

# Play it Again, Sam? Reference-Point Formation and Product Differentiation in the Music Industry

Abhishek Deshmane <sup>3</sup> • Victor Martínez-de-Albéniz <sup>4</sup>

## Appendix

### A Data Specifications and Variable Construction

#### A.1 Spotify Data

##### Song-Level Acoustic Attributes

	Features	Scale	Definition
1	Danceability	0-1	Danceability 0-1 Describes how suitable a track is for dancing. This measure includes tempo, regularity of beat, and beat strength.
2	Energy	0-1	A perceptual measure of intensity throughout the track. Typically, energetic tracks feel fast, loud, and noisy like death metal.
3	Key	0-11	The estimated, overall key of the track, from C through B.
4	Loudness	-60-0 dB	The overall loudness of a track measured in decibels.
5	Mode	0 or 1	Whether the song is in minor (0) or major (1) key.
6	Speechiness	0-1	Detects the presence of spoken word throughout the track. Sung vocals are not considered spoken word.
7	Acousticness	0-1	Measure of the acoustic nature of the track (as opposed to more electronic/electric).
8	Instrumentalness	0-1	Measure of the absence of vocal content in the track.
9	Liveness	0-1	Detects the presence of the live audience during the recording. Higher the value, higher the probability that the track was recorded live.
10	Tempo	Beats per minute	The overall estimated tempo of a track.
11	Valence	0-1	The musical positiveness conveyed by the track. (High valence: Cheerful/Happy songs; Low Valence: Sad/Angry Songs)
12	Time Signature	Beats per bar	Estimated overall number of beats in a bar.

Definitions are taken from *Spotify for Developers*.

Table A.1: Song-level audio features.

##### Album-Level Non-Acoustic Attributes

	Features	Scale	Definition
13	Avg. Duration	ms	Average duration of songs in an album.
14	% Explicit		Proportion of songs containing explicit language in an album.
15	% Collaboration		Proportion of collaboration songs in an album.
16	# Tracks		Number of tracks in an album.

Table A.2: Album-level audio features.

<sup>3</sup>abhishek.deshmane@scheller.gatech.edu. Georgia Institute of Technology, Scheller College of Business, 800 W Peachtree St NW, Atlanta, GA 30308, USA.

<sup>4</sup>valbeniz@iese.edu. IESE Business School, University of Navarra, Av. Pearson 21, 08034 Barcelona, Spain.

Album $j$ \ Album $j$	Song 1	Song 2	...	Song $S_{ij}$
Song 1	–	–	...	–
Song 2	$\Delta SongDist_{ij}^{2,1}$	–	...	–
...	...	...	...	...
Song $S_{ij}$	$\Delta SongDist_{ij}^{S_{ij},1}$	$\Delta SongDist_{ij}^{S_{ij},2}$	...	–

Table A.3: Intra-album song-level deviation

### Intra-Album Diversity

An important aspect, in conjunction with the audio features mentioned above, that sways the opinion of the audience on way or another about a newly released album is the diversity of the songs on offer. Here, the artist can either opt to provide a widely diverse combination of songs to appeal to a wider market or she may focus on producing songs that occupy a very narrow space within the musical feature continuum of the industry (Goldberg et al. 2016). As a result of these varied music assortment strategies, radios with specialized programming may favor albums that are less diverse and more homogeneous, while others may be tempted to play a wider subset of the given assortment because of the high variety on offer. We thus add a measure of album diversity as follows.

To capture the measure of intra-album diversity, we estimate the deviation in the musical attributes of each song on an album with respect to every other song on the same album.

Hence, the deviation between the musical attributes between songs on the same album are calculated to get  $\Delta SongDist_{ij}^{s_{ij},s'_{ij}}$  as shown in Table A.3.

$$\Delta SongDist_{ij}^{s_{ij},s'_{ij}} = 1 - \frac{\langle a_{ij}^{s_{ij}}, a_{ij}^{s'_{ij}} \rangle}{\|a_{ij}^{s_{ij}}\| \times \|a_{ij}^{s'_{ij}}\|}, \text{ where } s_{ij} \neq s'_{ij}, \text{ and}$$

$a_{ij}^{s_{ij}}$  is a musical attribute of song  $s_{ij}$  on album  $j$  by artist  $i$ . We then get a mean of these deviations for each of the albums to get the intra-album diversity as follows.

$$A_{ij} = \left( \frac{1}{S_{ij}[(S_{ij} - 1)! - 1]} \sum_{s_{ij}=1}^{s_{ij}=S_{ij}} \Delta SongDist_{ij}^{s_{ij},s'_{ij}} \right).$$

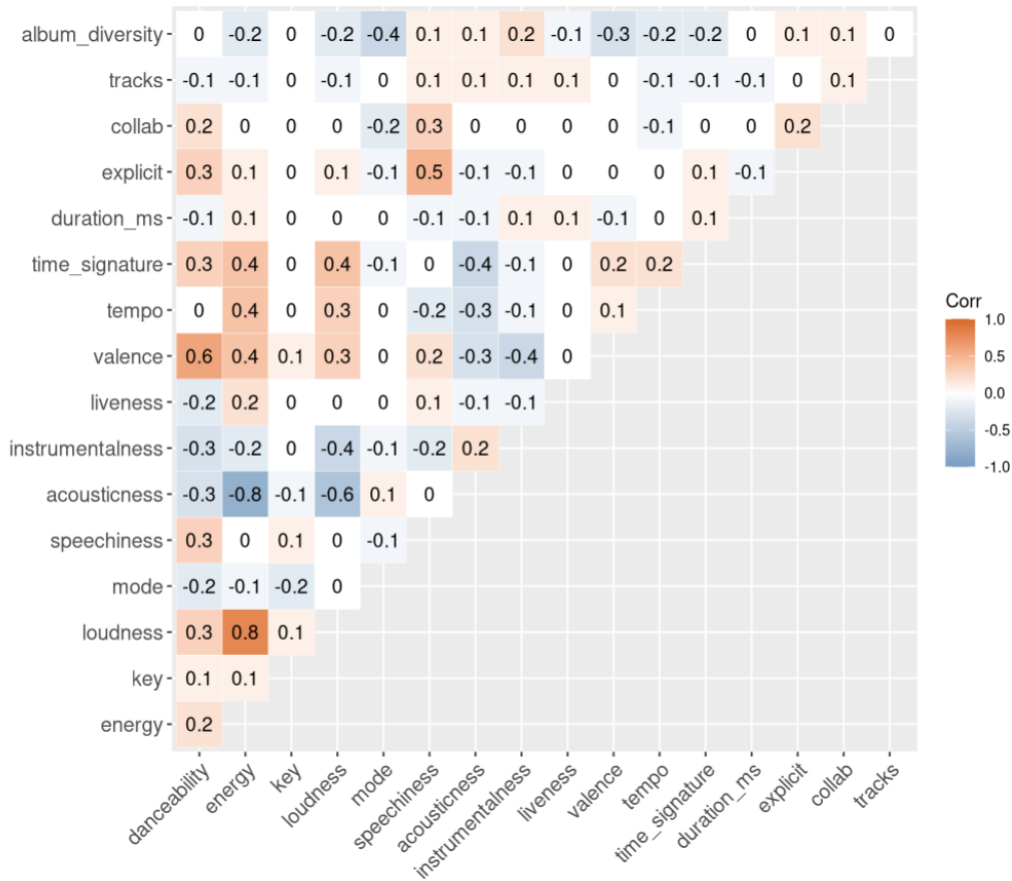


Figure A.1: Correlation between the audio features.

## A.2 Deezer Data: Album Genre Labels

A consolidated data on genre affiliations is only provided by the Deezer API. Around 49.6% albums in our initial sample have at least one genre labels associated with it. On average, an album has 2.3 genre labels associated with it. Our goal is to use supervised learning that loads the 17-dimensions already mentioned in Appendix A.1 on the genre labels of these albums to predict genre affiliations of the rest.

For this, we use K-Nearest Neighbor Classifier (KNN), Random Forest Classifier (RF), and Support Vector Machines (SVM). By having a randomly selected 10% subsample for out-of-sample testing, we train these classifiers on 90% data. For KNN, we try clusters from 1 to 50, and identify 21 to be the specification with lowest prediction error. We then use these trained classifiers to generate a prediction of genre classification for the remaining 10% sample. Accordingly, KNN generates predictions with lowest accuracy of 52.1% followed by RF with 61.8%. This is already a much better prediction than a benchmark of random assignment, which can produce predictions with an accuracy of 2.7%. SVM performs best with a prediction accuracy of 62.3% and is therefore used for predicting genre affiliations for the remaining sample

of albums.

### A.3 BMAT Data

Variable	Value	Variable	Value
Date	30/04/17	Track	Me Enamore
Time	17:24:52	Artist	Shakira
Duration	00:03:51	Label	Sony Music Entertainment
Channel	Cadena 100	Isrc	USSD11700088
Country	Spain	BMATID	53ff1a70-62c5-496e-9475-c0d24f568e11
City	Madrid (Madrid)	Album	

Table A.4: Sample observation in the BMAT dataset.

### A.4 Genre-based Product Differentiation Metrics

For album  $j$  by artist  $i$ , we construct a  $n$ -dimensional vector representing the different genres associated with the entry, i.e.,  $\mathbf{g}_{ij} = (g_{ij,1}, \dots, g_{ij,n})$ , in which  $g_{ij,k} = 1$  if artist  $i$ 's  $j^{\text{th}}$  album has been tagged the  $k^{\text{th}}$  genre and zero otherwise. Here, we take the genre affiliation of the penultimate album  $j - 1$  as the reference for end-users. Correspondingly, we measure the genre-based product differentiation metric between artist  $i$ 's  $j^{\text{th}}$  and  $j - 1^{\text{th}}$  albums as the fraction of the total number of tags between the two activities that are distinct:

$$\Delta \text{WithinArtist\_Genre}_{ij} = 1 - \frac{\mathbf{g}_{ij} \cdot \mathbf{g}_{i,j-1}}{\|\mathbf{g}_{ij} + \mathbf{g}_{i,j-1}\|_0}. \quad (3)$$

In the case of  $\Delta \text{WithinArtist\_Genre}_{ij}$ , the reference set of genres is based on the three dominant design albums (best performing in the market denoted by  $j^d$  by artist  $i^d$ , where  $i \neq i^d$ ) identified that are released in the year prior to focal album  $j$  by artist  $i$ . Hence, we have:

$$\Delta \text{DominantDesign\_Genre}_{ij} = 1 - \frac{\mathbf{g}_{ij} \cdot \mathbf{g}_{i^d,j^d}}{\|\mathbf{g}_{ij} + \mathbf{g}_{i^d,j^d}\|_0}. \quad (4)$$

As alternate specifications of these metrics, we have simplified versions of  $\Delta \text{WithinArtist\_Genre}_{ij}$  and  $\Delta \text{DominantDesign\_Genre}_{ij}$  which take value 1 if there is an exact overlap of genres between the focal album  $j$  and its corresponding comparison reference set ( $j - 1$  and  $j^d$ , respectively). The estimation results with this specification are given in Table C.15.

