# FRONTOTEMPORAL RESILIENCE TO AGING

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3	Abbreviated title: Frontotemporal resilience to aging
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7	Robust resilience of the frontotemporal syntax system to aging
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#### Abstract

46 Brain function is thought to become less specialized with age. However, this view is largely based on 47 findings of increased activation during tasks which fail to separate task-related processes (e.g., 48 attention, decision making) from the cognitive process under examination. Here we take a systems-49 level approach to separate processes specific to language comprehension from those related to 50 general task demands and to examine age differences in functional connectivity both within and 51 between those systems. A large population-based sample (N = 111; 22-87 years) from the Cambridge 52 Centre for Ageing and Neuroscience (Cam-CAN) was scanned using functional MRI (fMRI) during two 53 versions of an experiment: a *natural listening* version in which participants simply listened to spoken 54 sentences and an explicit *task* version in which they rated the acceptability of the same sentences. 55 Independent components analysis (ICA) across the combined data from both versions showed that 56 while task-free language comprehension activates only the auditory and frontotemporal (FTN) 57 syntax networks, performing a simple task with the same sentences recruits several additional networks. Remarkably, functionality of the critical FTN is maintained across age groups, showing no 58 59 difference in within-network connectivity or responsivity to syntactic processing demands despite 60 grey matter loss and reduced connectivity to task-related networks. We found no evidence for 61 reduced specialization or compensation with age. Overt task performance was maintained across 62 the lifespan and performance in older, but not younger, adults related to crystallized knowledge, 63 suggesting that decreased between-network connectivity may be compensated for by older adults' 64 richer knowledge base.

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Keywords: aging, language comprehension, syntax, ICA, functional connectivity, task demands

#### Significance Statement

- 69 Understanding spoken language requires the rapid integration of information at many different
- 70 levels of analysis. Given the complexity and speed of this process, it is remarkably well-preserved
- vith age. While previous work claims that this preserved functionality is due to compensatory
- 72 activation of regions outside the frontotemporal language network, we use a novel systems-level
- approach to show that these 'compensatory' activations simply reflect age differences in response to
- 74 experimental task demands. Natural, task-free language comprehension solely recruits auditory and
- 75 frontotemporal networks, the latter of which is similarly responsive to language-processing demands
- across the lifespan. These findings challenge the conventional approach to neurocognitive aging by
- showing that the neural underpinnings of a given cognitive function depend on how you test it.

# Introduction

79	Several cognitive abilities are thought to decline with age, but these abilities are rarely tested in a
80	process-pure manner. Indeed, the nature of most cognitive experiments necessarily requires the
81	recruitment of several domain-general processes which are specific to the task itself (e.g.,
82	maintenance of task instructions, goal switching; Dosenbach et al., 2006). These additional processes
83	not only affect one's ability to isolate and measure a particular cognitive function, but they may also
84	affect the neural mechanisms assigned to that function – for instance, giving the impression that a
85	certain process (e.g., memory binding) relies on a wider set of regions (Buckner et al., 1999) than is
86	known to be the case from patient and animal work (Squire, 1992).
87	This mixing of component processes may be particularly problematic in the study of
88	neurocognitive aging because age differences in the recruitment of domain-general processes may
89	be misattributed to age differences in how the brain carries out a specific cognitive process (Grady,
90	2012; Morcom and Johnson, 2015). For instance, research on syntactic processing with brain-
91	damaged patients emphasizes the dependence of this process on a left-lateralized, frontotemporal
92	system, the computations of which cannot be performed elsewhere in the brain (Caplan et al., 1996;
93	Hagoort et al., 2003). However, several studies of language comprehension and aging show an age-
94	related increase in right frontal activations during syntactic processing (Wingfield and Grossman,
95	2006), leading to the suggestion that these right hemisphere regions are somehow compensating for
96	the core left-lateralized system, allowing for preserved performance (Peelle et al., 2010; Tyler et al.,
97	2010a). An alternative explanation is that the core syntax system is relatively resilient to age and
98	these additional activations reflect domain-general functions associated with the task itself and not a
99	change in how the aging brain carries out syntactic computations. In line with this view, Davis and
100	colleagues (2014) recently showed that natural, task-free language comprehension activates the
101	auditory and left-lateralized frontotemporal networks alone, while performing an explicit task with
102	the same sentences activates several additional networks, and it is these domain-general networks
103	that show increased activation with age.

104 Thus, current models of neurocognitive aging may be wrong in important ways. One cannot 105 claim that a given cognitive function has become "dedifferentiated" or "compensated" for without 106 first separating that function from processes related to the task itself (Shafto and Tyler, 2014). Here, 107 we attempt to redress this issue by taking a systems-level approach: identifying networks uniquely 108 associated with specific cognitive functions and then relating functional connectivity both within and 109 between those networks to age, grey matter, and cognitive performance. A large population-based 110 sample from the Cambridge Centre for Ageing and Neuroscience (Cam-CAN) was scanned using 111 functional magnetic resonance imaging (fMRI) during two versions of an experiment: an explicit task 112 condition in which participants rated the acceptability of sentences varying in syntactic complexity 113 and a natural listening condition in which they simply listened to the same sentences. Data from 114 both experiments were jointly submitted to an independent components analysis (ICA; Calhoun et 115 al., 2008) which allowed us to separate functional networks uniquely involved in syntactic processing 116 from those associated with overt task performance.

117 We expected natural listening to solely recruit the auditory and frontotemporal networks, 118 while active task performance should additionally recruit domain-general networks. We also 119 examined the effects of age and experimental task demands on functional connectivity both within 120 and between the ICA-identified networks. While previous work has primarily focused on age 121 differences in connectivity either at rest (Ferreira and Busatto, 2013) or during multi-componential 122 tasks (Sambataro et al., 2010; Spreng and Schacter, 2012), this is the first study to examine systems-123 level interactions during a task with such well-defined and separable neural underpinnings (Tyler et 124 al., 2011). Finally, in light of evidence that prior knowledge can compensate for age-related declines 125 in processing efficiency (Salthouse, 1984; Soederberg Miller, 2009), we test whether crystallized 126 intelligence mitigates fluid declines by becoming increasingly related to syntactic performance with 127 age.

128

Materials and Methods

129 Participants

130	A population-derived sample (N = 111, 22-87 years old, M = 54.57, SD = 17.84) was recruited
131	as part of the Cam-CAN project (Shafto et al., 2014). Demographic information (including sex) is
132	provided in Table 1. Hearing was assessed using the Siemens HearCheck Screener, which tests
133	participants' ability to detect three sound pressure levels (75 dB SPL, 55 dB SPL, and 35 dB SPL) at
134	two frequencies (1000 Hz and 3000 Hz). Exclusion criteria for the Cam-CAN Stage 2 cohort (who
135	underwent extensive cognitive, MRI and MEG testing) included low performance (< 25) on the mini
136	mental state exam (MMSE; Folstein et al., 1975), poor hearing (failing to hear 35dB at 1000Hz in
137	both ears), poor vision (below 20/50 on the Snellen test; Snellen, 1862), non-native English speaker,
138	self-reported substance abuse, current serious health conditions (e.g., self-reported major
139	psychiatric conditions, current chemo/radiotherapy, or a history of stroke), and contraindications to
140	MRI (for full exclusion criteria, see Shafto et al., 2014). Handedness was assessed using the
141	Edinburgh Handedness Inventory and all but two participants were right-handed (excluding these
142	participants from the analyses did not change the pattern or significance of the results). Informed
143	consent was obtained from all participants and ethical approval for the study was obtained from the
144	Cambridgeshire 2 (now East of England – Cambridge Central) Research Ethics Committee.
145	Cognitive Tasks
146	Language comprehension. Participants were scanned while listening to spoken sentences
147	that varied in the level of syntactic processing required (Tyler et al., 2011). In both the natural
148	listening and task conditions, sentences either contained a syntactically ambiguous central phrase
149	(e.g., "cooking apples") or an unambiguous phrase that was similar in structure (e.g., "sneering
150	boys"). Unambiguous sentences (n = 42) had only one possible syntactic interpretation (e.g.,
151	"sneering boys are"), whereas ambiguous sentences had two possible interpretations: one that is
152	more expected or <i>dominant</i> (n = 42) given its higher frequency in the language (e.g., "cooking apples
153	are") and one that is less expected or <i>subordinate</i> (n = 42) given its relative infrequency (e.g.,
154	"cooking apples is"). This paradigm capitalizes on syntactic ambiguity, a naturally occurring

