Electronic Supplementary Materials

for

"*On the dynamics of social hierarchy: A longitudinal investigation of the rise and fall of prestige, dominance and social rank in naturalistic task groups*"

Peer-Report Measures

Prestige. To measure prestige participants rated all members of their task group on four items taken from the dominance-prestige scale questionnaires (Cheng, Tracy & Henrich, 2010). The four items were: "*Members of your group respect and admire them*", "*Their unique talents and abilities are recognized by others in the group*", "*They are considered an expert on some matters by members of the group*", "*Members of your group seek his/her advice on a variety of matters*". We used an abridged version of the scale to reduce participant fatigue. Use of the abridged scale substantially increased the internal consistency of both measures of prestige and dominance in comparison to the full scale. The abridged scale had a strong correlation (ρ =.921, α = .97) with the full scale that measured a subset of participants in classroom indicating that the measures captured the same variance. The measure had excellent internal consistency throughout the study. In time wave 1, α = .88, wave 2 α = .89, wave 3 α = .88, and in wave 4 α = .90.

Dominance. Participants rated all members of their task group on four items taken from the dominance-prestige scale questionnaires (Cheng, Tracy & Henrich, 2010). The four items were: "*They enjoy having control over other members of the group*", "*They often try to get their own way regardless of what others in the group may want*", "*They are willing to use aggressive tactics to get their way*", "*They try to control others rather than permit them to control them*". Again, use of the abridged scale substantially increased the internal consistency of both measures of prestige and dominance in comparison to the full scale. The abridged scale had a strong correlation (ρ =.939, α = .93) with the full scale that measured a subset of participants in classroom indicating that the measures captured the same variance.

The measure had excellent internal consistency throughout the study. In time wave 1, $\alpha =$ .82, wave 2 $\alpha = .86$, wave 3 $\alpha = .91$, and in wave 4 $\alpha = .93$.

Social Rank. As outlined in the current manuscript we used previously validated measures of social rank that predict the actual decision-making capacity of members within groups (Cheng et al., 2013). The measure had adequate to good internal consistency throughout the study. In time wave 1, $\alpha = .71$, wave 2 $\alpha = .79$, wave 3 $\alpha = .74$, and in wave 4 $\alpha = .68$.

Bivariate Correlations between Prestige, Dominance and Social Rank

As with the partial correlation matrix, we specified a uniform prior on the space of bivariate correlation matrices. Estimation was carried out using R package Stan and we again used a NUTS sampler with 4 chains and 2000 iterations. All parameters had above 1999 effective samples and an $\hat{R}$ of 1.00, indicating appropriate model convergence. As shown in ESM Figure 1, bivariate correlations between prestige and social are positive and substantial at every wave. Bivariate correlations between dominance and social rank were again positive and substantial in the initial wave of measurement ($\rho = 0.19$, $CI = [0.08, 0.30]$). However, throughout the remainder of the study the correlation between dominance and social rank was negligible.

Hierarchical Bayesian Continuous-Time Dynamic Modelling

Hierarchical Bayesian continuous-time dynamic modelling was chosen to analyse the current data as it provides several advantages to more traditional discrete time or trajectoryoriented models for longitudinal data (such as multi-level modelling and latent growth curve modelling). Dynamic models comprise a broad range of modelling techniques that assess how processes function within subjects over time. These processes often follow a smooth trajectory, are sequentially dependent (i.e. autocorrelation/autoregression) and are guided by small levels of stochastic inputs (i.e. there is a small amount of randomness in changes over time). These processes also unfold over continuous time and modelling change over time in discrete time points can amount to a number of issues. Discrete time models assume that there are equal time intervals between points of measurement and, in most cases, this assumption is not satisfied, which can cause bias in parameter estimates (de Haan-Rietdijk, Voelkle, Keijsers, & Hamaker, 2017; Voelkle & Oud, 2013). These strict assumptions associated with equally spaced periods between measurements further hinder the generalizability of results as comparison between studies that have differently spaced time intervals is not easy. The use of continuous time models overcome these problems by naturally accounting for differing time intervals by explicitly incorporating time interval into the equation, thus estimating latent continuous time parameters and therefore assessing the behaviour of a given processes at any point in time (regardless of whether it is observed or not). Moreover, unlike other approaches, continuous time structural equation models (and other state-space models) parse informative unpredictable fluctuations in the trajectory of the process (innovation variance)—which may be useful for future predictions—from deviations that are not meaningful (measurement error) and do not offer any predictive value (Driver & Voelkle, 2018). For more comprehensive outlines of dynamic structural equation models see Asparouhov, Hamaker, & Muthén (2018) and for continuous time structural equation models see Driver, Oud, & Voelkle (2017) and Voelkle, Oud, Davidov, & Schmidt (2012)

