Supplementary materials for:

Mental Health and Social Contact During the COVID-19 Pandemic: An Ecological Momentary Assessment Study

Data, code, and measures are available at https://osf.io/mvdpe/.

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Overview

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1. Univariate multilevel regression models

We performed univariate multi-level regression models on each of the 14 EMA variables separately: 26 different models per variable, leading to a total of 364 estimated models. Each model includes a random intercept, and included a combination (either fixed only or fixed and random effects) of day number, beep in day, and the previous measurement as predictors. Before analysis, day number, the dependent variable and the lagged variable were standardized as to obtain interpretable parameter estimates. All analyses were performed using R package *lme4* version 1.1.21. For each model, we computed the Bayesian information criterion (BIC), which we transformed into posterior model estimates (Wagenmakers, 2007) to get an estimate of which of the 26 models per variable describe the data best.

Figure S1 below summarizes the results of these univariate analyses, per variable. Model probabilities per variable add up to 1. For variable “Alone” in column 8, for instance, we see that one model is the clear favorite (probability ~.8): “day(R)+lag(R)”, row 11, i.e. a model with a random effect for both day and lag. The cell contains -0.01 (0.11), which denotes the fixed effect of day (i.e. very slight decrease), and the standard deviation of the random effect for day in brackets. A model that is less probable (probability ~.2) for the variable “Alone” is “lag(R)”, row 1, which a fixed effect coefficient for day of 0.

There was evidence for large heterogeneity across participants in auto-regressive effects: 10 out of 14 variables featured models in which random effects on the lagged variables were preferred. It can also be seen that trends across the time-series (trend on day number) were rather pervasive: in nine out of 14 variables, models that include a trend on day number (either fixed or fixed and random) were clearly preferred. In each preferred model, the fixed-effect linear trend was either zero (not included) or negative, indicating that across the sample, many participants reported reductions or stability in all EMA variables. The strongest negative trends were featured in the preferred models for being occupied with COVID-19 (mean = -0.125, SD = 0.131) and being worried about COVID-19 (mean = -0.102, SD = 0.143). These results indicate that for being occupied with COVID-19, 83% of the sample featured a negative trend below 0 and 57.6% featured a negative trend below -0.1. For being worried about COVID-19: 76.2% featured a negative trend below 0 and 50.6% featured a negative trend below -0.1.

