Online Supplement to Negro, Giacomo, Balázs Kovács and Glenn R. Carroll. 2022. "What's Next? Artists' Music After Grammy Awards." American Sociological Review 87: 644–674.

Part A: Construction of Data Files

The music album dataset draws on three sources: AllMusic, EchoNest/Spotify, and *Billboard*. This supplement gives an overview of how these sources were combined to create the files used in the analyses.

The AllMusic data contain information on recordings from multiple content pages organized by artist basic information; artist discography; record basic information; record styles; and record credits. The file containing artist basic information was used as a master file into which the other content was merged. The merging yielded a file with 1,264,644 recordings for 474,294 individuals/groups listed as primary artists. Recordings that were not albums (EPs/singles, and compilations or videos), or were credited to Various Artists, soundtrack records, studio cast records, or karaoke records were excluded. This process produced a dataset of 1,035,743 albums for 421,572 artists. These albums also had release year information; the release year ranged from 1938 to 2018. About 8 percent of records were listed under multiple artists (for example, *Lulu* is a collaborative album between Lou Reed and Metallica: https://www.allmusic.com/album/lulu-mw0002223324). We collected the data in Fall 2018.

We submitted the list of these albums to the Spotify API, an interface that allows users and programmers access to information about tracks, albums, and artists. The query matched 125,340 albums (matched on artist name and album title) on which the artistic differentiation measures were calculated. Spotify's API provided sonic information for albums at the track level, and because we conduct analyses at the album level, we aggregated the track-level information to the album level by taking the average sonic feature values of the tracks.

The data for the albums in the *Billboard 200* chart were collected from the *Billboard* magazine archive. A total of 27,462 albums appeared on the *Billboard 200* chart between 1967 and 2018. Of the total, 27,199 (99 percent) were found and merged in the AllMusic album and artist dataset. The remaining albums in the master file for analysis that did not reach the *Billboard 200* chart were assigned a position of 201.

Finally, the data for artists nominated for (and recipients of) Grammy awards were coded from www.grammy.com. A total of 2,169 individuals/groups were identified. Of these, 1,037 show primary roles as performing artists with an album discography and all but one—Canadian artist Bryan Adams who asked to be removed from the database (https://rateyourmusic.com/discussion/music/why-is-bryan-adams-no-longer-on-allmusic_com/1/)—were found and merged in the AllMusic data. The other individuals/groups do not have primary roles as artists and do not have album discographies to analyze (they still appear in AllMusic as credited personnel such as producer or engineer).

Part B: Application of the Neural Learning Model

We applied a neural learning model to represent albums in the genre space. This model combines the sonic and stylistic features of the albums. The sonic content provided by Spotify includes both continuous (e.g., tempo) and binary (e.g., minor/major key) variables, and can be inputted directly to the algorithm. Ten pieces of information define the sonic fingerprint, so the sonic content for each album can be stored in a 1×10 vector.

AllMusic provides a list of styles, which we converted to a numeric format. We did this by turning the categorical style information into a binary format: for each album we coded a 1×832 sized vector of 0's and

1's (832 is the count of unique style labels in the data used for estimation), where one denotes cases where the album is assigned the style label, and zero otherwise.[1]

Combining the sonic and style content, the input vector comprises a 1×842-sized vector for each album. For the measure using sonic information only, we used the 1×10 sonic vector as an input. For the style information only measure, we used the 1×832 style vector.

Next, we included a "hidden layer" of size 842. This hidden layer, as illustrated in Figure 1 in the main text, allows the neural network to capture the importance of any two-step interaction effects between the input variables.[2] Finally, because we applied a supervised learning algorithm that predicts genres, the network outputs a representation of the albums in the space of genres that maximizes the prediction power of a softmax function on genres. In other words, the neural learning algorithm learns to weigh the sonic and stylistic vectors such that the predicted location of the album in the genre space will be close (i.e., minimal distance) to the observed genres assigned to the album. The neural network was trained in batches of 64 for 3 epochs, which maximized out-of-sample fit without leading to overfitting. The network learning algorithm was implemented using the *keras* package in Python 3.7. The detailed code is available from the authors.

The final learned neural network provides a highly accurate representation of the albums: Using data on sonics and styles, it predicts the genre of the album with 84 percent accuracy. Using style data only as an input, we achieved 82 percent prediction accuracy, and we achieved 73 percent prediction accuracy with the sonic data only. These results illustrate that both sonic and stylistic information could be useful in predicting album genres, but styles provide significantly higher prediction power.

Alternative Approach: Multinomial Logit

In the main set of analyses, we used albums' location in the genre space as predicted by the neural learning model. This model does not rely on a pre-specified functional form of the relationship between styles or sonic data, and genre assignment; it also allows for multi-class categorization (it can also handle albums classified in multiple genres, such as Jazz and Pop/Rock).

One alternative to the neural learning model is multinomial logit regression. Multinomial logits are limited to single-class categorizations (i.e., an album is either Jazz or Pop/Rock) and must have the functional form pre-specified in the estimation equation (e.g., linear, quadrative, interactions). Because multinomial logit models are more commonly used in social science research, we also investigated how a multinomial logit model would work in our setting, and whether the results are robust to the distance measures calculated based on multinomial logit estimates.

