Supplementary results

Drivers of the age-related decrease in inter-subject synchrony

When interpreting the effect of age on inter-subject synchrony, it is important to consider potential confounding factors. It is known that aging affects the variability of the spontaneous signal (Tsvetanov et al., 2015) and that aging can impact the amount of non-neural noise in the data (Geerligs et al., 2017). We have taken care throughout the paper to account for differences in noise levels through elaborate corrections of head motion effects and by including multiple covariates of no-interest related to head motion and ICA denoising. However, to understand the causes underlying the loss of synchronization better, we investigate a number of other metrics in this section.

Let us assume that the BOLD time-series of a given brain region consists of three components, some spontaneous (background) neural signal, an evoked response to certain events in the movie and a noise component. For the sake of simplicity, we assume that those signals are additive. Computing the correlation between two time-series inherently involves z-scoring the data. Therefore, any differences in the total variability of the signal does not affect the correlation, but the relative contribution of the different data components (event-related, spontaneous and noise) could have an effect on the correlation estimate. Computing the synchrony for a given participant involves computing a correlation between the timecourse of that participant and an average timecourse over all other participants. The average time-course should only be driven by evoked responses that are shared across participants because the noise and spontaneous signal should not be correlated across participants. However, the timecourse of each participant could be shaped to different degrees by the three components (event-related, spontaneous signal and noise). With this in mind, the observed age-related decreases in synchrony (correlation with the group) could potentially be explained by four factors that shape the individual's timecourse:

1. Increased idiosyncrasy with advancing age; this could be due to more variability in in the events that drive an evoked response with advancing age or more variability in the nature of that response.
2. An age-related decrease in the amplitude of evoked responses to events in the movie
3. An age-related increase in noise in the data
4. An age-related increase in spontaneous signal fluctuations in the data

To disentangle these different options, we can evaluate how each of these changes would impact other measures. One measure of interest is the fluctuation amplitude of the signal in a given brain region (its average variability over time). If the three components (event-related, spontaneous signal and noise) are indeed additive, the fluctuation amplitude would not change with age if option 1 is true, it would show an age-related decrease if option 2 is true, and it should show an age-related increase for options 3 and 4.

We found that only 10 out of 748 ROIs showed a significant negative association between fluctuation amplitude and age (see Fig S1D), suggesting that in most brain regions, age-differences in fluctuation amplitude are not responsible for the observed differences in synchrony. To establish this further, we also repeated the analyses of the correlation-based synchrony measures (as reported in the main text), using the fluctuation amplitude of each region during movie watching as a covariate of no interest. The results were highly similar to the original results (compare Fig S1A and Fig S1C), suggesting that the age-effects on synchrony cannot be fully explained by the presence of additional noise, additional spontaneous fluctuations or by a lower amplitude of the evoked responses.

Another way to test whether age differences in synchrony are due to an increase in noise is to use a regression-based measure, instead of a correlation-based measure. This measure is obtained by predicting each participant's ROI timecourse with the average timecourse of all other participants, along with an intercept term. The beta coefficient thus reflects the scaling of the averaged signal that is required to best fit the data for the remaining participants. The estimate of this scaling parameter therefore should not be affected by the presence of additional noise or spontaneous fluctuations (options 3 and 4). It would however show a decline for options 1 and 2.

We found that with the regression-based synchrony measure, the loss of synchronization with advancing age was very similar to the results in the main text (compare Fig S1A and S1B). This suggests that the presence of additional noise or additional spontaneous fluctuations are not likely to be the main drivers of this age-effect.

Unfortunately, it is not possible to look at the evoked responses in a more direct way, because we do not know the events that trigger a response in each brain regions. However, if our assumption of additive signals is correct, these findings demonstrate that at least a part of the age-related differences must be due to an increase in idiosyncrasy of neural responses with advancing age.