### A.5 Descriptive Statistics

Note that the high number of albums are associated with a very small subset of long-enduring music producing groups such as the *City Of Prague Philharmonic Orchestra*.

	$Big\_Label_{ij}$	$Album\_Num_{ij}$	$Time\_Diff_{ij}$	$\Delta WithinArtist\_X_{ij}$	$\Delta WithinArtist\_Genre_{ij}$	$\Delta ProximalPeer\_X_{ij}$	$\Delta DominantDesign\_X_{ij}$	$\Delta DominantDesign\_Genre_{ij}$
$Big\_Label_{ij}$	1.00							
$Album\_Num_{ij}$	-0.00	1.00						
$Time\_Diff_{ij}$	0.04	-0.21	1.00					
$\Delta WithinArtist\_X_{ij}$	-0.02	0.10	-0.03	1.00				
$\Delta WithinArtist\_Genre_{ij}$	-0.01	-0.02	0.02	0.09	1.00			
$\Delta ProximalPeer\_X_{ij}$	-0.05	0.15	-0.09	0.44	0.09	1.00		
$\Delta DominantDesign\_X_{ij}$	-0.05	0.30	-0.15	0.46	0.04	0.66	1.00	
$\Delta DominantDesign\_Genre_{ij}$	-0.09	0.06	-0.02	0.12	0.20	0.21	0.26	1.00
Mean	0.69	16.51	110.95	0.06	0.44	0.08	0.09	0.64
Std. Dev.	0.46	22.31	132.47	0.06	0.47	0.05	0.06	0.44
Min.	0.00	1.00	0.14	-0.00	0.00	0.01	0.01	0.00
Max.	1.00	505.00	2780.00	0.47	1.00	0.39	0.43	1.00

Table A.5: Descriptive statistics for focal album plays.

	$Big\_Label_{ij}$	$Album\_Num_{ij}$	$Time\_Diff_{ij}$	$\Delta WithinArtist\_X_{ij}$	$\Delta WithinArtist\_Genre_{ij}$	$\Delta ProximalPeer\_X_{ij}$	$\Delta DominantDesign\_X_{ij}$	$\Delta DominantDesign\_Genre_{ij}$
$Big\_Label_{ij}$	1.00							
$Album\_Num_{ij}$	0.01	1.00						
$Time\_Diff_{ij}$	0.04	-0.11	1.00					
$\Delta WithinArtist\_X_{ij}$	-0.11	-0.02	-0.02	1.00				
$\Delta WithinArtist\_Genre_{ij}$	0.00	-0.07	0.03	0.04	1.00			
$\Delta ProximalPeer\_X_{ij}$	-0.05	0.06	-0.01	0.46	0.03	1.00		
$\Delta DominantDesign\_X_{ij}$	-0.07	0.03	-0.08	0.36	-0.04	0.55	1.00	
$\Delta DominantDesign\_Genre_{ij}$	0.00	0.03	-0.04	0.04	-0.04	0.06	0.21	1.00
Mean	0.53	7.15	33.36	0.04	0.53	0.07	0.09	0.83
Std. Dev.	0.50	8.44	30.82	0.04	0.48	0.04	0.05	0.20
Min.	0.00	1.00	0.03	0.00	0.00	0.01	0.01	0.00
Max.	1.00	94.00	370.57	0.49	1.00	0.37	0.36	1.00

Table A.6: Descriptive statistics for focal album reviews.

## B Results

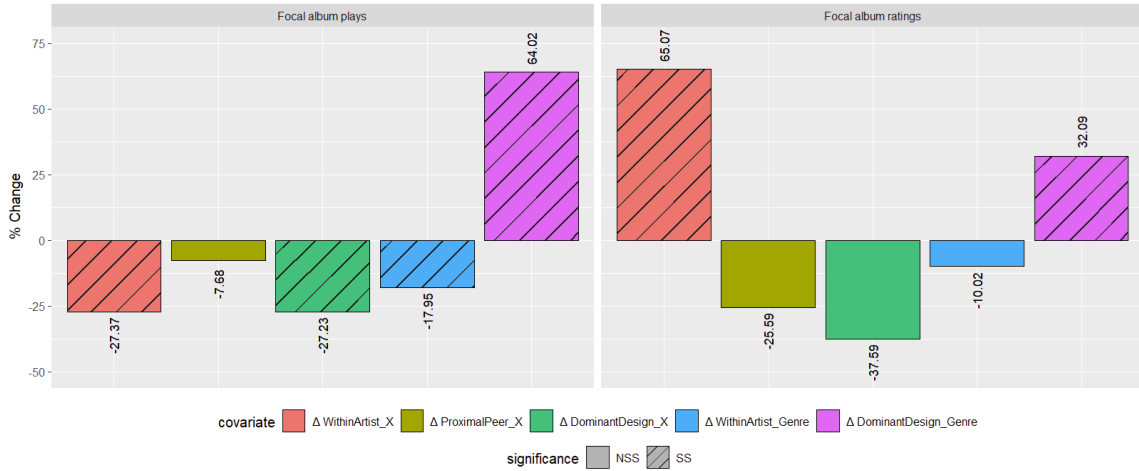


Figure B.1: Summary of marginal effects. % change in corresponding DV for 1 SD change in the covariate over no change at all. NSS: No statistical significance, SS: Statistically significant at p-value < 0.05.

### B.1 Focal Plays

Here, we provide results with extended specification of our main model in Equation (1) with  $Focal\_Plays_{ij}^k$  as the dependent variable.

	<i>Focal_Plays</i> <sub>ij</sub> <sup>k</sup>							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>log(Focal_Plays</i> <sub>ij-1</sub> <sup>k</sup> )	0.157*** (0.013)	0.157*** (0.013)	0.157*** (0.013)	0.157*** (0.013)	0.157*** (0.013)	0.156*** (0.013)	0.157*** (0.013)	0.156*** (0.013)
<i>Big_Label</i> <sub>ij</sub>	0.628*** (0.132)	0.629*** (0.132)	0.671*** (0.132)	0.613*** (0.132)	0.616*** (0.133)	0.579*** (0.133)	0.609*** (0.132)	0.612*** (0.132)
<i>Album_Num</i> <sub>ij</sub>	0.024* (0.011)	0.023* (0.011)	0.024* (0.011)	0.022* (0.011)	0.021† (0.011)	0.018 (0.011)	0.020 (0.011)	0.018 (0.011)
<i>Time_Diff</i> <sub>ij</sub>	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
<i>Danceability</i> <sub>ij</sub>	3.899*** (0.795)	3.760*** (0.786)	3.670*** (0.784)	3.756*** (0.796)	3.626*** (0.803)	3.428*** (0.801)	3.442*** (0.794)	3.150*** (0.789)
<i>Energy</i> <sub>ij</sub>	2.218* (1.047)	1.883 (1.040)	2.050* (1.031)	2.190* (1.044)	2.161* (1.047)	1.960† (1.043)	1.827 (1.038)	1.782 (1.026)
<i>Key</i> <sub>ij</sub>	-0.110 (0.500)	-0.157 (0.492)	-0.119 (0.492)	-0.115 (0.498)	-0.101 (0.497)	-0.019 (0.493)	-0.151 (0.489)	-0.038 (0.486)
<i>Loudness</i> <sub>ij</sub>	1.190 (1.756)	1.054 (1.743)	0.927 (1.735)	0.985 (1.754)	0.087 (1.797)	0.094 (1.789)	0.025 (1.784)	-0.030 (1.766)
<i>Mode</i> <sub>ij</sub>	0.502 (0.347)	0.242 (0.350)	0.191 (0.349)	0.419 (0.350)	0.248 (0.360)	0.233 (0.360)	0.003 (0.361)	-0.036 (0.359)
<i>Speechiness</i> <sub>ij</sub>	-7.448*** (1.138)	-6.896*** (1.149)	-7.023*** (1.140)	-7.303*** (1.138)	-7.330*** (1.137)	-7.088*** (1.140)	-6.681*** (1.151)	-6.569*** (1.142)
<i>Acousticness</i> <sub>ij</sub>	-0.169 (0.510)	-0.324 (0.508)	-0.274 (0.506)	-0.014 (0.516)	0.093 (0.519)	0.007 (0.518)	-0.016 (0.520)	-0.088 (0.515)
<i>Instrumentalness</i> <sub>ij</sub>	0.057 (0.503)	0.303 (0.506)	0.350 (0.504)	0.011 (0.503)	0.121 (0.498)	0.097 (0.495)	0.343 (0.502)	0.368 (0.498)
<i>Liveness</i> <sub>ij</sub>	-0.842* (0.393)	-0.420 (0.407)	-0.453 (0.408)	-0.720 (0.398)	-0.561 (0.407)	-0.597 (0.407)	-0.131 (0.419)	-0.231 (0.421)
<i>Valence</i> <sub>ij</sub>	-1.190 (0.747)	-1.403† (0.742)	-1.498* (0.737)	-1.326 (0.750)	-1.423† (0.750)	-1.516* (0.747)	-1.665* (0.747)	-1.845* (0.738)
<i>Tempo</i> <sub>ij</sub>	1.709 (0.953)	1.425 (0.953)	1.288 (0.952)	1.699 (0.956)	1.634 (0.960)	2.018* (0.963)	1.364 (0.960)	1.646 (0.962)
<i>Time_Signature</i> <sub>ij</sub>	0.029 (1.405)	-0.830 (1.410)	-0.667 (1.407)	-0.149 (1.406)	-0.345 (1.412)	-0.834 (1.413)	-1.166 (1.416)	-1.428 (1.411)
<i>Avg_Duration</i> <sub>ij</sub>	1.739 (5.674)	1.904 (5.634)	0.730 (5.636)	2.049 (5.644)	2.713 (5.691)	3.284 (5.680)	2.957 (5.632)	2.182 (5.626)
<i>Explicit_Prop</i> <sub>ij</sub>	0.312 (0.395)	0.315 (0.390)	0.325 (0.386)	0.356 (0.396)	0.900* (0.455)	0.946* (0.450)	0.831† (0.455)	0.874* (0.446)
<i>Collaboration_Prop</i> <sub>ij</sub>	-0.070 (0.207)	0.365 (0.228)	0.428† (0.228)	0.189 (0.247)	0.326 (0.253)	0.367 (0.254)	0.838** (0.287)	0.895** (0.285)
<i>Num_Tracks</i> <sub>ij</sub>	2.491 (1.675)	2.252 (1.662)	2.303 (1.664)	2.513 (1.675)	3.148† (1.696)	2.998 (1.698)	2.811 (1.692)	2.735 (1.718)
<i>Album_Diversity</i> <sub>ij</sub>	7.845*** (1.558)	6.331*** (1.592)	5.786*** (1.592)	7.119*** (1.604)	5.792*** (1.734)	4.977** (1.746)	4.239* (1.770)	2.986 (1.780)
$\Delta$ <i>WithinArtist_X</i> <sub>ij</sub>		-5.914*** (1.395)	-5.771*** (1.401)				-5.769*** (1.397)	-5.443*** (1.404)
$\Delta$ <i>ProximalPeer_X</i> <sub>ij</sub>				-2.917† (1.547)			-1.768 (1.619)	-1.663 (1.624)
$\Delta$ <i>DominantDesign_X</i> <sub>ij</sub>					-5.466** (2.009)	-6.507** (2.024)	-4.479* (2.099)	-5.289* (2.114)
$\Delta$ <i>WithinArtist_Genre</i> <sub>ij</sub>			-0.404*** (0.122)					-0.417*** (0.123)
$\Delta$ <i>DominantDesign_Genre</i> <sub>ij</sub>						1.079*** (0.324)		1.127*** (0.326)
<i>FixedEffects</i>								
<i>Artist – level</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Time – level</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Genre<sub>ij</sub> FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,068	21,068	21,068	21,068	21,068	21,068	21,068	21,068
Pseudo R <sup>2</sup>	0.103	0.103	0.103	0.103	0.103	0.103	0.103	0.103
Log-likelihood	-32,865.6	-32,855.9	-32,850.0	-32,863.7	-32,861.6	-32,855.6	-32,851.7	-32,839.9

