1 **Title:** The dark side of the mean: brain structural heterogeneity in schizophrenia and its

- 2 polygenic risk.
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35 Key Points

- 36 **Question:** Is schizophrenia and its polygenic risk associated with brain structural
- 37 heterogeneity in addition to mean changes?
- 38 Findings: In a sample of 1151 patients and 2010 controls, schizophrenia was associated with
- 39 increased heterogeneity in fronto-temporal thickness, cortical, ventricle, and hippocampal
- 40 volumes, besides robust reductions in mean estimates. In an independent sample of 12,490
- 41 controls, polygenic risk for schizophrenia was associated with thinner fronto-temporal
- 42 cortices and smaller CA2/3 of the left hippocampus, but not with heterogeneity.
- 43 **Meaning:** Schizophrenia is associated with increased inter-individual differences in brain
- 44 structure, possibly reflecting clinical heterogeneity, gene-environment interactions, or
- 45 secondary disease factors.

47	Abstract			
48	Importance: Between-subject variability in brain structure is determined by gene-			
49	environment interactions, possibly reflecting differential sensitivity to environmental and			
50	genetic perturbations. Magnetic resonance imaging (MRI) studies have revealed thinner			
51	cortices and smaller subcortical volumes in patients. However, such group-level comparisons			
52	may mask considerable within-group heterogeneity, which has largely remained unnoticed in			
53	the literature			
54	Objective: To compare brain structural variability between individuals with SZ and healthy			
55	controls (HC) and to test if respective variability reflects the polygenic risk for SZ (PRS) in			
56	HC.			
57	Design, Setting, and Participants: We compared MRI derived cortical thickness and			
58	subcortical volumes between 2,010 healthy controls and 1,151 patients with SZ across 16			
59	cohorts. Secondly, we tested for associations between PRS and MRI features in 12,490			
60	participants from UK Biobank.			
61	Main Outcomes and Measures: We modeled mean and dispersion effects of SZ and PRS			
62	using double generalized linear models. We performed vertex-wise analyses for thickness,			
63	and region-of-interest analysis for cortical, subcortical and hippocampal subfield volumes.			
64	Follow-up analyses included within-sample analysis, controlling for intracranial volume and			
65	population covariates, test of robustness of PRS threshold, and outlier removal.			
66	Results: Compared to controls, patients with SZ showed higher heterogeneity in cortical			
67	thickness, cortical and ventricle volumes, and hippocampal subfields. Higher PRS was			
68	associated with thinner frontal and temporal cortices, as well as smaller left CA2/3, but was			
69	not significantly associated with dispersion.			
70	Conclusion and relevance: SZ is associated with substantial brain structural heterogeneity			
71	beyond the mean differences. These findings possibly reflect higher differential sensitivity to			

72	environmental and genetic perturbations in patients, supporting the heterogeneous nature of
73	SZ. Higher PRS for SZ was associated with thinner fronto-temporal cortices and smaller
74	subcortical volumes, but there were no significant associations with the heterogeneity in these
75	measures, i.e. the variability among individuals with high PRS were comparable to the
76	variability among individuals with low PRS. This suggests that brain variability in SZ results
77	from interactions between environmental and genetic factors that are not captured by the
78	PGR. Factors contributing to heterogeneity in fronto-temporal cortices and hippocampus are
79	thus key to further our understanding of how genetic and environmental factors shape brain
80	biology in SZ.

81 Introduction

82	Schizophrenia (SZ) is a severe psychiatric disorder with a lifetime prevalence of about 1%,
83	rendering it a leading cause of disability worldwide with 26 million people affected ¹ . While
84	genetic and environmental factors contributing to disease risk have been identified, the
85	pathophysiology still remains elusive ^{2,3} . Patients diagnosed with SZ display substantial
86	heterogeneity in terms of their clinical characteristics and symptoms ⁴ , treatment response ⁵ and
87	long term prognosis ⁶ . The notion that the observed heterogeneity stems at least partially from
88	distinct subtypes of patients with differentially affected neurobiology and clinical and
89	cognitive profiles ⁷⁻⁹ , has not been fully confirmed ¹⁰ , and the question of whether there is one
90	unifying pathophysiological process shared across patients, or a multitude of disease
91	processes leading to a similar clinical syndrome remains salient ¹¹ .
92	SZ is associated with widespread brain abnormalities, with the most robust group-
93	level mean structural differences being ventricle enlargement, reduced thickness and area of
94	frontal and temporal cortices, as well as reduced hippocampal and amygdala volumes ¹²⁻¹⁴ .
95	However there is also substantial variability between patients ^{7,8,15,16} , presenting a major
96	challenge for achieving imaging based diagnostic predictions with any clinical utility ^{17,18} .
97	Rather than simply reflecting noise, this inter-individual variability in brain structure may
98	possibly carry relevant information regarding gene-environment interactions related to the
99	individual sensitivity to environmental and genetic perturbation. Only a few studies have
100	investigated whether heterogeneity differs between healthy participants and SZ patients. One
101	functional imaging study reported increased heterogeneity in both connectivity and spatial
102	extent of functional brain networks in SZ^{19} . Regions with altered spatial variance in functional
103	networks included areas previously implicated in SZ, such as auditory and sensorimotor
104	cortices and basal ganglia, and networks showing increased heterogeneity overlapped with
105	those showing mean volume differences, implying that the mean and variance measures

106	provide complementary but converging results ²⁰ . A recent meta-analysis reported increased
107	inter-individual volumetric variability in several cortical and subcortical structures, including
108	the temporal lobe, thalamus, hippocampus and amygdala in SZ, and lower variability in the
109	anterior cingulate cortex (ACC) ¹⁵ . These results point to the importance of modeling
110	heterogeneity as well as mean changes. Detecting brain regions that are more homogenous in
111	patients could point to a primary role in a shared underlying SZ pathophysiology, while
112	regions of increased heterogeneity might be informative of putative subtypes of disease, or
113	possibly reflect regional differences in the sensitivity to genetic and environmental
114	perturbations.
115	SZ is highly heritable ²¹ , motivating the ongoing efforts to identify intermediate brain
116	phenotypes associated with disease liability in order to elucidate the pathway from genes to
117	illness manifestation. Several SZ risk loci have been identified ²² , but the individual
118	contribution of each identified variant is weak and as of yet no common variants have been
119	conclusively linked to the disease. Polygenic risk scores (PRS) for SZ, which represent a
120	weighted sum of common genetic SZ risk alleles, have been proposed to account for the
121	polygenic nature of disease risk and to increase predictive power ²³ . Beyond being predictive
122	of case-control status ²² , SZ PRS have been associated with negative symptoms, anxiety and
123	lower cognitive ability in adolescents ²⁴ . Polygenic burden has also been linked to reduced
124	cortical thickness, as well as with prefrontal working memory-, and hippocampal encoding-
125	related activation and connectivity in both patients and healthy participants ²⁵⁻²⁸ . This is in line
126	with findings implicating both the frontal cortices and hippocampus as core regions in SZ
127	pathophysiology ²⁹ . Polygenic risk for SZ is however only weakly associated with subcortical
128	volumes ³⁰ . Importantly, risk alleles could also exert their effect by influencing the
129	environmental sensitivity, which could be reflected in the phenotypic variability between
130	individuals ³¹ .

