Report Supplementary Material 1

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Introduction to supplementary material

The are two parts to this supplement. Firstly, we present diagnostics in relation to the unconditional mixed-effects models. Secondly, we provide further considerations on the potential for bias due to both loss to follow-up and variability in the timing of follow-up data-collection waves.

Mixed-effect model diagnostics

We estimated a linear mixed-effects model with PCL-5¹ as the repeated dependent variable and time since baseline in years as the single covariate. For this we used the lme() function from the nlme package² using the R statistical software³ via Rstudio⁴.

This *unconditional model*, containing no covariates other than time, was estimated within three samples – (i) the complete case-sample with all three measures, (ii) those participants providing two measures (typically baseline and one follow-up), and (iii) participants providing one or repeated measure (the maximal sample). As we showed in the manuscript, these models demonstrate substantial variation in both intercept and slope (baseline levels and change) and we observe a modest negative correlation between these two quantities with participants who have higher symptom-scores at baseline demonstrating a greater improvement (in absolute terms).

Distribution of residuals

Figures 1 and 2 examine residual distributions for the maximal sample (333 participants, 773 observations). QQ-plots for the occasion-level residuals (Figure 1) and the intercept residuals (first row of Figure 2) indicate an acceptable degree of normality. Whilst the slope residuals (second row of Figure 2) deviate slightly from normality, with long upper and lower tails, we would expect that the inclusion of covariates would improve this situation. Furthermore, (i) the slope residuals have a decent level of symmetry and (ii) our sample size is such that we would not expect such a modest non-normal distribution to impact on our inference.

Figure 1 Distribution of Level-1 (occasion-level) residuals

Linearity of time trend

Our ability to accommodate a nonlinear relationship between PCL-5 and time is limited given the panel-data design with three distinct waves. Figure 3 shows no obvious pattern in the relationship between time and the occasion-level residuals.

Figure 3 Scatterplot of time against level-1 residuals

Figure 4 shows some further plots of the predicted values and residuals from the model against time alongside the observed data. The left-hand plot contains the average scores for the observed data at each month (points and 95% error-bars) along with the population mean trajectory. The right-hand plot contains the average level-1 residual at each month (points and 95% error-bars) plotted against time. Whilst at the macro-level the scatter of the points around the respective lines appears erratic, there is a suggestion of a pattern at the micro-level, i.e. within each data-collection wave. This is an indication that we should be mindful of the impact of non-random variability in the timing of followup waves.

Figure 4 Plots of (i) mean-trajectory against observed data and (ii) mean of level-1 residuals against time

Limiting the impact of bias in our mixed-effects models

We were mindful of two aspects of the data which might lead to bias, and we describe our approach to these in the pages which follow. Firstly, we consider the impact on variation in follow-up times which we regard as being beneficial provided it is modelled appropriately. Secondly, we consider the impact of missing data which pervades all quantitative analysis.

Potential bias due to covariate-differences in the timing of interviews

The study design for the quantitative element of the MESARCH study consisted of a baseline data collection at enrolment followed by two further waves of data collection at 6 months and 12 months after baseline. Some variation in the timing of subsequent waves is inevitable for a multitude of reasons, and the importance of incorporating this spread of follow-up times will depend in part on the range of values seen relative to the duration of follow-up itself, as well as the nature of the data being collected.

When studying a changing phenomenon, the optimal study design would consist of random timing of follow-up. This enables change to be modelled most accurately and precisely, however it is logistically more complex – representing a much greater challenge for those running the study, not to mention the participants who have to cope with irregular follow-up, leading to more drop-out.