Notes: Observations are at the Artist-album level. Standard errors are shown in parentheses.

† $p < 0.07$ ; \* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ .

Table B.1: Extended results for Focal Plays.

## B.2 Ratings

Here, we provide results with extended specification of our main model in Equation (1) with *Ratings*<sub>ij</sub><sup>k</sup> as the dependent variable.

	<i>Ratings</i> <sub>ij</sub> <sup>k</sup>							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	8
<i>Rating</i> <sub>ij-1</sub> <sup>k</sup>	0.176*** (0.007)	0.175*** (0.007)	0.175*** (0.007)	0.176*** (0.007)	0.176*** (0.007)	0.175*** (0.007)	0.175*** (0.007)	0.175*** (0.007)
<i>Big_Label</i> <sub>ij</sub>	0.318 (0.298)	0.359 (0.299)	0.372 (0.299)	0.324 (0.299)	0.324 (0.298)	0.341 (0.299)	0.391 (0.299)	0.419 (0.299)
<i>Album_Num</i> <sub>ij</sub>	0.094 (0.064)	0.083 (0.064)	0.085 (0.064)	0.092 (0.064)	0.095 (0.064)	0.092 (0.064)	0.077 (0.064)	0.076 (0.064)
<i>Time_Dif</i> <sub>ij</sub>	0.007 (0.007)	0.007 (0.007)	0.007 (0.007)	0.008 (0.007)	0.008 (0.007)	0.008 (0.007)	0.007 (0.007)	0.008 (0.007)
<i>Danceability</i> <sub>ij</sub>	-10.992*** (1.851)	-10.467*** (1.860)	-10.527*** (1.861)	-11.381*** (1.878)	-11.366*** (1.866)	-11.318*** (1.866)	-11.306*** (1.882)	-11.296*** (1.883)
<i>Energy</i> <sub>ij</sub>	2.696 (2.254)	3.167 (2.260)	3.196 (2.260)	2.567 (2.257)	2.548 (2.256)	2.512 (2.256)	2.977 (2.260)	2.973 (2.260)
<i>Key</i> <sub>ij</sub>	-0.589 (0.926)	-0.524 (0.926)	-0.498 (0.926)	-0.654 (0.927)	-0.683 (0.928)	-0.728 (0.928)	-0.708 (0.928)	-0.726 (0.929)
<i>Loudness</i> <sub>ij</sub>	-3.394 (5.027)	-2.874 (5.029)	-2.826 (5.030)	-3.957 (5.048)	-4.111 (5.047)	-3.955 (5.047)	-4.386 (5.055)	-4.162 (5.055)
<i>Mode</i> <sub>ij</sub>	-0.485 (0.673)	-0.185 (0.681)	-0.161 (0.681)	-0.639 (0.685)	-0.769 (0.697)	-0.771 (0.697)	-0.637 (0.700)	-0.611 (0.701)
<i>Speechiness</i> <sub>ij</sub>	5.210* (2.402)	3.690 (2.457)	3.653 (2.458)	5.412* (2.407)	5.689* (2.421)	5.623* (2.421)	3.955 (2.465)	3.859 (2.466)
<i>Acousticness</i> <sub>ij</sub>	0.715 (1.139)	0.752 (1.139)	0.765 (1.139)	0.833 (1.143)	0.857 (1.142)	0.959 (1.143)	1.116 (1.145)	1.223 (1.146)
<i>Instrumentalness</i> <sub>ij</sub>	3.873*** (1.005)	3.328** (1.022)	3.343** (1.022)	3.907*** (1.005)	3.898*** (1.005)	3.948*** (1.005)	3.196** (1.023)	3.261** (1.023)
<i>Liveness</i> <sub>ij</sub>	-3.173 (1.760)	-3.106 (1.760)	-3.129 (1.760)	-3.102 (1.761)	-3.106 (1.761)	-3.009 (1.761)	-2.889 (1.761)	-2.819 (1.761)
<i>Valence</i> <sub>ij</sub>	3.786** (1.413)	3.680** (1.413)	3.665** (1.413)	3.897** (1.416)	3.764** (1.413)	3.724** (1.413)	3.791** (1.416)	3.729** (1.416)
<i>Tempo</i> <sub>ij</sub>	4.363* (1.788)	4.833** (1.795)	4.777** (1.796)	4.169* (1.795)	4.103* (1.795)	4.039* (1.796)	4.412* (1.800)	4.302* (1.802)
<i>Time_Signature</i> <sub>ij</sub>	-4.156 (2.486)	-4.183 (2.485)	-4.164 (2.485)	-4.122 (2.486)	-4.194 (2.486)	-4.218 (2.486)	-4.182 (2.485)	-4.191 (2.485)
<i>Avg_Duration</i> <sub>ij</sub>	7.178 (5.558)	6.128 (5.569)	6.233 (5.570)	7.638 (5.571)	7.490 (5.562)	8.049 (5.566)	6.803 (5.574)	7.432 (5.580)
<i>Explicit_Prop</i> <sub>ij</sub>	-0.606 (0.603)	-0.519 (0.604)	-0.520 (0.604)	-0.595 (0.603)	-0.224 (0.650)	-0.136 (0.651)	-0.031 (0.661)	0.061 (0.662)
<i>Collaboration_Prop</i> <sub>ij</sub>	-2.162** (0.756)	-2.788*** (0.785)	-2.791*** (0.785)	-1.907* (0.784)	-1.596† (0.837)	-1.505 (0.838)	-1.982* (0.847)	-1.900* (0.848)
<i>Num_Tracks</i> <sub>ij</sub>	18.600 (21.730)	29.047 (22.020)	28.441 (22.031)	14.563 (21.979)	13.435 (21.976)	12.706 (21.975)	20.839 (22.196)	19.693 (22.205)
<i>Album_Diversity</i> <sub>ij</sub>	-5.028 (3.969)	-3.343 (4.010)	-3.331 (4.010)	-6.308 (4.105)	-7.205 (4.203)	-7.292 (4.203)	-7.206 (4.236)	-7.233 (4.235)
$\Delta$ <i>WithinArtist</i> <sub>X<sub>ij</sub></sub>		11.484** (3.940)	11.616** (3.943)				16.046*** (4.256)	16.096*** (4.257)
$\Delta$ <i>ProximalPeer</i> <sub>X<sub>ij</sub></sub>				-3.860 (3.155)			-6.187 (3.614)	-5.900 (3.616)
$\Delta$ <i>DominantDesign</i> <sub>X<sub>ij</sub></sub>					-5.530 (3.513)	-6.538† (3.538)	-6.301 (3.876)	-7.395† (3.903)
$\Delta$ <i>WithinArtist_Genre</i> <sub>ij</sub>			-0.222 (0.257)					-0.209 (0.257)
$\Delta$ <i>DominantDesign_Genre</i> <sub>ij</sub>						1.601* (0.676)		1.582* (0.676)
<i>FixedEffects</i>								
<i>Artist – level</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Time – level</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,656	21,656	21,656	21,656	21,656	21,656	21,656	21,656
Pseudo R <sup>2</sup>	0.038	0.038	0.038	0.038	0.038	0.038	0.0388	0.0388
Log-likelihood	-86,143.0	-86,138.5	-86,138.1	-86,142.2	-86,141.7	-86,138.7	-86,134.0	-86,130.8

Notes: Observations are at the Artist-album level. Standard errors are shown in parentheses.

†  $p < 0.07$ ; \*  $p < 0.05$ ; \*\*  $p < 0.01$ ; \*\*\*  $p < 0.001$ .

Table B.2: Extended results for Critics' Ratings.

### B.3 Past Plays

Here, we provide results by considering plays of albums released prior to the focal album  $j$ . Formally,  $Past\_Plays_{ij}^k$  is the number of plays garnered by all artist  $i$ 's albums released prior to the focal

album  $j$ , that is, albums  $j' = 1, \dots, j - 1$ , on radio station  $k$  in the first year following album  $j$ 's release. To account for the inherent inclination of radio station  $j$  to play focal artist  $i$ 's songs, we use  $Past\_Plays_{ij-1}^k$ . Furthermore, while analyzing the effect of newly released album on plays of the albums released in the past (for the dependent variable  $Past\_Plays_{ij}^k$ ), it is necessary to consider the initial performance of the corresponding past albums. Just as the opening weekend performance of movies is a significant predictor of the eventual ticket sales at the box office, albums that perform well in the first year of their release are more likely to have a larger number of plays when the new album by the same artist is released (Hendricks and Sorensen 2009, Hu et al. 2019). Hence, we employ an additional control for this scenario with  $FirstYr\_Plays_{ij'}^k$ , which is the number of plays garnered by artist  $i$  in album  $j'$  during its first year of release on radio station  $k$ . The remaining specification remains similar to that in Equations 1 and 2. Results are given in Table B.3. Note that the memory decay factor  $\theta$  estimated with grid search is 0.0. Implications of these results are discussed in 4.

