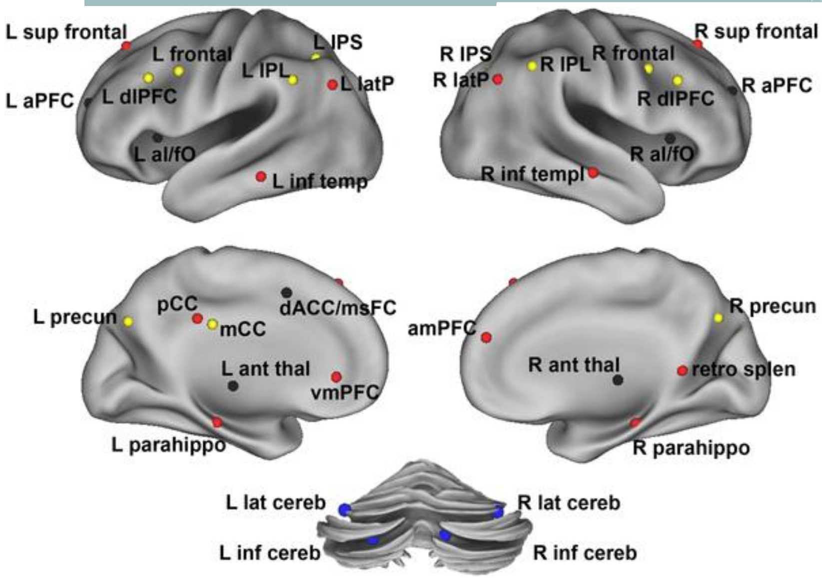
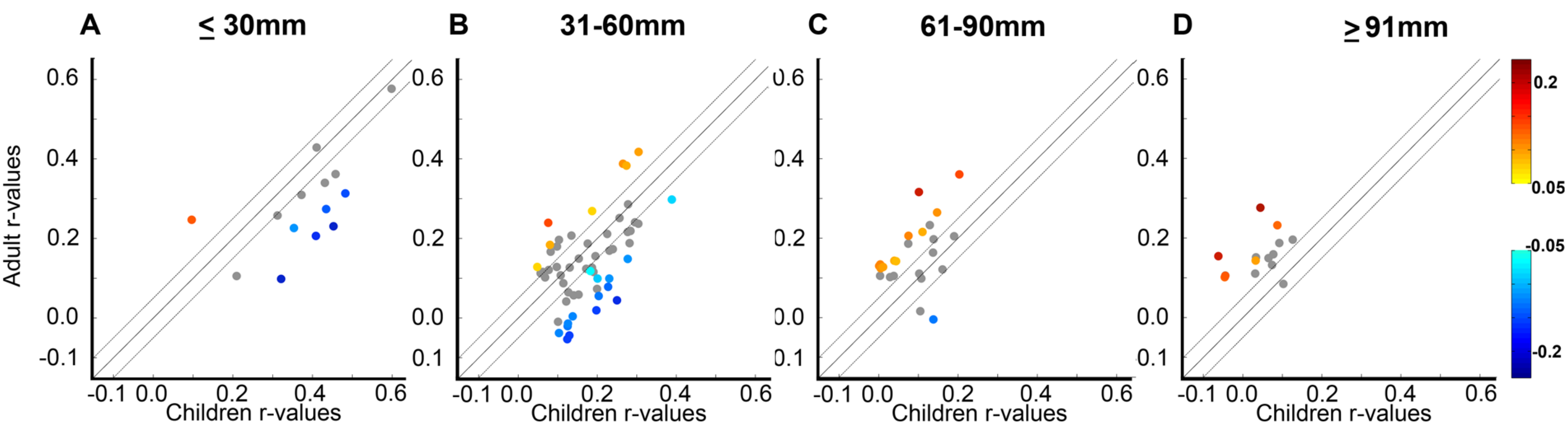
Motion & connectivity analyses

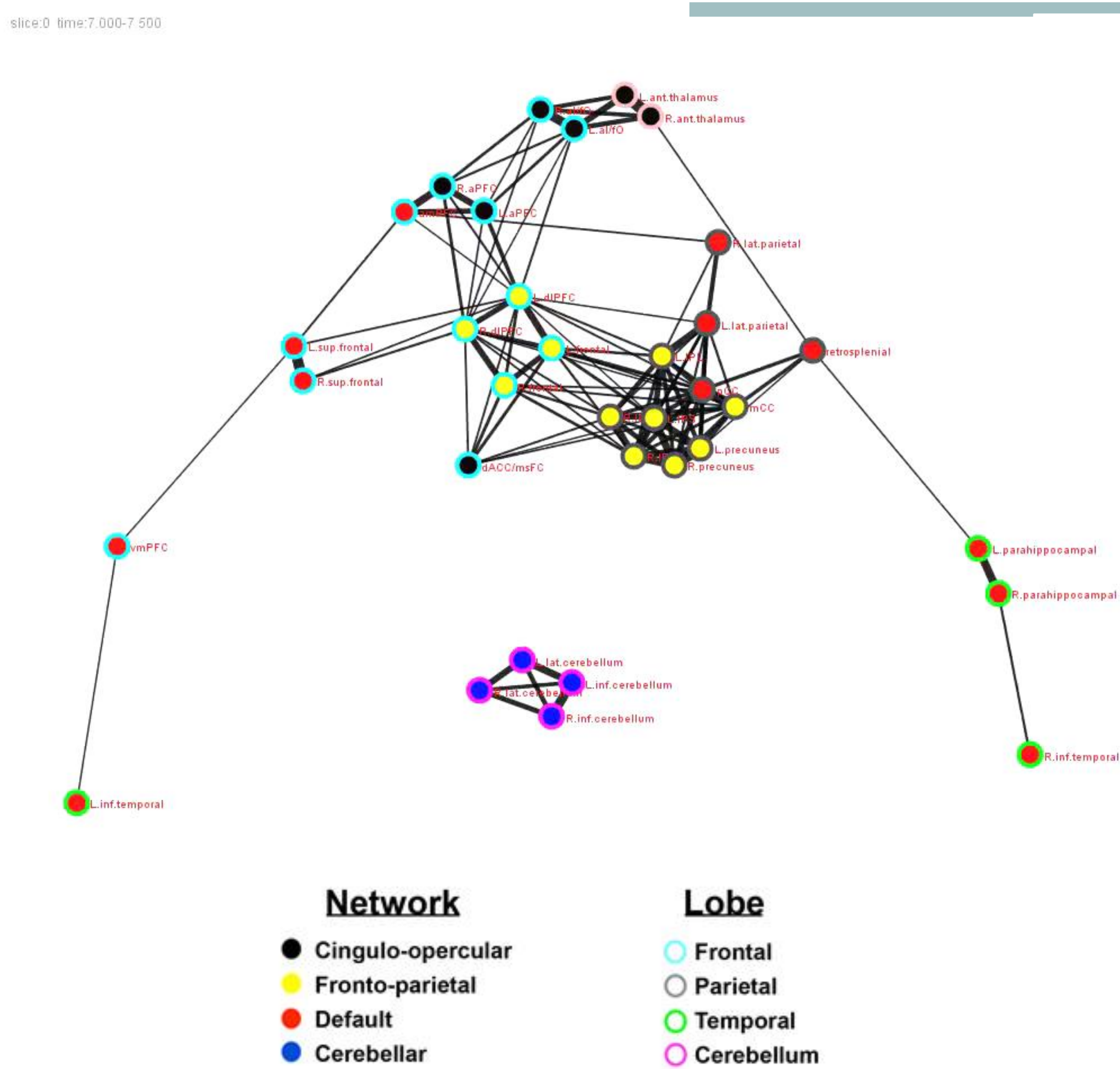
Martin M Monti
UCLA – Neuroimaging Meeting

Functional Brain Networks Develop from a "Local to Distributed" Organization



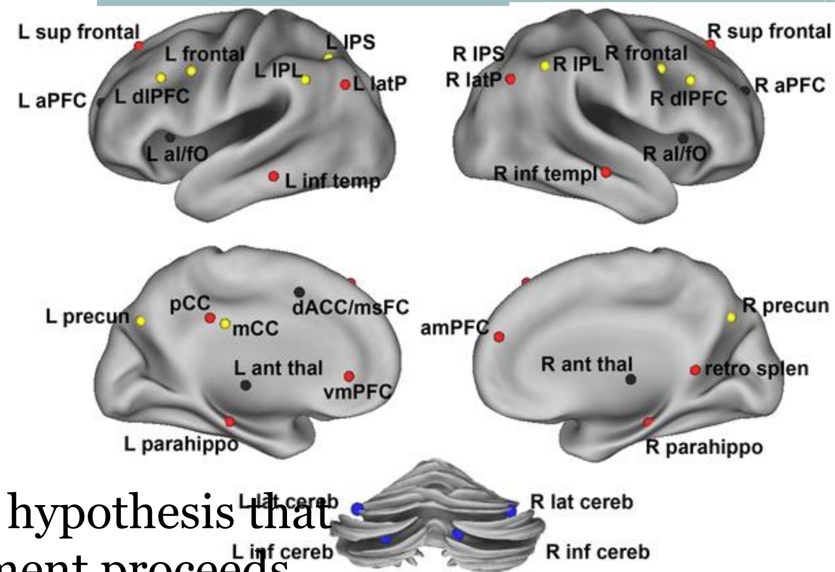


Fair DA, Cohen AL, Power JD, Dosenbach NUF, et al. (2009) PLoS Comput Biol 5(5): e1000381.

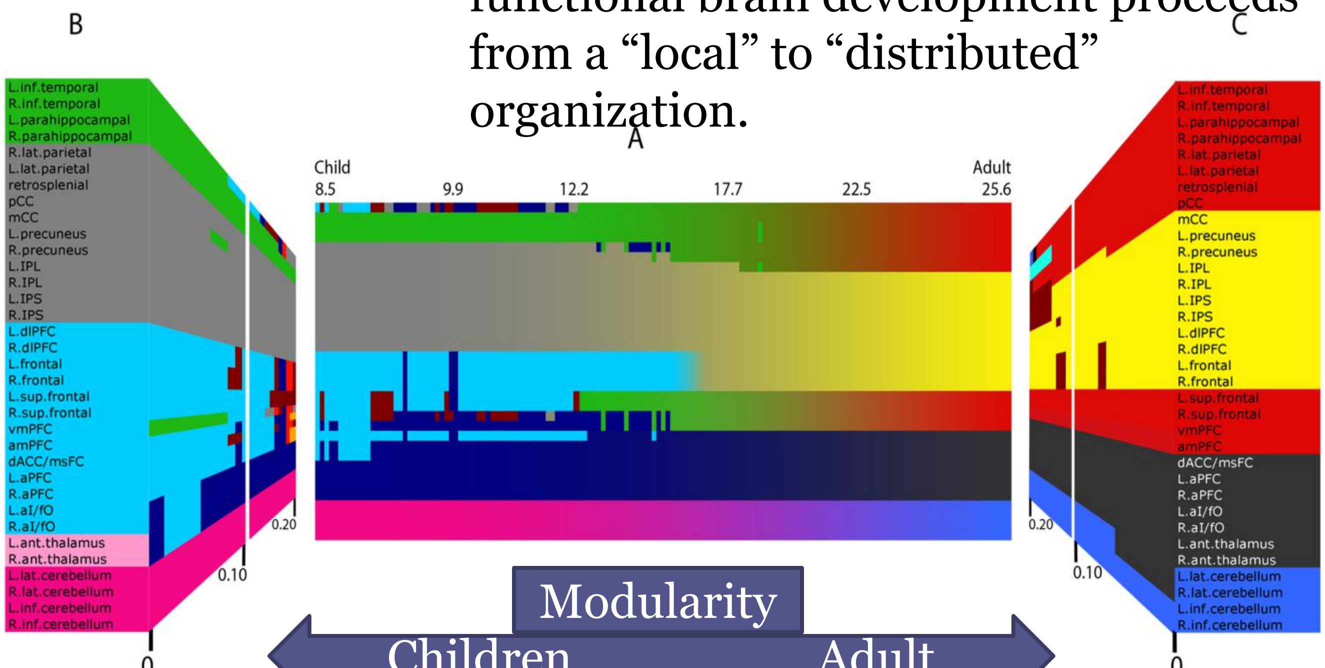


Fair DA, Cohen AL, Power JD, Dosenbach NUF, et al. (2009) PLoS Comput Biol 5(5): e1000381.

Functional Brain Networks Develop from a "Local to Distributed" Organization



These results support the hypothesis that functional brain development proceeds from a "local" to "distributed" organization.

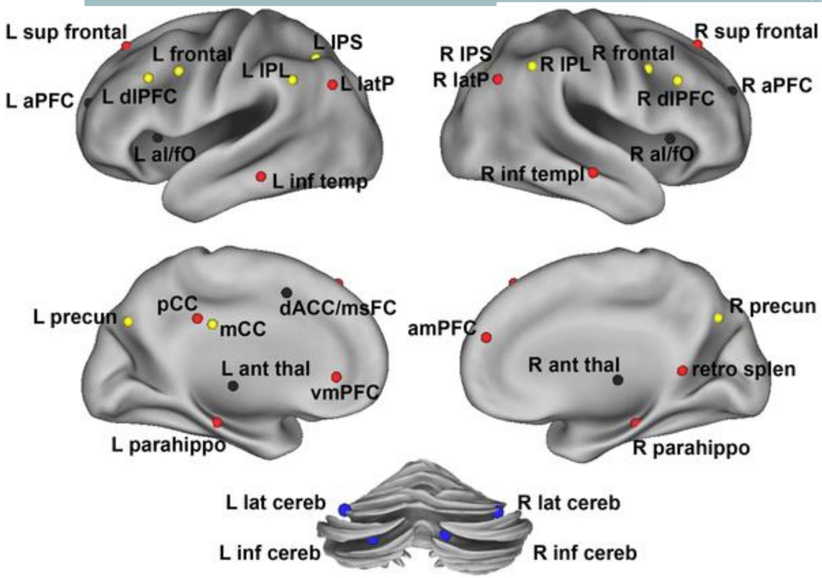


Modularity

Children Adult

Fair DA, Cohen AL, Power JD, Dosenbach NUF, et al. (2009) PLoS Comput Biol 5(5): e1000381.

Functional Brain Networks Develop from a "Local to Distributed" Organization

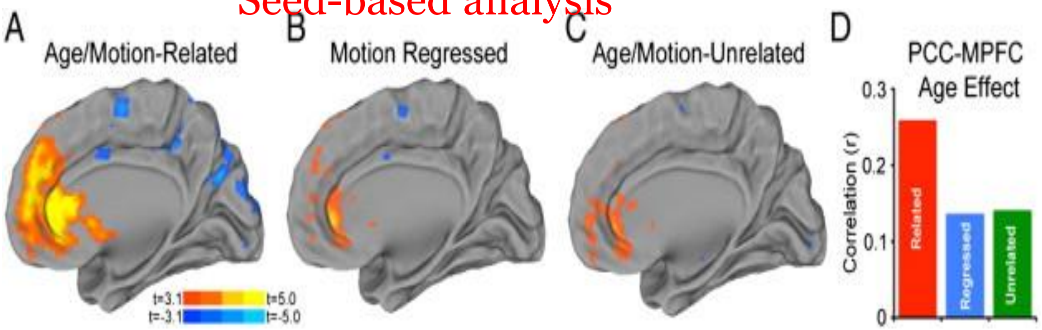


These results support the hypothesis that functional brain development proceeds from a "local" to "distributed" organization.