131	Thus, revealing brain structures with higher or lower heterogeneity in SZ could
132	facilitate discovery of intermediate brain phenotypes that may serve to identify putative sub-
133	types ^{8,32} of the disease, as well as by identifying phenotypes that are primary or common in
134	the neurobiology of SZ^{15} . Further, investigating how the genetic architecture of disease risk is
135	related to brain heterogeneity could reveal regions in which the cumulative burden of
136	common risk alleles influence the phenotypic variance ³³ . To this end, we directly compared
137	the within-group dispersion in several key brain structural phenotypes, including cortical
138	thickness, as well as in cortical, subcortical and hippocampal subfield volumes, between 1151
139	patients with SZ and 2010 healthy controls. Next, in order to test the whether between-subject
140	variability is associated with the cumulative polygenic risk for SZ, we tested for associations
141	between dispersion in the same brain features and PGR for SZ in 12,490 healthy individuals
142	from the UK Biobank.
143	
144	Material and methods
145	Samples: Sample characteristics are presented in Table 1 and eMethods (Samples), and cohort
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	details are presented in eTable 1.
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147 148	Image preprocessing
147 148 149	Image preprocessing T1-images where processed using Freesurfer 5.3.0 (<u>http://surfer.nmr.mgh.harvard.edu</u>) for
147 148 149 150	<i>Image preprocessing</i> T1-images where processed using Freesurfer 5.3.0 (<u>http://surfer.nmr.mgh.harvard.edu</u>) for cortical reconstruction and volumetric segmentation ³⁴⁻³⁷ and Freesurfer 6.0 for hippocampus
147 148 149 150 151	<i>Image preprocessing</i> T1-images where processed using Freesurfer 5.3.0 (<u>http://surfer.nmr.mgh.harvard.edu</u>) for cortical reconstruction and volumetric segmentation ³⁴⁻³⁷ and Freesurfer 6.0 for hippocampus subfield segmentation ³⁸ . Each participant's cortical thickness map was registered to the
147 148 149 150 151 152	<i>Image preprocessing</i> T1-images where processed using Freesurfer 5.3.0 (<u>http://surfer.nmr.mgh.harvard.edu</u>) for cortical reconstruction and volumetric segmentation ³⁴⁻³⁷ and Freesurfer 6.0 for hippocampus subfield segmentation ³⁸ . Each participant's cortical thickness map was registered to the
 147 148 149 150 151 152 153 	<i>Image preprocessing</i> T1-images where processed using Freesurfer 5.3.0 (http://surfer.nmr.mgh.harvard.edu) for cortical reconstruction and volumetric segmentation ³⁴⁻³⁷ and Freesurfer 6.0 for hippocampus subfield segmentation ³⁸ . Each participant's cortical thickness map was registered to the MNI305 fsaverage template and spatially smoothed (15 mm FWHM).

157	thresholds.	, from 0.001 to 0.5.	with intervals of 0.001 ((eMethods: Genetics)). PRS based on a
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threshold of .05 were used for the main analysis since this threshold has been reported as

159 optimal in terms of explaining case-control differences⁴⁰, but we also performed follow-up

analysis to test the robustness of findings to threshold selection.

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162 Statistical analysis

163 Statistical analyses were performed in R (3.2.2; https://www.r-project.org/) and MATLAB

164 (2014a, The MathWorks, Inc., Natick, Massachusetts, United States). For all included

165 measures in the multi-scanner case-control sample we used vertex/volume-wise generalized

additive models (GAM, R-Package: mgcv⁴¹) to regress out scanner effects while accounting

167 for age, sex and diagnosis. We then modeled vertex/volume-wise mean and dispersion effects

168 using double generalized linear models (DGLMs), which iteratively fits a GLM modeling the

169 mean parameter, and a second GLM modeling the dispersion parameter (eMethods: DGLMs;

170 R-package: dglm⁴²). We then permuted the SZ and PRS column vector, respectively, and

171 recalculated the mean and dispersion effects. For cortical thickness the true test statistics and

the permuted statistical maps where then submitted to PALM⁴³ to correct for multiple

173 comparisons using threshold-free cluster enhancement (TFCE) and tail approximation⁴⁷ (600

174 permutations: eMethods: Permutation). Maps were thresholded at a significance level of

175 p<.05. For the cortical, subcortical, and hippocampal subfields volumes we performed 5000

176 permutations per volume and extracted the maximum t-value across ROIs when computing p-

177 values in order to correct for multiple comparisons. Significance threshold was set at p<.05.

178 We also performed a meta-analysis of the multi-scanner thickness data (R-Package:

179 metafor⁴⁴) estimating case-control difference within each sample, and conducted analyses

180 both with and without covarying for estimated intracranial volume (eTIV) for the volumetric

181 measures. We performed follow-up analyses with more stringent exclusion criteria

182 (eMethods: Outliers). To assess the effect of PRS p-threshold selection, we performed a

183 principal component analysis (R-package: prcomp, factoextra⁴⁵) on PRS scores calculated

across several thresholds (eMethods: PRS-PCA), and reran cortical thickness analysis on

185 PCA-scores.

186

187 **Results**

188 *Vertex-wise thickness:* SZ was associated with decreased mean thickness globally, with the 189 exception of the visual cortex, as well as globally increased thickness dispersion (Figure 1, 190 panel A and B, Figure 2A; eFigure 2). Meta-analysis of within-sample effects with more 191 stringent exclusion criteria revealed significantly increased heterogeneity in SZ, indicating 192 that dispersion effects are not simply explained by multi-site variability or a few extreme 193 values (eFigure 3). PRS was associated with lower mean thickness in the right inferior frontal 194 gyrus, the right lateral orbitofrontal cortex, the right pre-central gyrus, the right medial 195 temporal cortex, and bilaterally in middle and superior temporal cortices (Figure 1, panels C 196 and D; eFigure 4). Converging results were obtained upon re-analysis with the addition of the 197 first four population components added as covariates (eFigure 5A), or with more stringent 198 exclusion criteria (eFigure 5B). Follow-up analysis using the first component from the PRS 199 principal component analysis (PRS-PC1) gave close to an identical pattern as the PRS-model 200 based on a threshold of .05 (eFigure 5C; vertex-wise r=.91). There was no significant 201 associations between polygenic risk and thickness dispersion, or between PRS-PC2 or PRS-202 PC3 and mean or dispersion of cortical thickness. Vertex-wise correlations between raw t-203 maps for SZ and polygenic risk were r=.2 and r=.1, for the mean and dispersion respectively 204 (eFigure 6).

205

206 Cortical and subcortical volumes: SZ was associated with lower mean cortical volume, 207 supratentorial volume, total and subcortical gray volume, cerebellar cortical volume, as well 208 as brain stem, hippocampus, amygdala, thalamus and nucleus accumbens, and several white 209 matter volumes, as well as increased ventricle, caudate nucleus, pallidum and putamen 210 volumes. SZ was further associated with increased dispersion in mean cortical volume, total 211 gray volume, left hippocampus and ventricle volumes (Figure 2B, Figure 3). Models without 212 eTIV (eFigure 7A) revealed no significant differences in the mean volumes of caudate 213 nucleus and left putamen, and resulted in an additional significant association with dispersion 214 in supratentorial volume. Reanalysis of mean and dispersion models with more stringent 215 exclusion criteria showed converging results (eTable 2). PGR was not associated with mean 216 or dispersion in any of the subcortical volumes (Figure 3B), this was also true for models 217 without adjustment for eTIV (eFigure 7B).

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219 Hippocampal subfields: Patients with SZ was associated with lower mean volume in both left 220 and right whole hippocampus as well as in all hippocampal subfields, accompanied with 221 larger right hippocampal fissures. There was increased dispersion in SZ in left whole 222 hippocampus, as well as in left molecular layer, left granule cell layer of the dentate gyrus 223 (GC-DG) and left CA4 (Figure 4A). Models without adjustment for eTIV gave the same 224 results for mean volumes with the exception for left hippocampal fissure, which did not 225 survive correction. Additional dispersion effects were observed for right whole hippocampus, 226 and left CA1 (eFigure 8A). When reanalyzing SZ mean and dispersion models with more 227 stringent exclusion criteria, we obtained similar results (eTable 3). PGR was associated with 228 smaller left CA2/3. None of the subfields showed an association between volume dispersion 229 and PRS (Figure 4B). Models without adjustment for eTIV revealed smaller left and right 230 CA2/3, left granule cell layer of the dentate gyrus (GC-DG), and left CA4 (eFigure 8B) in

patients with SZ. Re-analysis with population covariates added to the models, re-analysis with
stricter exclusion criteria, and modeling PRS using the first principal component, did not alter
conclusions (eTable 4).

