

This is a repository copy of Spontaneous neural activity relates to psychiatric traits in 16p11.2 CNV carriers: An analysis of EEG spectral power and multiscale entropy.

White Rose Research Online URL for this paper: https://eprints.whiterose.ac.uk/167679/

Version: Accepted Version

## Article:

Al-Jawahiri, R., Jones, M. orcid.org/0000-0002-4580-7559 and Milne, E. orcid.org/0000-0003-0127-0718 (2021) Spontaneous neural activity relates to psychiatric traits in 16p11.2 CNV carriers: An analysis of EEG spectral power and multiscale entropy. Journal of Psychiatric Research, 136. pp. 610-618. ISSN 0022-3956

https://doi.org/10.1016/j.jpsychires.2020.10.036

Article available under the terms of the CC-BY-NC-ND licence (https://creativecommons.org/licenses/by-nc-nd/4.0/).

#### Reuse

This article is distributed under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs (CC BY-NC-ND) licence. This licence only allows you to download this work and share it with others as long as you credit the authors, but you can't change the article in any way or use it commercially. More information and the full terms of the licence here: https://creativecommons.org/licenses/

#### Takedown

If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.



eprints@whiterose.ac.uk https://eprints.whiterose.ac.uk/

# Spontaneous Neural Activity Relates to Psychiatric Traits in 16p11.2 CNV Carriers: An Analysis of EEG Spectral Power and Multiscale Entropy

Reem Al-Jawahiri<sup>1\*</sup>, Myles Jones<sup>1</sup>, Elizabeth Milne<sup>1</sup>

<sup>1</sup>Department of Psychology, University of Sheffield, United Kingdom

\* Corresponding author

Department of Psychology, University of Sheffield, Cathedral Court, 1 Vicar Lane, Sheffield, S1 2LT, United Kingdom

+44 (0) 114 222 6558

r.jawahiri@sheffield.ac.uk

#### Abstract

Copy number variations (CNV) at the 16p11.2 chromosomal region are rare high-risk CNVs associated with various clinical features and psychiatric disorders including intellectual disability, developmental delays, and autism spectrum disorder. No study to date has investigated whether spontaneous neural activity is altered for 16p11.2 CNV carriers and whether this relates to psychiatric traits. The aim of this study is to examine the impact of 16p11.2 deletions (del) and duplications (dup) on spontaneous neural activity and its relationship to psychiatric problems. EEG was previously collected as part of the Simons Searchlight initiative. Using spectral power (delta, theta, alpha, and beta frequency bands), complexity index (CI), and multiscale entropy analysis techniques, we analyzed frontal resting-state EEG data collected from 22 16p11.2 del carriers, 14 dup carriers, and 13 controls. We then examined associations between neural activity and psychiatric traits, measured with the Child Behavior Checklist. Results indicated that EEG entropy was higher for del and dup compared to controls, respectively, at all timescales. CI was also higher for del and dup compared to controls. Theta power of 16p11.2 dup carriers was higher than controls. A strong association was found between entropy at higher timescales and anxiety problems. In addition, a strong correlation was found between theta power and pervasive developmental problems. Atypical spontaneous neural activity is implicated in 16p11.2 CNVs. With higher entropy or theta power, psychiatric traits increase in severity. Our findings provide evidence of the link between genotype, neural activity, and phenotypes in 16p11.2 CNVs.

*Keywords:* 16p11.2 Copy Number Variants, Rare Genetic Syndromes, CBCL, EEG, Resting-State, Entropy.

#### 1 Introduction

2 Deletions (del) and duplications (dup) of the 16p11.2 chromosomal region (~600 kb 3 breakpoints 4–5) are pathogenic copy number variations (CNVs) that increase the risk of 4 developing one or more of the possible associated disorders and difficulties (Shinawi et al., 5 2010; D'angelo et al., 2016; Hanson et al., 2015; Niarchou et al., 2019). The consequences of 6 this CNV are heterogenous as they vary from one individual to another in their severity and phenotypes (Girirajan and Eichler, 2010; Niarchou et al., 2019), including intellectual 7 8 disability, developmental delays, autistic and other psychiatric traits. Evidence suggests that 9 16p11.2 CNV carriers additionally present with atypical neural activity in response to various 10 sensory, sensorimotor, and social stimuli (see Table 1 for a summary of this work). Overall, 11 anomalies were identified in M/EEG signal features of event-related potentials (and its 12 variability) and power at alpha and beta frequencies, evoked by different events. These 13 studies are pioneering works investigating M/EEG activity in this rare CNV, however further 14 work is necessary to assess features detectable from spontaneous neural activity, using 15 conventional and other promising techniques, such as multiscale entropy (MSE). Entropy 16 features may serve as reliable endophenotypes informing prognosis and treatment progression 17 in 16p11.2 CNV carriers.

