Supporting Information

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SI Materials and Methods

SI Dataset 1

The codeword files for the compositions in our dataset. The file names are also their unique IDs formatted as "composition (or publication) year_composer_piece identifier." For example, the ID of Beethoven's *Für Elise* first publicized in 1867 with catalogue number WoO 59 is "1867_beethoven_WoO59." We created each file by converting the MIDI file of each piece into a sequence of codewords with the measures marked M. Each codeword consists of the MIDI numbers of the notes being separated by bar notations. For example, the codeword $\{C3, C4\}$ is shown as 48|60.

SI Dataset 2

The full list of the compositions in csv format. The list shows the ID, full name, composition or publication year, and the composer.

The distributions for the use of codewords over time

We plot the cumulative distributions $P(n > N)$ of the number of appearances n of the codewords in Fig. 1 over time. The skewed distribution was established early, with the highest value increasing from around 2 000 then saturating near 10 000 after year 1850.

The P- and H-novelty scores of compositions

We show the P- and H-novelty scores of compositions in our dataset in Figs. 2 A and B. The works show greater variations than the composers, but the trend (of a dip during the Classical period) is detectable.

The P- and H-novelty scores stability using ablation analysis with subsampled datasets

To test the stability of the measurement and analysis under incomplete date, we randomly subsampled the data and saw how the measures changed for the P- and H-novelty. The purpose of the subsampling is to simulate the missing data. We randomly sampled 75%, 50%, and 25% of the composers' pieces (100 such subsamples each). The results are shown in Figs. 3 and 4. The average scores are marked with colored dots, their standard errors are drawn with error bars and the black stars indicate the original P- and H-novelty scores with all available data. The overall trends are stable (a dip during the Classical period and an increase afterwards).

Musical influence of all composers during the Romantic period

Fig. 5 shows the influence scores of all Romantic composers, some of whom were omitted in Fig. 5 (from the main paper) for clarity.

Musical influence between composers

The influence dynamics in Figs. 5 (from the main paper) and 5 serves as the quantitative justification of "period" as a term for referring to a certain style based on works that are heavily referenced. Beyond the aggregate influence shown in the main text, one can also study the person-to-person influence network. We define the edge weight $\eta_{\mathrm{C}\to\mathrm{D}}$ to be the influence of composer C (the set of works by C to be precise) on composer D (the set of works by D) given by the average influence C on D, $\eta_{\mathrm{C}\to\mathrm{D}} \equiv \frac{1}{|\mathrm{D}|}\sum_{\zeta\in\mathrm{D}} \eta_{\mathrm{C}}(\zeta)$. In Fig. 6 we show the backbone of the influence network[1], where the radius of a node is proportional to the sum of its outgoing weights (total average influence onto others) normalized by the maximum edge weight found in each period. The position of the center of each node notes the composer's median year (between their birth and death years).

The significance of Handel is again evident, and now it further shows that the other two Baroque composers' works (Bach and Scarlatti) were influenced to a similar degree by him (Fig. 6 A). As we progress to the Classical period (Fig. 6 B), we see Handel's differing influence on those there; Haydn, as the earlier one of the period, shows the strongest influence from Handel. He is also influenced by Mozart who is younger than himself by 24 years, which was also well noted[2]. The relationship between Haydn and Mozart were mutual, Haydn being credited for having played in a role in the existence of dramatic elements and chromatic chords in Mozart's compositions[3,4]. Clementi does not enjoy such a mutual relationship with others, but borrow heavily from the former ones. But he has a noticeably small total influence on the posterior (small radius), reaffirming his lack of historical novelty, and broadly contribution to music community (Figs. 3 and 5in the main).

The Classical-to-Romantic Transition period sees the introduction of two major composers, Beethoven and Schubert (Fig. 6 C). Beethoven is heavily influenced by Handel, Mozart, and Haydn in particular, matching with historical facts: He idolized Handel, saying "Handel is the greatest composer who ever lived. I would uncover my head and kneel down at his tomb"[5]; He also studied Haydn and Mozart with zeal[3]. But unlike Clementi, Beethoven scores high in musical novelty and the total influence onto his posterior (Figs. 3 and 5in the main). This means that he also actively created novel transitions that his posterior eagerly adopted, fathering the emergence of a new style of music that hadn't existed before and bridging the two eras before and after him. The immediate successor Schubert is a testament to this: Compared with Beethoven, he is less influenced by the past greats than by Beethoven.

Lastly we see by whom each composer is influenced in Fig. 6 D during the Romantic period. We notice that after Beethoven and Schubert, Chopin and Liszt influence the later composers the most. Chopin is heavily influenced by Beethoven and Schubert[3,6]. Liszt, another giant figure of the piano and an even more successful one than Chopin during their time appears more influenced by Beethoven than by Schubert or Chopin. Liszt was openly very fond of the works by Beethoven and Schubert so often arranged and played their works. Also he praised Chopin's outstanding musicality so the elements from Chopin's music can be found in many of his later works[7,8]. Two other greatest Romantic composers, Mendelssohn and Schumann, meanwhile, show exert less influence.

Higher order Markov models for calculating the generation probability

Here we try higher-order Markov models and compare with the first-order Markov.

n-th order Markov model

Markov model is a stochastic model describing a sequence of possible states in which the probability of each state depends only on the previous state. We applied classical Markov model to model the musical piece with the sequence of codewords and estimate its likelihood of being created given a set of previous works, the generation probability. In the n-th order Markov model, the Markov transition depends on n number of previous states. So using the n-th order Markov model the generation probability can be mathematically expressed as follows:

$$\Pi_\Omega(\zeta) = \pi_\Omega(\gamma_1, \cdots, \gamma_n)\pi_\Omega(\gamma_1, \cdots, \gamma_n \to \gamma_{n+1}) \cdots \pi_\Omega(\gamma_{|\zeta|-n}, \cdots, \gamma_{|\zeta|-1} \to \gamma_{|\zeta|}) \tag{1}$$

where ζ is a target piece, Ω is a set of previous works, γ is a codeword, π_Ω is the transition probability from the sequence of codewords with its length n to the next codeword given the set of previous works Ω.

