MUSIC SUPPLY, CHART TURNOVER, AND THE RANDOM-COPYING HYPOTHESIS IN THE DIGITAL MUSIC AGE

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ABSTRACT

The framework of Klein and Slonaker (2010) is used to test the random-copying hypothesis proposed by Bentley, et al. (2007) using data on the recorded music industry for 1990-2010. This hypothesis holds that, in decisions with little intrinsic value, people simply copy one another's behavior at random. Bentley, et al. show through computer simulation that random copying results in a constant rate of turnover on a list of the top *y* items that is proportional to the size of the list, *y*, and independent of the population size. They point to a "constant" rate of turnover on Billboard's "Top 200" album chart from 1963 to 1985 as evidence of this behavior. Applying a structural time series approach to monthly data on Billboard's "Top 200" chart turnover, music sales, price indices for music and related goods, income, and demographics for 1990-2010, we find that population size, income, and the prices of music and related goods have significant effects on turnover in the Billboard Top 200. Chart turnover, moreover, is not constant, but increases over time. These results contradict random-copying behavior.

Keywords: random copying, chart turnover, music industry, unobserved component.

JEL: L82, L86

I. Introduction

The random-copying hypothesis posits that individuals often merely copy one another's behavior in situations involving little intrinsic value. Bentley, et al. (2007) use a biological mutation based computer simulation to show that random copying results in a rate of turnover on a list of the top y items that is proportional to the size of the list, y, and the square root of the rate of innovation (mutation), μ, where μ is the fraction of the population that chooses new items, or "variants," in each period. They point to a "constant" rate of turnover on Billboard's "Top 200" album chart from 1963 to 1985 as evidence of this behavior as well as the turnover in lists of the top baby names and dog breeds. Moreover, the turnover rate is independent of population size.

Below, the random-copying hypothesis is tested using monthly data on Billboard's "Top 200" chart turnover, music sales, price indices for music and related goods, income, and demographics. As in Klein and Slonaker (2010), a structural time series approach that allows for the capture of an unobserved component, including the effect of illegal file-sharing, is applied, but the data series is extended to 2010. We find that population size, income, and the prices of music and related goods have significant effects on the turnover in the Billboard Top 200 chart between 1990 and 2010. Chart turnover, moreover, is not constant, but increases over time and displays a small, but significant, unobserved component. These results contradict random-copying behavior.

The implication in the random-copying model of a non-constant rate of chart turnover is that the rate of "innovation" in the population is also non-constant. In Bentley, et al.'s (2007) examples of selections of baby names and dog breeds, the innovation is solely a matter of consumer choice, whereas in the music market, innovation may take place on the consumer or producer side of the market, or both. Increased innovation in music titles is consistent with the evidence provided by Handke (2006), Oberholzer-Gee and Strumpf (2007), and Waldfogel (2011(a), (b)) that the supply of new music titles (or variants) has increased since file-sharing via Napster began in 1999. Consequently, increasing chart turnover indicates increasing innovation in the music industry and, by implication, increasing music supply in the digital age.

By viewing the results through Bentley et al.'s (2007) framework, new insights are gained. The chart turnover equation estimated here, for example, can be interpreted as a reduced-form equation for the rate of innovation. This suggests that innovation is promoted by population growth as well as declining prices for recorded music and related goods.

The next section reviews the literature on chart turnover in the recorded music industry. This is followed by a discussion of theoretical and measurement issues, including specifics on the approach of Bentley, et al. (2007). The data and empirical models are presented next, then the results are presented and discussed, followed by a short conclusion.

II. Literature Review

Hahn and Bentley (2003) and Bentley, et al. (2007) develop the random-copying model as a value-neutral null hypothesis for cultural change against which alternative economic and cultural models should be tested. Based on computer simulations, they find that the distribution of consumer choices follows a power law due only to random sampling and a constant rate of mutation or innovation. They claim that the random-copying model predicts stable turnover in ranking lists, such as top 10 or top 100 lists, as has been observed for baby names, dog breeds, and Billboard's Top 200 Album Chart over 1963-1985. Random copying also suggests that turnover is only related to the size of the list and the rate of innovation, independent of population size or other factors.

While the distribution of music sales has been long known to follow a power law, other predictions of the random-copying model have not been observed in research on the music industry. Klein and Slonaker (2010), for example, find that turnover on the Billboard Top 200 Chart is influenced by total population and its age distribution as well as the prices of related goods during 1990-2005. An extensive literature examines the relationship between industry concentration and chart turnover in the music industry. The first attempts indicated a negative linear relationship between concentration, in terms of shares of "hits," to variety, in terms of chart turnover, in the music industry (Peterson and Berger, 1975; Black and Greer, 1986); but subsequent analyses have muddied this view.

Christianen (1995), using data from the Netherlands for 1975-1992, and Dowd (2004), using U.S. data for 1940-1990, have found that the negative association between concentration and variety in the music industry is offset by the adoption of decentralized organizational forms by the major record companies (labels). That is, the major record companies established multiple competing labels that operate independently to produce recordings, rather than being centrally controlled, and this innovation reversed the decline in variety and/or chart turnover that was associated with high concentration of overall sales in the Big Five.[1,2]

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1 Following a wave of consolidation starting in the 1960s, five major companies came to dominate the industry in the 1990s: Universal, Warner, Bertelsmann (BMG), Sony, and EMI. These five became four with the formation of the Sony-BMG joint venture in 2004. These firms have accounted for 80-90% of U.S. music sales since at least 1999 (Alexander, 2009).

2 Carroll (1985) found that increasing concentration in local newspapers was accompanied by increasing opportunities for expansion of small, niche publications, a conclusion that was similar to that reached by Mezias and Mezias (2000) for the early days of the feature film industry. Lee (2004), Alkvist and Fisher (2000) and Rossman (2004) have found that increasing concentration in ownership of radio stations did not reduce the number of formats

Alexander (1996) challenges the use of chart turnover as a measure of product variety by developing an entropy measure that takes into account factors such as harmonic form, time and meter, and melody. He finds that this measure of variety is nonlinearly related to concentration in songs reaching the Top 40 hits, with variety peaking at moderate levels of concentration during 1955-88. Peterson and Berger (1996) object, claiming that this measure of diversity does not capture innovation.

Rennhoff (2010) measures variety by creating an index based on musical styles of top 20 singles on the Billboard Hot 100 Singles Chart. He finds that the prohibition of payola reduced the musical variety of top 20 singles during 1959-61. Waldfogel (2011a,b) constructs a music quality index based on critics rankings of albums on "best-of" lists. He finds that both music supply (frequency of high-quality albums) and quality increased after the popularization of file-sharing by Napster in 1999. Oberholzer-Gee and Strumpf (2010, 2007) and Handke (2006) also provide evidence that music supply (albums or titles) has increased in the file-sharing era.

A number of recent analyses suggest that the reduced consumer search costs afforded by the Internet act to reduce the skewness or concentration in music sales. Brynjolfsson et al. (2003) find that online bookstores have contributed to both lower prices and increased variety, but the increased variety in the market for books has had a greater effect on consumer surplus than has the reduction in prices. Gopal et al. (2006) develop a model in which reducing the price of listening to samples of music online induces more consumers to purchase music online as the total cost of search and acquisition declines. This also erodes the superstar phenomenon.

