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INCREASING RETURNS TO INFORMATION IN THE U.S. POPULAR MUSIC INDUSTRY*

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Abstract

Using data relating to 'number one' hits on the *Billboard* Hot 100 chart, we find clear evidence of increasing returns to information in the U.S. market for popular music. This evidence supports related findings for the motion picture industry in various countries, and for Broadway productions.

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JEL Classifications: C4; D12; L1; L82; Z11

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1. Introduction

The entertainment industry is of considerable economic importance. It also has features that are of interest to economists, as is evidenced by the growing associated literature (*e.g.*, see Ginsburgh and Throsby, 2005). This note considers the U.S. popular music industry, and deals with just one aspect of the dynamic process which results in certain recordings becoming ‘number one hits’. Some popular tunes are dramatically more successful than others. Moreover, even among those recordings that reach the top of the charts, there is great variation in their success, measured in terms of sales or in terms of the length of time that they stay at ‘number one’.

Recently, Connolly and Krueger (2005) provided a wide-ranging economic analysis of the popular music industry, with a particular emphasis on concert revenues. Putting copyright, piracy and related legal issues to one side, there are surprisingly few empirical studies of this industry. By way of example, Hamlen (1991, 1994) undertook empirical tests of the “superstardom” hypothesis using U.S. recording sales; Chung and Cox (1994) analyzed the underlying probability distribution for the generation of “gold record” awards in the U.S.A.; and Giles (2005) modelled the duration of number one hits on the *Billboard* Hot 100 music chart. Burke (1996) and Strobl and Tucker (2000) investigated various aspects of the British recording industry.

There appear to be some similarities between the way in which particular music recordings gain popularity, and the ways in which this occurs for movies and theatrical performances. In each case, for example, word of mouth recommendations can play an important role. The more people who have listened to, and purchased, a musical recording, the more information there is available to other potential agents. This hypothesis of increasing returns to information has been tested empirically for the movie industry by De Vany and Walls (1996), Walls (1997) and Hand (2001). Maddison (2004) considers Broadway productions, and all of these authors find evidence of increasing returns to information. The only related evidence for the popular music industry appears to be that provided by Connolly and Krueger (2005). While they do not address increasing returns to information explicitly, they provide other evidence that is consistent with it in a particular sense

A discussion of increasing returns to information and the associated literature is provided in the next section. Section 3 describes our data; and our principal econometric results appear in section 4. The last section contains our conclusions.

2. Increasing Returns to Information

In economic terms, Pareto's Law (*e.g.*, Steindl, 1965; Zipf, 1965; Ijiri and Simon, 1974) is a relationship between firm size (S) and rank (R):

$$SR^b = A \qquad (1)$$

where 'A' and 'b' are constants. Note that 'A' is the size of the largest firm, and 'b' may be interpreted as a measure of concentration in the population. In the present context, 'size' may be measured in various ways. Some authors (*e.g*., Walls, 1997, and Hand, 2001) have used revenue to measure the size of artistic performances – in their case, movies. Others (*e.g*., Maddison, 2004) have used the number of performances. We follow the latter approach and use the number of weeks in the top spot on the *Billboard* Hot 100 music chart as our size measure for popular music recordings.

Taking logarithms, (1) becomes:

$$\log_e(S) = \log_e(A) - b\log_e(R)\,, \qquad (2)$$

which suggests a natural way of testing Pareto's Law *via* OLS regression. In particular, Ijiri and Simon (1974) augmented (2) with the term $[\log_e(R)]^2$, and tested if its coefficient was significantly different from zero. Those authors found a significant departure from Pareto's Law in their study of U.S. firms, and interpreted this as a situation in which larger firms are more likely to experience future growth. Various authors have termed this 'autocorrelated growth', but Vining (1976) showed that this phenomenon is not sufficient for Pareto's Law to fail. The rate at which past growth is discounted is also important. Autocorrelated growth has been interpreted as 'increasing returns to information' (*e.g*., Walls, 1997; Hand, 2001; Maddison, 2004), which in turn is used to explain the large differences in the successes of different artistic productions or performances. As Hand (2001) noted in the context of the U.K. film industry, this process can be viewed as an "informational cascade" (Bikchandani *et al*., 1992), and is similar to the dynamics associated with the Bose-Einstein distribution that arises in the Bayesian learning model of De Vany and Walls (1996).