In Fig. 7, we see how the n-grams of codewords are generated and used with different n. As we have seen from the use of single codeword, the use of n-gram codewords is also skewed. In other words, only a few n-gram codewords were used widely, while others were used scarcely, once or twice at most. The difference is the maximum occurrence of the n-grams of codewords. The maximum use of certain n-gram codewords decreases as the order increases. For instance, the maximum occurrence of a single codeword is about 10 000 but it shrinks down to 100 for 10-gram of codewords. This indicates that more transitions are likely to be novel (unused) in the higher order of Markov model, which raises novelty and lowers influence of pieces and composers on average. Despite this we see in Fig. 7 B, the trend of the cumulative number of distinct transitions from the n-grams of codewords over the years is similar; composers from the Classical period (1750–1800) experimented less with new transitions, and there was a steep growth during the early Romantic period (1800–1850) and the growth of harmonic space slowed down during the post Romantic period (1850–1900).

The novelty scores of compositions with the n-th order Markov model are given in Figs. 8 and 9. Although we observe a slight increase in the scores of the Baroque piano pieces, the scores of the Classical-period piano pieces are consistently lower than those of the Baroque and Romantic piano pieces regardless of the order of Markov model.

The novelty scores of composers over time are shown in Figs. 10 and 11. Despite the increasing order of Markov model, the results are again consistent; Classical composers appear to innovate less and the tendency of experimenting with new musical elements starts to grow during the end of the Classical period, the Romantic transition from the Classical. We also note that Debussy's novelty grows noticeably as the order increases. This stems from Debussy's biggest innovation coming from the use of non-traditional scales and chromaticism without too many vertical (simultaneous) notes[3,9] which necessitated looking at longer series of codewords achieved via high-order Markov (Fig. 12). Once under this framework, his musical novelty is comparable to Mendelssohn and Rachmaninoff, two Romantic composers with the highest novelty.

The influence of composers in higher-order Markov are shown in Fig. 13. Although the absolute degree of musical influence decreases with the increasing order of Markov model, the overall trends remain the same when the order of the Markov is not excessive (Fig. 13 E), showcasing the robustness of the first-order Markov.

Musical influence measured by shared codeword transitions

A simpler definition of influence would be the sheer shared number of elements between an old work and a new one, though it does not weight the influence according to the possibility of alternative sources as the version in the main paper naturally does. The result is shown in Fig. 14. The overall patterns of musical influence remains similar, with the biggest influence shown by Handel, Haydn, Mozart, and Beethoven through the years. Note that the number of compositions (correlated with the total number of codewords used) affects influence more now: Handel, Haydn, and Liszt, with large numbers of compositions, show an increase in influence; Schubert, with fewer compositions, decreases.

References

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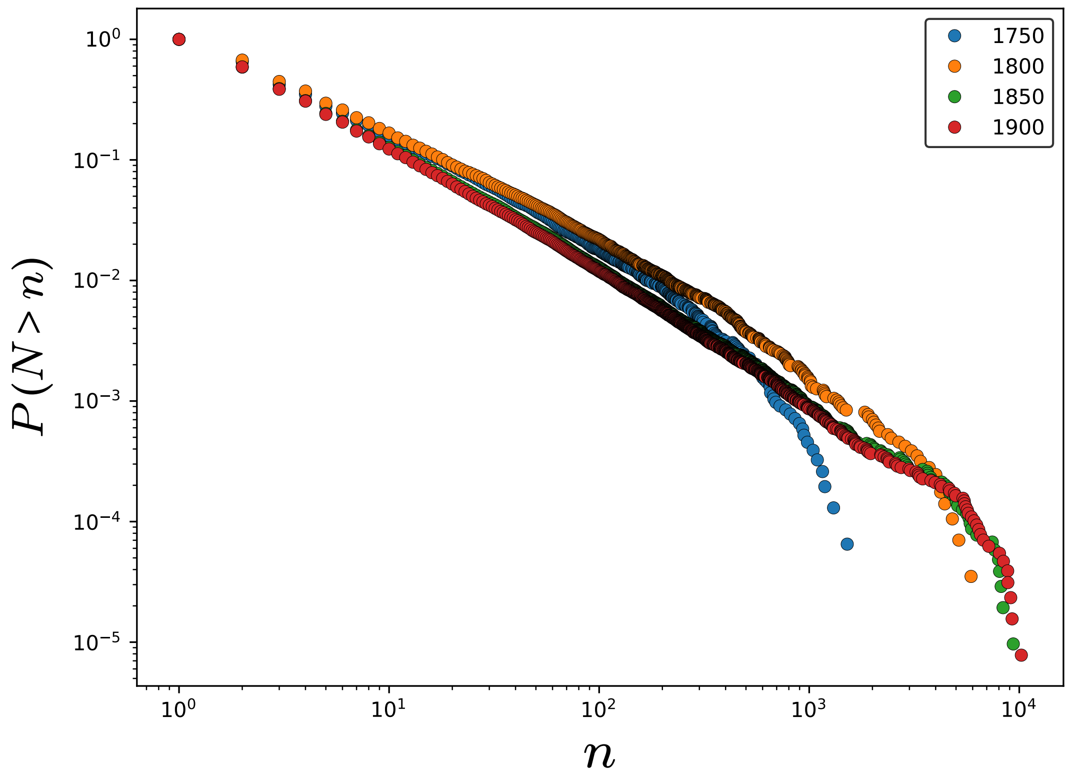

Figure 1. The cumulative distribution of the occurrences n of the codewords. It remains steadily skewed over time.

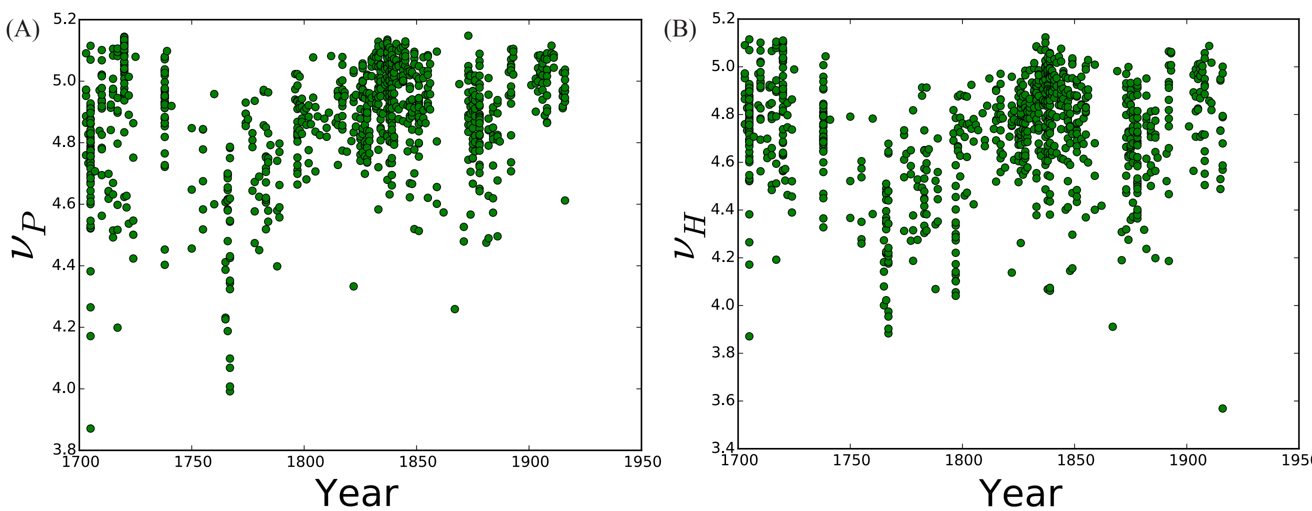

Figure 2. The (A) P- and (B) H-novelty scores of pieces.