18 Atypical M/EEG entropy has been implicated in various psychiatric disorders that are 19 associated with 16p11.2 CNVs (for a review, see Chu et al., 2017; Takahashi, 2013; Yang 20 and Tsai, 2013), but has not yet been investigated in individuals who have either a deletion or 21 a duplication at this chromosomal region. With MSE analysis (Costa et al., 2002; Costa et al., 22 2005), in particular, it is possible to quantify the level of entropy or irregularity of moment-23 to-moment patterns of amplitudes in the signal across different scales. Higher entropy indicates higher irregularity in the signal, while lower entropy indicates a more regular, 24 25 predictable pattern. Interestingly, both higher and lower entropy have been found in 26 psychiatric disorders (relative to typical controls) in a manner that is task- (e.g., Mišić et al., 27 2015), scale-, and brain region-dependent (e.g., Ghanbari et al., 2015). For example, 28 compared to controls, higher entropy was found in ASD at higher scales in the occipital, 29 parietal, and temporal areas at resting-state (Takahashi et al., 2016), while lower entropy at 30 higher scales was found in a face and chair detection task (Catarino et al., 2011) in the same 31 brain areas. In addition, Milne et al. (2019) found lower overall entropy in ASD at resting-32 state across all scales and brain regions. Other psychiatric disorders, associated with 16p11.2

33 CNVs, that have shown atypical MSE include epilepsy and seizures (Bosl et al., 2017; Lu et

al., 2015), attention deficit hyperactivity disorder (ADHD, Chenxi et al., 2016),

35 Schizophrenia (Takahashi et al., 2010), and Alzheimer's (Yang et al., 2013; Mizuno et al.,

36 2010).

37 To our knowledge, no study has investigated whether EEG neural activity is altered 38 for 16p11.2 CNVs at rest, using either entropy-based approaches or conventional analyses of 39 spectral power. As frontal resting-fMRI activity has been implicated in 16p11.2 del and 40 linked with cognitive and social traits (Bertero et al., 2018), the current study will focus on 41 frontal neural activity and its link to psychiatric traits in 16p11.2 CNVs. Thus, the purpose of 42 the current study is twofold: 1) To determine whether frontal spontaneous neural activity, 43 indexed by EEG power and entropy, in 16p11.2 CNVs is altered compared to controls; 2) To 44 establish whether this spontaneous neural activity is related to psychiatric traits in 16p.11.2 45 del.

46

## 47 Methods and Materials

## 48 Data source

- 49 The dataset was obtained from the Simons Foundation Autism Research Initiative (SFARI),
- 50 specifically the Simons Searchlight initiative, previously named Simons Variation in
- 51 Individuals Project (SVIP, The simons vip consortium, 2012). Datasets collected as part of
- 52 Simons Searchlight, which include 16p11.2 CNV data, are available to approved researchers
- 53 via the data request process (<u>https://www.sfari.org/resource/simons-searchlight/</u>). For this
- 54 study, data of individuals with 16p11.2 deletion, the reciprocal duplication, and typically
- 55 developing individuals were obtained from SFARI. Participant identification, recruitment,
- 56 and inclusion/exclusion criteria of Simons Searchlight have been described previously (see
- 57 The simons vip consortium, 2012; Jenkins et al., 2016; LeBlanc and Nelson, 2016). Briefly,
- 58 eligibility criteria consisted of having a deletion or duplication of the 16p11.2 region.
- 59 Exclusion criteria consisted of having any other pathogenic CNVs or known genetic
- 60 syndromes. The control participants analyzed in this study did not undergo the Simon's VIP
- 61 battery of assessments. LeBlanc and Nelson (2016) recruited the control group independently
- 62 through the Boston Children's Hospital participant registry. The group consisted of typical
- 63 individuals without any neurological or developmental disorders.

## 64 Ethical approval

65 The investigation was carried out in accordance with the latest version of the Declaration of 66 Helsinki. The local institutional ethical review board reviewed and approved the secondary 67 analyses presented here. Our request to obtain access to phenotypic and imaging data on 68 SFARI Base was approved after submitting the required information and signing the joinder 69 to the researcher distribution agreement (https://www.sfari.org/resource/sfari-base/). SFARI 70 obtained initial ethical approval for the SVIP (IRB of record: Columbia University Medical 71 Center, The simons vip consortium, 2012). As part of the SVIP, approval was obtained for 72 data collection on individuals with 16p11.2 deletions or duplications and for their de-

73 identified data to be shared with approved researchers.

## 74 Participants

- 75 Data from a total of 53 participants were obtained (n = 14 control, 25 del, and 14 dup).
- 76 Participants identified as extreme outliers for the respective entropy and power analyses were
- excluded (n = 1 control and 3 del for MSE and CI analyses; n = 2 control, 3 del, 2 dup for
- power analyses). Therefore, 49 participants (n = 13 control, 22 del, and 14 dup) were

analyzed using entropy analyses, and 46 participants were analyzed using power analyses (n
= 12 control, 22 del, and 12 dup). Participant information (of those included in the entropy
group analyses) relating to age, sex, CNV inheritance, number of diagnoses, and IQ scores
are reported in Table 2.

83 The diagnoses in the current sample are listed in **Supplementary Table S1**. 84 Information regarding current medication was extracted from the SFARI medication 85 questionnaire; four CNV carriers were currently taking medication for anxiety, ADHD, and epilepsy/ seizures. There was no significant age difference between the three groups ( $\chi^2(2)$  = 86 1.50, p = 0.472); and no association between group and sex ( $\chi^2(2) = 0.36$ , p = 0.834). Other 87 88 than age and sex, participant details and phenotypic data were not available for the control 89 group. Therefore, IQ comparisons between del and dup with controls, respectively, were not 90 possible.

