

Big-C Creativity in Artists and Scientists is Associated With More Random Global but Less Random Local fMRI Functional Connectivity

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Brain mechanisms underlying creativity are largely unknown and few studies have involved exceptionally creative individuals. We examined functional MRI (fMRI) connectivity in a “smart comparison group” (SCG; $n = 24$), and in exceptionally creative (“Big C”) visual artists (VIS; $n = 21$) and scientists (SCI; $n = 21$). Groups were matched on age, sex, and estimated IQ. fMRI scans were acquired during the resting-state and performance of two tasks: (a) alternative uses test (AUT), putatively measuring divergent thinking; and (b) remote associates test (RAT), putatively engaging convergent thinking. Graph theory measures of functional connectivity were compared across groups using generalized linear mixed models. Global connectivity measures included small-worldness (indexing efficiency), clustering coefficient, and characteristic path length. Local connectivity measures included local efficiency and clustering coefficients within default mode, dorsal attention, frontoparietal, salience, ventral attention, and visual networks. During the resting-state, global small-worldness was lower for SCI than SCG; VIS had intermediate values. Relative to SCG, the Big C groups had higher local clustering coefficients during the resting-state conditions but lower local clustering during the AUT condition. No significant differences were found during the convergent thinking test (RAT). These findings suggest that Big C creativity is associated with more “random” rather than more “efficient” global network functional architecture, with condition-dependent variations in local clustering and efficiency. Large condition-dependent correlations between global and local clustering measures deserve further examination in exceptionally creative and other groups to more fully characterize the functional topology of brain networks most relevant to creativity.

Keywords: creativity, fMRI, connectivity, artists, scientists

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Seven decades of research have led to theories about creative achievement, but there are limited empirical data about its biological bases (K. S. Knudsen et al., 2015). Evidence about brain mechanisms underlying exceptional, or “Big C,” creativity is even rarer. Converging hypotheses suggest that creative cognition is mediated by balanced

engagement of complementary systems involved in focused/diffuse, convergent/divergent, and stabilizing/novelty-biased processing (Beaty et al., 2019; Bilder, 2012; Bilder & Knudsen, 2014; Dietrich, 2004; Dietrich & Kanso, 2010; Heilman, 2005), but there is no consensus about the specific patterns of brain network organization that facilitate creative expression, and major questions remain about what specific domains of problem solving and creative expression are most important for creativity (Abraham, 2013).

Neuroimaging studies using tasks that putatively demand divergent thinking have revealed inconsistent findings, including increased activation in the frontal (Chávez-Eakle et al., 2007; Goel & Vartanian, 2005; Guilford, 1967; Howard-Jones et al., 2005; Simonton, 2011), right temporoparietal, medial frontal, and posterior cingulate (Fink et al., 2010), and occipitotemporal cortices (Chrysikou & Thompson-Schill, 2011). Other paradigms focused on novelty detection (Mashal et al., 2007) or convergent thinking (Dietrich & Kanso, 2010) have shown activation of the superior temporal and anterior cingulate cortex. Meta-analyses suggested that posterior prefrontal regions may generate creative ideas while more rostral prefrontal cortex may be activated when integrating ideas (Gonen-Yaacovi et al., 2013).

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Divergent thinking also has been linked to increased resting-state functional connectivity between the medial PFC and posterior cingulate cortex, which are major nodes within the default mode network (DMN; Takeuchi et al., 2011, 2012). The DMN has been suggested to underlie “blind variation” in the generation of creative ideas, while executive control (EC) networks have been associated with evaluation and purposeful selection of ideas (Beaty et al., 2016; Beaty et al., 2014; Fink et al., 2010; Fink et al., 2012; Jung et al., 2013). The blind variation and selective retention (BVSR) hypothesis suggests these complementary processes are biological substrates of creative thinking (Campbell, 1960; Simonton, 1999, 2010), and that coupling of default mode and salience networks might explain the dynamic interplay of idea generation and idea selection (Beaty et al., 2015).

A study using connectome-based predictive modeling identified “high-creative” and “low-creative” networks on fMRI scans in a sample comprising mostly university students, and showed that these network models could predict creative task performance and achievement; the high creative network involved predominantly fronto-parietal connectivity with engagement of default, executive, and salience systems, while the low-creative network emphasized connectivity of sensorimotor with subcortical, cerebellar and brainstem nodes (Beaty et al., 2018). These findings have led investigators to propose that coupling between the DMN and executive control or frontoparietal networks is critical to increase creative output (Beaty et al., 2015; Beaty et al., 2017; Heinonen et al., 2016; Shi et al., 2018).

The work cited above focused mostly on identifying specific brain regions or functional networks of regions-of-interest (ROIs). Another perspective is provided by analysis of the topological properties of networks using methods derived from graph theory, which represent ROIs as “nodes” and connections between nodes as “edges.” Graph theory metrics enable examination of global network properties, including the “small world” property that reflects the balance between network segregation and integration, and is considered an “efficient” organizational state in which most nodes are not directly interconnected, but have connections via short path lengths (Farahani et al., 2019; Rubinov & Sporns, 2010). The topology of graph networks can be conceptualized as a progression from a completely “regular” network (where randomness or $r = 0$) to a network in which all nodes are connected randomly (where $r = 1$).

