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Abstract

The paper analyses the impact of age on the ranking of recorded popular songs in the Dutch Radio2 Top2000 chart in the years 1999-2013. We measure the competition between the loss of collective memory and nostalgia with respect to popular songs. Nostalgic feelings seem to be relevant to recorded songs with an age of 20-40 years. It is shown that the superstar status of the performing artist, the length of the recorded song, and the use of the domestic language (Dutch in our sample) as well as the debut ranking are predictors of the lifespan of a song in the chart.

JEL-Code: Z110.

Keywords: collective memory, nostalgia, music chart, song age.

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1 Introduction

Recorded popular music is important in the construction of both personal and collective memory (see Van Dijck, 2006). For individuals recorded music can lead to emotions and even to nostalgic feelings (see for instance Barrett *et al.*, 2010). Nostalgia is a complex emotion that generally leads to positive feelings. It is well-known that nostalgia can be triggered by music. This applies not only to the individual agent, but also at the macro (or national) level and then we label this collective cultural memory and/or collective nostalgia. Analyzing emotions at the individual level can be performed in experimental randomized settings (see Rentfrow *et al.*, 2011), but at the macro level a controlled experiment is simply not feasible. In this paper we analyze the relationship between age of recorded music and its macro popularity using a unique database of Dutch collective musical preferences in the years 1999-2013: the Radio2 Top2000 database. Our basic assumption is that if recorded songs become older, the loss of memory will lead to a lower appreciation, but that nostalgic feelings can counteract the loss of popularity.

Popularity of recorded songs is timely and fashionable and therefore it is likely that different generations of agents have different musical tastes. As time goes by, the older generations will die, and younger generations come in, leading to a shift in the macro musical preferences. But older recorded songs can stay popular, because of individual nostalgic feelings or emotions or through intergenerational inheritance. It is well-known that musical preferences are likely to be formed during late adolescence or early adulthood (see Holbrook and Schindler, 1989). It is also known that musical taste is determined by social context in general and the family structure in particular (during the summer holiday listening on the backseat of the car to the parents' song-lists).

We analyse aggregated ranked preferences of popular songs. We use a large Dutch sample of annual data of the Radio2 Top2000 chart over the years 1999-2013 (see www.radio2.nl). Contrary to e.g. the *Billboard* Hot 100 chart, which is based on sales, the Radio2 Top2000 chart is constructed on the basis of votes. This implies that our measurement of musical taste is not blurred by monetary incentives (the price of the recorded songs). The main interest of the paper is to describe the impact of the age on the relative ranking of the song. The median age of a song in the Radio2 Top2000 list in 2013 is about 30 years, which implies that the majority (3196 of the 3733) of the all-time listed songs was 'born' before the start of the survey in 1999. This fact can be explained by the notion that in 2007 for instance the median voter ages about 47-48 years and the Holbrook-Schindler hypothesis of formation of musical preferences might apply. The impact of the age of a song on its popularity can in principle be twofold. If the age of a song increases it is likely that the song will become more well-known and appreciated. On the other hand, a song might be less memorized and fades away from the chart (as Bhattacharjee et al. (2007) argue the rapid increase in communication technology might stimulate exiting in charts based on weekly data). And if the voting population becomes relative younger, collective memories change and older songs might become less popular on average.

There is one other main determinant of recorded song popularity in a chart that focuses on the long run and that is the status of the performing artist. If the performing artist(s) is (are) very well-known, e.g. The Beatles or The Rolling Stones, it is likely that the impact of the superstar status on the relative preference for a song will be substantial. Why do people prefer specific performers more than others? Rosen (1981), following Marshall, describes the economics of superstars: relatively small numbers of people can earn enormous amounts of money and dominate the activities in which they engage. Rosen shows that persons with only a slightly greater talent command much higher incomes if less talent is a poor substitute for greater talent and either the activity can be reproduced endlessly at a fixed cost, or the cost of production does not rise in proportion to the size of the seller's market. If persons with differences in talent can monopolize their talent, they can get above normal returns and earn incomes that exceed their marginal contribution to welfare. In that case relative high incomes are not reflected by exceptional talent only, but also by the power to extract excessive rents (see Borghans and Groot, 1998). Adler (1985) states that there could be stars among individuals known to have equal talents if one allows for learning. If consumers accumulate consumption capital (e.g. appreciation increases with knowledge), the main question is how does one know about music? Listening in repetition and discussing it with other agents who know about the quality of specific music will stimulate the development of stars. The key to Adler's argument is that learning is based on the fact that consumers will not diversify indefinitely across different cultural activities. One must forgo some fields of interest for the sake of more knowledge about for instance popular music. Each person will end up with a limited number of artistic activities and a limited number of 'stars'. Discussing music with other knowledgeable individuals could lead to the phenomenon that people like the same stars. The costs of searching for knowledgeable individuals is minimized if one chooses the most popular artist. Stardom becomes a market device to downsize learning costs and is not necessarily a result of the hierarchy of talent.[1][2]