# 91 EEG recording and pre-processing

92 EEG data collection and some pre-processing were conducted prior to the current study by 93 collaborators of SVIP, as described in **Supplementary Information**. Briefly, using a 128 94 channel HydroCel Net (Electrical Geodesics Inc., Eugene, OR, USA), EEG was collected for 95 2 to 12 minutes during which participants rested and watched silent videos on a monitor. 96 Infant participants were seated on their caregiver's lap. Additional pre-processing steps were 97 conducted by the current authors after obtaining the dataset. For each participant, a channel 98 was identified as 'bad' (not suitable for further analyses) if more than 10% of its datapoints 99 were outside of the predefined range [-150 uV, 150 uV]. If a particular channel was bad for 100 more than 11 participants, then the channel was removed for all participants. Under this 101 criterion, 38 channels out of 128 channels were not used for main analyses or as input 102 channels for interpolation where required. From the remaining channels, 27 frontal channels 103 were selected for analysis (Supplementary Fig. S1). The frontal channels marked as bad, for 104 the respective participant, were removed and interpolated. On average, two channels [range: 105 0, 13] were interpolated per participant. The signal was then detrended by removing the linear 106 trend in the data. (Note that embedded in the sample entropy function described later, the 107 mean is subtracted and divided by the standard deviation of the signal prior to computing 108 sample entropy).

#### 109 Behavioral and psychiatric assessments

- 110 Child Behavior Checklist for ages 1.5-5 (CBCL) and IQ participant data were accessed from
- 111 the Simons VIP Phase 1 16p11.2 dataset at SFARI Base
- 112 (http://www.sfari.org/resources/sfari-base). The CBCL/1.5-5 (Rescorla, 2005) is an
- assessment of parent or caregiver report of behavioral and psychiatric problems in preschool
- 114 children. The CBCL yields the following categories based on the summed scores of items of
- 115 the respective category: affective problems, anxiety problems, attention deficit/hyperactivity
- 116 problems, pervasive developmental problems, oppositional defiant problems, and sleep
- 117 problems. For this paper, T-scores of each category were taken for correlational analyses with
- 118 the EEG measures of interest. Data from nine del carriers are missing. See **Supplementary**
- 119 Information for details regarding the CBCL assessment and the CBCL severity levels in the
- 120 current sample (**Supplementary Table S2**), in addition to details regarding the previously
- 121 conducted IQ assessments.

## 122 **EEG measures**

## 123 Multiscale entropy

- 124 Multiscale entropy (MSE) analysis was performed on scales 1-20 for a continuous EEG
- signal of 60,000 data-points (2 minutes; 500 Hz sampling rate). From the whole signal of
- 126 length <10 minutes, the chosen two-minute segment range was from 8000 to 68,000 data-
- 127 points. (This range allows the exclusion of the first 16 seconds of recording in order to avoid
- 128 potentially contaminated data due to participant movement and other artifacts while the
- 129 participant became settled at the start of the session. Visual inspection of the data suggested
- 130 that 'noise' was often present within the first 16 seconds of recording). The following
- 131 software and toolboxes were used for the analyses, MATLAB (The MathWorks Inc.),
- 132 EEGlab toolbox (Delorme and Makeig, 2004), and multiscale entropy toolbox
- 133 (<u>http://www.psynetresearch.org/tools.html</u>) (Liang et al., 2014). The MSE method measures
- 134 sample entropy (Richman and Moorman, 2000) on multiple time scales (see Supplementary
- 135 Information, Costa et al., 2002, 2005). MSE consists of two main steps as follows. Based on
- 136 previous M/EEG studies (e.g., Takahashi et al., 2016; Ghanbari et al., 2015) and
- 137 recommendations by Richman and Moorman (2000), the following MSE parameters were
- 138 chosen: *m* was set to 2 and r = 0.2. MSE was first determined for each channel and then
- averaged over the frontal region, in line with Takahashi et al. (2016). Entropy of scales 1-20
- 140 was averaged into four bins: scales of 1-5, 6-10, 11-15, and 16-20. The data was further

reduced for correlation analyses; Entropy was averaged into two 'bins' of scales 1-10 and 11-20.

## 143 Complexity index

144 The complexity index (CI) is another measure of entropy as described by Costa et al. (2005).

145 For each channel, CI was computed by estimating the area under the MSE curve via

146 integrating entropy values of all scales by using a trapezoidal numerical integration via the

147 'trapz' function in MATLAB. The average CI was then calculated over channels at the

148 frontal region.

#### 149 Power spectral density

150 Power spectral density (PSD) of each channel was computed using the 'pwelch' MATLAB 151 function. The signal was first detrended and subtracted from the mean signal amplitude. In 152 accordance with Welch's method, the signal (60,000 data-points or 2 minutes) was divided 153 into segments of equal length (2-second segments in this case) with a 50% overlap. Given a 154 sampling rate of 500 Hz and N = 1000 data-points per segment, the resultant frequency 155 resolution was 0.5 Hz. Each segment was windowed with a Hamming window and modified 156 periodograms (PSDs of each Hamming window) were estimated. The final PSD was obtained 157 by averaging the periodograms of all segments. Absolute and relative power were then 158 computed for the following frequency bands: delta [2-4 Hz], theta [4-8 Hz], alpha [8-14 Hz], 159 and beta [14-30 Hz]. Absolute power of each frequency band was obtained via the 160 trapezoidal integration method, using the 'trapz' MATLAB function. Prior to obtaining the 161 relative power, the total spectral power was defined as the entire range between 1-50 Hz (the 162 upper limit was set to avoid the frequency range effectively removed by a notch filter applied 163 at 60 Hz). Relative power at each frequency band was subsequently calculated as the ratio of 164 power of the respective frequency band to the total spectral power defined earlier. Relative 165 power of each frequency band was respectively averaged over the frontal region.

