

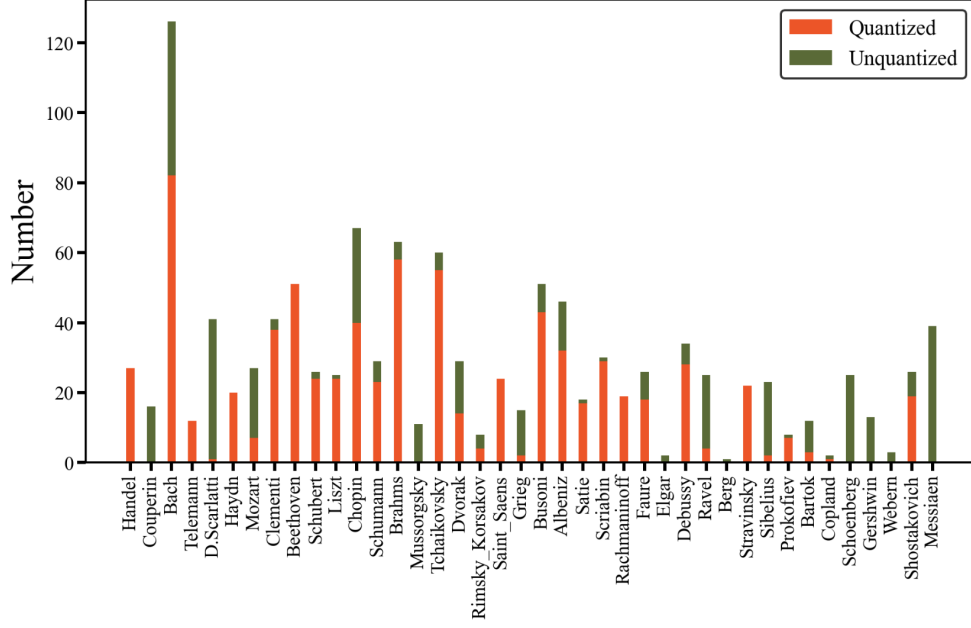


Fig. 1: The proportion of (quantized) score MIDI and (unquantized) performance MIDI for each composer in the dataset. In the entire dataset, quantized MIDI comprises 65.6%, while unquantized MIDI accounts for 34.4%.

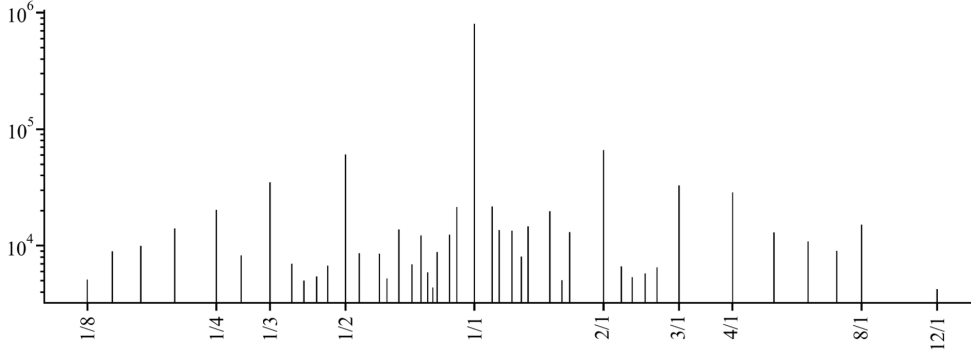


Fig. 2: The figure shows 44 final quantized IOI ratios combining all time resolution.