To estimate the multinomial logit model, we used albums that have a single label assigned to them (about 85 percent of all albums in our sample). In the regressions (estimated using the mlogit command in Stata), each album is represented by one observation, where the outcome variable is the observed genre assignment (e.g., Classical, Jazz, Rap, Pop/Rock), and the covariates are the values from the stylistic and sonic vectors. This approach implies 842 covariates in the models that utilize both stylistic and sonic data. We enter these covariates in a linear additive way, estimating the weights of each. Because of the categorical nature of the

[1] Styles are not strictly nested in genres. Styles are diagnostic of genres. For example, the Symphony style is quite likely a Classical music record. But styles can also be diagnostic of multiple genres. In the example above, the style Fusion leads to high prediction of the genres Jazz and Pop/Rock. The algorithm learns common style combinations as well. For example, Trumpet (style) + Bop (style) = Jazz (genre) but Trumpet (style) + Drums (style) = Latin (genre).
[2] We experimented with including additional hidden layers. The prediction power did not improve significantly, and we opted to present the simpler case with one hidden layer.

dependent variable, the mlogit command estimates 21 equations for each album (one for each possible observed genre). Formally, the model estimates regressions such as the ones below (Greene 2018):

$$Pr(album\ X, Jazz = 1) = f(\beta_1 style_1 + \beta_2 style_2 + \cdots + \beta_{832} style_{832} + \beta_{833} sonic\_dim_1 + \cdots + \beta_{842} sonic\_dim_{10})$$

After estimating the model with these parameters, we calculated the predicted probabilities of assignment of each album in each genre which, when combined, give a 1 × 21 vector. This vector is in the same format as the output of the neural learning model, and we use these genre weights in the same ways as with the neural learning model to calculate distances between albums. The average of these distances for each album was again used as the outcome variable for the artistic differentiation analyses.

The predicted probabilities can be calculated for the whole set of albums (not only for single genre albums). We also note that the predicted probabilities with the multinomial logit model and the neural learning models are highly similar, their pairwise correlation is .93. Below we report re-estimates of the main models in the text (Models 5.3, 5.4, and 5.5) that use the artistic differentiation measures obtained with the predicted vectors from the multinomial logit models. The pattern of results is similar to what we report in the main text.

Table B1. Regression Estimates of Artistic Differentiation from Other Artists – Multinomial Logit Measurement

Variable	***Model 1*** *Stylistic & Sonic Distance*	***Model 2*** *Sonic Distance*	***Model 3*** *Stylistic Distance*
Grammy win	.025†	–.013	.042**
	(.013)	(.011)	(.014)
Grammy nomination	–.013*	.003	–.015**
	(.005)	(.004)	(.005)
Experience	–.026***	–.011**	–.032***
	(.004)	(.003)	(.004)
Year	.002	–.004	–.001
	(.004)	(.004)	(.005)
Primary genre	Included	Included	Included
Primary genre × Year	Included	Included	Included
Constant	–2.069	8.192	1.440
	(9.833)	(7.896)	(9.828)
R^2	.10	.04	.11
Observations	45,012	45,012	45,012

Note: Estimates are obtained with artist fixed-effects regression. Robust standard errors are in parentheses. The data include Grammy nominees including winners, and a matched sample of non-Grammy nominees. The matched group was selected using Coarsened Exact Matching (CEM) procedure. Experience is log-transformed. Dummies for primary genre of each album and dummies for interactions between primary genre of each album and year are included but not reported.
†$p < .10$; *$p < .05$; **$p < .01$; ***$p < .001$ (two–tailed).

Part C. Comparisons of Grammy Winners and Nominees

Table C1. Pre-Award Differences between Winners and Nominees

	Winners	Nominees	*P*-value
Variables in Analysis			
Differentiation from other artists	.413 (.014)	.392 (.010)	.22
Differentiation from other artists – stylistic content	.435 (.014)	.419 (.010)	.36
Differentiation from other artists – sonic content	.309 (.007)	.299 (.004)	.22
Number of production credits	33.618 (.924)	31.572 (.642)	.07
Peak position in *Billboard 200* of artist's albums	46.881 (2.508)	41.393 (1.643)	.08
Experience as recording artist	6.633 (.207)	7.039 (.149)	.11
Works with major record label = 1	.543 (.017)	.515 (.011)	.17
Other Variables			
Maximum weeks in *Billboard 200*	45.482 (2.293)	44.513 (1.532)	.73
AllMusic rating of artist's albums	3.825 (.028)	3.774 (.020)	.14
Village Voice Best Album list = 1	.010 (.003)	.008 (.002)	.53
Elapsed time between albums (years)	1.422 (.038)	1.453 (.035)	.54
Repeated collaborations	.800 (.074)	.677 (.043)	.15
Network constraint	.111 (.006)	.120 (.004)	.20
Number of genres of artist's albums	1.446 (.077)	1.282 (.039)	.07
Number of moods of artist's albums	8.349 (.240)	8.622 (.162)	.35
White artist = 1	.617 (.014)	.645 (.009)	.10
Female artist = 1	.182 (.011)	.180 (.007)	.89

Note: Standard errors are in parentheses. Values of $p < .05$ indicate significant differences between the winners and nominees. None of the comparisons between the two groups differs significantly prior to the award.

Table C2. Comparison between Grammy-Nominated and Grammy-Winning Albums, Best Album Award

	Winners	Nominees	*P*-value Difference
Variables in Analysis			
Artistic differentiation from other artists	.397	.329	.29
	(.058)	(.026)	
Artistic differentiation from other artists – stylistic content	.429	.448	.76
	(.052)	(.031)	
Artistic differentiation from other artists – sonic content	.266	.277	.49
	(.014)	(.008)	
Number of production credits	73.302	61.969	.07
	(6.330)	(2.694)	
Peak position in *Billboard 200* of artist's albums	11.628	5.942	.10
	(5.475)	(1.184)	
Other Variables			
Maximum weeks in *Billboard 200*	45.482	44.513	.73
	(2.293)	(1.532)	
AllMusic rating of artist's albums	4.500	4.419	.40
	(.028)	(.051)	
Village Voice Best Album List = 1	.310	.185	.06
	(.062)	(.026)	
Number of genres	1.345	1.339	.95
	(.080)	(.042)	
Number of styles	4.035	3.872	.51
	(.210)	(.129)	
Number of moods	16.069	16.128	.97
	(.820)	(.557)	
Pop/Rock album	.517	.515	.98
	(.066)	(.332)	

Note: Standard errors are in parentheses. Values of $p < .05$ indicate significant differences between the winners and nominees. None of the comparisons between the two groups differs significantly prior to the award.