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that were offered in local markets, as commonly owned stations avoided direct competition, although Lee found that the number of songs that hit the airplay charts declined. Conversely, Bielby (2003) found that deregulation of vertical restrictions in the television industry led to increased concentration of production of prime-time shows, reducing the variety of suppliers, as the major networks vertically integrated into production.

Brynjolfsson et al. (2007) find that a differentiated product monopolist realizes lower profits and more concentrated product sales when consumer search costs for niche products are higher.

Fleder and Hosanagar (2007) find that recommender systems - the systems used by online retailers to suggest new products to customers based on past purchases - may increase variety for individuals by exposing them to new product niches, but may also decrease overall variety by concentrating sales in fewer products in each niche. Rosen (1981) derives a similar result that as costs fall, product variety may increase or decrease depending on the elasticity of demand.

Most recently, Hendricks and Sorenson (2009) find that the release of a new album, especially a hit, increases sales for an artist's old albums. This suggests that consumers are imperfectly informed and discover the artist by hearing the new release. They find that the distribution of sales is more skewed in favor of the major hits than it would be if consumers were better informed. A reduction in consumer search costs thus implies better informed consumers and a reduction in the variance of sales by title.[3,4]

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[3] Purely theoretical analysis of the effects of file-sharing has produced ambiguous results. Takeyama (1994) shows that, in the presence of demand network externalities, the profits earned by a copyright holder can actually increase when copying is allowed. The network effects and ease of sharing may increase a listener's willingness to pay for a legitimate copy, much as the consumer search literature suggests. Varian (2000), however, argues that sharing intellectual property leads to lower sales and higher prices, but it is unclear whether profits rise or fall. The magnitude of profits depends on transactions costs and the proportion of high-value to low-value users.

Alexander (1994) analyzes a Cournot-like model of the quantity of new releases to show that the number of new releases depends on whether the firms act independently or agree to divide the market in some fashion. He finds that profits are higher when firms apportion the market and restrict the number of new product releases, rather than acting independently. If concentration leads to collusion and fewer releases, then chart turnover may fall and variety may suffer.

The work of Bhattachargee et al. (2007a,b), is similar to our own as well as that of Hahn and Bentley (2003) and Bentley, et al. (2007). In both of these articles, the survival of albums on the Billboard Top 100 Chart is compared across two time periods: 1995-1997 and 2000-2002. They conclude that the time on the charts generally declined in the post-file sharing time period relative to the earlier period. This implies that turnover increased.

Bhattachargee et al. (2007b) also derive the result that as the number of weeks becomes large, the average proportion of titles that drop off the chart after *w* weeks approaches a steady state based on the probability of dropping off in week *w* and the product of the probabilities of staying on the chart in the previous *w-1* weeks.[5] This is consistent with the constant rate of chart turnover derived by Bentley, et al. (2007) for any given set of probabilities, but the results of

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4 Empirical studies of the demand for recorded music during and after the onset of illegal downloading yield similarly mixed results. Fader (2000) argues that the advent of new substitutes for recorded music, such as video games, DVDs, and chat rooms, along with a downturn in GDP growth, contributed to sales declines in 2000-2003. Stevans and Sessions (2005) suggest that digital downloads altered the price elasticity of demand for recorded music such that the demand fell; but after controlling for the prices of music, prices of substitutes, and income, they find that consumption of recorded music actually increased modestly (0.77%) between 2000 and 2004. Zentner (2006) and Oberholzer-Gee and Strumpf (2007) find that illegal downloading and file-sharing accounted for much less of a decline in sales than that claimed by the Recording Industry Association of America during 2002.

5 Bhattachargee et al. (2007b), show that: $lim_{k\to\infty} (TD_{k,w})/TN_k = (1 - p_w)\, \Pi^{w-1}_{j=1}\ p_j$, where $TD_{k,w}$ is the total number of titles observed over k weeks that have dropped off the chart after w weeks and TN_k is the total number of individual titles that have appeared on the chart at any time up to week k. $(1 - p_w)$ is the probability that a title drops off after w weeks on the chart and the p_j are the probabilities of surviving on the chart after $1 \leq j \leq (w\text{-}1)$ weeks. The p_j could all be equal, or all different, although we might expect that $p_j < p_{j+1} < \ldots p_{j+m}$, and this is assumed by Bhattacharjee et al. When all the p_i are equal, then the steady state is that of the geometric distribution.

Bhattachargee et al. (2007b) as well as Klein and Slonaker (2010) contradict both propositions by finding that the rate of turnover is increasing.

III. Theory and Measurement Issues

The recorded music industry is characterized by consumers who buy music repeatedly, but rarely buy the same product (title) in the same format (CD, LP, digital) more than once. This is partly due to the durable nature of recorded music. Once a title is purchased, it can be listened to multiple times without an additional purchase. In the recorded music industry, as in book publishing and motion pictures, the lack of repeat buying for the specific item leads business strategy to emphasize the creation of "hits" (best sellers, blockbusters, and superstars): individual titles that sell in extraordinary volumes, but only one unit to each consumer.[6]

Consequently, the ability of a title to make the chart and its longevity once listed are closely watched indicators of success in hit-making for the recorded music industry. Longevity near the top of the chart is an indicator of high sales volume, whereas short chart life and high chart turnover indicate that sales are spread across more titles. Given the cost structure of the industry (high fixed cost per title, but low marginal cost), the same sales spread over more titles likely also indicates lower profits. For these reasons, chart turnover is an indicator of sales

[6] Of course, the performer and the label hope that consumers will buy the future output – new singles and new albums – of the performer. Contrast this with nondurable, high repeat-purchase goods such as carbonated soft drinks, laundry detergents, or toothpaste. A major factor in business strategy in these industries is the building of brand loyalty in order to capture repeat sales of the same brand to the same consumer.

concentration by title as well as the ability, or lack thereof, of record labels to create hit titles and superstar artists.[7]

If chart turnover is governed by random copying behavior by consumers, then the resources expended by the music industry to create hits appears misguided. Most consumers will merely copy their peers with random frequency and few will "innovate" to try new variants or "mutations" as framed by Bentley, et al. (2007). The rate of turnover on the charts will be constant and determined by random processes alone. We propose to test the random copying hypothesis by investigating the determinants of recorded music sales and turnover on the Billboard 200 chart during the sample period 1990-2010.

What factors determine the rate of chart turnover? Bentley, et al. (2007) set up a simulation beginning with N individuals who are each assigned one of N different variants. In successive time steps, the N individuals are replaced by N new individuals. The majority of these new individuals is randomly assigned a variant copied from the previous time step, while an "innovating" minority (μN, where μ is the rate of innovation or mutation) adopts a novel variant. The simulation was run until a quasi-equilibrium was reached, then the variants and their frequencies were recorded for every other time step after that to create 25 samples. Top y charts of varying sizes (y = 5, 10, 20, etc.) were created for each sample and the number of variants that turnover was calculated at each time step relative to the previous one for each chart size. They find that the average turnover in variants is described by a simple equation

$$z_y = Ay \tag{1}$$

[7] The creation of superstars may appear to function much like brand loyalty in high-repeat-buying industries. Music superstars, however, are created to sell high volumes of individual titles by appealing to large numbers of customers, each buying one unit, rather than selling multiple units to each buyer. And, again, there is the hope that consumers will buy the future creations of the superstars.

where z_y is the number of new variants on the chart, A is a constant, and y is the size of the chart. It turns out that A and z_y are independent of the population size, N, but that A is proportional to μ, such that

$$z_y = y(\mu^{1/2}) \tag{2}$$

and the turnover rate for any chart size, y, is a constant determined only by the rate of innovation

$$z_y/y = \mu^{1/2} \quad . \tag{3}$$

The innovation rate, μ, is simply a "mutation" of preferences within the population. This mutation leads to a random drift in the musical preferences of a culture. Repeated random copying means that this mutation multiplies throughout the population. This may explain why some music becomes popular, even "viral," regardless of its quality. Hahn and Bentley (2003) construct a similar model of the selection of baby names.

