Supplemental Appendix: Psychological and Physiological Responses to Repeated Peer Loss

Judith Pizarro Andersen[*] Roxane Cohen Silver Billie Koperwas
Brandon M. Stewart Clemens Kirschbaum

October 2, 2013

Abstract

This supplemental appendix provides additional methodological details, additional results and visualizations of models in the main paper. Results are organized according to the dependent variable under study.

Contents

[*]To whom correspondence should be addressed.

1 Effect Sizes for Acute Reaction, Distress and Cortisol

This section provides several visualizations and effect sizes for the best subset models which are presented in the main text. Additional models are given in later sections of the appendix.

1.1 Severity of Acute Reaction

For the Severity of Acute Reaction we observe a rating on a 5-point Likert scale ranging from "No Reaction" to "Extreme Reaction." We analyze the data using an Ordinal Probit model which is appropriate for ordered data. Table 1 summarizes the findings of the model. In addition to typical coefficients and standard errors, we provide Risk Ratios for falling in the strong and extreme reaction categories along with 95% confidence intervals.

	Coef	SE	CI	P-value	RR Strong (95% CI)	RR Extreme (95% CI)
Female	0.89	0.23	(0.44, 1.35)	0	2.71 (1.51, 4.82)	13.69 (2.84, 45.55)
Num. Peers Known	0.54	0.16	(0.23, 0.85)	0	1.43 (1.15, 1.82)	3.53 (1.6, 7.25)
Media Exposure	0.25	0.06	(0.13, 0.36)	0	1.17 (1.08, 1.3)	1.73 (1.31, 2.38)

Table 1: Results of best subset model for Ordinal Probit model of Severity of Acute Reaction. Coefficients provided along with two measures of effect size: relative risk for a strong reaction and relative risk for an extreme reaction. Risk sets compare median and 3rd quantile values. The comparisons are (1) risk for female/ risk for male, (2) risk for female knowing 2 peers / risk for female knowing 1 peer, (3) risk for female consuming 3 hours of media / risk for female consuming 2 hours of media.

The Risk Ratio measures the relative probability of being in the outcome category based on different values of the independent variable. Thus the RR for the Strong Reaction category for Female can be understood as

$$RR_{\text{Strong}} = \frac{\Pr(\text{Strong Reaction}|\text{Female})}{\Pr(\text{Strong Reaction}|\text{Male})}$$

the expected probability of having a strong reaction if the subject is female divided by the expected probability of having a strong reaction if the subject is male. Thus, our results suggest that women are 2.7 times more likely to report a strong acute reaction than men, and 13.7 times more likely to report an extreme reaction than men. Similarly, moving from the median of knowing one peer personally to the third quartile of knowing two peers personally makes it 1.4 times more likely the subject experiences a strong reaction and 3.5 times more likely the subject experiences an extreme reaction. Finally, moving the median level of media consumption (2 hours) to the third quartile of media consumption (3 hours) makes a strong reaction 1.2 times more likely and an extreme reaction 1.7 times more likely.

We can understand the results better by examining plots of the expected probabilities of each level of reaction for different values of the independent variables. The left plot of Figure 1 shows the expected probability of each reaction for men (blue line) and women (pink line). The right plot shows the expected probabilities moving from 1 peer known personally to 4 peers known personally. Not depicted is the change in media exposure.

Figure 2 shows the importance of each variable in the full theoretical model averaged over all possible model subsets. This is explained in more depth in the section on Methodological Details.