phenomenon in human language, to manipulate the level of syntactic processing required by each 155

156 sentence. Subordinate sentences require the most processing, as listeners must overturn an 157 automatically activated dominant interpretation (e.g., "cooking apples are inedible without lots of 158 sugar", where "cooking apples" is a noun phrase) in favor of a less expected subordinate 159 interpretation (e.g., "cooking apples is an easy task", where "cooking" functions as a gerund). 160 Dominant sentences still contain ambiguity, and thus are more complex than unambiguous 161 sentences, but the resolution of that ambiguity is in line with the listeners' expectations so no 162 revision is required. Previous work has shown that listeners are sensitive to these varying demands, 163 responding slowest to subordinate sentences, followed by dominant and finally unambiguous 164 sentences (Tyler and Marslen-Wilson, 1977; Tyler et al., 2013).

165 During natural listening, participants were simply asked to listen attentively to the 166 sentences, with their eyes open. Sentence stimuli were pseudorandomly intermixed with non-167 linguistic baseline items (n = 21), consisting of envelope-shaped 'musical rain' which shares the 168 complex auditory properties of speech without any of the linguistic meaning (Uppenkamp et al., 169 2006). During the task version, participants listened to the same sentence and musical rain stimuli, 170 but were now asked to perform an explicit acceptability judgement task. In this task, participants 171 hear the first part of the sentence spoken in a female voice up until the end of the central phrase 172 (e.g., "The class observed that cooking apples..."), followed by a single word spoken in a male voice 173 (e.g., "are"). Participants' task was to decide if the final word was an acceptable continuation to the 174 sentence or not. All sentences were grammatically acceptable, but a normal pattern of responding 175 for people without language impairments is to reject more (and respond more slowly to) 176 subordinate sentences than dominant and unambiguous sentences, with little difference between 177 the latter two conditions (Tyler et al., 2011). Thus, we focus primarily on the difference between the 178 subordinate and unambiguous conditions in subsequent behavioral and fMRI analyses reported, as 179 these conditions differ most in syntactic processing demands. One participants' behavioral 180 responses were lost due to equipment error (N = 110 for all behavioral analyses, including those 181 relating brain to behavior).

182 Crystallized and fluid intelligence. In order to examine the potential compensatory role of 183 crystallized knowledge in older adults' maintained performance on the syntax task, we also obtained 184 measures of crystallized and fluid intelligence outside the scanner. Crystallized intelligence was 185 measured using the Spot-the-Word Test (Baddeley et al., 1993), in which participants see word-186 nonword pairs (e.g., pinnace-strummage) and decide which is a real word. Fluid intelligence was 187 measured using the Cattell Culture Fair (Cattell and Cattell, 1960), a timed pen-and-paper test in 188 which participants perform a series of nonverbal puzzles. Because fluid and crystallized intelligence 189 tend to be moderately correlated (Cattell, 1963; Baddeley et al., 1993), we wanted to control for 190 fluid intelligence in our analyses to isolate the unique contribution of crystallized knowledge. In 191 order to determine whether crystallized knowledge becomes a stronger predictor of syntax 192 performance with age, we used a moderation model predicting syntax performance from age, 193 crystallized knowledge, and the age x crystallized knowledge interaction (with fluid intelligence 194 included as a covariate).

## 195 MRI Acquisition and Preprocessing

196 Imaging was performed on a 3T Siemens TIM Trio System at the MRC Cognition Brain and 197 Sciences Unit, Cambridge, UK. A 3D-structural MRI was acquired for each subject using T1-weighted 198 sequence (Generalized Autocalibrating Partially Parallel Acquisition (GRAPPA); Repetition Time (TR) = 199 2250ms; Echo Time (TE) = 2.99ms; Inversion Time (TI) = 900ms; flip angle  $\alpha$  = 9°; matrix size 256mm x 200 240mm x 19 mm; field of view (FOV) = 256mm x 240mm x 192mm; resolution = 1mm isotropic; 201 accelerated factor = 2) with acquisition time of 4 minutes and 32 seconds. For the functional runs, 202 T2\*-weighted fMRI data were acquired using a Gradient-Echo Echo-Planar Imaging (EPI) sequence 203 (TR = 1970 milliseconds; TE = 30 milliseconds; flip angle = 78 degrees; 32 axial slices of thickness of 204 3.7mm with an interslice gap of 20%; FOV = 192mm x 192 mm; voxel-size = 3 mm x 3 mm x 4.44 205 mm). The natural listening and task versions were acquired in separate runs, with run times of 15.73 206 minutes (479 volumes) and 16.29 minutes (496 volumes), respectively.

207	Preprocessing was performed using SPM12 (Wellcome Department of Imaging
208	Neuroscience, University College London, London, UK), implemented in the automatic analysis (AA)
209	batching system ( <u>http://imaging.mrc-cbu.cam.ac.uk/imaging/AA</u> ; Cusack et al., 2015). The functional
210	images were motion-corrected and slice-time corrected. The T1-weighted images were coregistered
211	to an MNI template image, bias-corrected, and segmented into various tissue classes using unified
212	segmentation (Ashburner & Friston, 2005). The segmented grey matter images were then used to
213	create a study-specific anatomical template, using the DARTEL procedure to optimize inter-
214	participant alignment (Ashburner, 2007), which was then transformed to MNI space. The EPI images
215	were then coregistered to the T1 image, normalized to MNI space using the DARTEL flowfields, and
216	smoothed using an 8mm FWHM Gaussian kernel. The segmented grey matter images were also
217	smoothed for subsequent structural analyses using a 10mm FWHM Gaussian kernel.
218	Independent Components Analysis
219	ICA was used to identify networks that were either commonly activated across the two
220	experimental conditions (natural listening and task) or unique to one particular state. All
221	participants' data from both the natural listening and task conditions were temporally concatenated
222	and submitted to the same ICA analysis, using the Group ICA of fMRI Toolbox
223	( <u>http://mialab.mrn.org/software/gift/index.html;</u> Calhoun et al., 2001). This method decomposes
224	the fMRI signal into a set of independent components, each with a set of individual spatial maps and
225	timecourses which were standardized using z-scores. Given recent evidence favoring low model
226	order analyses for the purpose of examining large-scale brain networks (Smith et al., 2009; Laird et
227	al., 2011; Ray et al., 2013), and to allow for continuity of comparison with our previous report using
228	similar methods, we set the number of components to 33 (Davis et al., 2014).
229	Temporal regression was used to select components that related to our four language
230	conditions of interest. We used an event model previously shown to maximize sensitivity to
231	ambiguity by testing only the period immediately following the ambiguous phrase (Tyler et al.,
232	2011). To this end, we defined the onset of each condition separately as the onset of the