[1]Both Rosen (1981) and Adler (1985) believe that talent is an important determinant of stardom. But there are key differences between the Marshall-Rosen and the Adler interpretation though. According to Rosen superstars necessarily have superior talent and talent is observable at no costs to all agents. Adler (1985) allows the superstar to arise even among equally talented agents, talent is a hidden characteristic that needs to be discovered, and superstars only exist if the consumption of their services requires differentiated knowledge.

[2]It should be note that the hypothesis of superstardom is hard to test. One of the problems is that one needs to identify the demand curve for differentiated products. Hamlen (1991, 1994) has made two attempts to test for superstardom in the market for popular music. Hamlen (1991) uses an external measure of voice quality to identify demand in the US in the sample 1955-1987 and cannot support the Marshall-Rosen definition of superstardom. In a second, and related paper Hamlen (1994) uses more information for the same market and is able to describe the love for

Some previous studies have analyzed the life cycle of songs in charts, especially the *Billboard* Hot 100. Closest to our study is Bradlow and Fader (2001) who analyze 444 unique songs in the *Billboard* Hot 100 in 1993. Bradlow and Fader present a Bayesian latent lifetime model that uses a general gamma function per song to model its ranking development. After birth of the song, the song accumulated worth, which is unobservable, but leads to a ranking. One of the results of this paper is that songs that leave the top-40 ranks have a large probability to exit. Dowd and Blyler (2002) analyse the role of black artists in the charts over time in and Bhattacharjee et al. (2007) analyse the role of sharing networks in lifetime development of songs on the charts. The latter paper finds evidence of shortening of the life-cycle on the *Billboard* Hot 100. Crain and Tollison (1997) focus on the time development of music. They analyse whether the structure of music has changed in a time span of 50 years and find that the mid 1950s and again in the mid 1960s music has changed. None of these studies however takes a systemic approach like ours to focus on the interaction of age of the song and the superstar-nature of the performer.

In the remainder of the paper we first describe the data in Section 2. This section provides a description of the sources of the data and present basic descriptive statistics. We pay special attention to the age of the songs and to the superstardom of the performing artists. The descriptive statistics indicate the patterns that are analyzed in the following sections 3 and 4. In Section 3 we analyze the cross-song variation in the sample. We highlight the role of songs that have an One-Hit Wonder or an Evergreen character, the characteristics of debut, peak, low, and exit rankings, and the up- and downward potential of the songs. In Section 4 we analyze the cross-time variation of the joint distribution of the rank, age, and superstar character of the songs. We summarize and conclude in the final Section 5.

2 Radio2 Top2000 data

The Dutch Radio2 Top2000 list is comparable to the Billboard-100 list in the US. One of the key differences between the two charts is the frequency of observation: the *Billboard* Hot 100 list is published weekly, while the Top2000 is published once a year (in December). The *Billboard* Hot 100 list is based on sales of recorded music, while the Top2000 list is based on a large-scale survey. There is no precise information of the survey publicly available, but there is a steady growth in the number of respondents from about 150 thousand in 1999 to 3.3 million votes in 2013. The *Billboard* Hot 100 list focuses on new releases, while the Top2000 tries

variety of consumers even better. He finds that the rewards are less then the quality differences, again rejecting the Marshall-Rosen definition of stardom. Giles (2006) uses a stochastic model that allows success to be concentrated in the hands of a few lucky artists. He applies the Simon-Yule distribution for the *Billboard* Hot 100 data that reached number 1 position in the period January 1955 to December 2003. Contrary to Chung and Cox (1994) Giles (2006) does not find evidence that supports superstardom.

to measure relative Dutch preferences for all-time popular songs. Radio2 provides a source from which we retrieve the rankings of the songs, the language used in the song, and whether they are produced in The Netherlands. We complement these data with information on the length of the song using Spotify and/or iTunes.