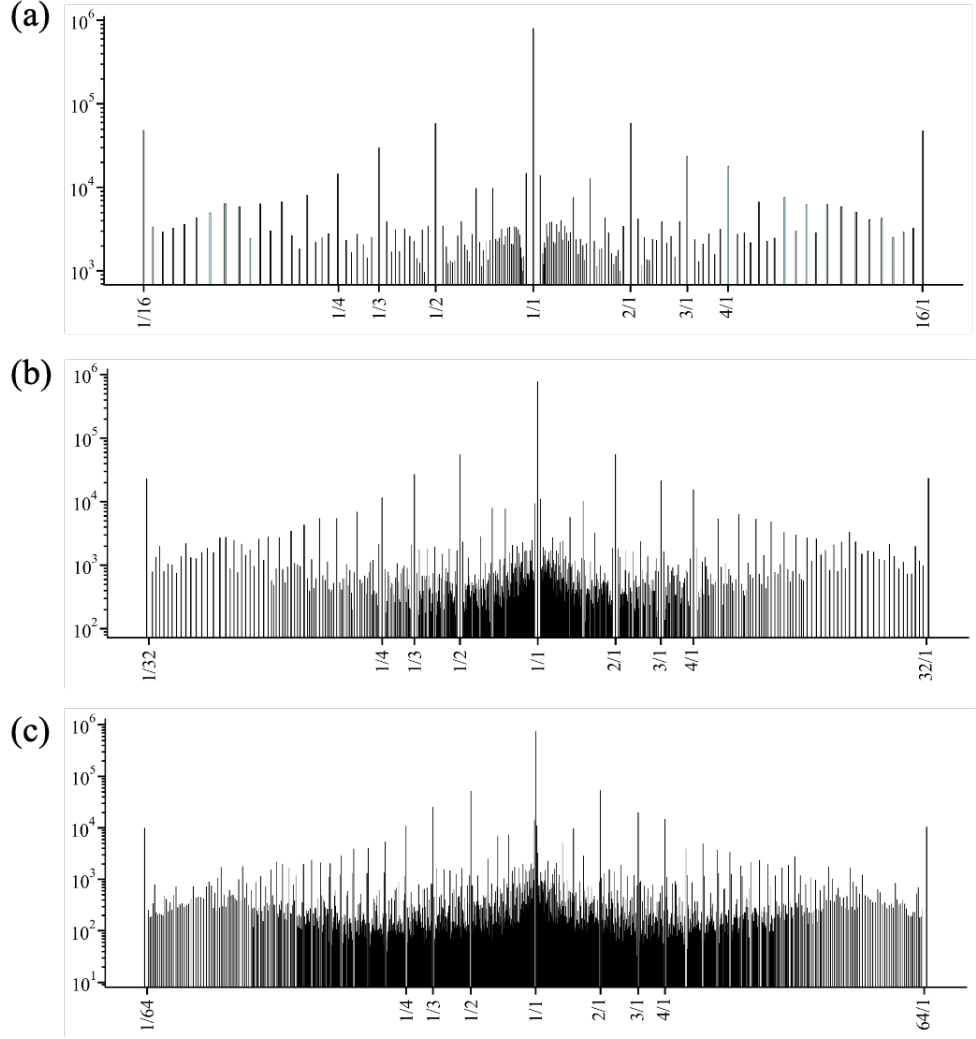


Fig. 3: The histogram of quantized IOI ratios for each time resolution. The figure illustrates candidate IOI ratios, ranging from $1/16$ to $16/1$ (a), ranging from $1/32$ to $32/1$ (b), ranging from $1/64$ to $64/1$ (c), serving as reference points for rhythm quantization. Each bin was delineated by the midpoints between these reference points, with the histogram depicting the number of IOI ratios falling within each bin. To enhance visibility, the x-axis represents the IOI ratio values with a logarithmic scale of base 2. As anticipated, the simplest IOI ratios such as $1/1$, $1/2$, and $2/1$ were the most frequently utilized.

Table 1: A sorted list of 44 IOI ratio categories.

Number	IOI ratio
1	1/8
2	1/7
3	1/6
4	1/5
5	1/4
6	2/7
7	1/3
8	3/8
9	2/5
10	3/7
11	5/11
12	1/2
13	7/13
14	3/5
15	5/8
16	2/3
17	5/7
18	3/4
19	7/9
20	4/5
21	9/11
22	7/8
23	10/11
24	1/1
25	11/10
26	8/7
27	11/9
28	9/7
29	4/3
30	3/2
31	8/5
32	5/3
33	2/1
34	11/5
35	7/3
36	5/2
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38	3/1
39	4/1
40	5/1
41	6/1
42	7/1
43	8/1
44	12/1

