



City Research Online

City, University of London Institutional Repository

Citation: Lohse, M., Garrido, L., Driver, J., Dolan, R. J., Duchaine, B. C. & Furl, N. (2016). Effective Connectivity from Early Visual Cortex to Posterior Occipitotemporal Face Areas Supports Face Selectivity and Predicts Developmental Prosopagnosia. *Journal of Neuroscience*, 36(13), pp. 3821-3828. doi: 10.1523/jneurosci.3621-15.2016

This is the accepted version of the paper.

This version of the publication may differ from the final published version.

Permanent repository link: <https://openaccess.city.ac.uk/id/eprint/23456/>

Link to published version: <https://doi.org/10.1523/jneurosci.3621-15.2016>

Copyright: City Research Online aims to make research outputs of City, University of London available to a wider audience. Copyright and Moral Rights remain with the author(s) and/or copyright holders. URLs from City Research Online may be freely distributed and linked to.

Reuse: Copies of full items can be used for personal research or study, educational, or not-for-profit purposes without prior permission or charge. Provided that the authors, title and full bibliographic details are credited, a hyperlink and/or URL is given for the original metadata page and the content is not changed in any way.

City Research Online:

<http://openaccess.city.ac.uk/>

publications@city.ac.uk

The Journal of Neuroscience

<http://jneurosci.msubmit.net>

JN-RM-3621-15R1

Effective Connectivity from Early Visual Cortex to Posterior Occipito-temporal Face Areas Predicts Developmental Prosopagnosia

Michael Lohse, University of Oxford
Brad Duchaine, Dartmouth College
Lucia Garrido, Brunel University London
Jon Driver,

Raymond Dolan, Wellcome Trust Centre for Neuroimaging, UCL
Nicholas Furl, Royal Holloway, University of London

Commercial Interest:

1 **Effective Connectivity from Early Visual Cortex to Posterior Occipito-**
2 **temporal Face Areas Supports Face Selectivity and Predicts**
3 **Developmental Prosopagnosia**

4

5 *Running Title: Effective connectivity and face perception ability*

6

7 **Michael Lohse^{1,2}, Bradley C. Duchaine³, Lucia Garrido⁴, Jon Driver^{5,6}, Raymond J. Dolan⁵,**
8 **Nicholas Furl^{1,7}**

9 ¹ Medical Research Council, Cognition and Brain Sciences Unit, 15 Chaucer Road, Cambridge CB2
10 7EF, United Kingdom

11 ² Department of Physiology, Anatomy, and Genetics, University of Oxford, Oxford OX1 3QX,
12 United Kingdom

13 ³ Psychological and Brain Sciences, Dartmouth College, Hanover, NH 03755, USA

14 ⁴ Division of Psychology, Department of Life Sciences, Brunel University London, Uxbridge UB8
15 3PH, United Kingdom

16 ⁵ Wellcome Trust Centre for Neuroimaging, University College London WC1N 3BG, United
17 Kingdom

18 ⁶ Institute of Cognitive Neuroscience, University College London, London WC1N 3AR, United
19 Kingdom

20 ⁷ Department of Psychology, Royal Holloway, University of London, Egham Hill, Egham, Surrey,
21 TW20 0EX, United Kingdom

22

23 Corresponding author:

24 Michael Lohse

25 Department of Physiology, Anatomy, and Genetics, University of Oxford

26 michael.lohse@sjc.ox.ac.uk

27

28 **23 pages, 4 figures, 1 table**

29 **Abstract (238 words), Introduction (648), Discussion (1280 words)**

30

31 **We declare no conflict of interest**

32

33 **Acknowledgements**

34 This work was supported by the Wellcome Trust (ML (105241/Z/14/Z), R. J. D., and J. D.). J.D.

35 was a Royal Society Research Professor when the research was performed. The authors are grateful

36 to their colleagues at the University College London, namely, Laura Germine and Raka Tavashmi

37 for assistance with behavioral measurement and/or fMRI data collection, and John Stevens for

38 clinical evaluation of the participants.

39

40 **Abstract**

41 Face processing is mediated by interactions between functional areas in the occipital and temporal
42 lobe, and the fusiform face area (FFA) and anterior temporal lobe play key roles in the recognition
43 of facial identity. Individuals with developmental prosopagnosia (DP), a lifelong face recognition
44 impairment, have been shown to have structural and functional neuronal alterations in these areas.
45 The present study investigated how face selectivity is generated in participants with normal face
46 processing, and how **functional abnormalities** associated with DP, arise as a function of network
47 connectivity. Using functional magnetic resonance imaging and dynamic causal modeling, we
48 examined effective connectivity in normal participants by assessing network models that include
49 early visual cortex (EVC) and face-selective areas and then investigated the integrity of this
50 connectivity in participants with DP. Results showed that a feedforward architecture from EVC to
51 **the** occipital face area, EVC to FFA, and EVC to posterior superior temporal sulcus (pSTS) best
52 explained how face selectivity arises in both controls and participants with DP. In this architecture,
53 the DP group showed reduced connection strengths on feedforward connections carrying face
54 information from EVC to FFA and EVC to pSTS. These altered network dynamics in DP **contribute**
55 **to** the diminished face selectivity in the posterior occipito-temporal areas affected in DP. **These**
56 **findings** suggest a novel view on the relevance of feedforward projection from EVC to posterior
57 occipito-temporal face areas in generating cortical face selectivity and differences in face
58 recognition ability.

59 **Significance statement**

60 Areas of the human brain showing enhanced activation **to** faces compared to other objects or places
61 have been extensively studied. However, the **factors** leading to this face selectivity have remained
62 mostly **unknown**. We show that effective connectivity from early visual cortex to posterior occipito-
63 temporal face areas gives rise to face selectivity. Furthermore, people with developmental
64 prosopagnosia, a lifelong face recognition impairment, **have** reduced face selectivity in the posterior

65 occipito-temporal face areas and left anterior temporal lobe. We show that this reduced face
66 selectivity can be predicted by effective connectivity from early visual cortex to posterior occipito-
67 temporal face areas. This study presents the first network-based account of how face selectivity
68 arises in the human brain.

69

70 **1. Introduction**

71 During the last two decades, functionally-localized areas relevant for face processing in humans
72 have been investigated. These face-selective areas show stronger blood oxygen level dependent
73 (BOLD) responses to faces compared to other objects (Kanwisher et al., 1997). However, these
74 areas do not function in isolation but rather as an integrated system (Moeller et al., 2008). **A model**
75 **of the functional integration of** face-selective areas is required **to understand the neural**
76 **underpinnings of face processing.** Most previous studies investigating connectivity in face-selective
77 networks have focused on anatomical connections (Gomez et al., 2014; Thomas et al., 2008) or
78 correlated BOLD responses between face-selective areas (functional connectivity) (George et al.,
79 2001; Idaka et al., 2001). A handful of studies have focused on the direction of information flow
80 between face-selective areas (Fairhall and Ishai, 2007; Furl et al., 2013). **A common** limitation of
81 these directional connectivity studies is that they do not isolate the flow of face-selective
82 information from other information. **Those** few studies **of the** directional flow of face-selective
83 information, used **network models limited to** relatively few face-selective regions (Furl et al., 2014;
84 Nagy et al., 2012). **Here, we** investigate the directional flow of face-selective information using the
85 most comprehensive face processing network investigated to date. **We further** compare the flow of
86 face-selective information between controls and people with developmental prosopagnosia (DP), a
87 lifelong face recognition impairment.

