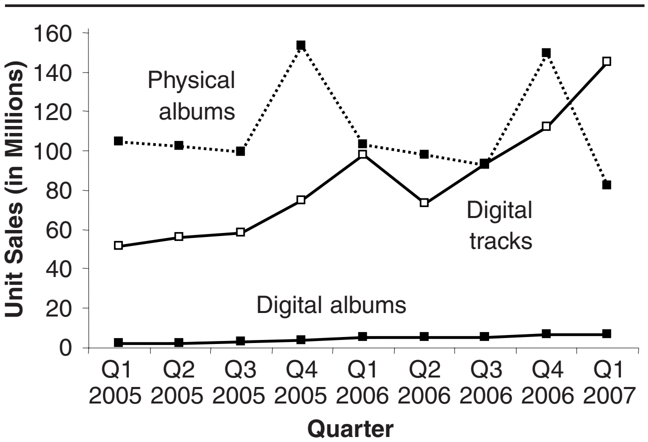
Second, because I am interested in the likely divergent sales paths for the bundled part (albums) and the unbundled part (songs) of the mixed bundle and what drives each of those, I construct a system of two equations: one album-sales equation, with the weekly sales for the full album in a

TABLE 1
Descriptive Statistics

A: By Mixed Bundle and Week (N = 226,963)						
		M	Mdn	SD	Minimum	Maximum
AlbumSales	Dollar sales for the (physical and digital) album in the bundle	11,348	328	97,717	0	13,216,000
SongSales	Dollar sales for the (digital) songs in the bundle	667	18	3,594	0	196,000
SongSalesPattern	The concentration in sales across the songs in the bundle	.43	.46	.23	.00	.93
DigitalBuying	The (monthly) percentage of households legally downloading music	5.04	5.00	1.53	2.50	9.00
DigitalSharing	The (monthly) percentage of households illegally downloading music	10.41	10.40	.99	8.50	12.70
NumberOfSongs	The number of individual songs belonging to the bundle	12.03	12.00	6.38	1.00	50
WeeksSinceRelease	The number of weeks elapsed since the bundle's release	253	162	262	.00	1357
ArtistAlbumHistory	The number of top 200 albums for an artist in the last four years	2.86	2.00	2.55	.00	15.00
ArtistSongHistory	The number of Hot 100 songs for an artist in the last four years	1.07	.00	1.75	.00	10.00
CompetingAlbums	The total number of albums on the market (in thousands)	3.015	3.237	.661	1.974	3.993
CompetingSongs	The total number of songs on the market (in thousands)	13.087	13.290	2.084	7.741	16.049

B: By Mixed Bundle (N = 2549)			
		Sum	%
AlbumNotOniTunes	Dummy: The digital album is not available on iTunes	71	3
GenreAlternative	Dummy: The bundle's genre is "alternative"	546	21
GenreChristian	Dummy: The bundle's genre is "Christian"	220	9
GenreCountry	Dummy: The bundle's genre is "country"	198	8
GenreMetal	Dummy: The bundle's genre is "metal"	338	13
GenrePop	Dummy: The bundle's genre is "pop"	143	6
GenreRap	Dummy: The bundle's genre is "rap"	260	10
GenreR&B	Dummy: The bundle's genre is "R&B"	650	26
GenreRock	Dummy: The bundle's genre is "rock"	945	37
MajorLabel	Dummy: The bundle is released by a major label	1527	60
SongsNotOniTunes	Dummy: One or more individual songs are not available on iTunes	84	3

FIGURE 3
Physical and Digital Unit Sales by Quarter



Notes: The figure plots unit sales for the nine quarters between January 2005 and April 2007 for a Nielsen SoundScan data set covering more than 3300 randomly sampled artists (224 of which were, in turn, randomly selected for this study).

mixed bundle as the dependent variable, and one song-sales equation, with the weekly sales summed across the individual songs in a mixed bundle as the dependent variable. Together, the dependent variables represent the total (dollar) sales per mixed bundle.

Third, to test H_1, I regress temporal patterns in sales for albums and songs on the changing rate of adoption of music downloading. To test H_2–H_4, I include three interaction effects. I control for any shifts in the number and composition of titles in the market that could also explain why mixed-bundle sales levels may decrease or increase over time. That digital music buying increased over the study period facilitates such an examination: As the population that buys in online stores that enable unbundling increases, the effect of the moderators should reveal itself over time.

Fourth, there is possibly a complex, intertwined relationship between sales for the different components in the mixed bundle: Sales of the bundle can drive sales of one or more individual components, sales for one or more components may stimulate purchases of the bundle, and sales of the bundle and its components likely experience the same "shocks" over time. Analyzing such interactions is necessary to develop an in-depth understanding of the unbundling phenomenon, particularly if the importance of the album component of the mixed bundle is decreasing and the songs component is increasing over time. I model album and song sales as being dependent on both their own lagged terms and the lagged terms of the other component, and I allow the errors of the equations to be correlated.