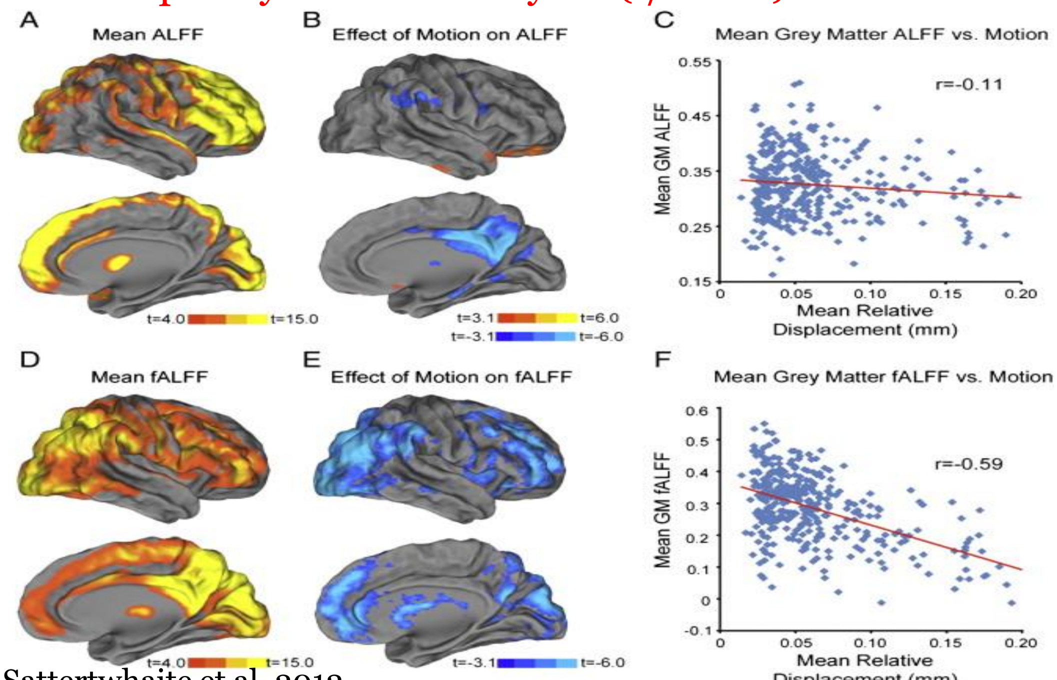
Fair DA, Cohen AL, Power JD, Dosenbach NUF, et al. (2009) PLoS Comput Biol 5(5): e1000381.

This problem affects all techniques

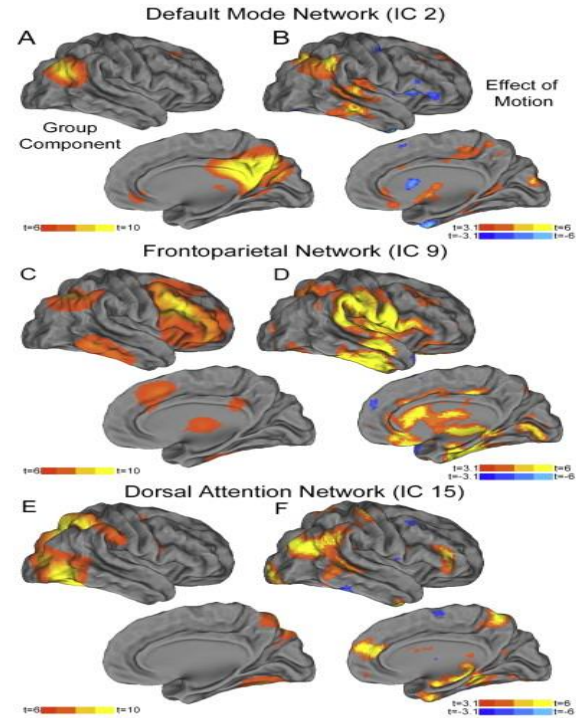
Seed-based analysis



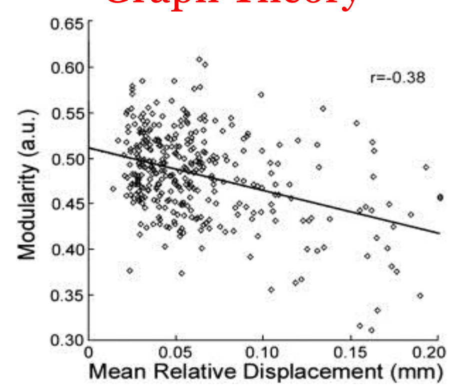
Frequency domain analyses (f/ALFF)