88 **Previous theory can guide hypotheses** about the **factors generating** face-selectivity. **An**
89 influential proposal for the neural architecture for face processing separates face-selective areas into

90 a core system that carries out visual analysis and which consists of the occipital face area (OFA),
91 fusiform face area (FFA), and posterior superior temporal sulcus (pSTS), and an extended system
92 carrying out further, higher level processing (Haxby et al., 2000). Extended areas process
93 information such as knowledge about the owner of a face in the anterior temporal lobe (ATL) and
94 emotional information in the amygdala. Formal models testing how interactions between these areas
95 give rise to face-selectivity have not been developed. Our first aim was to quantitatively compare
96 plausible connectivity architectures, using dynamic causal modeling (DCM) (Friston et al., 2003).

97 Occipito-temporal contributions to face processing can be investigated by studying
98 individuals with DP. People with DP have difficulty recognizing facial identity (Behrmann &
99 Avidan, 2005; Duchaine & Nakayama, 2006) and sometimes have problems with other aspects of
100 face processing as well (Duchaine et al., 2006; Nunn et al., 2001). Neural abnormalities in DPs have
101 been reported. Behrmann et al. (2007) and Garrido and colleagues (2009) reported decreased grey
102 matter in the fusiform gyrus, STS and ATL of participants with DP. Gomez et al. (2014) and Song et
103 al. (2015) found altered white matter around FFA in DP. Furl and colleagues (2011) examined DP
104 individuals and typical controls and showed that BOLD responses in bilateral FFA and ATL
105 correlated with face recognition ability. Furthermore, Furl et al. (2011), Dinckelacker et al. (2011),
106 and von Kriegstein et al. (2008) found participants with DP had reduced face selectivity in FFA.
107 Avidan et al. (2014) found reduced activation in ATL, and reduced functional connectivity between
108 the core system and ATL in DP. To better understand decreased face selectivity associated with the
109 DP population, our second aim was to contrast neural connectivity in participants with DP versus
110 participants with normal face recognition.

111 To establish the network architecture of face processing, we estimated the directionality of
112 informational flow, using DCM, when participants viewed faces. We further investigated the
113 relevance of the state of this system for behavior by identifying how it is altered in DP. We found a
114 network that best explains how face relevant information flows through a face-selective network
115 where the presence or absence of faces modulates connectivity from early visual cortex (EVC) to

116 posterior occipito-temporal areas (OFA, FFA, and pSTS). Also, We further show that the strength of
117 face-specific modulation in connections from EVC to FFA and pSTS is diminished in DP.

118 **2.Method**

119 *2.1. Participants*

120 We examined **the same** 15 DP and 15 control individuals from Garrido et al. (2009) who
121 returned for the fMRI experiment reported in Furl et al. (2011). The **participants with DP reported**
122 **great difficulties with face recognition in daily life and** were diagnosed using the Cambridge Face
123 Memory Test (CFMT in its original form; Duchaine & Nakayama, 2006a) and the Famous Faces
124 Test (FFT; Duchaine & Nakayama, 2005). Informed consent was obtained in accordance with
125 procedures approved by The Joint Ethics Committee of The National Hospital for Neurology and
126 Neurosurgery and The Institute of Neurology, London.

127 *2.2. Data Aquisition*

128 T2*-weighted echo-planar functional brain volumes were acquired using the Siemens Trio 3T
129 system (Siemens, Erlangen, Germany). For each participant, three sessions were run with 430
130 volumes each for a total of 1290 volumes per participant. Images were acquired at a volume
131 repetition time (TR) of 2176 milliseconds with an in-plane resolution of 3×3 mm, 2 mm slice
132 thickness, and 1 mm slice gap, with echo time = 30 msec and a flip angle of 90° . We discarded the
133 two volumes commencing each session to avoid magnetic equilibrium contamination. (See Furl et
134 al., 2011).

135 *2.3. Experimental Design*

136 The experimental design included a repetition suppression paradigm. Stimuli comprised **of**
137 images of emotional faces taken from the KDEF database (Lundqvist & Litton, 1998; The
138 Karolinska Directed Emotional Faces, Department of Clinical Neuroscience, Psychology Section,
139 Karolinska Institute) and photographs of cars.

140 Block designs **have been shown to be** statistically efficient for DCM and therefore practical
141 for the present study (Mechelli et al., 2013). There were two categories of blocks: faces and cars.

142 Ninety-six blocks displayed faces and 48 blocks displayed cars, **distributed equally over three runs.**
143 Each block lasted 15.2 seconds with 4 seconds of fixation between blocks. Eight stimuli with
144 alternating viewpoints (left and right three quarters and frontal) were presented in each block for
145 1700ms preceded by 200ms fixation. Face blocks varied on whether facial expressions (happy,
146 fearful, neutral, and angry) were different or the same within each block, and whether identities
147 (four male identities) were the same or different within each block. The car blocks varied on
148 whether cars (four cars) were the same or different. All images were grayscaled, normalized to
149 equal luminance mean and range, adjusted to similar size, and placed on a gray background. Faces
150 were cropped to occlude hair and clothing (see Furl et al., 2011).

151

152 ***2.5. Pre-processing and general linear model***

153 Following Furl et al. (2011) data pre-processing was carried out using SPM5 (Wellcome Trust
154 Centre for Neuroimaging, London; <http://www.fil.ion.ucl.ac.uk/spm/>) with MATLAB (The
155 Mathworks, Natick, MA). Pre-processing comprised realignment, normalization and 8mm spatial
156 smoothing. Slice timing was modeled in the DCM, where the precise acquisition time of each
157 region of interest (ROI) was taken into account. This has been shown to be an effective solution to
158 the slice time problem for DCM (Kiebel et al., 2007).

159 For ROI definition, we used general linear models (GLMs) from SPM8. First we analyzed
160 the timeseries data at the individual-participant level using a canonical hemodynamic response
161 function, a low-pass filter of 1/256Hz, AR(1) autocorrelation modeling, motion correction, and
162 proportional scaling. Then, contrasts of interest (faces versus cars and all stimuli versus baseline,
163 see ROI selection) were computed in each individual participant. The resulting contrast images
164 were subjected, at a second level, to right-sided t-tests treating participants as random effects.
165 Results images from the second level were thresholded at $P < 0.005$ (uncorrected) and clusters were
166 then identified that met family-wise error correction at $P < 0.05$ across either the whole brain or a
167 priori small volume correction using Gaussian random field theory.

168 In order to optimize the SPM for DCM, individual-participant level GLMs were recomputed
169 in SPM12b using regressors for all visual inputs (faces and cars) and faces only (these regressors
170 were collapsed over repetition condition and session), as well as covariates for each run and for
171 head motion. This allows us to assess the effective connectivity of face-selective information across
172 all three runs.

173 **2.6. ROI Selection**

174 We selected ROIs considered “core” face processing areas (i.e. OFA, FFA and pSTS) (Haxby
175 et al., 2000). We also selected ATL, because of its putative role in face recognition and coupling to
176 areas in the core system (Behrmann et al, 2007; Eifuku et al., 2004; Haxby et al., 2000; Yang et al.,
177 2014). Together, these areas were hypothesized to be the main occipito-temporal components in a
178 circuit that processes faces. For inclusion in DCM, these areas had to show significant face
179 selectivity at a second (group) level, right-sided, t-test of ‘all faces > all cars’ contrast using all
180 participants (both controls and DP). From these criteria, we identified five face-selective ROIs:
181 right OFA (rOFA), right FFA (rFFA), right posterior STS (rpSTS), left FFA (lFFA), and left ATL
182 (lATL). rOFA, lFFA and lATL were small volume corrected using a 10mm sphere around the
183 functional peak coordinates of at least one previous study (Allison, Puce, & McCarthy, 2000;
184 Andrews & Ewbank, 2004; Fox et al., 2009; Hein & Knight, 2008; Rotshtein et al., 2005; Von Der
185 Heide et al., 2013; Winston et al., 2004).