Table C3. Comparison between Grammy-Nominated and Grammy-Winning Albums, Best Song Award

	Winners	Nominees	*P*-value Difference
Artistic differentiation from other artists	.513	.356	.12
	(.065)	(.027)	
Artistic differentiation from other artists – stylistic content	.513	.448	.37
	(.064)	(.030)	
Artistic differentiation from other artists – sonic content	.266	.293	.11
	(.011)	(.013)	

Table C4. Comparison between Grammy-Nominated and Grammy-Winning Albums, Best Record Award

	Winners	Nominees	*P*-value Difference
Artistic differentiation from other artists	.431 (.072)	.407 (.032)	.77
Artistic differentiation from other artists – stylistic content	.477 (.076)	.500 (.033)	.78
Artistic differentiation from other artists – sonic content	.283 (.027)	.276 (.010)	.80

Table C5. Comparison between Grammy-Nominated and Grammy-Winning Albums, Best New Artist Award

	Winners	Nominees	*P*-value Difference
Artistic differentiation from other artists	.378 (.061)	.369 (.025)	.89
Artistic differentiation from other artists – stylistic content	.433 (.067)	.410 (.027)	.72
Artistic differentiation from other artists – sonic content	.312 (.030)	.276 (.010)	.25

Table C6. Comparison between Grammy-Nominated and Grammy-Winning Albums, Best Album Award + Best Song Award +Best Record Award + Best New Artist Award

	Winners	Nominees	*P*-value Difference
Artistic differentiation from other artists	.404 (.018)	.385 (.018)	.66
Artistic differentiation from other artists – stylistic content	.457 (.038)	.461 (.019)	.93
Artistic differentiation from other artists – sonic content	.286 (.013)	.284 (.007)	.85

Part D. Data Matching

We implemented "coarsened exact matching" (CEM), a nonparametric method that reduces data covariate imbalance and increases the comparability of the units in a sample (Iacus, King, and Porro 2012). The CEM method was applied to artist-year observations. The CEM procedure matches units in the two groups that are within the cut-points for every covariate, ensuring that matched units have similar values. The covariates included in the CEM matching were dummy variables for each primary genre used by AllMusic to classify an artist; a dummy variable for individual (vs. group) artist; the cumulative average of the number of genres for an artist's albums; the cumulative average of the number of styles for an artist's albums; the cumulative average of the number of moods for an artist's albums; the cumulative number of albums released with a major (vs. independent) label; years of tenure in the industry; the cumulative number of albums that reached the top-10 positions in the *Billboard 200* chart; and the lagged artistic differentiation from other albums in the same primary genre in the previous three years (matching on the lagged differentiation variable helps account for possible reversion to the mean effects). Artistic differentiation is not defined on a natural scale. To improve covariate balance, in supplemental analyses we conducted an alternative matching procedure using 10 cut-points based on each decile of the distribution of this variable for the matching. This alternative matching approach produced estimates similar to those reported here.

Implementing CEM found matches for 62 percent of the observations for the treated group, and led us to retain roughly 32 percent of the control group data. The CEM procedure calculates the imbalance statistic L_1, a distance measure based on the difference between the multidimensional histogram of all pretreatment covariates in the treated group and that of the control group. The value of the L_1 statistic does not have a specific interpretation, but a good matching solution reduces its value. In our data, the multivariate L_1 distance is .9825884 before the matching, and .7919578 after matching. These values suggest the matching method did indeed reduce the data imbalance.

Tables D1 and D2 provide more details about data imbalance before and after the matching. Table D1 reports the original L_1 statistic before the matching, computed for each variable used in the CEM procedure separately. The additional columns report univariate measures of difference between treated and control units: Means, and quantiles of the distributions of the two groups for the minimum, 25th, 50th, 75th, and maximum percentiles for each variable.

Table D2 provides the same information after the CEM procedure. Multiple measures are provided because balancing only the means between the treated and control groups does not necessarily guarantee balance in the rest of the distribution. By comparing the imbalance results to the original imbalance, we see a substantial reduction in imbalance, not only in the means, but also in the marginal and joint distributions of the data. The experience variable continues to show some significant imbalance even after the matching. We sought to adjust for the remaining imbalance by including this variable in the regression models.

The CEM procedure was conducted on the subset of records that were present in the AllMusic and Spotify data. The final number of observations in the main regressions ($N = 45{,}012$, corresponding to 36,808 distinct artists) is the result of the dataset pruned from matching for the period jointly covered by the three data sources (1967 to 2018) and for which covariate information is available.