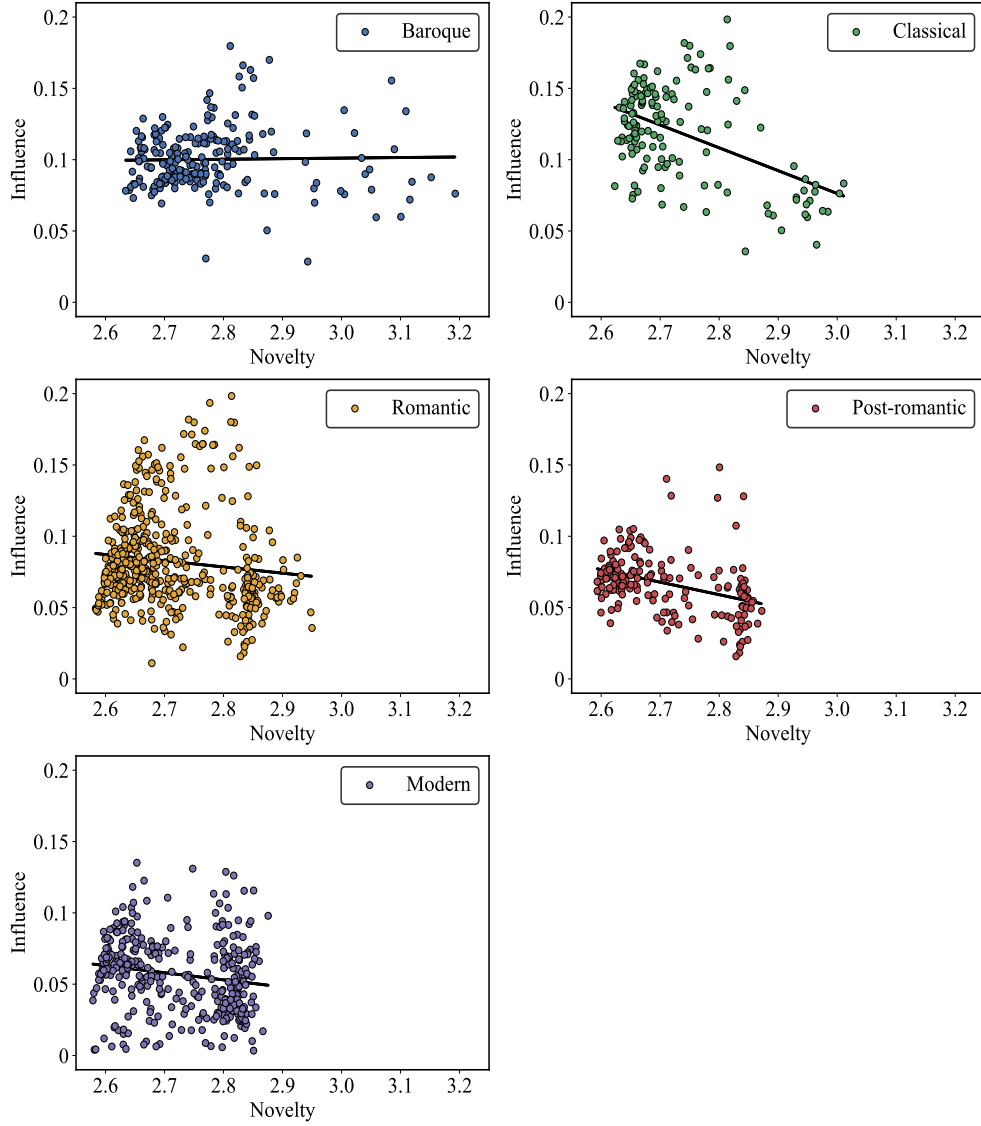


Fig. 4: This scatter plot shows the novelty and influence values of individual pieces, grouped by historical period. The black solid line represents the regression line for each corresponding period. Excluding the Baroque period, which is not statistically significant, the slopes of the regression lines are -0.1601 for the Classical period, -0.0435 for the Romantic period, -0.0878 for the Post-romantic period, and -0.0498 for the Modern period.

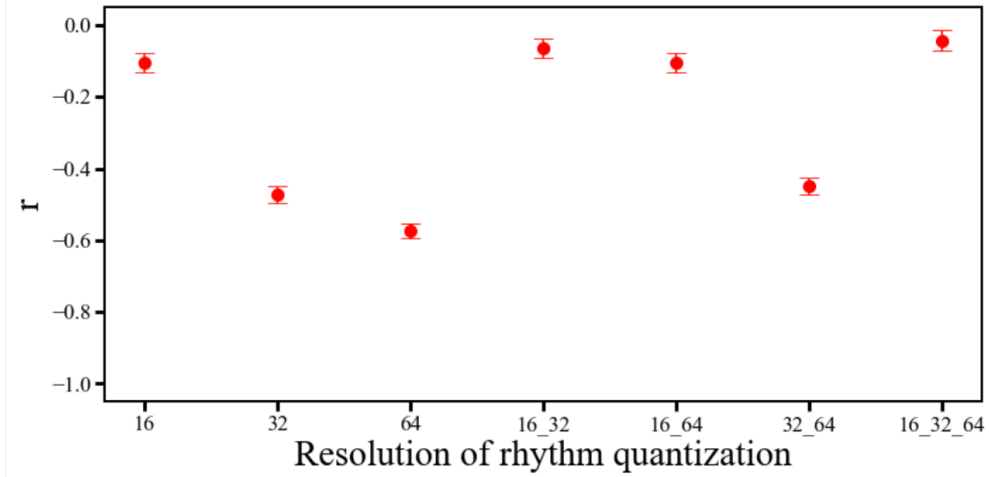


Fig. 5: The figure shows the Pearson correlation coefficients between novelty and influence after applying rhythm quantization at different IOI ratio resolutions. Error bars indicate the jackknife error of the correlation. The x-axis labels represent the resolution used for quantizing IOI ratios: for example, “16” indicates quantization using candidate IOI ratios of 1/16 to 16/1, while “16_32” includes both 1/16 to 16/1 and 1/32 to 32/1 as candidate values. The rightmost label on the x-axis, “16_32_64”, refers to the method used in the main analysis of the paper, where the final quantized IOI ratios were selected using a peak picking algorithm applied to candidate values from all three resolution sets: 1/16 to 16/1, 1/32 to 32/1, and 1/64 to 64/1.