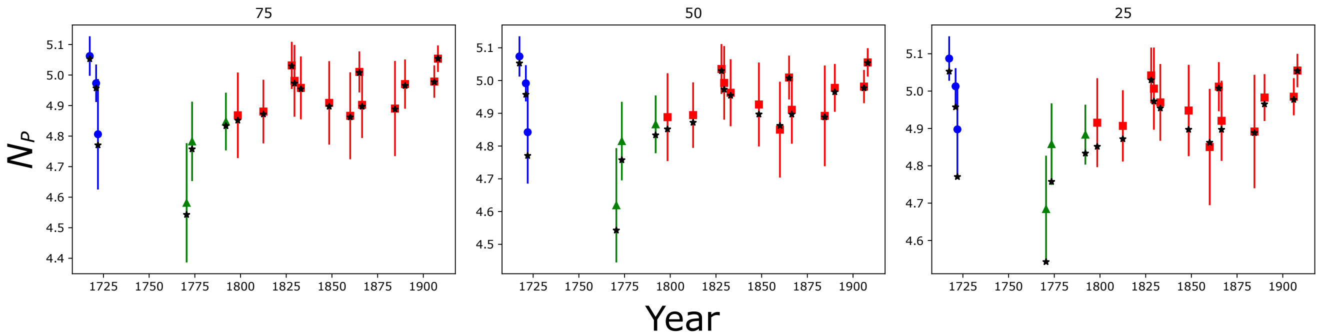

Figure 3. The P-novelty scores of composers from the subsampled datasets (0.75, 0.5 and 0.25 of the original data set). The colored dots and lines indicate the average and error of the estimated scores from the samples and the black stars show the original estimations.

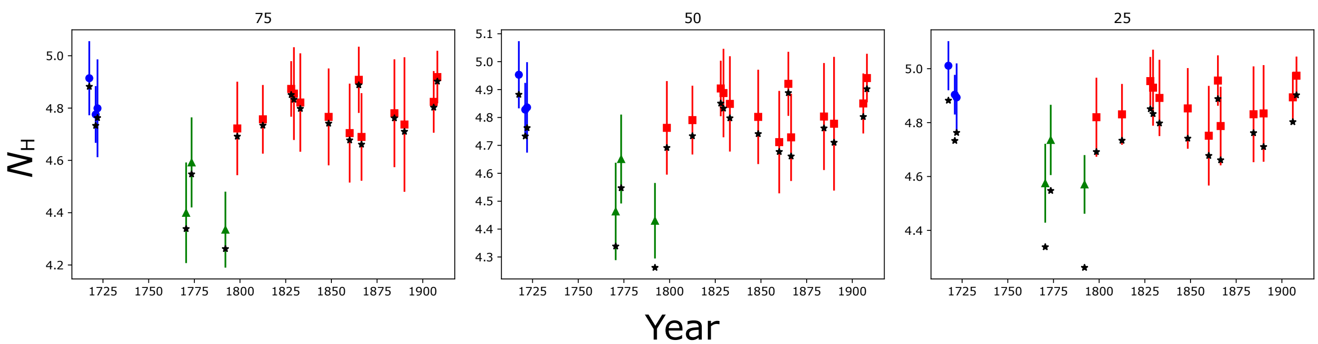

Figure 4. The H-novelty scores of composers from the downsampled datasets by the ratio of 0.75, 0.5 and 0.25. The colored dots and lines indicate the average and error of the estimated scores from the samples and the black stars show the original estimation.

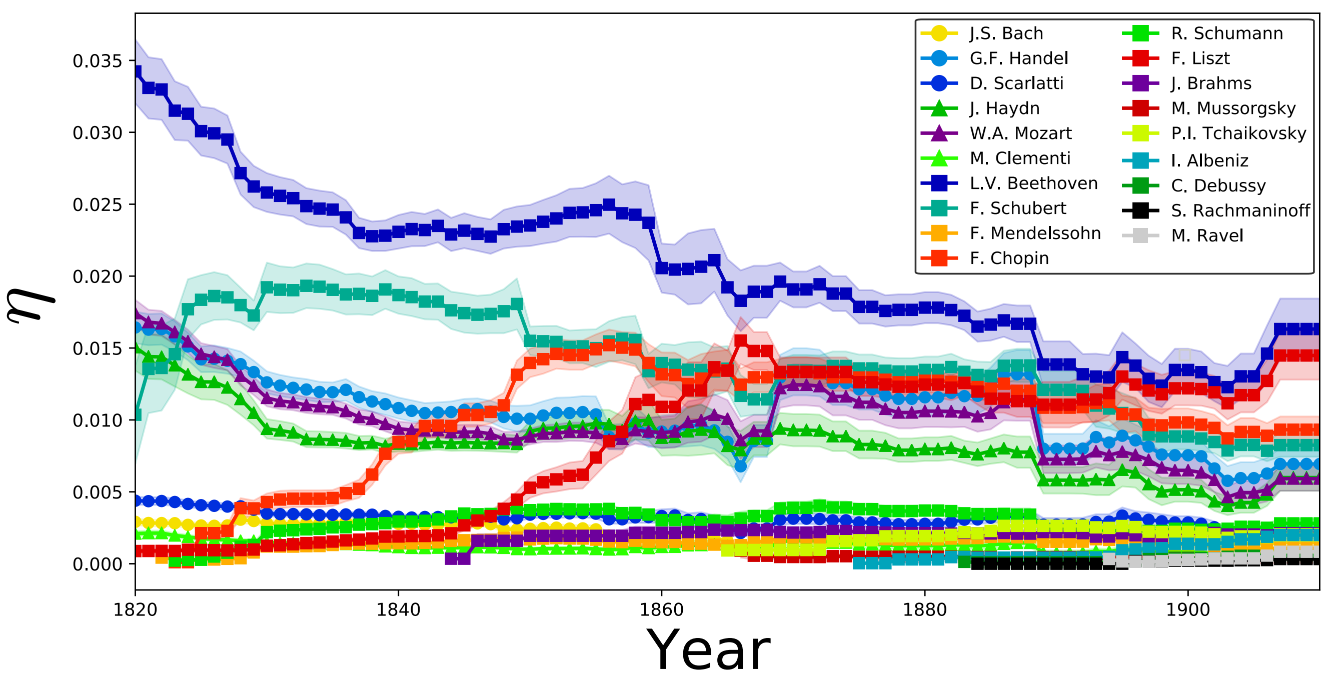

Figure 5. The musical influences of all 19 composers during the Romantic period.