#### 166 Statistical analyses

167 Permutation tests (Rodgers, 1999) were conducted to investigate whether there were group

- 168 differences in neural activity in the frontal region between del/control, dup/control, and
- 169 del/dup comparisons. This was conducted, as described previously in Al-Jawahiri et al.
- 170 (2019). To account for multiple comparisons, the false discovery rate (FDR) was controlled
- 171 using the Benjamini-Hochberg procedure, with q < 0.05. We also applied the permutation
- approach to Spearman's correlation analyses to examine whether age, IQ, and psychiatric

- 173 traits (i.e., CBCL) impact neural responses in 16p11.2 CNV. All the outcomes were corrected
- by controlling the FDR using the Benjamini-Hochberg procedure, with q < 0.05. Correlation
- 175 permutation tests between age and neural responses were performed separately for del, dup,
- and control groups (initial sample size: n = 14 control, n = 14 dup, n = 25 del). Prior to
- 177 conducting analyses, outliers were identified, using Cook's distance, for the respective
- 178 correlation pairs and removed (control: median number of outliers = 2, range = [1, 2]; dup:
- 179 median = 1.5, range = [1, 2]; del: median = 2.5, range = [2, 3]). As IQ and CBCL data were
- 180 either not available or insufficient for the control and dup groups (n = 14 prior to excluding
- 181 outliers for IQ vs EEG measures' correlations for dup), correlation permutation analyses were
- 182 conducted for only the del group (n = 25). However, there were some missing IQ (n = 3) and
- 183 CBCL (n = 9) data for del. Outliers from the remaining IQ (n = 22) and CBCL (n = 16) data
- 184 were removed (median number of outliers = 2; range = [0, 4]) prior to conducting analyses.

#### 185 **Results**

## 186 Multiscale entropy

- 187 Significant group differences ( $p \le 0.033$ ) were found in entropy at all the respective scales
- 188 (i.e., 1-5, 6-10, 11-15, and 16-20) in the frontal region (**Table 3**; **Fig. 1A**). Specifically,
- 189 entropy was higher in both del and dup than controls. No significant differences in entropy
- 190 were found between del and dup.

# 191 **Complexity index**

- 192 CI was significantly higher for del and dup compared to controls, respectively ( $p \le 0.033$ ), at
- 193 the frontal region (**Table 3**; **Fig. 1B**). No significant difference in CI was found between del
- and dup.

## 195 **Power spectral density**

- 196 Fig. 2 shows the average spectra used to derive the relative power for each group. Group
- 197 differences in relative power within each frequency band (delta, theta, alpha, and beta) at the
- 198 frontal region were examined (significance threshold at  $p \le 0.004$ , Table 3, Fig. 1C). Theta
- 199 power was significantly higher in dup than in controls (**Fig. 1D**). No other significant
- 200 differences in power were found between the three groups.

## 201 The impact of age on MSE and power

- 202 Due to the wide age range of participants, we assessed the impact of age on EEG measures of
- 203 interest. Correlation permutation tests were performed separately for del, dup, and control
- 204 groups. Specifically, correlations were performed between age and the following EEG
- 205 measures: lower scale entropy (1-10) and higher scale entropy (11-20); power of delta, theta,
- alpha, and beta bands (significance threshold at  $p \le 0.025$  for MSE measures and  $p \le 0.013$
- 207 for power measures). No significant correlations were found between age and any of these
- EEG measures at the frontal region in any group (Supplementary Table S3).

# 209 The relationship between EEG activity and psychiatric traits

- 210 Correlation permutation tests were performed to examine correlations between MSE (i.e., 1-
- 211 10 and 11-20 scales; Fig. 3A) and power measures (Fig. 3B) against psychiatric traits (i.e.,
- 212 CBCL and IQ) in the del group (**Table 4**). Due to the small sample size, the dup group was
- 213 not included in this analysis. A strong correlation was found between entropy at higher scales
- 214 (scales 11-20) and anxiety problems (significance threshold at  $p \le 0.004$ ). A strong

- 215 correlation was also found between theta power and pervasive developmental problems
- 216 (significance threshold at  $p \le 0.002$ ). Overall, with higher entropy or power, psychiatric traits,
- 217 i.e., anxiety and pervasive developmental problems, increase in severity in del. No other
- significant correlations were found between any of the EEG measures and CBCL subscales
- 219 or IQ.

## 220 The relationship between entropy and power

221 The EEG signal is information-rich and, thus, it can be challenging to perfectly isolate certain 222 features and determine all possible influences from other features in the signal. Nevertheless, 223 in recognition of the possible interplay between entropy and power features, we have 224 conducted correlation permutation tests to examine this, separately for each group 225 (significance threshold at  $p \le 0.033$ , corrected for multiple comparisons). Specifically, the 226 power measures of interest for this post-hoc analysis in the current study are theta and alpha 227 power as the former was correlated with anxiety in del and showed group differences in dup 228 compared to controls. The latter, i.e., alpha power, has been found to be a dominant 229 frequency impacting entropy in eyes-open resting-state paradigms (Kosciessa et al., 2020). 230 Here, entropy variables were collapsed into two categories: lower scales (1-10) and higher 231 scales (11-20) – consistent with the earlier correlation analyses in this study (see 232 Supplementary Fig. S2 for correlation analyses with entropy collapsed into four categories 233 scales 1-5, 6-10, 11-15, 16-20). Results (Fig. 4) showed moderate to strong positive 234 correlations between entropy, at lower scales and higher scales, and alpha power for the del, 235 dup, and controls groups, respectively. For del, there were also moderate positive correlations 236 between entropy, at lower and higher scales, and theta power. Overall, the results suggest that 237 alpha and, to a lesser extent, theta power may impact on entropy levels at all scales. 238 Therefore, it is important to note that entropy group differences, identified earlier, are not 239 solely due to signal features of entropy. Other factors, such as alpha and theta power, may 240 have contributed to the different presentation of entropy in each group (despite no group 241 differences in alpha power).

