in part by the static connectivity magnitude (as well as other factors, such as window length, whether windows overlap or not, the power spectrum of the time series, etc.). It is also worth noting that our approach aims to estimate this distribution as closely as possible by generating many surrogate time series samples that have many properties in common with the empirical fMRI BOLD time series.

Our results are limited, in part, by the length of fMRI scan sessions. For example, we estimated the static functional connectivity for each participant based on 885 observations (time points or TRs, corresponding to approximately 9.37 minutes), and as a result of the finite sample size, consequently may not know the *true* (i.e. very long term) values of static connectivity between pairs of regions (Laumann et al., 2015).

In this paper we focus on functional connectivity as calculated by Pearson's correlation coefficient, as it is the most frequently-used measure in the extant literature. It should be noted that there are many alternative functional connectivity metrics (Smith et al., 2011), some of which can be applied to time-varying networks as well. Determining whether static estimates of functional connectivity made from these alternative measures can be used to predict dynamic connectivity is beyond the scope of this report, though we suspect that a similar rationale applies to these alternative measures.

Concluding remarks

We show that the use of correlation as a measure of dynamic functional connectivity implies a number statistical sequelae, for example that connectivity over longer time-scales constrains the expected dynamic fluctuations expected at shorter time scales. We propose a method for identifying functional connections that are unexpectedly strong or weak, applying this technique to fMRI BOLD data. From these data, we show that dynamic functional connectivity