Table D1. Imbalance in Unmatched and Matched Samples Before CEM Matching

Variable	L_1	Mean	Min.	25%	50%	75%	Max.
Artist's genre	0	0	0	0	0	0	0
Blues	.0085	.0085	0	0	0	0	0
Children's	0	0	0	0	0	0	0
Classical	.0127	–.0127	0	0	0	0	0
Comedy/Spoken	.0082	.0082	0	0	0	0	0
Country	.08731	.08731	0	0	0	0	0
Easy Listening	.01298	.01298	0	0	0	0	0
Electronic	.00728	.00728	0	0	0	0	0
Folk	.01344	.01344	0	0	0	0	0
Holiday	0	0	0	0	0	0	0
International	.00507	.00507	0	0	0	0	0
Jazz	.03671	–.03671	0	0	0	0	0
Latin	.00018	–.00018	0	0	0	0	0
New Age	0	0	0	0	0	0	0
Pop/Rock	.19544	–.19544	0	0	–1	0	0
R&B	.12225	.12225	0	0	0	0	0
Rap	.03158	–.03158	0	0	0	0	0
Reggae	.00029	–.00029	0	0	0	0	0
Religious	.00724	.00724	0	0	0	0	0
Stage & Screen	.00516	.00516	0	0	0	0	0
Vocal	.06053	.06052	0	0	0	0	0
Number of genres of artist's albums	.23609	.26045	0	0	0	1	–3
Number of styles of artist's albums	.54278	1.7521	0	2	3	2	–3
Number of moods of artist's albums	.63857	5.4138	0	4	7	8	–35
Albums in *Billboard 200* chart	.5382	.5382	0	0	1	1	0
Albums in top-10 positions in *Billboard 200*	.23605	.23605	0	0	0	0	0
Experience as recording artist	.57562	1.6642	0	2.1972	2.1401	1.3863	–.04652
Albums with major record label	.38808	.38808	0	0	1	1	0
Group artist = 1	.02929	.02929	0	0	0	0	0
Lagged artistic differentiation of artist's	.32516	.06304	.12529	.02641	.05828	.09469	–.11531

Table D2. Imbalance in Unmatched and Matched Samples After CEM Matching

Variable	L_1	Mean	Min.	25%	50%	75%	Max.
Artist's genre	0	0	0	0	0	0	0
Blues	0	0	0	0	0	0	0
Children's	0	0	0	0	0	0	0
Classical	3.3e-14	-4.e-140	0	0	0	0	0
Comedy/Spoken	0	0	0	0	0	0	0
Country	1.3e-13	-1.7e-13	0	0	0	0	0
Easy Listening	9.3e-15	-9.3e-15	0	0	0	0	0
Electronic	0	0	0	0	0	0	0
Folk	2.6e-15	-2.8e-15	0	0	0	0	0
Holiday	0	0	0	0	0	0	0
International	1.1e-15	-9.3e-16	0	0	0	0	0
Jazz	1.4e-13	-6.0e-14	0	0	0	0	0
Latin	0	0	0	0	0	0	0
New Age	0	0	0	0	0	0	0
Pop/Rock	7.3e-13	-9.9e-13	0	0	0	0	0
R&B	1.3e-13	-1.16e-13	0	0	0	0	0
Rap	3.8e-14	-4.3e-14	0	0	0	0	0
Reggae	0	0	0	0	0	0	0
Religious	2.6e-15	-2.8e-15	0	0	0	0	0
Stage & Screen	6.0e-15	-6.5e-15	0	0	0	0	0
Vocal	4.6e-14	-5.3e-14	0	0	0	0	0
Number of genres of artist's albums	1.7e-13	-1.8e-13	0	0	0	0	0
Number of styles of artist's albums	6.8e-13	-1.8e-13	0	0	0	0	0
Number of moods of artist's albums	0.0086	0.0151	0	0	0	0	0
Albums in *Billboard 200* chart	7.3e-13	-7.3e-13	0	0	0	0	0
Albums in top-10 positions in *Billboard 200*	1.8e-13	-2.4e-13	0	0	0	0	0
Experience as recording artist	.05019	.00924	0	0	0	0	.0378
Albums with major record label	7.3e-13	-7.0e-13	0	0	0	0	0
Group artist = 1	1.0e-12	3.5e-13	0	0	0	0	0
Lagged artistic differentiation of artist's	3.0e-04	6.9e-05	.03811	0	0	0	.

Part E. Robustness Tests

To examine the robustness of the findings, we addressed some potential confounds for the artistic differentiation effects (Hypothesis 1). One concern is that artistic differentiation does not reflect making music different from other artists but simply music viewed as more "mainstream." This concern is two-fold. First, it can shift the genres used to classify an artist's music. In particular, the label Pop/Rock may be used more as a generic descriptor post-award and indicate that an artist's music has lost some of its distinctive features of another genre (Regev 2015). Second, if albums are more likely to be classified as Pop/Rock, then the measure of artistic differentiation shifts the comparison set from one genre to others (say R&B albums to R&B and Rock/Pop albums), which can include a wider (and more diverse) set of artists and styles. Models 1 and 2 in Table E1 used the model specification of artistic differentiation based on style descriptors (Model 5.5) to estimate, respectively, the probability that an album is classified in the Pop/Rock genre, and the probability that an artist's album is classified in a different genre (primary or secondary) from the prior album of the same artist. The models used the Grammy win and nomination variables as main covariates and additional controls. The estimations do not show statistically significant coefficients for the Grammy variables, suggesting the main effects reported in Model 5.5 are not due to an artist's music shifting closer to the Pop/Rock mainstream or a widening of the stylistic set of genres.

A related concern is that greater artistic differentiation of an artist's music simply reflects the spanning of multiple genres or styles. Models 3 and 4 in Table E1 estimated the number of music genres and styles in which an album was categorized. The models do not show significant coefficients for the Grammy win and nomination variables, suggesting that awards exert effects on making music that is different from others, rather than "generalist" music that simply combines multiple genre and style features.