Fifth, I use the natural logs of the sales variables. Because album and song sales are the dependent variables in both equations, both become semilog models in which the estimated parameters reflect the approximate percentage change in the dependent (sales) variable resulting from a one-unit change in an independent variable.[7]

The System of Equations

Consider an artist i with a mixed-bundle j that covers the (digital and physical) albums a_1 and a_2 and their associated digital songs (or tracks) s_1–s_m. The album-sales equation expresses the weekly sales for the albums in artist i's mixed-bundle j:

$$
\begin{aligned}
(1)\ \ln\left(\text{AlbumSales}_{ijt}\right) = {} & \alpha_0 + \alpha_1 \text{DigitalBuying}_t \\
& + \alpha_2 \text{NumberOfSongs}_{ij} \\
& + \alpha_3 \left(\text{DigitalBuying}_t \times \text{NumberOfSongs}_{ij}\right) \\
& + \alpha_4 \text{SongSalesPattern}_{ij(t-1)} \\
& + \alpha_5 \left(\text{DigitalBuying}_t \times \text{SongSalesPattern}_{ij(t-1)}\right) \\
& + \alpha_6 \text{ArtistAlbumHistory}_{it} \\
& + \alpha_7 \left(\text{DigitalBuying}_t \times \text{ArtistAlbumHistory}_{it}\right) \\
& + \alpha_8 \ln\left(\text{AlbumSales}_{ij(t-1)}\right) \\
& + \alpha_9 \ln\left(\text{SongSales}_{ij(t-1)}\right) \\
& + \alpha_{10} \text{BUNDLE}_{jt} + \alpha_{11} \text{CONTEXT}_t + \varepsilon_{1ijt},
\end{aligned}
$$

where AlbumSales_{ijt} denotes weekly sales for an album (in a physical and/or digital format; i.e., the sum of sales for a_1 and a_2) in artist i's mixed-bundle j in week t, ranging from t = 1 for the first week of January 2005 to t = 177 for the last week of the first quarter of 2007. The song-sales equation reflects the weekly sales for the corresponding tracks s_1–s_m in artist i's mixed-bundle j:

$$
\begin{aligned}
(2)\quad \ln\left(\text{SongSales}_{ijt}\right) = {} & \beta_0 + \beta_1 \text{DigitalBuying}_t \\
& + \beta_2 \text{NumberOfSongs}_{ij} \\
& + \beta_3 \left(\text{DigitalBuying}_t \times \text{NumberOfSongs}_{ij}\right) \\
& + \beta_4 \text{ArtistSongHistory}_{it} \\
& + \beta_5 \left(\text{DigitalBuying}_t \times \text{ArtistSongHistory}_{it}\right) \\
& + \beta_6 \ln\left(\text{SongSales}_{ij(t-1)}\right) \\
& + \beta_7 \ln\left(\text{AlbumSales}_{ij(t-1)}\right) \\
& + \beta_8 \text{BUNDLE}_{jt} + \beta_9 \text{CONTEXT}_t + \varepsilon_{2ijt},
\end{aligned}
$$

where SongSales_{ijt} denotes the weekly sales for the collection of songs s_1–s_m (in a digital format) in artist i's mixed-bundle j in week t of the study period.

The variable DigitalBuying_t expresses the monthly (legal) digital music downloading activity rate. The term $\text{NumberOfSongs}_{ij}$ counts the number of songs in artist i's bundle j; $\text{SongSalesPattern}_{ijt}$ expresses how sales are distributed across the different songs in the bundle; and $\text{ArtistAlbumHistory}_{it}$ and $\text{ArtistSongHistory}_{it}$ reflect artist i's reputation, measured by the number of his or her albums and songs, respectively, that made the *Billboard* charts in the four years preceding week t. The lagged sales terms $\text{AlbumSales}_{ij(t-1)}$ and $\text{SongSales}_{ij(t-1)}$ capture the weekly dollar sales for the albums and songs in artist i's mixed-bundle j in the week before week t. The vectors BUNDLE_{jt} and CONTEXT_t contain covariates describing the mixed-bundle j in week t and the competitive conditions in week t, respectively. Finally, ε_1 and ε_2 represent the error terms.

Testing the hypotheses. The estimates belonging to DigitalBuying reveal whether the sales per mixed bundle indeed decrease as music consumption switches to digital channels. That is, if H_{1a}–H_{1c} hold, respectively, the estimate for α_1 is significant and negative, the estimate for β_1 is significant and positive, and the predicted AlbumSales should decrease faster than the predicted SongSales increases. Similarly, the coefficients belonging to DigitalBuying, NumberOfSongs, SongSalesPattern, ArtistAlbumHistory, ArtistSongHistory, and their corresponding interaction terms (α_1–α_7 and β_1–β_5) show whether the impact of digital music consumption on sales differs depending on the number and relative popularity of songs as well as the artist's track record.

The variable SongSalesPattern. Testing H_3 calls for a measure of the relative popularity of bundle components; the idea is that the greater the number of songs on an album that reach a certain level of (relative) popularity, the more appealing buying the album may be for (future) consumers. To this end, $\text{SongSalesPattern}_{ijt}$ reflects the concentration in sales across the tracks s_1–s_m in artist i's mixed-bundle j. The variable is a variation of the Gini (1921) coefficient, mostly known for its applications in research on wealth inequality. Salganik, Dodds, and Watts (2006) use the coefficient to measure success inequality in music downloads. If the sales distribution curve is plotted in a graph with the cumulative percentage of tracks on the x-axis and the cumulative percentage of sales for those tracks on the y-axis, the Gini coefficient is the ratio of the area between the curve and a 45-degree line to the total area under a 45-degree line. When sales are evenly distributed across tracks (i.e., when every song is equally popular), the Gini coefficient equals zero. If all sales are concentrated with one track, the Gini coefficient equals one.