2.1 The sample

The Dutch Radio2 Top2000 is broadcasted between Christmas and New Year's day since 1999. After the initial success in 1999, Radio2 decided to extend the composition and broadcasting of the Radio2 Top2000. The first edition of the Radio2 Top2000 had the intention to describe the long-run musical taste of the Dutch at the end of the previous millennium. In the 1999- and 2000-editions the choice of the songs was free. Starting in 2001 Radio2 used a limited choice set to reduce the burden of data collection. The list was composed via a set of predescribed choices: the results of the 1999- and 2000-polls and a list of records that are broadcasted regularly by Radio2 in the prevailing year. Radio2 argued that this restricted choice set did not lead to a change in the composition of the chart, because people were free to vote via the Internet. In the first editions 1999-2008 each voter selected ten songs. From 2009 each voter can select 15 (non pre-defined) songs. The number-one listed song got more than 10.000 votes in 2007, while the number 2000 seeded still got more than 150 votes. Radio2 screens the data for multiple voting per individual. In the more recent editions about 200-300 thousand people voted. Goris (2008) describes that in a voter-survey of the 2007-voting 63.4 percent where male votes and the median age of the male voter was 47 years (female voters had a median age of 48). There is another lower peak in the frequency distribution in the class 16-20 years. Goris (2010) reports that in the 2010-survey this effect is confirmed: 8.8 percent of the votes in the class 16-20 is the fifth largest class after 46-50 (17.6 percent), 51-55 (17.2), 56-60 (12.5) and 41-45 (12.1). On the www.radio2.nl website it was announced in December 2013 that there has been a relative increase in the number of female voters in the age class 15-25 years old.

We include data from the fifteen years of the Radio2 Top2000 since 1999 up to and including the 2013 edition. In total 3733 different records are included. Although artists produce records in different team formations and it is hard to quantify how many artists/groups produced the records, we count 1633 different producing units in our sample in the years 1999-2013. Table 1 presents the basic descriptive statistics. We give the means, median values, and standard deviations of the production year, the length of the records in seconds, the percentages of Dutch-produced records, and the language shares (in percentages). One can see in Table 1 that the median production year of a recorded song in the total sample is 1978, a song uses about three and a half minutes, and is by and large in English or in Dutch. The percentage of Dutch-produced (but not necessarily in Dutch language) records is slightly less

Table 1: Descriptive Statistics of Recorded Dongs in the Radio2 Top2000

	mean	median	σ
Production year	1980.98	1978	14.09
Length (seconds)	224.39	220	62.62
Dutch produced (%)	9.93	0	29.92
English (%)	83.52	100	36.76
Dutch (%)	9.94	0	29.92
German (%)	0.67	0	8.16
French (%)	1.55	0	12.37
Spanish(%)	0.56	0	7.48
Italian(%)	0.93	0	9.64
Portuguese (%)	0.13	0	3.66
Instrumental (%)	2.09	0	14.31

Sample period: 1999 - 2013. σ: the standard deviation. Sources: www.radio2.nl, Spotify and iTunes. Number of observations is 3733.

then 10 percent[3]. Simple curve fitting of the length of a record in terms of a kernel function of the year of production reveals evidence that the average record length has increased up to 1994 and slightly decreases thereafter (although the majority of the observations is older than 1994).

2.2 Age of the song and Superstars

The age of the records in our sample is incomparable to e.g. the Bradlow-Fader 1993-*Billboard* Hot 100 data. The age of a song varies in our sample from 0 to 89 years old (George Gershwin's *Rhapsody in Blue*, produced in 1924). The average age of a listed song is 27.16 years (median 29 years). Given the fact that the average age is much older than the age of the Top2000 chart, it is also likely that songs will exit and possibly re-enter. Is is insightful to see the dynamics of the average and median age of the songs in the Top2000 over time. The mean age has increased from 23.7 to 28.3 years years in 15 years time (1999-2013) and the median age 7 years (24 to 31 years); see Table 2. In 1999 the median age of all the debut songs was 24 years. In the editions 2013 the 60 debut songs have a mean age of 4.81 year(s). The 128 songs that exited in 2012 were 28.35 years on average. All these data illustrate that songs tend to survive in the Top2000 chart. And if there is an age-effect on the ranking, it is likely that the impact will be negative.