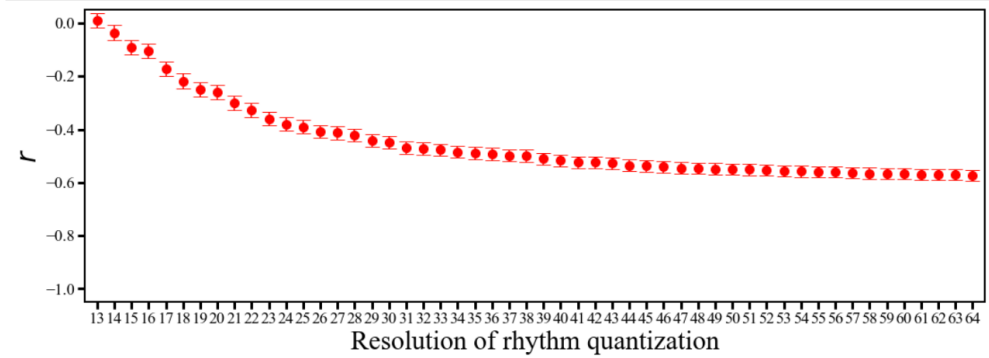


Fig. 6: Pearson correlation coefficient (r) between novelty and influence as a function of rhythmic quantization resolution. The resolution level of 13 corresponds to the coarsest level used in the main analysis, based on quantized IOI ratios. We observe a clear and smooth monotonic decrease in r values as the resolution increases. Except for the resolution at 13—which is overly coarse—all other resolutions yield statistically significant negative correlations. The decline is initially steep (up to resolution 25), after which it becomes more gradual toward the study’s maximum resolution of 64.

Table 2: Fixed and random slope estimates from the Linear Mixed-Effects Model (LMM) for the effect of novelty on influence across historical periods. β^{LMM} denotes the fixed slope; random deviations (b_{1j}^{LMM}) are group-specific.

Era	β^{LMM}	b_{1j}^{LMM}	Actual Slope
Baroque	-0.0422	+0.0300	-0.0122
Classical	-0.0422	-0.0495	-0.0917
Romantic	-0.0422	+0.0067	-0.0355
Post-Romantic	-0.0422	+0.0247	-0.0175
Modern	-0.0422	-0.0001	-0.0423

Applying Linear Mixed Model to Novelty-Influence Scatterplot

As it is possible the relationship between influence and novelty (i.e., the slope of the regression line) depends on the periods, we conducted a linear mixed model that accounts for the effects among compositions belonging to the same periods: laying out the mixed model in the following form,

$$Y = X\beta + Z\mu + \epsilon \quad (1)$$

where $X\beta$ is fixed effects, $Z\mu$ random effects, and ϵ is random errors. We applied it to the scatter plot in Figure 3 of the main text to yield the following result:

$$\text{influence}_{ij} = \gamma^{\text{LMM}} + \beta^{\text{LMM}} * \text{novelty}_{ij} + b_{0j}^{\text{LMM}} + b_{1j}^{\text{LMM}} * \text{novelty}_{ij} + \epsilon_{ij} \quad (2)$$

- influence_{ij} : influence value for i^{th} song in j^{th} musical era
- novelty_{ij} : novelty value for i^{th} song in j^{th} musical era
- γ^{LMM} : fixed intercept
- β^{LMM} : fixed slope
- b_{0j}^{LMM} : random intercept for j^{th} musical era
- b_{1j}^{LMM} : random slope for j^{th} musical era

In the first application of this method, we noted that the works by transitional composers such as Beethoven who is considered to belong to both the Classical and Romantic eras are set to belong to both to avoid arbitrariness. However, also to avoid arbitrarily inflating random effects due to such multi-membership, we normalized the Z matrix so that in Beethoven's case it is $[0, 0.5, 0.5, 0, 0]$.

Using this approach, the estimated slopes for each era from the mixed model were as follows: $-0.0122, -0.0917, -0.0355, -0.0175, -0.0423$, and the estimated intercepts were: $0.1870, 0.2690, 0.1851, 0.1572, 0.1712$. (Please refer to the Figure 7, Table 2, and Table 3.)