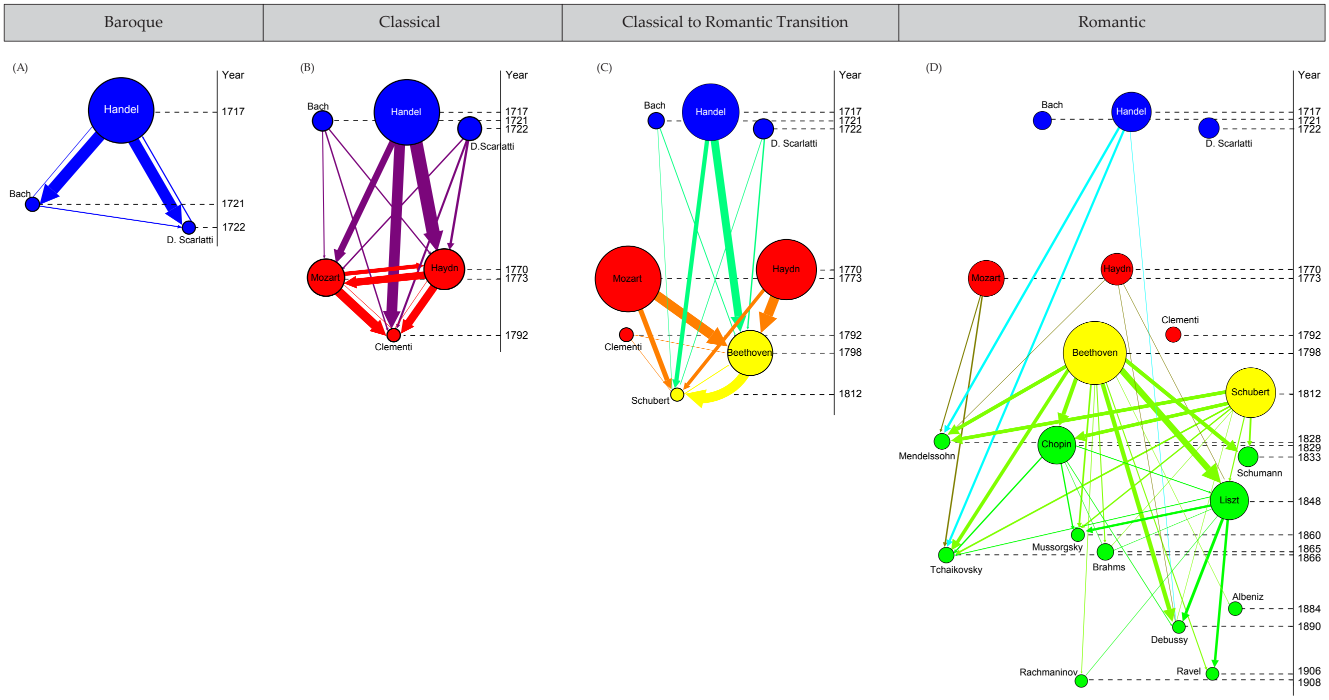

Figure 6. The musical influence network of composers for four major periods. The size of a node is proportional to its weighted out-degree, indicating one's influence onto other composers, normalized by the maximum weighted out-degree in each period. Its color shows the artistic period to which a composer belongs (blue for the Baroque, red for the Classical, yellow for the Transition and green for the Romantic period). The width of an edge indicates the strength of musical influence between the connected composers. The vertical position of each node is the active year, the average of his year of birth and death. The musical influences onto (A) the Baroque composers, (B) the Classical composers (C) the composers during the Transition and (D) the Romantic composers. The network in (D) is the backbone of the musical influence network between composers extracted by[1].

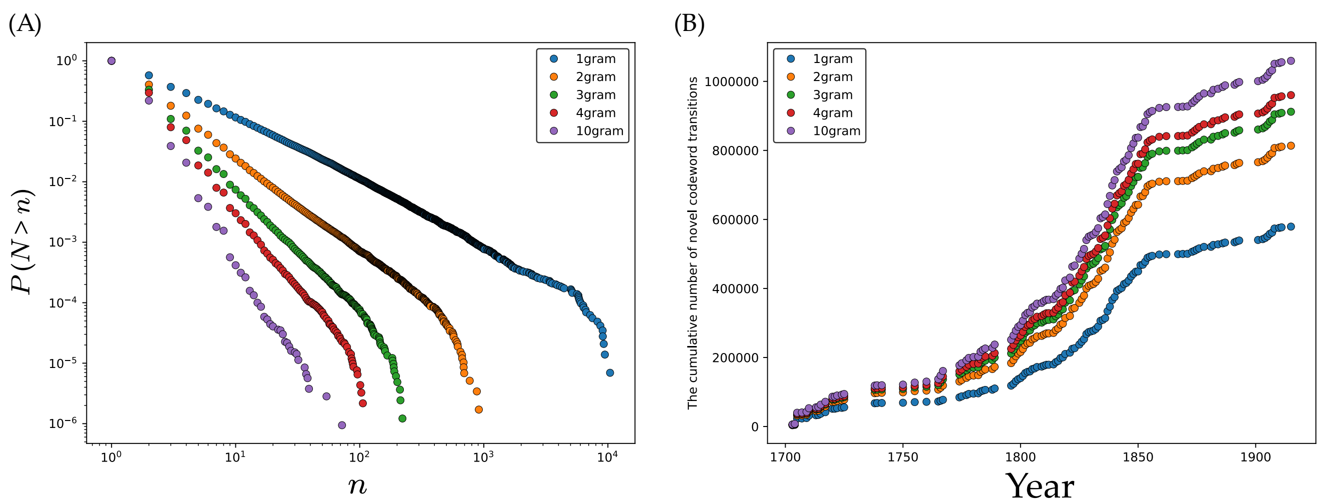

Figure 7. (A) The cumulative distribution of the occurrences n of the different n-grams of codewords. The occurrences follow skewed distributions on many orders, while the maximum occurrence of n-gram codewords decreases as the order increases. For instance, the occurrence of the most common codeword is about 10 000 for simple Markov, but decreases to 100 for 10-th order Markov. (B) The cumulative number of distinct transitions. The trends remain identical: Lack of experiment with new transitions during the Classical period (1750–1800), the steep growth during the early Romantic period (1800–1850) and the slowdown in the growth of harmonic space during the post Romantic period (1850–1900).