Only a few studies have assessed graph theory metrics in relation to creativity. Greater global efficiency was found on rest state fMRI (rsfMRI) scans of undergraduate students identified as being of “high” creativity based on results from the figural Torrance Tests of Creative Thinking (TTCT; Gao et al., 2017). Beaty et al. (2015) showed that greater global efficiency, assessed on fMRI scans during divergent thinking, was correlated with higher creativity ratings of divergent thinking task performance among undergraduates (Beaty et al., 2015). In another study, Beaty et al. (2016) showed that efficiency *within* the default network was correlated with self-report measures of openness to experience and intellect (Beaty et al., 2016). Another study examining *structural* connectivity using graph theory metrics reported a sexual dimorphism with males showing weak positive correlations of efficiency with creativity, while females showed the opposite effect, with less efficiency being associated with higher creativity (Ryman et al., 2014). These studies leave open questions about individual differences in brain connective topologies that may support creative cognition both across and within specific functional networks, and

whether different patterns of organization may be found at rest relative to task-activated conditions.

Most neuroscientific research on creativity has involved convenience samples of the general population, with much research on university students, and very few studies have recruited people specifically for high levels of creative achievement. Eminent creative achievers showed differences in the DMN and executive thinking brain regions compared with “smart control” individuals during a variation of the alternative uses test (AUT; Chrysikou et al., 2020). Near infrared spectroscopy (NIRS) showed increased prefrontal activation in trained musicians relative to demographically matched nonmusicians during a divergent thinking task (Gibson et al., 2009), but the musician group had a significantly higher full-scale IQ than the comparison group. A related study tied resting-state fMRI connectivity changes in the default mode, salience network, executive control, and motor planning to musicality (Bashwiner et al., 2020); but brain regions associated with musical creativity may differ depending on whether convergent or divergent thinking is being recruited (Slayton et al., 2019). Another study showed higher coupling of EC with DMN networks, along with lower connectivity within EC but higher connectivity within DMN, in a group of professional visual artists compared to an education-matched comparison group (De Pisapia et al., 2016). Another study of undergraduate student artists showed medial temporal (possibly DMN) engagement during idea generation and joint recruitment of executive-DMN engagement during idea selection (Ellamil et al., 2012). This emerging literature, while it has focused on connectivity of the DMN with other functional networks, does not yet lead to clear conclusions.

Several literature reviews have identified many inconsistencies that further limit prior work interpretation (Arden et al., 2010; Dietrich, 2004). A primary confounding variable is the relationship between creative cognition and intelligence (Benedek et al., 2014). The correlation between creativity and intelligence has been estimated as $r = .20$ (Silvia, 2015), with some suggesting that above-average intelligence is necessary but not sufficient for creativity. Our prior work showed that exceptionally creative “Big C” artists and scientists showed less activation relative to an IQ-matched comparison group in task-positive networks during a divergent thinking task, underscoring the possible value of controlling for intelligence (Japardi et al., 2018). Creative thinking in different domains also may take different forms. Recent research supports this view by showing domain-specific associations of creativity with personality (Feist, 2010) and subclinical psychopathology (Baer, 2015; Knudsen et al., 2017; Knudsen et al., 2019; Simonton, 2006; Vartanian et al., 2019; Zabelina et al., 2014).

In the present study, we aimed to address multiple challenges noted above by: (a) studying exceptionally creative (Big C) individuals; (b) using an IQ-matched comparison group; (c) examining individuals representing two different domains of creativity (visual arts and sciences) that may differ in cognitive and personality characteristics; (d) examining functional connectivity using fMRI in both divergent and convergent thinking task-activated activation conditions, and during the resting-state; and (e) using graph theory to calculate both global and local measures of functional network connectivity. Our primary hypotheses were that the two Big C groups would differ from the smart comparison group, or from each other, on global graph theory measures, and more specifically *sigma*, the index of small-worldness, which varies along a dimension from “regular” (highly ordered), through the “small-world” state, to “random” (Watts & Strogatz, 1998). Small-worldness

reflects a combination of higher clustering and shorter path lengths, and thus is computed as the ratio of γ (clustering coefficient) divided by λ (characteristic path length), so we planned to look at these measures if there were significant group differences on sigma. Modularity (“Q”) was also examined as a secondary hypothesis, given that small world networks are not necessarily modular (Meunier et al., 2010). We further tested secondary hypotheses about whether group differences might be specific to task conditions, or to specific brain networks, using local graph theory metrics. Given the paucity of prior research addressing this manifold of questions, along with conflicting results from prior research, we did not specify a priori hypotheses about the directions of group differences.

Method

Inclusion and Exclusion

We studied visual artists and scientists because previous factor analytic work on the Creative Achievement Questionnaire (CAQ) suggested that visual arts and science/invention comprise relatively distinct creative domains (Bilder & Knudsen, 2014; Carson et al., 2005). Recruitment and selection for this study are described briefly here; more details are published elsewhere (Japardi et al., 2018), and the selection process for this study is detailed in a STROBE diagram (Supplemental Figure S1).

Exceptionally creative visual artists (VIS) and scientists (SCI) were nominated by panels comprised of experts within their respective domains. These nominations were then validated as exceptional based on objective field-specific metrics, including scores on the CAQ (which had to be in the top 2% for their domain relative to a sample of 300 community volunteers not explicitly selected for creative achievement, who were included in a separate study of creativity; the “UCLA 300 Project”; Bilder & Knudsen, 2014), scientific publications (for scientists, as indicated by the h-index or other bibliometric statistics indicating outstanding achievement for their domain and age), and exhibitions/award (for visual artists). The “smart” comparison group was recruited from participants in the UCLA-300 Project who had agreed to be recontacted for participation in future studies and had high levels of education and estimated IQ, and from advertisements in the community for individuals with graduate

degrees, with efforts made to assure age, sex, race, and ethnicity comparable with those of participants in the Big C groups.