234

235 Discussion

236 In the current study we found that SZ is associated with increased brain heterogeneity in 237 cortical thickness, as well as in cortical volumes, lateral and third ventricles and hippocampal 238 volumes. The findings, based on harmonized analysis protocols for all included datasets, were 239 robust to strict procedures for removing outliers, and follow-up meta-analysis confirmed that 240 multi-site case-control difference cannot be explained by scanning site. These findings are 241 largely in line with a recent meta-analytic study showing increased volumetric heterogeneity in the temporal lobe and lateral and third ventricles¹⁵. It also extends this meta-analysis by 242 243 showing increased heterogeneity in cortical thickness as well as in specific hippocampal 244 subfields. Further, increased polygenic risk in healthy individuals was associated with 245 reductions in thickness in frontal and temporal regions, as well as in left dentate gyrus and 246 CA4 and bilateral CA2/3, but not related to thickness dispersion.

247 We found widespread reductions in cortical thickness in SZ patients, with the 248 characteristic pattern of stronger fronto-temporal effects, as well as global reductions in cortical volume⁴⁶. In addition to these mean changes, we found that SZ is also associated with 249 250 increased thickness heterogeneity compared to healthy controls. No cortical region showed 251 the opposite pattern of increased homogeneity among patients. As with previous studies we 252 found mean reductions in several brain volumes, with the most robust effects for cortical 253 volume, cerebellum and hippocampus, as well as ventricle enlargement. These regions 254 additionally showed increased heterogeneity in patients compared to controls, and again no 255 region showed increased homogeneity, as might result if a particular region was similarly

affected by a common pathophysiological mechanism¹⁵. Instead, the results are in line with 256 previous studies suggesting substantial neurobiological heterogeneity in SZ¹⁶. They do 257 however contrast with a recent report¹⁵ of increased volumetric homogeneity in SZ. One 258 259 possible explanation is differing sample inclusion criteria, as the previous study included only 260 first-episode psychosis patients. It is not unlikely that an earlier disease stage may offer a 261 more direct window into core aspects of the pathophysiology which later shift towards 262 increased inter-individual variability as patients vary across different illness stages and 263 degrees of severity, as well as differences in treatment and medication status. 264 PRS reflect cumulative risk across multiple genetic loci, and SZ PRS is associated 265 with several phenotypic traits, including liability for psychiatric disease such as bipolar 266 disorder and schizoaffective disorder, negative symptoms, as well as IQ, working memory performance and brain activation^{25,47,48}. SZ-PRS has been associated with cortical gyrification 267 in healthy participants⁴⁹, as well as reductions in global cortical thickness²⁷. The current 268 269 results show that higher SZ-PRS in healthy participants are associated with mean decrease in 270 thickness in fronto-temporal cortices. Interestingly, these shifts in mean thickness were not 271 associated with changes in brain heterogeneity, as was found for patients, pointing to 272 differential effects of genetic risk on mean and heterogeneity changes. A recent study found 273 that SZ environmental risk scores and SZ-PRS scores are both independently related to frontotemporal cortical thinning in patients, but not controls ²⁷. This underscores the 274 275 importance of also investigating environmental risk factors, as well as gene-environment 276 interplay, and their role in explaining the observed clinical and neurobiological heterogeneity 277 With regard to hippocampal volumes, we found that higher polygenic risk was 278 associated with smaller volumes of the left CA2/3, in the absence of an effect on total 279 hippocampal volume and after correcting for total intracranial volume, suggesting a specific 280 effect of genetic risk on this region. The hippocampus has been hypothesized to play a

281 primary role in the pathophysiology of SZ, through progressive changes to its neural circuits as the disease evolves²⁹. Our results also complement recent studies reporting that polygenic 282 risk for SZ is predictive of hippocampal activation during memory $encoding^{28}$, and of 283 polygenic overlap between SZ and hippocampus volume⁵⁰. Also, while the patients showed 284 285 increased hippocampal heterogeneity, only mean effects were associated with PRS, mirroring 286 the findings on cortical thickness. Thus, the dentate gyrus and CA2/3 emerge as key regions 287 both for the manifestation of, and the genetic risk for, SZ and potentially informative for the 288 classification of sub-types and degrees of severity. Despite reliable associations between SZ and brain morphometry¹⁴, PRS is only 289 290 weakly associated with subcortical volumes, however a recent study found polygenic overlap for SZ and hippocampal, putamen and intracranial volumes⁵⁰. The lack of associations 291 292 between PRS and subcortical volumes in the current study is in line with most previous reports or PRS^{30} . 293

294

295 Limitations

296 An important source of heterogeneity in the present case-control sample could be the large 297 number of different scanning-sites included. However, in addition to residualizing for 298 scanner-site in the main analysis, we also performed within-sample analysis and ran meta-299 analysis, which rule out scanner as a major contributor to the observed effects. Heterogeneity 300 could be associated with differences in medication status and duration of illness. While we did find increased caudate and putamen volumes, indicative of medication effects⁵¹, these 301 302 volumes did not show altered heterogeneity in SZ. Still, antipsychotic medication could 303 possibly affect brain heterogeneity in other regions, in absence of a change in mean volume. 304 Investigation of such effects requires carefully controlled settings, and is therefore difficult to 305 address in large-scale multi-site studies. Another possible explanation is that the increased 306 variability is caused by movement artefacts, which are typically greater in clinical

307	populations ⁵² , however running the analysis in a subset with stricter criteria for dataset
308	exclusion did not alter the conclusions. One important consideration for case-control studies
309	in general is the possibility that healthy controls are abnormally normal compared to the
310	general healthy population due to selection bias and strict exclusion criteria ⁵³ , underscoring
311	the importance of studying the full range of phenotypic variability in the population. Further,
312	the validity of choosing a given p-threshold selection among several possible thresholds when
313	calculating PRS is uncertain. We addressed this by performing follow-up analysis where we
314	performed PCA across PRS calculated across a wide range of thresholds, to derive a more
315	general score of polygenic risk. This approach yielded results converging with the main
316	analysis using a threshold of $p < .05$. The lack of association between SZ-PRS and brain
317	heterogeneity suggest that the current SZ-PRS scores do not strongly reflect variance-
318	controlling variants. As a composite score, SZ-PRS likely also hides a substantial genetic
319	heterogeneity. A PRS-score calculated using a variance-controlling trait loci (vQTL)
320	approach would likely be more sensitive in detecting such effects. Lastly, SZ is increasingly
321	understood as a neurodevelopmental disorder ⁵⁴ and disentangling the sources of heterogeneity
322	in the adult patient population likely requires investigation of the life-span trajectories and
323	aberrant developmental paths.
324	
325	Conclusion
326	There are ongoing efforts to account for brain heterogeneity by means of delineating patient

subtypes^{8,55}, as well as characterizing patients by their differential degree of affectedness along one or multiple symptom-axes^{11,56}. Here we report that SZ is associated with widespread and increased heterogeneity in cortical thickness, and cortical as well as hippocampal volume, beyond the known mean differences, compared controls. The results support to the notion that SZ is a highly heterogeneous disorder, and suggests that important information may be overlooked when only assessing mean differences. In healthy adults SZ-

- 333 PRS were associated with mean changes in brain areas implicated in SZ, but not associated
- 334 with altered brain heterogeneity. Taken together, these findings warrant future longitudinal
- 335 studies which can disentangle the genetic and environmental factors contributing to diverging
- trajectories and neurobiological heterogeneity, and in particular how these factors contribute
- to heterogeneity in fronto-temporal cortices and hippocampus.