We expected awards would affect artistic differentiation from all other artists. However, artistic differentiation could imply a move away from one's own work too. To separate these effects, in Table E2, Model 1 re-estimated the main specification (Model 5.5 in the text) and added a variable measuring stylistic distance from the artist's prior own albums. A significant positive coefficient for this variable leaves the effects of the Grammy variables unaffected. This finding suggests creative paths following awards remain distinct for nominees and winners relative to other artists, and that differentiation from one's prior work also implies a shift away from what others are doing. In unreported estimates, we used stylistic distance from the artist's prior own albums as the outcome and did not find significant effects of Grammy wins or nominations, suggesting stylistic distance is primarily a differentiation from others.

In Table E2, we also examined whether this effect is more specific to other artists consecrated by peers or the consumer public, as in a process that leads to differentiation based on status (Models 2–7). We re-estimated the main specification (Model 5.5) using a measure of stylistic distance limited to prior Grammy winners or nominees, and to prior Grammy non-winners and non-nominees. We also estimated stylistic distance from artists who had entered the Billboard charts and those who did not. The estimates generally show coefficients consistent with the main findings. These coefficients display statistical significance for all models for Grammy nominations and three out of six for Grammy wins, perhaps due to the small sample on which differentiation is calculated: significance is greater for differentiation from non-Grammy winners and non-nominees (who are lower status, but also for differentiation from artists in *Billboard* (who are higher status). These findings suggest the presence of a more general form of differentiation.

Next, we examined measurement artifacts in Table E3. We re-estimated the main model (Model 5.5) to see whether the findings depend on any one of the specific awards included, and excluded the variables for each of the four awards in sequence. The patterns are similar to the main findings (but one coefficient in one of the models does not show statistical significance). Bias in the estimates can also result from some albums having limited information about musical styles to calculate stylistic distance. To check robustness, we replicated Model 5.5 including only albums with at least two styles. The point estimates are similar and suggest no different interpretation. Next, we excluded albums of classical music in the sample, because these albums often contain music that can be composed prior to the recording. Although selecting and performing the compositions to include in a classical album involves original artistic work, such acts differ in some ways from musical production in other genres (Toynbee 2000). The estimates show a similar pattern to the previous models.

We also examined possible bias in the evaluation of genres, particularly Pop/Rock albums, which can shape selection in the data or likelihood of categorization. We reasoned that if artistic differentiation is simply a measure of change in reception rather than production, the differences between winners and nominees could be explained by changing audience preferences. These differences, in turn, could be reflected in evaluation bias by critics, in this case the AllMusic experts. An indication of this effect could be observed in differences in critical evaluation by genre.

In Table E4, we examined whether critical ratings, number of stars from one to five in the case of AllMusic, vary by genre. Using fixed-effects regressions with artist experience and year or release as additional controls and Pop/Rock as the reference category, we do not find significant differences in ratings between genres, with the exception of albums in the Vocal genre. In unreported analyses, we also explored the effects of interactions between the Grammy win and nomination variables and genre dummies. The patterns do not differ from Table E4.

In other analyses (details not reported here for brevity), we explored interactions of the Grammy effects with time periods. We did not find evidence of moderating effects on stylistic distance of interactions associated with (1) the changes in the Grammy selection and voting system; (2) the agreement between music distributors and retailers to affix stickers for Grammy nominees and winners to improve music marketing campaigns; (3) the trends in audio formats for music recording and reproduction (vinyl, cassette, CD, digital); or (4) the levels of market concentration in the U.S. record music industry.

Table E1. Regression Estimates of Genre Classification

	Model 1	*Model 2*	*Model 3*	*Model 4*
Variable	***Pop/Rock Album***	***Different Genre from Prior Albums***	***Number of Genres***	***Number of Styles***
Grammy win	.244	.517	.052	.032
	(.679)	(.863)	(.31)	(.122)
Grammy nomination	.157	–.184	–.015	.028
	(.175)	(.200)	(.012)	(.047)
Experience	–.088	1.014**	.028**	–.472***
	(.164)	(.317)	(.009)	(.036)
Year	–.038**	–.068	–.031**	–.020
	(.015)	(.94)	(.011)	(.043)
Primary genre		Included	Included	Included
Primary genre × Year		Included	Included	Included
Constant			64.452**	39.501
			(22.285)	(86.444)
Log likelihood	–635.855	–450.979		
R^2			.08	.39
Observations	2,082	1,815	45,012	45,012

Note: Models 1 and 2 are fixed-effects logit regressions; Models 3 and 4 are fixed-effects regressions. Robust standard errors are in parentheses. The data include Grammy nominees including winners, and a matched sample of non-Grammy nominees. The matched group was selected using Coarsened Exact Matching (CEM) procedure. Experience is log-transformed. Dummies for primary genre of each album and dummies for interactions between primary genre of each album and year are included but not reported (Models 2, 3, and 4).
*$p < .05$; **$p < .01$; ***$p < .001$ (two–tailed).