The economics literature (Dixit and Stiglitz, 1977) suggests that entry of new titles occurs when production costs fall or overall consumer demand for the product category increases. Models based on the music industry (Gopal et al., 2006; Brynjolfsson et al., 2007) point to reductions in consumer search costs as instigators to increased chart turnover. The nature of oligopolistic interaction among firms (Alexander, 1994; Dowd, 2004) may also affect the production of "hits" and turnover on the charts.

Here, the framework of Klein and Slonaker (2010) is adopted in which the determinants of chart turnover in the music industry are written as

$$\mathrm{V} = \mathrm{F}(\mathrm{C}, \mathrm{S}, \mathrm{c}, \mathrm{R}; \mathbf{X})$$

where V is chart turnover, C is production costs, S is industry sales, c is consumer search costs, R is the degree of oligopolistic rivalry, and **X** is a vector of demand determinants that includes the price of the product, prices of substitutes, consumer income, and population demographics.

Obviously, these factors may generate opposing forces on turnover which can only be sorted out empirically. For example, the growth of the Internet and reductions in the cost of computers and software may reduce both production costs and consumer search costs, but also may reduce sales through online file sharing.

On the other hand, sales of recorded music may be affected by the number and frequency of "hits". As hit titles increase, consumers to whom existing titles were not appealing may find one or more new varieties to their liking and start making purchases. Hence, increases in the variety of titles may increase sales. [8]

This suggests a multivariate system in which chart turnover (V) and music sales (S) are related:

$$V = F(C, S, c, R; \mathbf{Z})$$

$$S = G(C, V, c, R; \mathbf{Z})$$

These relationships are tested against the constant turnover predicted by the random-copying hypothesis in the implementation of the empirical model.[9] Note that the chart turnover equation

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[8] Another possible factor is technological change. As a new music format is introduced and its sales rise, sales of equipment for playing the new formats also grow. Higher sales of audio equipment may be associated with higher sales of music titles. We tested for and rejected an additional equation for audio equipment sales in the course of the empirical analysis.

[9] Even though chart turnover has frequently been used as a measure of product variety or diversity (Peterson and Berger, 1975; Black and Greer, 1986; Dowd, 2004), we make no claims in that regard. In what follows, less concentrated sales among numerous copy-cat products are indistinguishable from less concentrated sales among an equal number of truly dissimilar products. Subjective standards of "quality" are not captured; chart turnover at best captures only the relative frequency of hits.

can be interpreted as a reduced form of the determinants of the rate of innovation in Bentley (2007).

IV. Data

We assemble a monthly time-series for the period 1990-2010.[10] Table 1 shows that the number of debut albums per month increases considerably during the 1990-2010 period. The variable definitions used in the empirical model are shown in Table 2. The simple statistics of the raw data are provided in Table 3.

Data on sales of recorded music, prices, and income are gleaned from the National Income and Product Accounts (NIPA). The Bureau of Economic Analysis (BEA) collects both product and income data to construct the NIPA figures. All dollar denominated data as well as product-specific price indices are converted into real terms using the CPI for non-durable goods. Each of price indices is available on a monthly basis. Population figures are from the Census Bureau.

Both Personal Disposable Income data and the price index for recorded music from the NIPA are included here. A price index for movie tickets is included, because Stevans and Sessions (2005) find that movies are a substitute good for recorded music. The price index for recorded movie media, such as VHS and DVD, is also considered. The price index for audio equipment is included, since the most obvious complement to recorded music is an audio listening device.

Changes in chart turnover could be due simply to increases in the size of the industry’s target audience. Specifically, if the age 10-24 demographic group experiences large increases or

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[10] Although chart turnover is available weekly, sales and other crucial data are only available monthly.

decreases, the industry may respond by altering its release strategy. To control for this possibility, we include data for the proportion of the total population in three age groups: ages 10-24, ages 25-44, and age 45 and over. To test the Bentley, et.al. (2007) conclusion that the size of the population does not affect turnover, we include data on the total population for each month.

An unobserved component is estimated that captures the effects of unmeasured factors such as consumer behavior, industry behavior, and file-sharing. We turn now to a detailed discussion of the empirical method and the estimation of this unobserved component.

V. Empirical Methodology

Our general structural time series model can be written as:

$$V_t = \mu_{1,t} + \alpha_1 \mathbf{X}_t + \varepsilon_{1,t} \qquad \textit{for } t=1,\ldots,T \quad , \qquad (4)$$

$$S_t = \mu_{2,t} + \alpha_2 \mathbf{X}_t + \varepsilon_{2,t} \qquad \textit{for } t=1,\ldots,T \quad , \qquad (5)$$

where $$\boldsymbol{\mu}_{i,t} = \boldsymbol{\mu}_{i,t-1} + \boldsymbol{\beta}_{i,t-1} + \boldsymbol{\eta}_{i,t} \qquad \textit{for } t=1,\ldots,T \quad , \qquad (6)$$

and $$\boldsymbol{\beta}_{i,t} = \boldsymbol{\beta}_{i,t-1} + \boldsymbol{\xi}_{i,t} \qquad \textit{for } t=1,\ldots,T \quad . \qquad (7)$$

V is turnover or "variety", S represents sales of recorded music, and **X** is the matrix of covariates that are described in Table 2. It should also be noted that:

$$\boldsymbol{\varepsilon}_{i,t} \sim NID(0, \boldsymbol{\Sigma}_{\varepsilon}) \quad , \qquad (8)$$

$$\boldsymbol{\eta}_{i,t} \sim NID(0, \boldsymbol{\Sigma}_{\eta}) \quad , \qquad (9)$$

$$\xi_{i,t} \sim NID(0, \boldsymbol{\Sigma}_{\xi}) \quad . \qquad (10)$$

By including $\boldsymbol{\mu}_t$, we are able to capture any unobservable factors that are affecting the dependent variables, V_t and S_t, beyond those measured by $\mathbf{X}_t$. $\boldsymbol{\mu}_t$ serves as the "level" and $\boldsymbol{\beta}_t$ as the "slope" in the stochastic trend. Equation (6) indicates that the level component follows a random walk with drift. Equation (7) shows that the slope component is assumed simply to follow a random walk. $\mathbf{\Sigma}_{\varepsilon}$, $\mathbf{\Sigma}_{\eta}$, and $\mathbf{\Sigma}_{\xi}$ are the $N \times N$ variance matrices. Both components have white noise disturbances that are independent both of each other and $\boldsymbol{\varepsilon}_t$.