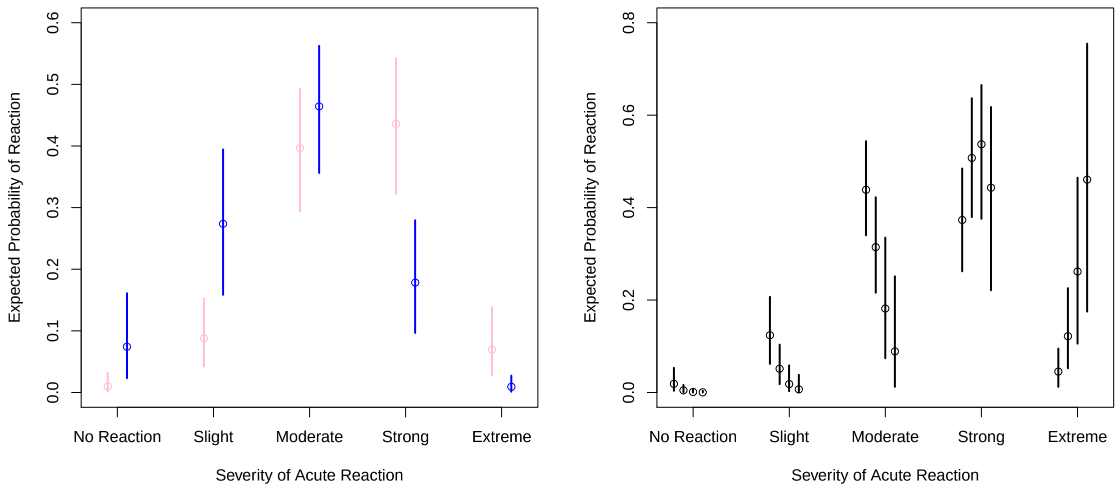

Figure 1: This plot shows the expected probabilities of being in each category of reaction given gender (left) and knowing 1 to 4 people (right) with 95% confidence intervals.

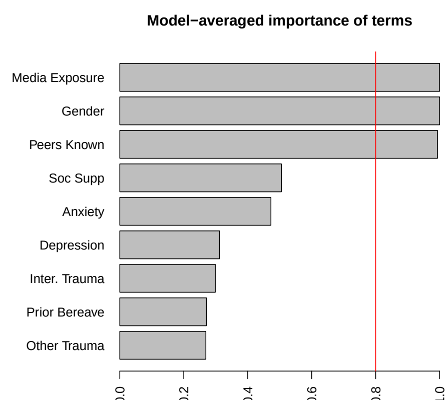

Figure 2: Variable Importance plot for Acute Reaction.

1.2 Ongoing Distress

Table 2 provides a summary of the best subset model for on-going distress. We analyze the data using a Negative Binomial model which is appropriate for possibly over-dispersed discrete data. In addition to standard coefficients we present first differences attributable to two levels of changes in the independent variable: 1 standard deviation shifts from the median, and minimum to max movements. These can be interpreted as standardized regression coefficients in the former case, and the maximal change in distress level attributable to the variable in the latter case.

	Coef	SE	CI	P-value	1 SD Shift	Min to Max
Depression	0.62	0.26	(0.1, 1.14)	0.019	-	8.24 (0.94, 18.4)
Inter. Trauma	0.25	0.07	(0.11, 0.4)	0.001	2.31 (0.97, 3.74)	31.93 (7.75, 75.64)
Num Social Supp.	-0.05	0.02	(-0.09, -0.02)	0.004	-2.31 (-3.88, -0.78)	-9.48 (-15.12, -3.59)
Media Exposure	0.09	0.04	(0.02, 0.16)	0.015	0.8 (0.14, 1.49)	12.61 (1.64, 28.97)

Table 2: Summary of results for a negative binomial model of on-going distress. 1 SD Shift indicates the expected change in the distress score associated with a one standard deviation increase from the median of the independent variable. The Min to Max shows the expected increase in distress associated with a move from the minimum to the independent variable to the maximum. Depression is a binary variable so we only show its min to max value. Interpersonal trauma gives findings for a shift from 0 to 1 and 0 to 6 respectively. Number of social supports gives the shift from 5 to 10 support and 0 to 25 supports respectively. Media exposure gives the shift from 2 to 3 hours and 0 to 11 hours respectively.

We can also plot the expected levels of distress for different values of the independent variable along with their 95% confidence intervals and the model-averaged importance of terms.