338 Collaborators

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349

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- 366

367 Author contribution statement

- 368 D.A. and L.T.W conceived of the study; D.A. performed the analysis with contributions from
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- 371 O.B.S., T.Q., M.Z., and O.A.A contributed with data preprocessing, quality assurance and
- 372 interpretation of results. D.A., T.K. and L.T.W. wrote the first draft of the paper, and all
- authors contributed to the final manuscript. D.A. and L.T.W. had full access to all the data in
- the study and takes responsibility for the integrity of the data and the accuracy of the data
- analysis.
- 376

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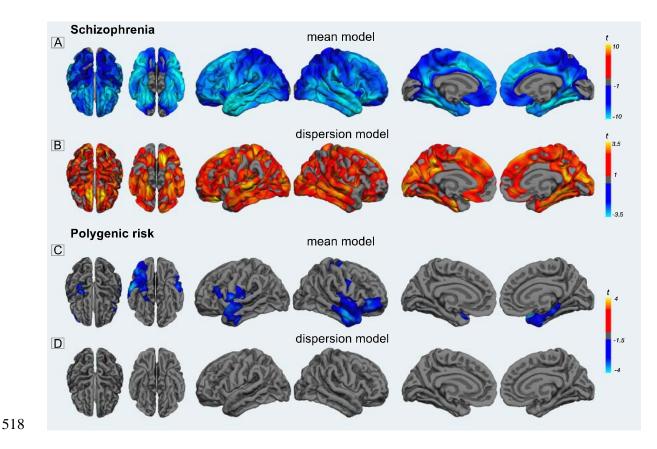
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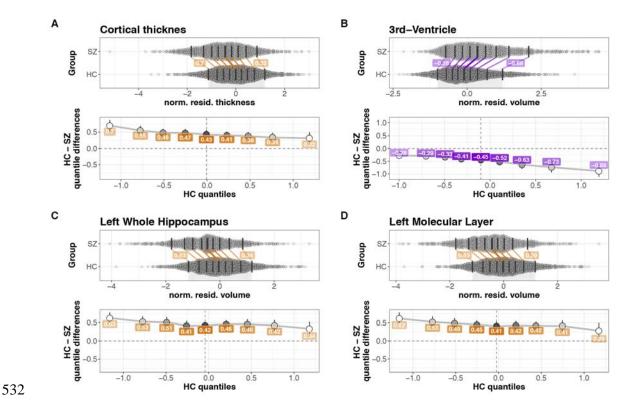
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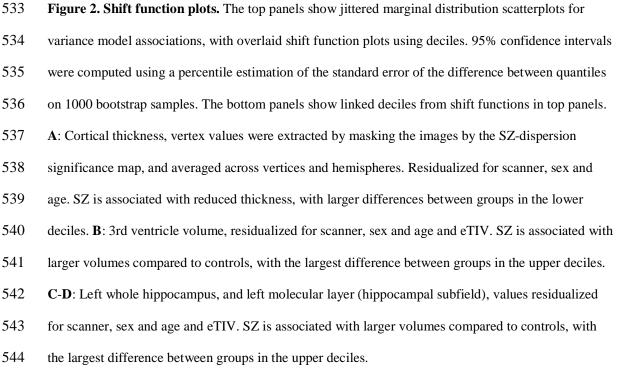
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 482 project.org/package=dglm. 2016. 483 43. Winkler AM, Ridgway GR, Webster MA, Smith SM, Nichols TE. Permutation inference for 484 the general linear model. <i>NeuroImage</i>. 2014;92:381-397. 485 44. Viechtbauer W. Conducting meta-analyses in R with the metafor. <i>Journal of Statistical</i> 486 <i>Software</i>. 2010;36(3): http://www.jstatsoft.org/v36/i03/. 487 45. Kassambara A, Mundt F. factoextra: Extract and Visualize the Results of Multivariate Data 	480		1.8-23). https://CRAN.R-project.org/package=mgcv. 2018.
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487 45. Kassambara A, Mundt F. factoextra: Extract and Visualize the Results of Multivariate Data	485	44.	Viechtbauer W. Conducting meta-analyses in R with the metafor. Journal of Statistical
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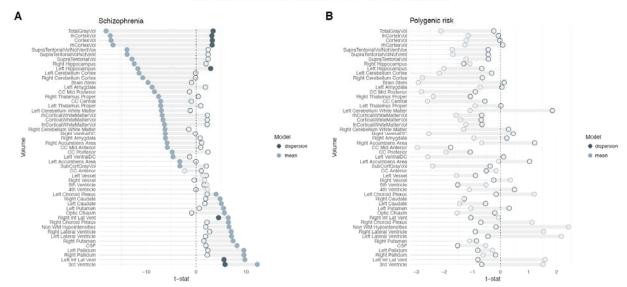


519 Figure 1. Mean and dispersion of cortical thickness. All maps were thresholded using 520 permutation testing, threshold free cluster enhancement, and fitting the tail of the permutation 521 distribution to a generalized Pareto distribution (500 permutations, p < .05, FWE). A: t-map 522 for the SZ mean model; cold colors represent areas with decreased mean thickness in SZ 523 compared to healthy controls. SZ was associated with decreased thickness globally, with the 524 exception of the visual cortex, and with strongest effects in frontal and temporal regions, 525 compared to healthy controls. B: t-map for the SZ dispersion model. Warm colors represent 526 areas with increased heterogeneity in SZ compared to healthy controls. Inter-individual 527 variability in cortical thickness showed a spatially global increase for the SZ-group compared 528 to healthy controls. C: In an independent sample of healthy adults, the mean model showed 529 that higher polygenic risk for SZ was associated with lower cortical thickness, represented by 530 cold colors, in frontal and parietal cortices. **D:** Polygenic risk was not associated with cortical 531 thickness heterogeneity in any region.





Cortical & subcortical volumes, mean and dispersion effects (eTIV adj.)



548 Figure 3. Mean and dispersion of cortical and subcortical volumes. t-statistic for both

549 mean (outline in light blue) and dispersion (outline in dark blue), filled blue dots mark

significant effects after correction for multiple comparisons across regions (5000

permutations, permuted p < .05, FWE, eTIV-adjusted). A: The SZ-group had both decreased

552 cortical and subcortical volumes, as well as increased ventricles and putamen and pallidum

volumes. Cortical, hippocampal and ventricle volume were more heterogeneous in the SZ-

554 group compared to healthy controls. B: Polygenic risk for SZ was not associated with mean

555 changes nor dispersion in any of the regions.

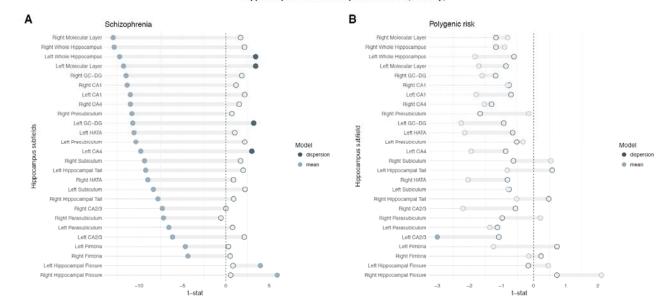
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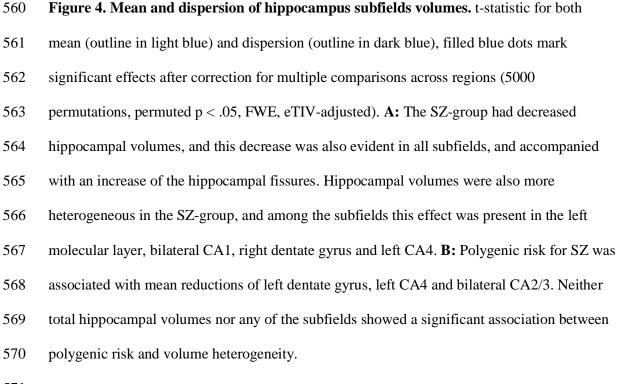


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Hippocampus mean and dispersion effects (eTIV adj.)