To understand the role of the unobserved component, consider the use of a simple time trend to capture the effect of unobserved factors that change over time, as has been done to measure technological change (Balcombe, Bailey, and Morrison, 2002). A simple linear, or even non-linear trend, imposes a smooth and uniform transition across periods throughout the series, as do more sophisticated ARMA and ARIMA methods. Harvey (1997) argues that "local linear trends" (LLTs), which may be positive or negative in sign or vary in magnitude at different periods in the series, are more common than many econometricians realize. These LLTs are obscured by the smoothing techniques that impose uniform transitions over the entire series.

The structural time series framework developed by Harvey (1989, 1997) and Koopman et al. (2007) can capture and test for these LLTs. This allows for complex series behavior, such as a cycle around a trend, as well as irregular transitions from period to period. The model can be made even more general by allowing for the possibility of seasonal, cyclical, and auto-regressive components.

The model parameters are estimated by maximum likelihood using the prediction error decomposition of Harvey (1981, pp.12-16).[11] A Kalman filter is then applied to derive estimates of the two unobserved component vectors, $\boldsymbol{\mu}_t$ and $\boldsymbol{\beta}_t$.[12] We start with a general stochastic specification with 12 lags of each variable and test the model down. If all unobserved

[11] The prediction error decomposition decomposes the likelihood function into the joint distribution of *N* independent prediction errors. The prediction errors are computed by the Kalman filter.

[12] A convenient introduction to the underlying econometric modeling approach is provided by Commandeur and Koopman (2007).

components turn out to be constant, the structural time series model degenerates to OLS with a constant trend.

The structural time series framework will allow the direct estimation of the effects of the measurable determinants of chart turnover. The results will indicate whether either the size or age distribution has an effect on turnover. The random-copying model predicts that the size of the total population will have no bearing on the turnover rate. The estimation will also indicate whether the size of different age groups affects the charts. Since the record industry typically tries to appeal to younger people, one would expect that an older population would negatively affect sales.

Another advantage of this framework is the ability to test the "innovation" portion of the random-copying theory. If the turnover equation is found to exhibit a random walk with drift, we can say that the mutations in musical preferences may be having some effect on the turnover in album charts.

The structural time series approach allows one to extract the unobserved component in the form of a stochastic trend (μ_t). It is possible, therefore, to gauge the likely impact of illegal downloading. If a significant unobserved trend is found, and if it is consistent with the hypothesized level of illegal downloading over time, then the extracted stochastic trend could be taken to be at least a rough approximation of the impact of illegal downloading on turnover. The approximation would not be exact simply because there are likely to be other factors that affect turnover but that are not represented by observed covariates in the model.

VI. Results

Model Selection

Using a general-to-specific methodology (GETS), a general model was estimated. This model included all covariates listed in TABLE 2 as well as stochastic level and trend components and an autoregressive component.[13] Lags were included up to twelve months. The results of the general model are used to move toward a more parsimonious specification.

The variables measuring the proportion of the population in each age group were found to be statistically insignificant and are, thus, dropped from the turnover equation in the restricted models. Lags of the remaining variables are also excluded. Likelihood ratio tests are performed in each case to ensure that any model restrictions relative to the unrestricted models are supported by the data.

Three restricted models for specifying the unobserved component are tested.[14] Model 1 allows both the level and slope of the trends to follow a stochastic process. Model 2 allows for the levels to change over time but maintains deterministic slopes. Model 3 fixes the level of the trends.

Table 4 displays the variances of the unobserved components for each model. The variance of the estimated slope in Model 1 is nearly 0. This shows that the slope of the trend is not changing over time and should be dropped from the estimation. In Model 2, the variance of the stochastic level is small but statistically significant. Model 3 is specified with a fixed level trend, so no variances are derived.

Goodness-of-fit tests are provided in Table 5. The results of these tests show that Model 2 has the best overall in-sample fit. To further check the data capturing properties of Model 2, a

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[13] The results of the unrestricted model are available from the authors upon request.

[14] Models containing many different combinations of the unobserved components were tested. The components for both equations were tested for cointegration using the method developed by Nyblom, et al (2001). None of the components share a common trend. The possibility of seasonal, cyclical, and auto-regressive components was also tested. Only those models that best captured the data-generating process are examined here. The detailed analysis is available from the authors on request.

cusum analysis (Durbin, 1969) was used to confirm the stability of the residuals over the estimation period. Figure 1 shows that the cusum residuals are well within acceptable bounds, providing further confidence that Model 2 is correctly specified. As shown in Figure 2, this model also performs quite well in the out-of-sample forecast. For these reasons, Model 2 is our model of choice for discussion below. [15]

Turnover Equation

The price of music recordings is found to have a small, negative relationship with turnover in the Billboard 200 charts. Over the period examined, the real price of music fell roughly 12%. For each 1% decrease in price, turnover increases by 0.1%. Falling real prices help explain the upward trend in turnover during the sample period.

There is anecdotal evidence that the industry has cut album prices in order to increase unit sales, but changes in the sales levels of recorded music are not necessarily indicative of changes in turnover.[16] An increase in turnover simply means that albums' longevity on the chart is falling. On the other hand, as real prices fall, firms may be increasing the number of new releases in the hope that sales may be bolstered by new albums that are more in line with current consumer tastes.

The price of audio equipment also has a small, negative impact on turnover. Audio equipment and recorded music are complementary goods. The real price of audio equipment has ebbed and flowed over the sample. When new technology is introduced, prices will generally be higher. During the sample period, compact disc players and MP3 players were introduced. When new technology is introduced, and prices of audio devices increases, people may be re-

[15] The models' residuals do not follow a normal distribution due to a few outliers. The addition of observation-specific dummy variables on the following dates corrects for this problem: July 1993, January 1995, October 2000, February 2010, and June 2010.

[16] See Klein and Slonaker (2010).

purchasing their old favorites in the new format. This would show up as an increase in sales of recorded music, but, assuming households have some fixed budget for music purchases, would harm the sales of newer albums. This would be reflected in a decreasing number of new albums entering the top 200 chart.

Our estimates show a small, negative impact on turnover from the both real price of software and the real price of personal computers. The real prices for both software and computers declined over the sample period. This would include software, such as Propellerhead which is widely used in the production of both commercial and independent recordings (Jeppesen and Frederiksen, 2006). The decline in these prices may increase the supply of independent recordings which may never sell enough units to show up on the Billboard 200 chart but are substitutes for more widely released albums that are candidates for the chart. Thus, as the prices of these technological elements have fallen, we would expect turnover to increase.

Both movie tickets and recorded movie media[17] are considered to be substitute goods for recorded music. The prices of both of these entertainment products have a small, negative effect on turnover. The real price of movie tickets has been fairly constant over the sample. A 1% decrease in movie ticket prices causes turnover to increase by 0.36%. A 1% fall in movie media prices leads to a 0.08% increase in turnover. This may seem so small as to be irrelevant, but this form of media has shown a dramatic decrease in prices over the sample, and thus, should not be ignored as an explanatory factor in increasing turnover. As the prices of the competing goods fall, firms may be altering their release behavior so that new music releases continue to attract the buyers of entertainment goods.

If household incomes were to fall, the household budget for music purchases would likely fall as well. Recording firms may need to introduce more new titles in order to entice the

[17] The term "movie media" used throughout refers to VHS and DVD formats.

consumers to use their slimmer budgets to purchase new music. Our data support this argument. When real personal disposable incomes fall by 1%, turnover increases by 0.3%.