When variation in response-time is not due to the study design there is the potential for bias. Figure 5 shows some imaginary data collected at a single wave. There is variation in the time of response indicated by the three vertical pairs of dots - these are one week apart so that all data has been collected over a 3-week period. We have two groups of individuals in this population – the red group typically score *higher* on PTSD and also typically have their data collected *earlier* during the data collection period (as indicated by the changing size of the dots). We can see that there is a gradual linear decrease in PTSD from week to week and that whilst the red group have higher levels on average, the rate of change is the same for both the red and green individuals. In the right-hand Figure 5 we have the same data, but we illustrate a model which has not accounted for the red/green grouping. Since grouping was related to timing of follow-up, and also the measure being studied, we see bias if the grouping is ignored – the relationship between PTSD and time is now steeper – it is upwardly biased due to the exclusion of this important aspect of our data.

Figure 5 An illustration of the bias that can result from the exclusion of a covariate related to both the timing of measurement and the dependent variable of interest (PTSD)

It would be reasonable to ask why, in this case, do we not simply ignore variation within a wave of data collection. The short-answer is that when fitting a longitudinal model across multiple waves of data, it is beneficial to incorporate time-variation when it exists – parameters pertaining to change will be estimated with greater precision and there will be more power for studying risk-factors related to degree of reduction in Y. Furthermore, if, as often happens there is time-variation in the form of a long-tail, then ignoring this variation can just as readily lead to bias as incorporating it incorrectly.

Potential bias due to non-random loss-to-follow-up.

Incomplete data can lead to issues with inference unless the problem is addressed in the analysis. At the very least, analyses carried out on the subset of participants who have provided complete data (a Complete Case Analysis) will have reduced statistical power and may provide estimates which do not generalize to the full sample of those who enrolled. Complications arise in the presence of selection bias which can induce *spurious* associations that align neither with the true estimates for the full sample nor for the Complete Case subset. Two independent risk-factors for dropout can appear (negatively) correlated within the sample of participants providing both measurements. Thus, if both males and participants with higher PCL-5 scores are less likely to be followed-up after the baseline wave, this will induce a spurious association between sex and symptoms of PTSD in the sample which remains.

Using m-DAGs to illustrate missing data mechanisms.

Figure 6 below depicts a scenario under which we would expect a complete-case analysis to be biased. Here the model of interest links the risk-factor to the continuous dependent variable PTSD. There is missing data for PTSD which is represented by the binary variable M_{PTSD} which takes the value 1 if PTSD is missing and 0 if PTSD is measured. There are systematic differences between those who have and have not provided data on PTSD as indicated by the double-headed arrow linking these two variables. This systematic difference $-$ a difference in mean symptom score between responders and non-responders is shown to be due to the existence of an auxiliary variable (Aux) which is a common cause of both PTSD and it's missingness status. In this setting, a Complete-Case analysis (i.e. estimated on the sample for whom $M_{PTSD} = 0$) of the univariable association between the risk factor and PTSD would be biased due to the presence of the open pathway linking PTSD and M_{PTSD} When we condition on M_{PTSD} we induce a backdoor pathway between the risk factor and PTSD via the auxiliary variable.

Footnote: Single-headed arrows indicate causation whilst the double-headed arrow indicates an induced association.

Figure 7 In the sample restricted to those with PTSD data we have induced an association between the risk-factor and the auxiliary variable which means we now have a backdoor pathway (i.e. confounding)

Multiple Imputation

Missing data is typically addressed using Multiple Imputation (MI) whereby any missing information in any model variable is imputed using a regression model, with other "model variables" plus auxiliary (non-model) variables used as predictors. This approach is reliant on the Missing Random Assumption (MAR) which states that whilst there may be systematic differences between the values of an incomplete variable Z between those participants who do and do not provide data, such differences in Z (i.e. a mean-difference or difference in risk/odds) can be adequately explained using other observed data. One advantage of a Multiple Imputation approach to missing data, in which the imputation and the substantive analyses form two separate steps, is that auxiliary data can be included in the imputation step, and then discarded before the analysis is performed. In the above example, including both the risk-factor and auxiliary variable in the imputation model for PTSD would then permit the model of interest to be estimated without bias.