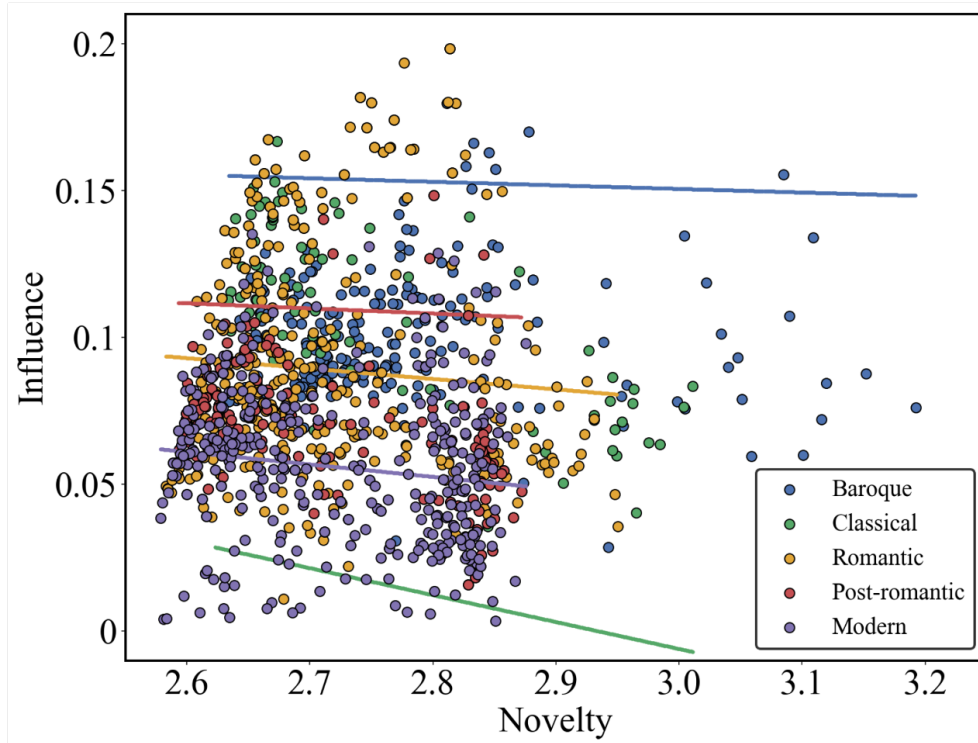


Fig. 7: Scatter plot with regression lines per period estimated using a linear mixed model.

Since the number of compositions varies across eras, however, there is a possibility that the model may not fully capture clear distinctions between era-specific effects. Furthermore, the issue of multiple era memberships may blur the estimated random effects. To increase the reliability of our mixed model results, therefore, we conducted an additional analysis. Specifically, we performed separate mixed model analyses using binary grouping for each era: compositions that belonged to a given era were labeled as 1, and all others as 0. This binary grouping allowed us to isolate the effect of each era more clearly. As a result of these analyses, we estimated the fixed and random slopes and intercepts for each binary grouping (in-era vs. out-of-era), and computed the overall slopes and intercepts by summing the fixed and random components. A summary of these results is provided in Figure 8, Table 4, and Table 5.

In summary, we were able to more effectively differentiate the eras using the mixed model, while reconfirming that our original observation—the influence tends to decrease as novelty increases—was still valid.

Table 3: Fixed and random intercept estimates from the Linear Mixed-Effects Model (LMM) for the effect of novelty on influence across historical periods. γ^{LMM} denotes the fixed intercept; random deviations (b_{0j}^{LMM}) are group-specific.

Era	γ^{LMM}	b_{0j}^{LMM}	Actual Intercept
Baroque	0.1734	+0.0136	0.1870
Classical	0.1734	+0.0956	0.2690
Romantic	0.1734	+0.0117	0.1851
Post-Romantic	0.1734	-0.0162	0.1572
Modern	0.1734	-0.0022	0.1712

Table 4: Estimated fixed and random slopes from the binary-grouping LMM analyses. For each era, compositions were divided into two groups: in-era (1) and out-of-era (0).

Era	Group	Fixed Slope	Random Slope	Actual Slope
Baroque	In-era	-0.0303	0.0264	-0.0039
	Out-of-era	-0.0303	-0.0264	-0.0567
Classical	In-era	-0.0805	-0.0792	-0.1597
	Out-of-era	-0.0805	0.0792	-0.0013
Romantic	In-era	-0.0201	-0.0143	-0.0344
	Out-of-era	-0.0201	0.0143	-0.0058
Post-Romantic	In-era	-0.0408	-0.0229	-0.0637
	Out-of-era	-0.0408	0.0229	-0.0179
Modern	In-era	-0.0304	-0.0088	-0.0392
	Out-of-era	-0.0304	0.0088	-0.0216

Table 5: Estimated fixed and random intercepts from the binary-grouping LMM analyses. For each era, compositions were divided into two groups: in-era (1) and out-of-era (0).

Era	Group	Fixed Intercept	Random Intercept	Actual Intercept
Baroque	In-era	0.1701	-0.0591	0.1110
	Out-of-era	0.1701	0.0591	0.2292
Classical	In-era	0.3168	0.2389	0.5557
	Out-of-era	0.3168	-0.2389	0.0779
Romantic	In-era	0.1347	0.0410	0.1757
	Out-of-era	0.1347	-0.0410	0.0937
Post-Romantic	In-era	0.1854	0.0546	0.2400
	Out-of-era	0.1854	-0.0546	0.1308
Modern	In-era	0.1562	0.0076	0.1638
	Out-of-era	0.1562	-0.0076	0.1486

