Supporting Information for

Network Science and the Effects of Music Preference on Functional Brain Connectivity: From Beethoven to Eminem

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SI Text

Supplemental Methods

Screening Session

Participants were asked to complete a comprehensive questionnaire during a screening session that was designed to eliminate any indication as to the intent of the study design prior to the scanning session. This screening session occurred several days to 2 weeks before the scanning session. The questionnaire included a Delphi survey of 26 exploratory questions about participants' ideas about music and their uses of music in their daily life. These questions ranged from such topic areas as whether participants use music to alter their mood to whether they enjoy mentally analyzing complex musical compositions. In addition, the participants were asked questions about their formal and/or informal musical training. The participants were asked to rank their personal preferences for eleven musical genres. The eleven musical genres included: rock, gospel, blues, rap/hip hop, jazz, classical, country, alternative (low-fi, experimental, punk, techno, mgmt, disco), metal, pop, and Broadway. The questions about participants formal years of musical training was defined by category: 0 years, 1-3 years, 4-7 years, 7-10 years and 10 plus years and a specific question about the musical instrument(s) the participant had received their formal or informal training on. This included their primary instrument as well as any secondary instruments (such as piano or guitar) and the number of years on each instrument. Participants were asked to estimate how much time they spend listening to music (average listening time was 3.4 hours per day). In addition, participants were asked whether they could speak or read a foreign language (French, Spanish, German or 'other') and were asked whether they could speak (or read) Chinese. Participants were also asked to rank their preferences for colors ranging from red to black (red, yellow, orange, blue, green, white, and black). Training was provided to participants on how to use the Visual Analog Scale (VAS) both in the screening session and just prior to the scanning session. Finally, each participant was asked to provide their most favorite song title and artist. In order to ensure that the favorite song was exactly what the participant requested, songs were carefully noted including artist, recording year, performing group and any other specific information that was needed. For example, one participant wanted the Prelude in D minor Op. 23 no.3 by Sergy Rachmaninoff performed by Vladimir Ashkenazy. Participants were allowed—and even encouraged—to feel free to change what they considered their favorite song up until the day before the scanning session. This was done to ensure that our participants had been given ample time to determine what they would consider their favorite song. Many of the participants needed several days to determine what they considered to be their number one song, the one that 'rocks their world', 'floats their boat', and 'is my favorite song.' No restrictions were given as to the genre (i.e. the type) of music or whether their favorite song should or should not have lyrics. Note that several of our participants had a favorite song that was outside of their preferred genre.

Additional MR Scanning Session Information

During the scanning session, all songs were presented to the participants without their prior knowledge of what music was to be played to them (apart from their favorite song). Thus, though they had reported a particular preference for a particular genre of music, all songs appeared to the participants as randomly presented. We include that the songs appeared as randomly presented because we presented the songs in an over-arching scheme that began with their preferred genre. However, given the enormous variety of choices for songs to present, that our participants did not know the music that they would be hearing (apart from their favorite song) and that our participants completed a questionnaire that highlighted 11 types of music to prioritize, we believe that, at least from our participants' perspective, the music was randomly presented. Thus, their brain responses would align with this perspective. Following the presentation of every song, each participant was asked to rate their preference for the song using the visual analog scale (VAS) as discussed in the Methods.

Participants' Pre-Selected Favorite Songs

Favorite Song	Artist(s)/Composer
April 29th, 1992	Sublime
Come, Thou Fountain of Every Blessing	Mormon Tabernacle Choir
Das Verlassene Magdlein	Hugo Wolf
Days of Elijah	Robin Mark
A Better Son/Daughter	Rilo Kiley
Friends in Low Places	Garth Brooks
Gimme Shelter	The Rolling Stones
Breakeven	The Script
Human Nature	Michael Jackson
Love Like Crazy	Lee Brice
Love the Way You Lie	Rhianna & Eminem
Motorcycle Drive By	Third Eye Blind
Name	Goo Goo Dolls
[1]Nessun Dorma from Turandot	Puccini
Non Je ne Regrette Rien	Edith Piaf
One More Chance	The Notorious B.I.G
[3]Symphony No. 2 in C minor	Gustav Mahler
Rockin That Thang	The Dream
She	Harry Connick Jr.
[2]Prelude in D Minor, Op. 23, No. 3	Rachmaninov
You're Not Alone	Meredith Andrews