#### B.4 Gini Index of Play Distribution over Songs

We consider the dependent variable Gini Index ( $Gini\_Index_{ij}^k$ ) of play distribution between songs in an album (Hendricks and Sorensen 2009). To account for the 'loyalty' effect, we use  $Gini\_Index_{ij-1}^k$ . The remaining specification remains similar to that in Equations (1)-(2). Results are given in Table B.3. We have the memory decay factor  $\theta$  estimated with grid search as 0.6. We see that the effect of product differentiation metrics is statistically insignificant implying that they are not predictors of the variation in the distribution of plays across songs in an album.

	$Past\_Plays_{ij'}^k$		$Gini\_Index_{ij}^k$	
	(1)	(2)	(3)	(4)
<b>Loyalty-related factors</b>				
$\log(Past\_Plays_{ij'-1}^k)$	0.128*** (0.009)	0.129*** (0.009)		
$\log(FirstYr\_Plays_{ij'}^k)$	0.710*** (0.008)	0.712*** (0.008)		
$Gini\_Index_{ij-1}^k$			-0.181*** (0.050)	-0.182*** (0.051)
<b>Product differentiation factors</b>				
$\Delta WithinArtist\_X_{ij}$	1.822*** (0.304)	1.746*** (0.305)	-0.124 (0.103)	-0.125 (0.105)
$\Delta ProximalPeer\_X_{ij}$	1.360** (0.478)	1.290** (0.478)	0.124 (0.099)	0.127 (0.100)
$\Delta DominantDesign\_X_{ij}$	-3.794*** (0.449)	-3.64*** (0.451)	-0.015 (0.127)	-0.023 (0.130)
$\Delta WithinArtist\_Genre_{ij}$		0.067 (0.044)		0.000 (0.007)
$\Delta DominantDesign\_Genre_{ij}$		-0.804*** (0.137)		0.006 (0.017)
<b>Fixed Effects</b>				
<i>Artist – level</i>	Yes	Yes	Yes	Yes
<i>Time – level</i>	Yes	Yes	Yes	Yes
<i>Genre<sub>ij</sub></i>	Yes	Yes	Yes	Yes
<i>Genre<sub>ij'</sub> FE</i>	Yes	Yes	–	–
Observations	115,463	115,463	1,396	1,396
Pseudo $R^2$	0.317	0.318	-0.381	-0.381
Log-likelihood	-59,463.2	-59,444.9	2,826.5	2,826.7

Notes: Observations are at the Artist-album level. Controls include  $Big\_Label_{ij}$ ,  $Album\_Num_{ij}$ ,  $Time\_Diff_{ij}$ , and all the audio features represented in  $X_{ij}$ . Standard errors are shown in parentheses.

\* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ .

Table B.3: Results for Past Plays and Gini Index as dependent variables.

## C Robustness Checks

### C.1 Poisson Model Estimation for Focal Album Plays

We consider alternative distributional assumptions for the response variable. When using a count variable as a dependent variable, both Poisson and NBD are popular econometric modelling choices. While our main analyses are carried out using the latter, in Table C.1, results are estimated using the former. We see that using Poisson distribution renders results to those in Table 4.1.

	<i>Focal_Plays</i> <sub><i>ij</i></sub> <sup><i>k</i></sup>	<i>Past_Plays</i> <sub><i>ij'</i></sub> <sup><i>k</i></sup>
	(1)	(2)
<b>Loyalty-related factors</b>		
$\log(\text{Focal\_Plays}_{ij-1}^k)$	0.106*** (0.0002)	
$\log(\text{Past\_Plays}_{ij'-1}^k)$		0.010*** (0.0002)
$\log(\text{FirstYr\_Plays}_{ij'}^k)$		0.331*** (0.0002)
<b>Product differentiation factors</b>		
$\Delta\text{WithinArtist\_}X_{ij}$	-0.178** (0.060)	0.445*** (0.026)
$\Delta\text{ProximalPeer\_}X_{ij}$	-2.313*** (0.072)	-1.392*** (0.050)
$\Delta\text{DominantDesign\_}X_{ij}$	-2.580*** (0.088)	0.379*** (0.051)
$\Delta\text{WithinArtist\_Genre}_{ij}$	-0.129*** (0.004)	-0.147*** (0.004)
$\Delta\text{DominantDesign\_Genre}_{ij}$	0.534*** (0.009)	0.403*** (0.006)
<i>Fixed Effects</i>		
<i>Artist – level</i>	Yes	Yes
<i>Time – level</i>	Yes	Yes
<i>Genre<sub>ij</sub></i>	Yes	Yes
<i>Genre<sub>ij'</sub></i>	–	Yes
Observations	21,068	115,463
Pseudo <i>R</i> <sup>2</sup>	0.618	0.763
Log-likelihood	-1,923,328.45	-2,184,109.00

Notes: Observations are at the Artist-album level. Controls include *Big\_Label<sub>ij</sub>*, *Album\_Num<sub>ij</sub>*, *Time\_Diff<sub>ij</sub>*, and all the audio features represented in *X<sub>ij</sub>*. Standard errors are shown in parentheses.  
\**p* < 0.05; \*\**p* < 0.01; \*\*\**p* < 0.001.

Table C.1: Results with Poisson models for focal and past album plays.

### C.2 Results with Radio Station and Reviewer Fixed Effects

In an alternate specification, we introduce radio station- and reviewer-level fixed effects, in addition to the lagged variables at the album-entity-level to control for the time-invariant factors associated with entity *k*. The results given in Table C.2 show that the effects of our key independent variables remain consistent with the main findings.

	<i>Focal_Plays</i> <sub><i>ij</i></sub> <sup><i>k</i></sup> (1)	<i>Ratings</i> <sub><i>ij</i></sub> <sup><i>k</i></sup> (2)
<b>Loyalty-related factors</b>		
<i>log(Focal_Plays</i> <sub><i>ij-1</i></sub> <sup><i>k</i></sup> )	0.052*** (0.012)	
<i>Ratings</i> <sub><i>ij-1</i></sub> <sup><i>k</i></sup>		0.104*** (0.007)
<b>Product differentiation factors</b>		
$\Delta$ <i>WithinArtist_X</i> <sub><i>ij</i></sub>	-4.316*** (1.346)	17.423*** (4.107)
$\Delta$ <i>ProximalPeer_X</i> <sub><i>ij</i></sub>	-1.308 (1.547)	-6.488 (3.489)
$\Delta$ <i>DominantDesign_X</i> <sub><i>ij</i></sub>	-1.648 (1.950)	-7.914* (3.674)
$\Delta$ <i>WithinArtist_Genre</i> <sub><i>ij</i></sub>	-0.183 (0.111)	-0.242 (0.242)
$\Delta$ <i>DominantDesign_Genre</i> <sub><i>ij</i></sub>	0.372 (0.311)	1.786** (0.652)
<i>FixedEffects</i>		
<i>Artist – level</i>	Yes	Yes
<i>Entity – level</i>	Yes	Yes
<i>Time – level</i>	Yes	Yes
<i>Genre</i> <sub><i>ij</i></sub>	Yes	Yes
Observations	21,068	21,656
Pseudo <i>R</i> <sup>2</sup>	0.130	0.048
Log-likelihood	-31,885.8	-85,291.5

Notes: Observations are at the Artist-album level. Controls include *Big\_Label*<sub>*ij*</sub>, *Album\_Num*<sub>*ij*</sub>, *Time\_Diff*<sub>*ij*</sub>, and all the audio features represented in *X*<sub>*ij*</sub>. Standard errors are shown in parentheses.

\**p* < 0.05; \*\* *p* < 0.01; \*\*\* *p* < 0.001.

Table C.2: Results with fixed effects for radio stations and reviewers.

### C.3 Considering Heterogeneity across Cultures of Origin

We have radio stations across different countries in Europe. Past works have shown that different cultures have differing sensitivities towards novelty. Here, we intend to unravel structural heterogeneity in the radio station responses to music differentiation based on their culture of origin. For this, we first make use of Hofstede’s cultural dimensions, that provide an insightful numerical representation of four fundamental cultural aspects of Power Differential, Masculinity, Collectivism, and Uncertainty Avoidance (Hofstede 1983). We choose the last one to be the most relevant of them all for the context being studied here. We believe that cultures with higher levels of Uncertainty Avoidance score will, in general, be less tolerant of music that deviates from their expectations. Hence, any differential from the past profile of the focal artist, and contemporaneous music of proximal peers and chart-toppers will result in lesser number of plays for the focal album. For this, we include interaction of main measures of product differentiation with the Uncertainty Avoidance score, *UAI*<sup>*k*</sup>, for the country that radio station *k* belongs to. Results are given in Model 1 of Table C.3. Indeed, we see that the moderating effect of *UAI*<sup>*k*</sup> on the relation between differentiation from acoustic metrics of the focal album with the corresponding artist’s past profile is negative and statistically significant at *p*-value  $\ll 0.001$ . This confirms our aforementioned conjecture on the heterogeneity of preferences towards musical differentiation across different cultures.