I construct the variable $\text{SongSalesPattern}_{ijt}$ by assessing, for bundle j in each week t, the concentration of sales across individual tracks:

[7]A log-transformation of the sales variables has the added advantage that it helps address heteroskedasticity. An extension of the model could be to consider physical-album and digital-album sales separately. While the relative preference for digital versus physical formats may increase over time for all consumers, levels and rates may vary over the population. This could have important implications for bundling strategies (Venkatesh and Chatterjee 2006).

$$(3)\ \text{SongSalesPattern}_{ijt} = \frac{1}{m-1}\left\{ m+1-2\left[\frac{\sum_{k=1}^{m}(m+1-k)\text{sales}_k}{\sum_{k=1}^{m}\text{sales}_k}\right]\right\},$$

where $\text{sales}_1, \text{sales}_2, \ldots, \text{sales}_m$ denote the cumulative sales for each of m individual tracks and $\text{sales}_1 \leq \text{sales}_2 \leq \ldots \leq \text{sales}_m$. The $\text{SongSalesPattern}_{ijt}$ measure varies between zero and one, with a score just above zero reflecting a context in which sales are spread out relatively evenly across tracks in a mixed bundle and a score close to one representing a situation in which a few tracks are receiving a large share of sales. In Figure 2, I illustrate the measure for two albums, Gwen Stefani's *The Sweet Escape* and Jack Johnson's *In Between Dreams*.

Accounting for album-sales and song-sales interactions. Both equations reflect the idea that past sales for each component of the mixed bundle can affect current sales of the same component: AlbumSales_{ijt} depend on $\text{AlbumSales}_{ij(t-1)}$ in Equation 1, and SongSales_{ijt} depend on $\text{SongSales}_{ij(t-1)}$ in Equation 2. This reflects a success-breeds-success trend often prevalent in the diffusion of creative and other goods (e.g., Elberse and Eliashberg 2003) and for which different reasons may exist. For example, commercial success for music titles may increase exposure for those titles (e.g., on music charts or the radio), which in turn may drive further sales. Past success could also be indicative of a high product quality and, thus, future success.

The equations capture three ways album and song sales may be interdependent.[8] First, by making SongSales_{ijt} dependent on $\text{AlbumSales}_{ij(t-1)}$ in Equation 2, the model allows sales of the bundle to drive sales of one or more individual components. Consider a band's album entering the *Billboard* Top 200 because of strong sales: The additional exposure that comes along with a strong market performance may stimulate some consumers who are unfamiliar with the band's music to sample one or more of its songs. In other words, there may be a spillover of information that causes some previously uninformed consumers to discover an artist.

Second, by making AlbumSales_{ijt} a function of $\text{SongSales}_{ij(t-1)}$ in Equation 1, the model allows sales for one or more components to stimulate purchases of the bundle. For example, it could be that consumers first purchase one or two tracks off an album and then, if those are to their liking, purchase the full album. It could also be that after learning that an artist has a hit song, consumers take a gamble on the full set of songs on that artist's album—another information spillover effect. Equation 2 captures the effect of song sales on album sales in another way—namely, through the variable $\text{SongSalesPattern}_{ijt}$, which (as described previously) expresses the expectation that the likelihood of consumers buying albums rather than songs depends on the relative popularity of the songs.

Third, sales for the album and song components in a mixed bundle are expected to experience the same "shocks" over time. Therefore, I assume that the error terms for Equations 1 and 2, denoted by ε_1 and ε_2, respectively, are correlated. Consider the example of an artist winning a Grammy, the music industry's most prestigious award, for his or her work: The attention such an event generates could positively affect both album and song sales. A wide range of (unobserved) factors could account for such common shocks—including high-profile television appearances, promotional opportunities, media publicity, future album and song releases, or other forms or exposure.

Controlling for alternative explanations for changes in sales. The model attempts to control for the most likely alternative explanations for why mixed-bundle sales levels may change over time. The vector BUNDLE_{jt} contains a set of Genre_j dummies (which Lee, Boatwright, and Kamakura [2003] show to be correlated with music sales) and three variables that describe the bundle's release—the dummies MajorLabel_i, $\text{AlbumsNotOniTunes}_j$ or $\text{SongsNotOniTunes}_j$, and $\text{WeeksSinceRelease}_{jt}$. Finally, the vector CONTEXT_t contains three time-varying covariates: the dummy 4thQuarter to denote the peak season for recorded music sales; CompetingAlbums_t or CompetingSongs_t, the total number of albums or songs offered by the artists in the sample in week t; and DigitalSharing, the rate of illegal music downloading. The latter informs a current debate about the impact of illegal file sharing on music sales. Some researchers maintain that file sharing has no discernable net effect on sales (e.g., Oberholzer-Gee and Strumpf 2007), while others find evidence that it erodes revenues, albeit sometimes to a relatively modest degree (e.g., Bhattacharjee et al. 2007a).

Estimation

My estimation approach consists of two stages. First, I generate the $\text{SongSalesPattern}_{ijt}$ variable using the formula expressed by Equation 3. Second, drawing on those results, I estimate the system of Equations 1 and 2 simultaneously, using the SUR method (Zellner 1962). This method accounts for correlated errors across equations. For SUR to be effective, the model must contain at least one regressor that is used in one equation but not the other (otherwise, SUR would produce the same results as ordinary least squares). The variable $\text{SongSalesPattern}_{i(t-1)}$ and its interaction term, which appear only in the album-sales equation, are important in that regard; other variables that are different across equations are ArtistAlbumHistory/ArtistSongHistory, AlbumNotOniTunes/SongsNotOniTunes, and CompetingAlbums/CompetingSongs. I include a set of week dummies in each equation to address unobserved time-specific heterogeneity.[9] I performed a Breusch–Pagan test for independent equations and confirmed that the disturbance

[8]The inclusion of these lagged sales terms allows for a carryover effect of the independent variables beyond the current period. Strictly speaking, this is a fourth way that interactions between album and song sales are modeled.