ICA

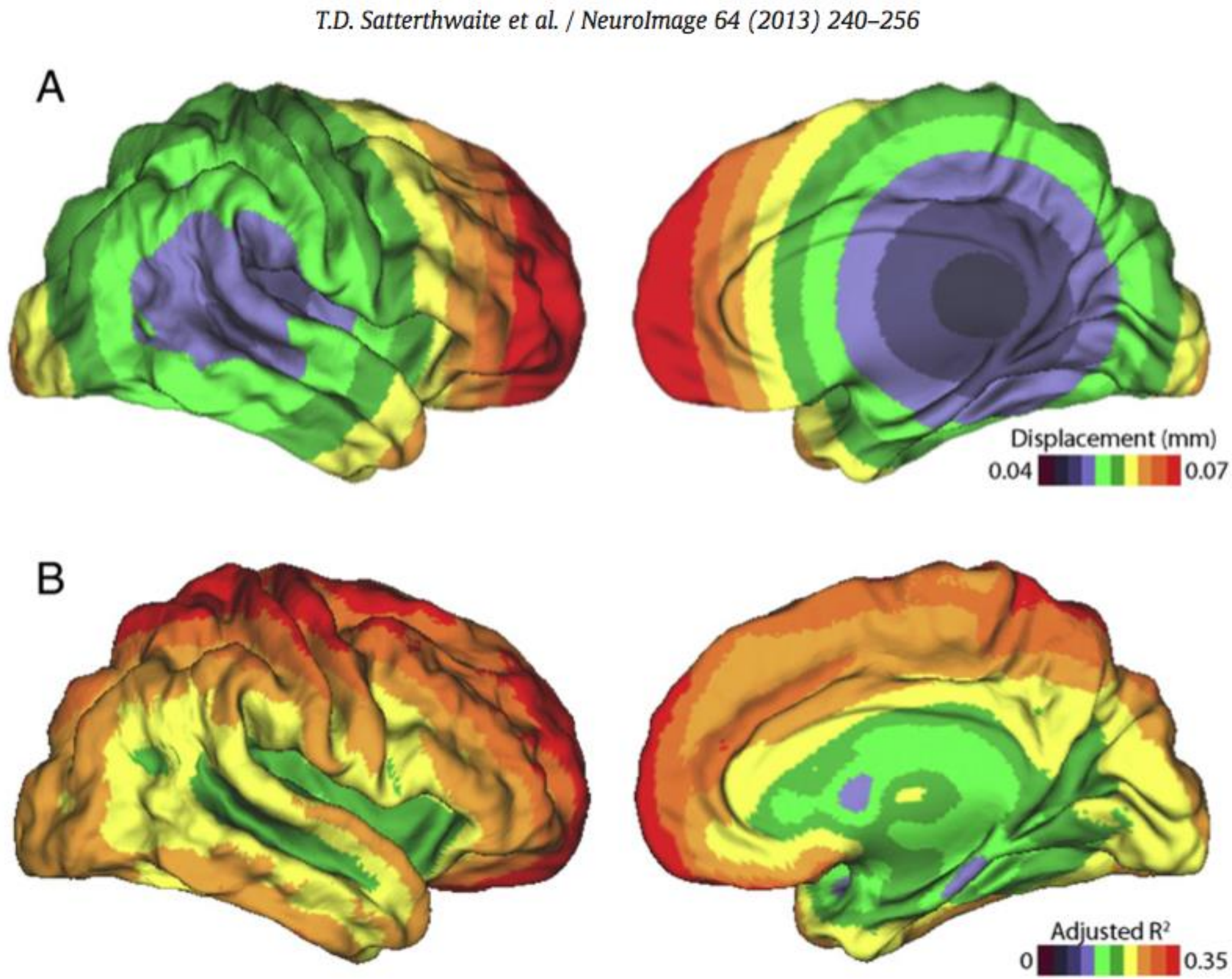


Graph Theory

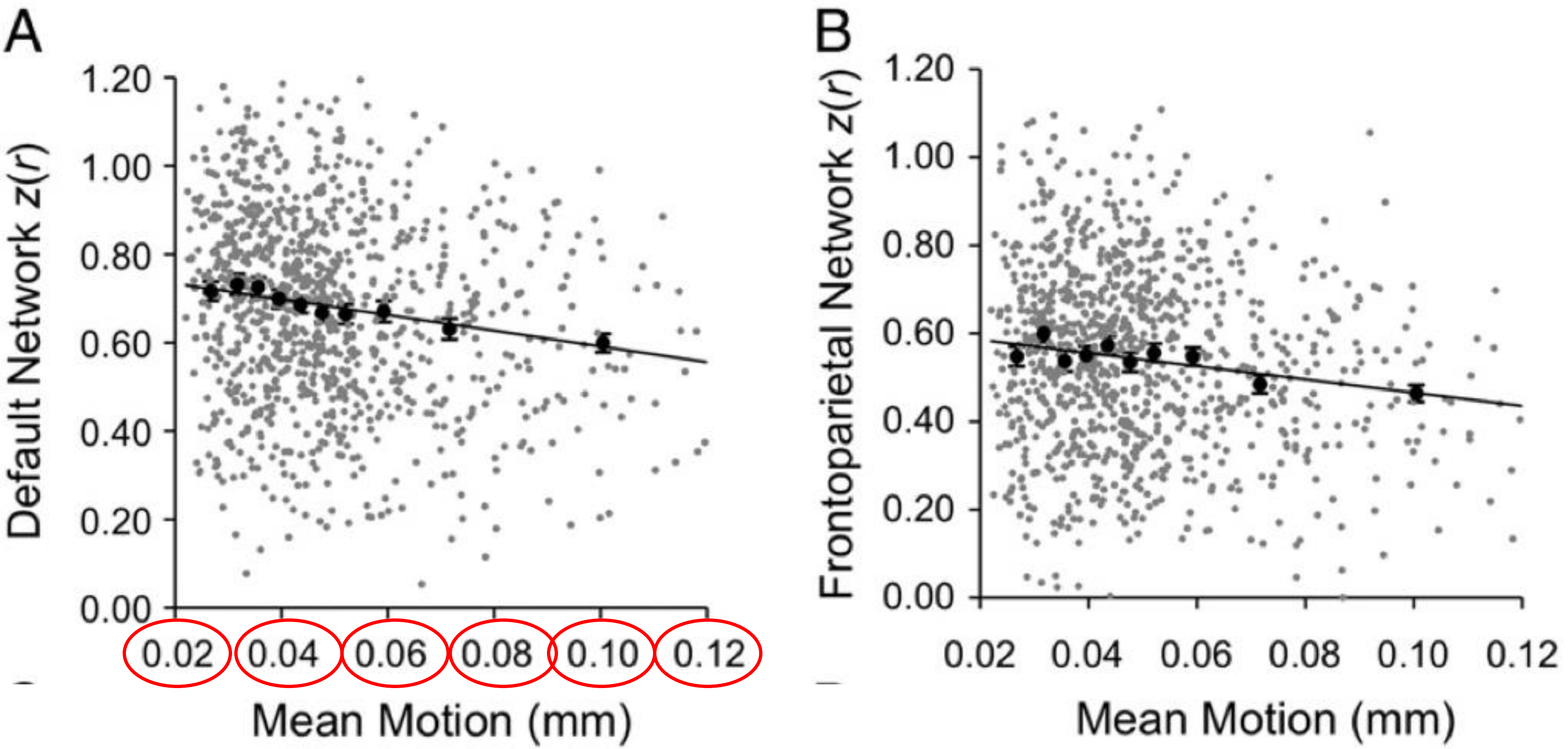


Sattertwhaite et al, 2012

Not all motion is created equal

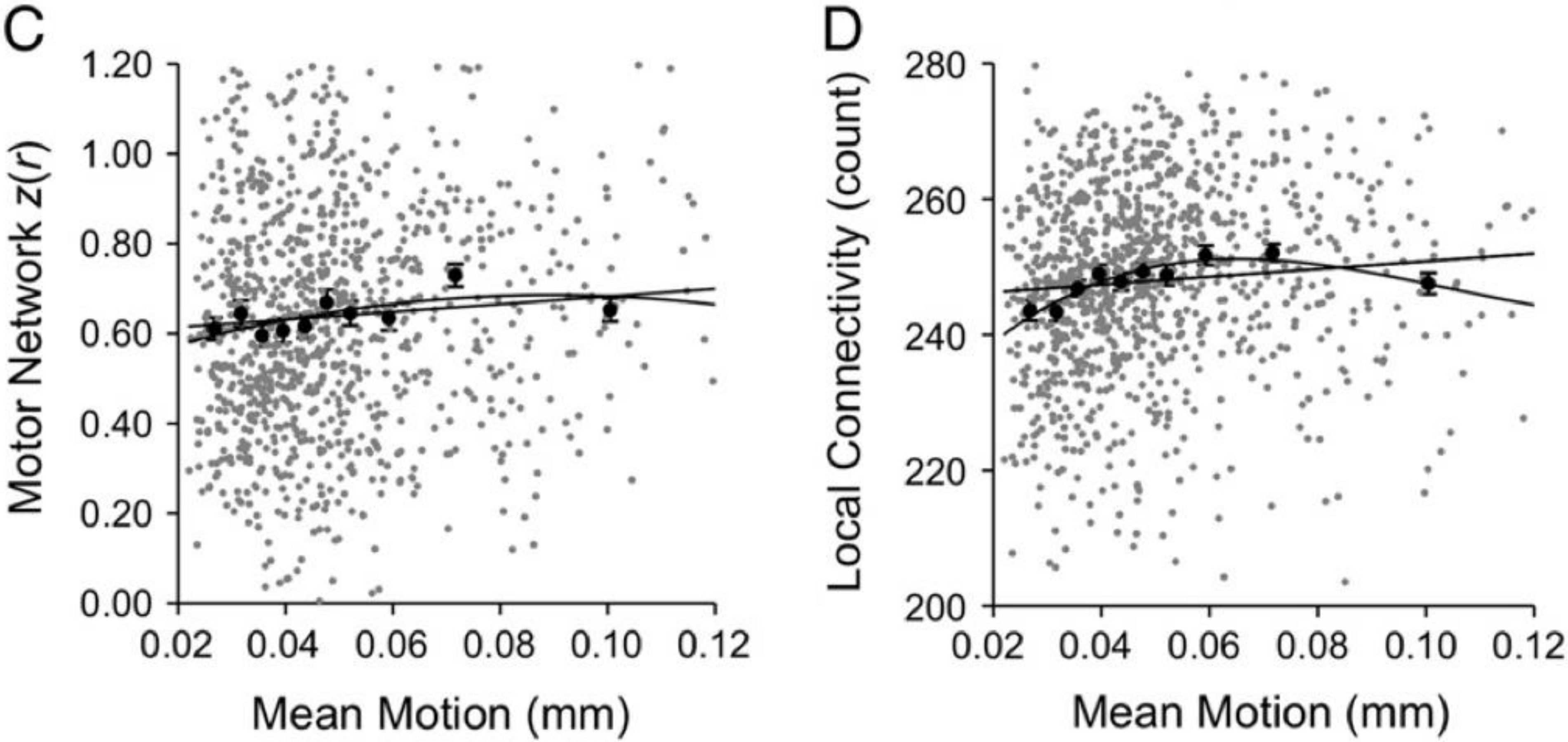


Long-range functional connectivity is diminished in wiggly subjects



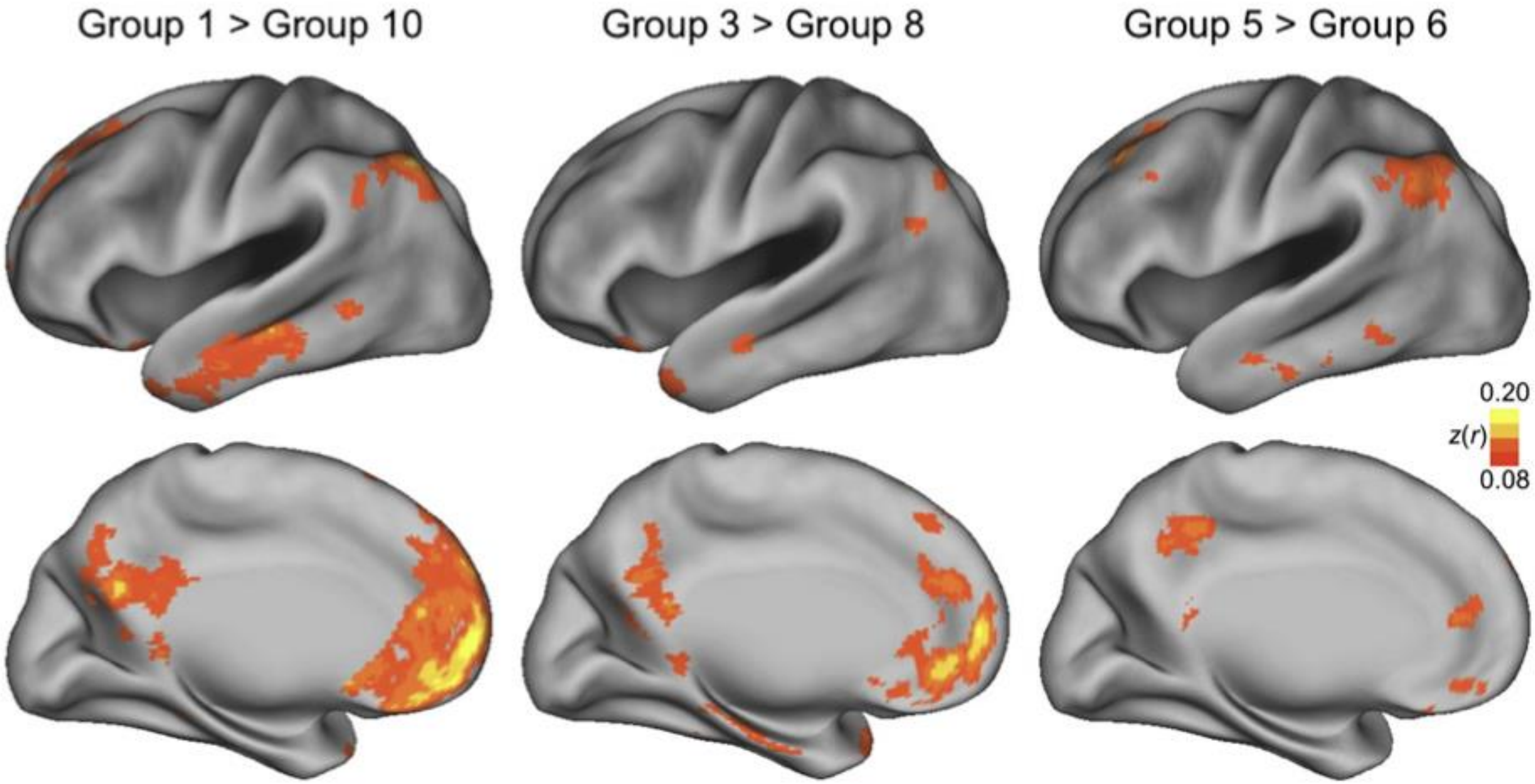
Van Dijk, Sabuncu, & Buckner (2012) *NeuroImage*

And short-range functional connectivity can be augmented in wiggly subjects



Van Dijk, Sabuncu, & Buckner (2012) *NeuroImage*

PCC connectivity X motion interaction



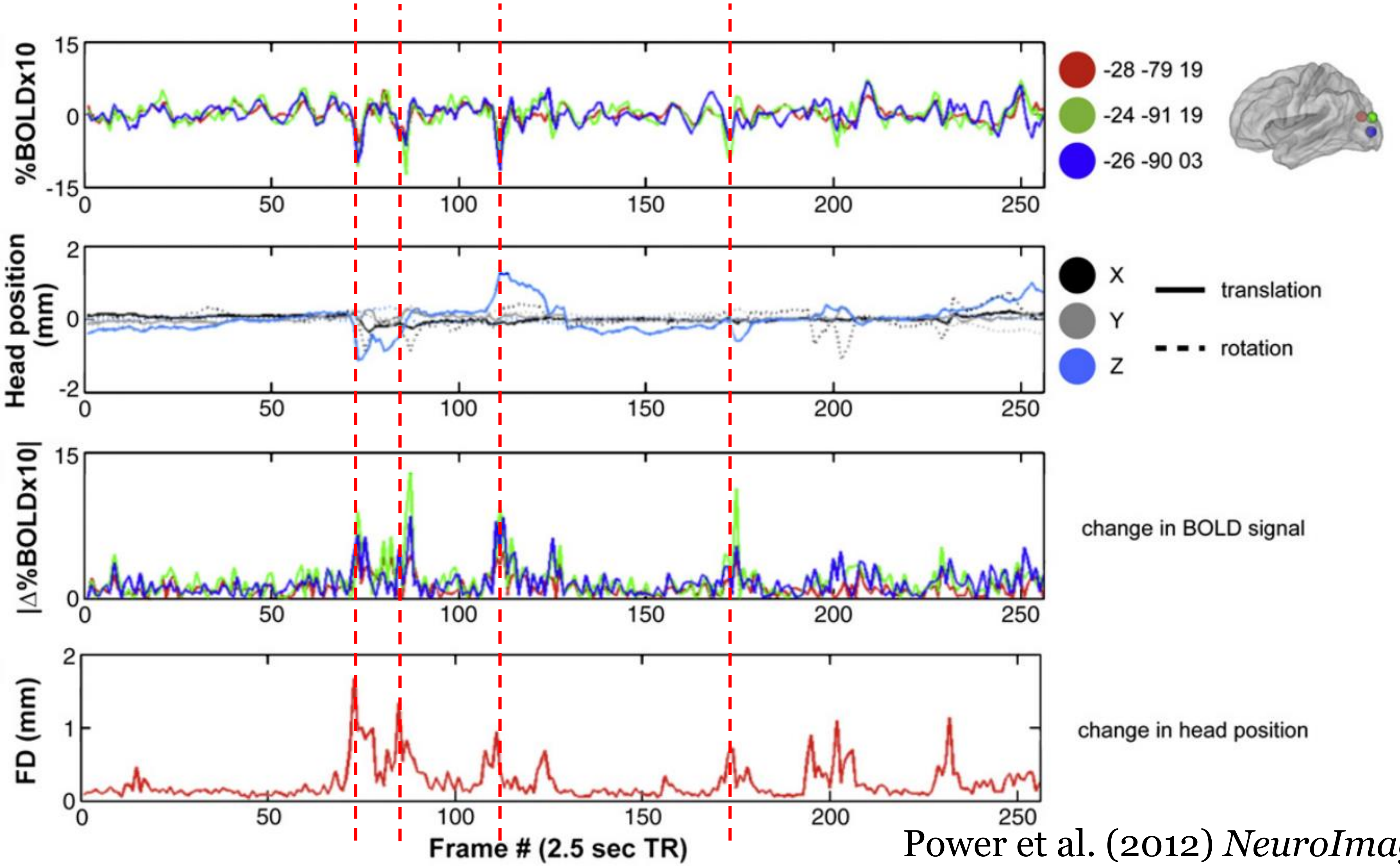
✧ Default Mode Network connectivity (PCC seed) is reduced in subject groups with more motion, even when differences are miniscule (0.044mm vs. 0.048mm mean motion)

Van Dijk, Sabuncu, & Buckner (2012) *NeuroImage*

Subject rejection and motion parameter regression

- Reject participants with more than *X*mm motion across a run
- For non-rejected participants, use estimated motion parameters as regressors of non-interest
- Might be insufficient to control for changes in signal intensity that accompany abrupt changes in head position (Power et al., 2012a; Satterthwaite et al., 2012; Van Dijk et al., 2012)

A "traditionally" high quality dataset



Power et al. (2012) *NeuroImage*

Head motion & BOLD relationship

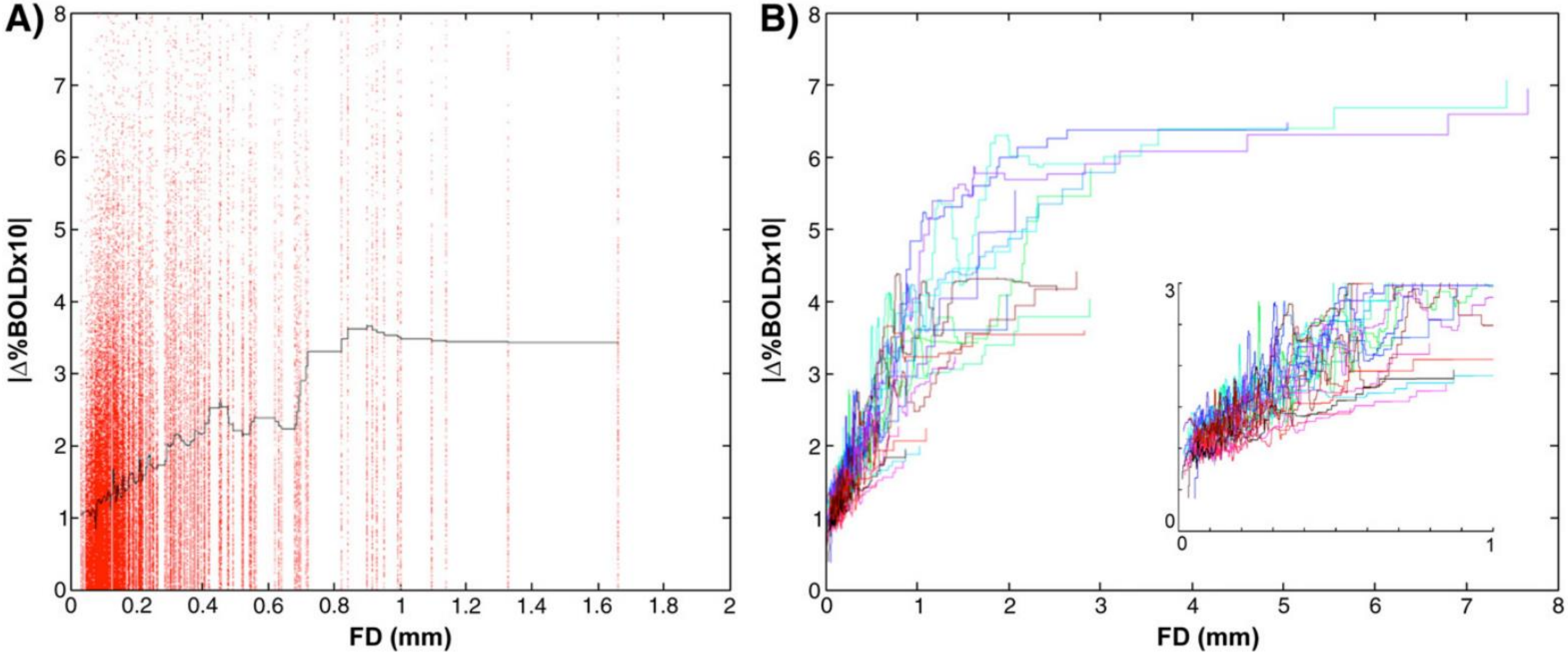


Fig. 2. Frame-by-frame head displacement is related to frame-by-frame changes in rs-fcMRI signal throughout the brain and across subjects. (A) For each frame of data in the same subject used in Fig. 1, the framewise displacement (FD) of a frame of data is plotted against the absolute values of the differentials of rs-fcMRI timecourses of 264 ROIs (locations listed and shown in Table S1 and Figure S3). These data are fitted with a loess curve (black line) sampling the nearest 5000 data points. (B) Identically produced loess curves from all 22 subjects in Cohort 1 are plotted against framewise displacement. There is a clear trend for larger frame-by-frame head displacement to co-occur with larger changes in rs-fcMRI signal. The inset magnifies the plot between framewise displacements of 0 and 1, demonstrating that this relationship exists even for very small movements.