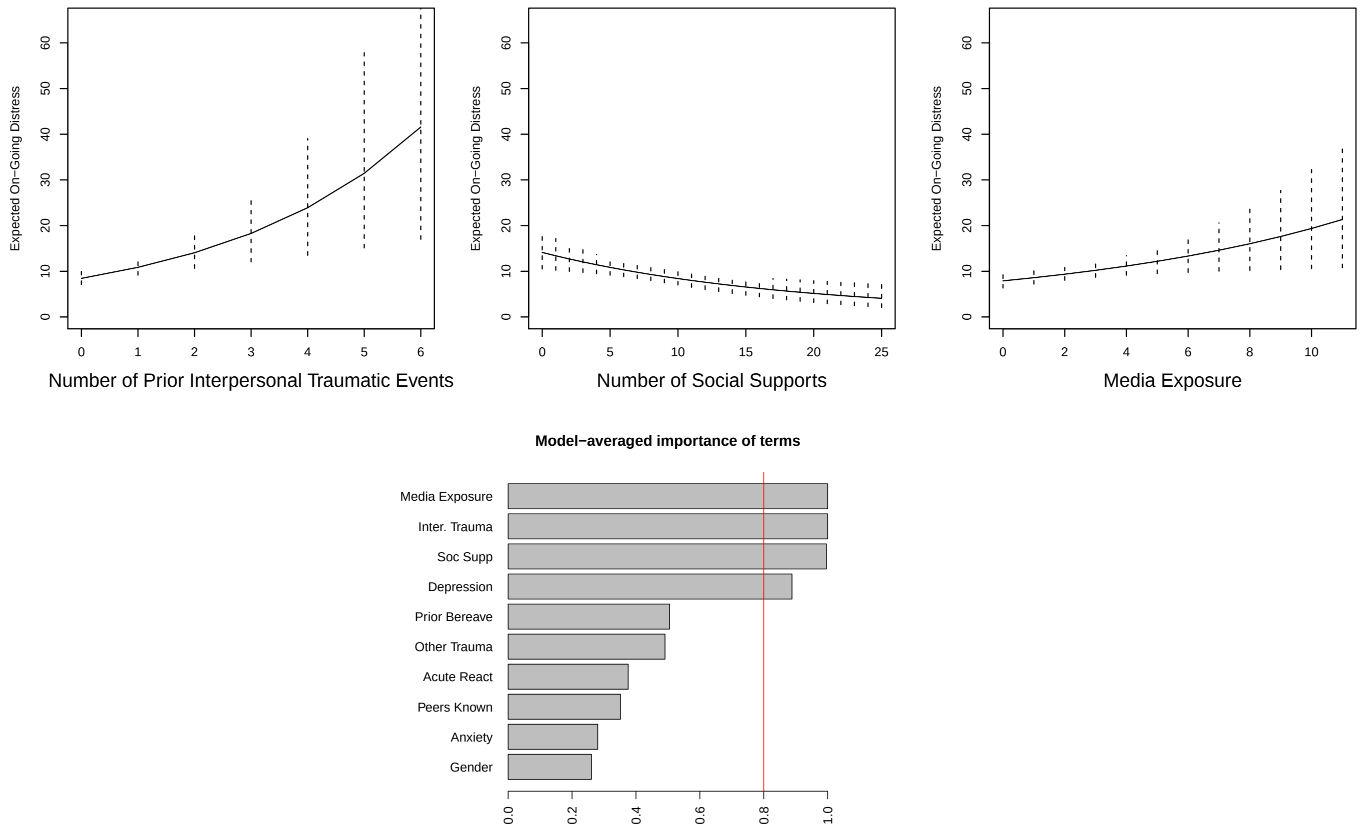

Figure 3: This plot shows the expected levels of stress conditional on the model across the three key variables. Depression is also a significant predictor producing an expected increase of 8.25 to the level of distress with 95% confidence interval $.91 - 18.58$.

1.3 Cortisol Findings

Analyses with Cortisol levels as the dependent variable are restricted to the 24 participants who returned sufficient hair samples to observe Cortisol levels at the 3-month level. We also include the 'prior bereavement' variable as an indicator for at least one prior bereavement. Because the bereavement measure is only observed as either $\{0, 1, 2\}$ in the cortisol sample, the need to model the non-linearity in the relationship becomes more important. We also tested a separate indicator for those who experienced 2 prior bereavements but the estimates were not significantly changed.