233 disambiguating verb following the ambiguous central phrase (or an equivalent point in the 234 unambiguous sentences and musical rain stimuli), with a variable duration equivalent to the 235 remaining length of the phrase (Task: mean duration = 403 ms, SD = 30 ms; Natural Listening: mean 236 duration = 1789 ms, SD = 451 ms). We also included an extra regressor of no interest with onset at 237 the start of each sentence and duration up to the onset of the disambiguating verb (Task and 238 Natural Listening: mean duration = 2185 ms, SD = 317 ms). This "first-half" regressor does not 239 distinguish between conditions (i.e., it is a single regressor which corresponds to the first half of all 240 sentences, or the equivalent time period for musical rain stimuli) and thus, does not correlate with 241 the disambiguating word regressors. This model tests for effects of the second half of the sentence while controlling for those of the first half. These onsets were then used to create stimulus 242 243 regressors in SPM12 by convolving the stimulus functions with the canonical hemodynamic response 244 function. Four task conditions were modelled in addition to the first-half of the sentences and 245 standard motion regressors (i.e., x/y/z translation, pitch, roll, and yaw): 1) subordinate or 246 unexpected continuations to ambiguous sentences, 2) dominant or highly predicted continuations to 247 ambiguous sentences, 3) matched continuations to syntactically unambiguous sentences, and 4) the 248 acoustic baseline condition. To determine which components related to our conditions of interest, 249 linear regression was used to predict each participant's component timecourse from the set of task-250 related and motion regressors. This analysis yields a set of  $\beta$  parameters (or 'loading values') for each 251 participant (for each condition) indicating the extent to which each of their component timecourses 252 relates to each of the task conditions during natural listening and task (similar to standard voxel-wise 253 modelling of the same design matrix, but with far fewer comparisons).

In order to identity networks related to our conditions of interest, components were rankordered according to their mean loading values (i.e., β parameters) across the language conditions
(subordinate, dominant, and unambiguous). The seven strongest components were selected for
further analysis, as subsequent components appeared to capture artefact. Conventional significance
testing of the β parameters (i.e., against zero; St Jacques et al., 2011) was not appropriate in this

259 case, as almost all components were highly significant due to the large sample size. Loading values 260 from the seven language-related networks were then tested for the effects of Task (task, natural 261 listening) and Language (subordinate, unambiguous) using a 2 x 2 multivariate analysis of variance 262 (MANOVA). As discussed in the Language comprehension section above, we focus primarily on the 263 difference between the subordinate and unambiguous conditions, as these conditions differ most in 264 syntactic processing demands. Network responsivity to syntactic processing demands (i.e., subordinate – unambiguous loadings) was then related to age, grey matter, and task performance 265 266 using Pearson's correlations (95% confidence intervals were calculated for each correlation using a 267 bootstrap estimate with 1000 samples). All correlation analyses were Bonferroni-corrected for 268 multiple comparisons. Grey matter estimates for each network were obtained by first creating 269 masks using the component spatial maps (thresholded at Z > 2.58, equivalent to p < .01) and then 270 extracting mean grey matter within those masks from the segmented grey matter images. 271 Within-network connectivity was quantified as the average correlation of the raw fMRI 272 timecourse between all pairs of voxels within the thresholded component maps (after detrending 273 the timecourses and compensating for motion artefacts by regressing out the six realignment 274 parameters, their derivatives, squared terms and squared derivatives; Satterthwaite et al., 2013). 275 Between-network connectivity was quantified as the correlation between pairs of component 276 timecourses (Allen et al., 2011; Arbabshirani et al., 2013). Similar to the calculation of within-277 network connectivity, motion parameters were regressed out of the subject-specific timecourses 278 and these were detrended before pairwise correlations were computed between each of the seven 279 components. For all statistical analyses, correlations were transformed to z-scores using Fisher's 280 transformation, z=atanh(k), where k is the Pearson's correlation coefficient between two network 281 timecourses. Within- and between-network connectivity were then related to age, grey matter, and 282 task performance using Pearson's correlations (p < .05, Bonferroni-corrected, 95% bootstrap 283 confidence intervals).

Results

# 285 *Summary of main findings*

286 In order to guide the reader, we preface our main results here. We find that 1) overt task performance is preserved with age, in that older adults' RTs vary to the same extent as younger 287 288 adults in response to syntactic processing demands; 2) natural listening only recruits AUD and FTN 289 networks, while performing a task with the same stimuli recruits several additional domain-general 290 networks; 3) responsivity of these networks to syntactic processing demands did not differ with age 291 or GMC, but did predict overt task performance, with the MDN as the strongest predictor (an effect 292 that was not moderated by age); 4) within-network connectivity during the task (not natural 293 listening) decreased with age/GMC loss in some domain-general networks, but not in the critical FTN; 5) between-network connectivity declined with age/GMC for several network pairs during the 294 295 task, and only connectivity between the critical FTN and other domain-general networks predicted 296 performance; and finally, 6) crystallized knowledge became increasingly related to performance with 297 age.

U

298 Behavioral data

299 On the syntax task, our critical measure of interest was the extent to which reaction times 300 (RTs) varied as a function of syntactic processing demands (Tyler et al., 2013). Anticipatory responses 301 (< 200 ms) were removed (< 1% of trials) and RT data were inverse transformed (Ratcliff, 1993) 302 before calculating cell means per condition per subject (means were then reverse-transformed to 303 standard ms units). Mean RTs were submitted to an ANOVA with condition (subordinate [most 304 demanding], dominant, and unambiguous [least demanding]; see Methods) as a within-subjects 305 factor and age as a continuous covariate. There was a main effect of condition, F (2, 216) = 16.41, p < .001,  $\eta_p^2$  = .13, with participants responding more slowly to subordinate continuations (*M* = 1330 306 307 ms, SD = 384) than dominant continuations (M = 1125 ms, SD = 381; t(109) = 12.14, M<sub>diff</sub> = 205.76, p 308 <.001, 95% CI [172.00, 239.53], d = 1.16), which in turn were slower than unambiguous sentences 309 (*M* = 1056 ms, *SD* = 390; *t*(109) = 5.79, *M*<sub>diff</sub> = 68.32, p < .001, 95% CI [44.83, 91.80], *d* = .55). There

was also a main effect of age F (1, 108) = 48.73, p < .001,  $\eta_p^2 = .31$ , due to older adults responding 310 311 more slowly on average (see Figure 1a; note that age is always treated as a continuous variable 312 throughout the analyses, though sometimes shown as a categorical variable for visualization 313 purposes, as in Figure 1a). Importantly, the age x condition interaction was not significant, F < 1, 314 confirming that our syntactic manipulation had the same effect on RTs across the lifespan. We also 315 calculated a syntactic sensitivity measure as the difference in RTs to subordinate and unambiguous 316 sentences for each subject and correlated this measure with age. As can be seen in Figure 1b, 317 syntactic sensitivity did not differ with age, r = -.01, p = .88. These results are in line with previous 318 results showing no effect of age on syntactic processing within this task (Tyler et al., 2010a; Davis et 319 al., 2014).