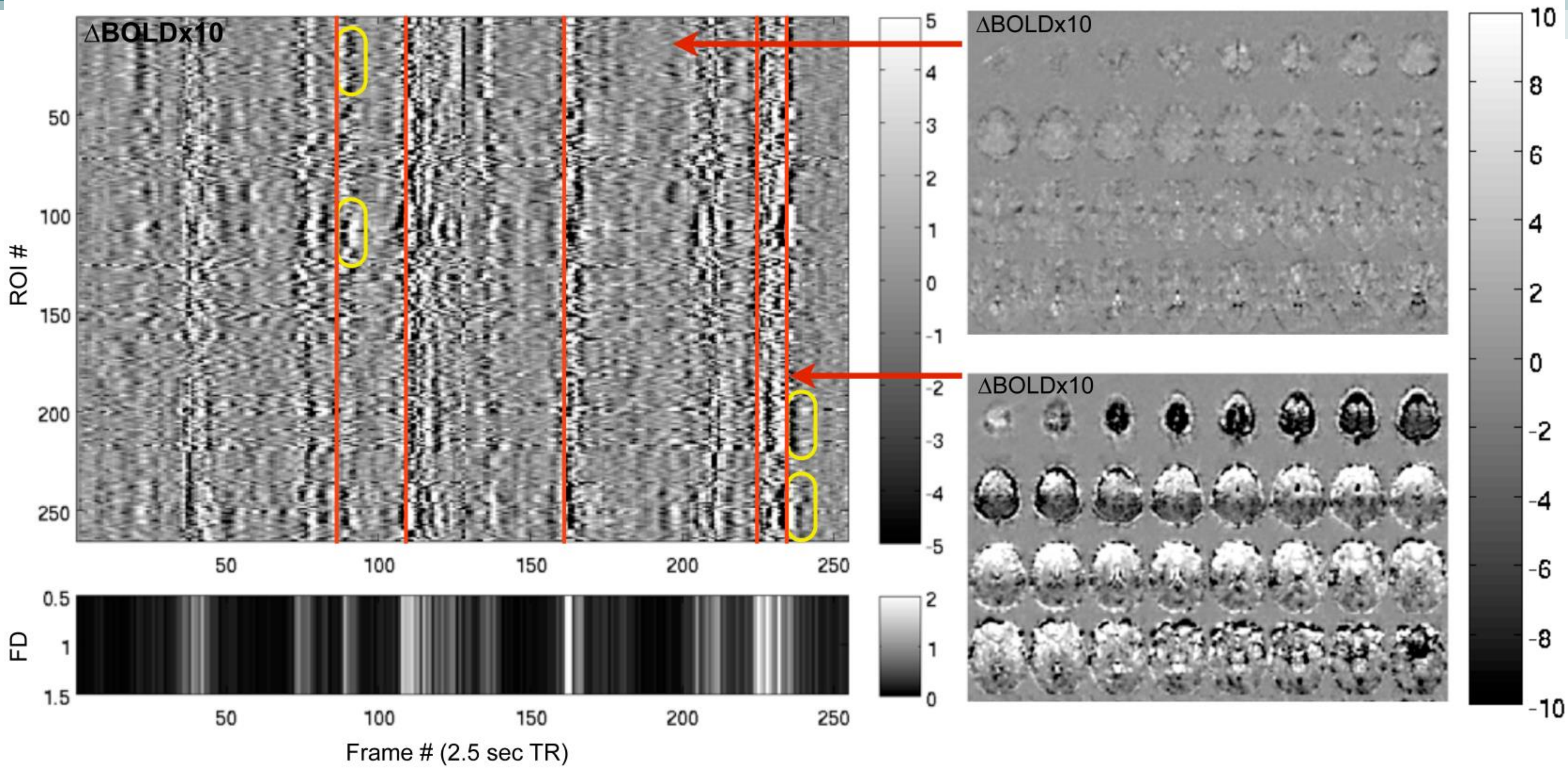
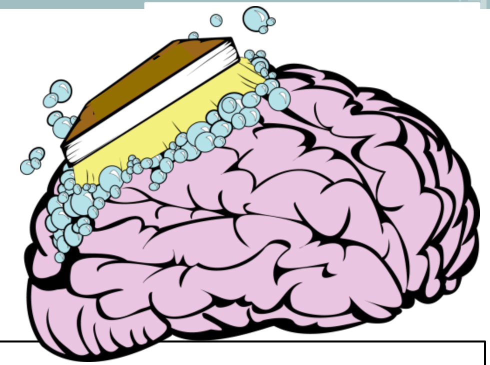


Figure S4: **Head motion simultaneously induces changes in BOLD signal in opposite directions in various parts of the brain.** In a single subject, the derivatives of 264 timecourses are plotted in grayscale, with time on the x-axis. Here, white indicates positive displacements of BOLD signal, and black indicates negative displacements of BOLD signal. Below this plot the framewise displacement (FD) is plotted in grayscale. Several periods of movement are indicated by the red lines in the upper plot. Looking directly to the right of the lines (using the red lines as a reference point), note that at identical time points, that BOLD signal is dramatically increased in some ROIs, and simultaneously dramatically decreased at other ROIs. Some examples are circled in yellow. At right, whole-brain images of the derivative of the BOLD signal are plotted for a low-motion frame (top) and a high-motion frame (bottom). Note the ringing artifact, as well as dorsal-ventral and anterior-posterior orientations of artifactual signal change. Plots in other subjects have similar characteristics.

Power et al. (2012) *NeuroImage*

"Scrubbing"



NeuroImage 59 (2012) 2142–2154

Contents lists available at SciVerse ScienceDirect

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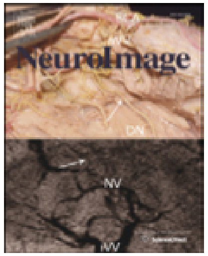
journal homepage: www.elsevier.com/locate/ynimg



Spurious but systematic correlations in functional connectivity MRI networks arise from subject motion

Jonathan D. Power [a,*], Kelly A. Barnes [a], Abraham Z. Snyder [a,b], Bradley L. Schlaggar [a,b,c,d], Steven E. Petersen [a,b,d,e]

[a] *Department of Neurology, Washington University School of Medicine, St. Louis, MO, USA*
[b] *Department of Radiology, Washington University School of Medicine, St. Louis, MO, USA*
[c] *Department of Pediatrics, Washington University School of Medicine, St. Louis, MO, USA*
[d] *Department of Anatomy & Neurobiology, Washington University School of Medicine, St. Louis, MO, USA*
[e] *Department of Psychology, Washington University in Saint Louis, St. Louis, MO, USA*

Framewise displacement (FD)

- $FD_i = |\Delta d_{ix}| + |\Delta d_{iy}| + |\Delta d_{iz}| + |\Delta\alpha_i| + |\Delta\beta_i| + |\Delta\gamma_i|$
  - Where $\Delta d_{ix} = d_{(i-1)x} - d_{ix}$
- This variable measures movement of any given frame relative to the previous frame (as opposed to relative to the reference frame of motion parameter estimation & regression).

Power et al. (2012) *NeuroImage*

DVARS

- **D** referring to temporal derivative of timecourses
- **VARS** referring to RMS variance over voxels
- Indexes the rate of change of BOLD signal across the entire brain at each frame of data.
- DVARS is thus a measure of how much the intensity of a brain image changes in comparison to the previous timepoint (as opposed to the global signal, which is the average value of a brain image at a timepoint).

$$\mathrm{DVARS}(\Delta I)_i = \sqrt{\left\langle \left[\Delta I_i\left(\vec{x}\right)\right]^2 \right\rangle} = \sqrt{\left\langle \left[I_i\left(\vec{x}\right) - I_{i-1}\left(\vec{x}\right)\right]^2 \right\rangle}$$

Power et al. (2012) *NeuroImage*

DVARS

- Because frame-to-frame changes in signal intensity related to movement are significantly greater than those caused by neurophysiologic changes in the BOLD signal, this measure provides a natural parameter with which to directly examine the relationship of movement measurements and the BOLD response (Fair et al 2013)

$$\mathrm{DVARS}(\Delta I)_i = \sqrt{\left\langle \left[\Delta I_i\left(\vec{x}\right)\right]^2 \right\rangle} = \sqrt{\left\langle \left[I_i\left(\vec{x}\right) - I_{i-1}\left(\vec{x}\right)\right]^2 \right\rangle}$$

Power et al. (2012) *NeuroImage*

Choice of a cut-off threshold

- From Power et al. (2012): "After studying the plots of dozens of healthy adults, values of **0.5 mm for framewise displacement** and **0.5% ΔBOLD for DVARS** were chosen to represent values well above the norm found in still subjects."
  - Also removed *1 TR before* and *2 TRs after* bad frame
- Fair et al. (2013) used an even more stringent FD cut-off of 0.2 mm and DVARS cut-off of 0.4%

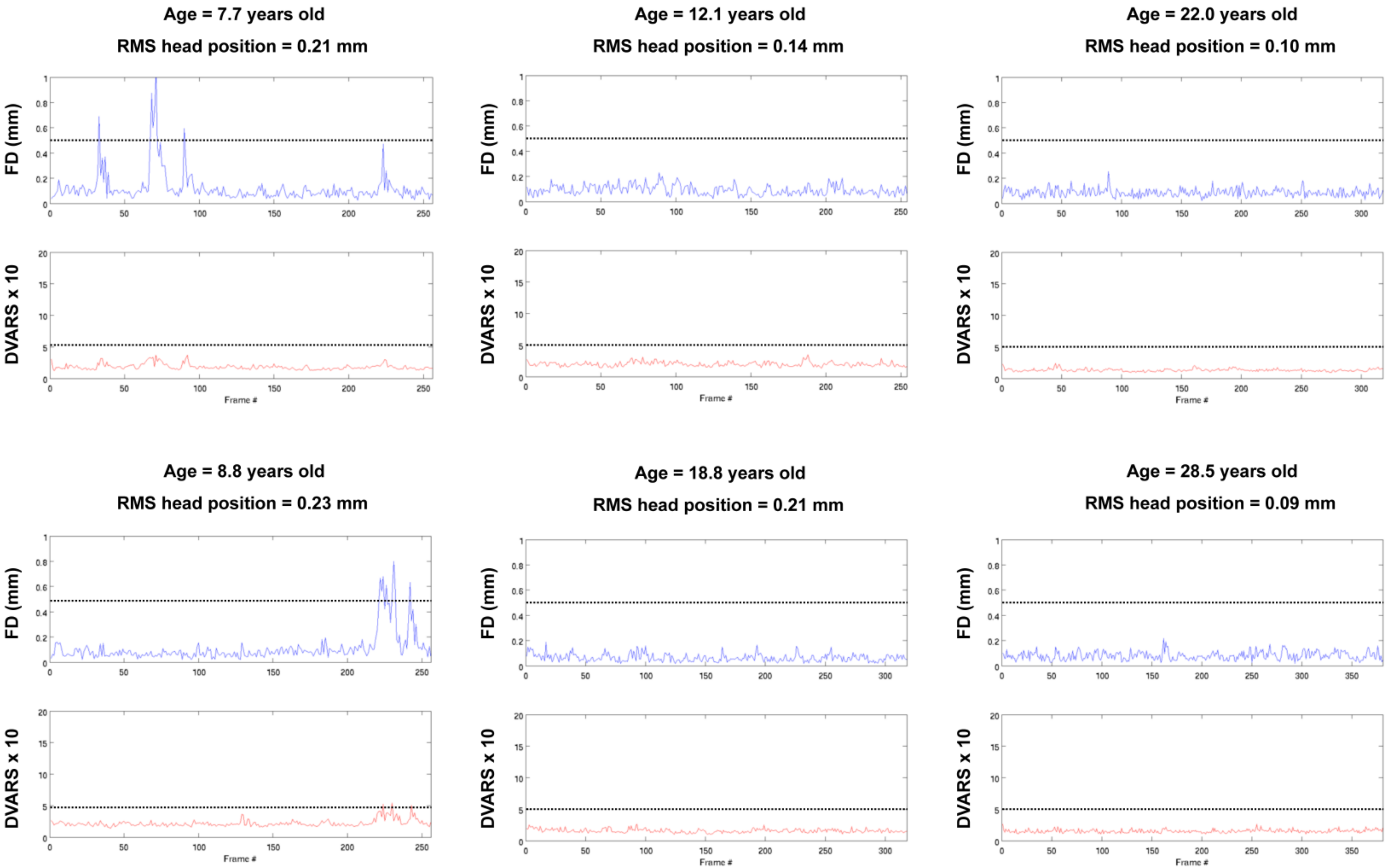
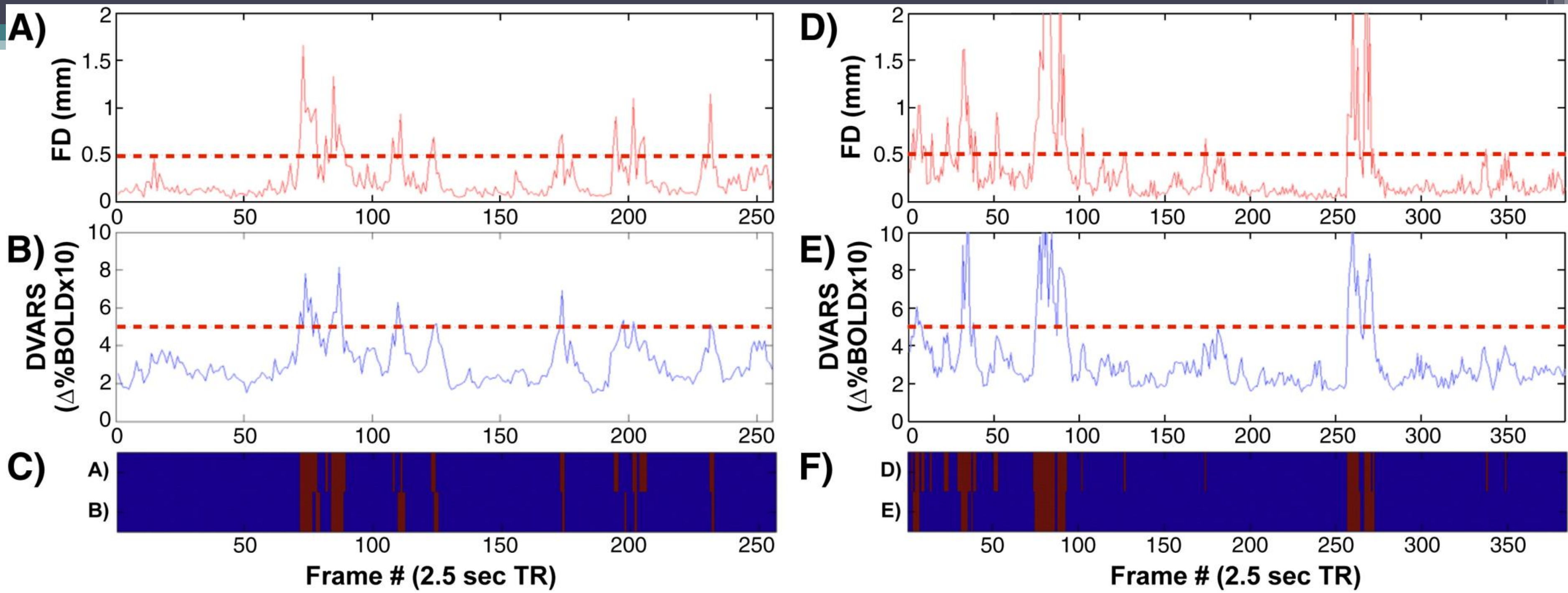


Figure S5: **Floors in DVARS and framewise displacement values exist at all age ranges.** Data from six relatively still subjects are shown, including the age, RMS head position, the framewise displacement (FD), and the DVARS calculations on the functional connectivity image. A floor in FD and DVARS values exists across all ages. Examination of these plots in hundreds of subjects gave rise to the standard thresholds used in this study to identify periods of movement, indicated by the horizontal black lines in the plots (0.5 mm framewise displacement and 0.5% ΔBOLD DVARS (5 on the scales of this figure)).