In related work, De Vany and Walls (2004) showed that the class of stable distributions (sometimes called stable-Paretian, or Lévy-stable distributions) provides a good representation of the distribution of profits in the movie industry. Stable distributions (which include the normal, Cauchy and Lévy distributions as special cases) are generally 'heavy-tailed', and may be skewed.

An excellent modern discussion of this family is given by Nolan (2005). Connolly and Krueger (2005) also used the stable distribution family in the context of popular music concert revenues, and their estimates for the tail weight parameter, α, were les than unity. This implies that all of the moments of the underlying statistical distribution are infinite, so there is a high probability of extreme outlier values occurring.

From our perspective, an important feature of the class of stable distributions is that they can represent various data characteristics that arise from the influence of early consumers of the musical recordings. In particular, they can capture dynamic processes for which the change in demand for the product depends on the previously revealed demand. Such processes have attracted terms such as bandwagon and network effects, momentum, contagion, and informational cascades. As noted above, the latter in particular are closely allied with increasing returns to information. Moreover, De Vany and Walls (2004, p.1052) show that if the tail weight parameter, α, exceeds unity, then the *conditional* mean of the distribution exists and grows linearly. In our context this implies that if a recording reaches the top of the Hot 100 chart, its *expected* life at the top continues to increase with time. De Vany and Walls term this the 'success breeds success' phenomenon.

3. Data

Our data have been constructed from information made available on the internet by De Haan (2005). The following variables are used:

YEAR Year in which number one spot was ***first*** achieved, 1955 to 2003
WEEKS Total number of weeks at "number one"
RANK Rank of WEEKS, with RANK = 1 for max(WEEKS), *etc*.

Our primary data-set relates to recordings that reached number one on the charts during the period August 1958 to December 2003. The start of this sample period is determined by the creation of the *Billboard* Hot 100 chart on 4 August 1958, and it largely avoids the recent impact of downloading digital music on the internet. We have also considered an extended sample, beginning in January 1955, so as to capture the start of the rock and roll era, and to include all of Elvis Presley's seventeen number one hits. The Hot 100 sample and the extended sample comprise 901 and 965 observations respectively, and the data for the WEEKS variable are shown in Figure 1. Giles (2005) provides a more detailed description of the data, and a brief chronology of the development of the associated popular music charts.

4. Model Specification and Results

Following Ijiri and Simon (1974) and Connolly and Krueger (2005) we first fit a simple regression model

$$\log(WEEKS) = \beta_0 + \beta_1 \log(RANK) + \varepsilon \qquad (3)$$

where (-1/ β_1) corresponds to the characteristic exponent (the tail weight parameter), α, for the general family of stable distributions. Distributions in this family have a finite variance if $\alpha > 2$, and a finite mean if $\alpha > 1$. Estimating (3) by OLS we obtain estimates of the characteristic exponent equal to 1.511 and 1.516 for the 1955 – 2003 and 1958 – 2003 samples respectively. By way of comparison, Connolly and Krueger (2005) obtain estimates of 0.45 and 0.55 respectively for the distributions of artists' and promoters' popular music concert revenues; and De Vany and Walls (2005) obtain estimates in the range 1.72 to 1.91 for motion picture box office revenues, depending on whether or not the movies include "stars".

Importantly, our estimates of α imply that the underlying distribution has an infinite variance (so that exceptionally successful hits can arise with reasonable probability), and it has a finite conditional mean that is consistent with the 'success breeds success' phenomenon. The fitted regression is compared with the actual data in Figure 2, and the omission of a non-linear effect immediately suggests itself. Moreover, the intercept predicts a maximum duration for a number one hit recording to be an unlikely 81 to 88 weeks (depending on the start date of the sample). This compares with the historical maximum of sixteen weeks set by Mariah Carey and Boyz II Men with *One Sweet Day*, beginning on 2 December 1995. So, as suggested by Ijiri and Simon (1974), Maddison (2004) and others, a quadratic term is added to the model:

$$\log(WEEKS) = \beta_0 + \beta_1 \log(RANK) + \beta_2 [\log(RANK)]^2 + \varepsilon \ . \qquad (4)$$