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НС						SZ	2	
Sample	n	mean age	std	females (n)	n	mean age	std	females (n)
BrainGluSchi	47	33,7	12,7	18	37	37,2	15,3	3
CIMH	43	30,6	11,5	14	53	31,2	8,6	17
CNP-1	102	31,7	8,9	47	25	36,9	9,3	8
CPN-1	23	30,7	8,6	12	25	36,0	8,6	4
COBRE	90	38,1	11,7	26	88	38,1	13,7	18
HUBIN	102	42,0	8,8	33	94	41,7	7,6	24
KaSP	45	25,7	5,2	21	37	28,5	7,5	12
MCIC-1	43	29,0	11,3	9	35	32,6	12,4	7
MCIC-2	26	33,1	12,4	11	32	32,4	10,3	8
MCIC-3	24	40,8	9,4	9	33	38,3	10,0	8
NUNA	44	31,3	8,5	22	44	33,0	6,8	14
NUSDAST	95	33,8	14,5	44	114	35,0	13,1	38
TOP-3T-1	294	31,8	7,6	121	112	28,0	8,1	38
TOP-3T-2	301	35,8	10,1	141	110	33,0	9,9	44
TOP-1.5	295	35,5	9,6	131	225	31,9	9,1	96
UNIBA	436	26,7	7,7	225	87	34,1	7,6	22
Total	2010	32, 7	10,4	884	1151	33,8	10,6	361
		PRS sample						
Sample	n	mean age	std	females (n)				
UKB	12490	55,9	7,5	6465				

573 574

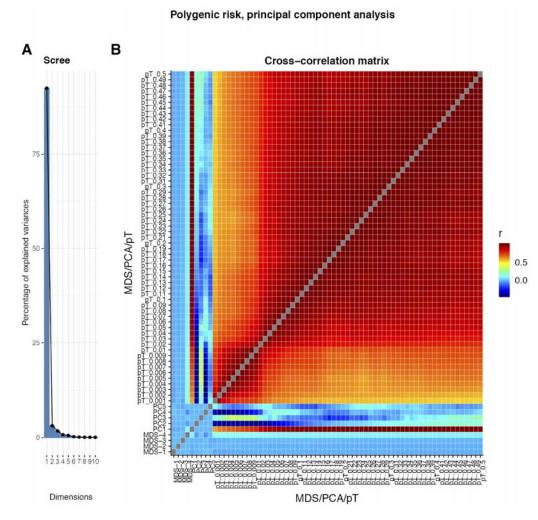
Table 1. Sample characteristics. We included data from 16 samples for the case-control

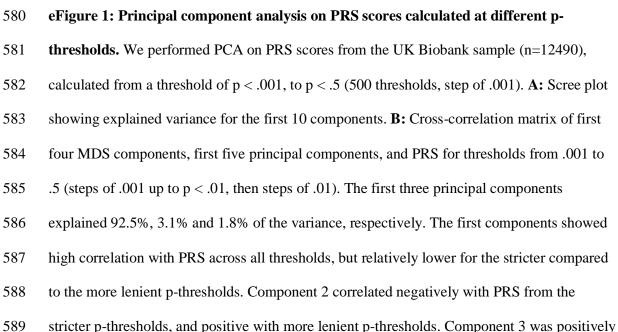
analysis, each sample contained MR-scans from both patients with SZ and healthy control

576 participants. -analysis was performed on UKB participants, excluding those with a diagnosed

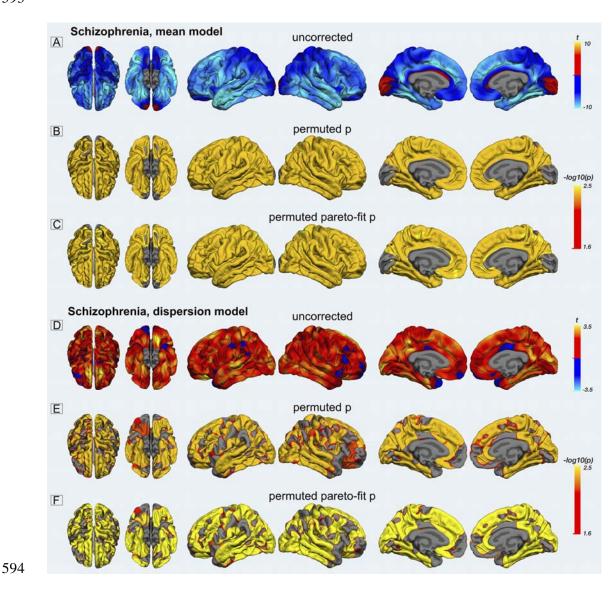
577 neurological or mental disorder. More detailed information about samples and

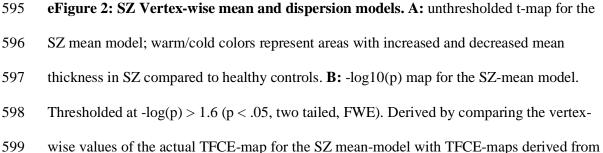
acknowledgements are provided in eTable 1.





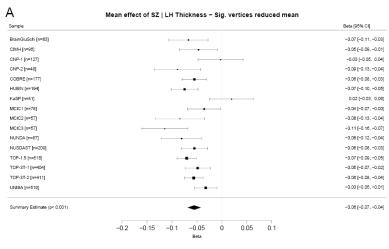
- 590 correlated with scores calculated with the strictest and most lenient p-thresholds, while
- 591 correlating negatively with PRS based on the intermediate p-thresholds.
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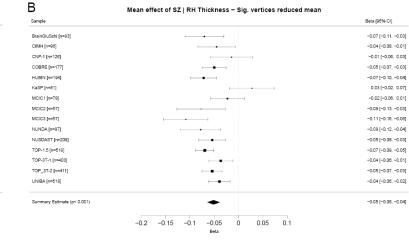


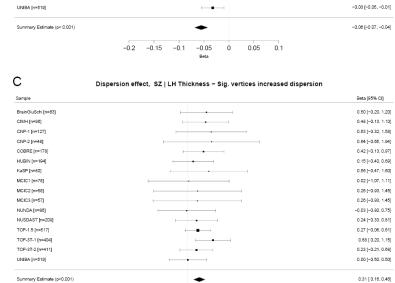


- 600 500 random permutations of the diagnosis labels. **C:** -log10(p) map derived from fitting a
- 601 generalized Pareto distribution to the tail of the permutation distribution. **D**: unthresholded t-
- 602 map for the SZ dispersion model; warm/cold colors represent areas with increased and
- 603 decreased thickness dispersion in SZ compared to healthy controls. E: -log10(p) map for the
- 604 SZ-dispersion model. Thresholded at $-\log(p) > 1.6$ (p < .05, two tailed, FWE). Derived by
- 605 comparing the vertex-wise values of the actual TFCE-map for the SZ dispersion-model with
- 606 TFCE-maps derived from 500 random permutations of the diagnosis labels. F: -log10(p) map
- 607 derived from fitting a generalized Pareto distribution to the tail of the permutation
- 608 distribution.
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Beta

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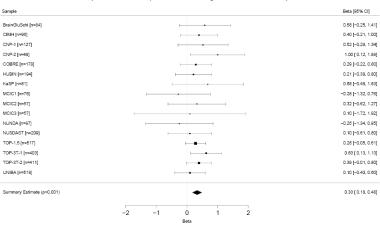
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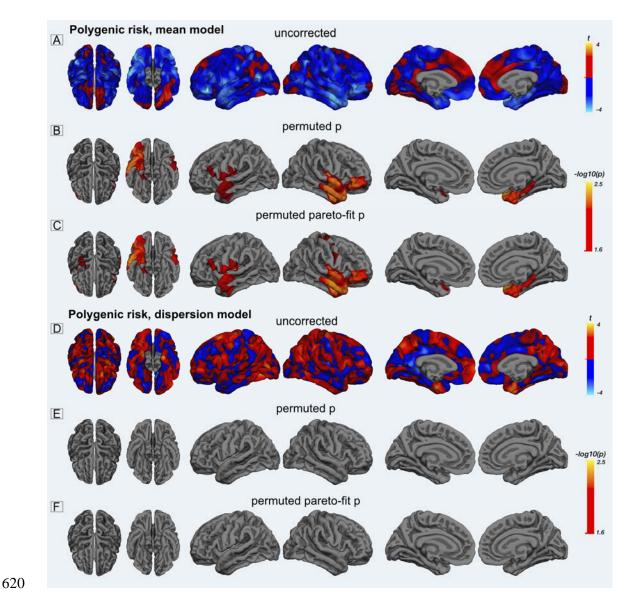
Dispersion effect, SZ | RH Thickness - Sig. vertices increased dispersion