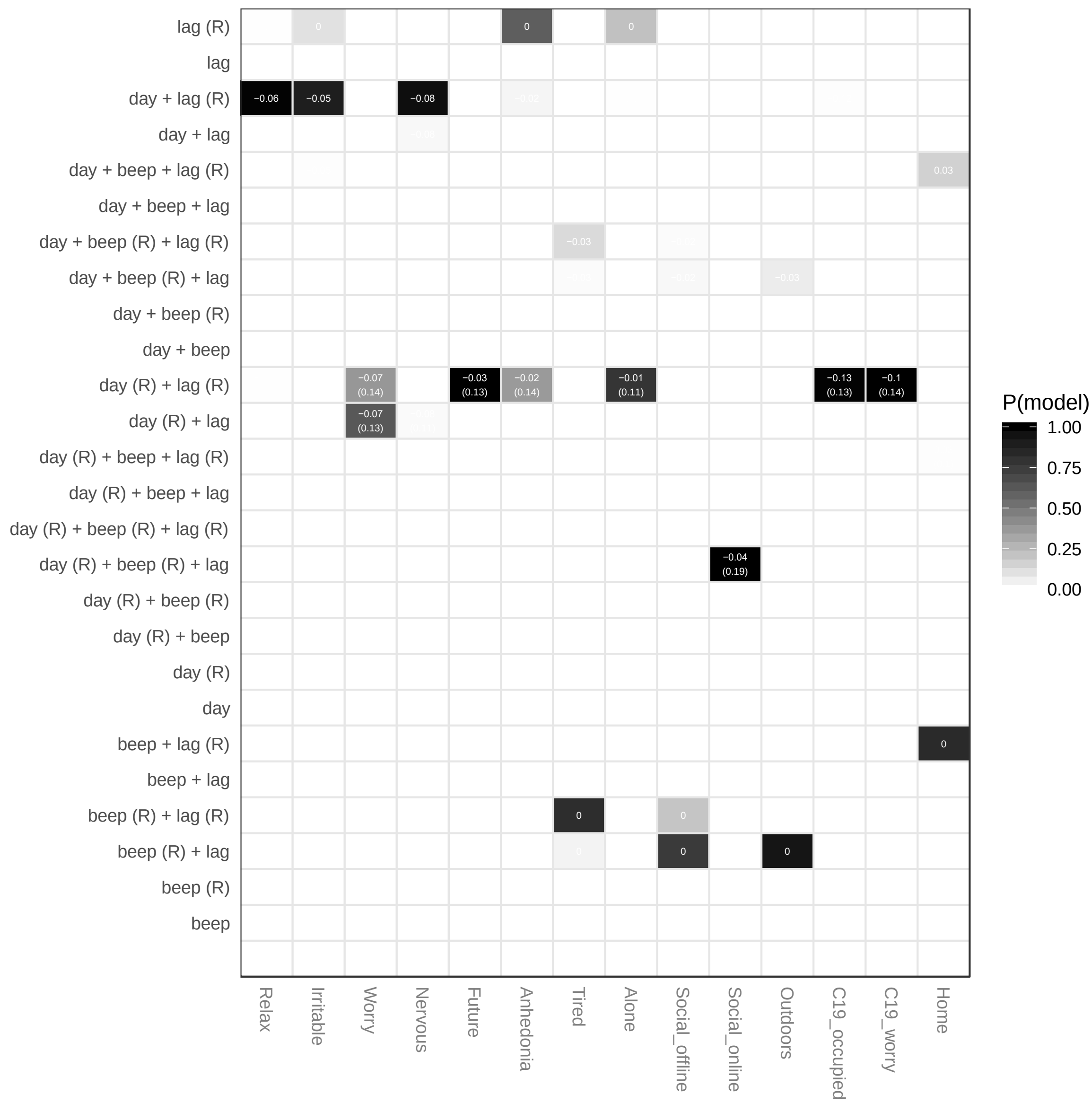


Figure S1. *Summary of univariate analyses. Y-axis shows different multi-level models tested and x-axis shows the variable of interest. On the y-axis: 'day' indicates a linear trend on day number, 'beep' a categorical effect of beep number during the day, and 'lag' a linear effect of the previous measurement. The bracketed R indicates a random effect was added to the model. Colors in the panels indicate estimates of posterior model probability obtained from transforming BIC values as per Wagenmakers (2007), and labels in the boxes indicate the estimated day-effect trend and its random effect standard deviation (if included in the model).*

2. Comparison between orthogonal and correlated estimation of mlVAR models

Overall, orthogonal and correlated estimation techniques led to highly similar results, meaning our results are robust to the particular estimation technique used. To assess similarity, we correlated the adjacency matrices of the contemporaneous and temporal networks across both estimation techniques; correlations r=0.993 (contemporaneous) and r=0.972 (temporal).

The AIC and BIC values for all 14 time series variables in network models estimated via mlVAR showed superior fit in the orthogonal, compared to the correlated, model. We compared the models using the mlVARcompare function of the mlVAR package; detailed see syntax.