Handling missingness in mixed-effects models for longitudinal data

As we describe in an earlier section, mixed-effects models are a commonly used approach for analysing repeated-measures data in that they permit heterogeneity in patterns of change to be described using one or more (typically Gaussian) random effects. In the ubiquitous "random intercept/slope model", a pair of random effects describe heterogeneity in both baseline-levels of the repeated variable and rates of linear change. Potential risk factors can then be incorporated as independent variables to explain between-subject variation in these two latent quantities.

Mixed-effects models can accommodate partial missingness in the repeated-measures data through the use of Full Information Maximum Likelihood (FIML) which means that any participant with at least one measurement can be included in the model. Dealing with missing data using Maximum likelihood estimation can be more efficient than MI⁵ but at the heart of both is the Missing at Random assumption. However, whilst Multiple Imputation relies on missing data being MAR conditional on all the variables used in the imputation model, mixed-models address missing-data within the same step as performing the substantive analysis. This is illustrated in Figure 8 in which the auxiliary variable is added to the model to address the problem of bias. The analyst must be mindful that the inclusion of auxiliary variables for the purpose of removing bias may affect the model of interest and inadvertently change the research question. This can occur when there is a causal link between the auxiliary variable and the risk factors of interest. In Figure 9 the auxiliary variable is a confounder and so would already be expected to be included in the model, however in Figure 10 the auxiliary variable mediates the effect of the risk-factor on PTSD so its inclusion would require more deliberation.

Finally, a further drawback of the ML-approach to missing data is that this does not extend to missingness within any independent variables. Fortunately, in our situation the baseline risk factors considered are essentially complete, so this is not a concern.

Figure 8 Conditioning on the auxiliary variability has severed the link between PTSD and MPTSD

Footnote: the box around a variable indicates that this variable has been conditional on. the box surrounding M_{PTSD} shows that here we are focussing on the subsample for whom PTSD outcome data is available.

Figure 9 Auxiliary variable is a confounder in the substantive model of interest

Figure 10 Auxiliary variable is a mediator in the substantive model of interest

Our modelling strategy in the face of these challenges

Given our interest in using mixed-effects models for the analysis of change in symptoms of PTSD, and studying baseline risk factors associated with this change, the use of Maximum Likelihood for addressing partial missingness is a prudent decision. The strategy for avoiding bias due to nonrandom dropout is essentially the same as the strategy for handling non-random variability in the timing of follow-up waves. We will seek to condition on risk factors for PTSD which are also either associated with dropout or time-variation. As described above, we will need to be cautious about the choice of variables and consider the potential direction of causality between these auxiliary variables and the variables of substantive interest.

The tables spanning the subsequent pages are of two forms. Firstly (top table in each pair) we present the unadjusted association between each risk factor of interest and the baseline and slope for PCL-5 across three different sample sizes. Below this we present estimates from the mixed-effects models estimated using the maximal sample, adjusting for factors found to be associated with either loss-to-follow up or variation in time at response.

The goal here with this set of adjusted models is merely to account for differences in PTSD symptoms either by timing of response or between responders and non-responders. We are not interested in the parameters obtained for these factors. Aside from the type of SARC and type of ISVA, the baseline factors chosen were Sex assigned at birth (female/male), Ethnicity – White versus non-White (mixed/Asian/black/Chinese/other-ethnic), Religion – no religion versus some form of religion (Christian/Buddist/Jewish/Muslim/other) and sexual orientation – heterosexual/straight versus asexual/gay/bisexual/lesbian/pansexual/queer. The final column from these lower tables mirrors those presented in the main text.

Organisational level – ISVA type

Table 1 Unadjusted effects across different samples

Table 2 Adjusting for factors associated with loss to follow-up and variation in response time

Reference category = ISVA off-site

Adjusted 1: adjusted for religion (yes/no), sex (male/female), ethnicity (white/non-white), and sexual orientation (straight/other).