Participant Characteristics

The participants in this study overlap with those reported previously (Japardi et al., 2018; Knudsen et al., 2019). Among 107 enrolled participants, only 92 received fMRI scans (15 were excluded and due to claustrophobia, limited availability, or participant refusal for other reasons). Forty-one had missing data or at least one unusable fMRI scans based upon quality control analyses, leaving 66 participants with complete fMRI data for analyses: 24 smart comparison group individuals (SCG), 21 Big-C visual artists (VIS), and 21 Big-C scientists (SCI; for details about exclusions see STROBE diagram in supplemental materials, Figure S1). These analyses differ from the report by Japardi et al. (2018) by including only individuals with usable fMRI scans across all three conditions (i.e., with data from both AUT and remote associates test [RAT] tasks, and rest state), to enable direct examination of the condition effect across all participants. The included participants did not differ significantly on any demographic variables from the 41 who were excluded. The Big C groups did not differ significantly from the SCG or each other on age, sex, race, ethnic group, and estimated IQ using the Wechsler Adult Intelligence Scale, 4th Edition (WAIS-IV, Wechsler, 2008) age-corrected scaled scores on vocabulary and matrix Reasoning subtests (see Table 1).

As expected, the groups differed significantly on CAQ scores, with both VIS and SCI groups possessing much higher scores (see Table 1). Given marked deviations from normality, we used the Independent-Samples Kruskal-Wallis test to examine group differences. These tests confirmed that VIS and SCI groups had higher CAQ total scores than SCG, with Bonferroni-corrected p -values $<.001$, while VIS and SCI did not differ significantly from each other. Additional analyses confirmed that the VIS group had higher scores than both other groups on the visual art domain of the CAQ, and that the SCI group had higher scores than both other groups on the science and invention domain (we summed scores for these domains as our SCI group had a higher score on both domains). These analyses helped to validate the inclusion criteria that aimed to identify exceptionally creative achievers; indeed, the Big C groups’ CAQ scores are outliers with respect to the

Table 1
Demographics

Covariate	Group			Test statistic	DF	p	Post hoc
	SCG	VIS	SCI				
Age	42.8 ± 9.2	41.2 ± 6.9	44.7 ± 7.5	F = 0.99	2, 65	.38	NA
Sex	11M, 13F	12M, 9F	12M, 9F	F = 0.39	2, 65	.69	NA
CAQ	93.5 ± 261.4	571.5 ± 1,034.5	205.7 ± 263	$\chi^2 = 21.87$	2	$p < 0.001$	VIS, SCI > SCG
Estimated IQ	115 ± 10.7	113.8 ± 8.6	116.4 ± 11.4	F = 0.33	2, 59	.72	NA
Education	19.2 ± 1.1	18.8 ± 0.5	21.0 ± 0.0	KW = 39.4	2	.001	SCI > VIS, SCG
Race (W, B, other)	20, 2, 2	13, 6, 2	17, 1, 3	$X^2 = 10.7$	8	.22	NA
Ethnicity (H, NH, Other)	22, 1, 1	21, 0	19, 2	2.17	2	.34	NA

Note. KW = Kruskal-Wallis (nonparametric test of differences between independent groups); SCG = smart comparison group; VIS = visual artists; SCI = scientists; CAQ = Creative Achievement Questionnaire; W = White; B = Black; H = Hispanic; NH = Non Hispanic. Education was assessed on a continuous scale where 18 is a bachelor’s degree, 19 is a master’s degree, 20 is a professional school degree (e.g., MD, JD), and 21 is a doctoral degree (e.g., PhD).

distribution of scores in the smart comparison group. While the groups were all highly educated, everyone in the SCI group had advanced (doctoral or similar) degrees. Because there was no variance on this variable, the SCI group had significantly higher education. Although the groups did not differ on other demographic variables, age and gender were included in the generalized linear mixed model (GLMM) as covariates of interest.

Functional MRI Methods

MRI Acquisitions

Participants were scanned on a Siemens Magnetom Trio head-only 3 T scanner with a 12-channel head coil. For each participant, a high-resolution T1-weighted sagittal magnetization-prepared rapid acquisition gradient-echo (MPRAGE) structural image was obtained (repetition time [TR] = 2,530 ms, echo time [TE] = 3.31 ms, matrix size = 256 × 256, field-of-view = 256 mm, flip angle = 7°, 176 slices with 1 mm isometric voxels). Functional blood oxygenation level-dependent (BOLD) images were acquired using an echo-planar imaging (EPI) sequence (TR = 2,000 ms, TE = 30 ms, matrix size = 64 × 64, field-of-view = 192 mm, 34 slices with 3-mm isometric voxels). An additional high-resolution T2-weighted segmented spin-echo structural image (TR = 5,000 ms, TE = 34 ms, matrix size = 128 × 128, field-of-view = 192 mm, 36 slices, 1.5 mm in-plane resolution, 3 mm thick) in the same anatomical planes as the BOLD images was acquired to improve alignment to a standard coordinate system.

fMRI Preprocessing

fMRI data were preprocessed using FMRIB Software Library (FSL) using a standard pipeline (e.g., motion correction, brain extraction, spatial smoothing at 5 mm full width at half maximum [FWHM], and temporal filtering). All participant data were registered to a standard space using a three-stage registration procedure: Preprocessed images were first registered to the high-resolution T₂-weighted structural scan via a rigid body linear registration using 6 ° F of freedom (three rotational, three translational), then to the MPRAGE using FSL's Boundary-Based Registration, and finally normalized to standard space (Montreal Neurological Institute [MNI]) using a linear affine transform with 12 ° F of freedom.

fMRI Conditions and Behavioral Assessments

Subjects were studied using fMRI in three different conditions: resting-state, the AUT, and the remote associates test (RAT). The AUT requires participants to propose alternative uses of common objects. These stimuli are described in full in a previous article (Japardi et al., 2018), which we briefly summarize here. The RAT requires participants to identify words that connect to three seemingly unrelated words (Mednick, 1968; e.g., “*sick*” connects with *the sea*, *home*, and *stomach*). A practice test was provided prior to MRI scanning, which contained AUT and RAT questions not included during the scanning tests. Each task consisted of two runs, each containing unique counterbalanced stimuli. Stimuli were presented using MRI-compatible stereoscopic goggles, with responses collected using a button box, positioned in the participant's dominant hand.