	Coef	SE	CI	P-value	1 SD Shift	Min to Max
Female	8.44	4.29	(0.03, 16.85)	0.065	-	8.44 (0.03, 16.85)
Any Prior Bereave	-10.36	4.69	(-19.55, -1.18)	0.04	-	-10.36 (-19.55, -1.18)
Peers Known	5.67	3.2	(-0.61, 11.94)	0.094	3.64 (-0.4, 7.75)	11.33 (-1.21, 23.88)
Num Social Supp.	0.9	0.43	(0.05, 1.76)	0.053	4.48 (0.2, 8.71)	22.57 (1.25, 43.88)
Media Exposure	1.73	1.01	(-0.26 ,3.71)	0.106	3.66 (-0.57, 7.86)	18.98 (-2.89, 40.85)

2 Methodological Details

This section contains methodological details many of which were omitted for space in the main text.

2.1 Variable Selection

We believe that each of our three outcome variables (Severity of Acute Reaction, On-going Distress and Cortisol Levels) is potentially the product of a variety of mental, physical and social health factors. Due to the limited size of the dataset, we cannot include all possible covariates into the model. Instead we specify a complete theoretical model and perform a model selection procedure to choose the best subset. Our complete model includes: Gender, Number of Peers Known Personally, Depression, Anxiety, Prior Bereavement Events, Prior Interpersonal Trauma, Prior Other Adverse Events, Number of Social Supports, Media Exposure and Severity of Acute Reaction. For each of our outcomes, we run all possible subset models (512 and 1024 combinations respectively) using the software designed by Calcagno and Mazancourt (2010). We rank each subset by its Akaike Information Criterion (AIC), a goodness of fit measure based on the log-likelihood which penalizes for complexity. This has the advantage of allowing us to present parsimonious models, but also allows us to present summaries across all possible models. For each outcome we present estimated effects for our preferred subset model as well as a plot of the relative importance of each variable in the complete theoretical model over all possible subset models. In later sections of the appendix we also present the estimation details for the full theoretical model as well as additional details about the subsets.

Here we present the derivation of the variable importance metrics. Using the interpretation of AIC as the comparative information loss to the true data generating unction, we can derive the relative probability of each model being the true model relative to the minimum specification. This gives us a set of weights, which we normalize so the sum of those weights is equal to 1. Then for each variable we simply add up the model weight for each model that contains that variable. Thus, a variable with a score of close to one means that all the models it is in make up almost the entirety of the mass of most probable models.

Calcagno, V., & de Mazancourt, C. (2010). glmulti: an R package for easy automated model selection with (generalized) linear models. Journal of Statistical Software, 34(12), 29.

3 Severity of Acute Reaction

Here we provide simple regression tables for full and alternate models of acute reaction. Also as a technical note, the variable selection routine needs to be run with a Gaussian approximation to the ordinal probit. However, results in the tables are given based on actual ordinal probit models.

3.1 The Full Model

	Value	Std. Error	t-stat	p-value
Female	0.98	0.24	4.02	0.00
Depression	0.29	0.42	0.70	0.48
Anxiety	-0.85	0.56	-1.52	0.13
Prior Berevement	0.01	0.14	0.09	0.93
Other Trauma	-0.01	0.07	-0.07	0.94
Interpersonal Trauma	0.06	0.11	0.53	0.60
Peers Known	0.58	0.17	3.49	0.00
Social Support	0.03	0.02	1.28	0.20
Media Exposure	0.27	0.06	4.48	0.00
1|2	-0.01	0.44	-0.03	0.97
2|3	1.17	0.42	2.80	0.01
3|4	2.63	0.46	5.72	0.00
4|5	4.45	0.57	7.77	0.00

3.2 Complete Subsets

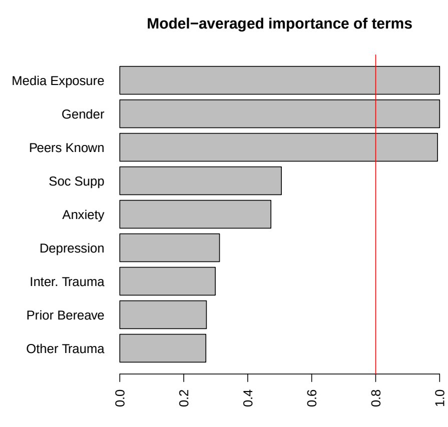

Figure 4: This plot shows the variable importance measure averaged across all possible subsets.