186 We also selected early visual cortex (EVC) as an ROI for DCM. EVC is not face-selective,
187 but is the first cortical area in the visual processing stream, and, as expected, responded robustly to
188 both faces and cars. Using models that assume that the information initially passes through EVC
189 allows us to estimate the signal sent into the face-selective system in a biologically plausible
190 manner, instead of assuming that the signal remains unchanged until reaching a face-selective area.
191 Such models also allow us to explore pertinent theoretical explanations for face selectivity in which
192 face-selective areas are receptive to low-level face-diagnostic information already present in early
193 visual areas (See Discussion). We identified EVC using a second level one-sample, right-sided, t-

194 test on an '(all faces + all cars) > rest' contrast, and identified the peak activation around the
195 posterior occipital lobes.

196 In accordance with conventional methods, we identified the locations of the ROIs in each
197 individual participant (den Ouden et al., 2012; Grefkes et al., 2008; Mechelli et al., 2003; Mechelli
198 et al., 2004). Using the second-level (group) clusters to define a search space, we identified the
199 individual participants' face-selective peak voxel within the second level clusters (for EVC the
200 visual versus baseline peak voxel was identified). Second level (group) clusters used for search
201 spaces consist of all voxels around the area of interest, which SPM recognized as a single cluster
202 around the peak voxel. The clusters were identified with a significance level at an uncorrected
203 threshold of $p < 0.005$ in a second level SPM analysis. If a second level (group) cluster was
204 overlapping with another area, we limited the inclusion of $p < 0.005$ thresholded voxels within 10mm
205 of the peak voxel of the area. This was relevant for EVC, rSTS and IATL. In order to ensure that the
206 search spaces were not dominated by one of the groups, we also computed the clusters from each of
207 the groups separately. We found that the peak of the control group and DP group clusters were
208 located within the search spaces, which indicates that our search spaces were representative for each
209 group. After identification of individual peak voxels for all selected ROIs, we created 6mm spheres
210 with no threshold around the peak voxels to create participant-specific ROIs. We extracted ROI
211 mean percentage signal change across voxels (faces>cars contrast for face-selective areas and all
212 visual>rest contrast for EVC) for ROI analysis using MarsBar 0.42 (Brett et al., 2002). This
213 approach reduces the multiple comparison problem from a voxel-wise issue to one involving only
214 the number of ROIs investigated. This is done by focusing only on the activity within the ROI
215 chosen (i.e. six ROIs), and removing the variability between voxel signals within the ROI by
216 averaging the signal of the voxels, and therefore treating each ROI as a single signal measurement
217 (Poldrack, 2007). We used two-sample, two-tailed, t-tests for testing group differences in ROI face
218 selectivity. The analyses were multiple comparison corrected for the number ROIs tested (Poldrack,
219 2007). For DCM, the first eigenvariate timeseries of all participant-specific ROIs were extracted

220 from the individual participant analyses.

221 ***2.7. Dynamic Causal Modeling***

222 DCM uses a generative Bayesian model of effective connectivity between hidden neuronal
223 responses to predict fMRI BOLD responses in pre-specified areas (Friston et al., 2003). DCM
224 allows testing of specific hypotheses regarding effective connectivity. It uses Bayesian model
225 selection (BMS) to **determine** which model of connectivity best explains the data. Furthermore, it
226 allows for inference on individual connection parameters within a GLM framework (Penny et al.,
227 2004; Stephan et al., 2010). It allows inference on three types of parameters. Endogenous
228 connectivity (A parameters) **is** the estimated effective connectivity averaged over conditions.
229 Modulatory connectivity (B parameters) models effects of a specific experimental factor on
230 effective connectivity. Last, exogenous parameters (C parameters) model stimulus input effects on
231 areas in the specified system. In the present paper, our primary interest was in measuring
232 connections that are modulated by faces (B parameters). We used DCM12 to carry out the DCM.

233 **2.7.1. Model Selection and Parameter Analysis**

234 Our first goal was to ascertain a model architecture that demonstrates a likely mechanism for
235 producing face selectivity in our face-selective ROIs. Once this model was established, we then
236 could test whether this face selectivity generating mechanism **differed** in **participants with DP and**
237 **controls**. Such **differences would provide a potential account of** the reductions in face selectivity in
238 posterior areas that we observed in our sample of participants with DP (see also Furl et al., 2011).

239 We used **bayesian model selection (BMS)** to infer which model best explained the data
240 (Penny et al., 2004). This approach is based on the posterior probability associated with each
241 model's evidence (Free energy), summed across the participants. We performed BMS on the whole
242 sample and separately for the control and DP groups to estimate the most likely model architecture
243 for every group.

244 Using Bayesian model averaging (BMA), we estimated A, B, and C parameters, averaged
245 over the model space and weighted by the exceedance probability of each model (the likelihood that

246 one model is more likely than any other model, given all participant data). This approach to
247 parameter estimation does not assume that participants all use the same model, but allows for
248 different participants to have different model weighting (Penny et al., 2010; Stephan et al., 2010).

249 We compared the B parameters of controls versus DP participants. This analysis included
250 face modulated connections present in the model architecture showing highest posterior probability
251 in BMS (Fig. 1). This model architecture accounts for the flow of face information in the present
252 data and so differences in face-modulation strength in this model architecture **may** be relevant for
253 **the functional abnormalities** in DP. We tested if controls show greater face modulation than
254 participants with DP by submitting B parameters (modulation by faces) to two-sample, right-sided,
255 t-tests. The analyses were multiple comparison (Bonferroni) corrected for number of connections
256 tested.

257 **2.7.2. Specification of Model Space**

258 To identify which connections were most likely to create face selectivity in the face-
259 selective ROIs, we tested modulation by faces on different configurations of connections. Given no
260 a priori assumptions about how non-specific visual information spreads through the system, we
261 endogenously connected all areas reciprocally in all models. We assumed EVC to be the exogenous
262 input area (where activity is driven by all visual experimental stimuli) (see section on ROI
263 selection).

264 This template was used to formulate the thirteen models that we tested (Fig. 1). The first six
265 models were motivated by the Haxby et al. (2000) model of face processing and, specifically, the
266 features of this model that refer to visual analysis of faces (i.e., a dedicated "core" system). In
267 models 1-3, face selectivity arises from face modulation between areas in the core system alone (i.e.
268 between rOFA, FFA, and rpSTS), with feedforward (model 1), backward (model 2) or reciprocal
269 (model 3) face modulation. In models 4-6, face selectivity arises from modulation by faces between
270 the core system and IATL with either feedforward (model 4), backward (model 5) or reciprocal
271 (model 6) modulation. In models 7-9, face selectivity arises from interactions between EVC and

272 downstream face-selective areas. These three models instantiate networks where faces are
273 discriminated from other objects through a feedforward mechanism from EVC. Faces could
274 modulate feedforward connections from EVC to rOFA (model 7), to the core system (model 8) or to
275 all face-selective areas (model 9). In models 10 and 11, face selectivity arises from
276 backward/feedback modulation by faces from ATL to FFA (model 10), or to the core system (model
277 11). Finally, in models 12 and 13, face selectivity arises through horizontal modulation by faces
278 between left and right FFA (model 12), or between FFA and STS (model 13). This model space
279 explores the network mechanisms that are currently plausible for the selected areas, including
280 possible feedforward, backward and reciprocal interactions between EVC, core system and anterior
281 temporal areas.