[1] Performed by Luciano Pavarotti
[2] Performed by Vladimir Ashkenazy
[3] Performed by The City of Birmingham Symphony Orchestra Conducted by Simon Rattle (last 5 min. from Mvt IV)

Additional Description of Network Methodology

Threshold Determinations

1. Thresholds for Binarization of the Network

For the voxel-wise network, a Pearson's correlation coefficient was used to correlate the time series in each voxel. After creating the correlation matrix, a threshold was applied to yield a sparse matrix. There are researchers that suggest it is preferred to not threshold the networks and utilize a fully connected, weighted network (1). However, we have demonstrated that when connected networks are utilized in an information processing model, they do not exhibit behaviors expected from a small-world network (2). In addition, fully connected networks must be much smaller (100s of nodes) than the networks that we use (~21,000 nodes) due to the computational complexity of the algorithms used to analyze the networks. We feel that the optimal solution to this issue remains equivocal and believe that either method is currently valid. We prefer the use of sparse networks because it allows for higher resolution networks with many more nodes. We apply a threshold using the formula of $N = K^S$ that has been shown to relate network size to density in random small-world networks (3). This threshold ensures that comparisons are being made between networks of comparable density relative to the number of network nodes. For the networks used here, all subjects had approximately the same number of nodes so network size was not a limiting factor. For this paper, a threshold $S = 2.5$ was used, so the relationship of $N = K^{2.5}$ was used. The choice of $S=2.5$ results in networks that exhibit comparable size:density ratios observed in other naturally occurring networks (4). In addition, we have demonstrated in prior work that networks tend to fragment when S is above 3.0 (5), and the reproducibility of brain networks is highest at thresholds with S between 2 and 3 (6). Once the threshold was applied, correlations above the threshold were given a value of 1, and those below the threshold were given a value of 0.

2. Definition of Network Hubs

We used the top 20% to generate representative images to allow visualization of the data. Based on the Pareto Law, the 20% choice is an heuristic. This is common in systems that exhibit power law or power law-like behaviour. We acknowledge that this cutoff is arbitrary but it was used only for the visual depiction of the location of network hubs. In fact, there is no absolute definition of a hub. We have recently shown that reproducibility of hubs within subjects across runs falls off dramatically above 20% and is relatively stable between 20 and 25% (7). All comparisons across conditions used actual network statistics without applying this cutoff.

Determination of Community Structure

1. Module Determination

One can identify the community structure or modular organization of a network with modules or neighborhoods defined as groups of nodes that are more connected to each other than other groups of nodes (8). Modularity is currently considered the gold standard to define community structure whereby a modularity metric Q is calculated that describes optimal modular partition. Newman-Girvan developed modularity to define the resolution at which one looks at the community structure after hierarchical partitioning is performed (9). Q identifies the partition that maximizes the within community links relative to the number of within community links in a random network. We used an algorithm called Qcut (10) to break each participant's functional brain networks into the modules. The partition that mazimized Q was chosen for each run of Qcut. As with all community structure algorithms, Qcut potentially yields different solutions each time it is run. We ran Qcut on each subject's network 10 times for each condition. Over these 10 runs, it became clear which run(s) yielded the highest value for Q; in practice, the same modular structure with highest Q value would usually occur in many of the 10 runs, increasing our confidence in the optimal result for modular organization. The run with the highest Q was selected as the representative modular partition for that subject.

2. Scaled Inclusivity

Comparing modular organization across individuals is difficult and an ongoing area of research. Scaled Inclusivity (SI) is a metric that makes it possible to evaluate the consistency of the community structure across different subjects with similar brain functional networks (11). In brief, SI measures the overlap of modules across subject's networks. If modules exhibit disjunction, then the SI values are penalized. The equation for SI is:

$$SI_V = \frac{|S_A \cap S_B|}{|S_A|} \frac{|S_A \cap S_B|}{|S_B|}$$

where SI_v represents the scaled inclusivity of a node V which is in module A in subject i and module B in subject j. S_A and S_B represent sets of nodes in modules A and B, respectively, and $\| \|$ denotes the cardinality of a set (12). An $SI_v = 1$ would indicate perfect overlap of modules from 2 different subjects. As the overlap decreases, the SI_v becomes less than 1. There are also penalties to the value of SI_v for different sizes of the modules as shown by increasing the denominator in the equation.