The size of the total population of the United States has a fairly large, positive effect on turnover. We find that for each percentage increase in the population, turnover increases by 0.47%. As the population has grown, musical tastes may have become more diverse and the industry may have responded by increasing the number of albums released. For example, in 1990 the Recording Industry Association of America (RIAA) reported that 36% of shipments of recorded music were from the "Rock" genre,[18] but by 2010 "Rock" shipments had fallen to 26% with all other genres showing increases[19].

We find that turnover in the Billboard 200 chart is subject to a stochastic trend. Specifically, the intercept, or level term μ_t, of the trend is changing over time. This component captures the combined effects of any unobservable variables. These unobservables may include certain demand determinants, consumer behaviors, or "innovations" that are not captured by the covariates. The estimated stochastic level component shown in FIGURE 3 exhibits some interesting characteristics.

The unobserved component has a small effect on turnover throughout the sample. The trend is in decline from the beginning of the sample until 2000 at which point it begins a gradual upward climb. Around 2003, the unoberservables actually begin to have a positive effect on turnover. Although the effects of each unobservable factor cannot be disentangled, one cannot ignore the fact that this is around the time that file-sharing became prominent. It is quite possible that the industry altered its release behavior in response to dragging album sales due to piracy,

[18] www.riaa.org
[19] http://www.businesswire.com/news/home/20110106006565/en/Nielsen-Company-Billboard%E2%80%99s-2010-Music-Industry-Report

although it is also possible that consumers' exposure to more artists through file-sharing changed their buying habits in favor of niche artists rather than superstars.

The positive effect of the unobservables began to decline around 2007. By this time, the recording industry was beginning to work with the change to digital music, rather than fighting against it. Digital Rights Management (DRM) free music became available via iTunes in late 2008. The unobserved component continued to decline through the end of the sample in 2010.

Music Demand Equation

As we would expect, the price of recorded music has a fairly large, negative effect on music demand. The real price of music has fallen over the sample. For a 1% decrease in prices, the demand for music increases 0.55%.

Real disposable income is another significant determinant of demand for recorded music. The income elasticity of demand is found to be 0.16. While not as strong as some other factors discussed here, it does appear that music is a normal good and its demand is subject to the ebbs and flows of the macro-economy.

The real price of audio equipment has a large, negative effect on music sales. Listening devices and recorded music would be considered complements. When the real price of equipment increases by 1%, the demand for the complementary recorded music will fall by 0.55%.

It should be noted, that this relationship may not hold when new technology is introduced. For a time after a new device is on the market, the price may be high. At the same time, consumers may be forced to re-purchase titles that they already own in order to enjoy the new listening technology. For example, when compact disk players were introduced, consumers may have increases their demand for music overall by purchasing, in CD format, recorded music they already owned on cassette or record album. While this is a phenomenon that deserves more in depth study, these introductions are few and far between over our sample period.

The real price of personal computers has a small, negative effect on music sales. The real price of computers has fallen drastically over the sample. This would be responsible for only a small increase in music sales.

As population increases, so do sales of recorded music. For each 1% increase in population, we find that music sales increase by 0.5%. The relative size of each age group only has a small influence on sales. The portion of the population that falls in youngest age group (ages 10 to 24) has a negative effect on sales while the older groups have a positive effect. This is an interesting result given that music marketing is often aimed at younger audiences. We often think of teenagers as being the main consumers of music. It may be the case, however, that it is the older demographic that is actually making the purchases, or that the younger group is more susceptible to downloading "free" music through file-sharing, or both.

The estimation of an unobserved level component, shown in Figure 3, shows that some unobserved factors are affecting the demand for recorded music over the sample period. While the specifics of these factors cannot be determined, there are some parallels between the behavior of the stochastic trend component and the timing of certain events affecting the recorded music industry.

In the early part of the sample, the unobserved component was fairly small and positive. Between mid-1993 and 1995, the unobserved component trended upward. From 1995 through 1999, however, the stochastic trend was relatively level with a positive effect on sales of roughly 0.5%. This corresponds to a period in which the major record labels allegedly adopted minimum advertised pricing policies, a practice that ended with consent agreements with the Federal Trade Commission in May 2000.[20]

In the middle of 2000, the unobserved component starts a sharp trend downward. In June 1999, Napster, one of the first and most popular file-sharing services, became available, followed by the RIAA's announcement to sue Napster for copyright infringement in early 2000. Subsequently, the RIAA made public its intent to prosecute individuals for illegal file-sharing in June 2002. If successful, such litigation should reduce copyright infringement, but could also shrink demand and recommendation networks, raising consumer search costs and reducing sales. The behavior of the unobserved seems to support the latter hypothesis. By the end of the sample in 2010, the positive effect of this component on record sales nearly disappeared.[21]

Although the unobserved component captures the combined effect of *all* significant unobserved variables, one cannot rule out the possible influence of file-sharing and the RIAA's subsequent litigation. Nevertheless, we cannot distinguish causality; that is, whether the file-sharing litigation was a response to, or a cause of, the decline in the unobserved component.

Another possibility is that the 1990's were an aberration in that sales were abnormally high during the decade. A possible cause is that consumers were replacing their vinyl collections with CD's, a behavior that was largely completed by the turn of the century. The subsequent decline in the unobserved component may merely represent a return to more historically representative sales levels.

VII. Conclusion

[20] Labels threatened to withhold promotional payments from retailers violating this policy, which the FTC found equivalent to illegal Resale Price Maintenance. The Labels' intent, however, may have been to maintain variety by preserving large-assortment specialty retailers in the face of competition from limited-assortment discounters such as Wal-Mart and Target (Marvel and Peck, 2008).

[21] These results are very similar to those found in Klein and Slonaker (2010).

The predictions of the random copying hypothesis are rejected for the turnover behavior of the Billboard 200 chart since 1990. Turnover during this period is significantly affected by the size of the population in direct contradiction of the findings of Bentley, et al. (2007). Moreover, the turnover rate is not a constant, but has increased during the digital age, again contradicting random copying behavior. This suggests that the rate of innovation – by producers, consumers, or both – has also increased.

The estimated turnover equation suggests that innovation is induced by increases in the total population and decreases in the prices of recorded music and related goods. The declining price of recorded music as well as declines in the prices of complementary consumer goods likely prompted consumers to innovate in their listening choices. Declining prices for computers and software likely reduced the cost of producing recordings and, along with the positive effect of population on sales, increased the supply of titles available to consumers. Economies of scale were reduced, allowing more titles to gain sufficient sales to become profitable. These phenomena had the effect of spreading sales over more titles and increasing turnover.

The music demand equation shows largely expected demand relationships. Demand increases in response to lower prices for music and complementary goods as well as increases in income and total population. The most likely contributors to the decline in album unit sales since 2000 reported by the RIAA are an increase in the 10-24 age group and the decline in the unobserved component. Both of these are compatible with Internet activity and illegal file-sharing as causes of declining sales.

Nevertheless, one cannot rule out the hypothesis that the 1990-2000 decade was an aberration in music sales relative to decades before and since. The unobserved component of music demand rises and stabilizes during this decade before declining after 2000. The underlying causes of this behavior have yet to be accurately measured or confirmed, leaving fertile ground for future research.

References:

Alexander, Peter J. (1994). Entry barriers, release behavior, and multi-product firms in the music recording industry. Review of Industrial Organization, 9(1), 85-98.