AIC and BIC for orthogonal estimation were:

Range AIC 5297.03 to 7624.41

Mean AIC 6411.589

Range BIC: 5557.24 to 7884.62

Mean BIC: 6671.8

AIC and BIC for correlated estimation were:

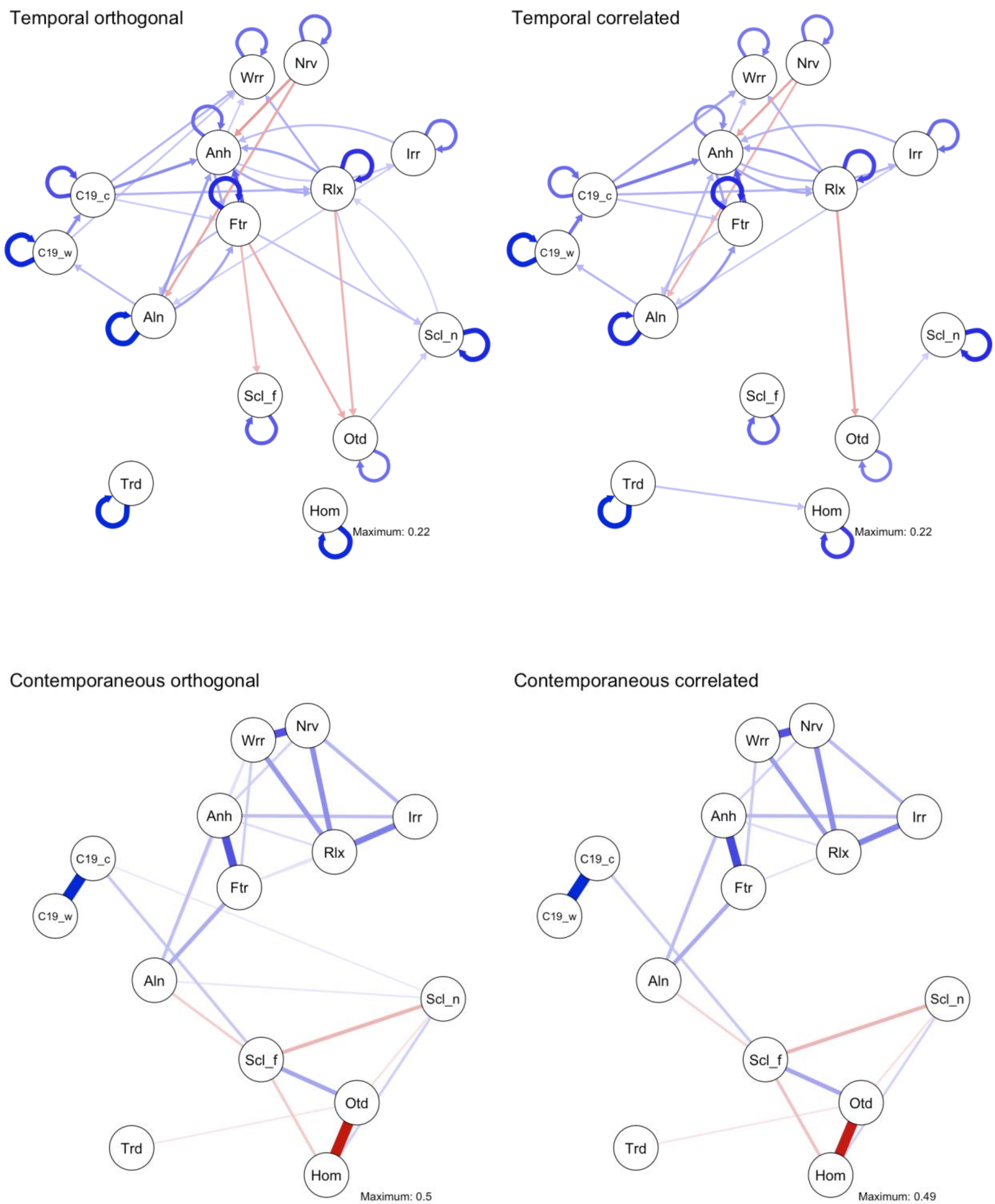
Range AIC 5409.88 to 7799.85

Mean AIC 6576.516

Range BIC: 6291.92 to 8681.88

Mean BIC: 7458.553

As described above, the resulting network models showed considerable similarities:


Temporal orthogonal
Wrr
Nrv
Anh
Irr
C19_c
Rlx
Ftr
C19_w
Aln
Scl_n
Scl_f
Otd
Trd
Hom
Maximum: 0.22
Temporal correlated
Wrr
Nrv
Anh
Irr
C19_c
Rlx
Ftr
C19_w
Aln
Scl_n
Scl_f
Otd
Trd
Hom
Maximum: 0.22
Contemporaneous orthogonal
Nrv
Wrr
Anh
Irr
Rlx
C19_c
Ftr
C19_w
Aln
Scl_n
Scl_f
Otd
Trd
Hom
Maximum: 0.5
Contemporaneous correlated
Nrv
Wrr
Anh
Irr
Rlx
C19_c
Ftr
C19_w
Aln
Scl_n
Scl_f
Otd
Trd
Hom
Maximum: 0.49

3.Adjacency matrices

Contemporaneous network:

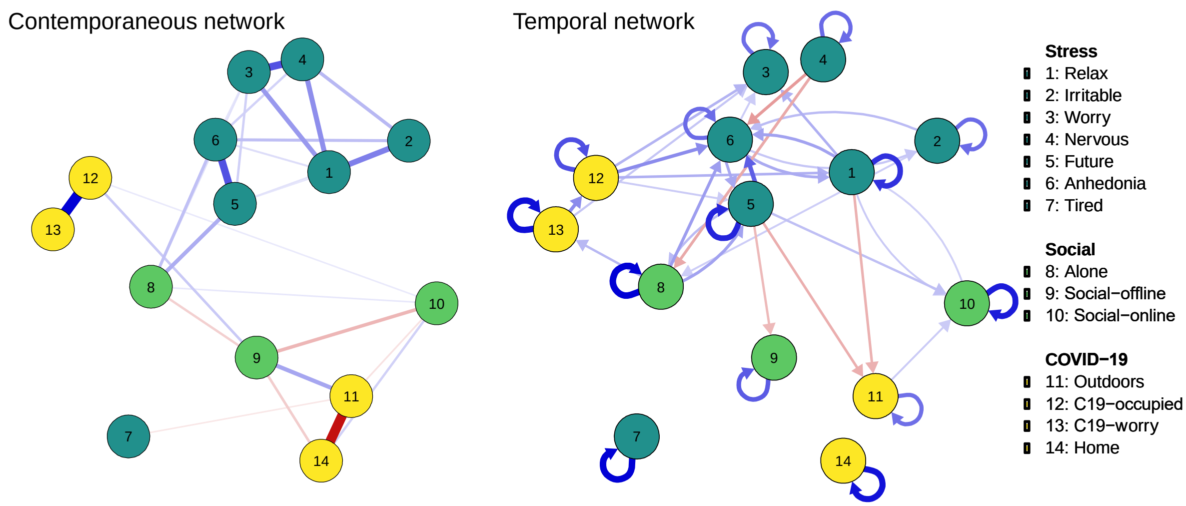
	Relax	Irritable	Worry	Nervous	Future	Anhedonia	Tired	Alone	Social_off	Social_onl	Outdoors	C19_occup	C19_worry	Home
Relax	0.00	0.25	0.20	0.22	0.05	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Irritable	0.25	0.00	0.00	0.14	0.06	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Worry	0.20	0.00	0.00	0.34	0.09	0.05	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00
Nervous	0.22	0.14	0.34	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Future	0.05	0.06	0.09	0.00	0.00	0.34	0.00	0.16	0.00	0.00	0.00	0.00	0.00	0.00
Anhedonia	0.07	0.13	0.05	0.09	0.34	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00
Tired	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.05	0.00	0.00	0.00
Alone	0.00	0.00	0.06	0.00	0.16	0.12	0.00	0.00	-0.09	0.05	0.00	0.00	0.00	0.00
Social_off	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.09	0.00	-0.14	0.17	0.11	0.00	-0.10
Social_onl	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	-0.14	0.00	-0.06	0.04	0.00	0.09
Outdoors	0.00	0.00	0.00	0.00	0.00	0.00	-0.05	0.00	0.17	-0.06	0.00	0.00	0.00	-0.47
C19_occup	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.04	0.00	0.00	0.50	0.00
C19_worry	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.00	0.00
Home	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.10	0.09	-0.47	0.00	0.00	0.00