The AUT lasted approximately 10 min, consisting of eight alternating blocks of alternative uses (AU) and TQ trials. Each AU and TQ block consisted of four items displayed for 20 s each. Control

blocks, in which participants were cued to make five button presses over 20 s, were presented after every two AU or TQ trials. The task also included an interstimulus interval between 2 s and 5 s. Participants were instructed to think of as many different alternative uses or typical qualities for the presented word and to respond with a button press for each distinct thought that came to mind. For example, a typical quality of an “umbrella” may be that it is “waterproof,” but an unusual use would be “a hat.” We captured the numbers of button presses in each block, and separately analyzed the postscan recall of responses during the AU condition, generating measures of both fluency and originality (see Japardi et al., 2018 for further details).

The RAT lasted approximately 14 min and consisted of three different stimulus blocks where subjects were provided different word rules to apply to stimuli, described previously (Japardi et al., 2018). In the “association” condition, after the presentation of three stimulus words, subjects pressed a button to indicated on a four-button response device when they had identified a word common to three stimulus words among the four possible answers presented on the response screen (e.g., for the stimulus set including the three words: “sea,” “rocking,” and “shoe,” the correct response was “horse”). Control conditions included a “perceptual” (character matching) and “synonym” identification tasks. Task presentation included a jittered interstimulus interval before the start of the next trial. Behavioral outcomes included the number of correct responses in each of the perceptual, synonym, and association conditions.

Additionally, subjects were scanned in the resting state. During the 6-min scan, subjects were instructed to lie still with their eyes open and to view a white fixation cross on a black background. All functional scans used identical acquisition parameters and differed only in the number of acquisitions. We reported behavioral results of the tasks during fMRI activation procedures in Japardi et al. (2018); because there were no significant between-group differences in performance, we did not consider those results in the current set of analyses.

Functional Connectivity Analyses

Preprocessing of fMRI data used a 333 ROI atlas (Gordon et al., 2016) following methods similar to those detailed in Power et al. (2014) and Cole et al. (2014). Graph theory metrics, extracted within each condition using the Brain Connectivity Toolbox (Rubinov & Sporns, 2010) in MATLAB, evaluated changes among networks (global) and within networks depending on group and task. Connectivity measures were calculated over a sparsity range (12%–32% by 2% intervals) using the area under the curve approach. The following graph theory measures were considered: modularity (Q), small-worldness (sigma), clustering coefficient (gamma), characteristic path length (lambda), and local efficiency and clustering (Rubinov & Sporns, 2010). For the AUT and RAT, stimulus times were used to extract portions of the scans where specific tasks were being performed, leaving only data within task trials.

Following the extraction of global and local (network) graph theory measures for each scan, statistical analyses were conducted using the R lme4 statistical package to test the hypothesis that global connectivity may differ by groups and that local connectivity may show network-dependent connectivity changes depending on group membership. Global and local models were run within each condition (resting state, AUT, RAT) using a GLMM to control for repeated measures and unequal variances in model residuals seen across

conditions. Analyses were duplicated with and without “outlier” removal using the R package LMERConvenienceFindings.

Global Connectivity Analyses

The GLMM, testing the hypothesis that global connectivity may differ between groups, was run within each of the three conditions. A random effect for subject ID was included to account for within-subject repeated measures. Global dependent variables included modularity (Q), small-worldness (sigma), clustering coefficient (gamma), and characteristic path length (lambda; Rubinov & Sporns, 2010). The fixed effects used to explain these metrics included measure type (Q, sigma, gamma, lambda), stimulus, age, gender, and group (SCI, VA, SCG). Our primary hypothesis was that small-worldness (sigma) would differ between groups, without specifying the direction of possible differences.

Local Connectivity Analyses

To test hypotheses about local network connectivity, a GLMM was used to examine the effects of group, network, and group by network interaction and account for repeated measures. A random effect for subject ID was included to account for within-subject repeated measures. Similar to the global analyses, these models were run separately within each of the three conditions.

Local connectivity metrics included local efficiency and clustering coefficient, computed within six networks: default mode, dorsal attention, frontoparietal, salience, ventral attention, and visual. The visual network was set as the reference for the GLMM given that prior hypotheses have not invoked it specifically (in contrast to the default mode network, and selected other elements of working memory, salience, and attentional networks that have been the focus of prior hypotheses), but our interpretations remained agnostic, and we did examine the values of this reference condition across all combinations of group and condition. Fixed effects included the local connectivity measure type (local efficiency, clustering coefficient), age, gender, brain network, group, and stimulus. An interaction effect between group and brain network was included to test the hypothesis that brain network connectivity metrics may differ between groups. This was an exploratory analysis without a priori specification of the direction of group differences as a function of specific metrics or networks.

Intercorrelations of Global and Local Graph Theory Measures and Correlations With Covariates

Possible associations between global and local graph theory measures were explored, as were correlations with other participant characteristics, using Pearson product-moment correlations, and significance was tested using the Hmisc package in R. The null hypothesis was that the correlations were zero.