Alexander, Peter J. (1996). Entropy and popular culture: product diversity in the popular music recording industry. American Sociological Review, 61(1), 171-4.

Alexander, Peter J. (2009). The music recording industry. (In James W. Brock (Ed.), The structure of american industry. Upper Saddle River: Pearson, 12th ed.)

Anand, N. and Richard A. Peterson. (2000). When market information constitutes fields: sensemaking of markets in the commercial music industry. Organization Science, 11(3), 270-284.

Anderson, Chris. (2006). The long tail: why the future of business is selling less of more. (New York: Hyperion).

Alkvist, Jarl A. and Gene Fisher. (2000). And the hits just keep on coming: music programming standardization in commercial radio. Poetics, 27, 301-325.

Balcombe, Kevin, Alistair Bailey, and Jamie Morrison. (2002). Stochastic biases in technical change in u.s. agriculture: a bootstrap approach. Canadian Journal of Agricultural Economics, 50, 67-83.

Bhattachargee, Sudip, Ram D. Gopal, Kaveepan Lertwachara, James R. Marsden, and Rahul Telang. (2007a). The effect of digital file sharing technologies on music markets: a survival analysis of albums on the ranking charts. Management Science, 53(9), 1359-1374.

Bhattachargee, Sudip, Ram D. Gopal, Kaveepan Lertwachara, and James R. Marsden. (2007b). Stochastic dynamics of music album lifecycle: an analysis of the new market landscape. International Journal of Human-Computer Studies, 65(1), 85-93.

Bentley, R. Alaxander, Carl P. Lipo, Harold A. Herzog, and Matthew W. Hahn. 2007. "Regular Rates of Popular Culture Change Reflect Random Copying." Evolution and Human Behavior, 28: 151-58.

Bielby, William T. and Denise D. Bielby. (2003). Controlling prime-time: organizational concentration and network television programming strategies. Journal of Broadcasting and Electronic Media, 47(4), December, 573-596.

Black, Michael and Douglas Greer. 1986. Concentration and non-price competition in the recording industry. Review of Industrial Organization, 3(2), 13-37.

Brynjolfsson, Erik, Yu (Jeffrey) Hu and Duncan Simester. (2007). Goodbye pareto principle, hello long tail: the effect of search costs on the concentration of product sales. Retreived from Social Sciences Research Network website: http://ssrn.com/abstract=953587.

Brynjolfsson, Erik, Yu (Jeffrey) Hu and Michael D. Smith. (2003). Consumer surplus in the digital economy: estimating the value of increased product variety at online booksellers. Management Science, 49(11), 1580-96.

Carroll, Glenn R. (1985). Concentration and specialization: dynamics of niche width in populations of organizations. The American Journal of Sociology, 90(6), May, 1262-1283.

Christianen, Michael. (1995). Cycles in symbol production? a new model to explain concentration, diversity and innovation in the music industry. Popular Music, 14(1), January, 55-93.

Dixit, Avinash K. and Joseph E. Stiglitz. (1977). Monopolistic competition and optimum product diversity. American Economic Review, 67(3), 297-308.

Doornik, Jurgen A. and Henrik Hansen. (2008). An omnibus test for univariate and multivariate normality. Oxford Bulletin of Economics and Statistics, 70(s1), 927-939.

Dowd, Timothy J. (2004). Concentration and diversity revisited: production logics and the u.s. mainstream recording market, 1940-1990. Social Forces, 82(4), 1411-1455.

Durbin, J. (1969). Tests for serial correlation in regression analysis based on the periodogram of least-squares residuals. Biometrika, 56(1), 1-15.

Fader, Peter S. (2000). Expert report. A&M Records, Inc. v. Napster, Inc., 114 F. Supp. 2d 896.

Fleder, Daniel and Kartik Hosanagar. (2007). Blockbuster culture's next rise or fall: the impact of recommender systems on sales diversity. Retrieved from Social Sciences Research Network website: http://ssrn.com/abstract=955984.

Gopal, Ram D., Sudip Battacharjee, and G. Lawrence Sanders. (2006). Do artists benefit from online music sharing? Journal of Business, 79(3), 1503-1533.

Hahn, Matthew W. and R. Alexander Bentley. 2003. "Drift as a Mechanism for Cultural Change: An Example from Baby Names." *Proceedings of the Royal Society, London, B: Biological Sciences*, 270: S120-S123.

Handke, Christian. 2006. "Plain Destruction or Creative Destruction? Copyright Erosion and the Evolution of the Record Industry." *Review of Economic Research on Copyright Issues*, 3(2): 29-51.

Harvey, Andrew C. (1989). Forecasting structural time series models and the kalman filter. (Cambridge: Cambridge University Press).

Harvey, Andrew C. (1997) Trends, cycles, and autoregressions. Economic Journal, 107, 192-201.

Hendricks, Ken and Alan Sorensen. (2009). Information and the skewness of music sales. Journal of Political Economy, 117(2), 324-69.

Jeppesen, Lars Bo and Lars Frederiksen. (2006). Why do users contribute to firm-hosted user communities: the case of computer controlled musical instruments." Organization Science, 17(1), 45-63.

Klein, Christopher C. and Shea W. Slonaker. 2010. "Chart Turnover and Sales in the Recorded Music Industry: 1990-2005." *Review of Industrial Organization*, 36: 351-72.

Koopman, Siem Jan, Andrew C. Harvey, Jurgen A. Doornik, and Neil Shephard. (2007). STAMP 8.0: structural time series analyser, modeller and predictor. (London: Timberlake Consultants).

Lee, Steve S. (2004). Predicting output diversity in the radio industry, 1989-2002. Poetics, 32, 325-342.

Lee, Wendy. (2010). Music's sales slump persists. The Tennessean, 106(10), A1.

Marvel, Howard P. and James Peck. (2008). Inventory turnover and product variety. The Journal of Law and Economics, 51(3), 461-78.

Mezias, John M. and Stephen J. Mezias. (2000). Resource partitioning, the founding of specialist firms, and innovation: the american feature film industry 1912-1929. Organization Science, 11(3), 306-322.

Nyblom, Jukka and Andrew C. Harvey (2001). Testing against smooth stochastic trends. Journal of Applied Econometrics, 16(3), 415-29.

Oberholzer-Gee, Felix, and Koleman Strumpf. (2007). The effect of file haring on record sales: an empirical analysis. Journal of Political Economy, 115(1), 1-42.

Oberholzer-Gee, Felix, and Koleman Strumpf. 2010. “File-Sharing and Copyright.” Working Paper.

Peterson, Richard A. and David G. Berger. (1975). Cycles in symbol production: the case of popular music. American Sociological Review, 40(2), April, 158-173.

Peterson, Richard A. and David G. Berger. (1996). Measuring industry concentration, diversity, and innovation in popular music. American Sociological Review, 61(1), 175-178.

Rennhoff, Adam D. 2010. “The Consequences of ‘Consideration Payments’: Lessons from Radio Payola.” Review of Industrial Organization, 36: 133-147.

Rosen, Sherwin. (1981). The economics of superstars. American Economic Review, 71(5), 845-858.

Rossman, Gabriel . (2004). Elites, masses and media blacklists: the Dixie chicks controversy. Social Forces, 83(1), 61-79.

Ryan, John and Michael Hughes. (2006). Breaking the decision chain: the fate of creativity in the age of self-production. (In Michael D. Ayers (Ed.), Cybersounds (pp. 239-53). New York: Peter Lang.)