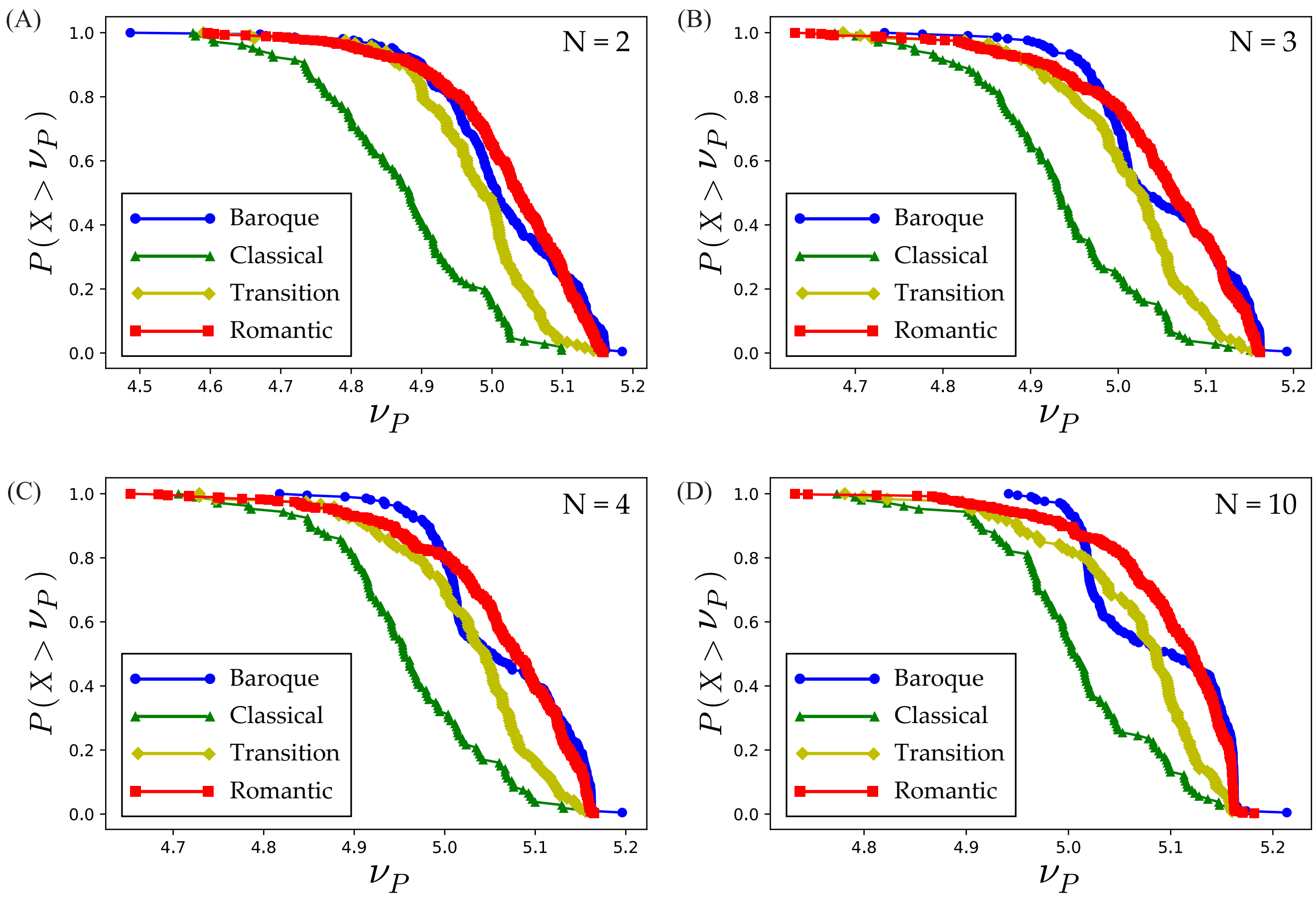

Figure 8. The P-novelty scores of piano works under Markov of varying orders. The shape of dots indicate artistic periods, circle for the Baroque, triangle for the Classical, diamond for the Transition and square for the Romantic period. The cumulative distributions of the P-novelty scores of pieces from (A) the 2nd-order, (B) the 3rd-order, (C) the 4th-order, (D) the 10th-order Markov model. The pieces in the Classical period show relatively low P-novelty scores and the pieces from the Romantic period show high P-novelty scores regardless of the order of Markov model.