[3]This seems to be consistent with the estimate made by Hitters and Van de Kamp (2010) that the share of US and UK-acts in the Dutch recorded music market is about 80 percent.

Superstars are common in popular music. Some performing artists have multiple 'hits' in different charts through time and some have contemporaneous multiple success records. The Beatles have 58 records in the overall 1999-2013 Top2000-list, followed by The Rolling Stones with 46 and a joint top-3 position for ABBA and Michael Jackson with 27 records. 52 artists have more than 10 records in the list and of the total number of 1633 performing artists 1022 have a single Top2000 position. This implies that indeed the rankings are concentrated around superstars. It is most likely that top-rankings correlate with income revenues. Connolly and Krueger (2006) show that for the US markets in 2002 the average income generated by live concerts exceeded the average recordings and publishing income by far for the top-35 performing artists/bands. But a band's live concert popularity increases with a good ranking. When information is costly to obtain, rankings provide simple and cheap information, especially for goods that have social externalities. So we measure the skewness of the distribution of our popularity indicator by an approximation of the Gini coefficient[4]. We order the data of the number of songs NS per artist i in the overall dataset such that $NS_i \leq NS_{i+1}$, where i indicates the artist and compute for n=1635 performing artists:

$$GINI = \frac{2\Sigma_{i=1}^{n} i * NS_i}{n\Sigma_{i=1}^{n} NS_i} - \frac{n+1}{n} \tag{1}$$

which yields a GINI coefficient of 0.459. Comparing this value to income distributions around the world, this value resembles the value found for the US income distribution, which is generally considered to be skewed. In Table 2 we provide information on the distribution of $NS_{i,t}$, the number of songs per artist per year. The median number of records per artist per edition has doubled in the first 8 years of the sample, but now stabilizes.

Superstars are also likely to have permanent success. Four records have been on the top-5 positions in 1999-2013: *Hotel California* by The Eagles, *Bohemian Rhapsody* by Queen, *Child in Time* by Deep Purple, and *Stairway to Heaven* by Led Zeppelin. The Eagles (12 records) and Queen (23) can be considered to be superstar groups, but Deep Purple (4) and Led Zeppelin (4) only have a modest number of records in the Top2000. We come back to the dynamic patterns of records hereafter.

2.3 Patterns of rankings

An interesting feature of the Top2000 listing dataset is that there is a lot of information about the dynamic patterns of the listing of records. We can measure the following indicator variables per song:

- $R_{i,t}$ = rank of song i in year t. R runs from 1 to 2000.

[4]Giles measures the frequency distribution of songs in the *Billboard* Hot 100 listed in the top position using a Simon-Yule distribution and rejects the null hypothesis of superstars

Table 2: Production Year and Number of Recorded Songs per Performing Artist per Year

	Age of the Song		Superstar-indicator	
	mean	median	mean	median
1999	23.68	24	4.24	2
2000	24.64	25	5.55	2
2001	24.83	25	5.53	2
2002	25.76	26	6.16	3
2003	26.64	27	6.50	3
2004	27.28	28	6.82	3
2005	27.75	29	6.97	3
2006	28.20	29	7.27	4
2007	28.04	30	7.21	4
2008	29.83	31	7.24	4
2009	27.54	30	7.73	4
2010	28.73	31	7.39	4
2011	28.08	31	7.58	4
2012	28.05	30	7.67	4
2013	28.35	31	7.62	4

Sample period: 1999 - 2013. Source: www.radio2.nl.

Table 3: Average Ranking Indicators

	mean	median	σ
Debut Rank	1089	1140	576
Peak Rank	947	911	586
Bottom Rank	1498	1738	538
Exit Rank	1352	1581	591
Number of Listings	8.04	8	5.40
Overall Potential	-26.56	-22.25	81.36
Upward Potential	42.50	1.75	85.91
Downward Potential	66.12	46.29	87.19
Exit Speed	57.52	41.57	68.45
Recovery Speed	35.69	5.33	65.58

Sample period: 1999 - 2013. σ: standard deviation. Source: www.radio2.nl.

- D_i = rank of debut year of song i.
- P_i = peak position of song i.
- B_i = bottom position of song i.
- E_i = exit rank of song i.
- T_i = total number of listings of song i.