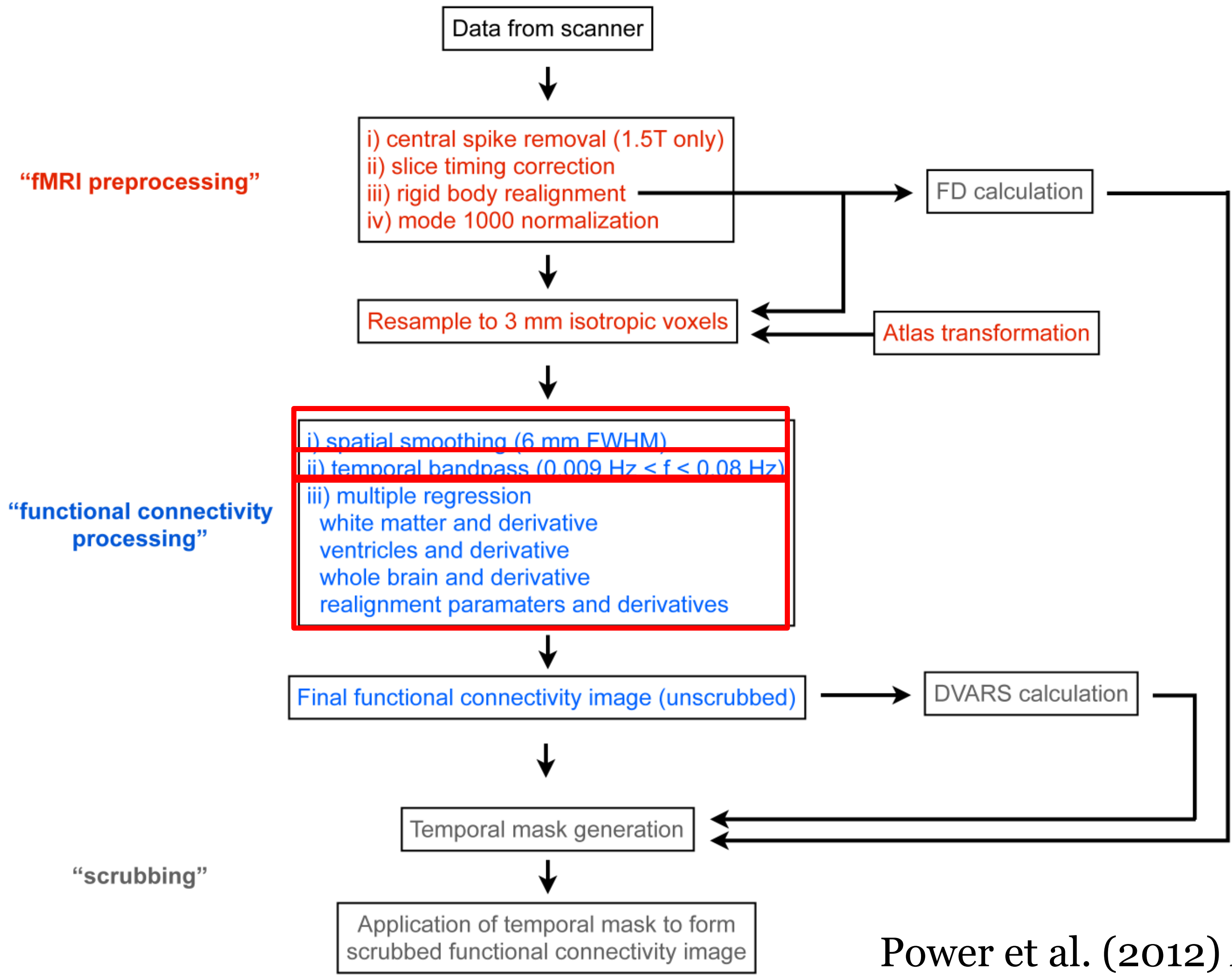
Power et al. (2012) *NeuroImage*



- Temporal masks (red bars) were augmented by also marking the frames 1 back and 2 forward
- All removed frames must *both*:
  1) be high-motion frames (based on FD)
  2) display evidence of widespread and/ or large amplitude changes in BOLD signal (based on DVARS)

Power et al. (2012) *NeuroImage*

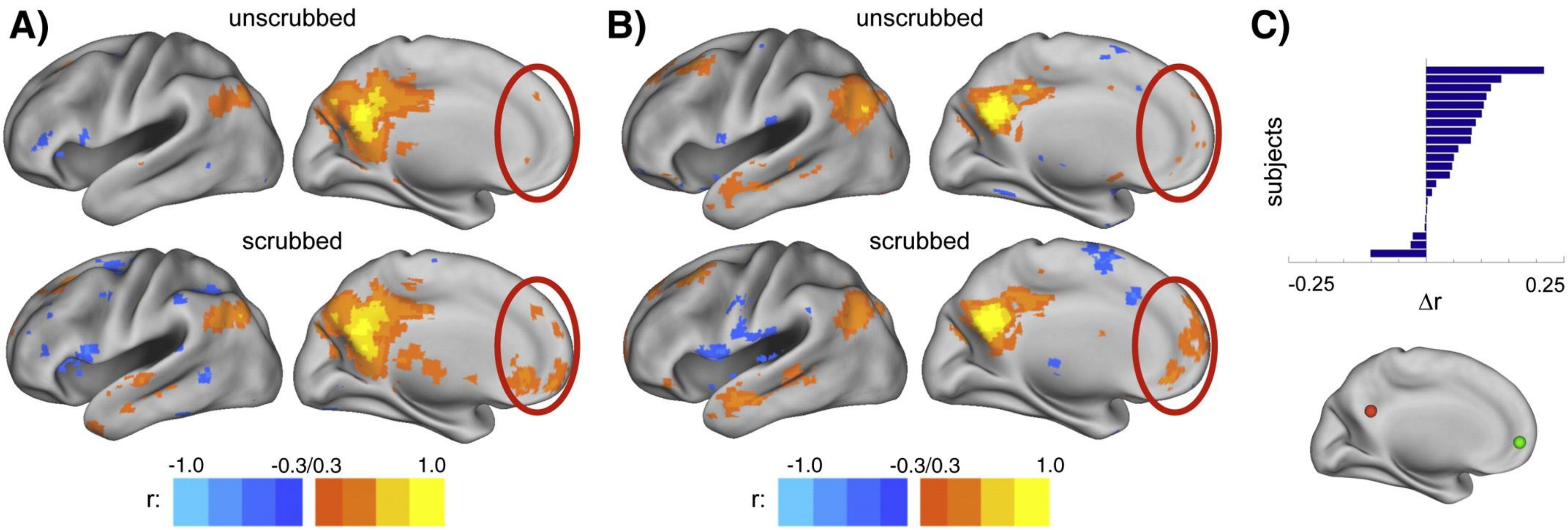
Example data processing workflow



Power et al. (2012) *NeuroImag*

Impact of scrubbing on rs-fMRI data

Subject 1 **Subject 2**

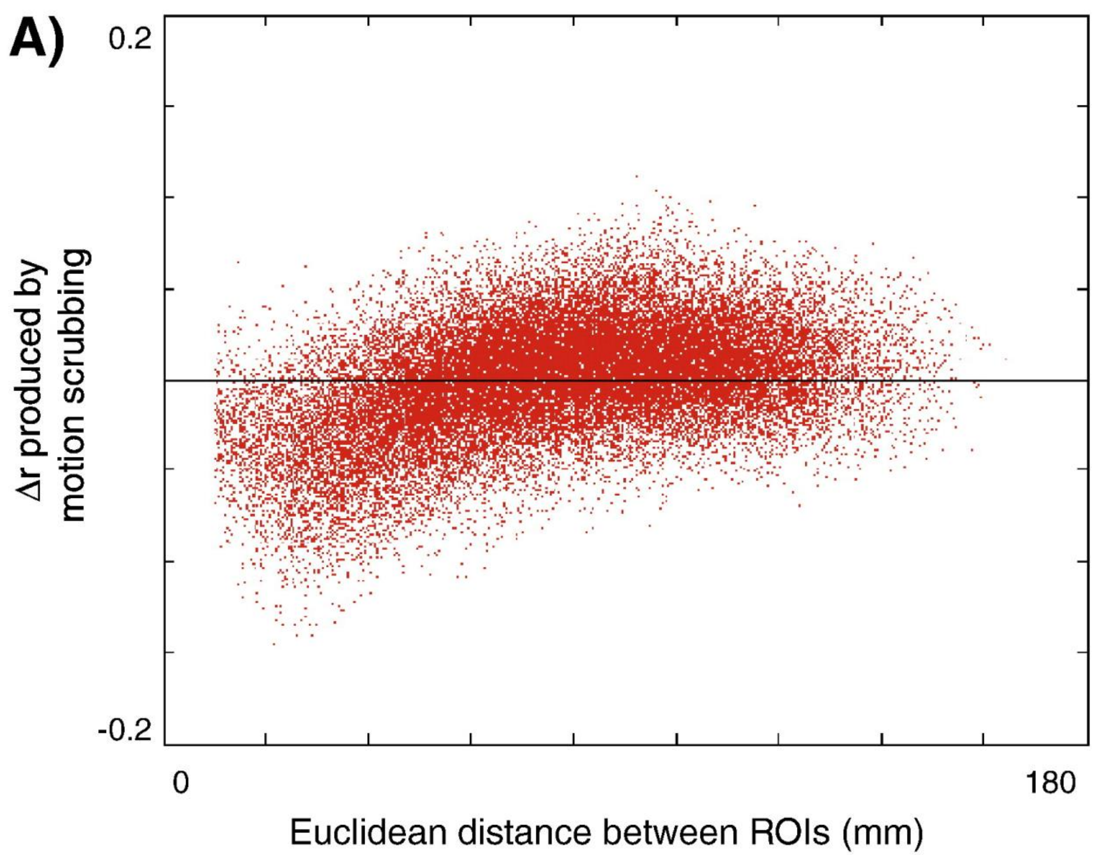


35% of data scrubbed out **39% of data scrubbed out**

- Scrubbing increases this long-distance correlation in most subjects, does not substantially alter it in others, and reduces it in a small number of subjects.

Power et al. (2012) *NeuroImage*

Impact of scrubbing on rs-fMRI data



- Scrubbing high-motion frames decreases short-distance correlations and augments long-distance correlations

Power et al. (2012) *NeuroImage*

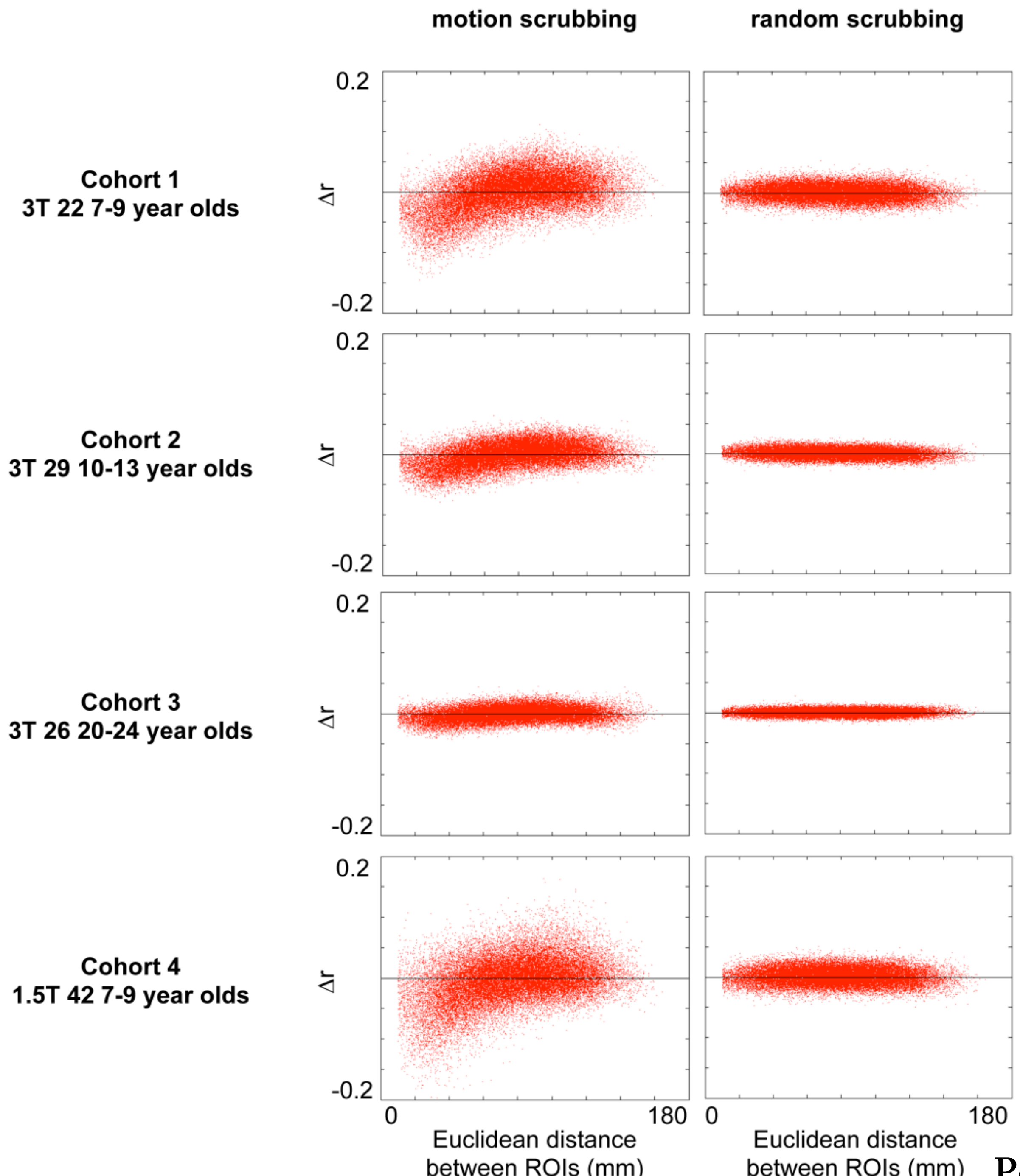
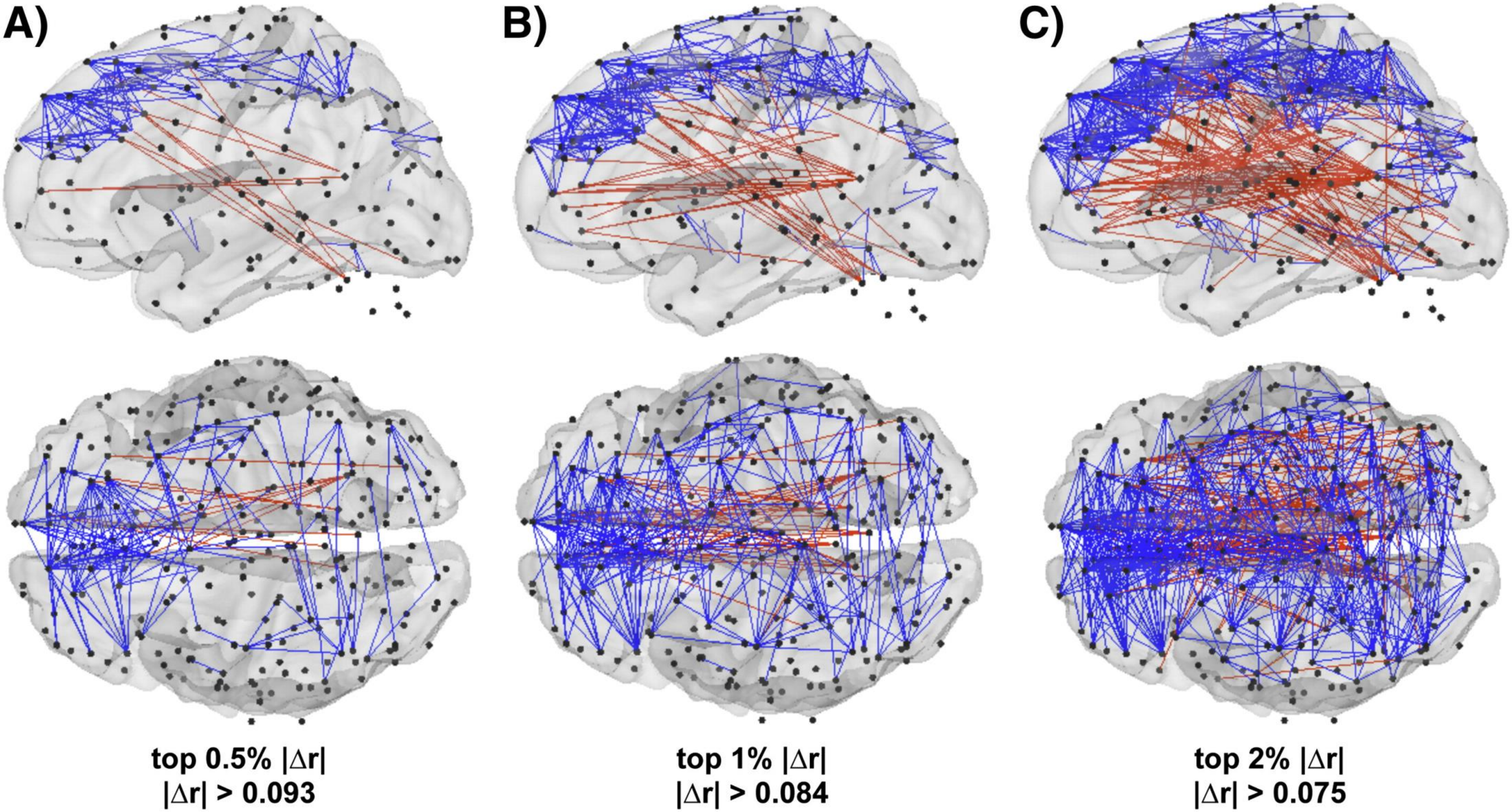