Temporal network:

	Relax	Irritable	Worry	Nervous	Future	Anhedonia	Tired	Alone	Social_off	Social_onl	Outdoors	C19_occup	C19_worry	Home
Relax	0.18	0.00	0.07	0.00	0.00	0.08	0.00	0.00	0.00	0.05	-0.07	0.00	0.00	0.00
Irritable	0.00	0.13	0.00	0.00	0.00	0.06	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00
Worry	0.00	0.00	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nervous	0.00	0.00	0.00	0.13	0.00	-0.09	0.00	-0.08	0.00	0.00	0.00	0.00	0.00	0.00
Future	0.00	0.00	0.00	0.00	0.19	0.14	0.00	0.06	-0.06	0.06	-0.07	0.00	0.00	0.00
Anhedonia	0.07	0.05	0.04	0.00	0.08	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tired	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Alone	0.00	0.00	0.00	0.00	0.08	0.09	0.00	0.22	0.00	0.00	0.00	0.00	0.06	0.00
Social_off	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.00	0.00	0.00	0.00	0.00
Social_onl	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00
Outdoors	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.13	0.00	0.00	0.00
C19_occup	0.07	0.00	0.07	0.00	0.05	0.10	0.00	0.00	0.00	0.00	0.00	0.15	0.00	0.00
C19_worry	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.21	0.00
Home	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.21

4. Temporal network with autoregressive coefficients

We removed the autoregressive edges from the visualization of the temporal network in the main manuscript to make the figure easier to understand; here is the corresponding figure with autoregressive coefficients:



5. Pre-post comparison

Below, we provide an overview of the pre-post comparison of the DASS-21 scale, subscales, and the loneliness scales.

	t	df	p	Mean difference	Cohen's D
DASS pre vs post	0.45	76	0.66	0.44	0.05
Depression	-2.33	76	0.02	-1.23	0.27
Anxiety	2.87	76	0.005	0.94	0.33
Stress	1.72	76	0.09	0.70	0.20
Loneliness	3.14	76	0.002	0.79	0.36

6. R sessionInfo()

```
> sessionInfo()
R version 3.6.1 (2019-07-05)
Platform: x86_64-apple-darwin15.6.0 (64-bit)
Running under: macOS Mojave 10.14.5

Matrix products: default
BLAS:
/System/Library/Frameworks/Accelerate.framework/Versions/A/Frameworks/vecLib.framework/Versions/A/libBLAS.dylib
LAPACK: /Library/Frameworks/R.framework/Versions/3.6/Resources/lib/libRlapack.dylib

Random number generation:
 RNG:     Mersenne-Twister
 Normal:  Inversion
 Sample:  Rounding

locale:
[1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

other attached packages:
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 [7] lme4_1.1-21        Matrix_1.2-18      e1071_1.7-3        summarytools_0.9.4 Rmisc_1.5          plyr_1.8.5
[13] lattice_0.20-38    viridis_0.5.1      viridisLite_0.3.0  qgraph_1.6.5       tidyr_1.0.0        dplyr_0.8.3
[19] bootnet_1.3        ggplot2_3.2.1

loaded via a namespace (and not attached):
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```

7. References

Wagenmakers, E.-J. (2007). A practical solution to the pervasive problems ofp values. *Psychonomic Bulletin & Review, 14*(5), 779–804. https://doi.org/10.3758/BF03194105