Results

Behavioral Results

General linear models (GLMs) on behavioral results of performance during the AUT and RAT tasks (with condition treated as a within-subjects repeated measure) revealed expected main effects of conditions but no interactions of condition with group, indicating that the groups did not differ significantly in their performance

of the fMRI tasks (see Supplemental Table S1). As expected, the number of responses during the AU condition was lower than the number of responses during the TQ condition. The AUT control condition (simple cued button pressing during 20 s blocks) showed that participants were all relatively attentive to task demands with average response rates (4.88 to 4.97) very close to the actual number of stimuli shown (five). In addition to the GLM on the RAT accuracy scores with condition as a within-subject variable, because there was heterogeneity of variance, we conducted separate analyses to test for group differences on each condition separately using robust tests (IBM SPSS Statistics Version 27), and these additional analyses did not reveal significant group effects in any condition (Brown-Forsythe statistics < 1.185 , $p > .32$).

Global Connectivity Analyses

Estimated marginal means for all connectivity measures (Figure 1; Supplemental Table S8) showed consistent trends with regression analyses. During the resting state, scientists showed reduced small-world functional connectivity compared with the SCG, holding constant all else ($p < .05$; see Supplemental Table S2). Small-worldness (sigma) was lower in the SCI relative to SCG, and the VIS group had intermediate values, as shown in Figure 2. Given that sigma (small-worldness) is computed as gamma (clustering coefficient) divided by lambda (characteristic path length), the figure further illustrates that the differences in small-worldness are primarily due to lower global clustering in the SCI and VIS groups, rather than differences in characteristic path length, which was similar across groups and only slightly larger in SCI and VIS groups. No global connectivity differences were found during the AUT for group or stimulus (Supplemental Table S3). For the RAT, reduced functional connectivity was observed during the *char* stimulus relative to other conditions of this task ($p < .001$; Supplemental Table S4), but there was no significant effect of group nor a group by condition interaction effect.

Local Connectivity Analyses

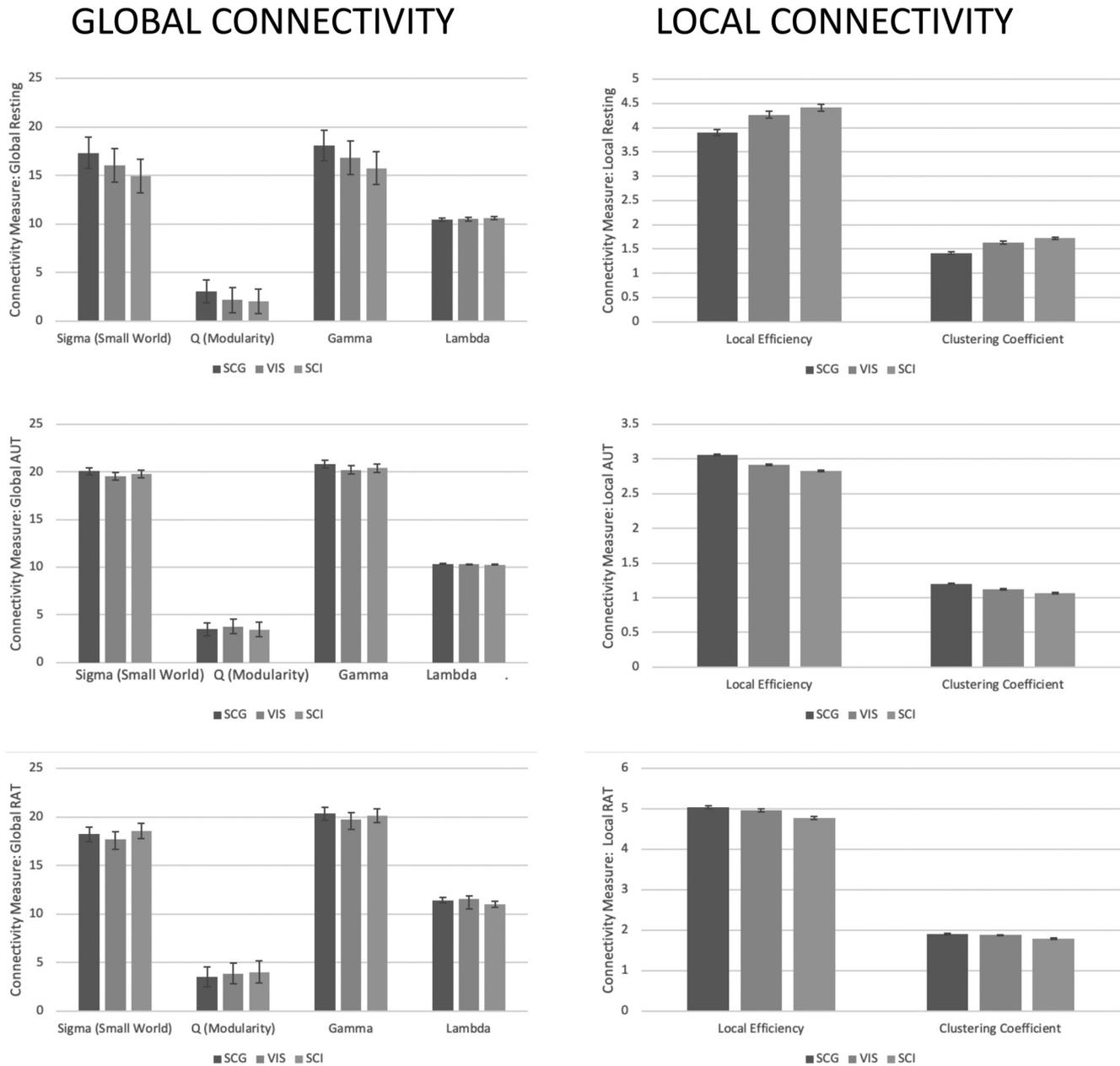
Compared with the SCG, the Big C groups showed increased local efficiency and clustering coefficients within most resting-state networks ($p < .05$; Figure 3; Supplemental Figure S2; Supplemental Table S5). The opposite local connectivity pattern was observed during the AUT, where both local efficiency and clustering coefficients were lower among the Big C groups relative to SCG across almost all brain networks (Figure 3; Supplemental Figure S2; Supplemental Table S6). During the RAT, significant differences between groups were not observed (Figure 3, Supplemental Figure S2; Supplemental Table S7). Estimated marginal means for all connectivity measures similarly illustrate these patterns (Figure 1; Supplemental Table S8).