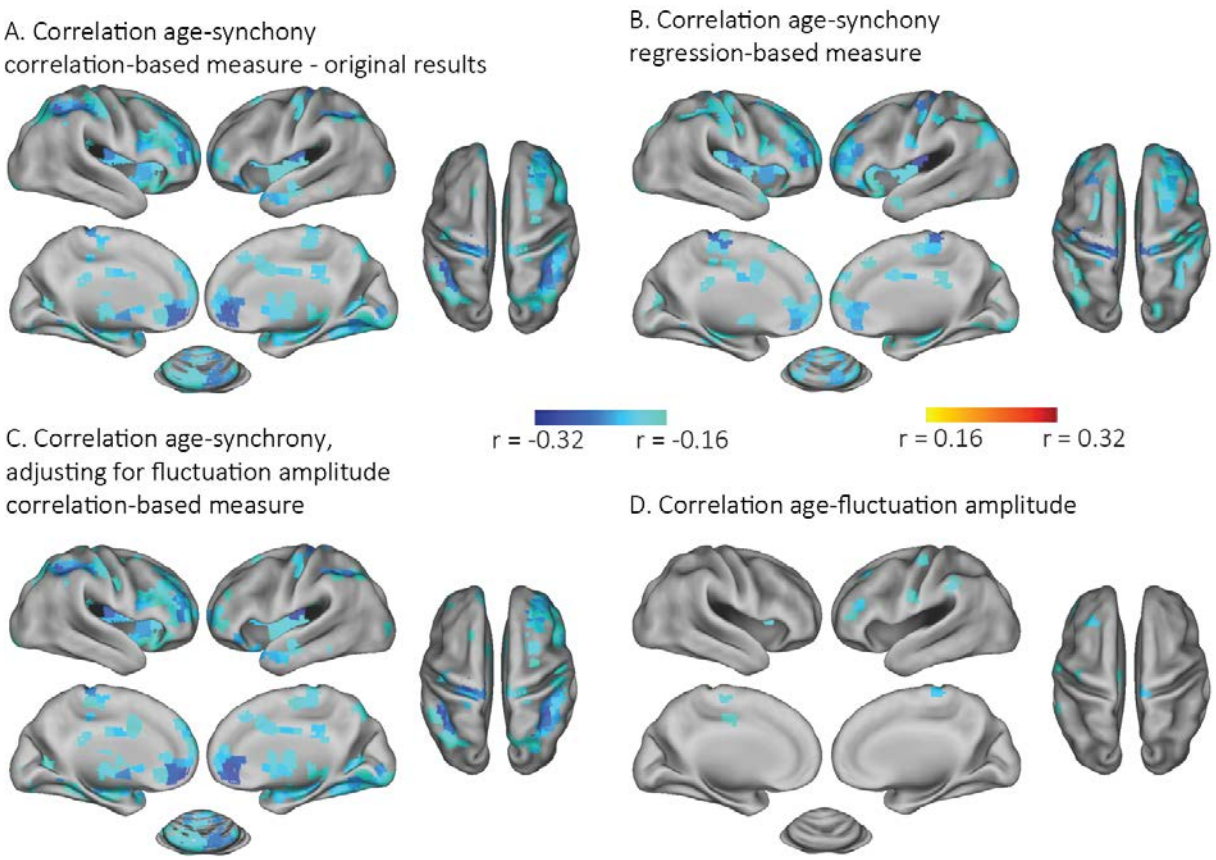

Figure S1: A. the correlation between age and synchrony, when using the correlation based synchrony measure – also shown in the main paper. B. the correlation between age and synchrony, when using the regression based synchrony measure. C. the correlation between age and synchrony, when using the correlation based synchrony measure, where fluctuation amplitude was used as an additional covariate of no interest. D. The correlation between synchrony and fluctuation amplitude of the BOLD signal. Results were Bonferroni corrected for multiple comparisons. Results in A-C were adjusted for covariates of no interest related to head motion and ME-ICA denoising.

Cluster selection

The regions of interest that demonstrated a significant age-related decline in synchrony are shown in Fig S2. These regions are the same as those in Fig 1B, however, in this figure we have shown the functional network labels of each of these regions, based on (Geerligs et al., 2015b see Fig 5C for a the networks labels of all ROIs). Most of the regions showing significant age-related change were part of the fronto-parietal control network (FPCN; 32 ROIs fell within the FPCN), the default mode network (DMN; 25 ROIs fell within the DMN), and the brainstem-medial temporal lobe (MTL) network (22 ROIs; with the visual network being the next most affected network with 19 ROIs). We focused on these three networks in the paper, as they not only showed the strongest age-related declines (indicated by darker blue in Fig. 1B), but are also repeatedly implicated in the neurocognitive aging literature (Grady, 2012; Turner and Spreng, 2015). For the FPCN, we observed that the decline in synchrony spanned across most of the network, including the right and left inferior parietal and left middle frontal gyrus. For the DMN and the brainstem-MTL network, the age-effects were more region-specific. For the DMN, most of the age-effects were located in the medial prefrontal cortex (mPFC), with only six ROIs in other parts of this network being affected by age. For the brainstem-MTL network, we observed that the effects were mainly restricted to the MTL, including the hippocampus, temporal pole and parahippocampal areas, with only two ROIs outside these areas (partially overlapping with the thalamus) being affected as well. Thus to promote interpretability, for these latter two networks, we focused on regional rather than network-level effects. While the FPCN is critical for cognitive control and working memory (Vincent et al., 2008), areas in the MTL are associated with memory encoding and retrieval (Squire et al., 2004) and the mPFC is associated with memory, imagination, and affective processing (Benoit et al., 2014; Van Kesteren et al., 2012; Winecoff et al., 2013). For the MTL and mPFC, we computed average synchrony scores for ROIs that were significantly changing with age, and that were located in and around the MTL and in the mPFC, respectively. For the FPCN we computed a mean synchrony score by averaging the synchrony scores across all the ROIs in that network that were significantly changing with age.