9

#### 242 **Discussion**

243 The aims of the current study were 1) to determine whether frontal spontaneous neural 244 activity, as revealed by EEG power and MSE, in 16p11.2 CNVs is altered compared to 245 controls; and 2) to examine links between spontaneous neural activity and psychiatric traits in 246 16p11.2 del. The main findings are 1) MSE and CI were higher for 16p11.2 CNVs (i.e., del 247 and dup) than controls at all respective scales over the frontal region; 2) Theta power was 248 higher for dup compared with controls; 3) In del, strong associations were found between 249 MSE and anxiety problems, and between theta power and pervasive developmental problems 250 as measured with the CBCL. Together, these results suggest atypical frontal spontaneous 251 neural activity that seems to strongly reflect or impact on certain psychiatric traits.

252 Taking the ESSENCE approach of considering interrelated psychiatric disorders 253 together (Gillberg, 2010), certain commonalities emerge in neural entropy between these 254 disorders and 16p11.2 CNVs. We have shown similar neural changes in a genetic condition 255 that underpins various psychiatric disorders, thus suggesting a mechanism for which genetic 256 conditions could lead to these diagnoses or psychiatric traits. Notably, the current study found 257 higher entropy in 16p11.2 CNVs at both lower and higher scales compared to controls, as 258 jointly reflected by CI and MSE analyses. This is reminiscent of findings previously reported 259 in relation to ASD and absence epilepsy (Bosl et al., 2017) where an overall higher entropy at 260 resting-state was also found compared to controls. Findings from many other studies, though, 261 suggest that it is more common in psychiatric disorders for there to be scale-dependent 262 variations in the level of entropy, compared to controls. Higher spontaneous frontal entropy 263 has been more frequently observed at higher scales in particular (ASD, Ghanbari et al., 2015; 264 Schizophrenia, Takahashi et al., 2010; Alzheimer's, Yang et al., 2013; Mizuno et al., 2010). 265 This implies that psychiatric disorders, in the aforementioned studies, showed atypical long-266 range spontaneous neural connectivity involving the frontal region, as it has been suggested 267 that neural entropy at lower and higher scales respectively reflect local/shorter-range and 268 longer-range neural connectivity (McDonough and Nashiro, 2014; Vakorin et al., 2011). In 269 contrast, findings in the current study may indicate a disruption in both shorter- and longer-270 range neural connectivity involving the frontal region and spontaneous neural activity in 271 general.

272 Our findings additionally implicate theta power in 16p11.2 dup. Interestingly, 273 although we found higher entropy in both 16p11.2 del and dup compared to controls, higher 274 theta power was observed solely in dup. This could indicate that entropy, relative to power, is 275 a more sensitive measure useful for capturing certain properties of neural information 276 processing in 16p11.2 del, not possible by conventional power analyses alone. Notably, this 277 finding of higher theta is consistent within the literature of a range of psychiatric disorders 278 (e.g., Schizophrenia, ADHD) and genetic syndromes (e.g., Angelman syndrome, Frohlich et 279 al., 2019; Newson and Thiagarajan, 2018; Wang et al., 2013). Higher power at lower 280 frequencies in these disorders and 16p11.2 dup may indicate a similar dysfunction or 281 compensatory mechanism that affects psychiatric traits shared among these disorders. Theta 282 power has been commonly regarded as implicating memory processes (Berens and Horner, 283 2017). In this study, higher theta was associated with higher severity in pervasive 284 developmental problems, which could be affected by disruptive learning and memory 285 processes.

286 Evidence from a previous study (Takahashi et al., 2010) suggests that higher entropy 287 might relate to atypical dopaminergic and/or serotonergic activity – both systems associated 288 with anxiety and cognitive processes. Specifically, Takahashi et al. (2010) studied EEG MSE 289 activity in drug-naïve schizophrenia participants, pre- and post-treatment with antipsychotics, 290 and compared MSE with typical controls. Takahashi et al. (2010) found increased entropy at 291 higher scales in fronto-centro-temporal areas in schizophrenia (pre-treatment) compared to 292 typical controls. This is somewhat similar to the findings in the current study as higher 293 entropy was found at higher scales (but also lower scales) in the frontal region in 16p11.2 294 CNVs compared to controls. Notably, Takahashi et al. (2010) also found that this higher 295 entropy in schizophrenia was lowered to the control participants' level in fronto-central areas 296 in response to antipsychotic treatment. In other words, the observed atypically high entropy 297 observed in schizophrenia was reversed in response to medications that act on attenuating 298 dopaminergic and, to a lesser extent, serotonergic activity. Thus, the identified atypical neural 299 entropy in 16p11.2 CNVs, in the current study, along with the observed strong links between 300 neural activity and psychiatric traits, could, therefore, signify a dysregulation in multiple 301 neurotransmitter systems including dopamine and serotonin, in 16p11.2 CNVs.