282

283 **3. Results**

284 ***3.1. SPM Group Analysis and ROI analysis***

285 We performed an SPM group analysis of all the participants to test for face selectivity (i.e.
286 faces>cars contrast) and to identify face-selective ROIs for DCM. Significant clusters and peaks at
287 $P < 0.05$ (family-wise error corrected) were identified. We observed significant face selectivity in
288 rOFA, bilateral FFA, rpSTS, bilateral amygdala, precuneus, orbito-frontal cortex, and IATL. From
289 these results and from our *a priori* assumption that occipito-temporal face-selective areas are
290 associated with face recognition, we selected for DCM the face-selective areas rOFA, bilateral FFA,
291 rpSTS and IATL (Fig. 2). Furl et al. (2011) already reported the face selectivity results separately
292 for controls and DPs and found similar results. Here, the analysis combined all participants, as we
293 intended to use the second level (group) results to define a search space for ROI definition that
294 could be applied to the whole sample.

295 We also report an ROI analysis using the participant-specific ROIs that we obtained from the
296 whole sample search space and that we included in the DCM (Fig. 3). All p-values for this ROI
297 analysis are reported as uncorrected and are inferred to be significant according to a Bonferroni

298 corrected alpha value: $\alpha = 0.0083$ ($\alpha = 0.05/6$). We observed significantly greater face selectivity in
299 controls compared to the DP group in rFFA $t(28) = 3.304$, $p = 0.0026$, IFFA $t(28) = 3.172$, $p =$
300 0.0037 and rpSTS $t(28) = 2.970$, $p = 0.0061$. We found no significant group difference in face
301 selectivity following Bonferroni correction in rOFA $t(28) = 0.379$, $p = 0.708$ and lATL $t(28)=2.691$,
302 $p = 0.012$, as well as no significant group difference in BOLD response (all visual>rest) in EVC
303 $t(28) = 1,994$, $p = 0.055$. These results generally agree with the results found in Furl et al. (2011).
304 However, we also identified an additional role for rSTS in DP and the comparison of lATL face-
305 selectivity in controls and DPs narrowly failed to reach significance after Bonferroni correction.

306

307 **3.2. Dynamic Causal Modeling**

308 **3.2.1. Bayesian Model Selection**

309 The model in which faces modulate the connections from EVC to the core system (EVC to
310 Core (Model 8)) achieved a posterior probability of approximately 1.0 in both groups and in the
311 whole sample (Table 1; Fig. 1). Model architecture in DP and control groups was therefore
312 qualitatively similar.

313 Face processing is often regarded as primarily lateralized to the right hemisphere. To test if
314 some models were less likely due to inter-hemispheric connections (e.g. rOFA to IFFA), we also ran
315 a post-hoc model space only containing areas from the right hemisphere as well as EVC (EVC,
316 rOFA, rFFA, rSTS). Again these results showed that EVC to core areas was the most probable
317 model in a BMS including all participants (posterior probability for EVC to core ~ 1). This makes
318 us confident that the original model space was not biased by inter-hemispheric connections in the
319 model space, and all subsequent analysis are based on the original model space.

320

321 **3.2.2. Face Modulation Parameters**

322 We assessed the difference between controls and DPs in the magnitudes of their face-
323 modulated B connections, which we considered relevant for face processing. We selected for

324 comparison the four face-modulated connections present in the model architecture that had the
325 highest posterior probability in both groups (i.e. Model 8). All p-values are reported as uncorrected
326 and are inferred to be significant according to a Bonferroni corrected alpha value $\alpha = 0.0125$ ($\alpha =$
327 $0.05/4$).

328 Three out of the four effective connections that were modulated by faces in the most likely
329 model architecture showed altered modulation strength between control and DP (Fig. 4). Face
330 modulation on the connection from EVC to rOFA did not show a significantly greater face
331 modulation for controls compared to the DP group $t(28) = -0.110, p = 0.5432$. In contrast, we found
332 significantly greater face modulation for controls compared to the DP group on the connections
333 from EVC to rFFA $t(28) = 2.536, p = 0.0085$, from EVC to IFFA $t(28) = 2.253, p = 0.0088$ and from
334 EVC to rpSTS $t(28) = 2.912, p = 0.0035$.

335

336 **4. Discussion**

337 We aimed to understand network properties contributing to face processing and how these
338 network properties support accurate face recognition. We assessed this latter question by
339 investigating how the face processing network is altered in DP individuals, who cannot accurately
340 recognize faces. We focused on effective connectivity using DCM and show that the network model
341 that best explains how face-relevant information flows through a face-selective network is one
342 where the presence or absence of faces modulates feedforward effective connectivity from EVC to
343 occipito-temporal areas (OFA, FFA and STS). This model was selected out of 13 different models in
344 a BMS and best explained our data when analyzing DP and control groups separately or combined.
345 We then related the properties of this network to facial recognition ability by testing for differences
346 in modulation strength between DP and control groups on model-relevant parameters (i.e.
347 modulation parameters present in the model which best explained our data). We found that
348 modulation of connections from EVC to rFFA, IFFA, and rpSTS was significantly diminished in
349 DP, relative to controls. Our results indicate that these connections may contribute to normal face-

350 selective responses as well as accurate facial recognition.

351

352 ***4.1. Connections that give rise to face-selective responses***

353 Most previous studies investigating directional flow of information between face-selective
354 areas have not contrasted face information versus other types of object stimuli when testing for
355 modulations of effective connectivity (Fairhall and Ishai, 2007; Ewbank et al., 2013). The
356 advantage of quantifying the relative contribution of face-specific modulation to connectivity
357 strength is that it allows for an inference of how face selectivity arises as a function of connectivity.
358 The few studies that modeled the effect of faces compared to other stimuli considered model spaces
359 **with relatively few regions** (Furl et al., 2014; Nagy et al., 2012). **Here**, we have performed the most
360 comprehensive model space to date and found that the model that best explained our data contained
361 face-modulated connections from EVC to occipito-temporal areas.

362 We found that models (inspired by Haxby et al. (2000)) where connections from OFA to
363 FFA and STS created face selectivity in occipito-temporal areas were suboptimal. This result is
364 consistent with findings in patients with lesions covering face-selective areas. Steeves et al. (2006)
365 presented a patient (DF) who had bilateral lesion of OFA, but **continued to show** face selectivity in
366 FFA and STS. **Similarly**, patient PS who had lesioned rOFA and IFFA showed **preserved** face-
367 selective responses in rFFA (Rossion et al., 2003). In addition, two patients with lesioned rOFA and
368 rFFA still **had face selective responses** in rpSTS (Dalrymple et al., 2011). These neuropsychological
369 studies are in accordance with a model where face selectivity is created through effective
370 connectivity from EVC to all core face processing areas (OFA, FFA, and STS).

371 Several of the models that we tested were theoretically motivated, but were nevertheless
372 found to be sub-optimal. For example, **our results** offer **support** for some features of the model
373 proposed by Haxby et al. (2000). Our results agree on “core” areas responsible for visual analysis
374 (OFA, FFA, pSTS). We found that face selectivity in the core areas was driven by visual cortex.
375 Nevertheless, Haxby et al. (2000) further predicts that FFA and STS receive facial feature

376 information from OFA. We did not find a special role for OFA in driving face selectivity in FFA and
377 STS. Our results instead partly accord with a previous study showing face-relevant effective
378 connectivity from Brodmann area 18 (BA18) (partly equivalent to EVC here). Furl et al. (2014)
379 showed that face modulation on the connection from BA18 to OFA (but not FFA) partly creates face
380 selectivity in posterior occipito-temporal areas.

381 Our model space also tested the possibility that backward influences, including those from
382 ATL, contributed to face selectivity. The present results suggest no role for ATL in creating face-
383 selective responses **in posterior areas**. Instead, the face-selective responses observed in ATL appear
384 to be either a function of the dynamics created in the interaction between EVC and occipito-
385 temporal areas or a result of a mechanism that was not captured in the present model space. For
386 example, face selectivity generated in core areas (resulting from their coupling with EVC) could be
387 propagated forward to ATL via endogenous (unmodulated) connections. It should be noted that
388 these results do not imply that interactions between other areas do not occur or are not involved in
389 generating other functional responses that are relevant to face processing. We show that face-
390 selective occipito-temporal responses are supported by effective connectivity from EVC to occipito-
391 temporal core areas, rather than by interactions between different core areas or ATL.