[9]As a robustness check, I estimated other model specifications that more comprehensively use the panel data structure, including fixed-effects and random-effects estimations for Equations 1 and 2 separately. The results regarding the hypotheses are substantively similar.

covariance matrix is not diagonal. I ran a Breusch–Godfrey test to verify that the errors in both equations were not serially correlated.

By means of comparison, among other things to alleviate any possible concerns that trends in average per-bundle revenues are primarily caused by divergent price levels across digital and physical album formats (rather than by the unbundling facilitated by online channels), I also estimated a model with the dependent variable in each equation expressed in unit sales. Because I calculated dollar sales by multiplying unit sales with average annual industry prices, because songs are uniformly priced at nearly $1, and because lower-priced digital albums are only a small fraction of total album sales (see Figure 3), this yields similar results for the focal relationships. Therefore, I report only estimates for the model with the dependent variables expressed in dollar sales.

Findings

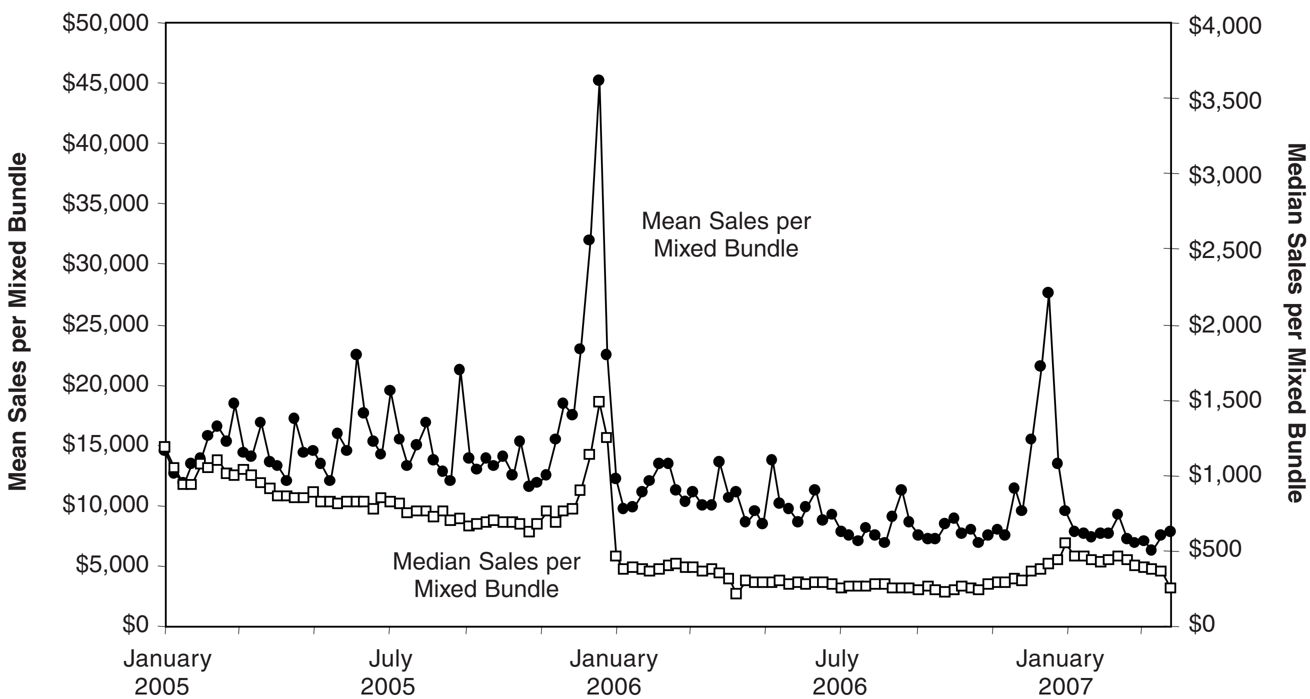
As background to a discussion of the estimation results, Figure 4 plots the mean and median dollar sales per bundle (including all its components) over the course of the study period. Three main patterns are visible. First, mean sales per mixed bundle trend downward. The average weekly sales per mixed bundle drop from approximately $15,000 in early 2005 to less than half that amount, just over $7,000, in early 2007. Second, the median sales per mixed bundle also are on a downward path, dropping from approximately $1,000 in early 2005 to $300 in early 2007. Third, there is considerable seasonality in sales, with the fourth quarter typically generating higher sales. For example, the mean sales per mixed bundle are as much as three to four times higher in the top week—the week before Christmas—than in a regular week.

Can this decrease in overall mixed-bundle sales be attributed to the growth in (legal) digital downloading? What factors drive the trend? Table 2 displays the estimates for Equations 1 and 2. The fit for the model is strong: The system-weighted R-square is .90. Underscoring the desirability of a SUR estimation approach, the cross-model correlation is .16 and significant.