Future work should examine whether these EEG features are similarly present in 16p11.2 CNV mouse models by conducting parallel human and mouse studies. If common conserved EEG features are identified cross-species, the mouse model can be used to investigate the reversibility of these features and associated phenotypes/ pathophysiology. In
 addition, parallel studies could examine whether these EEG features are indeed
 endophenotypes that reflect particular dysregulations in dopaminergic or serotonergic activity
 - thus paving the way to identifying potential drug treatments.

309 As is typical of EEG studies of rare CNVs and genetic syndromes, key limitations 310 include the small sample size and therefore the lack of examination of possible confounding 311 factors such as seizure susceptibility/epilepsy (Table S1) and current medication use. 312 Nevertheless, analyses in this study were based on group averages and conservative 313 significance thresholds. Despite this, it is important to highlight that it would be valuable to 314 support the current findings by replicating the results in future samples. Another limitation of 315 this, and CNV studies in general, is the complexity of CNV screening, which may generate 316 false-positive or false-negative results for pathogenic CNV. In addition, inclusions of 317 unknown benign versions of the same CNV, based on the allelic background, are also 318 possible.

319 Overall, the current study established that 16p11.2 CNVs present with atypical 320 resting-state neural activity as revealed with entropy and power measures. Neural entropy 321 levels were consistently higher in the frontal region for 16p11.2 CNVs relative to controls at 322 all scales. Therefore, we speculate that this implicates interactions between local and long-323 range neural processing at resting-state networks. Higher theta power was additionally 324 identified in 16p11.2 dup carriers. Whether reflecting a compensatory or dysfunctional 325 mechanism, neural activity in 16p11.2 CNVs was strongly associated with psychiatric traits, 326 namely, anxiety and pervasive developmental problems. Thus, this study presents the first 327 evidence of links between the 16p11.2 CNV genotype, spontaneous neural activity, and 328 psychiatric phenotypes.

# Acknowledgments

We are grateful to all of the families at the participating Simons Variation in Individuals Project (Simons VIP) sites, as well as the Simons VIP Consortium. We appreciate obtaining access to phenotypic and imaging data on SFARI Base. Approved researchers can obtain the Simons VIP population dataset described in this study

(https://www.sfari.org/resource/simons-vip/) by applying at https://base.sfari.org/. We would like to thank Dr. Jocelyn J. LeBlanc, Dr. Charles A. Nelson, and research staff members at Boston Children's Hospital and Harvard Medical School for their contributions in generating this data.

## References

- Al-Jawahiri, R., Jones, M., Milne, E., 2019. Atypical neural variability in carriers of 16p11.2 copy number variants. Autism Res 12(9), 1322-1333.
- Berens, S.C., Horner, A.J., 2017. Theta Rhythm: Temporal Glue for Episodic Memory. Curr Biol 27(20), R1110-R1112.
- Bertero, A., Liska, A., Pagani, M., Parolisi, R., Masferrer, M.E., Gritti, M., Pedrazzoli, M.,
  Galbusera, A., Sarica, A., Cerasa, A., Buffelli, a., Tonini, R., Buffo, A., Gross, C.,
  Pasqualetti, M., Gozzi, A., 2018. Autism-associated 16p11.2 microdeletion impairs
  prefrontal functional connectivity in mouse and human. Brain 141(7), 2055-2065.
- Bosl, W.J., Loddenkemper, T., Nelson, C.A., 2017. Nonlinear EEG biomarker profiles for autism and absence epilepsy. Neuropsychiatric Electrophysiology 3(1), 1.
- Catarino, A., Churches, O., Baron-Cohen, S., Andrade, A., Ring, H., 2011. Atypical EEG complexity in autism spectrum conditions: a multiscale entropy analysis. Clin Neurophysiol 122(12), 2375-2383.
- Chenxi, L., Chen, Y., Li, Y., Wang, J., Liu, T., 2016. Complexity analysis of brain activity in attention-deficit/hyperactivity disorder: A multiscale entropy analysis. Brain Res Bull 124, 12-20.
- Chu, Y.J., Chang, C.F., Shieh, J.S., Lee, W.T., 2017. The potential application of multiscale entropy analysis of electroencephalography in children with neurological and neuropsychiatric disorders. Entropy 19(8), <xocs:firstpage xmlns:xocs=""/>.
- Costa, M., Goldberger, A.L., Peng, C.K., 2002. Multiscale entropy analysis of complex physiologic time series. Phys Rev Lett 89(6), 068102.
- Costa, M., Goldberger, A.L., Peng, C.K., 2005. Multiscale entropy analysis of biological signals. Phys Rev E Stat Nonlin Soft Matter Phys 71(2 Pt 1), 021906.
- Delorme, A., Makeig, S., 2004. EEGLAB: an open source toolbox for analysis of single- trial EEG dynamics including independent component analysis. Journal of Neuroscience Methods 134(1), 9-21.
- D'angelo, D., Lebon, S., Chen, Q., Martin-Brevet, S., Snyder, L.G., Hippolyte, L., Hanson,
  E., Maillard, A.M., Faucett, W.A., Macé, A., Pain, A., Bernier, R., Chawner, S.J.R.A.,
  David, A., Andrieux, J., Aylward, E., Baujat, G., Caldeira, I., Conus, P., Ferrari, C.,
  Forzano, F., Gérard, M., Goin-Kochel, R.P., Grant, E., Hunter, J.V., Isidor, B.,
  Jacquette, A., Jønch, A.E., Keren, B., Lacombe, D., Le Caignec, C., Martin, C.L.,
  Männik, K., Metspalu, A., Mignot, C., Mukherjee, P., Owen, M.J., Passeggeri, M.,