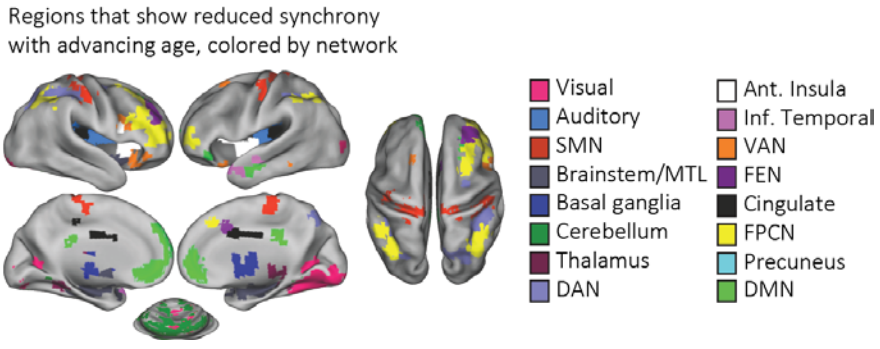

Figure S2: The functional network label of each of the ROIs showing significant age-related change is shown.

Clustering and age-related shifts in neural responses

In the main text, we investigate if there are subgroups of participants (or older adults) who consistently respond to the movie in a different way, which caused the observed decline in

synchronization. This was done using a community detection algorithm. Here, we show in figure S3 that the results of the community detection algorithm were the same for all three regions and across a range of settings for the number of communities. In each case, no evidence was observed for modular communities, suggesting that there are not subgroups of participants (of any age) that are consistently responding to the movie in a different way

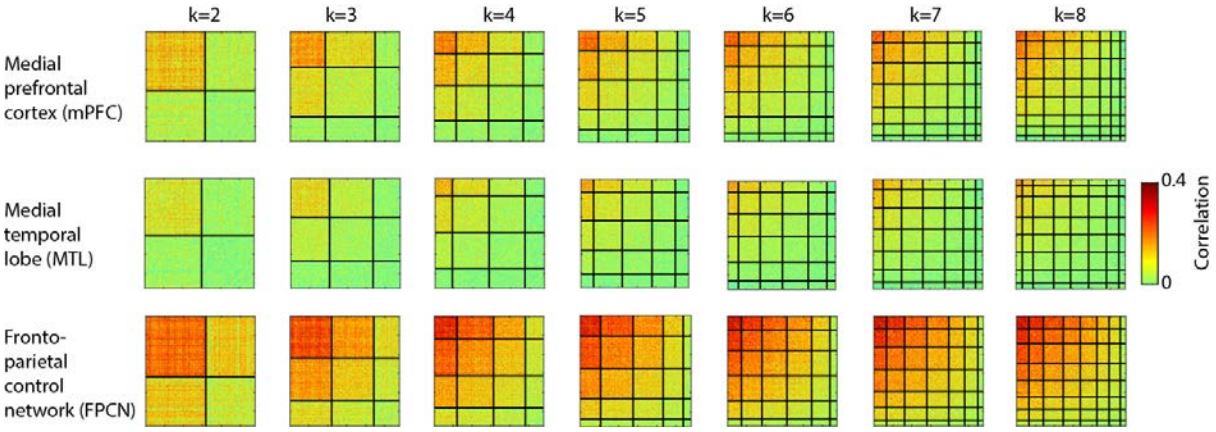

Figure S3: Community structure for k=2-8, for the FPCN, mPFC and the MTL. Communities are ordered from the highest to the lowest inter-subject synchrony.

We also performed another analysis that supports these findings. Here we looked at whether there was a *systematic* change in the neural responses to the movie with age. If so, we would expect older adults to be more similar to their age-matched peers than to younger adults. Therefore, we looked at the synchrony between participants of a similar age (comparing each participant's time-course to the mean timecourse of 20 age-matched participants). With this approach, age-effects in the FPCN, mPFC and MTL were even more pronounced than with the original synchrony measure (FPCN, $r=-0.44$, $p<0.001$; mPFC, $r=-0.48$, $p<0.001$; MTL, $r=-0.53$, $p<0.001$), suggesting that there were no systematic changes with age in the neural responses. This in line with the results of the community detection algorithm.