Si is calculated for all the community structure between all participants. In order to determine the consistency of any particular module, the individual with the highest SI values in the region of interest is identified. A subject-specific SI map is then created from a weighted sum of the maps comparing the subject's modules to all other subject's modules. This subject-specific SI map shows the consistency of a particular node falling within the same module across subjects. SI is the weight used in these weighted sums. In an ideal situation with all subjects having the exact same community structure, SI_v would = n-1 in every voxel. However, this is highly unlikely in biological data, so SI values are typically smaller than N-1. As part of this study, these SI modularity maps are the maps presented in Figures 2 and 4 of the main manuscript. For a more detailed description of SI, see Steen et al (12). Because the final SI calculations yield a single value in each voxel, there is no variance, and traditional hypothesis tests cannot be utilized on this data.

Supplemental Results

1. **Issue of Song Order**

While we do not believe that there was an effect of song order on our results, we present here all of the data about song order. Each participant's favorite song was presented last (6^{th}) after presenting the 5 pre-selected songs. These 5 pre-selected songs were presented for each participant in an order determined by how the participant ranked 11 genres of music at the screening session, which occurred several days before the MR scan. We chose to present the songs in order from the participant's most preferred genre to least, always ending with the unfamiliar Chinese opera (5^{th} song presented). The song with the highest VAS score (i.e. most Liked song) was the first song for 8 participants, the second song for 8 participants, the third song for 2 participants, and the fourth song for 3 participants. The song with the lowest VAS score (i.e. most Disliked song) was the second song for 3 participants, third song for 4 participants, the fourth song for 3 participants, and the fifth song (unfamiliar, Chinese Jinna Opera Band for all participants) for 12 participants. The participants did not rank the musical selections. Rather, they simply used the VAS to show how much they liked the different songs (nothing was said about genres). 11 subjects reported a top "Like" VAS preference for the classical, 4 for the country, 3 for the rock, 3 for the rap, and 0 for the unfamiliar song. For the Dislike condition (subjects' lowest VAS score), 1 reported the classical, 2 reported the country, 3 reported the rock and 3 reported the rap song. 12 reported the unfamiliar music as their least preferred music.

2. **Connectivity between the precuneus and the Default Mode Network**
A *post-hoc* analysis was performed to measure the connectivity between the precuneus and the remainder of the DMN. Figure S1 shows the ROI's used for the precuneus (an 12 mm radius sphere located at 0, -54, 34 in MNI space) and the DMN; these were derived from the work of Shirer et al as determined using independent components analysis (13). The red areas show the DMN in its entirety. This image was kindly provided by Vinod Menon. The Cyan sphere shows the precuneus ROI used in this work. The green regions show the ROI that was used in this work to count connections from the precuneus ROI to the other portions of the DMN. The number of direct connections from the precuneus to voxels within the remaining DMN was minimal with the average ranging from 2 to 3 connections per voxel across the study conditions. We therefore measured connections one step further in the network. We term these 2^{nd} order connections. 2^{nd} order connections are those connections that emanate from voxels directly connected to the precuneus ROI. Figure S2 shows the statistics for the number of 2^{nd} order connections from precuneus ROI to the ROI located in the other portions of the DMN. These findings support the modularity findings showing differences in the precuneus module's connection to the rest of the DMN. The results showed a significant ($p = 0.04$) increase in connectivity in the Like condition compared to the Dislike condition. There was no significant difference between Like and Favorite ($p = 0.08$) or between Dislike and Favorite ($p = 0.71$).