Rooryck-Thambo, C., Rosenfeld, J.A., Spence, S.J., Steinman, K.J., Tjernagel, J., Van Haelst, M., Shen, Y., Draganski, B., Sherr, E.H., Ledbetter, D.H., van Den Bree, M.B.M., Beckmann, J.S., Spiro, J.E., Reymond, A., Jacquemont, S., Chung, W.K., 2016. Defining the Effect of the 16p11.2 Duplication on Cognition, Behavior, and Medical Comorbidities. JAMA Psychiatry 73(1), 20-30.

- Frohlich, J., Miller, M.T., Bird, L.M., Garces, P., Purtell, H., Hoener, M.C., Philpot, B.D., Sidorov, M.S., Tan, W.H., Hernandez, M.C., Rotenberg, A., Jeste, S.S., Krishnan, M., Khwaja, O., Hipp, J.F., 2019. Electrophysiological Phenotype in Angelman Syndrome Differs Between Genotypes. Biol Psychiatry 85(9), 752-759.
- Ghanbari, Y., Bloy, L., Christopher Edgar, J., Blaskey, L., Verma, R., Roberts, T.P., 2015. Joint analysis of band-specific functional connectivity and signal complexity in autism. J Autism Dev Disord 45(2), 444-460.
- Gillberg, C., 2010. The ESSENCE in child psychiatry: Early Symptomatic Syndromes Eliciting Neurodevelopmental Clinical Examinations. Res Dev Disabil 31(6), 1543-1551.
- Girirajan, S., Eichler, E.E., 2010. Phenotypic variability and genetic susceptibility to genomic disorders. Hum Mol Genet 19(R2), R176-187.
- Hanson, E., Bernier, R., Porche, K., Jackson, F.I., Goin-Kochel, R.P., Snyder, L.G., Snow,
  A.V., Wallace, A.S., Campe, K.L., Zhang, Y., Chen, Q., D'angelo, D., Moreno-De-Luca, A., Orr, P.T., Boomer, K.B., Evans, D.W., Kanne, S., Berry, L., Miller, F.K.,
  Olson, J., Sherr, E., Martin, C.L., Ledbetter, D.H., Spiro, J.E., Chung, W.K., 2015.
  The Cognitive and Behavioral Phenotype of the 16p11.2 Deletion in a Clinically
  Ascertained Population. Biological Psychiatry 77(9), 785-793.
- Jenkins, J., Chow, V., Blaskey, L., Kuschner, E., Qasmieh, S., Gaetz, L., Edgar, J.C., Mukherjee, P., Buckner, R., Nagarajan, S.S., Chung, W.K., Spiro, J.E., Sherr, E.H., Berman, J.I., Roberts, T.P.L., 2016. Auditory Evoked M100 Response Latency is Delayed in Children with 16p11.2 Deletion but not 16p11.2 Duplication. Cerebral Cortex 26(5), 1957-1964.
- Kosciessa, J.Q., Kloosterman, N.A., Garrett, D.D., 2020. Standard multiscale entropy reflects neural dynamics at mismatched temporal scales: What's signal irregularity got to do with it? PLoS Comput Biol 16(5): e1007885. https://doi.org/10.1371/journal.pcbi.1007885
- LeBlanc, J.J., Nelson, C.A., 2016. Deletion and duplication of 16p11.2 are associated with opposing effects on visual evoked potential amplitude. Molecular Autism 7(1).

- Liang, W.K., Lo, M.T., Yang, A.C., Peng, C.K., Cheng, S.K., Tseng, P., Juan, C.H., 2014. Revealing the brain's adaptability and the transcranial direct current stimulation facilitating effect in inhibitory control by multiscale entropy. Neuroimage 90, 218-234.
- Lu, W.Y., Chen, J.Y., Chang, C.F., Weng, W.C., Lee, W.T., Shieh, J.S., 2015. Multiscale Entropy of Electroencephalogram as a Potential Predictor for the Prognosis of Neonatal Seizures. PLoS One 10(12), e0144732.
- McDonough, I.M., Nashiro, K., 2014. Network complexity as a measure of information processing across resting-state networks: evidence from the Human Connectome Project. Front Hum Neurosci 8, 409.
- Milne, E., Gomez, R., Giannadou, A., Jones, M., 2019. Atypical EEG in autism spectrum disorder: Comparing a dimensional and a categorical approach.
- Mizuno, T., Takahashi, T., Cho, R.Y., Kikuchi, M., Murata, T., Takahashi, K., Wada, Y., 2010. Assessment of EEG dynamical complexity in Alzheimer's disease using multiscale entropy. Clin Neurophysiol 121(9), 1438-1446.
- Mišić, B., Doesburg, S.M., Fatima, Z., Vidal, J., Vakorin, V.A., Taylor, M.J., McIntosh,
   A.R., 2015. Coordinated Information Generation and Mental Flexibility: Large-Scale
   Network Disruption in Children with Autism. Cereb Cortex 25(9), 2815-2827.
- Newson, J.J., Thiagarajan, T.C., 2018. EEG Frequency Bands in Psychiatric Disorders: A Review of Resting State Studies. Front Hum Neurosci 12, 521.
- Niarchou, M., Chawner, S.J.R.A., Doherty, J.L., Maillard, A.M., Jacquemont, S., Chung, W.K., Green-Snyder, L., Bernier, R.A., Goin-Kochel, R.P., Hanson, E., Linden, D.E.J., Linden, S.C., Raymond, F.L., Skuse, D., Hall, J., Owen, M.J., Bree, M.B.M.v.D., 2019. Psychiatric disorders in children with 16p11.2 deletion and duplication. Translational psychiatry 9(1), 8-8.
- Rescorla, L.A., 2005. Assessment of young children using the Achenbach System of Empirically Based Assessment (ASEBA. Mental Retardation and Developmental Disabilities Research Reviews 11(3), 226-237.
- Richman, J.S., Moorman, J.R., 2000. Physiological time-series analysis using approximate entropy and sample entropy. Am J Physiol Heart Circ Physiol 278(6), H2039-2049.
- Rodgers, J.L., 1999. The Bootstrap, the Jackknife, and the Randomization Test: A Sampling Taxonomy. Multivariate Behavioral Research 34(4), 441-456.
- Shinawi, M., Liu, P., Kang, S.-H.L., Shen, J., Belmont, J.W., Scott, D.A., Probst, F.J., Craigen, W.J., Graham, B.H., Pursley, A., Clark, G., Lee, J., Proud, M., Stocco, A.,