# 320 Independent components analysis

321 Effects of task and syntactic processing demands. In order to separate task-related networks 322 from those specific to language processing, we performed an ICA over the combined data from task and natural listening. This analysis identified seven components that related to language processing 323 324 (Figure 2). These included 1) a left-lateralized frontotemporal network (FTN) including the left 325 inferior frontal gyrus (BA45 and BA47) and middle temporal gyrus (MTG; BA22) similar to previously 326 reported (Tyler et al., 2011), 2) an extended auditory (AUD) network which included primary 327 auditory cortex, extending into superior temporal gyrus and, to a more limited extent, MTG, 3) a 328 bilateral frontal network highly similar to the previously established multiple demand network 329 (MDN; Duncan, 2010), comprising bilateral middle and inferior frontal gyri, a superior medial frontal 330 region, and (just below threshold, at Z > 2.3) the left intraparietal sulcus, 4) an opercular (OPRC) 331 network including anterior cingulate cortex and bilateral anterior insula, 5) a basal ganglia (BG) 332 network, 6) a bilateral motor (MOT) network, and 7) a negatively loading default mode network 333 (DMN).

To determine the effect of the experimental manipulations on network activity, we
 submitted condition-specific loading values (i.e., β parameters) for our seven event-related networks

336 to a 2 x 2 multivariate analysis of variance (MANOVA) with Task (task, natural listening) and 337 Language (subordinate, unambiguous) as within-subject factors. Reporting the results of the omnibus multivariate tests first, overall there were main effects of Task, T = 7.31, F(7, 104) = 108.62, 338 p < .001,  $\eta_p^2 = .88$ , and Language, T = 3.26, F(7, 104) = 48.39, p < .001,  $\eta_p^2 = .77$ , and a significant 339 interaction between Task and Language, *T* = 1.85, *F*(7, 104) = 27.47, *p* < .001,  $\eta_p^2$  = .65. As Table 2 340 341 shows, there was a main effect of Task for all seven networks, and a main effect of Language for all 342 networks except the DMN. Further, the Task x Language interaction was significant for all networks, 343 with the largest effect seen for the MDN. Pairwise comparisons revealed that during the task, there 344 was significantly greater activity in response to subordinate than unambiguous sentences in all 345 networks except the DMN (see Table 2). Critically, during natural listening, only the FTN and AUD 346 networks increased activation in response to syntactic processing demands (i.e., subordinate > 347 unambiguous; Table 2). Although 3 other networks showed a significant difference between 348 Language conditions, none of these showed greater activation to the language conditions relative to 349 the musical rain baseline (see Figure 2). Taken together, these results suggest that while natural 350 listening recruits language-specific networks which are sensitive to syntactic processing demands, 351 when listeners hear the same sentences within the context of an explicit task, a dissociable set of 352 domain-general networks are also activated.

353 Relationship to age and grey matter. What effect do increasing age and grey matter decline 354 have on the ability of these networks to respond to syntactic processing demands (i.e., subordinate - unambiguous loadings) during natural listening and task conditions? Looking at the effect of age 355 356 during natural listening, there was no age-related difference in network responsivity during task-free 357 language comprehension (Table 3). In fact, even during the task, network responsivity was not significantly related to age (Table 3; smallest p = .03 for the FTN, which does not survive Bonferroni 358 359 correction). Further, despite the robust decline in mean grey matter concentration (GMC) within 360 each network with age (Table 3), individual differences in network GMC did not relate to network

responsivity, either during natural listening (Table 4; smallest p = .02 for MDN, which does not survive correction) or during the task (Table 4; smallest p = .048 for the FTN, which does not survive correction). These findings suggest that syntactic processing, even within the context of an artificial task, is relatively robust to both age and age-related structural declines.

365 Relationship to performance. What is the strongest predictor of overt task performance – 366 responsivity of the syntax system itself or that of the domain-general networks? Performance was 367 measured as the difference in RTs to subordinate and unambiguous sentences (i.e., our "syntactic 368 sensitivity" measure above) and was positively correlated to responsivity of the FTN ( $r_{110}$  = .19, p <.05), AUD ( $r_{110}$  = .23, p < .05), MDN ( $r_{110}$  = .38, p < .001), and BG ( $r_{110}$  = .22, p < .05) during the task 369 370 (only MDN survives Bonferroni correction). If we enter all seven networks into the same regression predicting task performance, the overall model is significant,  $R^2 = .19$ , F(7, 102) = 3.31, p < .01, and 371 372 only MDN responsivity is a significant predictor ( $\beta$  = .37, t = 3.29, p < .01, 95% CI [.14, .58]; for this 373 and all subsequent regression analyses, we report standardized coefficients). Thus, despite the fact 374 that syntactic processing critically depends on a left-lateralized frontotemporal system (Caplan et al., 375 1996; Hagoort et al., 2003; Tyler et al., 2010b), performance on the task was most strongly related to 376 responsivity of the domain-general MDN. Indeed, MDN responsivity, but not that of the other 377 networks, also correlated with a measure of fluid intelligence performed outside the scanner (r = 378 .26, p < .01, controlling for age; see Methods), further suggesting that the MDN plays a role in 379 flexible adaptation to experimental demands across a wide range of tasks (Duncan and Owen, 2000). 380 Nevertheless, in a moderation analysis, MDN responsivity did not interact with age to affect syntax 381 performance (t = 1.26, p = .21), suggesting that recruitment of this domain-general network aids 382 performance at any age and is not simply a compensatory response amongst older adults. 383 Within-network connectivity.

384 Connectivity during task and natural listening. The ICA analysis identified a set of networks
 385 that relate to our conditions of interest, but how is the internal coherence of (or functional
 386 connectivity within) those networks affected by task manipulations, age, and grey matter decline? In

387 order to address this question, we first quantified within-network connectivity as the average 388 correlation between all pairs of voxels within the thresholded component maps (after detrending 389 and regressing motion parameters from the raw fMRI timecourses; see Methods). Mean 390 connectivity within each network during task and natural listening is shown in Table 5. To determine 391 whether task demands affect within-network connectivity, we submitted mean connectivity for each 392 of our seven networks to a MANOVA with Task (task, natural listening) as a within-subjects factor. Reporting the results of the omnibus multivariate test first, overall there was a main effect of Task, T 393 = 0.39, F(7, 104) = 5.80, p < .001,  $\eta_p^2$  = .28. Follow-up pairwise comparisons show that connectivity 394 increased slightly from natural listening to task in the MDN, t(110) = 3.38, M<sub>diff</sub> = .02, p < .01, 95% CI 395 396 [.01, .03], *d* = .32, and MOT network, *t*(110) = 2.61, *M*<sub>diff</sub> = .02, p < .05, 95% CI [.004, .03], *d* = .25, 397 with no other networks differing between the two states (see Table 5). Thus, connectivity within 398 most of these networks remains remarkably stable across different experimental states, despite the 399 increase in loading values (or relationship to task conditions) of many of these networks during the 400 task. This is in line with previous work showing that the brain's functional architecture during active 401 task performance is primarily determined by an intrinsic network structure that is also apparent at 402 rest and across different task states, and to a lesser extent by domain-specific changes linked to a 403 particular task (Cole et al., 2014; Krienen et al., 2014).