Results for the Hypotheses

H_1. Regarding the estimates of the parameters, the parameter for the critical variable in testing the first hypothesis, DigitalBuying, is significant and negative in the album equation. Thus, the more people switch to consuming music digitally, the fewer albums they purchase, and thus the lower are the album sales per bundle. The estimate of –.06 for α_1 indicates that the drop-off is large: Based on this parameter, every 1% increase in the music downloading rate leads to an decrease of approximately 6% in album sales per bundle. Given the value of the intercept and the other parameters, all else being equal, this translates into a drop for the average mixed bundle from just under $13,000 in weekly album sales at the beginning of the study period (when the digital music purchase rate was approximately 2.5%) to approximately $8,500 at the end of the study period (when the penetration of digital buying had risen to 9%). The results provide strong support for H_{1a}.

FIGURE 4
Temporal Pattern in Mean and Median Mixed-Bundle Sales



Notes: Using data for all 2549 mixed bundles covered in the study, the figure plots mean weekly sales per mixed bundle and median weekly sales per mixed bundle for the 117 weeks from January 2005 to April 2007.

TABLE 2
Model Estimates

		DV = AlbumSales$_{ijt}$	
		Estimate	SE
α_0	Intercept	1.541	.196***
α_1	DigitalBuying	–.057	.002***
α_2	NumberOfSongs	.029	.001***
α_3	DigitalBuying × NumberOfSongs	–.000	.001
α_4	SongSalesPattern$_{t-1}$	–.284	.011***
α_5	DigitalBuying × SongSalesPattern$_{t-1}$	–.193	.006**
α_6	ArtistAlbumHistory	.051	.002***
α_7	DigitalBuying × ArtistAlbumHistory	.032	.000***
α_8	AlbumSales$_{t-1}$	.893	.001***
α_9	SongSales$_{t-1}$	.041	.001***
$\alpha_{10.1}$	GenreAlternative	–.046	.007***
$\alpha_{10.2}$	GenreChristian	–.049	.009***
$\alpha_{10.3}$	GenreCountry	–.001	.009
$\alpha_{10.4}$	GenreMetal	.042	.006***
$\alpha_{10.5}$	GenrePop	–.038	.010***
$\alpha_{10.6}$	GenreRap	–.011	.002***
$\alpha_{10.7}$	GenreR&B	–.014	.007*
$\alpha_{10.8}$	GenreRock	.029	.006***
$\alpha_{10.9}$	MajorLabel	.212	.005**
$\alpha_{10.10}$	AlbumNotOniTunes	–.187	.016***
$\alpha_{10.11}$	WeeksSinceRelease	–.001	.000***
$\alpha_{11.1}$	4thQuarter	.054	.005***
$\alpha_{11.2}$	CompetingAlbums	–.058	.005***
$\alpha_{11.3}$	DigitalSharing	–.034	.005***
		DV = SongSales$_{ijt}$	
		Estimate	SE
β_0	Intercept	.029	.020
β_1	DigitalBuying	.091	.002***
β_2	NumberOfSongs	.023	.002***
β_3	DigitalBuying × NumberOfSongs	.001	.001
	—	—	—
	—	—	—
β_4	ArtistSongHistory	.028	.002***
β_5	DigitalBuying × ArtistSongHistory	.007	.001**
β_6	SongSales$_{t-1}$	.907	.001***
β_7	AlbumSales$_{t-1}$	.020	.000***
$\beta_{8.1}$	GenreAlternative	.003	.005
$\beta_{8.2}$	GenreChristian	–.019	.006***
$\beta_{8.3}$	GenreCountry	.030	.006***
$\beta_{8.4}$	GenreMetal	–.022	.005***
$\beta_{8.5}$	GenrePop	–.015	.007**
$\beta_{8.6}$	GenreRap	–.026	.006***
$\beta_{8.7}$	GenreR&B	.031	.005***
$\beta_{8.8}$	GenreRock	.030	.004***
$\beta_{8.9}$	MajorLabel	.278	.003***
$\beta_{8.10}$	SongsNotOniTunes	–.211	.015
$\beta_{8.11}$	WeeksSinceRelease	–.002	.000**
$\beta_{9.1}$	4thQuarter	.082	.003***
$\beta_{9.2}$	CompetingSongs	–.040	.006***
$\beta_{9.3}$	DigitalSharing	–.021	.003***

N = 226,963
System-weighted R^2 = .897
Cross-model correlation = .158

*p = .10.
**p = .05.
***p = .01.
Notes: DV = dependent variables.

The estimate belonging to DigitalBuying in the song-sales equation (β_1) is .09. That is, for every 1% increase in the music download activity rate, the sales across the individual songs in a bundle increase with 9%. Given the value of the other parameters (the intercept is not significantly different from zero), all else being equal, this corresponds to an increase for the average bundle from approximately \$400 in song sales in early 2005 to approximately \$800 in early 2007 that is attributable to the increased digital downloading rate. The shift to digital consumption is associated with a significant rise in song sales, thus providing strong support for H_{1b}.

While the percentage sales growth for song sales is higher than the percentage decline for album sales, the absolute sales increase for song sales remains substantially lower than the sales decline for album sales. As a result, all else being equal, the weekly sales for the average bundle implied by the estimates for α_1 and β_1 decrease to approximately \$4,000 [(\$13,000 – \$8,500) – (\$800 – \$400)] over the course of the study period, a relatively large drop given that weekly bundle sales average approximately \$12,000 over the period (see Table 1). Taking into account the confidence intervals around both parameters, the difference is significant and well above \$3,500 with 99% probability, lending strong support for H_{1c}.

Tellingly, when expressed in unit sales, the predicted drop in album sales from 2005 to 2007 (approximately 300 weekly units) is three quarters of the estimated gain in song sales per bundle: Each album no longer bought is “traded in” for typically one, or perhaps two, songs bought. This finding speaks to two of the main arguments given for H_1: People’s tastes may converge a narrow set of components in a bundle, and the relatively low prices that online stores have set for those components may not give labels enough of a surplus under a mixed-bundling approach.