Scherer, F. M. (1980). Industrial market structure and industrial performance, Second Ed. (Boston: Houghton Mifflin)

Sterne, Jonathan. (2006). On the future of music. (In Michael D. Ayers (Ed.), Cybersounds (pp. 256-63). New York: Peter Lang.)

Stevans, Lonnie K. and David N. Sessions. (2005). An empirical investigation into the effect of music downloading on the consumer expenditure of recorded music: a time series approach. Journal of Consumer Policy, 28(3), 311-324.

Takeyama, Lisa N. (1994). The welfare implications of unauthorized reproduction of intellectual property in the presence of demand network externalities. The Journal of Industrial Economics, 42(2), 155-166.

Varian, Hal R. (2000). Buying, sharing, and renting information goods. The Journal of Industrial Economics, 48(4), 473-88.

Waldfogel, Joel. 2011(a). "Bye, Bye, Miss American Pie? The Supply of new Recorded Music Since Napster." NBER Working Paper 16882, http://www.nber.org/papers/w16882.

Waldfogel, Joel. 2011(b). "Copyright Protection, Technological Change, and the Quality of New Products: Evidence from Recorded Music Since Napster." NBER Working Paper 17503, http://www.nber.org/papers/w17503.

Zentner, Andrew (2006). Measuring the effect of file sharing on music purchases. The Journal of Law and Economics, 49(1), 63-90.

TABLE 1

AVERAGE SALES AND NEW CHART DEBUTS PER MONTH

Period	Chart Debuts per Month	Real Monthly Sales
1990-1994	36.56	1,093.25
1995-1999	47.27	1,650.73
2000-2004	62.37	1,910.23
2005-2010	81.02	2,021.74

Notes: Music sales figures are in millions. Base year is 2005.

TABLE 2
DEFINITION OF VARIABLES

Variable	Definition	Source
new	New chart debuts	Billboard Magazine - The Top 200
pirecording	Price index for expenditures on tapes, LPs, and CDs (Base year 2005=100)	NIPA: Table 2.5.4 Price Indexes for Personal Consumption Expenditures by Type of Expenditure
piequip	Price index for expenditures on audio listening and recording devices (Base year 2005=100)	NIPA: Table 2.5.4 Price Indexes for Personal Consumption Expenditures by Type of Expenditure
picomp	Price index for expenditures on personal computers (Base year 2005=100)	NIPA: Table 2.5.4 Price Indexes for Personal Consumption Expenditures by Type of Expenditure
pivideo	Price index for expenditures on recorded video materials (Base year 2005=100)	NIPA: Table 2.5.4 Price Indexes for Personal Consumption Expenditures by Type of Expenditure
pisoft	Price index for expenditures on computer software (Base year 2005=100)	NIPA: Table 2.5.4 Price Indexes for Personal Consumption Expenditures by Type of Expenditure
pimovie	Price index for expenditures on movie tickets (Base year 2005=100)	NIPA: Table 2.5.4 Price Indexes for Personal Consumption Expenditures by Type of Expenditure
pdi	Disposable personal income = Personal income - Personal current taxes (in millions)	NIPA: Table 2.1 Personal Income and Its Disposition
totpop	U.S. population over the age of 10 (in millions)	Census Bureau: National estimates by demographic characteristics
age1024	Percentage of the U.S. population between the ages of 10 and 24	Census Bureau: National estimates by demographic characteristics
age2544	Percentage of the U.S. population between the ages of 25 and 44	Census Bureau: National estimates by demographic characteristics
agegt44	Percentage of the U.S. population over the age of 44	Census Bureau: National estimates by demographic characteristics

TABLE 3
BASIC STATISTICS, 1990-2010

Variable	Mean	Std. Dev.	Min	Max
new	57.87	27.62	11	164
music	1,684.46	3.75	845	2,120
pimusic	96.27	4.32	83.83	104.61
piequip	127.64	29.47	77.35	167.90
picomp	346.62	431.22	35.05	1,615.59
pivideo	129.12	39.68	69.82	216.35
pisoft	316.15	334.42	73.17	1,317.29
pimovie	84.02	18.33	56.64	114.89
pdi	152.76	82.93	67.45	581
totpop	279.33	18.90	248.79	310.61
age10-24	0.21	.003	.203	0.326
age25-44	0.30	0.02	0.27	0.33
agegt45	0.35	0.03	0.31	0.40

Notes: Music sales and total population figures are in millions. Income figures are in billions. Age groups are percentages of total population. All data are monthly and relate to the United States for the years 1990-2010.

TABLE 4
VARIANCES OF THE UNOBSERVED COMPONENTS

		Model 1		Model 2		Model 3	
Equation	**Component**	**Variance**	**q-value**	**Variance**	**q-value**	**Variance**	**q-value**
Music Demand							
	Slope	1.31*e^-7	0.0009				
	Level	0.0002	1	0.0002	1		
	Irregular	9.53*e^-8	0.084	0	0	0.001	1
Turnover							
	Slope	1.46*e^-8	0.0017				
	Level	8.74*e^-6	1	1.01*e^-5	1		
	Irregular	2.74*e^-6	0	2.22*e^-6	0.2197	3.73*e^-5	1

Note: The q-value is the ratio of the standard deviation to the standard deviation associated with the largest variance. A q-value close to 1 indicates the respective trend components are exhibiting stochastic behavior.

TABLE 5
FIT TESTS FOR RESTRICTED MODELS

	Model 1		Model 2		Model 3	
	Music Demand	Turnover	Music Demand	Turnover	Music Demand	Turnover
std.error	0.013686	0.0036955	0.014134	0.003721	0.056099	0.008945
Normality	8.9676	13.363	6.8187	15.044	8.2881	10.432
DW	1.9917	1.967	1.859	1.9762	0.14692	0.30787
q	16	16	15	15	15	15
Q(q,q-p)	16.466	12.564	29.617	10.788	1442.1	947.64
LR Test	1.3624		1.3646		1.0321	
R^2_D	0.99924	0.99995	0.99959	0.99995	0.99355	0.9997

Notes: Normality is tested using the Doornik and Hansen (2008) test. The null is normality and the 5% critical value is 5.99. The Durbin-Watson test checks for first-order autocorrelation. The null is no autocorrelation and the 5% critical range is 1.61 to 1.92. q is the number of restrictions. The Box-Ljung Q is the Ljung and Box (1978) test for higher-order autocorrelation. The null is no autocorrelation. LR Test is the likelihood ratio test which checks whether the parameter restrictions are supported by the data. The null is that the restrictions do not apply. The 5% critical value for Q and LR is 23.68. R^2_D is the coefficient of determination based on differences and is appropriate for testing goodness-of-fit when the dependent variable exhibits trend movements (Koopman, *et.al*. 2007).