404 Relationship to age and grey matter. During both natural listening and the task, connectivity 405 within the FTN did not differ with age. In fact, only the BG network showed a significant age-related 406 decline (see Table 3). We also examined the effect of mean GMC within each network on that 407 network's within-network connectivity strength. Grey matter did not significantly relate to within-408 network connectivity during natural listening (Table 4), but it did relate to connectivity within some 409 of the networks during the task (Table 4), with the MDN, OPRC, and BG surviving correction. 410 Entering each of these networks into a regression predicting connectivity from age and GMC, as a 411 means to determine the unique contribution of each factor, we see that connectivity within the 412 MDN is predicted by GMC ( $\beta$  = .34, t = 2.92, p < .01, 95% CI [.11, .58]), not age ( $\beta$  = .01, t = 0.11, p =

413 .92, 95% CI [-.23, .26]; model  $R^2 = .11$ , F(2, 108) = 6.82, p < .01); OPRC by GMC ( $\beta = .27$ , t = 2.30, p < .05, 95% CI [.04, .49]), not age ( $\beta = -.07$ , t = 0.64, p = .53, 95% CI [-.32, .16]; model  $R^2 = .10$ , F(2, 108) = .4155.94, p < .01); and BG by age ( $\beta = -.42$ , t = 4.10, p < .001, 95% CI [-.66, -.23]), not GMC ( $\beta = .04$ , t = .039, p = .70, 95% CI [-.17, .25]; model  $R^2 = .20$ , F(2, 108) = 13.47, p < .001). Thus, connectivity within the MDN and OPRC networks related to GMC within these networks, irrespective of age, while connectivity within the BG network showed a steep age-related decline which does not appear to be due to age-related declines in grey matter within that network.

420 *Relationship to performance.* Within-network connectivity was not significantly related to 421 task performance for any of the individual networks ( $r_{110} = .11, .21, -.00, .08, .09, .05, .01$ , for the 422 FTN, AUD, MDN, OPRC, BG, MOT, and DMN, respectively; smallest p = .03 for the AUD, which does 423 not survive correction).

424 Between-network connectivity.

425 Connectivity during task and natural listening. We have shown that relative to natural 426 listening, task-based language comprehension recruits several networks in addition to the critical 427 frontotemporal syntax system, but do these networks interact with the FTN to affect performance? 428 To address this question, we calculated between-network connectivity as the correlation between 429 each pair of network timecourses during the task and natural listening separately (see Methods; 430 Allen et al., 2011). As shown in Figure 3a, most networks were strongly connected to each other 431 during the task, but less so during natural listening (Figure 3b). Figure 3c shows the difference in 432 connectivity between the two experimental states (p < .05, Bonferroni corrected). Between-network 433 connectivity was stronger during the task than natural listening in most cases with the notable 434 exception of FTN-AUD connectivity, which was stronger during natural listening. This finding fits well 435 with the observation that only the FTN and AUD networks are active during natural listening, 436 whereas a host of other networks come online during active task performance. Moreover, these 437 domain-general networks show significantly greater connectivity to the critical frontotemporal

438 syntax system during the task; this pattern suggests that this integration between networks has439 implications for task performance (see below).

440 Relationship to within-network connectivity. Is stronger between-network connectivity related to weaker within-network connectivity (as suggested by findings of decreased network 441 442 segregation with age at rest; Chan et al., 2014; Geerligs et al., 2014b)? To address this question, for 443 each pair of networks (separately for task and natural listening), we calculated the correlation 444 between within-network connectivity for each network in the pair and the connectivity between the 445 two networks. As shown in Figure 3d, in general, stronger within network connectivity during the 446 task related to stronger between network connectivity (and this relationship was not moderated by 447 age, t's < 2, p's > .10, except for the age x MOT-within interaction predicting MOT-DMN, t = 2.13, p =448 .04, and the age x DMN-within interaction predicting DMN-BG, t = 2.24, p = .03, both of which do not 449 survive correction). Natural listening shows a similar pattern to the task, in that stronger within 450 relates to stronger between, but with fewer significant correlations (Figure 3e), likely due to weaker 451 connectivity between networks during natural listening (Figure 3c). Focusing on the FTN during the 452 task, we see that stronger connectivity within this network relates to stronger connections to other, 453 domain-general networks (and as mentioned above, this does not differ with age), further 454 reiterating the fact that these between-network connections are likely not compensatory (i.e., in 455 response to decreased WNC; cf. Meunier et al., 2014) but reflect normal systems-level interactions 456 in the service of task goals.

457 *Relationship to age and grey matter*. We were primarily interested in the effect of age and 458 GMC on between-network connectivity during the task, when all seven networks were most strongly 459 activated (however, for the sake of completeness, the same analyses are shown for the Natural 460 Listening condition in Figure 4c-d). Figure 4a shows the relationship between age and between-461 network connectivity during the task (p < .05, Bonferroni corrected). Age was associated with 462 decreased connectivity during the task between the following network pairs: FTN-AUD, FTN-MDN, 463 AUD-MDN, AUD-DMN, BG-OPRC, BG-DMN, and MOT-OPRC. In contrast, connectivity increased with

increasing age between the AUD-BG networks, and between the MDN-DMN systems. A similar, but
less robust, pattern of results is seen for GMC (averaged across both networks in the pair; Figure 4b).
More grey matter was associated with stronger connectivity between the FTN-MDN, AUD-MDN, and
BG-OPRC networks; while less grey matter was associated with stronger connectivity between the
MDN-DMN networks.

469 In order to determine whether age and grey matter make independent contributions to 470 functional connectivity between the FTN-MDN, AUD-MDN, MDN-DMN, and OPRC-BG, we entered 471 each network pair into a regression predicting between-network connectivity from age and mean GMC. We found that connectivity between the FTN-MDN is predicted by age ( $\beta$  = -.37, t = 3.50, p < 472 473 .001, 95% CI [-.61, -.17]), with a trend for GMC ( $\beta$  = .18, t = 1.72, p = .088, 95% CI [-.03, .40]; model  $R^2$ 474 = .26, F(2, 108) = 18.98, p < .001; AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, p < .001); AUD-MDN connectivity is predicted by age ( $\beta = -.50$ , t = 5.07, .001, 95% CI [-.73, -.32]), not GMC (p = .32; model  $R^2$  = .32, F(2, 108) = 25.57, p < .001); MDN-DMN 475 connectivity is predicted by age ( $\beta$  = .36, *t* = 3.30, *p* < .01, 95% CI [.15, .60]), not GMC (*p* = .24; model 476 477  $R^2$  = .21, F(2, 108) = 13.88, p < .001); and OPRC-BG connectivity is predicted by both age ( $\beta$  = -.40, t = 4.11, p < .001, 95% CI [-.62, -.22]) and GMC ( $\beta$  = .26, t = 2.68, p < .01, 95% CI [.07, .45]; model  $R^2$  = 478 479 .36, F(2, 108) = 29.91, p < .001). Thus, between-network connectivity was most strongly related to 480 age, with GMC only making an independent contribution to some of the network pairs.

481 Relationship to task performance. In line with the critical role of the frontotemporal network 482 in syntactic processing, performance on the task only related to functional connectivity between the 483 FTN and other networks (Figure 5a). Specifically, better performance related to stronger connectivity 484 between the FTN-MDN (r = .24, p = .01, 95% CI [.05, .40]) and FTN-OPRC (r = .25, p = .008, 95% CI 485 [.09, .41]). Further, between-network connectivity did not interact with age to predict performance 486 (t = 1.46, p = .15, and t = 0.24, p = .81, for the interaction between age and the FTN-MDN and FTN-487 OPRC, respectively), suggesting that connectivity between the FTN and these domain-general 488 networks is not a compensatory response, but rather contributes to successful performance across 489 the lifespan. Moreover, if we enter average connectivity between these networks (FTN-MDN and

490 FTN-OPRC) into a regression model with FTN responsivity to predict performance, the overall model 491 is significant,  $R^2 = .10$ , F(2, 107) = 6.06, p < .01, and we see that between-network connectivity is a 492 significant predictor ( $\beta = .26$ , t = 2.76, p < .01, 95% CI [.07, .43]), while the FTN alone is not ( $\beta = .15$ , t493 = 1.55, p = .13, 95% CI [-.04, .32]). Taken together, these findings suggest that explicit task 494 performance is not a straightforward reflection of FTN responsivity, but a mixture of the FTN (doing 495 syntactic computations) and other, more domain-general networks contributing task-related 496 processing.