392

393 ***4.2. A network-based account of diminished face recognition ability in DP***

394 DP has been proposed to **result from** a disconnection between posterior and anterior face-selective
395 areas (Behrmann & Plaut, 2013), in part, on the basis of diffusion tensor imaging (DTI) results.
396 Thomas et al. (2008) found evidence for diminished axonal integrity in **major** pathways projecting
397 between posterior occipito-temporal areas and anterior areas in ATL and frontal cortex. Because
398 Avidan et al. (2005) found evidence that functional BOLD signal is not altered in DP within
399 occipito-temporal areas, Thomas et al. (2008) proposed that DP is related to disconnection with
400 ATL, rather than dysfunctional processing in posterior occipito-temporal areas. However, more
401 recently, **two studies reported that** white matter deficits were not present in **major pathways in DP**;

402 **instead** DP was associated with atypical white matter structure around the FFA (Gomez et al., 2014;
403 **Song et al., 2015**). **These findings are in accordance with our findings implicating the connectivity**
404 **of FFA in face processing**. A limitation of previous studies investigating DP is the small sample
405 sizes such as four (Avidan et al., 2005) or six (Thomas et al., 2008) participants with DP and the
406 lack of appropriately-powered group statistics. In contrast, our data (15 DP and 15 control
407 participants) showed that DP had diminished BOLD response in posterior occipito-temporal areas
408 (originally reported in Furl et al., 2011; **and see Dinckelacker et al. (2011) and von Kriegstein et al.**
409 **(2008)**). We here expand on the results by Furl et al. (2011) by identifying potential network
410 explanations for the differences between DP and the normal population. In this study we find
411 evidence for diminished effective connectivity from EVC to FFA, and EVC to pSTS that results in
412 reduced activation in occipito-temporal areas to faces, compared to other objects, as well as reduced
413 face recognition performance (Furl et al., 2011).

414 Avidan et al. (2014) found reduced functional connectivity between core areas and ATL.
415 However, in the present study, the model identified to be most likely to give rise to face selectivity
416 (model 8) did not contain face-modulated effective connectivity to or from lATL. lATL connections,
417 therefore, are not a good candidate for explaining the reduced face selectivity observed in posterior
418 areas in our sample of DP participants. Nevertheless, there is reduced grey matter and functional
419 responses in ATL associated with DP (Behrmann et al., 2007; Garrido et al., 2009; Furl et al., 2011).
420 It is possible that **these abnormalities** in the ATL of people with DP may instead be caused by
421 chronically diminished propagation of face-specific activity from more posterior areas, or they may
422 be a separate manifestation of the dysfunctions associated with DP.

423

424 **4.3. Conclusions**

425 We have presented evidence for a model of how face selectivity arises in the human brain
426 and how this model is compromised in DP. We have shown that a model in which face selectivity
427 arises from effective connectivity from EVC to posterior occipito-temporal areas is more likely than

428 other plausible models tested. Furthermore, we suggest that the functional BOLD response in FFA
429 and rpSTS and behavioral deficits in DP can partly be accounted for by diminished effective
430 connectivity from EVC to posterior occipito-temporal areas.

431

432 **References**

433 Allison, T., Puce, A., & McCarthy, G. (2000). Social perception from visual cues: Role of the STS

434 region. *Trends in Cognitive Sciences*, 4(7), 267–278. <http://doi.org/10.1016/S1364->

435 6613(00)01501-1

436 Andrews, T. J., & Ewbank, M. P. (2004). Distinct representations for facial identity and changeable

437 aspects of faces in the human temporal lobe. *NeuroImage*, 23(3), 905–913.

438 <http://doi.org/10.1016/j.neuroimage.2004.07.060>

439 Avidan, G., Hasson, U., Malach, R., & Behrmann, M. (2005). Detailed exploration of face-related

440 processing in congenital prosopagnosia: 2. Functional neuroimaging findings. *Journal of*

441 *Cognitive Neuroscience*, 17(7), 1150–1167. <http://doi.org/10.1162/0898929054475154>

442 Avidan, G., Tanzer, M., Hadj-Bouziane, F., Liu, N., Ungerleider, L. G., & Behrmann, M. (2014).

443 Selective dissociation between core and extended regions of the face processing network in

444 congenital prosopagnosia. *Cerebral Cortex*, 24(6), 1565–1578.

445 <http://doi.org/10.1093/cercor/bht007>

446 Behrmann & Avidan. (2005). Congenital prosopagnosia: face-blind from birth. *Trends in*

447 *Cognitive Neuroscience*, 9(4), 180-187. [doi:10.1016/j.tics.2005.02.011](http://doi.org/10.1016/j.tics.2005.02.011)

448 Behrmann, M., Avidan, G., Gao, F., & Black, S. (2007). Structural imaging reveals anatomical

449 alterations in inferotemporal cortex in congenital prosopagnosia. *Cerebral Cortex*, 17(10),

450 2354–2363. <http://doi.org/10.1093/cercor/bhl144>

451 Behrmann, M., & Plaut, D. C. (2013). Distributed circuits, not circumscribed centers, mediate

452 visual recognition. *Trends in Cognitive Sciences*, 17(5), 210–219.

453 <http://doi.org/10.1016/j.tics.2013.03.007>

454 Brett, M, Anton, J, Valabregue, R, Poline, J. (2002). Region of interest analysis using an SPM
455 toolbox [abstract] *Presented at the 8th International Conference on Functional Mapping of the*
456 *Human Brain*, June 2-6,, Sendai, Japan. Available on CD-ROM in NeuroImage, Vol 16, No 2

457 Dalrymple, K. a., Oruç, I., Duchaine, B., Pancaroglu, R., Fox, C. J., Iaria, G., Barton, J. J. S. (2011).
458 The anatomic basis of the right face-selective N170 IN acquired prosopagnosia: A combined
459 ERP/fMRI study. *Neuropsychologia*, 49(9), 2553–2563.
460 <http://doi.org/10.1016/j.neuropsychologia.2011.05.003>

461 Den Ouden, D. B., Saur, D., Mader, W., Schelter, B., Lukic, S., Wali, E., Thompson, C. K. (2012).
462 Network modulation during complex syntactic processing. *NeuroImage*, 59(1), 815–823.
463 <http://doi.org/10.1016/j.neuroimage.2011.07.057>

464 Dinckelacker, V., Gruter, M., Klaver, P., Gruter, T., Specht, K., Weis, S., Kennerknecht, I., Elger,
465 C.E., Fernandez., G. (2011). Congenital prosopagnosia: multistage anatomical and functional
466 deficits in face processing circuitry. *Journal of Neurology*, 258, 770-782.
467 <http://doi.org/10.1007/s00415-010-5828-5>

468 Duchaine, B., & Nakayama, K. (2005). Dissociations of face and object recognition in
469 developmental prosopagnosia. *Journal of Cognitive Neuroscience*, 17(2), 249–261.
470 <http://doi.org/10.1162/0898929053124857>

471 Duchaine, B., & Nakayama, K. (2006). The Cambridge Face Memory Test: Results for
472 neurologically intact individuals and an investigation of its validity using inverted face stimuli
473 and prosopagnosic participants. *Neuropsychologia*, 44(4), 576–585.
474 <http://doi.org/10.1016/j.neuropsychologia.2005.07.001>

475 Eifuku, S., De Souza, W. C., Tamura, R., Nishijo, H., & Ono, T. (2004). Neuronal correlates of face
476 identification in the monkey anterior temporal cortical areas. *Journal of Neurophysiology*,
477 91(1), 358–371. <http://doi.org/10.1152/jn.00198.2003>