Whilst continuous time modelling does overcome many issues relating to modelling longitudinal data, many approaches do not account for the potentially hierarchical nature of temporal processes. More traditional approaches (i.e. autoregressive cross-lagged panel models) often estimate a single set of fixed-parameter effects, which assume that the processes unfold in exactly the same way for all subjects. However, it is common for the intercept in dynamic models to vary between subjects and not accounting for the subject-specific differences in the average level of a process may bias parameters within the model that are assessing the temporal dynamics (Hamaker, Kuiper, & Grasman, 2015). The current hierarchical Bayesian approach provides a middle ground between fixed-effects models and subject-specific models by estimating population distributions for model parameters (For a technical outline and mathematical description see Driver & Voelkle (2018). The present model simultaneously estimates the population distribution mean and variance, which serves as prior information and informs the sampling of the subject level parameters as hyperpriors. Hyperpriors are priors that reflect the expectations for the population distribution. Thus, the subject specific parameter estimates are joint-posterior population distributions that are conditional on a combination of the estimated population distribution, which fully accounts for between-subject differences, and the calculated likelihood of parameters being subject specific.

References

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Figures

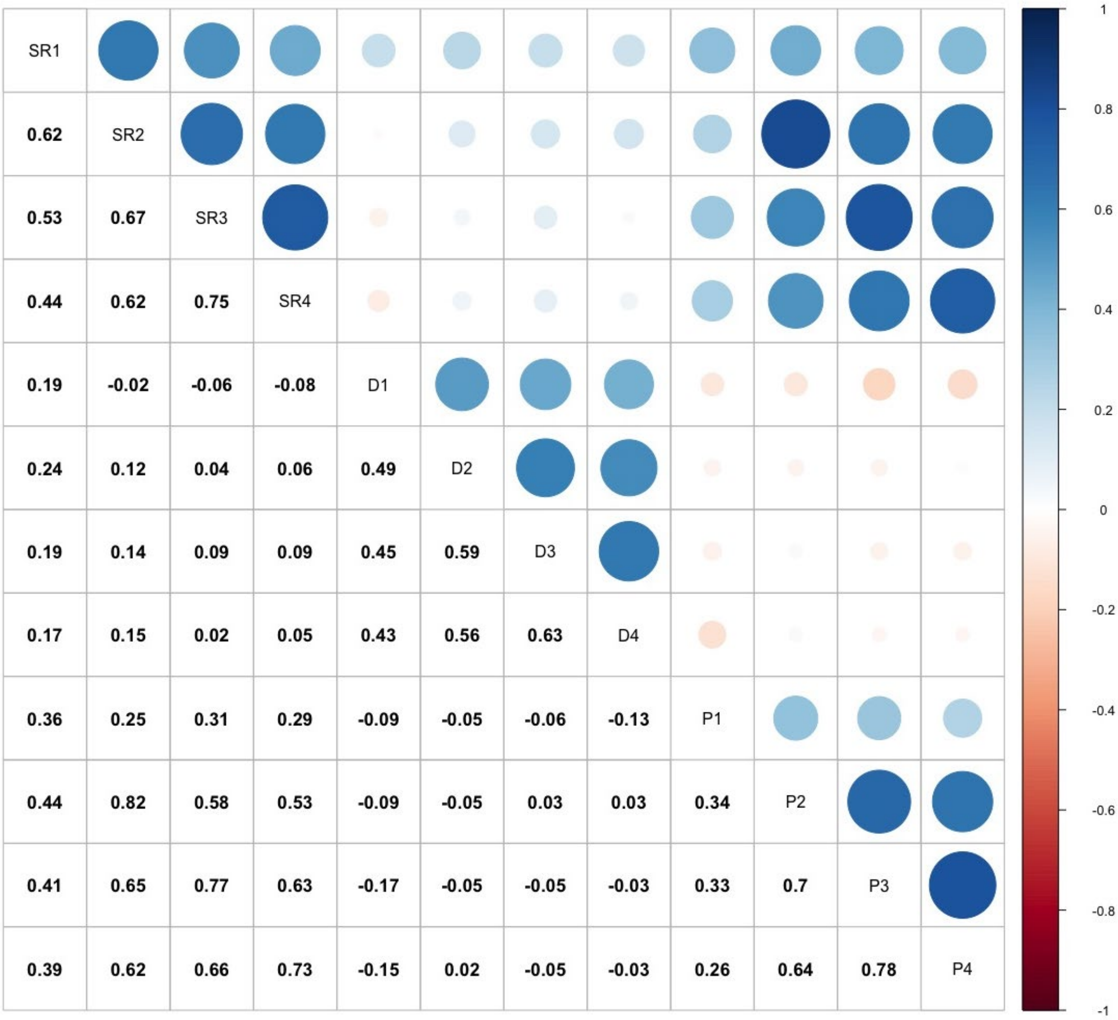

Figure 1. Bayesian estimates of bivariate correlations between social rank, prestige and dominance at all waves during the study. Variable names are presented on the diagonal of the figure. The number associated with the variable names indicates the wave of observation (i.e. between wave 1 and 4).

SR = Social Rank
D = Dominance
P = Prestige