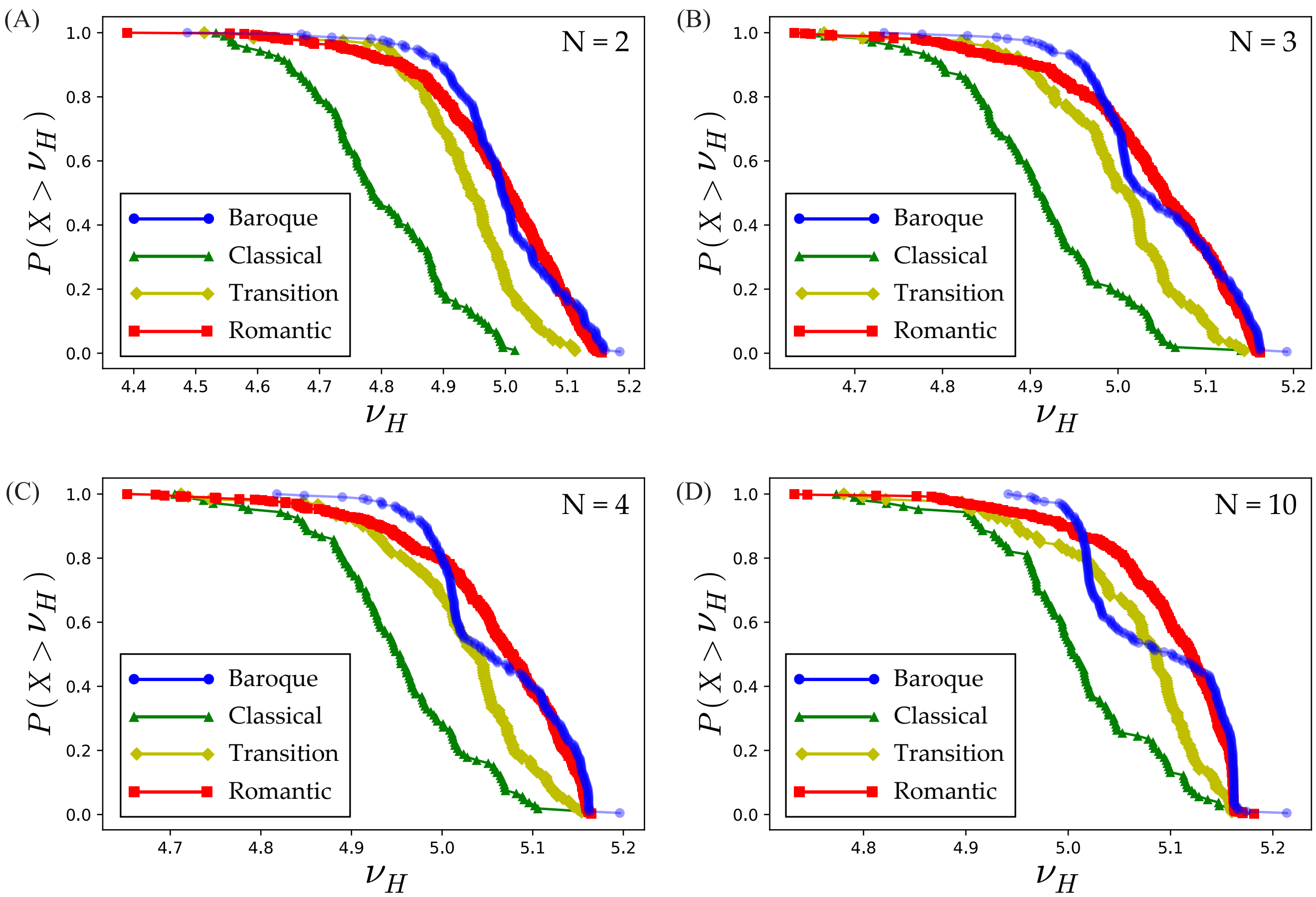

Figure 9. The H-novelty scores of piano works under Markov of varying orders. The shape of dots indicate artistic periods, circle for the Baroque, triangle for the Classical, diamond for the Transition and square for the Romantic period. The cumulative distributions of the H-novelty scores of pieces from (A) the 2nd-order, (B) the 3rd-order, (C) the 4th-order, (D) the 10th-order Markov model. The pieces in the Classical period show relatively low H-novelty scores and the pieces from the Romantic period show high H-novelty scores regardless of the order of Markov model.

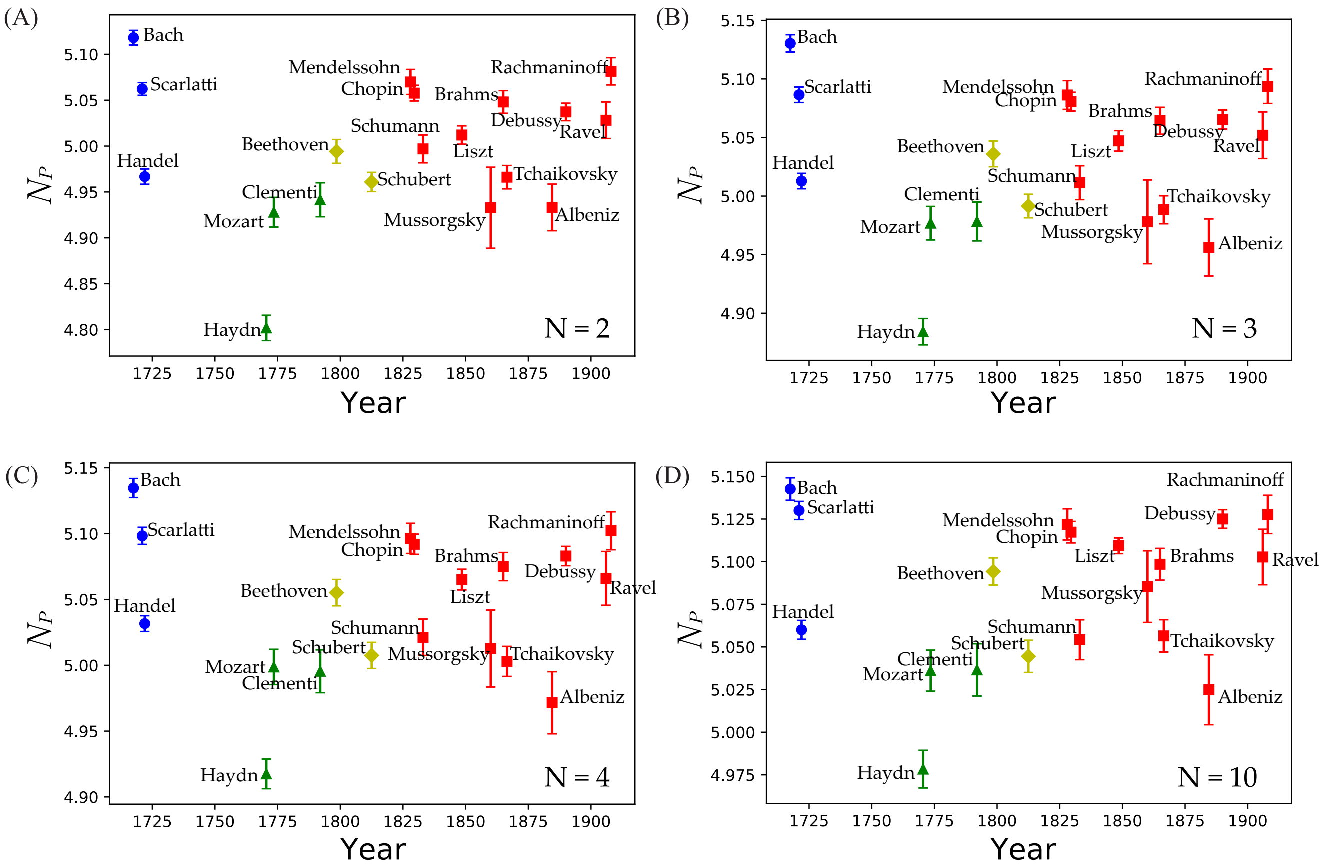

Figure 10. The P-novelty scores of composers under Markov of varying order. The shape of dots indicate artistic periods, circle for the Baroque, triangle for the Classical, diamond for the Transition and square for the Romantic period. The P-novelty scores of composers from (A) the 2nd-order, (B) the 3rd-order, (C) the 4th-order, (D) the 10th-order Markov model. A composer's year (x-axis) is the midpoint of his birth and death years. Despite the increasing variance of the novelty scores of Romantic composers, composers in the Classical period show relatively low P-novelty scores and composers from the Romantic period show high P-novelty scores regardless of the order of the Markov model.