- 478 Ewbank, M. P., Henson, R. N., Rowe, J. B., Stoyanova, R. S., & Calder, A. J. (2013). Different
479 neural mechanisms within occipitotemporal cortex underlie repetition suppression across same
480 and different-size faces. *Cerebral Cortex*, *23*(5), 1073–1084.
481 <http://doi.org/10.1093/cercor/bhs070>
- 482 Fairhall, S. L., & Ishai, A. (2007). Effective connectivity within the distributed cortical network for
483 face perception. *Cerebral Cortex*, *17*(10), 2400–2406. <http://doi.org/10.1093/cercor/bhl148>
- 484 Fox, C. J., Moon, S. Y., Iaria, G., & Barton, J. J. S. (2009). The correlates of subjective perception
485 of identity and expression in the face network: An fMRI adaptation study. *NeuroImage*, *44*(2),
486 569–580. <http://doi.org/10.1016/j.neuroimage.2008.09.011>
- 487 Friston, K. J., Harrison, L., & Penny, W. (2003). Dynamic causal modeling. *Neuroimage*, *19*(4),
488 1273–1302. [http://doi.org/10.1016/S1053-8119\(03\)00202-7](http://doi.org/10.1016/S1053-8119(03)00202-7)
- 489 Furl, N., Coppola, R., Averbeck, B. B., & Weinberger, D. R. (2013). Cross-Frequency Power
490 Coupling Between Hierarchically Organized Face-Selective Areas. *Cerebral Cortex*, 2409–
491 2420. <http://doi.org/10.1093/cercor/bht097>
- 492 Furl, N., Garrido, L., Dolan, R. J., Driver, J., & Duchaine, B. (2011). Fusiform gyrus face selectivity
493 relates to individual differences in facial recognition ability. *Journal of Cognitive*
494 *Neuroscience*, *23*(7), 1723–1740. <http://doi.org/10.1162/jocn.2010.21545>
- 495 Furl, N., Henson, R. N., Friston, K. J., & Calder, A. J. (2014). Network Interactions Explain
496 Sensitivity to Dynamic Faces in the Superior Temporal Sulcus. *Cerebral Cortex*, *1*, 1–7.
497 <http://doi.org/10.1093/cercor/bhu083>
- 498 Garrido, L., Furl, N., Draganski, B., Weiskopf, N., Stevens, J., Tan, G. C. Y., Duchaine, B. (2009).
499 Voxel-based morphometry reveals reduced grey matter volume in the temporal cortex of
500 developmental prosopagnosics. *Brain*, *132*(12), 3443–3455.
501 <http://doi.org/10.1093/brain/awp271>
- 502 George, N., Driver, J., & Dolan, R. J. (2001). Seen gaze-direction modulates fusiform activity and

503 its coupling with other brain areas during face processing. *NeuroImage*, 13(6), 1102–1112.
504 <http://doi.org/10.1006/nimg.2001.0769>

505 Gomez J, Pestilli F, Yoon J, Grill-Spector K. (2015). Functionally defined white matter reveals
506 segregated pathways in human ventral temporal cortex associated with category-specific
507 processing. *Neuron* 85: 216-227

508 Grefkes, C., Eickhoff, S. B., Nowak, D. a., Dafotakis, M., & Fink, G. R. (2008). Dynamic intra- and
509 interhemispheric interactions during unilateral and bilateral hand movements assessed with
510 fMRI and DCM. *NeuroImage*, 41(4), 1382–1394.
511 <http://doi.org/10.1016/j.neuroimage.2008.03.048>

512 Gschwind, M., Pourtois, G., Schwartz, S., Van De Ville, D., & Vuilleumier, P. (2012). White-matter
513 connectivity between face-responsive regions in the human brain. *Cerebral Cortex*, 22(7),
514 1564–1576. <http://doi.org/10.1093/cercor/bhr226>

515 Haxby, J. V, Hoffman, E. A., & Gobbini, M. I. (2000). The distributed human neural system for face
516 perception, *Trends in Cognitive Neuroscience*, 4(6), 223–233. [http://doi.org/10.1016/S1364-](http://doi.org/10.1016/S1364-6613(00)01482-0)
517 [6613\(00\)01482-0](http://doi.org/10.1016/S1364-6613(00)01482-0)

518 Hein, G., & Knight, R. T. (2008). Superior temporal sulcus--It's my area: or is it? *Journal of*
519 *Cognitive Neuroscience*, 20(12), 2125–2136. <http://doi.org/10.1162/jocn.2008.20148>

520 Iidaka, T., Omori, M., Murata, T., Kosaka, H., Yonekura, Y., Okada, T., & Sadato, N. (2001). Neural
521 interaction of the amygdala with the prefrontal and temporal cortices in the processing of facial
522 expressions as revealed by fMRI. *Journal of Cognitive Neuroscience*, 13(8), 1035–1047.
523 <http://doi.org/10.1162/089892901753294338>

524 Kanwisher, N., McDermott, J., & Chun, M. M. (1997). The fusiform face area: a module in human
525 extrastriate cortex specialized for face perception. *The Journal of Neuroscience : The Official*
526 *Journal of the Society for Neuroscience*, 17(11), 4302–4311.
527 <http://doi.org/10.1098/Rstb.2006.1934>

528 Kiebel, S. J., Klöppel, S., Weiskopf, N., & Friston, K. J. (2007). Dynamic causal modeling: A
529 generative model of slice timing in fMRI. *NeuroImage*, *34*(4), 1487–1496.
530 <http://doi.org/10.1016/j.neuroimage.2006.10.026>

531 Mechelli, A., Price, C. J., Friston, K. J., & Ishai, A. (2004). Where bottom-up meets top-down:
532 Neuronal interactions during perception and imagery. *Cerebral Cortex*, *14*(11), 1256–1265.
533 <http://doi.org/10.1093/cercor/bhh087>

534 Mechelli, A., Price, C. J., Henson, R. N. a, & Friston, K. J. (2003). Estimating efficiency a priori: A
535 comparison of blocked and randomized designs. *NeuroImage*, *18*(3), 798–805.
536 [http://doi.org/10.1016/S1053-8119\(02\)00040-X](http://doi.org/10.1016/S1053-8119(02)00040-X)

537 Mechelli, A., Price, C. J., Noppeney, U., & Friston, K. J. (2003). A dynamic causal modeling study
538 on category effects: bottom-up or top-down mediation? *Journal of Cognitive Neuroscience*,
539 *15*(7), 925–934. <http://doi.org/10.1162/089892903770007317>

540 Moeller, S., Freiwald, W. a, & Tsao, D. Y. (2008). Patches with links: a unified system for
541 processing faces in the macaque temporal lobe. *Science*, *320*(5881), 1355–1359.
542 <http://doi.org/10.1126/science.1157436>

543 Nunn, J. a, Postma, P., & Pearson, R. (2001). Developmental prosopagnosia: should it be taken at
544 face value? *Neurocase : Case Studies in Neuropsychology, Neuropsychiatry, and Behavioural*
545 *Neurology*, *7*(1), 15–27. <http://doi.org/10.1093/neucas/7.1.15>

546 Penny, W. D., Stephan, K. E., Daunizeau, J., Rosa, M. J., Friston, K. J., Schofield, T. M., & Leff, A.
547 P. (2010). Comparing families of dynamic causal models. *PLoS Computational Biology*, *6*(3).
548 <http://doi.org/10.1371/journal.pcbi.1000709>

549 Penny, W. D., Stephan, K. E., Mechelli, a, & Friston, K. J. (2004). Comparing dynamic causal
550 models. *Ni*, *22*(3), 1157–1172.