The upper panel of Table 3 gives the mean and median values of these indicators over the whole sample. The indicators reveal that songs stay alive for about 8 years on the chart on average, enter a little lower than the Top-1000 position on average , climb about 100 positions and/or drop about 400 positions and leave the charts at about this level. The interesting patterns are of course around these mean values and will be discussed hereafter.

In order to describe the listing patterns in more detail, we distinguish the following basic types:

1. The One-Hit Wonder: a song that gets a single listing. If we exclude the observations that have a single listing in 2013, we have 12.99 percent of the records in this class.
2. Evergreens: songs that have a full-listing over their sample years (and at least 10 years): 1182 songs (31.66 percent).

3. Songs that improve on average their position over the total listing period to a peak position, and possibly get a lower ranking thereafter until exiting (or getting at the end of the sample in 2013).

4. Songs that get a lower listing after the debut ranking, but possibly improve thereafter prior to exiting (or getting in 2013).

The latter two types are of the inverted V or V-type respectively. Evergreens are of a type 3 or 4. In order to measure the patterns we compute:

- The upward first move: the difference between the (first) peak and the debut position: $D_i - P_i$;
- The downward first move: the difference between the (first) bottom and the debut rank: $B_i - D_i$;
- The downward second move: the difference between the (first) peak and the exit (or 2013) position: $E_i - P_i$;
- The upward second move: the difference between the (first) bottom and the exit (or 2013) position: $B_i - E_i$.

Moreover we measure the length of these four types of moves in years: YP_i: years to peak (including the peak year), YB_i: years to the bottom rank (including the year of the lowest rank), PE_i: years of peak to exit (including the exit year), LE_i: years between the bottom position and the exit year (including the year of exit). Based on these indicators we can compute the following ratio's:

- Overall potential: $(E_i - D_i)/T_i$;
- Upward potential: $(D_i - P_i)/YP_i$;
- Downward potential: $(B_i - D_i)/YB_i$;
- Recovery Potential: $(B_i - E_i)/LE_i$;
- Exit Potential: $(E_i - P_i)/PE_i$.

Note that the latter four indicators are defined in such a way that they can only take nonnegative values. These ratio's indicate the change in the ranking per year of the songs along their career in the Top2000 chart. We present the summary statistics in the lower panel of Table 3. Table 3 shows that the overall potential of records is a negative one, implying that on average records tend to reach lower positions on the rankings over time. This finding is consistent with earlier descriptive statistics showing that the debut rank is better than the exit rank on average. Also for the intermediate steps, the downward potential and the exit speed are larger than the upward potential and the recovery speed, again indicating that the debut ranking is crucial for the lifetime of the recorded song in the Top2000 chart. This finding is important for one of our main topics: the impact of the age of the song on the dynamics of the ranking of the song in the Top2000 chart. On average the impact is by definition negative in case no new and younger songs enter the Top2000.

3 Cross-song properties

The Radio2 Top2000 ranking dataset is an unbalanced panel of 15 years of data of 3733 songs, in total 30 thousand song-year observations. We have three variables that have a panel data nature: the rank of the song, the age of the song and the superstar-indicator (the number of times that the same artist has a song in the same year in the chart). For the remainder we have song-specific time-invariant information, like the home production states, the language, and the length of the song. Before discussing the main dynamic analysis of the relation between ranking position and age of the recorded songs (we do this in the next Section 4), we first analyze some cross-song properties. We analyse the probabilities of songs to become One-Hit Wonders or Evergreens, the determinants of debut, peak, bottom, and exit rankings, and the up- and downward potential.

3.1 One-Hit Wonders and Evergreens

First we describe the probabilities of songs to become a One-Hit Wonder or an Evergreen by estimating a binary choice model (logit). We take record-characteristics as explanatory variables: the length of the song, the year of production, and the superstar-indicator of the performing artist(s). Moreover, we include the debut-ranking, since the descriptive statistics indicate that this could be a predictor of duration of the lifetime of a recorded song. Table 4 presents the results. The table shows that the main indicator of becoming an Evergreen or an One-Hit Wonder is the debut ranking of the song. Getting a better initial position increases the probability of becoming an Evergreen, while the reverse is true for becoming an One-Hit Wonder. The longer a song, the larger the probability to become an One-Hit Wonder. Older songs have a larger probability to become a One-Hit Wonder and a lower probability to become an Evergreen. This seems to be at odds with the observation that the average age of the songs in the Top2000 chart is over thirty years old. Finally, Dutch-produced songs have a lower probability to become an Evergreen. The language of the song is irrelevant to the probabilities.