I lack the necessary information to give precise estimates of the impact of the shift to mixed bundling on the profitability (rather than revenues) for record labels. Online and offline retailers claim approximately 30% of music revenues. The costs for labels are almost surely lower online because digital distribution costs are only a fraction of physical distribution costs, and the royalties paid to artists are typically less than \$1.50 on digital albums, compared with approximately \$2.25 on physical albums. However, per-unit revenues are also lower for digital albums (\$9.99) than for physical albums (approximately \$14). Even if the labels’ profit margins on digital products exceed the 35% gross margin typically attributed to physical albums, the estimated drop in revenues is almost certainly far too steep to make mixed bundling at least as profitable for the labels as pure bundling.

Extreme caution needs to be observed when extrapolating these findings to values well outside the boundaries of the sample and the study period. Nevertheless, it is informative: Simulations show that if the trends implied by the estimates in Table 2 were to continue at the same rate in the future, the percentage of households that engage in (legal) digital downloading would need to increase dramatically to make up for the losses caused by the decreasing album sales. Specifically, if album sales continue to decrease with

6% and if song sales continue to increase with 9% for each 1% increase in the digital buying rate, all else being equal, song sales per bundle will first surpass album sales per bundle when the digital music download penetration measure, DigitalBuying, is close to 25%, while the total sales per bundle will again match the totals in early 2005 when close to 40% of all households engaged in digital downloading. The latter target seems a long way off given the penetration levels recorded by the NPD Group in early 2007 and given the slowing growth rates for products associated with music downloading (Apple Inc. 2008).

H_2. The estimates for α_2 and β_2 show that the greater the number of songs in a bundle (NumberOfSongs), the higher are the album and song sales. However, particularly given the uniform prices for recorded music—meaning that consumers benefit from but do not pay more for extra songs—the estimates seem low: With each additional song, album sales increase with approximately 3%, and song sales increase with 2%. This underscores the core problem of unbundling: Most of the (on-average) 12 songs (see Table 1) in a bundle hardly move the needle in sales.

Do bundles with a larger number of songs have less to fear from the losses associated with unbundling, as H_2 posited? The estimates for α_1–α_3 and β_1–β_3 do not support this view. The estimates for the interaction terms α_3 and β_3 are not significant: The rate with which album or song sales per bundle decrease over time appears to be unrelated to the number of songs on that bundle. In other words, although bundles with a greater number of components may, objectively speaking, represent a higher dollar value, such bundles are just as much at risk from the shift to mixed bundling as bundles with fewer components. The simple prospect of getting more items for the same price does not appear to entice people to continue to buy certain bundles.

H_3. Providing some initial insight into how song sales drive album sales, the coefficient (α_4) for the variable SongSalesPattern is negative and significant. In other words, the lower the concentration in song sales, the higher are album sales. The value for the coefficient, –.28, indicates that album sales are 28% higher for albums with a completely equal distribution of sales across the album's songs (SongSalesPattern = 0) than for albums with a completely unequal distribution of sales (SongSalesPattern = 1). (In the sample, the actual values for SongSalesPattern range from .00 to .93; see Table 1). Thus, the results support the idea that, after other factors are controlled for, the most successful albums are those that contain several worthwhile songs: One hit song does not make a hit album when people can purchase individual songs.

Is there an interaction effect, as implied in H_3? The estimates for α_1, α_4, and α_5 support this view. In the album-sales equation, the coefficient for the DigitalBuying and SongSalesPattern interaction term (α_5) is –.19. Taken together, the results indicate that sales for the album portion of the bundle decrease as the digital music buying rate increases—and particularly so for bundles with more concentrated sales across items. Simulations show that, all else being equal, an album with a score of .86 on the SongSalesPattern variable (indicating a highly skewed distribution of past sales across items) will have sales drop more than 20% faster over the course of the study period than an album with the average score for SongSalesPattern of .43 and more than 40% faster than an album with a low concentration score for SongSalesPattern of approximately .20. In other words, bundles that are more even in their appeal indeed appear to suffer less from the shift to mixed bundling than those that have one or two items that "stand out from the pack"; for those albums, as hypothesized, people turn to buying individual items at a faster rate.

H_4. The estimates for ArtistAlbumHistory (α_6 = .05) and ArtistSongHistory (β_4 = .03) are both significant and positive. In other words, not surprisingly, artists with a strong reputation are associated with higher revenues: An album on the charts in the previous four years is "worth" approximately 5% higher album sales per bundle, while a song on the charts is good for an additional 3% in weekly song sales per bundle. Thus, a superstar artist with, for example, one hit album and two hit songs in the past four years is expected to generate approximately 11% [(1 × 5%) + (2 × 3%)] higher sales per bundle. This translates into $1,300 (11% × $12,000) per week or $68,000 per year—still a relatively modest amount, which may speak to the short life cycles of artists and the fickle nature of audiences.