551 Poldrack R.A (2007). Region of interest analysis for fMRI. *Social Cognitive and Affective*
552 *Neuroscience*. *2*(1). 67-70. doi: 10.1093/scan/nsm006

- 553 Rossion, B., Caldara, R., Seghier, M., Schuller, A. M., Lazeyras, F., & Mayer, E. (2003). A network
554 of occipito-temporal face-sensitive areas besides the right middle fusiform gyrus is necessary
555 for normal face processing. *Brain*, *126*(11), 2381–2395. <http://doi.org/10.1093/brain/awg241>
- 556 Rotshtein, P., Henson, R. N. a, Treves, A., Driver, J., & Dolan, R. J. (2005). Morphing Marilyn into
557 Maggie dissociates physical and identity face representations in the brain. *Nature*
558 *Neuroscience*, *8*(1), 107–113. <http://doi.org/10.1038/nn1370>
- 559 Song, S., Garrido, L., Nagy, Z., Mohammadi, S., Steel, A., Driver, J., Dolan, R.J., Duchaine, B.,
560 Furl, N. (2015). Local but not long-range microstructural differences of the ventral temporal
561 cortex in developmental prosopagnosia. *Neuropsychologia*. *78*. 195-206
562 [doi:10.1016/j.neuropsychologia.2015.10.010](https://doi.org/10.1016/j.neuropsychologia.2015.10.010)
- 563 Steeves, J. K., Culham, J. C., Duchaine, B. C., Pratesi, C. C., Valyear, K. F., Schindler, I.,
564 Humphrey, G. K., Milner, A. D., Goodale, M. A. (2006). The fusiform face area is not
565 sufficient for face recognition: Evidence from a patient with dense prosopagnosia and no
566 occipital face area. *Neuropsychologia*, *44*(4), 594–609.
567 <http://doi.org/10.1016/j.neuropsychologia.2005.06.013>
- 568 Stephan, K. E., Penny, W. D., Moran, R. J., den Ouden, H. E. M., Daunizeau, J., & Friston, K. J.
569 (2010). Ten simple rules for dynamic causal modeling. *NeuroImage*, *49*(4), 3099–3109.
570 <http://doi.org/10.1016/j.neuroimage.2009.11.015>
- 571 Thomas, C., Avidan, G., Humphreys, K., Jung, K., Gao, F., & Behrmann, M. (2009). Reduced
572 structural connectivity in ventral visual cortex in congenital prosopagnosia. *Nature*
573 *Neuroscience*, *12*(1), 29–31. <http://doi.org/10.1167/6.6.88>
- 574 Von Der Heide, R. J., Skipper, L. M., & Olson, I. R. (2013). Anterior temporal face patches: a meta-
575 analysis and empirical study. *Frontiers in Human Neuroscience*, *7*(February), 17.
576 <http://doi.org/10.3389/fnhum.2013.00017>
- 577 Von Kriegstein, K., Dogan, Ö., Grüter, M., Giraud, A., Kell, C.A., Grüter, T., Kleinschmidt, A.,

578 Kiebel, S.J., (2008). Simulation of talking faces in the human brain improves auditory speech
579 recognition. *Proceedings of the National Academy of Sciences of the United States of America*,
580 *105*(18), 6747-6752

581 Winston, J. S., Henson, R. N. a, Fine-Goulden, M. R., & Dolan, R. J. (2004). fMRI-adaptation
582 reveals dissociable neural representations of identity and expression in face perception.
583 *Journal of Neurophysiology*, *92*(3), 1830–1839. <http://doi.org/10.1152/jn.00155.2004>

584 Yang, H., Susilo, T., & Duchaine, B. (2014). The anterior temporal face area contains invariant
585 representations of identity that can persist despite the loss of right FFA and OFA. *Cerebral*
586 *Cortex*.

587

588 Figure 1: Model space.

589 Thirteen models were chosen to test different hypotheses about the model architecture giving rise to
590 face selectivity in a occipito-temporal network. The models vary only in which configuration of
591 connections are modulated by faces. The titles above the models summarize which connections are
592 modulated by faces. The colors of the bold lines between areas signify which direction are
593 modulated by faces. All models are fully endogenously connected (including self connections) and
594 have all visual stimuli (Faces and Cars) as driving input to EVC. Model 8 is highlighted, because
595 the BMS showed this model as the best explanation for the data in both groups. Abbreviations:
596 EVC:Early visual cortex, rOFA: Right occipital face area, rFFA: Right fusiform face area, lFFA:
597 Left fusiform area, rpSTS: Right posterior superior temporal sulcus, lATL: Left anterior temporal
598 lobe

599

600 Figure 2: SPM group analysis.

601 SPM group analysis of faces>cars contrast (A,B,C) and faces+cars>baseline (D). Threshold at
602 $P < 0.005$ (uncorrected).

603

604 Figure 3: Group differences in ROI signal (faces>cars) intensities for face-selective areas.
 605 Abbreviations: EVC:Early visual cortex, rOFA: Right occipital face area, rFFA: Right fusiform face
 606 area, lFFA: Left fusiform area, rpSTS: Right posterior superior temporal sulcus, lATL: Left anterior
 607 temporal lobe, * = $p < 0.05$, ** = $p < 0.01$. Error bars = 1 sem

608

609 Figure 4: Group differences in modulation of connectivity by faces.
 610 Abbreviations: EVC: Early visual cortex, **rOFA: Right occipital face area**, rFFA: Right fusiform
 611 face area, lFFA: Left fusiform area, * = $p < 0.05$, ** = $p < 0.01$. Error bars = 1 sem