Table 4: Binary Choice Models of One-Hit Wonders and Evergreens

	One-Hit Wonder	Evergreen
Length/60	-0.122	-0.077
	(0.085)	(0.054)
Year/1000	0.715	-7.068*
	(0.475)	(0.428)
Superstar/10	-0.093	0.067
	(0.082)	(0.046)
Debut rank	3.870*	-3.379*
	(0.225)	(0.119)
Intercept	-21.145*	142.60*
	(9.231)	(8.500)
Number $x = 1$	490	1182
Number $x = 0$	2962	2551
$CPR(x = 1)$	21.44	67.09
$CPR(x = 0)$	97.66	89.42

Sample period: 1999 - 2013. Logit estimation results: the dependent variable takes the value 1 if the song is a One-Hit Wonder (or an Evergreen song respectively), else the value 0. * = significant at the 95% confidence level. CPR = the correct prediction rate (in %) of the estimated model.

Table 5: Determinants of Debut, Exit, Peak, and Bottom Ranks (scaled by 1000)

	Debut Rank	Exit Rank	Peak Rank	Bottom Rank
Dutch	-0.169*	-0.095*	-0.212*	-0.085*
	(0.030)	(0.108)	(0.030)	(0.028)
Length/60	-0.127*	-0.005	-0.134*	-0.116*
	(0.009)	(0.079)	(0.009)	(0.008)
Year/1000	-2.892*	-2.032*	-3.169*	-5.275*
	(0.664)	(0.527)	(0.673)	(0.617)
Superstar/10	-0.143*	-0.013	-0.141*	-0.130*
	(0.009)	(0.008)	(0.009)	(0.008)
Intercept	7.412*	5.806*	7.849*	12.484*
	(1.305)	(1.030)	(1.323)	(1.213)
adjusted R^2	0.137	0.024	0.144	0.146

Sample period: 1999 - 2013. * = significant at the 95% confidence level. Stand errors between parentheses.

3.2 Debut, exit, peak, and bottom ranking

Next we analyse the determinants of the four main ranking of each record: debut, exit, peak, and bottom ranking. Both the debut-peak ranking correlation coefficient ($r = 0.877$) and the bottom-exit ranking correlation coefficient ($r = 0.796$) are rather large. The debut-bottom correlation coefficient ($r = 0.269$) and the debut-exit rank ($r = 0.267$) are lower, as is the peak-bottom correlation coefficient ($r = 0.204$). Table 5 presents the results for the debut, exit, peak, and bottom rankings (note again that a better ranking implies a lower ranking number). Note that we include only the exit ranks of the recorded songs that are not listed in the last edition 2013 (which gives 1733 exit rankings in total). Table 5 shows that Dutch-language records, longer recorded songs, younger songs, and songs produced by superstars have better (that is lower) debut rankings in the Top2000. Dutch-language songs also have typically better exit ranks, while older songs have higher exit ranks. Dutch-language songs reach better (lower) peak and bottom levels. The same holds for longer songs, younger songs and songs produced by superstars.

3.3 Potential

Next we describe the upward, downward, recovery, and exiting potential of the recorded songs. The upward and downward potential is the average change in ranking per year to the first peak or the first lowest rank. The recovery potential is

Table 6: Upward, Downward, Recovery, and Exit Potential (scaled by 100)

	Upward Potential	Downward Potential	Recovery Potential	Exit Potential
Dutch	0.351*	0.187*	0.012	0.337*
	(0.083)	(0.061)	(0.061)	(0.047)
Length/60	0.088*	-0.023	0.105*	-0.051*
	(0.025)	(0.018)	(0.018)	(0.014)
Year/1000	-2.260	4.734*	2.991*	1.307
	(1.949)	(1.396)	(1.395)	(1.085)
Superstar/10	0.031	0.049*	0.047*	-0.001
	(0.025)	(0.018)	(0.018)	(0.014)
Intercept	4.547	-8.859*	-6.367*	-1.985
	(3.832)	(2.744)	(2.745)	(2.132)
Number $x > 0$	1917	2809	2031	2832
Number $x = 0$	1816	924	1702	901

Sample period: 1999 - 2013. Tobit estimation results. * = significant at the 95% confidence level. Stand errors between parentheses.

the annual change in ranking from the bottom to the exit rank, and the exiting potential is the average change in ranking from the peak to the exit rank. We use a Tobit-estimator in order to take account of the truncated dependent variable and use the same independent variables as in the previous models. Table 6 presents the results.