D

Sample

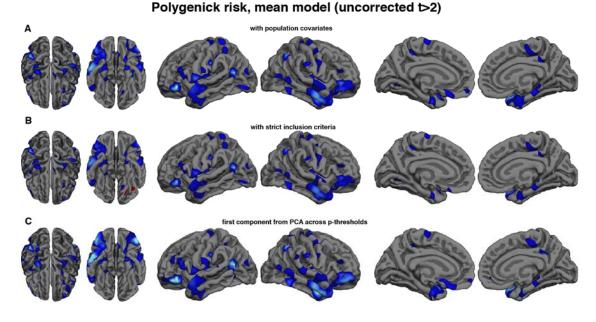


eFigure 3: Meta-analysis of SZ mean and dispersion effects with stricter inclusion criteria. The above panel shows the within-sample
effects of the mean-model in the vertices showing a significant group-level effect for the left and the right cortical hemisphere. The bottom panel
displays the dispersion effects. Both hemispheres showed a significant meta-analytic thickness decrease, as well as a dispersion increase,
suggesting that the results from the main analysis are not driven by site-related variance not accounted for in the multi-site regression models.
The analysis also included removal of subjects with either eTIV or mean thickness-values at | z | > 3, or significant outlier test (corrected p < .05).
For CNP-2, right hemisphere, the DGLM did not converge.



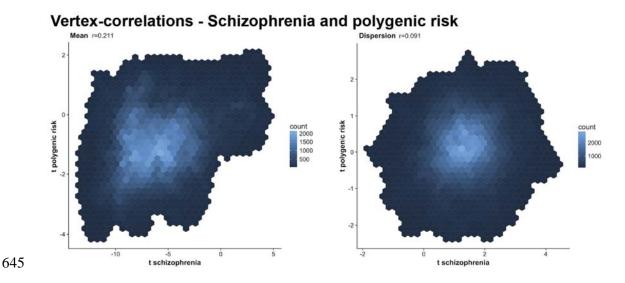
eFigure 4: Polygenic risk, vertex-wise mean and dispersion models. A: unthresholded tmap for the PRS mean model; warm/cold colors represent areas with increased and decreased mean thickness with increased PRS. B: $-\log 10(p)$ map for the PRS-mean model. Thresholded at $-\log(p) > 1.6$ (p < .05, two tailed, FWE). Derived by comparing the vertex-wise values of the actual TFCE-map for the PRS mean-model with TFCE-maps derived from 500 random permutations of the PRS scores. C: $-\log 10(p)$ map derived from fitting a generalized Pareto distribution to the tail of the permutation distribution. D: unthresholded t-map for the PRS

- 628 dispersion model; warm/cold colors represent areas with increased and decreased thickness
- 629 dispersion with increased PRS. E: -log10(p) map for the PRS-dispersion model. Thresholded
- 630 at $-\log(p) > 1.6$ (p < .05, two tailed, FWE). Derived by comparing the vertex-wise values of
- the actual TFCE-map for the SZ dispersion-model with TFCE-maps derived from 500 random
- 632 permutations of the PRS scores. **F:** -log10(p) map derived from fitting a generalized Pareto
- 633 distribution to the tail of the permutation distribution.
- 634
- 635



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eFigure 5: Reanalysis of polygenic risk score models on cortical thickness. To test the robustness of the mean effect of PRS on cortical thickness, we performed several follow-up analysis: A: Uncorrected t-map for PRS-scores, including the four first population covariates derived from multidimensional scaling (MDS) analysis. B: Uncorrected t-map for reanalysis with extreme scoring individuals removed (mean thickness or eTIV, |z| > 3, or outlier test significant at p < .05, FWE). C: Uncorrected t-map for the analysis using the first principal component from the PCA on PRS scores calculated across a wide range of p-thresholds.



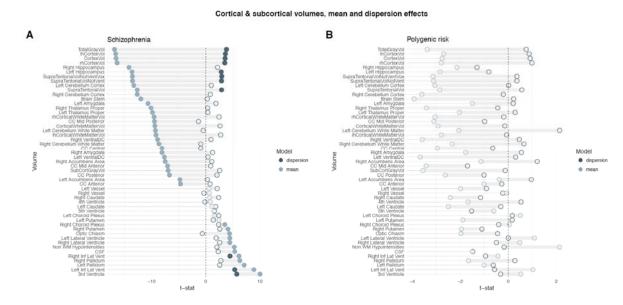
646 eFigure 6: Spatial overlap between SZ and PRS. The vertex-wise t-values for the SZ-

647 models are shown on the x-axis and the vertex-wise t-values for the PRS-models on the Y-

648 axis. The left plot shows the mean-model (vertex-wise correlation of .2) and the right plot

shows the dispersion models (vertex-wise correlation of .1). The heatmaps represent the count

- 650 of vertices at a value.
- 651
- 652

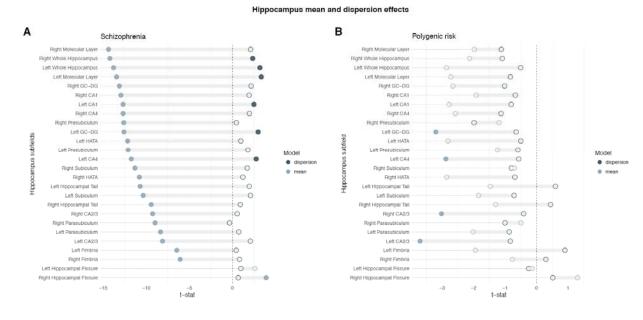


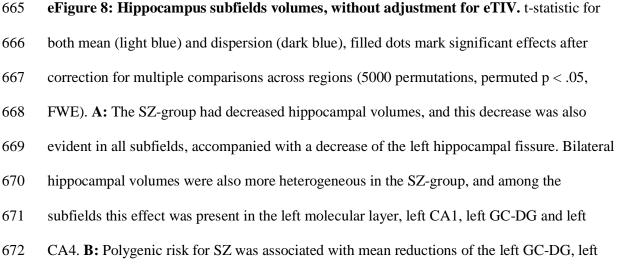
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654 **eFigure 7: Cortical and subcortical volumes, without adjustment for eTIV.** t-statistic for

both mean (light blue) and dispersion (dark blue), filled dots mark significant effects after

- 656 correction for multiple comparisons across regions (5000 permutations, permuted p < .05,
- 657 FWE). A: The SZ-group showed decreased cortical and subcortical volumes, as well as
- 658 increased ventricles and putamen and pallidum volumes. Cortical, right hippocampal and
- 659 ventricle volumes were more heterogeneous in the SZ-group compared to healthy controls. B:
- 660 Polygenic risk for SZ was not associated with mean changes nor dispersion in any of the
- 661 regions.
- 662
- 663





- 673 CA4, and bilateral CA2/3. Neither total hippocampal volumes nor any of the subfields
- showed a significant association between polygenic risk and volume heterogeneity.