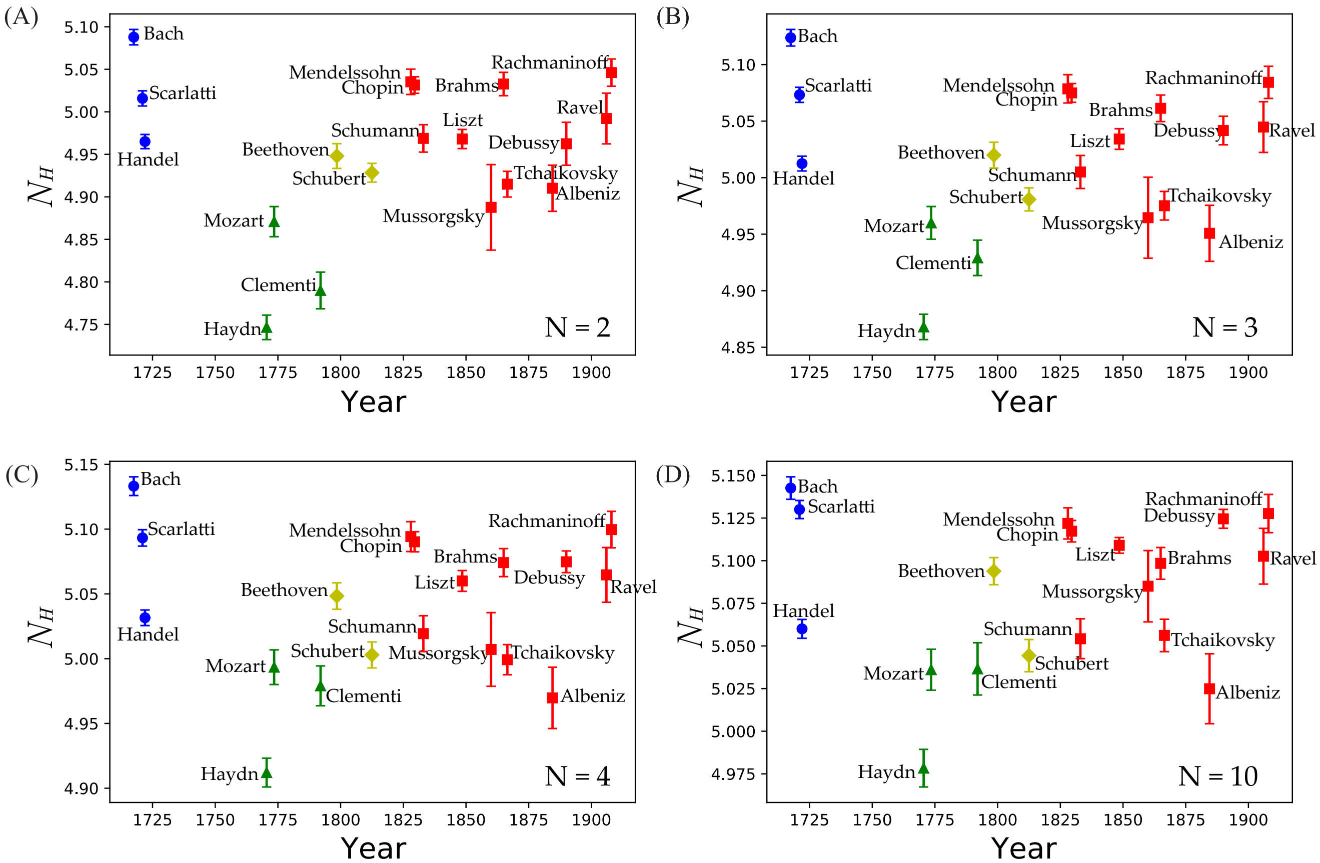

Figure 11. The H-novelty scores of composers under Markov of varying order. The shape of dots indicate artistic periods, circle for the Baroque, triangle for the Classical, diamond for the Transition and square for the Romantic period. The H-novelty scores of composers from (A) the 2nd-order, (B) the 3rd-order, (C) the 4th-order, (D) the 10th-order Markov model. A composer's year (x-axis) is the midpoint of his birth and death years. Despite the increasing variance of the novelty scores of Romantic composers, composers in the Classical period show relatively low H-novelty scores and composers from the Romantic period show high H-novelty scores regardless of the order of the Markov model.

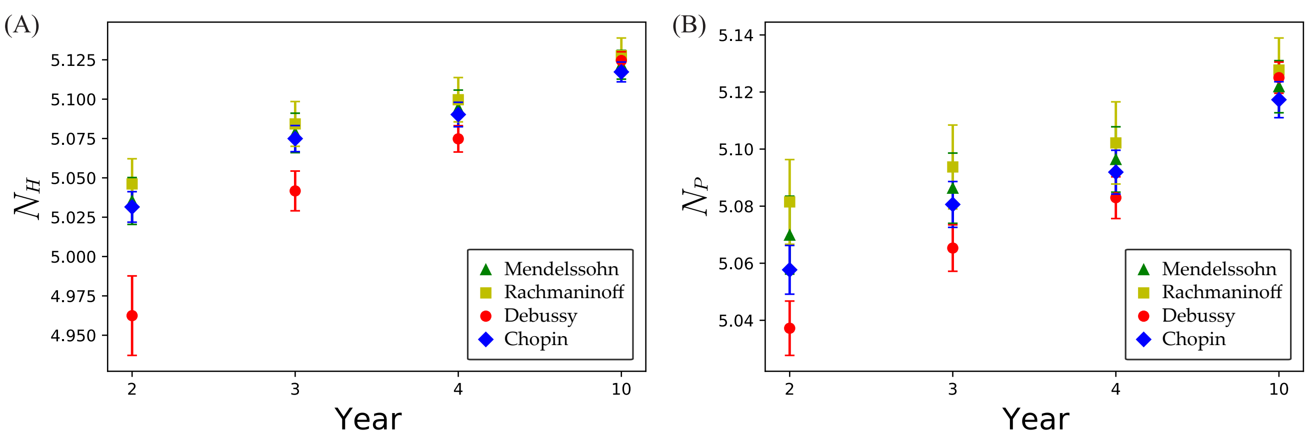

Figure 12. The (A) H- and (B) P-novelty scores of Debussy (red circle) and three highly innovative composers, Mendelssohn (green triangle), Chopin (blue diamond) and Rachmaninoff (yellow square) estimated under Markov of varying order. As the order increases, Debussy's musical novelty increases and eventually becomes nearly equivalent to the others'. This confirms the nature of Debussy's innovation which involved novel scales rather than simultaneous notes.