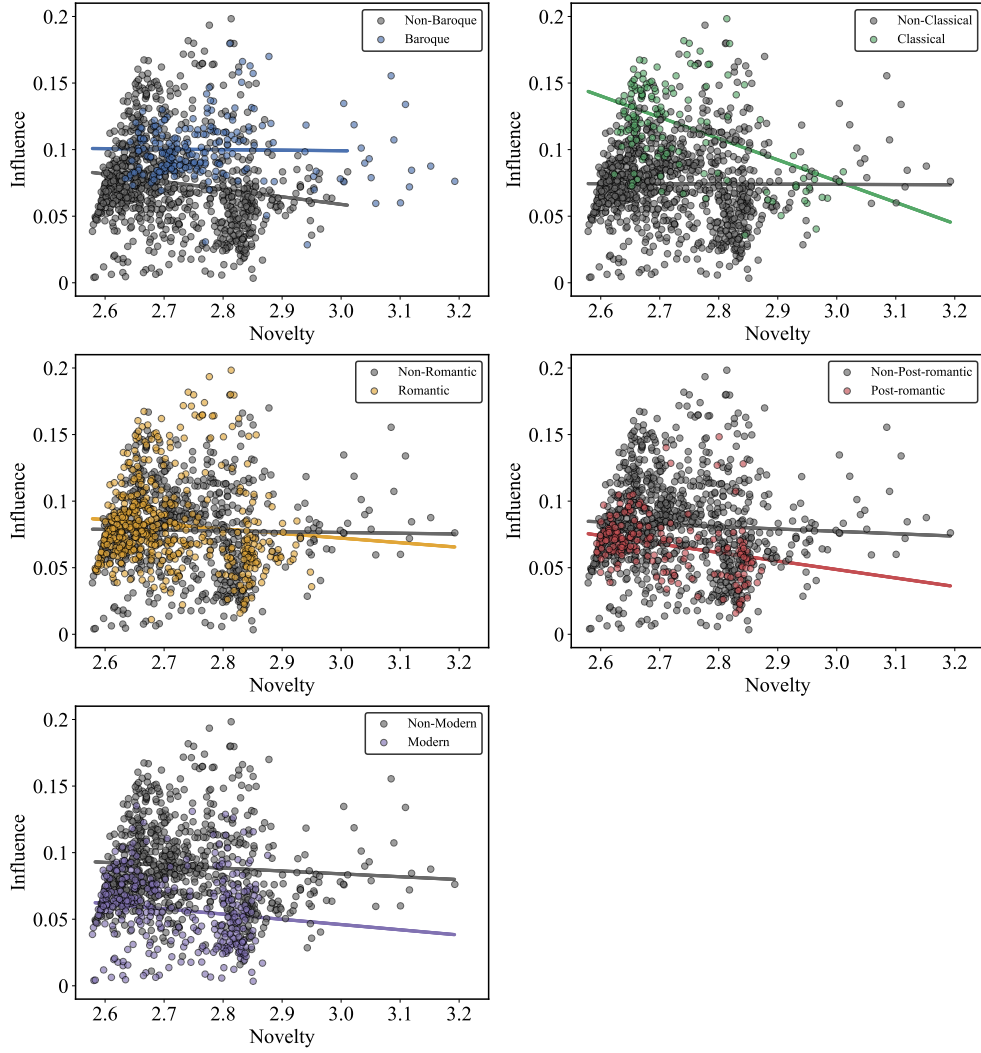


Fig. 8: Mixed model analyses using binary grouping for each era: compositions that belonged to a given era were labeled as 1, and all others as 0. This binary grouping allowed us to isolate the effect of each era more clearly.

Table 6: PCC of the novelty-influence scatterplot by musical era

Era	PCC $\pm$ jackknife error
Baroque	0.0204 ± 0.0829
Classical	-0.4818 ± 0.0718
Romantic	-0.1174 ± 0.0426
Post-romantic	-0.3607 ± 0.0781
Modern	-0.1689 ± 0.0534

Table 7: PCC of the novelty-influence scatterplot by composer

Composer	PCC $\pm$ jackknife error
Prokofiev	0.7281 ± 0.1774
Shostakovich	0.6800 ± 0.1109
Beethoven	0.5499 ± 0.1180
Bach	0.4203 ± 0.0810
Brahms	0.3996 ± 0.1426
Liszt	0.2843 ± 0.2548
Schumann	0.2067 ± 0.2270
Gershwin	0.1765 ± 0.2568
Stravinsky	0.1495 ± 0.2480
Schoenberg	0.1127 ± 0.2338
Haydn	0.0492 ± 0.2624
Busoni	-0.0322 ± 0.1461
Bartok	-0.0495 ± 0.4767
Rachmaninoff	-0.0822 ± 0.2466
Faure	-0.0971 ± 0.1301
Tchaikovsky	-0.1413 ± 0.0806
Schubert	-0.1518 ± 0.1604
Handel	-0.2671 ± 0.2176
Dvorak	-0.2859 ± 0.1315
Messiaen	-0.2981 ± 0.2777
Couperin	-0.3197 ± 0.1659
Debussy	-0.3243 ± 0.1501
Satie	-0.3307 ± 0.1678
Albeniz	-0.4381 ± 0.1872
Scriabin	-0.4470 ± 0.1766
Saint Saens	-0.4626 ± 0.2150
Sibelius	-0.4967 ± 0.2297
Rimsky Korsakov	-0.4992 ± 0.2196
Clementi	-0.5047 ± 0.1645
Ravel	-0.5198 ± 0.1531
Telemann	-0.5200 ± 0.3060
Chopin	-0.5411 ± 0.0877
Grieg	-0.6752 ± 0.1789
D.Scarlatti	-0.7122 ± 0.3067
Mussorgsky	-0.7301 ± 0.1448
Mozart	-0.8652 ± 0.0483