Sample	Source	Comment	Reference
BrainGluSchi	http://schizconnect.org/ SchizConnect was funded by NIMH cooperative agreement 1U01 MH097435.	Data obtained from COINS source. Supported by NIMH- grant R01MH084898-01A1.	1
CIMH Authors		CIMH was supported by the Deutsche Forschungsgesellschaft (DFG, projects KI 576/14-2, ZI1253/3-1, ZI1253/3-2) and the European Community's Seventh Framework Programme (FP7/2007–2013) grant agreement #602450 (IMAGEMEND)	2-4
CNP 1 & 2	https://openfmri.org/	Data sets were obtained from the OpenfMRI database. Data from 2 imaging sites. DS000030 was supported by the	5,6
(DS000030)		Consortium for Neuropsychiatric Phenomics (NIH Roadmap for Medical Research grants UL1-DE019580, RL1MH083268, RL1MH083269, RL1DA024853, RL1MH083270, RL1LM009833, PL1MH083271, and PL1NS062410).	
COBRE	http://schizconnect.org/	Data obtained from COINS source. Supported by grant 5P20RR021938 /P20GM103472 from the NIH to Dr. Vince Calhoun.	7
HUBIN	Authors	HUBIN was supported by the Swedish Research Council (2006-2992, 2006-986, K2007-62X-15077-04-1, 2008-2167, 2008-7573, K2010-62X-15078-07-2, K2012-61X-15078-09- 3, 14266-01A,02-03, 2017-949), the regional agreement on medical training and clinical research between Stockholm County Council and the Karolinska Institutet, the Knut and Alice Wallenbergs Foundation and the HUBIN project	8,9
KaSP	Authors	KaSP was supported by grants from the Swedish Medical Research Council (SE: 2009-7053; 2013-2838; SC: 523- 2014-3467), the Swedish Brain Foundation, A□hlén- siftelsen, Svenska La□karesa□llskapet, Petrus och Augusta Hedlunds Stiftelse, Torsten So□derbergs Stiftelse, the AstraZeneca-Karolinska Institutet Joint Research Program in Translational Science, So□derbergs Ko□nigska Stiftelse, Professor Bror Gadelius Minne, Knut och Alice Wallenbergs stiftelse, Stockholm County Council (ALF and PPG), Centre for Psychiatry Research, KID-funding from the Karolinska Institutet.	10,11
MCIC-1/2/3	http://schizconnect.org/	Data obtained from COINS source. MCIC was supported by the Department of Energy under Award Number DE- FG02- 08ER64581.	12
NUNDA	http://schizconnect.org/	Data obtained from schizconnect.org. Source: NUNDA Supported by NIMH grant MH056584.	13
NUSDAST	http://schizconnect.org/	Data obtained from schizconnect.org. Source: NU_REDCAP. Supported by NIMH Grant 1R01 MH084803	14,15
TOP3T 1 & 2, TOP- 1.5	Authors	The work was funded by the Research Council of Norway (213837, 223273, 204966/F20, 213694, 229129, 249795/F20, 248778), the South-Eastern Norway Regional Health Authority (2013-123, 2014-097, 2015-073, #2017-112) and Stiftelsen Kristian Gerhard Jebsen.	16-19
UKB	https://www.ukbiobank.ac.uk	This research has been conducted using the UK Biobank Resource (access code 27412)	20
UNIBA	Authors	This work was supported by a "Capitale Umano ad Alta Qualificazione" grant by Fondazione Con II Sud awarded to Alessandro Bertolino and by a Hoffmann-La Roche Collaboration Grant awarded to Giulio Pergola. This project has received funding from the European Union Seventh Framework Programme for research, technological development and demonstration under grant agreement no. 602450 (IMAGEMEND). This paper reflects only the author's views and the European Union is not liable for any use that may be made of the information contained	21

675

676 **eTable1: Summary of included samples.** We included publicly available data as well as data

677 provided by co-authors. Sample reference list contains publications related to the sample as

678 well as data sources.

Volume	SZ mean (t)	SZ Disp (t)	SZ mean outlier (t)	SZ disp outlier (t)
Total GrayVol	-18,04	3,41	-17,97	2,19
hCortexVol	-17,20	3,15	-17,15	2,03
CortexVol	-17,05	3,24	-17,07	1,63
rhCortexVol	-16,65	3,20	-16,68	1,23
Right-Hippocampus	-13,86	2,43	-12,49	1,83
Left-Hippocampus	-13,83	2,39	-11,66	2,51
SupraTentorialVolNotVentVox	-12,85	2,40	-13,69	0,17
SupraTentorialVolNotVent	-12,41	1,99	-13,65	0,17
Left-Cerebellum-Cortex	-11,69	2,92	-11,20	-0,65
SupraTentorialVol	-11,43	-0,09	-12,63	0,03
Right-Cerebellum-Cortex	-10,69	-0,09	-10,53	-0,19
Brain-Stem	-9,64	-0,91	-9,20	-1,08
Left-Amygdal a	-8,82	1,86	-8,60	1,58
Right-Thalamus-Proper	-8,35	-1,32	-7,00	1,96
Left-Thalamus-Proper	-7,53	0,45	-6,83	2,12
rhCortical White Matter Vol	-7,11	-0,97	-6,12	0,75
CC Mid Posterior	-7,09	0,93	-8,25	-1,81
Cortical White Matter Vol	-6,97	-1,17	-6,26	1,49
Left-Cerebellum-White-Matter	-6,82	2,27	-7,38	-1,42
hCortical White Matter Vol	-6,64	2,27	-6,15	1,42
Right-VentralDC	-6,35	2,24	-5,87	0,12
Right-Cerebellum-White-Matter		-1,47		-1,30
•	-6,25		-6,34	
CC_Central	-6,18	-0,14	-7,15	-0,95
Right-Amygdal a	-6,16	0,81	-6,03	1,51
Left-VentralDC	-5,82	1,13	-4,44	-1,19
Right-Accumbens-area	-5,78	0,91	-5,18	0,76
CC_Mid_Anterior	-4,81	2,37	-6,31	-0,27
Sub Cort Gray Vol	-4,63	-1,30	-2,72	1,57
CC_Posterior	-3,28	-0,04	-4,57	1,44
Left-Accumbens-area	-3,26	2,04	-2,80	-0,20
CC_Anterior	-2,33	1,05	-2,14	-0,18
Left-vessel	1,37	2,03	0,79	0,09
Right-vessel	1,69	-0,39	1,94	-0,03
Right-Caudate	2,16	1,56	4,60	1,57
4th-Ventricle	2,29	-0,05	2,51	0,66
Left-Caudate	4,00	2,20	4,76	1,57
5th-Ventricle	4,80	1,89	0,68	0,09
Left-choroid-plexus	5,05	1,74	4,07	1,72
Left-Putamen	5,48	0,62	5,62	0,06
Right-choroid-plexus	5,67	-0,91	6,52	2,43
Right-Putamen	6,44	4,48	7,94	0,20
Optic-Chiasm	6,48	2,17	5,83	-0,86
Left-Lateral-Ventricle	7,03	2,70	7,50	1,74
Right-Lateral-Ventricle	7,09	1,88	6,94	2,18
non-WM-hypointensities	7,40	1,54	8,19	1,69
CSF	8,19	1,95	5,31	2,04
Right-Inf-Lat-Vent	8,82	3,18	9,83	1,53
Right-Pallidum	9,55	2,33	9,70	1,99
Left-Pallidum	9,57	2,21	9,60	3,87
Left-Inf-Lat-Vent	9,77	5,57	12,03	4,19
3rd-Ventricle	12,24	5,78	9,741	4,190

681 eTable2: SZ cortical and subcortical analysis with and without outlier removal. We

682 excluded participants based on extreme values (described in Methods) and reran mean and

683 dispersion models without these participants.