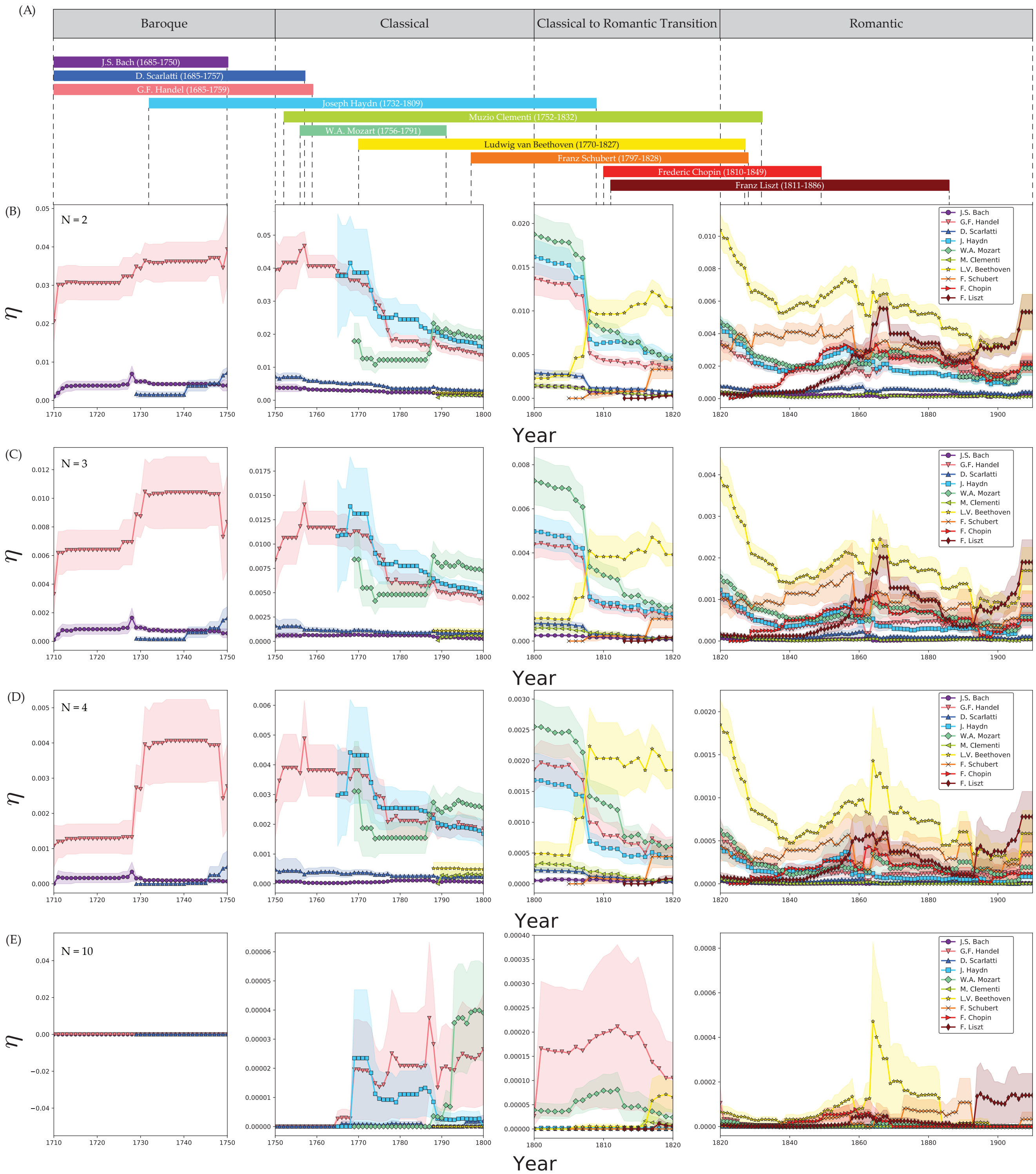

Figure 13. The dynamics of musical influences of composers over time under Markov of varying order. (A) The living years of ten major composers in our data set and the common period designations. The musical influences of composers over time from (B) the 2nd-order, (C) the 3rd-order, (D) the 4th-order and (E) the 10th-order Markov models. The dynamics of musical influences of composers remains identical overall throughout; most influential figures change from Handel, Haydn and Mozart of the Baroque and the Classical era to Beethoven, Schubert, Chopin and Liszt of the Romantic era when the order is not excessive, such as 10

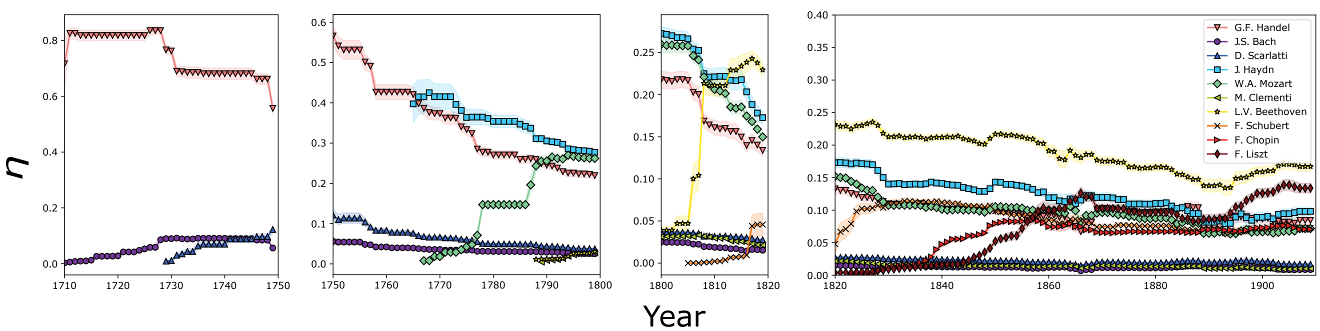

Figure 14. The dynamics of musical influences of composers over time estimated from the number of overlapping codeword transitions. The dynamics of musical influences of composers remains consistent overall; most influential figures change from Handel, Haydn and Mozart of the Baroque and the Classical era to Beethoven and Liszt of the Romantic era.