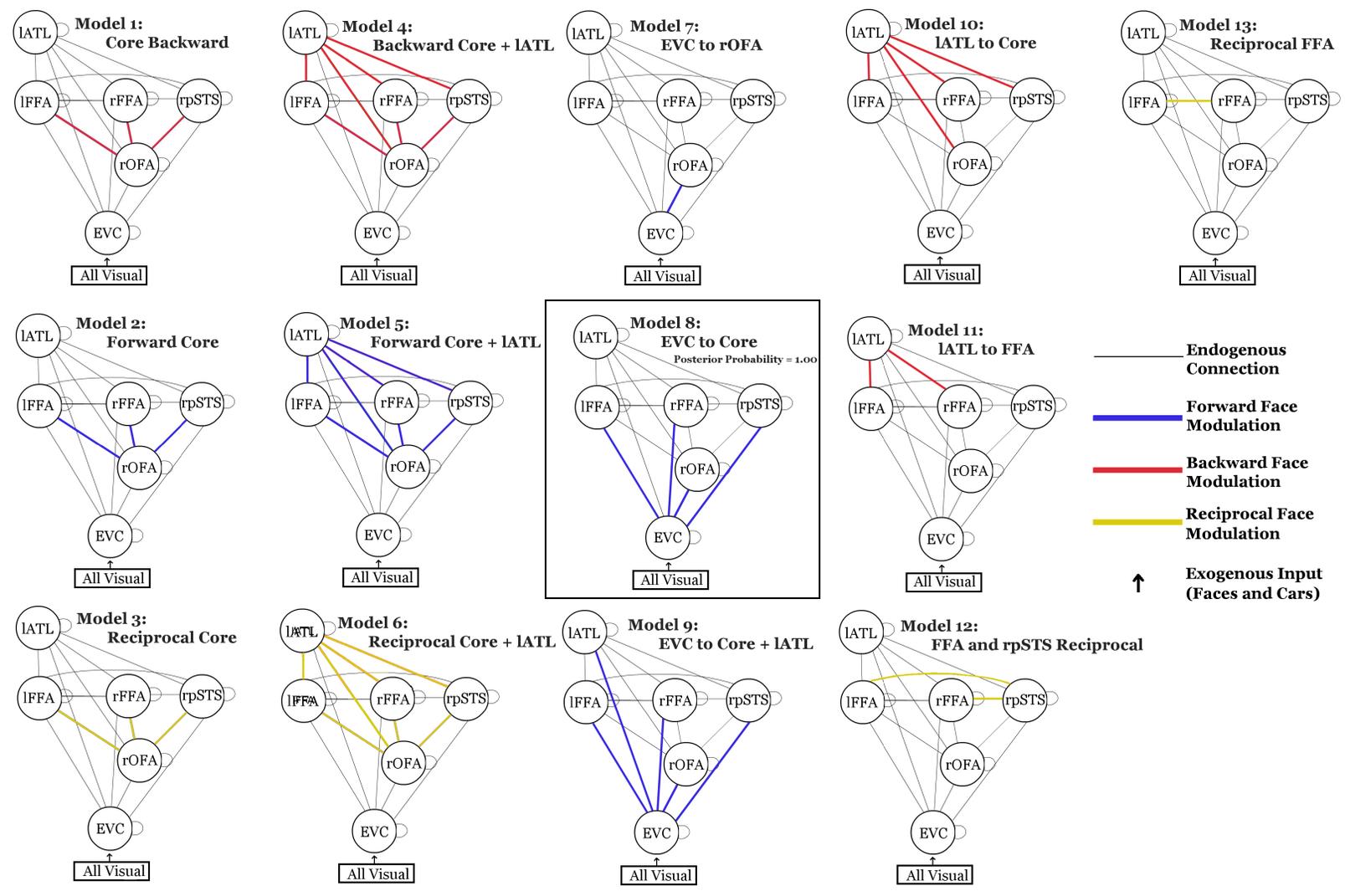
612

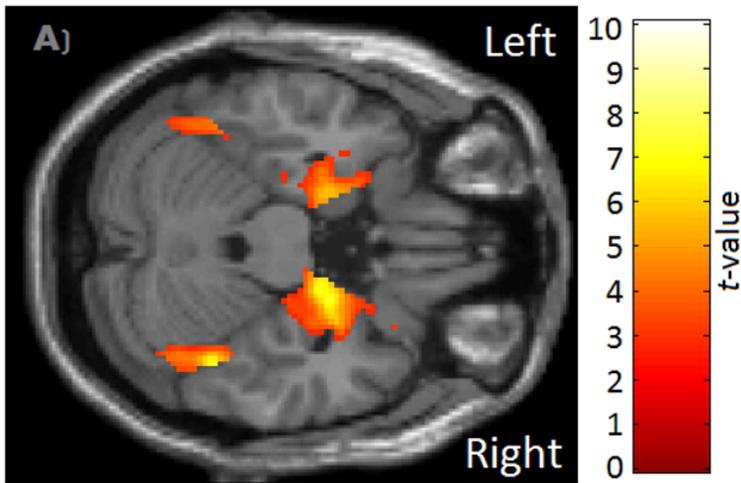
613 Table 1: Bayesian Model Selection
 614 Posterior probabilities for specified model architectures. Posterior probabilities were estimated for
 615 control participants and DP participants separately, as well as all participants combined. Model
 616 architectures are illustrated in figure 1.

617

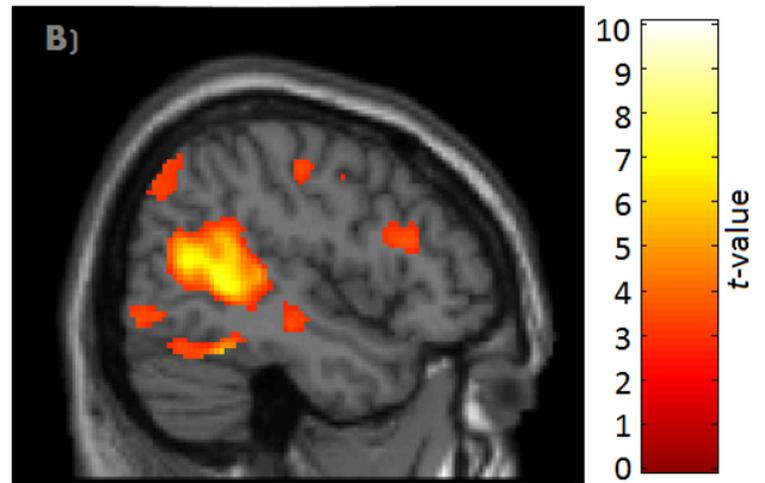
Model Architecture	Posterior Probability		
	Controls	DP	All
Backward Core (Model 1)	0	0	0
Forward Core (Model 2)	0	0	0
Reciprocal Core (Model 3)	0	0	0
Backward Core + IATL (Model 4)	0	0	0
Forward Core + IATL (Model 5)	0	0	0
Reciprocal Core + IATL (Model 6)	0	0	0
EVC to rOFA (Model 7)	0	0	0
EVC to Core (Model 8)	1	1	1
EVC to Core + IATL (Model 9)	0	0	0
IATL to Core (Model 10)	0	0	0
IATL to FFA (Model 11)	0	0	0
Reciprocal FFA and rpSTS (Model 12)	0	0	0
Reciprocal FFA (Model 13)	0	0	0

618

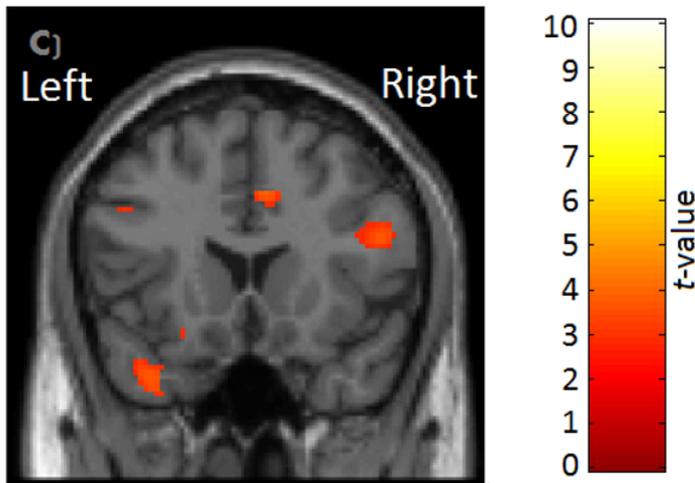




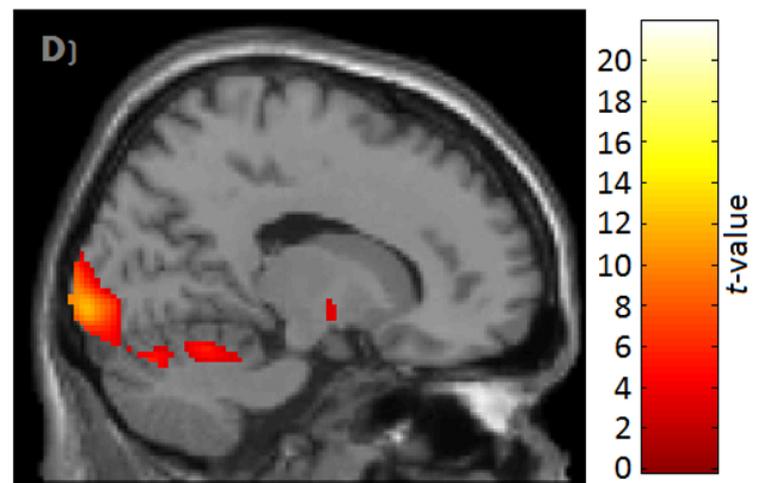
Z = -24, Bilateral FFA (Faces>Cars)



X = 48, rFFA and rpSTS (Faces>Cars)



Y = 18, LATL (Faces>Cars)



X = 16, EVC (All Visual>Rest)