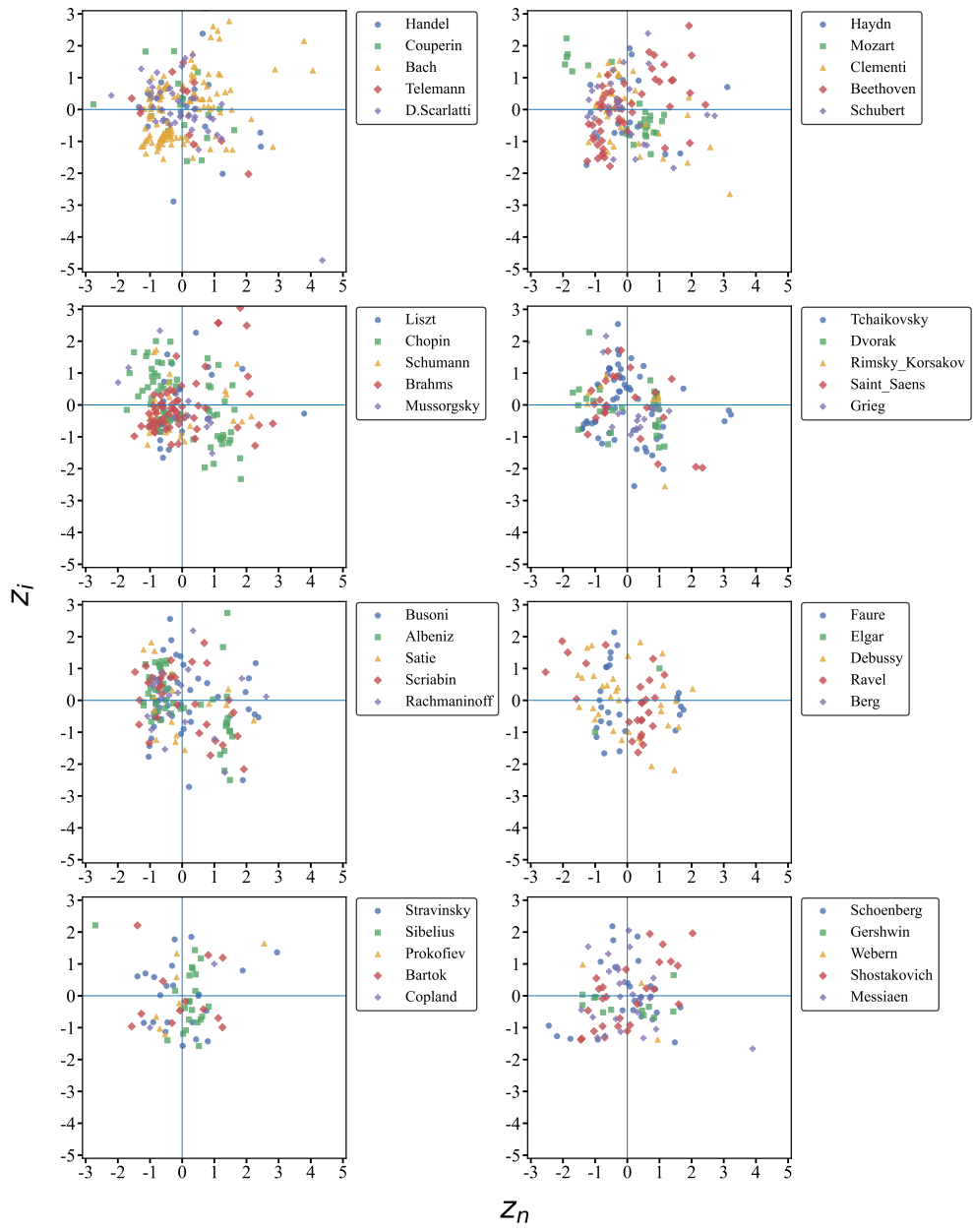


Fig. 9: Z -scores of novelty and influence calculated for all composers in the dataset. Composers are grouped into eight subplots, five per subplot, in chronological order.