Do artists with stronger brands have less to fear from the losses associated with unbundling, as H_4 suggests? The estimates indeed support this view. Consider the album-sales equation: The coefficient for DigitalBuying (α_1) is –.06, the estimate for ArtistAlbumHistory (α_6) is .05, and the coefficient for their interaction term (α_7) is .03. Together, these results imply that sales for the album portion of the bundle are decreasing as the digital music buying rate increases, but particularly so for artists with a weaker reputation. Simulations show that, all else being equal, an artist without any *Billboard* album chart hits in the previous four years could expect his or her weekly album sales per bundle to drop from approximately $12,600 to $7,600 as the digital download activity jumps from 2.5% to 9% over the course of the study period, while an artist with one album on the *Billboard* charts could expect his or her weekly album sales to decrease from approximately $14,000 to $9,700. Thus, the premium of having a hit album increases from $1,400 ($14,000 – $12,600) to $2,100 ($9,700 – $7,600) in weekly album sales per bundle.

Similarly, as the estimates in the song-sales equation reveal, superstar artists on average also benefit—albeit only slightly—more from the growth in song sales. The coefficient for DigitalBuying (β_1) is .09, the estimate for ArtistSongHistory (β_4) is .03, and the coefficient for their interaction term (β_5) is nearly .01. Thus, sales for songs in a bundle increase as the digital music buying rate increases, and particularly so for artists with a strong reputation. The difference is not as pronounced as for the album-sales equation: All else being equal, an artist without any *Billboard* hit songs in the previous four years could expect his or her weekly song sales per bundle to increase from approximately $400 to $750 over the course of the study period, while an artist with one *Billboard* Hot 100 hit could expect his or her weekly song sales to increase from approximately

$450 to $850. Here, the premium of having a hit song increases from $50 ($450 – $400) to $100 ($850 – $750) in weekly song sales per bundle—a statistically significant, but in absolute terms only modest, advantage.

Other Results

Interactions between album and song sales. The estimates further show that album and song sales are dependent on their own lags—that is, past success breeds future success. The coefficient belonging to $AlbumSales_{t-1}$ in the album-sales equation, α_8, is .89, and the coefficient belonging to $SongSales_{t-1}$ in the song-sales equation, β_6, is .91. Thus, there is a reasonably high level of carryover in recorded music sales, just as in other media industries (for evidence from the film industry, see Elberse and Eliashberg 2003).

In addition, there are significant effects across bundled and unbundled titles: Lagged album sales drive song sales, and lagged song sales drive album sales. First, β_7, the coefficient for $AlbumSales_{t-1}$ in the song-sales equation, has a value of .02. Thus, all else being equal, a 1% increase in lagged album sales leads to an approximately .02% increase in song sales per bundle, perhaps because high album sales go along with more free publicity for an artist. In other words, the shift to digital music consumption has a direct and indirect negative consequence for the music industry: Album sales per bundle decrease, and because album sales are associated with song sales, this decrease also appears to somewhat limit the growth in song sales. The effect is small but significant.

Second, the value for α_9, the coefficient belonging to $SongSales_{t-1}$ in the album-sales equation, is .04. Thus, all else being equal, a 1% increase in lagged song sales leads to an approximately .04% increase in album sales per mixed bundle. With weekly average song sales per bundle doubling over the course of the study period, the estimate suggests that the growth in song sales accounted for an approximate growth of 4% (100 × .04%) in album sales—or rather, it prevented an even steeper decline in album sales.

Control variables. The estimates for α_{10}, α_{11}, β_8, and β_9 cover the BUNDLE and CONTEXT vectors with control variables. Regarding the bundle characteristics, the estimates reveal that bundles in the alternative, Christian, pop, rap, and R&B genres have relatively low album sales, and those in the metal and rock genres have relatively high album sales. Similarly, bundles in the Christian, metal, pop, and rap genres have relatively low song sales, and those in the country, R&B, and rock genres have relatively high song sales. Bundles that are released by one of the four major labels (MajorLabel) are associated with both higher album and higher song sales.[10] In addition, an unavailability in the iTunes store decreases album and song sales (AlbumNotOniTunes and SongsNotOniTunes). The effect is the strongest for song sales, in which bundles with one or more songs not available on iTunes generate more than approximately 20% lower song sales than other bundles. Furthermore, both album and song sales decrease as the number of weeks since the release increases (WeeksSinceRelease). The percentage drop in song sales is slightly higher (the estimates are –.001 in the album-sales equation and –.002 in the song-sales equation), which may reflect the higher "staying power" of albums.

With regard to the CONTEXT vector, the estimate for the 4thQuarter dummy confirms the seasonal nature of sales. All else being equal, it accounts for a 5% increase in album sales per bundle and a slightly higher 8% jump in song sales per bundle. According to the estimates for CompetingAlbums, –.06 in the album-sales equation, and CompetingSongs, –.04 for in the song-sales equation, every 1000-unit increase in the number of competing albums and songs leads to an approximate drop in album sales of 6% and a decrease in song sales of 4%, respectively. Because the number of music recordings available through online stores increases rapidly, competition for audiences intensifies, creating a downward pressure on the sales per bundle. Finally, as expected, DigitalSharing, the percentage of households that engage in illegal music downloading, is negatively associated with album and song sales. For each 1% increase in the penetration rate, expected album sales per bundle drop approximately 3%, and expected song sales per bundle drop approximately 2%. As noted previously, the variance in DigitalSharing is lower than that in DigitalBuying, which contributes to the rising song sales: The positive impact of the shift toward legal digital consumption appears to outweigh the negative impact of file sharing on song sales per bundle.

Conclusion

Conclusions and Implications

Digital technology is fueling a trend toward unbundling of many kinds of information or entertainment products. In this study, making use of the increasing rate of digital consumption, I quantify the revenue impact of unbundling in the context of the music industry and, gaining more general insights into how consumers decide between competing mixed-bundled offerings, examine three possible moderators of that effect.