Hippocamus subfield	SZ mean (t)	SZ Disp (t)	SZ mean outlier (t)	SZ dispoutlier (t)	
Right Molecular Layer	-12,98	1,71	-12,53	1,54	
Right Whole Hippocampus	-12,86	2,16	-12,58	1,74	
Left_Whole Hippocampus	-12,23	3,45	-12,28	2,30	
Left Molecular Layer	-11,78	3,45	-11,70	2,43	
Right GC-DG	-11,48	1,85	-11,11	1,61	
Right CA1	-11,37	1,18	-10,89	1,00	
Left CA1	-11,00	2,18	-11,10	1,04	
Right CA4	-10,99	1,55	-10,67	1,39	
Right presubiculum	-10,81	0,71	-10,45	0,46	
Left GC-DG	-10,72	3, 22	-10,62	2,33	
Left HATA	-10,57	1,04	-10,57	0,56	
Left presubiculum	-10,36	2,18	-10,44	1,27	
Left CA4	- 9, 80	3,00	-9,69	2, 30	S
Right subiculum	- 9, 36	1,71	-9,23	1,12	
Right HATA	- 9, 23	2,01	-8,81	0,90	
Left Hippocampal tail	- 8, 99	0,89	-9,06	1,14	
Left subiculum	- 8, 34	2, 22	-8,30	1,22	
Right Hippocampal tail	-7,81	0,91	-7,36	0,43	
Right CA2/3	- 7, 31	0,02	-6,87	0,23	
Right parasubiculum	-7,18	-0,55	-7,15	-0,57	
Left parasubiculum	-6,56	0,78	-6,37	0,35	
Left CA2/3	-6,14	2,14	-6,20	1,47	
Left fimbria	-4,66	0, 30	-4,52	0,65	
Right fimbria	-4,36	0,51	-4,23	1,10	
Left hippocampal fissure	3,99	0,83	4,71	0,23	
Right hippocampal fissure	5,93	0,57	6,33	-0, 28	

684

685 eTable3: SZ hippocampal subfields analysis with and without outlier removal. We

- 686 excluded participants based on extreme values (described in Methods) and reran mean and
- 687 dispersion models without these participants.

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Hippocamus subfield	PRS mean (t)	PRS Disp(t)	PRS mean MDS (t)	PRS disp MDS (t)	PRS mean outlier (t)	PRS dis poutlier (t)	PCA1 mean (t)	PCA1 dis p (t)
Left CA 2/3	-3,00	-1,08	- 2,99	-0,90	-2,67	- 1,07	-2,76	-0,48
Left GC-DG	-2,26	-0,93	- 2,15	-0,70	-2,10	- 1,43	-1,95	-0,12
Right CA2/3	-2,20	-0,56	- 2,10	-0,15	-1,98	- 0, 11	- 2, 34	0,21
Left CA4	-1,95	-0,87	-1,86	-0,65	-1,70	- 1, 35	-1,65	-0,13
Left Whole hippocampus	-1,83	-0,61	-1,62	-0,34	- 1,68	- 1,12	-1,36	-0,19
Right HATA	-2,04	-0,81	-1,96	-0,64	-2,18	- 0,92	- 2, 39	-0,82
Left HATA	-2,15	-0,65	- 2,14	-0,37	- 2,0 3	- 0,87	-2,06	-0,47
Left CA1	-1,79	-0,70	-1,55	-0,45	-1,87	- 1, 38	-1,41	-0,32
Left molecular layer	-1,71	-0,86	-1,47	-0,65	- 1,48	-1,58	-1,31	-0,47
Right GC-DG	-1,61	-1,18	-1,39	-0,86	- 1, 59	-0,87	-1,51	-0,43
Right CA4	-1,54	-1,31	-1,33	-0,94	-1,44	-0,78	-1,45	-0,63
Right Whole hippocampus	-0,90	-1,17	-0,56	-0,82	-0,82	- 1,03	-0,37	-0,63
Left parasubiculum	-1,37	-1,13	-1,35	-0,88	- 1,09	-0,70	-1,50	-0,65
Right molecular layer	-0,81	-1,17	-0,46	-0,83	-0,84	- 0,84	-0,35	-0,60
Left fim bria	-1,25	0,73	-1,29	0,89	-1,73	0,78	-1,90	0,55
Right CA1	-0,82	-0,76	-0,54	-0,39	-0,81	-0,66	-0,36	-0,11
Left s ubiculu m	-0,79	-0,76	-0,58	-0,59	- 0,72	-1,62	-0,57	-0,69
Left Hippocam pal tail	-0,82	0,58	-0,75	0,77	-0,91	0,99	0,04	0,74
Right Hippocampal tail	-0,53	0,47	-0,41	0,70	-0,46	0,48	0,66	0,42
Left presubiculum	-0,32	-0,52	-0,07	-0,37	0,07	- 0, 60	0,17	-0,35
Right presubiculum	-0,15	-1,67	0,23	-1,40	0,49	- 1, 29	0,62	-0,85
Right fimbria	-0,15	0,24	-0,12	0,50	-0,78	0,12	-0,67	0,64
Right subiculum	0,54	-0,63	0,85	-0,27	0,57	- 0,45	0,93	0,05
Right parasubiculum	0,21	-0,98	0,36	-0,80	0,74	0,03	0,40	-0,27
Left hippocam pal fissure	0,46	-0,16	0,60	-0,21	0,41	- 0, 52	0,64	-0,09
Right hippocampal fissure	2,12	0,73	2,30	0,83	2,19	0,88	2,35	0,60

690 eTable4: SZ-PRS hippocampal subfields analysis with and without outlier removal. We

691 excluded participants based on extreme values (described in Methods) and reran mean and

692 dispersion models without these participants.

693	eMethods:
694 695	Samples: For the case-control analysis of cortical thickness and cortical and subcortical
696	volumes we included MRI-scans from 16 cross-sectional study samples with a total of 3161
697	participants of which 2010 were healthy controls, and 1151 patients diagnosed with SZ. The
698	case-control hippocampus subfield analysis was performed in a sub-sample of 2870
699	participants. The polygenic risk analysis was performed in a non-overlapping sample
700	consisting of 12490 participants from the UK Biobank (UKB) that had MRI scans and genetic
701	data available, all scanned on the same scanner ³⁵ . All UKB participants diagnosed with any
702	ICD-10 mental or neurological disorder were excluded.
703 704	Genetics: Filtering include removal of SNPs with ambiguous alleles (AT or CG) and of
705	variants in the major histocompatibility complex (MHC; chromosome 6, 26-33Mb), and
706	pruning of SNPs based on linkage disequilibrium (LD) and p-value. All variants in LD with
707	the local SNP with the smallest p-value were removed (the SNP with the smallest p-value
708	within a 250kb window was retained, and all neighbours with a LD $r^2 > 0.1$ were removed; a
709	step known as clumping).
710	
711	DGLM: Modeling the dispersion is important for obtaining correct mean parameter estimates
712	if dispersion varies as a function of the predictor, and also allows for systematic investigation
713	into factors associated variability in observations ⁴⁵ . DGLMs where fitted using the following
714	model specifications for both the mean and dispersion part; case control: $Y \sim Age + Sex + SZ$
715	, and for polygenic risk: $Y \sim Age + Sex + PRS$, where Y is the mean in the first step, and the
716	dispersion in the second step. For the group comparison we then obtain an estimate of the

717 mean difference between groups, as well as an estimate of the difference in dispersion around

the mean between SZ and controls for the outcome measure. For the PRS, we obtain an

restimate of the linear relationship with PRS and an estimate of the relationship between PRS

- and the dispersion of the outcome measure.
- 721

722 *Permutation:* Due to the computational demand of the vertex-wise analysis (~5 minutes pr.

data chunk, one permutation totals 328 chunks) we ran 600 permutations for each model

724 (case-control, polygenic risk) before fitting a generalized Pareto distribution to the tail of the

permutation distribution⁴⁷. For transparency both the raw and fitted permuted p-values are

726 provided.

727

728	Outliers: Partic	pants with a z-scor	e for either eTIV	or for volume	of interest at $ z > 3$ were

removed, as well as participants with extreme values based on a statistical outlier-test

730 (Rpackage: car⁴⁹, corrected p < .05 for the linear models $Y \sim Age + Sex + SZ$ and $Y \sim Age +$ 731 *Sex* + *PRS*).