We are especially interested in the sign and significance of β_2. Other covariates and interaction terms have also been considered to control for particular effects of the type found to be significant by Giles (2005) in his duration models. These include the year in which the recording first reached the number one spot (YEAR); dummy variables to discriminate between recordings by groups, male and female soloists; dummy variables to account for purely instrumental recordings and durations that were achieved in non-consecutive weeks; and dummy variables to allow for mega-stars such as Elvis and The Beatles. Finally, dummy variables were considered for the important changes in the Hot 100 compilation in 1958 and 1998. With the exception of YEAR, none of these other variables were statistically significant when we undertook a general-to-specific specification search, so our final model specification is:

$$\begin{aligned}\log(WEEKS) &= \beta_0 + \beta_1 \log(RANK) + \beta_2[\log(RANK)]^2 + \\ &\beta_3 YEAR + \beta_4[YEAR * \log(RANK)] + \varepsilon\end{aligned} \tag{5}$$

The estimation results for equations (4) and (5) appear in Table 1 for each of the sample periods noted in section 3. As there was evidence of heteroskedasticity in the errors, White's (1980) robust covariance matrix estimator was used in constructing the t-values. This was also the case in the related studies by Hand (2001) and Maddison (2004). As can be seen, regardless of the model specification or sample period, the estimated coefficient of $[\log(\text{RANK})]^2$ is negative, and we strongly reject the hypothesis that β_2 is zero. This is not surprising, given the visual evidence in Figure 2. The estimated coefficients on the quadratic terms are somewhat smaller in absolute value than their counterparts in the corresponding studies for movies and Broadway productions. In those cases the estimated coefficients are of the order -0.3 to -0.4. The statistical significance of these terms is very comparable, however. (See De Vany and Walls, 1996; Walls, 1997; Hand, 2001; Maddison, 2004). The significance of the estimated coefficient of $[\log(\text{RANK})]^2$ suggests a departure from Pareto's law, and its sign indicates that there is autocorrelated growth. So, there is strong support for the hypothesis of increasing returns to information in this market for U.S. popular music.

5. Conclusions

We find evidence of a departure from Pareto's Law in the success of popular music recordings in the U.S.A., and this is consistent with the phenomenon of increasing returns to information. Popular music recordings that have enjoyed recent success are more likely to stay at the top of the charts than are hits whose success occurred at an earlier time. In this respect, there are similarities between this industry and those associated with movies in the U.S.A., the U.K. and Hong Kong, as well as for Broadway productions.

Table 1: OLS Regression Results for Equations (4) and (5)

Sample Period:	**1958 – 2003**		**1955 – 2003**	
Intercept	2.1158	-4.5019	2.0223	-10.7193
	(13.418)	(-1.2106)	(11.489)	(-4.480)
log(RANK)	0.4016	1.7654	0.4602	2.8367
	(6.259)	(2.711)	(6.471)	(6.581)
log(RANK)^2	-0.1139	-0.1160	-0.1188	-0.1228
	(-18.085)	(-16.763)	(-17.152)	(-17.908)
YEAR		0.0033		0.0064
		(1.878)		(5.294)
YEAR*log(RANK)		-0.0007		-0.0012
		(-2.193)		(-5.466)
$\bar{R}^2$	0.982	0.982	0.984	0.984
N	901	901	965	965

Note: The t-ratios in parentheses are based on White's (1980) heteroskedasticity-robust standard errors.