497 *Effect of crystallized knowledge on performance.* 

498 If functional connectivity between the FTN and MDN is positively related to performance on 499 the task, but negatively affected by age and decreasing grey matter, how is it that performance 500 remains stable across the lifespan? Some work suggests that age differences on tasks which place 501 heavy demands on domain-general processes (and typically decline with age) are sometimes 502 minimized when older adults can make use of existing knowledge (Charness, 1981; Castel, 2005; 503 Soederberg Miller, 2009). Indeed, this may be the case during normal language comprehension, 504 which depends on well-practiced, largely automatized processes and highly familiar language inputs 505 (Marslen-Wilson and Tyler, 1975; Zhuang et al., 2014). Thus, we might expect that preserved 506 performance on this task may become increasingly dependent on crystallized knowledge with age, 507 potentially compensating for decreased domain-general control. To test this, we entered age, 508 crystallized knowledge, and the age x crystallized knowledge interaction into a regression model 509 predicting task performance, controlling for fluid intelligence (which is known to correlate with crystallized intelligence; Cattell, 1963). The model was significant,  $R^2 = .18$ , F(4, 105) = 7.53, p < .001, 510 511 and while the main effect of age was not significant ( $\beta$  = .16, t = 1.60, p = .11, 95% CI [-.04, .37]), 512 there were main effects of fluid intelligence ( $\beta$  = .29, t = 2.38, p < .05, 95% CI [.05, .52]) and 513 knowledge ( $\beta$  = .22, t = 2.24, p < .05, 95% CI [.03, .42]), and importantly, an age x knowledge 514 interaction ( $\beta$  = .26, *t* = 2.05, *p* < .05, 95% CI [.01, .50]). This interaction appears to be due to 515 crystallized knowledge becoming increasingly related to task performance with age (Figure 5b).

Separate regression analyses performed in each age group (group N's provided in Table 1) confirms this, with crystallized intelligence becoming a significant predictor of task performance in the oldest group (young: model F < 1,  $\beta_{crystallized} = .09$ , t = .73, p = .47; middle-aged: model F < 1,  $\beta_{crystallized} = .11$ , t= .66, p = .51; older: overall model  $R^2 = .32$ , F(2, 36) = 8.60, p < .001,  $\beta_{crystallized} = .46$ , t = 3.30, p < .01, 95% CI [.20, .83],  $\beta_{fluid} = .26$ , t = 1.85, p = .07, 95% CI [-.04, .80]). Thus, older adults may be able to compensate for age-related declines in domain-general abilities by relying more heavily on an evergrowing body of crystallized knowledge.

### Discussion

524 We used a systems-level approach to separate processes specific to language 525 comprehension from those related to general task demands and to interrogate age differences in 526 functional connectivity both within and between those systems in the service of syntactic 527 processing. We show that task-free language comprehension solely recruits the auditory and 528 frontotemporal syntax networks, while active task performance calls upon several additional 529 networks which interact with the critical FTN to predict overt task performance. Despite age-related 530 declines in FTN grey matter, functionality of this network remains remarkably intact with age, 531 showing no age-related difference in within-network connectivity or responsivity to syntactic 532 processing demands. However, in the context of a task, although aging did not affect the expression 533 of individual networks, connectivity between the FTN and MDN decreased with age, suggesting that 534 even if a network remains functionally intact with age, its ability to flexibly interact with other 535 networks in the service of task goals may be affected. However, despite the decline in FTN-MDN 536 connectivity with age, we found that overt task performance was maintained across the lifespan, 537 possibly due to older adults' richer reserve of verbal knowledge which helps to offset fluid declines. 538 The BOLD activity measured with fMRI represents a mix of signals from different sources 539 within the brain. Independent components analysis (ICA) allows for the separation of those signals 540 (Calhoun et al., 2009; Beckmann, 2012) and in this case, enabled us to tease apart those networks 541 which are required for syntactic processing from those required for general task demands. This

542 method, combined with our use of two versions of the same syntactic processing experiment (one 543 which isolated our cognitive process of interest, and another which introduced simple task demands 544 common to many cognitive experiments), allowed us to more accurately characterize the nature of 545 age-related functional differences. Contrary to previous reports of an age-related increase in right-546 frontal activation during language comprehension (Peelle et al., 2010; Tyler et al., 2010a), we did not 547 find evidence for this "compensatory" response – either during task-free language comprehension 548 or during the active task version. We have argued previously that the topography of the core 549 frontotemporal syntax network changes little with age (Davis et al., 2014; Shafto and Tyler, 2014), 550 and that increased right-frontal activation commonly identified using standard univariate analysis 551 methods may actually be attributable to task-related processes – processes that would fall under the 552 purview of domain-general networks if the covariance between regions was taken into account.

553 In this case, we did not observe an age-related increase in the activation of frontal control 554 networks. Furthermore, increased reactivity of the MDN, as well as greater FTN-MDN connectivity, 555 related to better task performance across the lifespan (i.e., was not moderated by age), suggesting 556 that this was not a compensatory response in older adults, but related to better performance in all 557 participants. These divergent findings may be due to the population-representativeness of our 558 sample. Our recruitment process excluded term-time students (Shafto et al., 2014) and thus, our 559 sample of younger adults was more diverse than those typically used in psychological experiments, 560 which primarily consist of students from (often top-tier) universities. Thus, the task may have been 561 similarly demanding to all of our participants and as a result, we did not observe an age-related 562 increase in frontal control regions that older adults typically show at lower levels of demand (Reuter-563 Lorenz and Cappell, 2008).

564 Another aim of the study was to examine the effect of age and experimental task demands 565 on functional connectivity both within and between ICA-identified networks. Previous work 566 examining the effect of age on large-scale network organization has primarily focused on the resting 567 state (Ferreira and Busatto, 2013) or age differences in large-scale systems (such as the DMN and

568 FPN, the precise functions of which remain unclear) during attentionally demanding tasks (e.g., 569 Madden et al., 2010; Clapp et al., 2011; Spreng and Schacter, 2012; Geerligs et al., 2014a), but no 570 study to date has isolated a higher-order network with as clearly defined a function as the FTN (Tyler et al., 2011) and examined how age and task demands affect both its internal functioning and 571 572 interactivity with other networks. We found that connectivity within this network, as well as other 573 domain-general networks, changed very little moving from natural listening to task (although the 574 MDN and MOT did show a modest increase), suggesting that network architecture remains 575 remarkably stable across varying task states task (Cole et al., 2014; Krienen et al., 2014; Geerligs et 576 al., 2015b). Functional connectivity between networks, on the other hand, increased during active 577 task performance, particularly between networks generally thought to be responsible for attentional 578 control (MDN, OPRC; Dosenbach et al., 2008; Duncan, 2010) and those responsible for 579 sound/language processing (AUD, FTN), likely reflecting the reliance of task-based decisions on 580 auditory and linguistic processing output. While only the BG showed a significant decline in within-581 network connectivity with age, between-network connectivity decreased with age during the task 582 for several network pairs (although MDN-DMN and AUD-BG connectivity increased). While some 583 work has shown an age-related decline in network segregation during rest (i.e., decreased within-584 network connectivity coupled with increased between; Chan et al., 2014; Geerligs et al., 2014b), we 585 see little evidence of this during an active language comprehension task. Thus, age differences in 586 functional connectivity observed at rest may not extrapolate to cognitive tasks.