Adjusted 2: additionally adjusted for SARC type.

Slope parameters represent expected reduction in symptoms per year.

Organisational level – SARC type

Table 3 Unadjusted effects across different samples

Table 4 Adjusting for factors associated with loss to follow-up and variation in response time

Reference category = Police-led

Adjusted 1: adjusted for religion (yes/no), sex (male/female), ethnicity (white/non-white), and sexual orientation (straight/other).

Adjusted 2: additionally adjusted for ISVA type.

Service experience – service utilisation

Table 5 Unadjusted effects across different samples

Table 6 Adjusting for factors associated with loss to follow-up and variation in response time

Adjusted 1: adjusted for religion (yes/no), sex (male/female), ethnicity (white/non-white), and sexual orientation (straight/other).

Service experience – perceived harm/benefit of policing and justice response

Table 7 Unadjusted effects across different samples

Table 8 Adjusting for factors associated with loss to follow-up and variation in response time

Reference category = Neutral perception (rating between -30 and 30)

Adjusted 1: adjusted for religion (yes/no), sex (male/female), ethnicity (white/non-white), and sexual orientation (straight/other).

Service experience – status of criminal case at baseline

Table 9 Unadjusted effects across different samples

Table 10 Adjusting for factors associated with loss to follow-up and variation in response time

Reference category = case remains open

Adjusted 1: adjusted for religion (yes/no), sex (male/female), ethnicity (white/non-white), and sexual orientation (straight/other).

Characteristics of the individual and the offence – burden of adverse childhood experiences

Table 11 Unadjusted effects across different samples

Table 12 Adjusting for factors associated with loss to follow-up and variation in response time

Adjusted 1: adjusted for religion (yes/no), sex (male/female), ethnicity (white/non-white), and sexual orientation (straight/other).

Characteristics of the individual and the offence – evidence of prior mental health problems

Table 13 Unadjusted effects across different samples

Table 14 Adjusting for factors associated with loss to follow-up and variation in response time

Adjusted 1: adjusted for religion (yes/no), sex (male/female), ethnicity (white/non-white), and sexual orientation (straight/other).

Characteristics of the individual and the offence – time between trauma and visit to SARC

Table 15 Unadjusted effects across different samples

Table 16 Adjusting for factors associated with loss to follow-up and variation in response time

Reference category = Up to ten days

Adjusted 1: adjusted for religion (yes/no), sex (male/female), ethnicity (white/non-white), and sexual orientation (straight/other).

Characteristics of the individual and the offence – perpetrator type

Table 17 Unadjusted effects across different samples

Table 18 Adjusting for factors associated with loss to follow-up and variation in response time

Reference category = Partner of survivor

Adjusted 1: adjusted for religion (yes/no), sex (male/female), ethnicity (white/non-white), and sexual orientation (straight/other).

Characteristics of the individual and the offence – educational attainment of survivor

Table 19 Unadjusted effects across different samples

Table 20 Adjusting for factors associated with loss to follow-up and variation in response time

Reference category = Less than A-levels

Adjusted 1: adjusted for religion (yes/no), sex (male/female), ethnicity (white/non-white), and sexual orientation (straight/other).

Characteristics of the individual and the offence – financial problems (ease with which participant could find £100)

Table 21 Unadjusted effects across different samples

Table 22 Adjusting for factors associated with loss to follow-up and variation in response time

Reference category = Impossible to find £100

Adjusted 1: adjusted for religion (yes/no), sex (male/female), ethnicity (white/non-white), and sexual orientation (straight/other).

Characteristics of the individual and the offence – inability to work e.g., due to disability

Table 23 Unadjusted effects across different samples

Table 24 Adjusting for factors associated with loss to follow-up and variation in response time

Reference category = Able to work

Adjusted 1: adjusted for religion (yes/no), sex (male/female), ethnicity (white/non-white), and sexual orientation (straight/other).

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