TABLE 6
ESTIMATION RESULTS FOR RESTRICTED MODELS

	Model 1		Model 2		Model 3	
Variable	**Coefficient**	**P-value**	**Coefficient**	**P-value**	**Coefficient**	**P-value**
	Music Demand		Music Demand		Music Demand	
ln(*pimusic*)	-0.57386	[0.00000]	-0.55832	[0.00000]	-0.19138	[0.00000]
ln(*pdi*)	0.14694	[0.08010]	0.16477	[0.02066]	-0.4859	[0.00000]
ln(*piequip*)	-0.56033	[0.00000]	-0.54766	[0.00000]	-0.17913	[0.00000]
ln(*picomp*)	-0.01381	[0.81557]	-0.05979	[0.10797]	-0.1399	[0.00000]
ln(*totpop*)	0.00755	[0.00000]	0.50066	[0.00002]	0.47929	[0.00000]
ln(*age10-24*)	0.00601	[0.00000]	-0.01033	[0.00000]	0.01181	[0.00000]
ln(*age25-44*)	0.00902	[0.00000]	0.01536	[0.00000]	0.00547	[0.00000]
ln(*agegt44*)	0.48904	[0.00000]	0.01375	[0.00000]	0.00488	[0.00000]
	Turnover		Turnover		Turnover	
ln(*pimusic*)	-0.09802	[0.00000]	-0.09787	[0.00000]	-0.22477	[0.00000]
ln(*pdi*)	-0.28557	[0.00000]	-0.29226	[0.00000]	-0.33547	[0.00000]
ln(*pisoft*)	-0.05404	[0.00000]	-0.06174	[0.00000]	-0.05416	[0.00000]
ln(*pimovie*)	-0.35971	[0.00000]	-0.36464	[0.00000]	-0.20286	[0.00000]
ln(*pivideo*)	-0.07685	[0.00017]	-0.07555	[0.00018]	0.04736	[0.02825]
ln(*picomp*)	-0.04533	[0.01073]	-0.02284	[0.00007]	-0.01561	[0.00000]
ln(*piequip*)	-0.08129	[0.00000]	-0.08592	[0.00000]	-0.213	[0.00000]
ln(*totpop*)	0.47325	[0.00000]	0.47002	[0.00000]	0.46851	[0.00000]

FIGURE 1
RESIDUALS ANALYSIS OF MODEL 2 OF TABLE 6

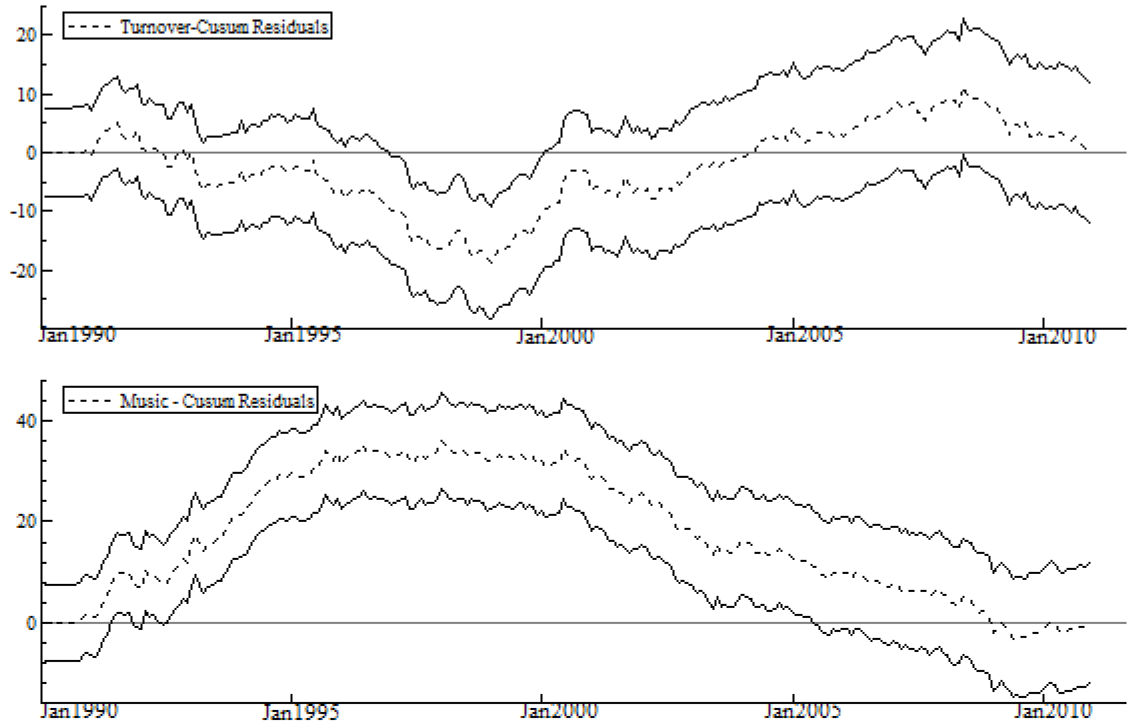

FIGURE 2
OUT-OF-SAMPLE PERFORMANCE - MODEL 2 OF TABLE 6

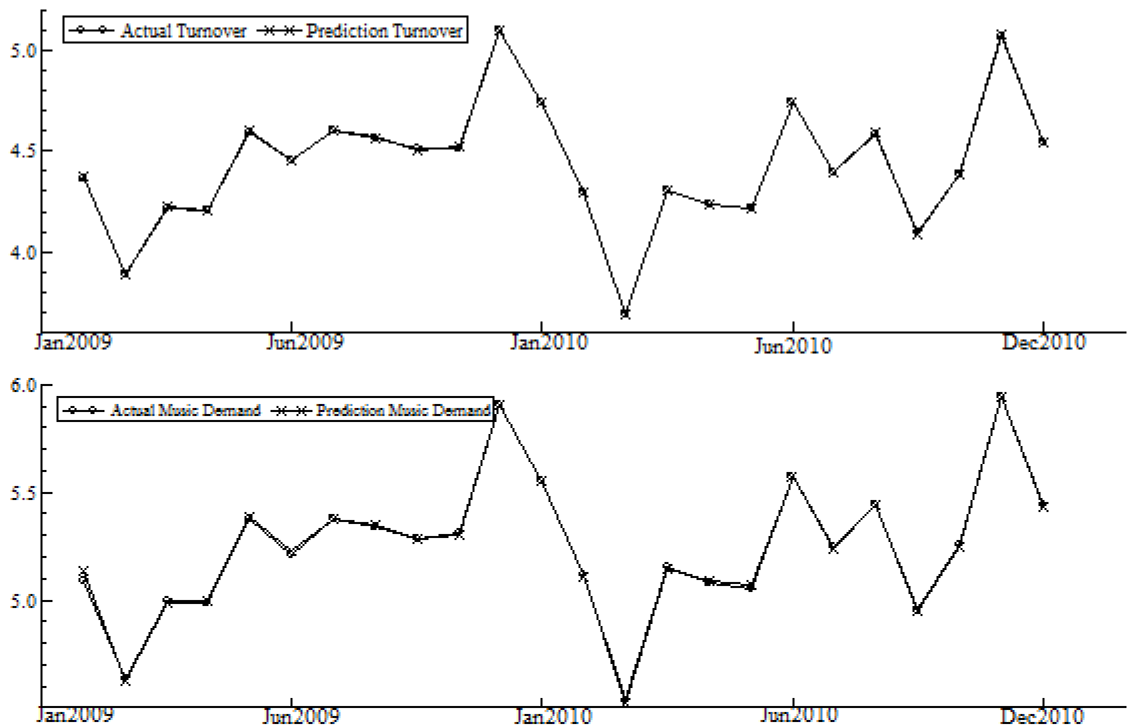

FIGURE 3
COMPONENT OF STOCHASTIC TREND - MODEL 2 OF TABLE 6