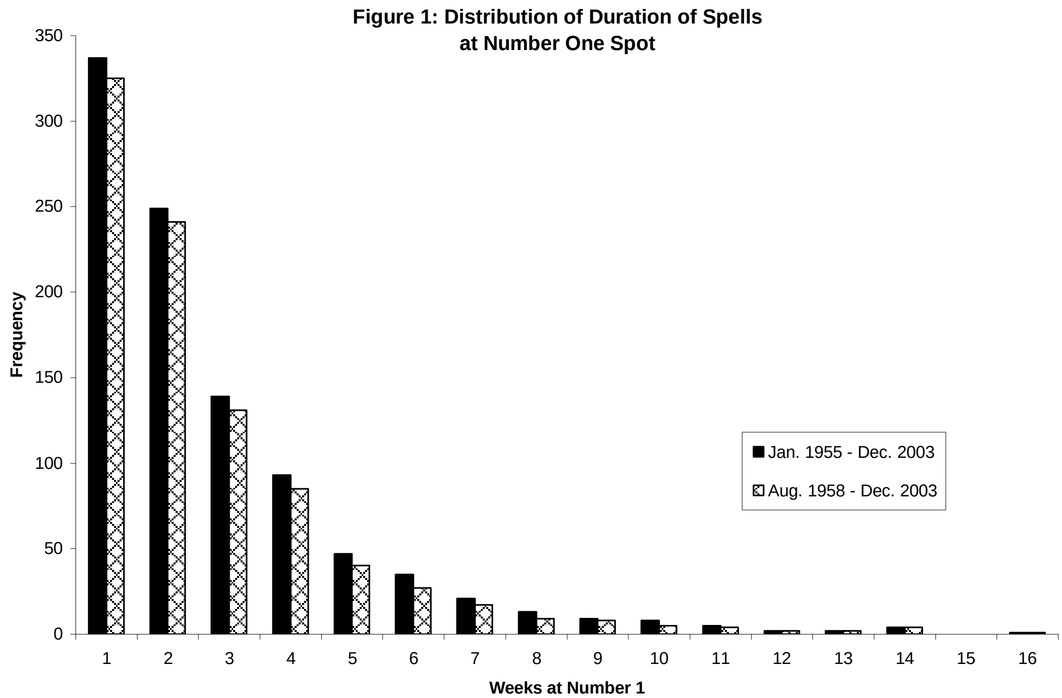
Figure 1: Distribution of Duration of Spells
at Number One Spot
Frequency
Weeks at Number 1
Jan. 1955 - Dec. 2003
Aug. 1958 - Dec. 2003
0
50
100
150
200
250
300
350
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16

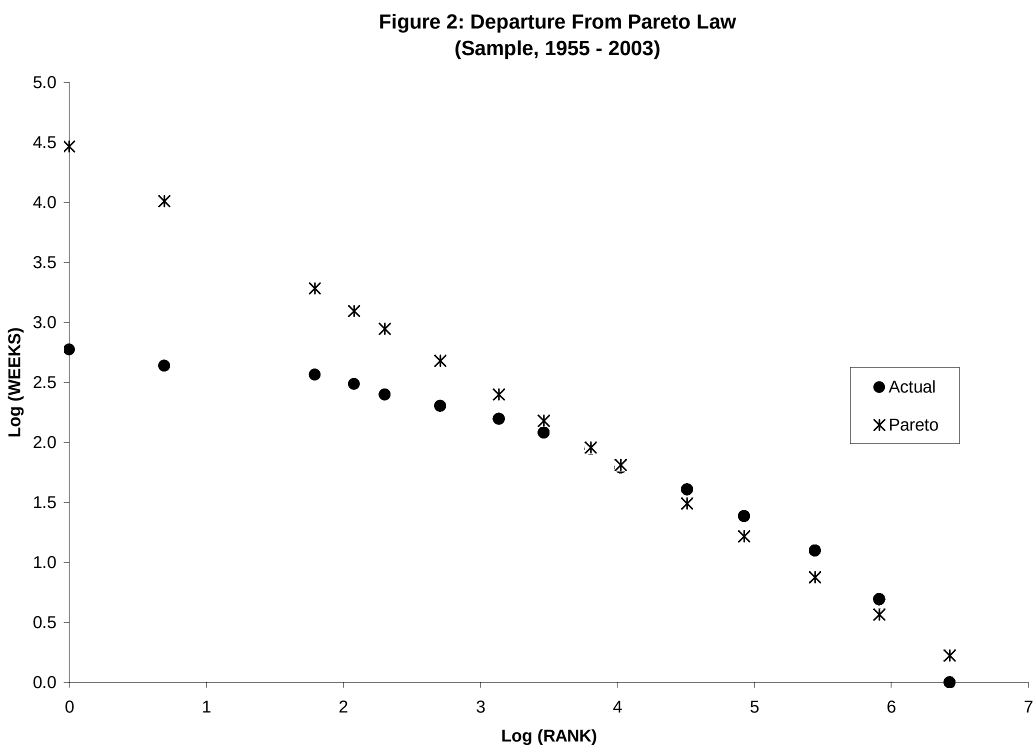
Figure 2: Departure From Pareto Law
(Sample, 1955 - 2003)
Log (WEEKS)
Log (RANK)
Actual
Pareto
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
0
1
2
3
4
5
6
7

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