Figure S9: **Scrubbing high-motion frames from rs-fcMRI data decreases short-distance correlations and augments long-distance correlations in four independent cohorts.** Within an N-subject cohort, 264 ROIs were applied to scrubbed and unscrubbed data to produce two 264x264xN correlation matrices. The unscrubbed matrix was subtracted from the scrubbed matrix and then averaged over subjects to produce a difference matrix (Δr). The mean values of this matrix are plotted as a function of the Euclidean distance between ROIs in the left column for each cohort. In each cohort, short-distance correlations are decreased by scrubbing high-motion frames from the data, and medium- to long-distance correlations are increased. To demonstrate that these effects arise from the removal of high-motion frames and not frame removal in general, the number of frames and the size of contiguous chunks of removed data were calculated for each subject, and identical sized chunks of data and numbers of frames were removed at random from each subject's data. Difference matrices were calculated as before, and data are presented in the right column. Random scrubbing abolishes the Δr by distance effect. This process was repeated 10 times in each cohort with similar results. For each cohort, the difference in Δr magnitudes between motion and random scrubbing was highly significant (paired two-tail t-test: t = 305; t = 303; t = 260; t = 360, p = 0 in all cases)

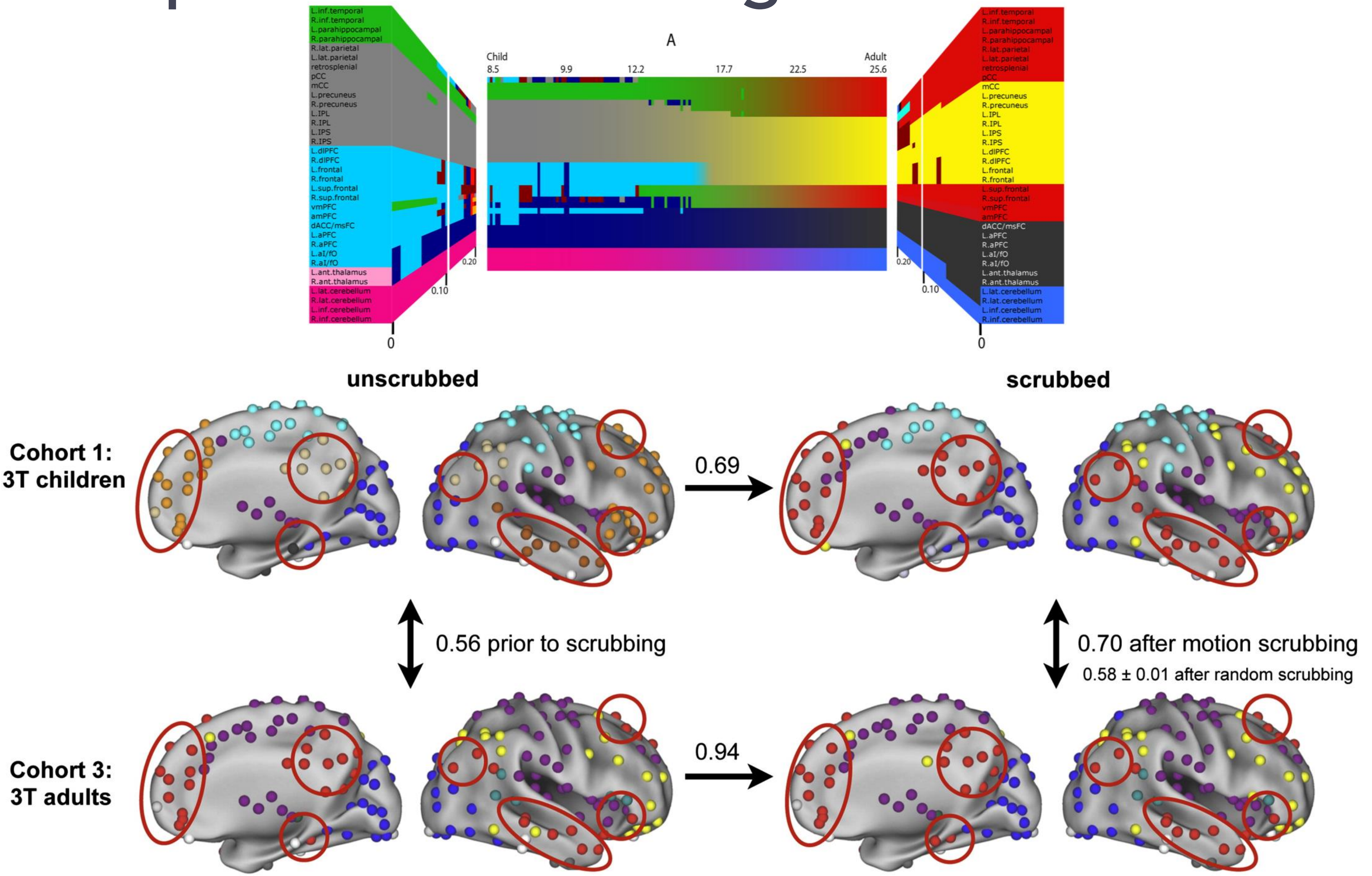
Power et al. (2012) *NeuroImage*

Impact of scrubbing on rs-fMRI data



Power et al. (2012) *NeuroImage*

Impact of scrubbing on rs-fMRI data



Power et al. (2012) *NeuroImage*

So is scrubbing *the* thing?

- Exclusion of TRs might have unwanted effects:
  1. Loss of dfs (might/might not be a big deal at 1st lvl)

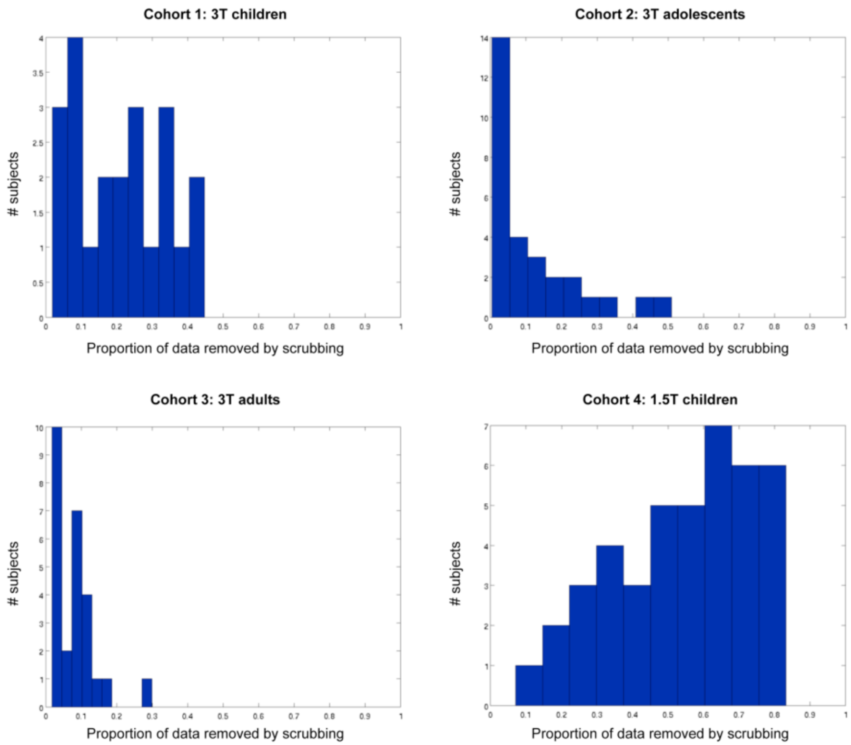
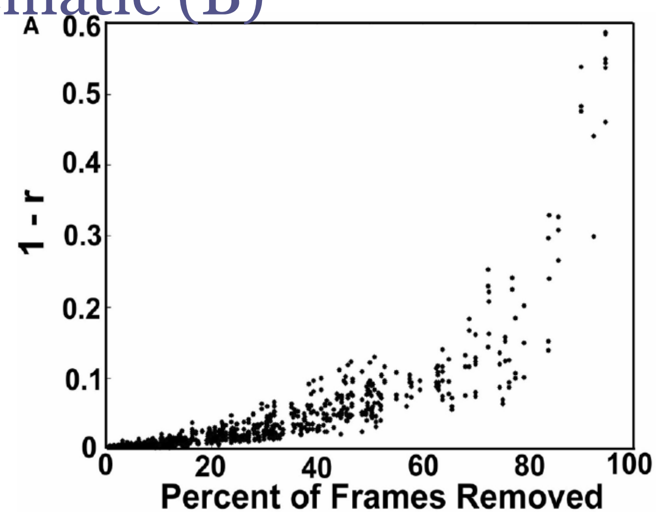


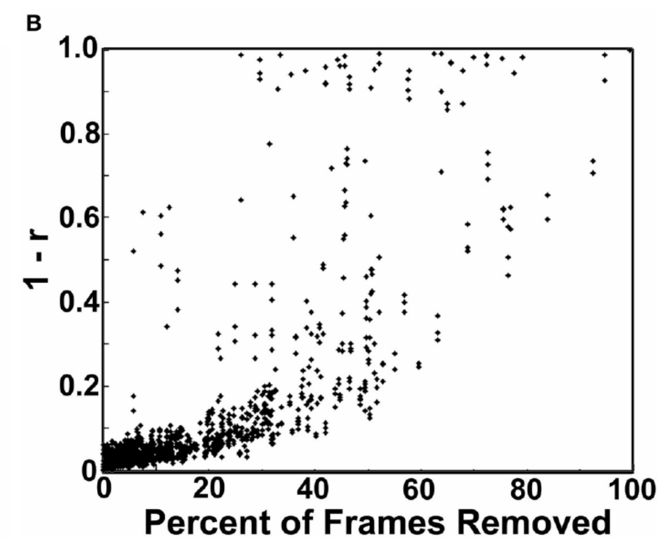
Figure S7: **The impact of scrubbing on data retention.** For each cohort analyzed in this report, the proportion of data removed within each subject is plotted as a histogram. More data was removed in younger subjects, who tended to move more than older subjects (see Table 1). All subjects had more than 125 frames (~5 min) of data remaining after scrubbing.

Power et al. (2012) *NeuroImage*

So is scrubbing *the* thing?

- Exclusion of TRs might have unwanted effects:
  1. Loss of dfs (might/might not be a big deal at 1st lvl)
  2. Uneven loss of dfs across groups/conditions
     - Randomly remove equal # of TRs from 'good' runs?
     - Turns out, that might be problematic too (A)
     - Using interpolations to "impute" excised data is also problematic (B)



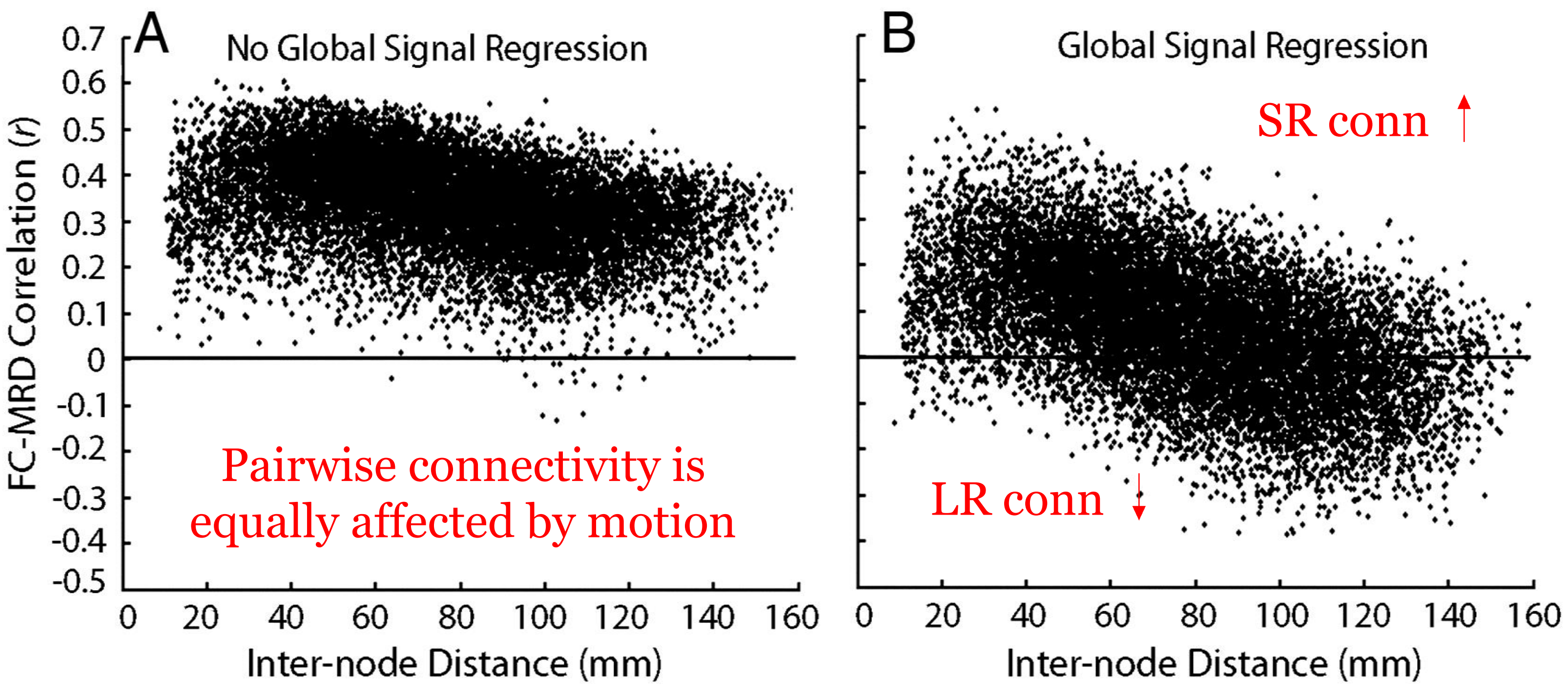


Fair et al. (2012) *Frontiers*

So is scrubbing *the* thing?