We also carry out split-sample analyses by dividing the main sample based on countries of origin and grouping them across five major geographical zones of Northern, Eastern, Southern, and Western

<i>Focal_Plays</i> <sub>ij</sub> <sup>k</sup>						
UN Geoscheme Areas						
	(1)	Northern Europe (2)	Eastern Europe 3	Southern Europe (4)	Western Europe (5)	Western Asia (6)
<b>Loyalty-related factors</b>						
<i>log(Focal_Plays</i> <sub>ij-1</sub> <sup>k</sup> )	0.162*** (0.014)	-0.045 (0.037)	-0.374* (0.167)	0.143*** (0.027)	0.104*** (0.021)	-0.248* (0.104)
<b>Product differentiation factors</b>						
$\Delta$ <i>WithinArtist</i> <sub>ij</sub> <i>X</i> <sub>ij</sub>	3.426 (2.901)	-3.176 (3.848)	-59.558** (20.114)	-0.802 (3.289)	-4.403* (2.054)	-22.667 (35.484)
$\Delta$ <i>ProximalPeer</i> <sub>ij</sub> <i>X</i> <sub>ij</sub>	-1.699 (3.542)	6.908 (4.236)	3.703 (20.022)	7.178 (3.897)	-2.939 (2.454)	6.197 (31.224)
$\Delta$ <i>DominantDesign</i> <sub>ij</sub> <i>X</i> <sub>ij</sub>	-4.551 (3.378)	-5.446 (5.255)	-0.982 (31.001)	4.451 (4.985)	-6.627* (3.208)	-31.977 (41.695)
$\Delta$ <i>WithinArtist</i> <sub>ij</sub> <i>Genre</i> <sub>ij</sub>	0.143 (0.289)	0.302 (0.301)	2.152 (1.411)	-0.936*** (0.277)	0.120 (0.180)	0.419 (1.516)
$\Delta$ <i>DominantDesign</i> <sub>ij</sub> <i>Genre</i> <sub>ij</sub>	1.149** (0.445)	1.576 (0.831)	-1.069 (3.815)	0.878 (0.659)	0.103 (0.542)	7.486* (3.139)
<b>Moderators</b>						
$\Delta$ <i>WithinArtist</i> <sub>ij</sub> × <i>UAI</i> <sup>k</sup>	-0.122*** (0.036)					
$\Delta$ <i>ProximalPeer</i> <sub>ij</sub> × <i>UAI</i> <sup>k</sup>	-0.008 (0.047)					
$\Delta$ <i>DominantDesign</i> <sub>ij</sub> × <i>UAI</i> <sup>k</sup>	0.018 (0.038)					
$\Delta$ <i>WithinArtist</i> <sub>ij</sub> <i>Genre</i> <sub>ij</sub> × <i>UAI</i> <sup>k</sup>	-0.008* (0.004)					
$\Delta$ <i>DominantDesign</i> <sub>ij</sub> <i>Genre</i> <sub>ij</sub> × <i>UAI</i> <sup>k</sup>	-0.006 (0.004)					
Artist Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
<i>Genre</i> <sub>ij</sub>	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	20,254	4,362	818	5,957	9,346	585
Pseudo <i>R</i> <sup>2</sup>	0.111	0.190	0.363	0.176	0.130	0.260
Log-likelihood	-31,169.4	-6,259.6	-725.15	-8,420.8	-14,340.8	-712.09

Notes: Observations are at the Artist-album level. Controls include *Big\_Label*<sub>ij</sub>, *Album\_Num*<sub>ij</sub>, *Time\_Diff*<sub>ij</sub>, and all the audio features represented in *X*<sub>ij</sub>. Standard errors are shown in parentheses. \**p* < 0.05; \*\**p* < 0.01; \*\*\**p* < 0.001.

Table C.3: Model 1: Results for interaction with Hofstede’s Uncertainty Avoidance Cultural Index for origin of radio station *k*. Models 2 to 6: Effect of product differentiation on focal and past album plays across areas as per the UN Geoscheme in Europe.

Europe, and Western Asia. This division is based on United Nations’ geoscheme<sup>5</sup>. Results are given in Table C.3, Models 2-6. We see that Eastern Europe is mainly averse to within artist differentiation while Southern Europe favors past profile more when focal albums diverge from audience expectations.

Finally, due to the lack of a reliable source of country of origin for professional critics, we take the following approach. The website links of all the reviewers on AlbumoftheYear.org are provided that either take the domain names of *.com*, *.net*, or *.co.uk*. The last of these provides a clear indication of the corresponding reviewer being based in the United Kingdom. By focusing our attention on the subsample, which is reliably verified to hail from the United Kingdom, for both radio stations and reviewers, we replicate our main analyses. Results are given in Table C.4. We do not see strong influence of music differentiation on radio stations’ and critics’ responses in this limited sample of the UK-based intermediaries.

<sup>5</sup>[https://en.wikipedia.org/wiki/List\\_of\\_countries\\_by\\_the\\_United\\_Nations\\_geoscheme](https://en.wikipedia.org/wiki/List_of_countries_by_the_United_Nations_geoscheme)

	<i>Focal_Plays</i> <sub><i>ij</i></sub> <sup><i>k</i></sup> (1)	<i>Ratings</i> <sub><i>ij</i></sub> <sup><i>k</i></sup> (2)
<b>Loyalty-related factors</b>		
<i>log(Focal_Plays</i> <sub><i>ij-1</i></sub> <sup><i>k</i></sup> )	-0.104* (0.047)	
<i>Ratings</i> <sub><i>ij-1</i></sub> <sup><i>k</i></sup>		0.024 (0.037)
<b>Product differentiation factors</b>		
$\Delta$ <i>WithinArtist_X</i> <sub><i>ij</i></sub>	-2.097 (4.013)	-13.063 (26.838)
$\Delta$ <i>ProximalPeer_X</i> <sub><i>ij</i></sub>	-0.920 (4.088)	22.232 (23.189)
$\Delta$ <i>DominantDesign_X</i> <sub><i>ij</i></sub>	-1.501 (5.534)	-35.818 (24.558)
$\Delta$ <i>WithinArtist_Genre</i> <sub><i>ij</i></sub>	0.981** (0.329)	1.471 (1.513)
$\Delta$ <i>DominantDesign_Genre</i> <sub><i>ij</i></sub>	0.238 (1.097)	-2.964 (3.974)
<i>FixedEffects</i>		
<i>Artist – level</i>	Yes	Yes
<i>Time – level</i>	Yes	Yes
<i>Genre</i> <sub><i>ij</i></sub>	Yes	Yes
Observations	2,100	1,108
Pseudo <i>R</i> <sup>2</sup>	0.249	0.084
Log-likelihood	-2,511.2	-4,262.4

Notes: Observations are at the Artist-album level. Controls include *Big\_Label*<sub>*ij*</sub>, *Album\_Num*<sub>*ij*</sub>, *Time\_Diff*<sub>*ij*</sub>, and all the audio features represented in *X*<sub>*ij*</sub>. Standard errors are shown in parentheses.

\**p* < 0.05; \*\**p* < 0.01; \*\*\**p* < 0.001.

Table C.4: Results for radio stations and reviewers based in the United Kingdom.

## C.4 Endogeneity Test

As shown in Tereyağoğlu et al. (2018), references developed by audiences may be endogenous which can potentially give inconsistent estimates and raise doubts over the validity of our interpretations. For example, the success of the last project, both in terms of the number of plays it garners over radios, *Plays*<sub>*ij-1*</sub><sup>*k*</sup>, and the ratings it gets from reviewers, *Ratings*<sub>*ij-1*</sub><sup>*k*</sup>, could affect the rate of product differentiation that artists choose to inculcate in their new albums. We check for this relation and find that neither of them significantly predict the variation in the differentiation rate employed by the artist in the newly released album. As shown in Table C.5, only the differentiation of the last album is significant and negatively related to the corresponding product differentiation metric, which we already account for while constructing our main variable of interest. This provides evidence for the exogeneity of product differentiation metrics.

	$\Delta WithinArtist\_X_{ij}$ (1)	$\Delta WithinArtist\_Genre_{ij}$ (2)	$\Delta ProximalPeer\_X_{ij}$ (3)	$\Delta DominantDesign\_X_{ij}$ (4)	$\Delta DominantDesign\_Genre_{ij}$ (5)
$\Delta WithinArtist\_X_{ij-1}$	-0.360* (0.152)				
$\Delta ProximalPeer\_X_{ij-1}$			-0.406*** (0.058)		
$\Delta DominantDesign\_X_{ij-1}$				-0.445*** (0.085)	
$\Delta WithinArtist\_Genre_{ij-1}$		-0.469*** (0.076)			
$\Delta DominantDesign\_Genre_{ij-1}$					-0.135** (0.044)
$\log(Focalplays_{ij-1})$	$-5.34 \times 10^{-5}$ ( $6.02 \times 10^{-5}$ )	$-5.08 \times 10^{-5}$ (0.0001)	$6.87 \times 10^{-7}$ ( $8.48 \times 10^{-6}$ )	$-1.06 \times 10^{-5}$ ( $5.9 \times 10^{-6}$ )	$-3.54 \times 10^{-5*}$ ( $1.55 \times 10^{-5}$ )
$Rating_{ij-1}$	0.0003 (0.0003)	-0.0005 (0.003)	$-3.61 \times 10^{-5}$ (0.0002)	0.0003 (0.0002)	0.001 (0.0007)
<i>FixedEffects</i>					
Artist – level	Yes	Yes	Yes	Yes	Yes
Time – level	Yes	Yes	Yes	Yes	Yes
Genre <sub>ij</sub>	Yes	Yes	Yes	Yes	Yes
Observations	432	498	493	487	498
R <sup>2</sup>	0.90	0.88	0.91	0.90	0.98

\* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ .

Table C.5: Effect of past plays and ratings on product differentiation.

## C.5 Deviation from References as Euclidean Distances

	$Focal\_Plays_{ij}^k$ (1)	$Ratings_{ij}^k$ (2)
<b>Loyalty-related factors</b>		
$\log(Focal\_Plays_{ij-1}^k)$	0.155*** (0.013)	
$Ratings_{ij-1}^k$		0.175*** (0.007)
<b>Product differentiation factors</b>		
$\Delta WithinArtist\_X_{ij}$	-0.990*** (0.284)	2.556*** (0.760)
$\Delta ProximalPeer\_X_{ij}$	-0.346 (0.365)	-0.550 (0.770)
$\Delta DominantDesign\_X_{ij}$	-1.538** (0.508)	-1.490 (0.855)
$\Delta WithinArtist\_Genre_{ij}$	-0.411*** (0.124)	-0.192 (0.261)
$\Delta DominantDesign\_X_{ij}$	1.237*** (0.327)	1.358* (0.681)
<i>FixedEffects</i>		
Artist – level	Yes	Yes
Time – level	Yes	Yes
Genre <sub>ij</sub>	Yes	Yes
Observations	20,961	21,245
Pseudo R <sup>2</sup>	0.10394	0.03872
Log-likelihood	-32,671.4	-84,507.5

Notes: Observations are at the Artist-album level. Controls include  $Big\_Label_{ij}$ ,  $Album\_Num_{ij}$ ,  $Time\_Diff_{ij}$ , and all the audio features represented in  $X_{ij}$ . Standard errors are shown in parentheses.

\* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ .

Table C.6: Results with Euclidean distances for estimating product differentiation metrics.

We consider Euclidean distances (as opposed to cosine similarity) to measure the deviation of newly released albums by music artists from audience references. Results are given in Table C.6 which replicate the findings in our main analyses.

## C.6 Deviation from References at the Individual Metric Level

The musical setting that we explore our theoretical framework in allows a multi-dimensional representation of albums which are then condensed down to one metric through cosine or Euclidean distances.

This is done to provide a holistic view of the dynamics in the music industry without focusing on specific musical characteristics such as *Danceability* or *Energy* in order to not make this a work on music theory. Nevertheless, our theoretical framework can be applied at the independent-dimension level which is shown in Table C.7. More detailed look into the estimates associated with individual metric-level differentiation, without the other covariates, is provided in Table C.8. Deviations from reference *Time Signature*, *Tempo*, average song duration, and number of tracks on an album are highly influential for radio stations and critics.