Correlations Between Global and Local Clustering Metrics

During the resting state, global clustering was negatively correlated with local clustering. We examined these correlations during each condition, and then within each group separately. The results are shown in Supplemental Figure S3, demonstrating that during resting state, the global clustering is anticorrelated with local

Figure 1

Estimated Marginal Means for All Brain Connectivity Measures, After Controlling for Other Covariates



Note. SCG = smart comparison group; VIS = visual artists; SCI = scientists. Relative to SCG, the Big C groups had higher local clustering coefficients during the resting-state conditions but lower local clustering during the AUT condition. No significant differences were found during the convergent thinking test (RAT).

clustering within most networks, across all three groups. These correlations were statistically significant ($p < .05$).

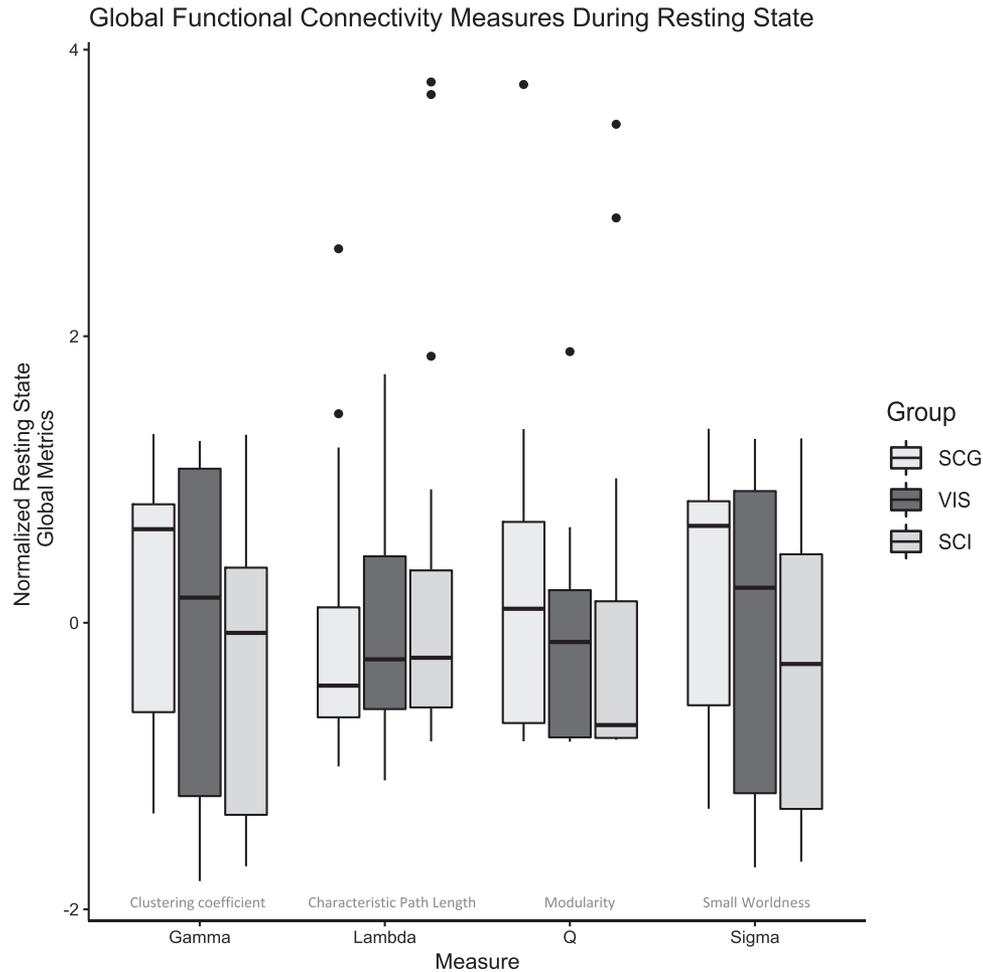
We examined correlations of the global graph theory metrics with estimated IQ. Estimated IQ was positively correlated at a nominal level ($p < .05$) with gamma and sigma metrics obtained during the RAT condition (see Supplemental Table S9) but not during the other conditions. The effect sizes of these correlations were small to medium (maximum $r < .36$), and none of these would be considered statistically significant after correcting for multiple (24) tests. Figure

1 shows the estimated marginal means of the graph theory metrics, adjusted for gender. All analyses were replicated with and without outlier removal, with equivalent findings.