- Exclusion of TRs might have unwanted effects:
  1. Loss of dfs (might/might not be a big deal at 1st lvl)
  2. Uneven loss of dfs across groups/conditions
  3. Lose the ability to perform any frequency-based analysis
- The distance-dependent bias *does not* appear to be driven by the mere presence of motion!

Effect of GSR on motion-dependent correlation



Satterthwaite et al (2013) *NeuroImage*

Does scrubbing correct distance-dependent bias?

model GS + MO

$$Y^i = X_{\mathrm{GS}}B^i_{\mathrm{GS}} + X_{\mathrm{WM}}B^i_{\mathrm{WM}} + X_{\mathrm{LV}}B^i_{\mathrm{LV}} + X_{\mathrm{MO}}B^i_{\mathrm{MO}} + X_{\mathrm{DT}}B^i_{\mathrm{DT}} + \text{residual}$$

model GS

$$Y^i = X_{\mathrm{GS}}B^i_{\mathrm{GS}} + X_{\mathrm{WM}}B^i_{\mathrm{WM}} + X_{\mathrm{LV}}B^i_{\mathrm{LV}} + X_{\mathrm{DT}}B^i_{\mathrm{DT}} + \text{residual}$$

model MO

$$Y^i = X_{\mathrm{MO}}B^i_{\mathrm{MO}} + X_{\mathrm{DT}}B^i_{\mathrm{DT}} + \text{residual}$$

model MO + $\mathrm{WMe}_{\mathrm{LOCAL}}$

$$Y^i = X_{\mathrm{MO}}B^i_{\mathrm{MO}} + X^i_{\mathrm{WMe}_{\mathrm{LOCAL}}}B^i_{\mathrm{WMe}_{\mathrm{LOCAL}}} + X_{\mathrm{DT}}B^i_{\mathrm{DT}} + \text{residual}$$

model Despike + MO + $\mathrm{WMe}_{\mathrm{LOCAL}}$

$$Y^i = X_{\mathrm{MO}}B^i_{\mathrm{MO}} + X^i_{\mathrm{WMe}_{\mathrm{LOCAL}}}B^i_{\mathrm{WMe}_{\mathrm{LOCAL}}} + X_{\mathrm{DT}}B^i_{\mathrm{DT}} + \text{residual}$$

Jo et al. (2013) *Journal of Applied Mathematics*

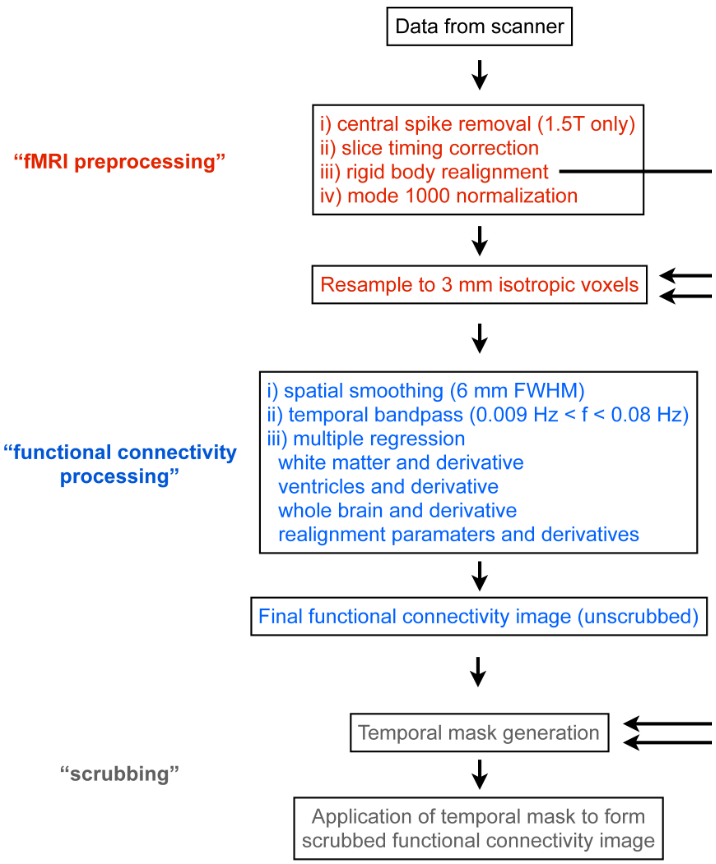
Does scrubbing correct distance-dependent bias?

Pearson correlation difference

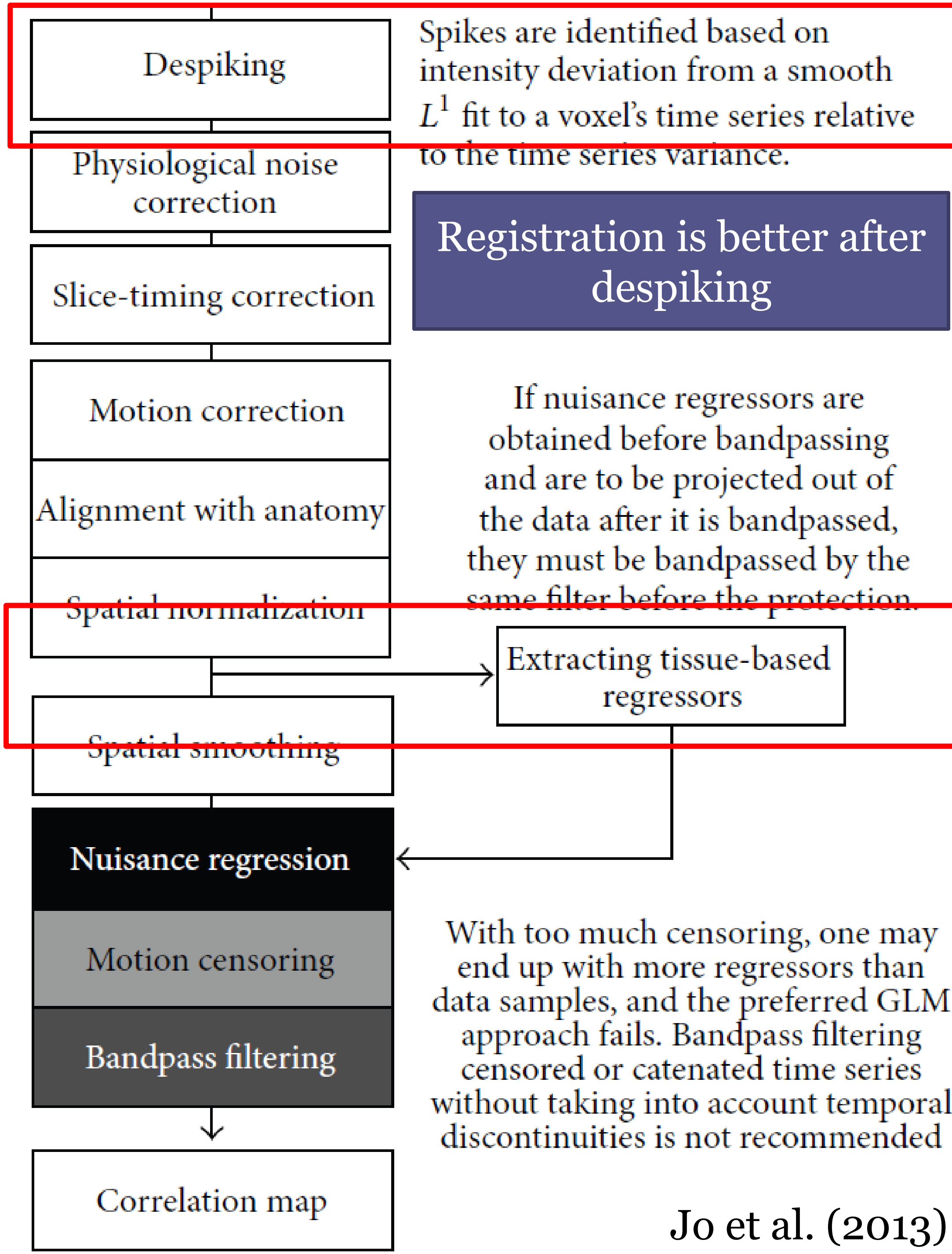
The addition of GS to the model exacerbates the distance-dependence of the correlation estimates on motion, with results that are more dependent on the level of motion censoring.
Only use WMlocal, since “global” regressors can cause group differences by spreading hardware artifacts not visually detectable

Jo et al. (2013) *Journal of Applied Mathematics*

The order of t



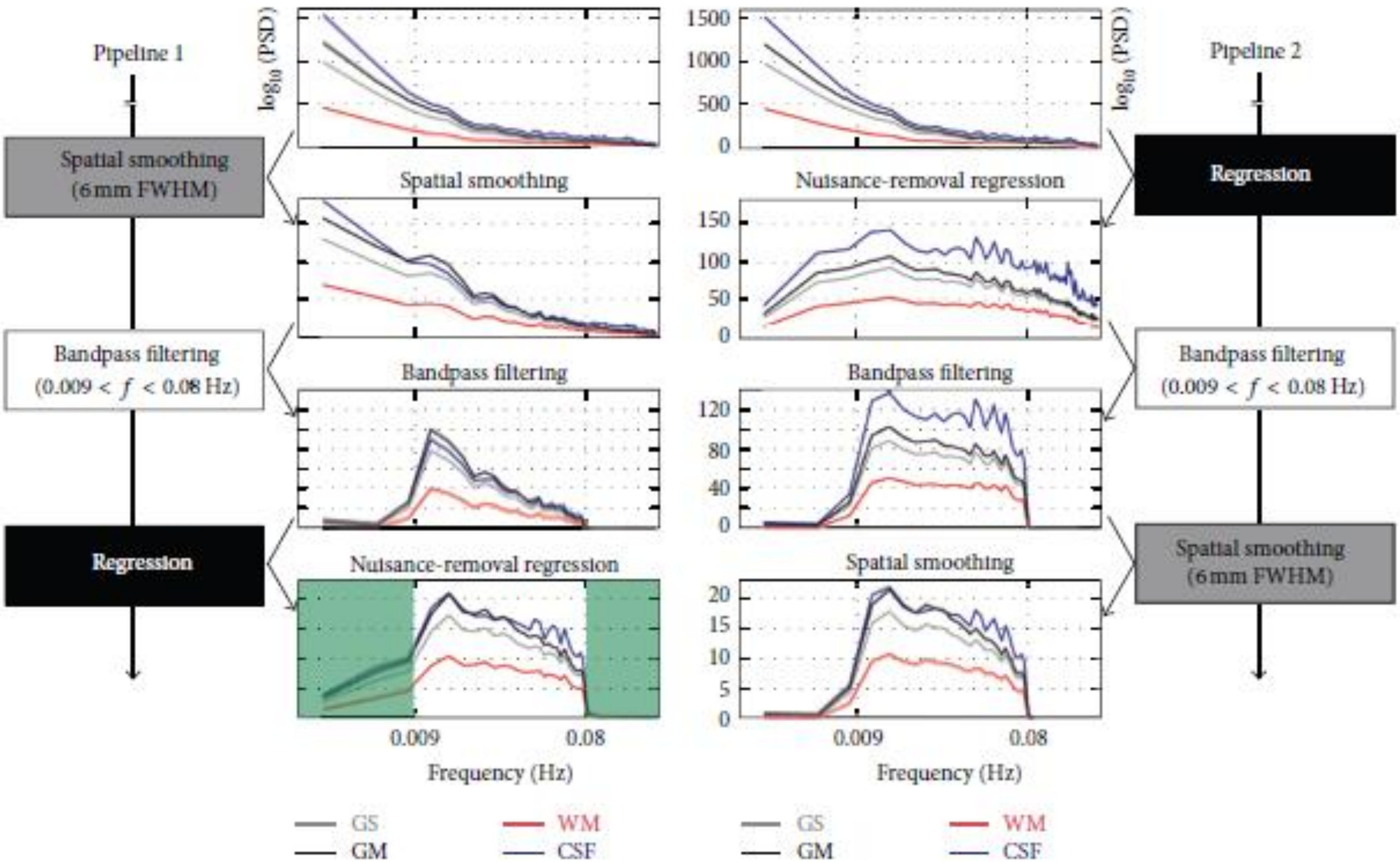
Power et al. (2012) *NeuroImage*



Jo et al. (2013)

The order of things matters!