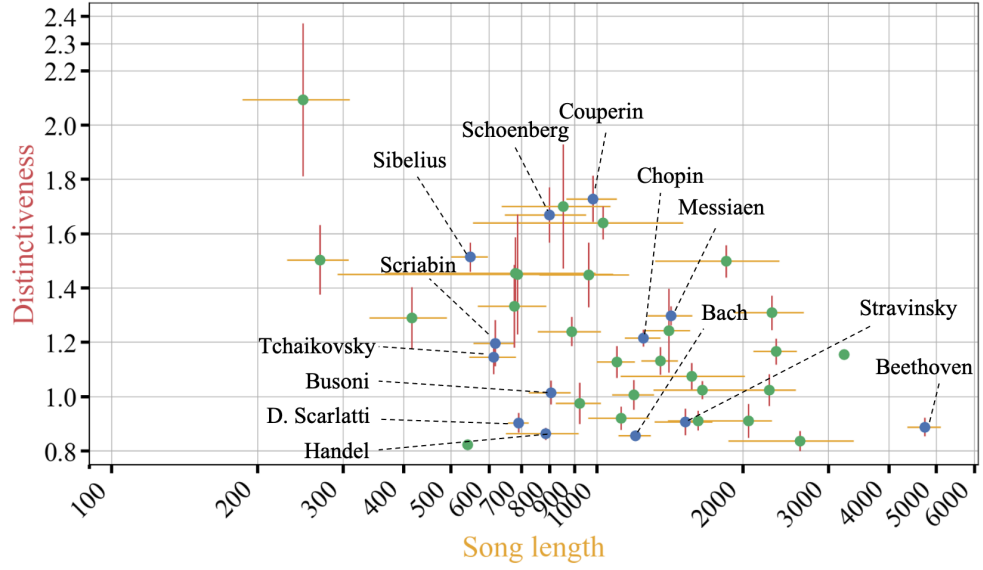


Fig. 10: The mean distinctiveness and composition length of the composers with jackknife error bars. The highlighted blue dots indicate composers who form the pairs compared in Figure 8 in the main text in terms of novelty and distinctiveness.

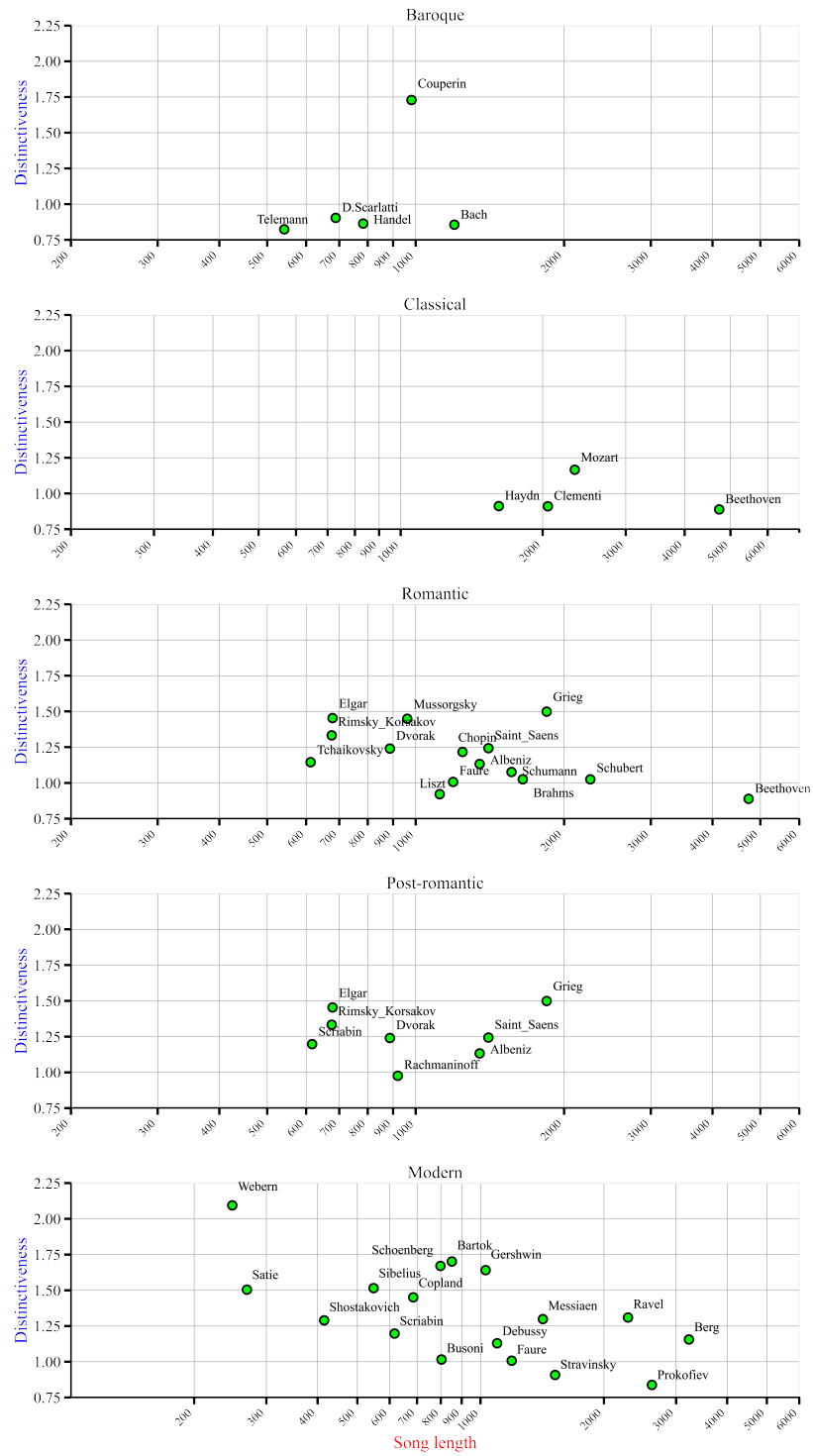


Fig. 11: Average distinctiveness of composers over different eras. The x-axis represents the average length of compositions on a logarithmic scale.