Upward and exit potential depend on the Dutch-language nature and length of the songs. Dutch-language songs seem to move faster from the debut to the peak ranking, but once the peak has reached the exit speed is larger as well. Longer songs have more speed to the peak, but exit at a slower pace. Younger songs and songs produced by superstars tend to move faster from the debut to the bottom rank but also move at a faster pace in recovery.

4 Life-cycle models

In the previous section we analyzed cross-sectional properties of recorded songs in the Radio2 Top2000. The results indicate that the production year, length of the song and the superstar-indicator of the performing artist are important in explaining the ranking of the song across the lifetime. Next we analyze the dynamics of the rankings $R_{i,t}$ of record i in year t. We are able to use time-varying information on the age of the song $A_{i,t}$ and the superstar ranking (number of records by the same artist in the chart): $NS_{i,t}$ (other song specific characteristics like the length of the song are constant over time). Like Bradlow and Fader (2001) we assume that the ranking of a song could be (invertedly) related to societal worth. After birth a song starts to develop a societal worth: the accumulated appreciation by an audience. This worth $w_{i,t}$ can develop through learning and adaptation. Adaptation can for instance be influenced by stardom. Shocks to worth are a sudden revival of a song via news about the performer (e.g. through a sudden change in personal circumstances, like death (for instance Michael Jackson in 2009 and Lou Reed in 2013)) and/or a change in media attention. In general terms we assume that societal worth consists of a deterministic component $v_{i,t}$ and some noise $\epsilon_{i,t}$:

$$w_{i,t} = v_{i,t} + \epsilon_{i,t} \tag{2}$$

Bradlow and Fader (2001) discuss the dynamics of the deterministic component $v_{i,t}$. They argue that recorded songs can show a different life-time development on the charts. Some songs enter at a prestigious rank and fade away. Others take more time to reach a peak and drop out early after the peak. Some songs have high peaks relative to the debut and exit ranking, others have a more flat curve. Bradlow and Fader describe the lifetime patterns by a generalized gamma curve. Bradlow and Fader use a weekly sample of 444 songs and are able to use individual song information to fit the parameters of the gamma function.

We use the Bradlow-Fader approach, but in a different setting. In the case of Bradlow and Fader the weekly observations measure the short-run popularity of the recorded song and memory and/or nostalgic emotions do not play a role. The Radio Top2000 measures the collective memory and preferences for popular recorded songs and it can be that aging of the song leads to an increases in appreciation and positive emotions as time goes by or to a loss of interest and perceived quality. To that extent we assume a nonlinear spline of the order three relation between the rank and age of a recorded song A. A similar approach is taken with respect to the superstar-nature NS. So we have:

$$v_{i,t} = \beta_1 A_{i,t} + \beta_2 A_{i,t}^2 + \beta_3 Age_{i,t}^3 + \beta_4 NS_{i,t} + \beta_5 NS_{i,t}^2 + \beta_6 NS_{i,t}^3 \tag{3}$$

Finding estimates for the β's allows to find general conclusions for the impact of age and superstar status on rankings of songs.

We estimate a static pooled models with both cross-sectional and year dummy variables (see Table 7). The first two columns describe the results for models that include all recorded songs in the sample, while the latter two give the same models for the Evergreen songs. We present two model versions: one includes the Debut Rank as a regressor, while the other version leaves the Debut Rank out. Our cross-sectional results that the lifetime pattern of the song depends on the Debut Rank. On the other hand we do not want to double use data, so we present both estimated models. Based on the cross-sectional results we also include the Dutch language dummy variable and the length of the recorded song as regressors (the latter two of course do not have a time-varying nature). At the bottom of the table we present the turning points for the splines in age and in the superstar indicator.

The estimation results show that the two models that include the Debut Rank do have a better fit. If we consider the model of all recorded songs with the debut rank we cab observe that younger songs reach better (that is with a lower rank) positions on the Top2000 chart. Until the song age of 23 years recorded songs reach a higher (that is worse) rank (207 positions at age 23). After that songs tend to increase in popularity to the age of 40 years and gain 20 positions on average by then. Songs over 40 years face worse positions by the year again. The age classes 23-40 cover about 40-50 percent of the total song population, so indeed nostalgia might be relevant. For the superstar status of the songs we find that bands with up to 12 songs benefit (up to 171 positions with 12 songs), but over 12 to 30 songs loose this advantage (and even get a penalty from 30-48 songs, the penalty being at the maximum at 40 songs: 67 positions). There is only one band, The Beatles, who benefits from the bonus over 48 songs. We also clearly observe that longer songs reach better positions and that there is a positive ranking bias for Dutch language songs.