587 One of the most remarkable findings of this study is the maintained functionality of the 588 frontotemporal syntax system, despite age-related declines in grey matter integrity and disrupted 589 connectivity to task-related networks. Unlike the reduced function seen after focal damage to the 590 FTN (Tyler et al., 2010b, 2011), which itself tends to track with the extent of the damage (Wright et 591 al., 2012), the relatively diffuse and gradual reduction in structural integrity associated with normal 592 aging seems to have little effect on FTN function. This may be because syntactic processing is a 593 relatively automatic process (e.g., Marslen-Wilson and Tyler, 1975), involving a set of obligatory

594 computations and relying on a separate pool of "resources" from conscious, control processes 595 (Waters and Caplan, 1996). Compared to effortful control, automatic processes are thought to be 596 relatively preserved with age (Hasher & Zacks, 1979). As long as the input is audible (Gordon-Salant 597 and Fitzgibbons, 1997; Pichora-Fuller, 2003) and not presented too quickly (Wingfield et al., 1999, 598 2003), both older and younger adults alike obligatorily (and rapidly) integrate the syntactic and 599 semantic properties of each word into an online sentential representation. However, it remains 600 unclear, from a neural perspective, why automatic processes are preserved while controlled 601 processes decline. Both cross-sectional and longitudinal work suggests that frontal control regions 602 tend to be more affected by age than more posterior regions (e.g., Raz et al., 2005, 2010; Peelle et 603 al., 2012), with the latter more closely tied to obligatory functions (e.g., object recognition [Clarke 604 and Tyler, 2015]; reading [Gold et al., 2009]; memory binding [Moscovitch, 1992]). Indeed, in our 605 sample, grey matter within the left inferior frontal cortex (LIFG; BA44, 45, and 47) declined more 606 with age ( $r_{111} = -.68$ , p < .001, 95% CI [-.77, -.56]) than that within the MTG (BA 21 and 22;  $r_{111} = -.51$ , 607 p < .001, 95% CI [-.63, -.36]; Meng's Z test for dependent correlations sharing a variable: Z = 3.25, p = 608 .001), albeit decline within the MTG was clearly substantial. It may be that this relative preservation 609 of structure in the MTG is sufficient to sustain connectivity with the left inferior frontal cortex and 610 maintain functionality. A critical question for future research is how much is enough? That is, at 611 what point do structural declines become so great that automatic processes, such as syntax, start to 612 break down?

Finally, we show that when language comprehension occurs within the context of a task, even a simple task conducted online, successful performance relates most strongly to the MDN, a network previously shown to be under-recruited by older adults as attentional demands increase (Cappell et al., 2010; Nagel et al., 2011; Campbell et al., 2012). Despite the observed age-related decline in FTN-MDN connectivity during the task, overt performance on the task did not differ. Older, but not younger, adults with higher crystallized intelligence performed better on the syntax task, in line with previous work showing that older adults can make up for generalized declines with

increased domain-specific knowledge (Charness, 1981; Salthouse, 1984; Soederberg Miller, 2009).
Future work, with better temporal resolution (Tyler et al., 2013), is required to determine whether
this benefit of verbal knowledge to performance arises from better prediction of upcoming words,
faster revision of misinterpreted ambiguities, or post-syntactic decision processes.
Our aim was to gain a more accurate picture of neurocognitive aging by separating natural
language comprehension from task-based processes which are far from natural. In our view, this

separation of domain-specific from domain-general processes is a necessary step in order to move
beyond ill-defined terms, such as "dedifferentiation" and "compensation", to more detailed models

of how age affects the instantiation of specific cognitive processes in the brain. A challenge going

629 forward will be to find ways to test other cognitive functions (e.g., memory encoding and retrieval,

630 verbal production) in more naturalistic ways (e.g., Stephens et al., 2010; Hall et al., 2013; Campbell

et al., 2015), minimizing task demands. We are ultimately interested in how age affects the brainand cognition, not the task itself.

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#### **Figure Legends**

Figure 1. (A) Mean RTs for the subordinate, dominant, and unambiguous conditions (error bars =
 standard errors). Data are split into 3 age groups detailed in Table 1. (B) Scatterplot showing the
 relationship between age and syntactic sensitivity (i.e., subordinate – unambiguous RTs).

809 *Figure 2*. Functional networks differentially active during natural listening and task. Left panel shows

810 the group average spatial map for each component rendered on a canonical brain. Right panel

shows mean loading values for each network during Natural Listening and Task for the four

812 conditions (acoustic baseline, subordinate, dominant, and unambiguous). Error bars = standard

813 errors.

814 Figure 3. Effects of task and within-network connectivity (WNC) on between-network connectivity 815 (BNC). BNC matrices for (A) Task and (B) Natural Listening. Pairwise correlations were computed 816 between subject-specific timecourses for each of the seven networks and then averaged across 817 participants. Color bar indicates the strength of the average correlation (avg corr), with grey squares 818 indicating non-significant correlations (p > .05, Bonferroni corrected). (C) Difference in BNC between 819 task and natural listening. (D) and (E) are asymmetrical matrices showing the correlation between 820 WNC in each network and BNC during Task and Natural Listening, respectively. Network labels listed 821 down the left-hand side signify both the WNC value being correlated, as well as one of the networks 822 in each BNC pair (the other is listed along the bottom). FTN = frontotemporal, AUD = auditory, MDN 823 = multiple demand, OPRC = opercular, BG = basal ganglia, MOT = motor, DMN = default mode.

*Figure 4.* Relationship of between-network connectivity (BNC) to age and grey matter during the task
(A-B) and natural listening (C-D). Background color indicates average BNC strength. Black dots
indicate the correlation between BNC and age or grey matter concentration (GMC), with diamonds
indicating a negative relationship and circles indicating a positive relationship. The size of the dot
indicates the strength of the correlation. Some of the effects seen during the task are also replicated

- during Natural Listening (e.g., age to AUD-FTN, MDN-DMN, and GMC to MDN-DMN), while other
- 830 effects are novel.
- 831 *Figure 5*. Predictors of overt task performance. (A) Background color indicates average BNC strength
- 832 during the task and black dots indicate a significant correlation (p < .05, uncorrected) between
- 833 connectivity and syntactic sensitivity (i.e., subordinate unambiguous RTs). (B) Scatterplot showing
- that crystallized intelligence becomes a stronger predictor of task performance with age.

A		Vaura		Older
Age group		roung	wiidale	Older
Ν		35	37	39
Age range (years)		22 – 45	46 – 64	65 – 87
Sex (male/female)		17/18	18/19	20/19
Highest Education				
	University	30	23	19
	A' Levels	4	9	11
	GCSE grade	1	5	5
	None over 16	0	0	4
Proportion of tones		.99 (.03)	.93 (.11)	.89 (.16)
MMSE		29.34(1.1)	29.08(0.9)	28.08(1.5)
Crystallized intelligence		53.71(3.9)	54.38(4.8)	53.23(5.8)
Fluid intelligence		37.31(4.4)	33.32(4.6)	27.28(5.5)

Table 1. Participant demographics and mean cognitive performance

Note. Values in parentheses are standard deviations. Proportion of tones detected on Siemens HearCheck Screener test; MMSE = mini mental status examination; Crystallized intelligence = Spotthe-Word test; Fluid intelligence = Cattell culture fair test.