Discussion

These functional connectivity analyses showed that exceptionally creative “Big C” groups had more random patterns of global functional connectivity. More specifically, among the global graph

Figure 2
Global Functional Connectivity Measures During Resting State Demonstrate Group-Specific Changes



Note. SCG = smart comparison group; VIS = visual artists; SCI = scientists. Small-worldness reflects a combination of higher clustering and shorter path lengths, and thus is computed as the ratio of gamma (clustering coefficient) divided by lambda (characteristic path length). During the resting-state, global small-worldness was lower for SCI than SCG; VIS had intermediate values.

theory metrics, exceptionally creative scientists had significantly lower “small-worldness” relative to the SCG. The Big C visual artist group had intermediate values. Given that the pooled Big C groups (scientists and artists together) showed lower small-worldness than the SCG, this offers evidence that reduced small-worldness may characterize exceptional creativity across creative domains. Small worldness is a property thought to increase efficiency in many networks, generally by increasing the clustering of nearby nodes into “cliques” or “hubs” where the average path between nodes is short. Further inspection of the global graph theory metrics confirmed that the small-worldness property reduction was due to decreased global clustering rather than differences in path length in the Big C groups. Therefore, these analyses of global graph theory metrics suggest that the Big C groups possess less “efficient” global networks, technically reflecting a more random pattern of global functional connectivity relative to the smart comparison group. This pattern is consistent with the idea that Big

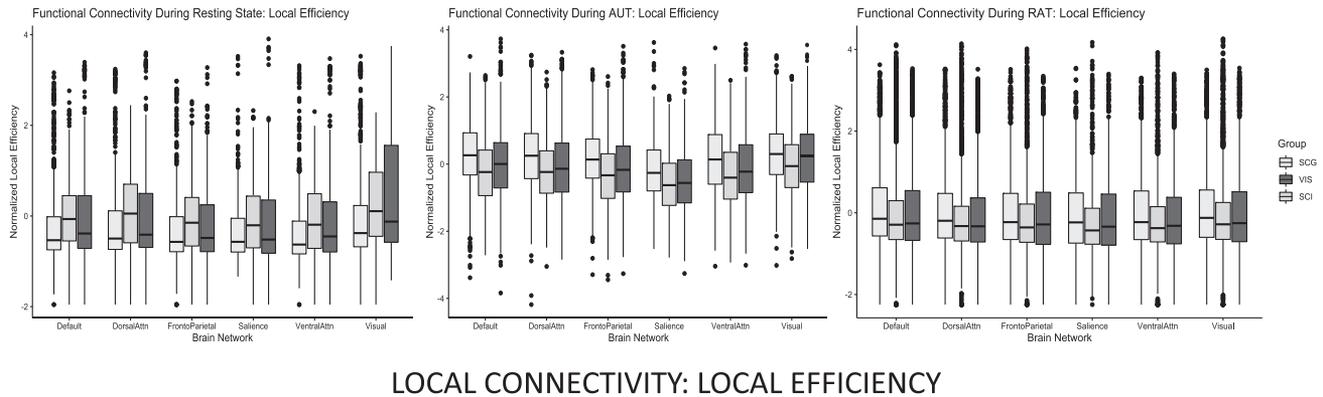
C individuals may possess a capacity to connect widely separated regions in the brain, spanning individual networks, to support creative cognition.

Analyses of local connectivity demonstrated a different pattern. The Big C groups tended to show increased local clustering and efficiency during the resting state but decreased local clustering and efficiency during task-activated conditions, particularly in the AUT condition. We previously documented relatively less activation in task-positive networks during the AUT in this sample, while there were no apparent differences among groups during the RAT (Japardi et al., 2018). The current findings may be seen as extending the prior results and suggest that during tasks like the AUT that may be less demanding for our Big C participants, they do not show the same degree of local clustering as do the comparison group members.

It is intriguing that we observed the opposite pattern during the rest state, with Big C groups showing *greater* local clustering, despite

Figure 3

Local Connectivity Analyses Demonstrate that Compared With the SCG, the Big C Groups Showed Increased Local Efficiency and Clustering Coefficients Within Most Resting State Networks ($p < .05$)



Note. SCG = smart comparison group; VIS = visual artists; SCI = scientists; AUT = alternative uses test.

lower global clustering. Indeed, the magnitude of the negative correlation between local and global clustering in the rest state is so high (with correlation coefficients in the range .6 to .8) that a mechanistic explanation of their covariation seems likely. Thus, the organization of functional networks during the rest state appeared to depend on the scale of our analysis. Increased randomness was observed in Big C groups on global metrics that indicate functional connectivity across networks, while decreased randomness was seen at the local level during rest, with more clustering within multiple individual networks. It is conceivable that a shared process drives increases in local clustering locally at the “expense” of global clustering, or that a more random pattern of associations on a global level “leads to” local clustering. Across groups, the lower global clustering and higher local clustering was observed in the rest state relative to the AUT condition, and this tradeoff was most extreme in the Big C groups (see Supplemental Table 8 for estimated marginal means and a graphical representation of this tradeoff in Supplemental Figure S4). Further work may serve to identify the “sweet spot” on the brain connectome landscape that provides the optimal balance of global and local efficiency that best supports an increased capacity for creative cognition, by optimizing the “costs” of more extensive wiring with efficiency of small-world networks (van den Heuvel & Sporns, 2019).

It is possible that these findings about local connectomics during the rest state may in part replicate prior work showing increased efficiency, particularly within the DMN, being associated with openness to new experience (e.g., Beaty et al., 2016). In the current study, however, we found the higher levels of local efficiency were found across all networks without specificity to the DMN. Our results thus suggest this may be a more generalized topological property of local networks during the rest state in Big C individuals. On the other hand, our results appear to conflict with the finding of less efficient global networks in our Big C groups, compared with the findings of Beaty et al. (2015), that showed higher global efficiency is related to divergent thinking ability. The explanation of this inconsistency may have to do with the samples (Big C and smart comparison groups vs university sample), or experimental design and methods used to define what nodes to include in the graph metrics (we used GLMM to identify group effects across

three conditions, while Beaty et al., 2015 used a four-step process focused on rest-state images and divergent thinking).