The model without the Debut Rank in the second column of Table 7 yields comparable results, except that there is a monotonically increasing function in age A, so there are no turning points. We present in columns 3 and 4 the models for the Evergeen songs. These models also show strong similarities to the model outcomes in column 1, indicating the robustness of the specification.

The estimation results confirm that there is a nonlinear relation between the rank and the age of a recorded song in the Radio2 Top2000 chart. The type of nonlinearity appeals to a battle between (collective) memory loss and nostalgia. The first twenty years of a popular recorded song the memory effect rules: older songs reach lower positions in the charts. But in the next twenty years, recorded songs become more popular again. It is very likely that the Holbrook-Schindler hypothesis, people favor songs that they first listened to in the age range of 15-25 years old, holds, since many people around 50 years old tend to vote. Nostalgia helps these older songs to survive, but the effect basically vanishes after 40-45 years.

5 Summary and conclusion

Popular music charts give a direct measurement of the revealed aggregated musical preferences. We use a large survey sample from the Dutch Radio2 Top2000 chart in the years 1999-2013 to analyze the impact of age on the ranking of a recorded song. We find that the popularity of songs decreases in the first twenty years after production, but can have a revival in the years 20-40. This effect might be due to the

Table 7: Static pooled ranking models

	All Recorded songs		Evergreens	
Age	22.62*	11.30*	36.74*	28.22*
	(1.464)	(2.276)	(2.686)	(4.127)
Age^2	-0.785*	-0.267*	-1.368*	-0.961*
	(0.055)	(0.085)	(0.095)	(0.146)
Age^3	0.008*	0.002*	0.015*	0.010*
	(0.001)	(0.001)	(0.001)	(0.002)
Superstar	-31.395*	-74.51*	-26.19*	-56.61*
	(2.097)	(3.244)	(2.534)	(3.880)
$Superstar^2$	1.688*	3.441*	1.329*	2.216*
	(0.155)	(0.241)	(0.183)	(0.282)
$Superstar^3$	-0.022*	-0.042*	-0.017*	-0.024*
	(0.002)	(0.004)	(0.003)	(0.004)
Length/60	-41.91*	-125.8*	-40.99*	-125.2*
	(2.194)	(3.346)	(2.924)	(4.389)
Dutch Language	-50.03*	-123.4*	-66.41*	-116.3*
	8.508)	(13.22)	(11.42)	(17.55)
Debut Rank	0.849*		0.902*	
	(0.004)		(0.007)	
Intercept	362.7*	1587.6*	203.7*	1232.8*
	(16.32)	(23.40)	(28.23)	(41.75)
Cross-section units	3733	3733	3650	3650
Observations	30000	30000	16870	16870
Adjusted R^2	0.670	0.201	0.673	0.227
Turning point 1 - Age	23	-	20	24
Turning point 2 - Age	40	-	40	38
Turning point 1 - Superstar	12	15	13	18
Turning point 2 - Superstar	40	40	42	42

Sample period: 1999 - 2013; 3733 recorded songs. Estimation by Panel Least Squares.
* = significant at the 95% confidence level. Standard errors between parentheses. Song and year dummy parameters not reported.

nostalgic feelings triggered by popular music. Knowing that musical preferences are likely to have a bias for songs first heard in the late adolescence or early adulthood and the fact that in polls like the Top2000 in the Netherlands people in the age range 45-55 years old have stronger incentives to vote, the nostalgia effect can be explained. We also find that records produced by superstars reach better chart positions (up to about 12-13 songs per artist per edition), that Dutch language songs have a positive bias, that lengthier songs reach better positions and that the debut ranking is a strong determinant of life expectancy of the song in the chart.

This macro result on the relation between song age and popularity might lead to more individual investigations why some older songs are still popular or even gain popularity. Do children inherit musical taste from their parents? Is there a strong individual preference for superstars? Do song producers experience that longer songs tend to be more popular? All these issues are subjects for further research.

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