				A	NOVAs								Pairwise C	omparison	5
	Task			Lo	Language Task x Language			ge	Sub vs. Unamb during Task			Sub vs. Unamb during Natural Listening			
Component	F	p	$\eta_{\scriptscriptstyle p}^{\scriptscriptstyle 2}$	F	p	$\eta_{\scriptscriptstyle p}^{\scriptscriptstyle 2}$	F	p	$\eta_{\scriptscriptstyle p}^{\scriptscriptstyle 2}$	M <sub>diff</sub> [95% CI]	t(108)	p	M <sub>diff</sub> [95% CI]	t(108)	p
Frontotemporal	108.99	< .001	.49	51.73	< .001	.32	15.11	< .001	.12	1.12 [.73, 1.50]	5.77	< .001	0.36 [.23, .48]	5.87	< .001
Auditory	103.62	< .001	.48	32.46	< .001	.23	7.25	< .01	.06	0.76 [.40, 1.12]	4.20	< .001	0.27 [.17, .38]	4.97	< .001
Multiple demand	375.35	<.001	.77	302.69	< .001	.73	139.29	< .001	.56	3.48 [3.02, 3.94]	15.03	< .001	0.77 [.64, .90]	11.78	< .001
Opercular	215.63	< .001	.66	18.76	< .001	.15	10.27	< .01	.08	0.88 [.42, 1.34]	3.82	< .001	0.13 [002, .26]	1.95	.054
Basal ganglia	154.56	< .001	.58	27.57	< .001	.20	47.61	< .001	.30	1.09 [.74, 1.45]	6.09	< .001	-0.11 [21,03]	2.66	< .01
Motor	164.71	< .001	.60	17.22	< .001	.13	18.95	< .001	.15	0.71 [.38, 1.04]	4.28	< .001	-0.01 [11, .08]	29	.77
Default mode	99.61	< .001	.47	< 1	.99	.00	7.99	< .01	.07	0.28 [12, .67]	1.39	.17	-0.27 [37,17]	5.21	< .001

Table 2. Main effects and interactions of Task and Language condition in the seven ICA networks related to language processing

*Note*: Lefthand results are from follow-up ANOVAs testing the main effect of Task (task, natural listening) and Language (subordinate, unambiguous), as well as the Task x Language interaction on the loading values (i.e.,  $\beta$  parameters) for each component. Righthand results are from paired samples t-tests testing the difference between subordinate and unambiguous  $\beta$  parameters separately during Task and Natural Listening.

	GMC		Respo	nsivity		WNC				
		Task		Natural Listeni	ing	Task		Natural Listening		
Component	r [95% CI]	ρ	<i>r</i> [95% CI]	р	r [95% CI]	p	<i>r</i> [95% Cl]	p	<i>r</i> [95% CI]	р
Frontotemporal	56 [67,44]	<.001	21 [37,03]	.03	08 [27, .10]	.39	.03 [13, .20]	.73	.14 [04, .32]	.14
Auditory	49 [62,36]	<.001	16 [33, .02]	.09	10 [25, .08]	.31	20 [35,04]	.04	04 [23, .15]	.65
Multiple demand	64 [73,52]	<.001	15 [32, .03]	.11	16 [33, .02]	.09	21 [35,04]	.03	06 [25, .13]	.52
Opercular	61 [71,50]	<.001	.03 [17, .23]	.78	01 [18, .16]	.92	24 [39,06]	.01	09 [28, .12]	.37
Basal ganglia	55 [67,43]	<.001	.07 [13, .25]	.49	.06 [12, .22]	.56	45 [56,33]	<.001	30 [45,13]	.001
Motor	57 [69,43]	<.001	.15 [04, .33]	.13	.14 [03, .32]	.15	.14 [06, .33]	.15	.21 [.002, .38]	.03
Default mode	55 [66,41]	<.001	05 [24, .15]	.63	.10 [08, .28]	.29	.05 [12, .24]	.61	.16 [04, .36]	.10

Table 3. Pearson's correlation between age and mean grey matter concentration, responsivity, and within-network connectivity for each component

*Note:* Responsivity (to syntactic processing demands) = subordinate – unambiguous loadings; GMC = grey matter concentration; WNC = within-network connectivity. Cl = 95% bootstrap confidence intervals.

		Respons	sivity		WNC			
	Task		Natural Listenir	ng	Task		Natural Listening	
Component	<i>r</i> [95% Cl]	р	<i>r</i> [95% CI]	p	<i>r</i> [95% CI]	p	r [95% CI]	p
Frontotemporal	.19 [.00, .36]	.05	.10 [09, .28]	.30	.18 [01, .34]	.07	.03 [16, .21]	.76
Auditory	.06 [11, .23]	.53	06 [26, .16]	.52	.22 [.04, .38]	.02	.17 [004, .34]	.07
Multiple demand	.11 [09, .31]	.24	.21 [.07, .35]	.02	.34 [.18, .47]	<.001	.18 [.03, .33]	.06
Opercular	07 [27, .11]	.44	.03 [19, .23]	.79	.31 [.16, .44]	.001	.24 [.09, .39]	.01
Basal ganglia	02 [18, .13]	.82	01 [18, .18]	.95	.27 [.12, .42]	.004	.19 [.04, .34]	.04
Motor	.03 [18, .22]	.80	12 [29, .04]	.21	14 [32, .03]	.14	17 [33, .02]	.08
Default mode	.07 [14, .28]	.50	12 [31, .08]	.20	.05 [13, .23]	.57	01 [20, .19]	.95

Table 4. Pearson's correlation between GMC and network responsivity and WNC

*Note*: Correlation values for each component are between mean grey matter concentration (GMC) within that component and 1) its responsivity to syntactic processing demands (i.e., subordinate – unambiguous loadings; first two columns) and 2) its mean within-network connectivity (WNC; second two columns). CI = 95% bootstrap confidence intervals.

Component	Task	Natural listening	Task vs. Natur	ral Listenin	g
			M <sub>diff</sub> [95% CI]	t (110)	Ρ
Frontotemporal	.43 (.08)	.43 (.07)	.007 [005, .02]	1.19	.24
Auditory	.48 (.09)	.49 (.08)	006 [02, .01]	97	.34
Multiple demand	.52 (.09)	.50 (.08)	.02 [.01, .03]	3.38	< .01
Opercular	.46 (.09)	.46 (.08)	001 [01, .01]	17	.87
Basal ganglia	.49 (.08)	.48 (.08)	.004 [01, .01]	.67	.50
Motor	.57 (.08)	.55 (.08)	.02 [.004, .03]	2.61	< .05
Default mode	.54 (.09)	.54 (.08)	.002 [01, .01]	.34	.73

Table 5. Mean within-network connectivity during task and natural listening

*Note*: Values in the two left-hand columns reflect mean within-network connectivity across participants during Task and Natural Listening (standard deviations in parentheses). Right-hand columns show results from follow-up paired samples t-tests testing the difference in WNC between Task and Natural Listening.











# Figure 3





E Corr between WNC and BNC during Nat Listening