Activity within the DMN) or changes in connectivity between the DMN and other networks, particularly the executive and salience networks, have been linked to creativity (Beaty et al., 2015; Beaty et al., 2017; Heinonen et al., 2016; Heinonen et al., 2016; Kühn et al., 2014; Shi et al., 2018). These hypotheses are attractive and in some ways superficially compatible with our prior work (Japardi et al., 2018), which showed less engagement of “task-positive” networks during divergent thinking in the Big C groups. The findings reported here, however, do not highlight the unique role of the DMN, which showed the same overall pattern of results on graph theory measures that characterized other local networks. Instead, our findings suggest that there may exist broader differences in how exceptionally creative individuals coordinate activity across and within functional networks, depending on task demands.

We did not find significant functional connectivity differences in the RAT using global or local measures. One criticism of the RAT has been that it tests verbal recall (Worthen & Clark, 1971), associated with crystallized intelligence. The absence of functional connectivity differences during the RAT in our study is consistent with the proposition that RAT performance depends heavily on convergent thinking abilities that are often closely linked with overall intellectual ability. This effect may have been eliminated because our Big-C individuals were IQ-matched with our comparison group. The only difference in the RAT was found for the ventral attention network of visual artists. We note that patients with schizophrenia (Jimenez et al., 2016; Smucny et al., 2016) have shown this pattern, and also that visual artists in our study had increased expression of subclinical psychopathology (Knudsen et al., 2019). These results may support the hypothesis that these groups share differences in the ventral attention network’s functional organization, resulting in unique approaches to perceptual classifications.

It may be valuable to consider our findings of exceptionally creative individuals in the context of research on clinical syndromes. Functional connectivity differences during the resting state have been observed in neuropsychological disorders, ranging from Alzheimer’s disease (Zhao et al., 2012) to schizophrenia (Anderson &

Cohen, 2013; Liu et al., 2008; Whitfield-Gabrieli et al., 2009) and attention deficit hyperactivity disorder (ADHD; Anderson et al., 2014). People with Alzheimer's disease showed a pattern of resting-state decreased global but increased local efficiency. In contrast, people with schizophrenia showed a pattern of reduced small-worldness that was interpreted as a "disruption" of the healthy pattern. Our findings suggest that there may be both advantageous and harmful effects of different functional connectivity architectures. Prior work, including our results in this sample, shows that individuals with exceptional artistic creativity also show elevations on selected scales associated with subthreshold psychopathology (Knudsen et al., 2017; Knudsen et al., 2019; Simonton, 2006). The current findings may be seen as further evidence that creativity reflects brain functioning "on the edge of chaos" (Bilder & Knudsen, 2014). Functional connectivity patterns that balance "efficiency" with "randomness" may be valuable for creative cognition but also associated with functional risks if the departures from norms are more severe (i.e., detrimental to mental and physical health and safety). The idea that there may be "healthy" and "unhealthy" connectome landscapes (van den Heuvel & Sporns, 2019) is compatible with this idea, and deserves further exploration in diverse clinical syndromes as well as individuals who differ in creative expression.

There are multiple limitations to this study. It is challenging to recruit and conduct extensive studies of exceptionally creative individuals, so sample sizes are necessarily modest, and this means we risk making Type II errors by failing to detect true group differences. Post hoc power estimates show that with this sample size, and three groups, we only had power greater than 80%, with $\alpha = .05$, to detect differences between groups of Cohen's $f > .35$, which is a large effect size. Thus, more subtle but possibly meaningful effects may have been missed by our analyses.

There are further questions about the best methods to classify creative individuals as "Big C" relative to "Proc" or professional-level expertise (Kaufman & Beghetto, 2009), without the benefit of historical perspective. Who knows how many of our "Big C" artists and scientists will still be recognized in 100 years? Supporting the assertion that they should be considered "Big C" rather than "Proc," the CAQ scores of our Big C group appear to be substantially higher than most other groups reported in the literature (indeed our comparison group has higher CAQ scores than some other groups considered exceptionally creative in the literature). Further, our Big C group were not only professionals in their domains, but they were also among the highest-achieving professionals within these domains, and further commended by their peers specifically for making creative contributions to these domains; thus, they occupy a territory above the threshold identified by Kaufman and Beghetto for Proc, but only over time will we know who may satisfy the most stringent criteria that demand demonstration of lasting, transformative genius. As Kaufman and Beghetto stated, following the most rigorous criteria for Big C creativity makes research on the topic "nearly impossible." A few landmark studies (Andreasen & Ramchandran, 2012; Levitin & Grafton, 2016)¹ attempt to prove that it is possible, yet so far we are only aware of a handful of individuals who are widely recognized for such genius that have been investigated using the labor-intensive tools of neuroimaging. Rather than attempting to add to Kaufman and Beghetto's model yet another level in between Proc and Big-C, we believe it is appropriate to refer to our sample as

"Big C," given the clear specification of our inclusion-exclusion criteria.

Additional limitations include the possible differences between activation and rest conditions. While we were able to examine these participants at rest and during two distinct task activation conditions, it would be valuable to examine functional connectivity under a range of additional task conditions, and to relate functional connectivity measures to indicators of structural connectivity. Further, the brain networks that we examined were predefined based on prior studies of healthy "normal" individuals, limiting our ability to identify possible differences not represented in these specific networks. Perhaps exceptionally creative individuals use functional networks that differ from those widely used by healthy people and those with clinical syndromes. Despite these limitations, we hope our results provide evidence that will be useful for those seeking a deeper understanding of the brain mechanisms underlying exceptional creativity, and that these findings will promote future research on the neural substrates of exceptional abilities.

¹ Relevant to the Levitin and Grafton (2016) case study of Sting, it is noteworthy that we have studied the drummer Stewart Copeland who played with Sting, along with others who have been regarded as manifesting genius within their domains (e.g., Geena Davis in acting; Richard Melville Hall, aka "Moby" in music and production), but they were not included in this study of visual artists and scientists.

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