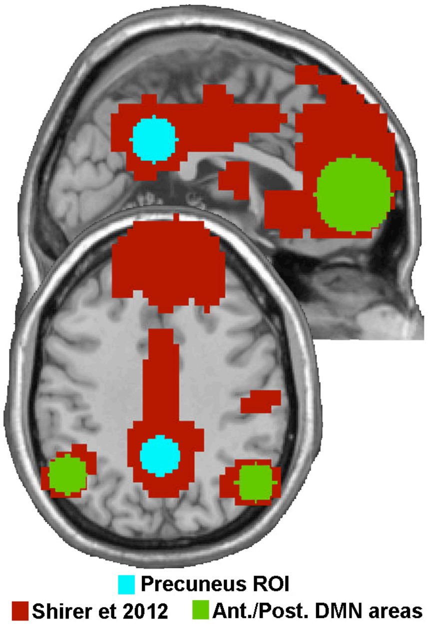

Figure S1: Depiction of region-of-interests used in the statistical analyses.

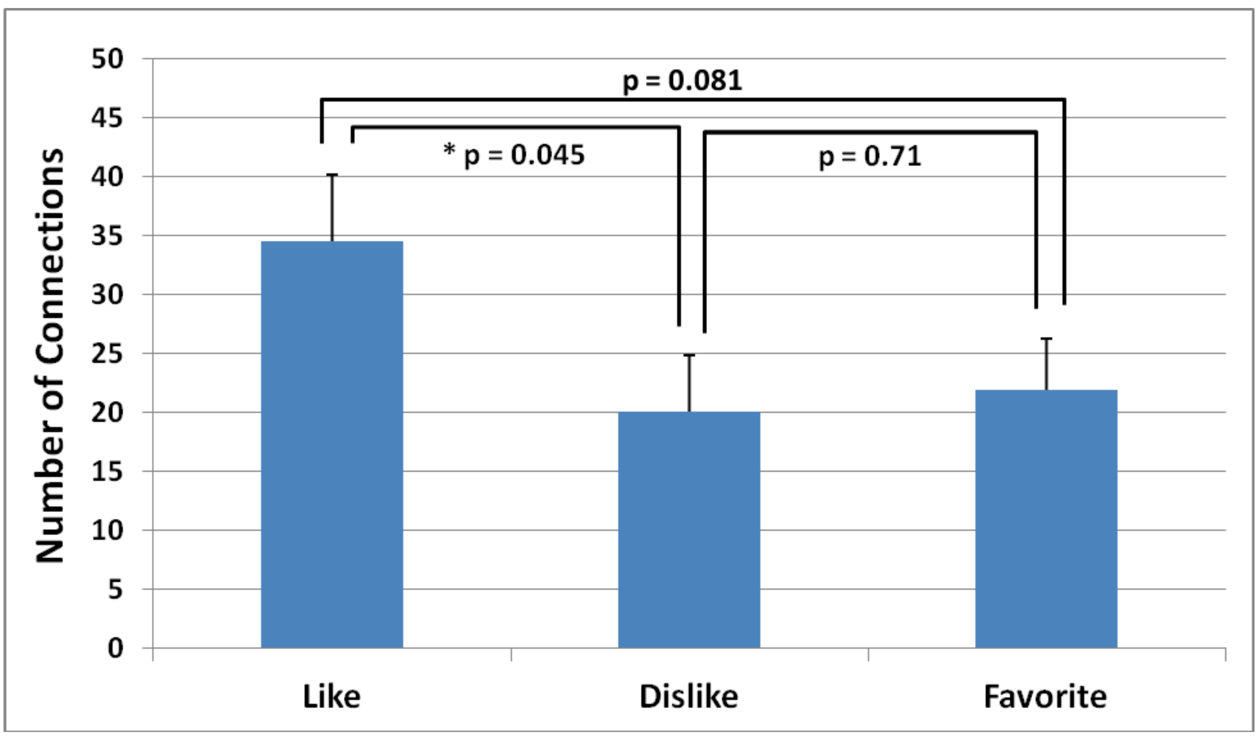

Figure S2: Average number of 2^{nd} order connections for each voxel between the precuneus ROI and the ROI located in the anterior and posterior aspects of the default mode network (DMN). There was a significantly greater number of 2^{nd} order connections between the precuneus and the DMN ($p = 0.04$) in the Like condition compared to the Dislike condition.

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