Rodriguez, D.L., Kozel, B.A., Sparagana, S., Roeder, E.R., McGrew, S.G., Kurczynski, T.W., Allison, L.J., Amato, S., Savage, S., Patel, A., Stankiewicz, P., Beaudet, A.L., Cheung, S.W., Lupski, J.R., 2010. Recurrent reciprocal 16p11.2 rearrangements associated with global developmental delay, behavioural problems, dysmorphism, epilepsy, and abnormal head size. Journal of Medical Genetics 47(5), 332.

- Takahashi, T., 2013. Complexity of spontaneous brain activity in mental disorders. Prog Neuropsychopharmacol Biol Psychiatry 45, 258-266.
- Takahashi, T., Cho, R.Y., Mizuno, T., Kikuchi, M., Murata, T., Takahashi, K., Wada, Y.,
  2010. Antipsychotics reverse abnormal EEG complexity in drug-naive schizophrenia: A multiscale entropy analysis. NeuroImage 51(1), 173-182.
- Takahashi, T., Yoshimura, Y., Hiraishi, H., Hasegawa, C., Munesue, T., Higashida, H., Minabe, Y., Kikuchi, M., 2016. Enhanced brain signal variability in children with autism spectrum disorder during early childhood. Hum Brain Mapp 37(3), 1038-1050.
- The simons vip consortium, 2012. Simons Variation in Individuals Project (Simons VIP): A Genetics- First Approach to Studying Autism Spectrum and Related Neurodevelopmental Disorders. Neuron 73(6), 1063-1067.
- Vakorin, V.A., Lippé, S., McIntosh, A.R., 2011. Variability of brain signals processed locally transforms into higher connectivity with brain development. J Neurosci 31(17), 6405-6413.
- Wang, J., Barstein, J., Ethridge, L.E., Mosconi, M.W., Takarae, Y., Sweeney, J.A., 2013. Resting state EEG abnormalities in autism spectrum disorders. J Neurodev Disord 5(1), 24.
- Yang, A.C., Tsai, S.-J., 2013. Is mental illness complex? From behavior to brain. Progress in Neuropsychopharmacology & Biological Psychiatry 45, 253-257.
- Yang, A.C., Wang, S.J., Lai, K.L., Tsai, C.F., Yang, C.H., Hwang, J.P., Lo, M.T., Huang, N.E., Peng, C.K., Fuh, J.L., 2013. Cognitive and neuropsychiatric correlates of EEG dynamic complexity in patients with Alzheimer's disease. Prog Neuropsychopharmacol Biol Psychiatry 47, 52-61.

# **Figure legends**

**Fig. 1. Group differences in entropy and power.** Error bars representing 95% confidence intervals. Subfigure (**A**) shows entropy group differences across scales collapsed into four categories. Subfigure (**B**) shows group distributions of CI. Subfigure (**C**) shows power group differences in delta, theta, alpha, and beta bands. Subfigure (**D**) shows group distributions of theta power. Asterisks in subfigures (**B**) and (**D**) indicate significant results.

**Fig. 2. Power spectral densities of each group.** The power spectrum was used to estimate the relative power of delta, theta, alpha, and beta for each participant. Shaded region representing standard error.

**Fig. 3. Correlations between EEG activity and psychiatric traits in del.** Radar plots displaying associations (Spearman's r coefficient) between (**A**) entropy (lower scales 1-10 and higher scales 11-20) and CBCL traits, and (**B**) power (delta, theta, alpha, and beta) and CBCL traits. Asterisks indicate significant correlations.

**Fig. 4. Correlations between entropy and power.** Heatmaps displaying associations (Spearman's r coefficient) between entropy (lower scales 1-10 and higher scales 11-20) and power (theta and alpha) for each group. Asterisks indicate significant correlations.

Power spectral densities of each group. The power spectrum was used to estimate the relative power of delta, theta, alpha, and beta for each participant. Shaded region representing standard error.