We compare the model fit (Log-likelihood) of this expanded specification at individual metric level with that of our main consideration in Models 2, 7, and 12 from Table 4.1. The improvement in log-likelihood is marginal - 0.3% and 0.08% for focal album plays and ratings, respectively. Hence, the added complexity of having 74 parameters instead of 26, excluding the fixed effects, does not produce synonymously better results in terms of model fit. However, we are able to isolate the effect of differentiation for every metric considered in the analysis. This is crucial for the development of managerial implications in §5.

Furthermore, we also selectively exclude a consideration of differentiation for every album-level metric in an iterative manner to compute the loss in fit. These results are in Table C.9. We see that Acousticness and Tempo contribute the highest towards understanding the variation in the data as each of them has a loss of 0.05% for focal album plays and 1.88% and 1.84% for ratings upon exclusion, respectively.

	$Focal\_Plays_{ij}^k$ (1)	$Ratings_{ij}^k$ (2)
<b>Loyalty-related factors</b>		
$\log(Focal\_Plays_{ij-1}^k)$	0.164*** (0.013)	
$Ratings_{ij-1}^k$		0.174*** (0.007)
<b>Product differentiation for <math>\Delta WithinArtist\_X_{ij}</math></b>		
$\Delta WithinArtist\_Danceability_{ij}$	1.358 (0.846)	-2.717 (2.244)
$\Delta WithinArtist\_Energy_{ij}$	1.079 (0.845)	-0.654 (2.166)
$\Delta WithinArtist\_Acousticness_{ij}$	-2.658*** (0.485)	4.008** (1.378)
<b>Product differentiation for <math>\Delta ProximalPeer\_X_{ij}</math></b>		
$\Delta ProximalPeer\_Danceability_{ij}$	0.309 (0.886)	1.715 (1.967)
$\Delta ProximalPeer\_Energy_{ij}$	2.165* (0.841)	3.831 (2.066)
$\Delta ProximalPeer\_Acousticness_{ij}$	-0.660 (0.586)	-4.683*** (1.294)
<b>Product differentiation for <math>\Delta DominantDesign\_X_{ij}</math></b>		
$\Delta DominantDesign\_Danceability_{ij}$	-3.613*** (0.930)	1.690 (1.778)
$\Delta DominantDesign\_Energy_{ij}$	-1.718 (0.985)	7.825*** (1.970)
$\Delta DominantDesign\_Acousticness_{ij}$	0.059 (0.717)	-6.096*** (1.326)
<b>Product differentiation at genre level</b>		
$\Delta WithinArtist\_Genre_{ij}$	-0.319* (0.129)	-0.048 (0.265)
$\Delta DominantDesign\_Genre_{ij}$	0.772* (0.355)	1.050 (0.699)
<i>FixedEffects</i>		
<i>Artist – level</i>	Yes	Yes
<i>Time – level</i>	Yes	Yes
<i>Genre<sub>ij</sub></i>	Yes	Yes
Observations	21,068	21,668
Pseudo $R^2$	0.107	0.040
Log-likelihood	-32,713.1	-86,061.7

Notes: Observations are at the Artist-album level. Few reference effects represented in the table for sake of brevity. Controls include  $Big\_Label_{ij}$ ,  $Album\_Num_{ij}$ ,  $Time\_Diff_{ij}$ , and all the audio features represented in  $X_{ij}$ . Standard errors are shown in parentheses.

\* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ .

Table C.7: Results with reference effects at the individual metric level.

Features	<i>Focal_Plays</i> <sub>ij</sub> <sup>k</sup>			<i>Ratings</i> <sub>ij</sub> <sup>k</sup>		
	Within Artist	Proximal Peer	Dominant Genre	Within Artist	Proximal Peer	Dominant Genre
1 Danceability	1.358	0.309	-3.613***	-2.717	1.715	1.69
2 Energy	1.079	2.165*	-1.718	-0.654	3.831	7.825***
3 Key	0.104	1.017	1.532	6.762***	2.931	-6.424***
4 Loudness	3.810*	-5.232**	6.929*	-4.989	-8.139	0.947
5 Mode	-0.452	0.097	-1.518**	1.55	-1.867	1.038
6 Speechiness	3.862*	-3.15	2.475	0.673	-8.322**	4.951
7 Acousticness	-2.658***	-0.66	0.059	4.008**	-4.683***	-6.096***
8 Instrumentalness	0.393	-0.623	-5.796	-3.390*	0.123	-1.08
9 Liveness	-1.948**	0.066	1.03	-2.268	0.564	0.461
10 Tempo	-6.710***	1.986	-1.466	1.527	-1.907	1.513
11 Valence	-0.26	-1.782*	1.904*	1.399	0.608	-1.877
12 Time Signature	7.927***	-0.958	-3.466	-6.975	3.661	2.286
13 Avg. Duration	-18.278*	24.781**	-38.076***	-47.146**	17.163	-33.586*
14 % Explicit	-0.433	1.627**	0.57	0.337	4.394***	-3.555**
15 % Collaboration	0.065	-1.497**	-1.009*	6.129***	-1.09	-3.246**
16 # Tracks	-28.792***	-8.977	8.088	32.836	-118.260**	65.122
17 Album diversity	7.093**	-6.317*	-1.561	2.993	-10.683*	17.651**

\* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$

Table C.8: Salience of effects of differentiation along 17 acoustic and non-acoustic metrics on corresponding album performance.

Interpretation:  $\Delta WithinArtist\_Loudness_{ij}$  for  $Focal\_Plays_{ij}^k$  has an estimate of 3.81, at a significance level p-value  $< 0.05$ .

Features	Focal Album Plays	Focal Album Ratings
1 Danceability	-0.03	-1.84
2 Energy	-0.01	-1.86
3 Key	-0.02	-1.85
4 Loudness	-0.02	-1.84
5 Mode	-0.02	-1.84
6 Speechiness	-0.01	-1.85
7 Acousticness	-0.05	-1.88
8 Instrumentalness	-0.01	-1.84
9 Liveness	-0.01	-1.84
10 Valence	-0.01	-1.84
11 Tempo	-0.05	-1.84
12 Time signature	-0.03	-1.84
13 Avg. duration	-0.05	-1.85
14 % Explicit	-0.01	-1.86
15 % Collab	-0.03	-1.86
16 Tracks	-0.02	-1.85
17 Album diversity	-0.03	-1.85

Table C.9: % Change in log-likelihood in comparison with corresponding full models when differentiation metric is dropped from estimation.

## C.7 References for Acoustic and Non-Acoustic Features

In line with the previous subsection, we consider a segregated consideration of acoustic and non-acoustic features and their corresponding deviations. Results are shown in Table C.10.

Again, we compare the model fit (Log-likelihood) of this specification with that of our main consideration in Models 2, 7, and 12 from Table 4.1. There is no improvement in log-likelihood, with a change of -0.01%, -0.02%, and -0.04%. Hence, our main specification explains the variation in the data better than the consideration in this robustness check.

	<i>Focal_Plays</i> <sub><i>ij</i></sub> <sup><i>k</i></sup> (1)	<i>Ratings</i> <sub><i>ij</i></sub> <sup><i>k</i></sup> (2)
<b>Loyalty-related factors</b>		
<i>log(Focal_Plays</i> <sub><i>ij-1</i></sub> <sup><i>k</i></sup> )	0.156*** (0.013)	
<i>Ratings</i> <sub><i>ij-1</i></sub> <sup><i>k</i></sup>		0.175*** (0.007)
<b>Product differentiation for acoustic factors</b>		
$\Delta$ <i>WithinArtist_Acoustic_X</i> <sub><i>ij</i></sub>	-7.367** (2.513)	8.131 (5.409)
$\Delta$ <i>ProximalPeer_Acoustic_X</i> <sub><i>ij</i></sub>	-2.446 (2.109)	-13.258** (4.609)
$\Delta$ <i>DominantDesign_Acoustic_X</i> <sub><i>ij</i></sub>	0.286 (2.636)	3.662 (4.584)
<b>Product differentiation for non-acoustic factors</b>		
$\Delta$ <i>WithinArtist_NonAcoustic_X</i> <sub><i>ij</i></sub>	-0.074 (0.254)	2.417** (0.755)
$\Delta$ <i>ProximalPeer_NonAcoustic_X</i> <sub><i>ij</i></sub>	0.471 (0.384)	0.964 (0.807)
$\Delta$ <i>DominantDesign_NonAcoustic_X</i> <sub><i>ij</i></sub>	-1.018* (0.398)	-3.443*** (0.881)
$\Delta$ <i>WithinArtist_Genre</i> <sub><i>ij</i></sub>	-0.445*** (0.123)	-0.269 (0.258)
$\Delta$ <i>DominantDesign_X</i> <sub><i>ij</i></sub>	1.101*** (0.328)	1.610* (0.674)
<i>FixedEffects</i>		
<i>Artist – level</i>	Yes	Yes
<i>Time – level</i>	Yes	Yes
<i>Genre</i> <sub><i>ij</i></sub>	Yes	Yes
Observations	21,068	21,668
Pseudo <i>R</i> <sup>2</sup>	0.104	0.039
Log-likelihood	-32,843.3	-86,171.1

Notes: Observations are at the Artist-album level. Controls include *Big\_Label*<sub>*ij*</sub>, *Album\_Num*<sub>*ij*</sub>, *Time\_Diff*<sub>*ij*</sub>, and all the audio features represented in *X*<sub>*ij*</sub>. Standard errors

are shown in parentheses.

\**p* < 0.05; \*\**p* < 0.01; \*\*\**p* < 0.001.

Table C.10: Results with a separate consideration of references for acoustic and non-acoustic features.

## C.8 Variations in Building References

In our main analysis, we allowed  $\Delta$ *WithinArtist\_X*<sub>*ij*</sub> to be built as a convex combination with  $\theta \in [0, 1]$  as our memory factor. As robustness, a battery of alternate considerations for the construction of references is used. These are introduced and the corresponding results are given in subsequent subsections. Note that across all these variations in specifications, results from our main Table 4.1 are mostly replicated.

### C.8.1 Anchoring on the First Album Release

Here,  $R_{ij}^{WithinArtist} = X_{i1}$ . This allows us to anchor the reference of the audience at any stage in the career of an artist *i* on her first album.