Table E2. Regression Estimates of Artistic Differentiation from Other Artists

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*	*Model 7*
Variable	***Stylistic Distance from All Artists***	***Stylistic Distance from Other Grammy Winners***	***Stylistic Distance from Non-Grammy Winners***	***Stylistic Distance from Other Grammy Nominees***	***Stylistic Distance from Non-Grammy Nominees***	***Stylistic Distance from Other Artists in Billboard***	***Stylistic Distance from Other Artists Not in Billboard***
Grammy win	.036*	.005	.035*	.029	.035*	.034*	.014
	(.014)	(.029)	(.015)	(.020)	(.015)	(.036)	(.014)
Grammy nomination	–.021**	–.028**	–.030***	–.030***	–.029***	–.027***	–.012*
	(.006)	(.011)	(.006)	(.008)	(.006)	(.014)	(.006)
Stylistic distance from prior own albums	.138***						
	(.011)						
Experience	–.044***	.011	–.031***	–.023***	–.031***	–.043***	–.027***
	(.004)	(.008)	(.005)	(.006)	(.005)	(.005)	(.005)
Year	.001	.002	–.007	.003	–.007	.024	.009
	(.005)	(.010)	(.005)	(.007)	(.005)	(.006)	(.005)
Primary genre	Included	Included	Included	Included	Included	Included	Included
Primary genre × Year	Included	Included	Included	Included	Included	Included	Included
Constant	–.471	–3.505	15.382	–5.78	15.533	–46.766**	17.86
	(10.232)	(20.313)	(10.908)	(14.203)	(10.893)	(12.203)	(10.257)
R^2	.18	.01	.48	.23	.47	.34	.11
Observations	45,012	45,012	45,012	45,012	45,012	45,012	45,012

Notes: Estimates are obtained with artist fixed-effects regression. Robust standard errors are in parentheses. The data include Grammy nominees including winners, and a matched sample of non-Grammy nominees. The matched group was selected using Coarsened Exact Matching (CEM) procedure. Experience is log-transformed. Dummies for primary genre and for interactions between primary genre of each album and year are included but not reported.
**p* < .05; ***p* < .01; ****p* < .001 (two–tailed).

Table E3. Regression Estimates of Artistic Differentiation from Other Artists

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*
Variable			***Stylistic Distance***			
	Excludes *Best Album Award*	**Excludes *Best New Artist Award***	**Excludes *Best Song Award***	**Excludes *Best Record Award***	**Excludes Albums with Fewer than 2 Styles**	**Excludes Classical Music Albums**
Grammy win	.041*	.034*	.052**	.026	.032*	.035*
	(.018)	(.015)	(.019)	(.020)	(.014)	(.014)
Grammy nomination	–.032***	–.022**	–.030***	–.019*	–.026***	–.022***
	(.008)	(.006)	(.008)	(.008)	(.005)	(.006)
Experience	–.041***	–.041***	–.041***	–.040***	–.013	–.040***
	(.004)	(.004)	(.004)	(.004)	(.007)	(.004)
Year	–.001	–.001	–.001	–.001	.001	.002
	(.005)	(.005)	(.005)	(.005)	(.006)	(.005)
Primary genre	Included	Included	Included	Included	Included	Included
Primary genre × Year	Included	Included	Included	Included	Included	Included
Constant	2.063	2.079	2.169	2.191	1.622	5.153
	(10.330)	(10.334)	(10.333)	(10.339)	(11.091)	(10.443)
R^2	.16	.16	.16	.16	.21	.17
Observations	45,012	45,012	45,012	45,012	12,274	44,226

Note: Estimates are obtained with artist fixed-effects regressions. Robust standard errors are in parentheses. The data include Grammy nominees (including winners) and a matched sample of non-Grammy nominees. The matched group was selected using Coarsened Exact Matching (CEM) procedure. Experience is log-transformed. Dummies for primary genre of each album and dummies for interactions between primary genre of each album and year are included but not reported.

*$p < .05$; **$p < .01$; ***$p < .001$ (two–tailed).

Table E4. Regression Estimates of Critical Ratings

	Model 1
Variable	*AllMusic Rating*
Experience	–.314***
	(.038)
Year	.020***
	(.003)
Avant-Garde	–.213
	(.249)
Blues	.183
	(.202)
Children’s	.157
	(.378)
Classical	.294
	(.275)
Comedy/Spoken	.161
	(.467)
Country	.014
	(.123)
Easy Listening	–.008
	(.343)
Electronic	–.083
	(.265)
Folk	.210
	(.165)
Holiday	.004
	(.160)
International	.001
	(.202)
Jazz	.158
	(.136)
Latin	–.410
	(.384)
New Age	–.425
	(.743)
R&B	.257
	(.173)
Rap	.163
	(.786)
Reggae	.255
	(.988)
Religious	.188
	(.307)
Stage & Screen	–.090
	(.182)
Vocal	–.429*
	(.198)
Constant	–36.162***
	(5.260)
R^2	.02
Observations	12,105

Note: Estimates are obtained with artist fixed-effects regression. Robust standard errors are in parentheses. The data include Grammy nominees including winners, and a matched sample of non-Grammy nominees. The matched group was selected using Coarsened Exact Matching (CEM) procedure. Experience is log-transformed. Omitted category is Pop/Rock.
**p* < .05; ***p* < .01; ****p* < .001 (two–tailed).

Part F. Endogeneity Checks

We examined possible bias that might arise from endogeneity in the classification of genres and styles in the AllMusic data. A specific concern is that albums may be categorized into a genre not because of the music an artist made, but because the artist or album was nominated or won a Grammy.

First, we conducted additional analyses and modeled the probability that a genre is assigned to an album by AllMusic using genre predicted by the sonic features from the EchoNest/Spotify data, the Grammy win, and nomination variables. If album categorization was influenced by Grammys, then we would expect to see statistically significant coefficients for the win and nomination variables. The estimates included additional controls. One such control is number of genres. About 10 percent of albums in the data have two or more genres, which should increase the likelihood of any one genre to be assigned to an album. To estimate this model, we expanded the album dataset to include all possible album-genre combinations.