Time-dependent changes in synchrony – effect of window width

In the main text, we describe how average synchrony, as well as the association between age and synchrony, varies over time. We also describe how these changes were associated with specific events in the movie. Here, we repeat this analysis for different window widths of the sliding window. Fig. S3 shows good correspondence between the results at different window widths. As expected, time-courses do get smoother as the width of the sliding window increases. These results demonstrate that the results we describe in the main text are not specific to the width of the sliding window we used.

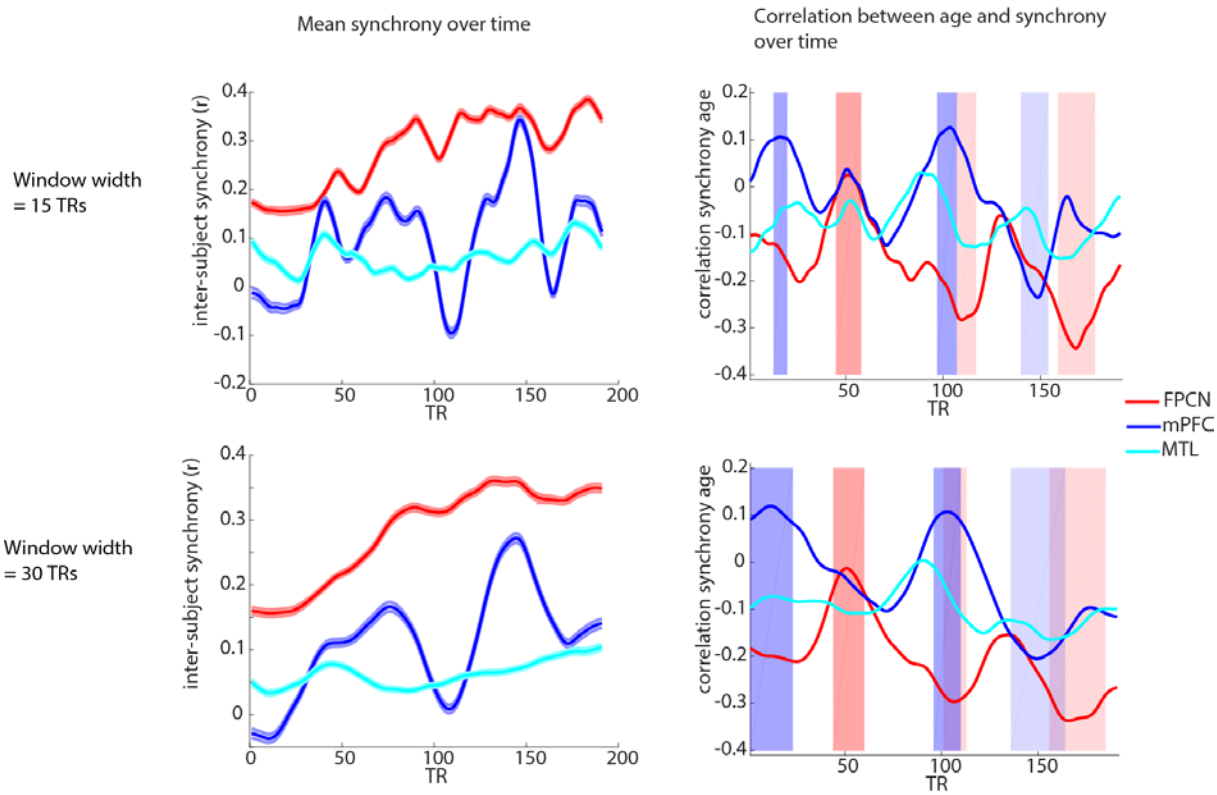

Figure S4: Changes over time in inter-subject synchrony for the mean across the group and the effect of age on inter-subject synchrony, for two different sizes of the sliding window. On the left, the mean in represented by the line and the standard error around the mean in shown by the shaded regions around the lines. On the right, time-points where the age-effects were significantly stronger or weaker than average are shown in light (stronger than average) or dark (weaker than average) patches (after Bonferroni correction).

Age-related changes in functional connectivity

In Fig. 5B, we showed how aging affected functional connectivity estimates. Here we describe those results in more detail. In line with previous studies, we observed that with age, there was a decrease in within-network connectivity and an increase in connectivity between distinct functional networks (Chan et al., 2014; Geerligs et al., 2015a, 2014) (Fig. 5B). In particular, we observed reduced connectivity within the FPCN, DMN and the dorsal attention network (DAN), as well as within the anterior insula and the auditory network. Increased connectivity with advancing age was observed for many of the ROI pairs in higher order networks that showed no correlations or negative correlations in the average connectivity matrix. These were connections between the inferior temporal and DAN, between the inferior temporal and FPCN, between the DMN and DAN, as well as between the FPCN and the DMN.

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