	<i>Focal_Plays</i> <sub><i>ij</i></sub> <sup><i>k</i></sup> (1)	<i>Ratings</i> <sub><i>ij</i></sub> <sup><i>k</i></sup> (2)
<b>Loyalty-related factors</b>		
$\log(\text{Focal\_Plays}_{ij-1}^k)$	0.155*** (0.013)	
$\text{Ratings}_{ij-1}^k$		0.174*** (0.007)
<b>Product differentiation factors</b>		
$\Delta\text{WithinArtist\_First\_}X_{ij}$	-4.578** (1.401)	8.029* (3.387)
$\Delta\text{ProximalPeer\_}X_{ij}$	-1.265 (1.622)	-3.669 (3.533)
$\Delta\text{DominantDesign\_}X_{ij}$	-6.626** (2.116)	-7.285 (3.891)
$\Delta\text{WithinArtist\_Genre}_{ij}$	-0.388** (0.123)	-0.133 (0.257)
$\Delta\text{DominantDesign\_Genre}_{ij}$	1.154*** (0.325)	1.665* (0.676)
<i>FixedEffects</i>		
<i>Artist – level</i>	Yes	Yes
<i>Time – level</i>	Yes	Yes
<i>Genre<sub>ij</sub></i>	Yes	Yes
Observations	21,232	21,768
Pseudo <i>R</i> <sup>2</sup>	0.103	0.038
Log-likelihood	-33,017.9	-86,604.3

Notes: Observations are at the Artist-album level. Controls include *Big\_Label<sub>ij</sub>*, *Album\_Num<sub>ij</sub>*, *Time\_Diff<sub>ij</sub>*, and all the audio features represented in *X<sub>ij</sub>*. Standard errors are shown in parentheses. \**p* < 0.05; \*\**p* < 0.01; \*\*\**p* < 0.001.

Table C.11: Results with references for within-artist product differentiation with the first album as the reference.

### C.8.2 Anchoring on the Last Album Released

Here,  $R_{ij}^{\text{WithinArtist}} = X_{ij-1}$ . This allows us to anchor the reference of the audience at any stage in the career of an artist *i* on her penultimate album.

	<i>Focal_Plays</i> <sub><i>ij</i></sub> <sup><i>k</i></sup> (1)	<i>Ratings</i> <sub><i>ij</i></sub> <sup><i>k</i></sup> (2)
<b>Loyalty-related factors</b>		
$\log(\text{Focal\_Plays}_{ij-1}^k)$	0.152*** (0.013)	
$\text{Ratings}_{ij-1}^k$		0.174*** (0.007)
<b>Product differentiation factors</b>		
$\Delta\text{WithinArtist\_Last\_}X_{ij}$	-3.277 (5.390)	-50.926*** (13.065)
$\Delta\text{ProximalPeer\_}X_{ij}$	-1.281 (1.656)	-0.640 (3.451)
$\Delta\text{DominantDesign\_}X_{ij}$	-6.991** (2.126)	-4.525 (3.881)
$\Delta\text{WithinArtist\_Genre}_{ij}$	-0.406*** (0.123)	-0.141 (0.257)
$\Delta\text{DominantDesign\_Genre}_{ij}$	1.204*** (0.325)	1.612* (0.676)
<i>FixedEffects</i>		
<i>Artist – level</i>	Yes	Yes
<i>Time – level</i>	Yes	Yes
<i>Genre<sub>ij</sub></i>	Yes	Yes
Observations	21,232	21,768
Pseudo <i>R</i> <sup>2</sup>	0.103	0.038
Log-likelihood	-33,023.9	-86,599.9

Notes: Observations are at the Artist-album level. Controls include *Big\_Label<sub>ij</sub>*, *Album\_Num<sub>ij</sub>*, *Time\_Diff<sub>ij</sub>*, and all the audio features represented in *X<sub>ij</sub>*. Standard errors are shown in parentheses. \**p* < 0.05; \*\**p* < 0.01; \*\*\**p* < 0.001.

Table C.12: Results with references for within-artist product differentiation with the latest album as the reference.

### C.8.3 References as Arithmetic Mean of Past Albums

	<i>Focal_Plays</i> <sub><i>ij</i></sub> <sup><i>k</i></sup> (1)	<i>Ratings</i> <sub><i>ij</i></sub> <sup><i>k</i></sup> (2)
<b>Loyalty-related factors</b>		
$\log(\text{Focal\_Plays}_{ij-1}^k)$	0.156*** (0.013)	
$\text{Ratings}_{ij-1}^k$		0.175*** (0.007)
<b>Product differentiation factors</b>		
$\Delta\text{WithinArtist\_Mean\_}X_{ij}$	-6.548*** (1.937)	21.643*** (4.614)
$\Delta\text{ProximalPeer\_}X_{ij}$	-0.745 (1.665)	-7.522* (3.659)
$\Delta\text{DominantDesign\_}X_{ij}$	-5.179* (2.117)	-7.801* (3.902)
$\Delta\text{WithinArtist\_Genre}_{ij}$	-0.417*** (0.123)	-0.211 (0.257)
$\Delta\text{DominantDesign\_Genre}_{ij}$	1.128*** (0.326)	1.608* (0.676)
<i>FixedEffects</i>		
<i>Artist – level</i>	Yes	Yes
<i>Time – level</i>	Yes	Yes
<i>Genre<sub>ij</sub></i>	Yes	Yes
Observations	21,068	21,656
Pseudo <i>R</i> <sup>2</sup>	0.103	0.038
Log-likelihood	-32,841.8	-86,126.8

Notes: Observations are at the Artist-album level. Controls include *Big\_Label<sub>ij</sub>*, *Album\_Num<sub>ij</sub>*, *Time\_Diff<sub>ij</sub>*, and all the audio features represented in *X<sub>ij</sub>*. Standard errors are shown in parentheses.  
\**p* < 0.05; \*\**p* < 0.01; \*\*\**p* < 0.001.

Table C.13: Results with references for within-artist product differentiation with the arithmetic mean as the reference.

Here,

$$R_{ij}^{\text{WithinArtist}} = \frac{\sum_{j'=1}^{j-1} X_{ij'}}{j-1}.$$

This allows us to anchor the reference of the audience on the arithmetic mean of corresponding musical metrics for all albums by artist *i* prior to the new release *j*. With this consideration, we get the following results.

### C.8.4 References with Album Success and Memory Effects

$$R_{ij}^{\text{WithinArtist}} = (\theta + \theta' \text{Success}_{ij-1}) R_{ij-1}^{\text{WithinArtist}} + (1 - \theta - \theta' \text{Success}_{ij-1}) X_{ij-1}$$

where,  $\text{Success}_{ij} = \frac{\text{Plays}_{ij-1}}{\max\{\text{Plays}_{i1}, \text{Plays}_{i2}, \dots, \text{Plays}_{ij-1}\}}$  takes values between 0 and 1. This allows us to also consider the relative success of past albums in tracking how much retention occurs in reference building. We get the following results.

	<i>Focal_Plays</i> <sub>ij</sub> <sup>k</sup> (1)	<i>Ratings</i> <sub>ij</sub> <sup>k</sup> (2)
<b>Loyalty-related factors</b>		
<i>log(Focal_Plays</i> <sub>ij-1</sub> <sup>k</sup> )	0.154*** (0.013)	
<i>Ratings</i> <sub>ij-1</sub> <sup>k</sup>		0.195*** (0.012)
<b>Product differentiation factors</b>		
$\Delta$ <i>WithinArtist_Success</i> <sub>X<sub>ij</sub></sub>	0.216 (0.170)	0.205 (1.017)
$\Delta$ <i>ProximalPeer</i> <sub>X<sub>ij</sub></sub>	-1.364 (1.634)	5.504 (9.245)
$\Delta$ <i>DominantDesign</i> <sub>X<sub>ij</sub></sub>	-6.842** (2.125)	-28.520* (13.048)
$\Delta$ <i>WithinArtist_Genre</i> <sub>ij</sub>	-0.403** (0.123)	1.099 (0.750)
$\Delta$ <i>DominantDesign_Genre</i> <sub>ij</sub>	1.203*** (0.325)	4.970** (1.838)
<i>FixedEffects</i>		
<i>Artist – level</i>	Yes	Yes
<i>Time – level</i>	Yes	Yes
<i>Genre</i> <sub>ij</sub>	Yes	Yes
Observations	21,232	7,351
Pseudo <i>R</i> <sup>2</sup>	0.102	0.049
Log-likelihood	-33,022.8	-28,612.2

Notes: Observations are at the Artist-album level. Controls include *Big\_Label*<sub>ij</sub>, *Album\_Num*<sub>ij</sub>, *Time\_Diff*<sub>ij</sub>, and all the audio features represented in *X*<sub>ij</sub>. Standard errors are shown in parentheses. \**p* < 0.05; \*\**p* < 0.01; \*\*\**p* < 0.001.

Table C.14: Results with references for within-artist product differentiation by considering the past success of the albums.

### C.8.5 Results with Alternate Genre Differentiation Metrics

	<i>Focal_Plays</i> <sub>ij</sub> <sup>k</sup> (1)	<i>Ratings</i> <sub>ij</sub> <sup>k</sup> (2)
<b>Loyalty-related factors</b>		
<i>log(Focal_Plays</i> <sub>ij-1</sub> <sup>k</sup> )	0.156*** (0.013)	
<i>Ratings</i> <sub>ij-1</sub> <sup>k</sup>		0.175*** (0.007)
<b>Product differentiation factors</b>		
$\Delta$ <i>WithinArtist</i> <sub>X<sub>ij</sub></sub>	-5.453*** (1.404)	16.051*** (4.258)
$\Delta$ <i>ProximalPeer</i> <sub>X<sub>ij</sub></sub>	-1.526 (1.630)	-6.080 (3.614)
$\Delta$ <i>DominantDesign</i> <sub>X<sub>ij</sub></sub>	-5.381* (2.114)	-6.275 (3.875)
$\Delta$ <i>WithinArtist_GenreBinary</i> <sub>ij</sub>	-0.298* (0.117)	-0.125 (0.253)
$\Delta$ <i>DominantDesign_GenreBinary</i> <sub>ij</sub>	0.670*** (0.178)	-5.099* (2.259)
<i>FixedEffects</i>		
<i>Artist – level</i>	Yes	Yes
<i>Radiostationlevel</i>	Yes	Yes
<i>Time – level</i>	Yes	Yes
<i>Genre</i> <sub>ij</sub>	Yes	Yes
Observations	21,068	21,656
Pseudo <i>R</i> <sup>2</sup>	0.103	0.038
Log-likelihood	-32,841.4	-86,131.2

Notes: Observations are at the Artist-album level. Controls include *Big\_Label*<sub>ij</sub>, *Album\_Num*<sub>ij</sub>, *Time\_Diff*<sub>ij</sub>, and all the audio features represented in *X*<sub>ij</sub>. Standard errors are shown in parentheses.

\**p* < 0.05; \*\**p* < 0.01; \*\*\**p* < 0.001.

Table C.15: Results with binary genre differentiation metrics.