The estimates in Model 1 in Table F1 show that the probability of genre assignment is significantly associated with genre predicted by sonic features and multiple genres, but not the Grammy win or nomination variables. In Model 2, we excluded albums with multiple genres rather than controlling for them and observed the same pattern of findings. In these models, we do not find evidence of main effects of Grammy nominations and wins on genre assignments. We conducted a related test predicting an album's genre count as a function of the concentration of the predicted album likelihoods from sonic features, the Grammy variables, and other controls. The goal was to test whether winning albums were seen as more boundary spanning than they are. We used a Herfindahl index to measure concentration of the likelihoods. For example, if an album is predicted P(Pop/Rock) = .7, P(Jazz) = .3, then the Herfindahl would be .49 + .09 = .58. The estimates were obtained with negative binomial regressions and did not show evidence of Grammys influencing assigned genre counts.

We also examined the probability a style is assigned to an album by AllMusic as a function of the Grammy win and nomination variables. Similar to assigning a genre, if album categorization was influenced by Grammys, then we would expect to see statistically significant coefficients for the win and nomination variables. To predict styles, we could use a deep learning model that predicts styles from sonic features, but we do not have enough data—the model would have a very low prediction performance. Instead, we estimated a model with fixed effects for style and additional controls. We used a linear probability model because a logit model of the kind estimated for Models 1 and 2 could not converge. In Model 3, we present estimates that show winning a Grammy and being nominated do not have significant effects on observing a specific musical style.

Table F1. Regression Estimates of Observed Genre Categorization

	Model 1	*Model 2*	*Model 3*
Variable	***Observed Genre***	***Observed Genre***	***Observed Style***
Grammy win	.016	.009	.0001
	(.064)	(.067)	(.0001)
Grammy nomination	–.017	–.018	–.0001
	(.025)	(.026)	(.0001)
Genre predicted	7.251***	7.293***	
	(.013)	(.014)	
Genre spanning album	.470***		
	(.035)		
Experience	.026*	.026*	.0001**
	(.011)	(.011)	(.00004)
Year	–.003	–.004	2.90e–08
	(.011)	(.017)	(6.20e–06)
Primary genre	Included	Included	Included
Primary genre × Year	Included	Included	Included
Constant			.003
			(.012)
Log likelihood	–187,754.16	–179,434.67	
R^2			.03
Observations	2,751,021	2,720,021	137,416,891

Note: Estimates are obtained with artist fixed-effects regression. Robust standard errors are in parentheses. The data include Grammy nominees including winners, and a matched sample of non-Grammy nominees. The matched group was selected using Coarsened Exact Matching (CEM) procedure. Experience is log-transformed. Dummies for primary genre of each album and dummies for interactions between primary genre of each album and year are included but not reported.
**p* < .05; ***p* < .01; ****p* < .001 (two–tailed).

Next, we describe an earlier data collection effort that allowed us to examine whether and how frequently the data was updated. For a separate earlier project, we conducted an initial data collection from the AllMusic archive that coded information in the database as it appeared between May and October of 2010. When we sought the data for this project in late 2018, rather than merging old and new data, we collected the information from the AllMusic archive anew. This situation gave us the opportunity to compare the old and new data, and to determine whether the old data were later reclassified. We conducted two comparisons, one specific and the other more general. The specific comparison was for the artists and albums nominated for the 2011 Grammy Awards. In 2010, we collected the data before the 2011 Grammy nominations and selections (nominations take place between November and December, and winners are announced in March of the next year). All the artists shortlisted for the four major prizes analyzed in the study were included in the data. For this comparison, we did not observe any case of reclassification of genres and styles for winners and nominees.

We also examined the re-categorization of Grammy winners and nominees in the whole of the data. We found only one album of a Grammy-winning artist that was recategorized since 2010—Seal's 2008 album *Soul*. Note that this album did not contain music that was nominated or won a Grammy—Seal won two Grammys for *Best Song of the Year* and *Best Record of the Year* but in 1995. So it seems unlikely that the recategorization of the 2008 album *Soul* was due to the 1995 awards. Seal's *Soul* album was categorized as Pop/Rock and R&B in 2010, and in 2018 was only Pop/Rock. In terms of styles, the album had styles Adult Contemporary, Neo Soul, and Soul, and now it was Adult Contemporary and Adult Contemporary R&B. Neo Soul is considered a substyle of Contemporary R&B (https://www.allmusic.com/style/neo-soul-ma0000004426). This single case of reclassification corresponds to .20 percent of the albums of Grammy winners, similar to the value for the whole sample. For nominees, we observed a reclassification of seven albums, or .6 percent of the albums of Grammy nominees. Four are now Holidays and used to be R&B, Pop/Rock, or religious. As mentioned earlier, the exclusion of albums in the Holidays genre produces a pattern of findings similar to what is reported in the main analyses.

We also compared the data more generally beside the music that received Grammy nominations of wins. We examined recategorization of all albums in the data and found that .18 percent of albums (68 of them) showed a change in genre between 2010 and 2018. Table F2 reports regression estimates of overlap in genre categorization for the albums with year of release and genre dummies as covariates. We did not find any significant coefficient for the release year dummies, and for brevity we do not report them. For genres, we find one significant coefficient for Holiday albums. (Avant-Garde was used as the omitted category.) Nine albums were recategorized as Holiday: four were previously Pop/Rock, three R&B, one Religious, and one Vocal. While the significant result for Holiday indicates that albums in this genre can introduce some bias in the estimates, the very small number of cases also suggests the bias is unlikely to change the pattern of results we report. When we re-estimated our main model (Model 5.5 in text) excluding Holiday albums ($N = 49$), the effects of the Grammy win and nomination variables remain very similar to those reported in the main analysis ($\beta = .031$; p-value $= .03$) and ($\beta = -.020$; p-value ~ 0).