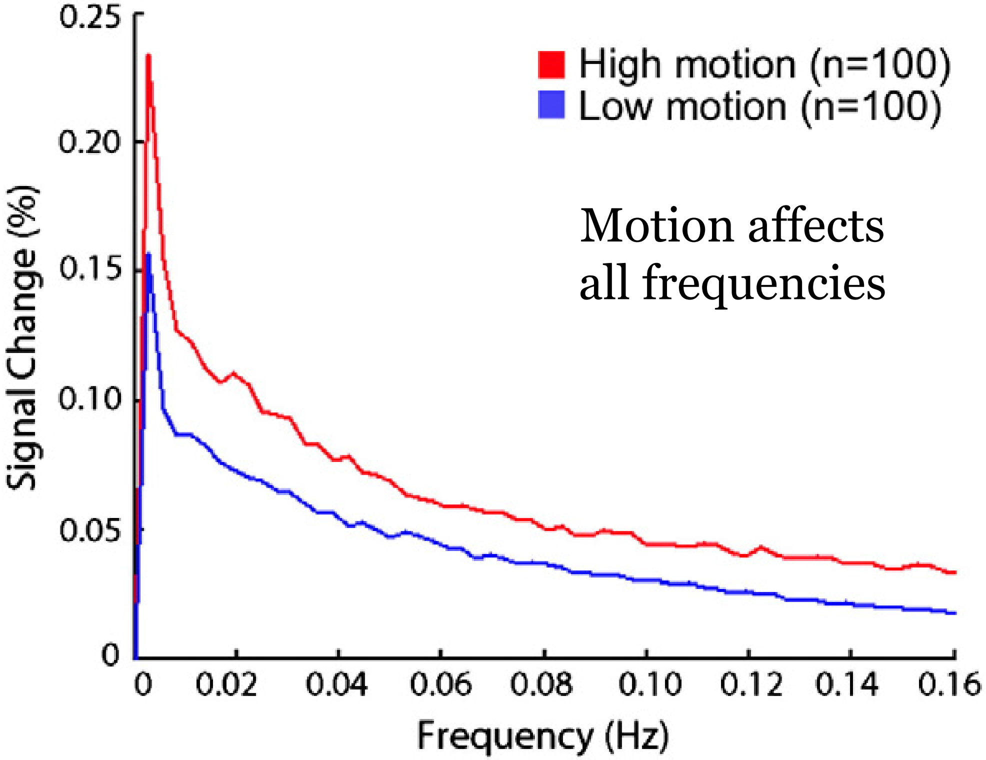
Power spectra analysis



Jo et al. (2013)

“The best model” – reprise

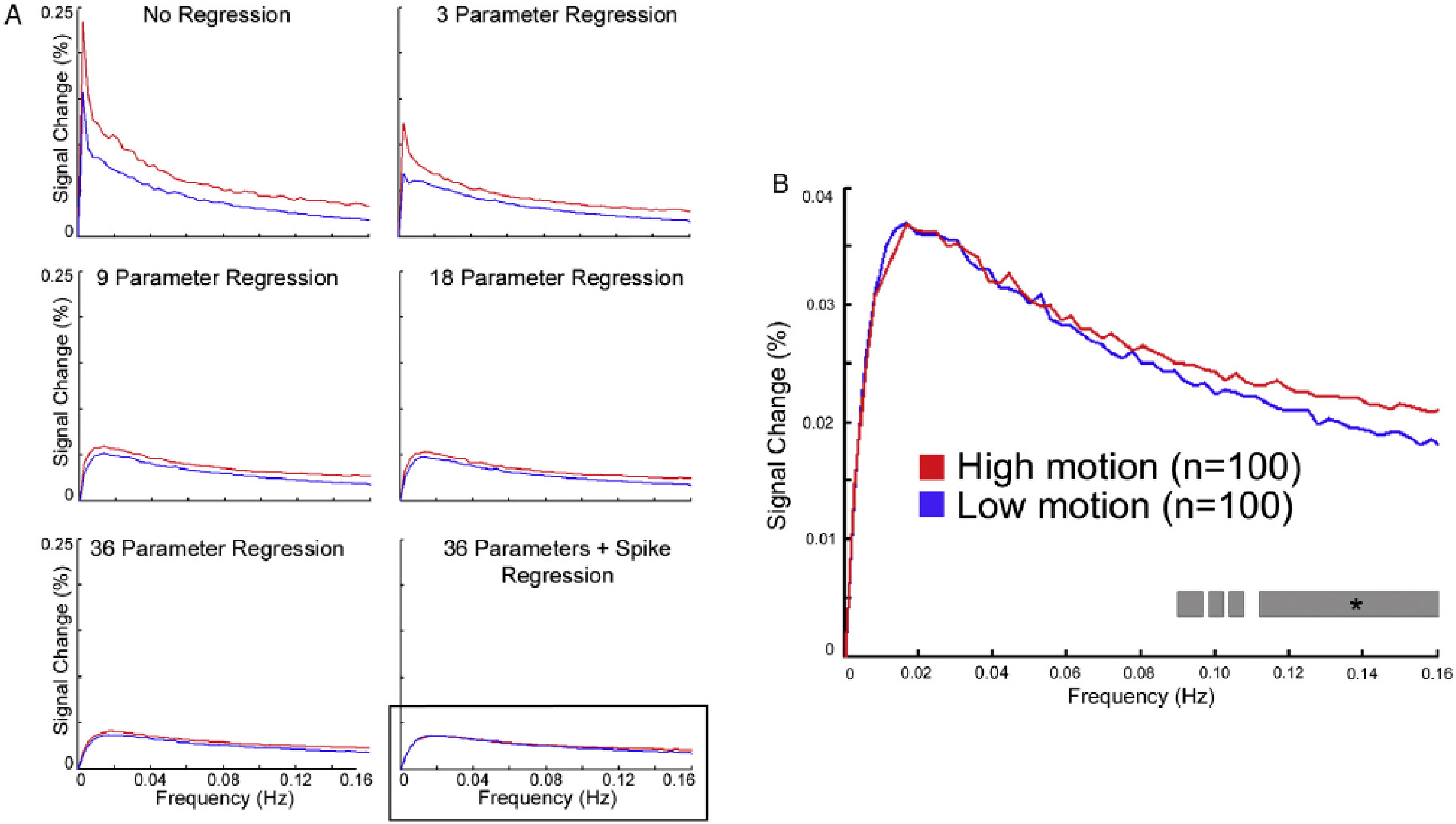
- 3 par: GMS, WM, CSF
- 9 par: 3par + 6Motion (tra,rot)
- 18 par: 9par + f’(t)
- 36 par: 18 par + f’’(t)



Motion affects all frequencies

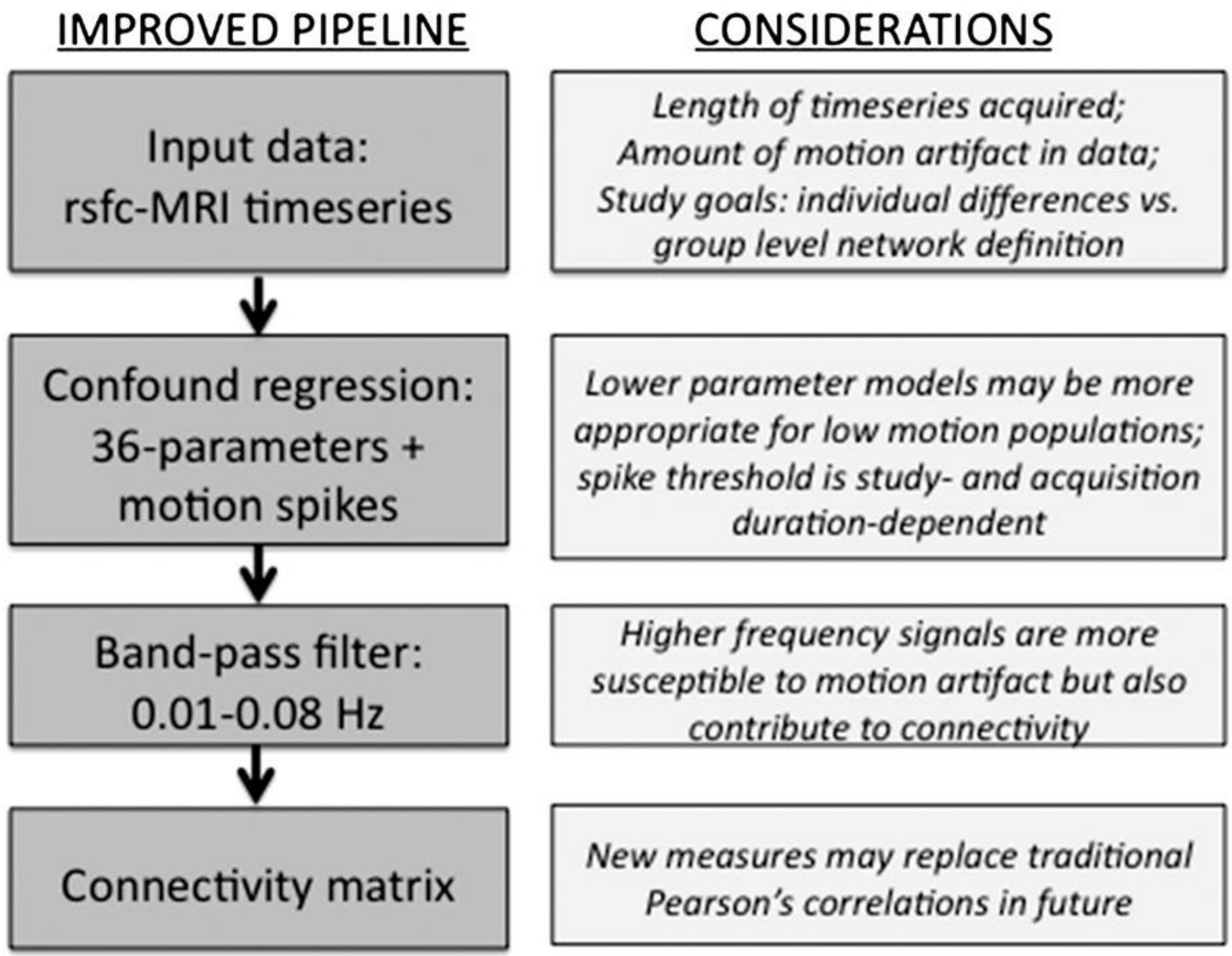
Satterthwaite et al. (2013)

“The best model” – reprise



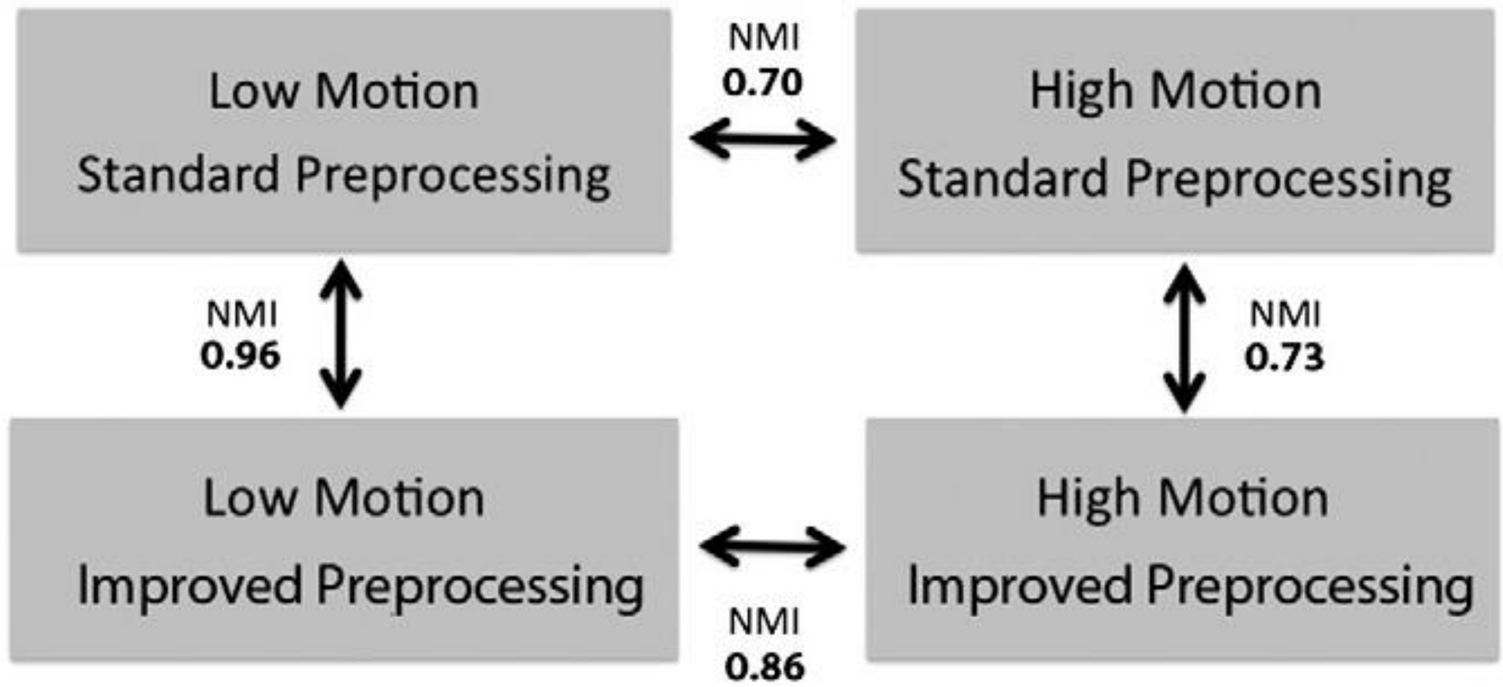
Satterthwaite et al. (2013)

“The best model” – reprise



Satterthwaite et al. (2013)

“The best model” – reprise



Modularity is no longer affected by motion!

Satterthwaite et al. (2013)

Reading list (i)

- Description of the problem:
  - Power JD, Barnes KA, Snyder AZ, Schlaggar BL, Petersen SE. (2012) *Spurious but systematic correlations in functional connectivity MRI networks arise from subject motion*. Neuroimage 59(3):2142-54
  - Van Dijk KR, Sabuncu MR, Buckner RL. (2012) *The influence of head motion on intrinsic functional connectivity MRI*. Neuroimage. 59(1):431-8.
  - Satterthwaite TD, Wolf DH, Loughead J, Ruparel K, Elliott MA, Hakonarson H, Gur RC, Gur RE. (2012) *Impact of in-scanner head motion on multiple measures of functional connectivity: relevance for studies of neurodevelopment in youth*. Neuroimage. 2012 Mar;60(1):623-32

Reading list (ii)

- What can we do about it?
  - Satterthwaite TD, Elliott MA, Gerraty RT, Ruparel K, Loughead J, Calkins ME, Eickhoff SB, Hakonarson H, Gur RC, Gur RE, Wolf DH. (2013) *An improved framework for confound regression and filtering for control of motion artifact in the preprocessing of resting-state functional connectivity data*. Neuroimage. 64:240-56.
  - Hang Joon Jo, Stephen J. Gotts, Richard C. Reynolds, et al., (2013) *Effective Preprocessing Procedures Virtually Eliminate Distance-Dependent Motion Artifacts in Resting State FMRI*. Journal of Applied Mathematics, 2013.
  - Hallquist MN, Hwang K, Luna B (2013) *The nuisance of nuisance regression: Spectral misspecification in a common approach to resting-state fMRI preprocessing reintroduces noise and obscures functional connectivity.* Neuroimage. 82:208-25.
  - Yan CG, Cheung B, Kelly C, Colcombe S, Craddock RC, Di Martino A, Li Q, Zuo XN, Castellanos FX, Milham MP. (2013) *A comprehensive assessment of regional variation in the impact of head micromovements on functional connectomics*. Neuroimage. 76:183-201.

  - **Note**: this is work-in-progress and a moving target, as new papers come out the field might converge – The two paper above, however, will give you a good understanding of the kind of pipeline you should use.

Reading list (iii)

- For task based analyses
  - Christodoulou AG, Bauer TE, Kiehl KA, Feldstein Ewing SW, Bryan AD, Calhoun VD. (2013) *A quality control method for detecting and suppressing uncorrected residual motion in fMRI studies*. Magn Reson Imaging. 31(5):707-17.

  - You can find the list (with PubMed links) here: **http://montilab.psych.ucla.edu/fmri-wiki**