Here, we use alternate specification of differentiation metrics that track genre-level comparisons.  $\Delta WithinArtist\_Genre_{ij}$  and  $\Delta DominantDesign\_Genre_{ij}$  from the main analysis represent the proportion of overlapping genre labels between two albums subtracted from 1. We use  $\Delta WithinArtist\_GenreBinary_{ij}$  and  $\Delta DominantDesign\_GenreBinary_{ij}$  as binary representation which take value 1 if  $\Delta WithinArtist\_Genre_{ij}$  and  $\Delta DominantDesign\_Genre_{ij}$  are greater than 0 and 0 otherwise, respectively. However, we choose not to use this coarser metric in our main analysis to leverage this variation at a more granular level.

### C.8.6 References with Alternate Considerations for Proximal Peer and Dominant Design Differentiation

	<i>Focal_Plays</i> <sub>ij</sub> <sup>k</sup> (1)	<i>Ratings</i> <sub>ij</sub> <sup>k</sup> (2)
<b>Loyalty-related factors</b>		
$\log(Focal\_Plays_{ij-1}^k)$	0.155*** (0.013)	
$Ratings_{ij-1}^k$		0.175*** (0.07)
<b>Product differentiation factors</b>		
$\Delta WithinArtist\_X_{ij}$	-5.255*** (1.401)	16.255*** (4.316)
$\Delta ProximalPeer\_Alt\_X_{ij}$	-2.540 (1.802)	-6.191 (4.247)
$\Delta DominantDesign\_Alt\_X_{ij}$	-6.556* (2.560)	-9.164 (4.833)
$\Delta WithinArtist\_Genre_{ij}$	-0.428*** (0.123)	-0.201 (0.257)
$\Delta DominantDesign\_Genre_{ij}$	1.029** (0.323)	1.520* (0.673)
<i>FixedEffects</i>		
<i>Artist – level</i>	Yes	Yes
<i>Time – level</i>	Yes	Yes
<i>Genre<sub>ij</sub></i>	Yes	Yes
Observations	21,068	21,668
Pseudo R <sup>2</sup>	0.103	0.038
Log-likelihood	-32,838.6	-86,179.6

Notes: Observations are at the Artist-album level. Controls include *Big\_Label<sub>ij</sub>*, *Album\_Num<sub>ij</sub>*, *Time\_Diff<sub>ij</sub>*, and all the audio features represented in *X<sub>ij</sub>*. Standard errors are shown in parentheses. \**p* < 0.05; \*\**p* < 0.01; \*\*\**p* < 0.001.

Table C.16: Results with alternate considerations for proximal peer and dominant design references.

Here, instead of 3 proximal peer chart-topping albums as dominant design used in the main analysis, we use 2 additional albums for each comparisons giving us 5 proximal peers and 5 chart-toppers to build the corresponding differentiation metrics with.

## D Managerial Implications

We estimate a simple variation of the base model in Equation 1 by considering the genre-level transition pairs in successive albums of the focal artist. Hence, we have the following.

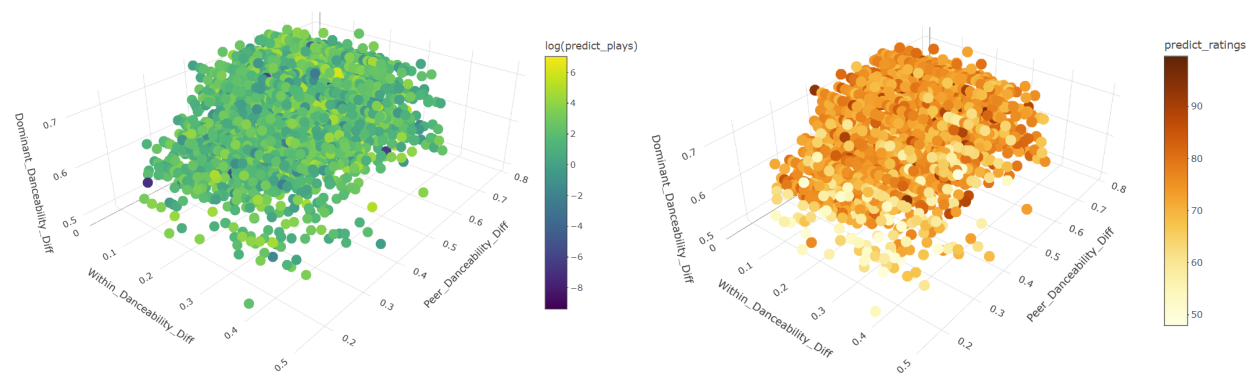
$$Z_{ij}^k = \alpha^k Z_{ij-1}^k + \beta^k X_{ij} + \gamma^k Genre_{ij-1,j} + \nu^k C_{ij} + \mu_t + \epsilon_{ij}^k. \quad (5)$$

Here,  $Genre_{ij-1,j}$  is in the form of a factor variable for every artist *i* and album *j* pair. The remaining variables are similar to those explained in §3.2. Note that the only difference is that for

identification purposes, we remove artist- and genre-level fixed effects. The results of the estimation procedure are not provided in full here. However, lower log-likelihood values of these extended models (around 6.5%) indicate that the variation in the dependent variables is much better explained by our base specification. Despite this, it allows us to get an idea about which genre-level transitions are favored by radio stations and critics. Here, our focus is to see the effect on focal album plays and ratings. Accordingly, in Table 5.1 we show top and bottom 3 pairs of genre-level transitions identified for the corresponding dependent variable in our analyses, respectively.

## E Counterfactual Study

Here, we illustrate how our framework can be utilized in the form of a counterfactual analysis for artists and record labels to make their NPD decisions. Consider, for instance, the last album released by the pop artist Rihanna in the year 2016 named ‘ANTI’. By using the estimated results from Table 4.1, we can predict the responses of the radio stations and reviewers for variable ranges of differentiation rates she may employ in her upcoming release. Accordingly, the follow-up project by Rihanna could be designed to be very similar to her previous release ‘ANTI’, the albums released by her proximal peers, and the chart-topping success. Alternatively, she may opt to innovate a lot by adopting higher product differentiation rates. Thus, we build approximately 6,000 different and random combinations of the underlying 17 musical dimensions that generate 6,000 potential albums for Rihanna. To illustrate the significance of our framework at a granular level, we rely on the estimation results in Appendix C.6. Having identified the control variables, we estimate the the resulting differentiation rates for every acoustic and non-acoustic metric based on her updated references. By setting the release time for the new album to December 2020, we estimate the predicted values of plays across radio stations and scores given by the reviewers for the newly designed album. We plot the expected plays on radio stations and average ratings given by the reviewers in Figure E.1 for varied values of differentiation of the *Danceability* index of the focal album.



(a) Predicted number of plays on radio for *Danceability* references. (b) Predicted reviewer ratings for *Danceability* references.

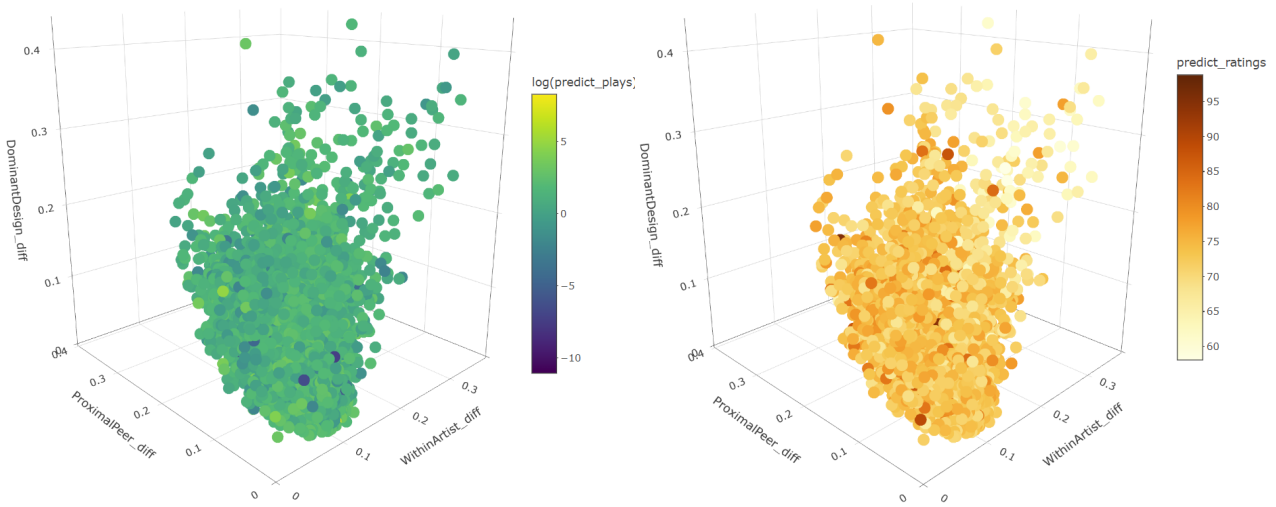
Figure E.1: Expected response across for Rihanna’s next album by considering product differentiation along individual metrics (here *Danceability*).

We see that Rihanna will, on average, benefit on radios by maintaining lower levels of *Danceability* differentiation in comparison to her past profile (within-artist references between 0.2 and 0.3), while

moderate differentiation from her proximal peers and the chart-toppers (around 0.5) would ensure commercial success. On the other hand, she will get increasingly better responses from reviewers for higher values of *Danceability* differentiation from peers and chart-toppers (more than 0.5) but a lower value for within-artist product differentiation (around 0.2). Note that there are 16 other dimensions that need to be considered in conjunction with these values to estimate given predicted plays. Graphs for these other 16 dimensions can hence be constructed in a similar manner.

For the ease of interpretation, based on the aforementioned exploration, we identify music profiles and corresponding equivalent albums in our consideration for maximizing the likelihood of success on radio stations and with reviewers, see Table 5.2 for more details. For radio success, Rihanna could emulate albums like *A Skiela Wy?* by Enej or *2.0* by A. R. Rahman, both of which feature high *Loudness* and *Instrumentalness* metrics. To appeal to reviewers, she might opt for low *Speechiness* and high *Acousticness* and *Valence* metrics, as exemplified by Them’s *British Invasion* or Luis Miguel’s *¡MÉXICO Por Siempre!* However, to balance these distinct tastes, our analysis suggests that Rihanna could create an album similar to Ennio Morricone’s *The Art of Ennio Morricone*, characterized by shorter songs, a few collaborations with peers, and low *Energy* and *Liveness*.

An alternate analysis by considering the global metric of differentiation from base specification is used to get results shown in Figure E.2.



(a) Predicted number of plays on radio.

(b) Predicted reviewer ratings.

Figure E.2: Expected response across for Rihanna’s next album.