Although the existing economics and marketing literature mostly emphasizes the benefits of a mixed-bundling versus a pure-bundling strategy, the study's results provide strong evidence of the negative consequences of a shift to mixed bundling in digital channels for the recorded music business, given the existing pricing levels. Specifically, I find strong support for the hypothesis that revenues for mixed bundles substantially decrease as music becomes increasingly consumed digitally. Although the demand for individual songs is growing at a faster rate than the demand for albums is declining, the dollar amounts gained through new song sales remain far below the level needed to offset

[10]This is intuitive: Major labels typically have a larger portfolio of projects and often stage elaborate mass-marketing campaigns before and around the launch of titles, while the independent labels usually focus more on developing artists, using grassroots techniques (e.g., Elberse and Ofek 2007), which leads to lower average weekly sales.

the revenues lost due to lower album sales. According to my estimations, a drop of approximately one-third of the average weekly mixed-bundle sales are directly attributable to increased digital music downloading activity from January 2005 to April 2007, which confirms recent concerns about the recorded music business: The unbundling of music online poses a significant risk to record labels, which, over time, will probably experience further erosion of revenues.

While the magnitude of this main effect may be specific to the music industry, the findings regarding possible moderators of the effect have a broader relevance for the bundling literature. I do not find support for the first of three hypotheses that relate bundle characteristics to the revenue impact of unbundling: Perhaps surprisingly, mixed bundles with a greater number of components (which, given that each is priced uniformly, directly expresses the bundle's total dollar value) do not appear to suffer less from the decrease in bundle revenues than those with a lesser number of components. However, and I argue consistent with what assimilation and contrast theory prescribes about how consumers evaluate a set of alternatives, I find that bundle revenues decrease less the more bundles consist of items that are relatively consistent in their appeal. Highlighting the importance of brands, the findings show that bundles by creative workers with a strong reputation suffer less from the decrease in revenues.

What are the implications for suppliers of information or entertainment goods, such as television programs, music songs, and magazine articles? First, content producers trying to avoid declining sales will likely benefit from having the flexibility to price mixed bundles as they deem fit—the key is to capture a high enough markup on individual components to make up for any lost revenues on bundles. In theory, a mixed-bundling strategy cannot be suboptimal if sellers are free to price a bundle and its components optimally. In the context of entertainment products, this probably means nonuniform, and generally higher, prices for unbundled products. Second, content producers could resort to simply refusing to offer their goods in an unbundled form online (e.g., Smith and Wingfield 2008). However, such a strategy may reduce consumers' ability to learn about products and their propensity to try those products, so effects in the long run are difficult to predict. Third, a related strategy worth considering would be to sequentially release bundles and their components. Studying the market for concert tickets, DeGraba and Mohammed (2000) show that by initially selling goods only in bundles and subsequently selling unsold units individually, a seller can create a buying frenzy in which profit is higher than it would be if all units were sold individually at their market clearing prices. In their setting, high-valuation customers bought a bundle because they expected quantity rationing when units were sold individually. Although selling out is impossible with digital goods, "windowing" is a common strategy for entertainment products because their value often sharply decreases with time, and many loyal fans are willing to pay more to access content before others do.

In general, the study's findings should prompt suppliers of information goods to rethink the design, and perhaps the very essence, of a bundle. For example, although the number of items does not appear to be a factor, it seems that offering consistent bundles helps limit any losses due to unbundling. In the context of the music industry, this implies that the common practice of bundling—for example, 11 marginally appealing titles with 1 highly attractive "hit" item in the hopes that the latter will drive bundle sales—may quickly lose its power. Perhaps counterintuitively, in the future, content producers may be better off releasing a (mixed) bundle with only the 11 less appealing items and selling the highly attractive title separately. Similarly, providers may increasingly want to give preference to quality over quantity and design smaller bundles if eliminating items means that the quality is then more evenly distributed. The findings further imply that it may benefit content producers to invest more in developing and marketing bundles made by established artists and to resort more to single-item releases for creative workers without a strong reputation.

Future Research Avenues

Further empirical research into the impact of the shift to mixed bundling in online channels and the optimal design of mixed bundles in those settings, particularly bundles with many items, is needed. The current study has some limitations that future research efforts could address. First, this study could not fully distinguish between the effect of differences in price levels and the varying formats in offline versus online channels. That is, had the market for recorded music been characterized by other price levels for bundles and individual bundle components (e.g., \$1.99 rather than \$.99 for individual songs or upward of \$15 rather than \$9.99 for digital albums) or by a different pricing structure, it is plausible that the study would have yielded more (or even less) favorable results for a mixed-bundling strategy. Although this affects only the main effect documented here—the limitation should not influence the direction of the results regarding the moderators and, thus, the research's theoretical contributions—further research could more explicitly examine the relationship among (actual or optimal) pricing levels, bundling strategies, and sales. In the music industry, iTunes' recent move to three-tiered pricing (in April 2009, it decided to allow labels to price songs at \$.69, \$.99, or \$1.29) may offer some initial opportunities in that regard. Second, if such data are available, it would be worthwhile to examine the implications of unbundling at the level of individual consumers instead of the market. This would help broaden the understanding of exactly how consumers evaluate bundles and what that implies about the factors that determine the extent to which firms can benefit or are at risk from unbundling. Third, more generally, the music industry is extreme in how much to date it has been affected by the growing popularity of the Internet. The peculiar nature of the music industry raises questions about the external validity of the study. Therefore, additional research on unbundling in other settings is much needed.

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