Table F2. Regression Estimates of Genre Overlap between First and Second Data Collections

	Model 1
Variable	***Genre Overlap***
Blues	–.062
	(.035)
Children's	.0004
	(.001)
Classical	–.005
	(.003)
Comedy/Spoken	–.0004
	(.001)
Country	.001
	(.001)
Easy Listening	–.041
	(.030)
Electronic	–.029
	(.016)
Folk	–.015
	(.011)
Holiday	–.561***
	(.123)
International	–.024
	(.017)
Jazz	–.001
	(.001)
Latin	.001
	(.001)
New Age	.0003
	(.001)
Pop/Rock	–.001
	(.001)
R&B	–.007
	(.004)
Rap	–.0002
	(.001)
Reggae	–.001
	(.001)
Religious	–.079
	(.044)
Stage & Screen	.001
	(.002)
Vocal	–.005
	(.007)
Year dummies	Included
Constant	–36.162***
	(5.260)
R^2	.09
Observations	38,236

Note: Estimates are obtained with artist fixed-effects regression. Robust standard errors are in parentheses. *p < .05; **p < .01; ***p < .001 (two–tailed).

Part G. Analysis of Critical Response to Grammy Nominations

We collected data on the year-end top-40 critics list published by the *Village Voice* from 1971 to 2018. Based on a polling of hundreds of popular music critics (van Venrooij and Schmutz 2021), this list is published at the end of each year, typically after the announcement of the Grammy nominations but before the winners' selection. We estimated a logit regression of an album appearing on this list of best albums with Grammy nomination in any of the general interest categories and stylistic distance as main covariates (additional controls include artist experience, major record label release, a linear year trend, primary genre dummies, and their interaction with year). In Table G1, Model 1 shows a positive and significant statistical association between Grammy nominations and being listed among the best albums of the year. The estimates show a positive but not significant association between stylistic distance of an album and critics listing it among the best albums of the year. These findings suggest that while attention and legitimation with the critics' audience are positively associated with nomination for an award, they are not necessarily associated with artistic differentiation post-award.

Table G1. Regression Estimates of Likelihood of Being Listed in Best Albums of the Year by the *Village Voice's Pazz and Jop Poll*

	Model 1
Variable	***Listed in Pazz & Jop***
Grammy nomination	1.825***
	(.242)
Stylistic distance	.320
	(.428)
Experience	.272***
	(.061)
Major record label	.842***
	(.143)
Year	.035
	(.050)
Primary genre	Included
Primary genre × Year	Included
Constant	.434**
	(.006)
Log likelihood	–377.402
Observations	38,750

Note: Estimates are obtained with random-effects logit regression. Robust standard errors are in parentheses. The data include Grammy nominees including winners, and a matched sample of non-Grammy nominees. The matched group was selected using Coarsened Exact Matching (CEM) procedure. Experience is log-transformed. Dummies for primary genre and for interactions between primary genre of each album and year are included but not reported.
**p* < .05; ***p* < .01; ****p* < .001 (two–tailed).

Part H. Analysis of Pulitzer Prize for Music

Named after pioneer journalist Joseph Pulitzer, the Pulitzer Prize for Music was first given in 1943 and is awarded for a distinguished musical composition "of significant dimension by an American that has had its first performance in the United States during the year." The prize includes a monetary component of 15,000 dollars, but its significance is primarily symbolic. Jurors for the award include past winners, music composers, academics, critics, and other artists. Considered perhaps the highest achievement in musical excellence, the Pulitzer Prize was typically awarded to Classical and Avant-Garde music. The definition and entry requirements beginning with the 1998 competition were broadened to attract a wider range of American music, particularly Jazz. In 2018, the prize was awarded to the first Rap artist (Kendrick Lamar).

In Table H1, we replicate the estimations of the main analyses of artistic differentiation (Models 4.2–4.5) using dummies for post-Pulitzer Prize nomination and win as covariates. The prize was awarded in many instances to compositions that were not recorded or artists who had a limited number of album recordings. The estimates are obtained with random-effects regressions. We find similar patterns in the regressions with the Pulitzer Prize as well, ensuring a more general validity of the findings that awards increase artistic differentiation for winners and decrease differentiation for nominees.

Table H1. Regression Estimates of Artistic Differentiation from Other Artists Following Pulitzer Prize in Music

	Model 1	***Model 2***	***Model 3***	***Model 4***
Variable	***Stylistic & Sonic Distance***	***Stylistic & Sonic Distance***	***Sonic Distance***	***Stylistic Distance***
Pulitzer win	.079*	.122***	.006	.128***
	(.038)	(.018)	(.019)	(.021)
Pulitzer nomination		–.121***	–.119***	–.056*
		(.020)	(.022)	(.023)
Experience	–.028	–.021	–.021	–.022
	(.043)	(.043)	(.045)	(.044)
Year	–.003	–.003	.023	–.004*
	(.002)	(.002)	(.031)	(.002)
Primary genre	Included	Included	Included	Included
Constant	6.876*	6.979*	–3.887	7.473*
	(3.104)	(3.164)	(2.335)	(3.275)
R^2	.76	.77	.12	.63
Observations	61	61	61	61

Note: Estimates are obtained with random-effects regression. Robust standard errors are in parentheses. The data include Pulitzer nominees including winners, and a matched sample of non-Pulitzer nominees. The matched group was selected using Coarsened Exact Matching (CEM) procedure. Experience is log-transformed. Dummies for primary genre of each album are included but not reported.
**p* < .05; ***p* < .01; ****p* < .001 (two–tailed).

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