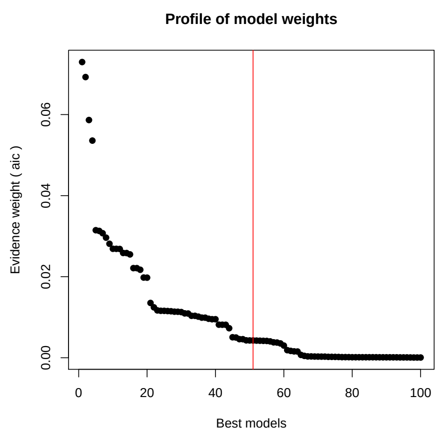

Figure 5: This plot shows the normalized AIC (model fit) across the different models, indicating in this case the dramatically improved fit of the top model.

3.3 Best Subset

This is the top performing model.

	Value	Std. Error	t-stat	p-value
Gender	0.89	0.23	3.88	0.00
Peers Known	0.54	0.16	3.40	0.00
Media Exposure	0.25	0.06	4.32	0.00
1|2	-0.35	0.34	-1.03	0.30
2|3	0.79	0.30	2.59	0.01
3|4	2.21	0.35	6.39	0.00
4|5	4.01	0.48	8.43	0.00

4 On-Going Distress

Here we provide simple regression tables of the models for on-going distress.

4.1 The Full Model

	Value	Std. Error	t-stat	p-value
(Intercept)	1.58	0.34	4.64	0.00
Female	-0.03	0.18	-0.15	0.88
Depression	0.61	0.29	2.13	0.03
Anxiety	-0.18	0.38	-0.48	0.63
Prior Bereave	0.12	0.09	1.24	0.22
Other Trauma	0.05	0.05	0.99	0.32
Interpersonal Trauma	0.21	0.07	2.80	0.01
Peers Known	0.03	0.11	0.23	0.82
Social Support	-0.05	0.02	-2.73	0.01
Acute Reaction	0.15	0.10	1.44	0.15
Media Exposure	0.07	0.04	1.67	0.10

4.2 Complete Subsets

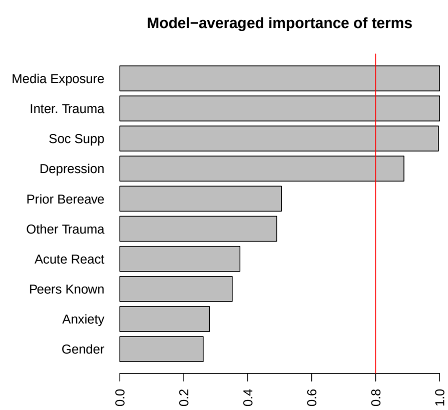

Figure 6: This plot shows the variable importance measure averaged across all possible subsets.

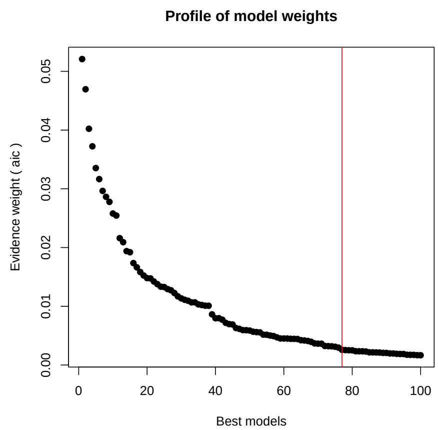

Figure 7: This plot shows the normalized AIC (model fit) across the different models. Note here that there are several relatively equally high performing models, hence the conflict between the best subset variables and the single best model.

4.3 Best Subset

Here we actually have a difference between the best subset of variables and the best model. The best model includes bereavement although that variable does not make the model-averaged importance cutoff. Thus, we present both for transparency. They are quite similar

Table 3: Best Performing Model

	Value	Std. Error	t-stat	p-value
(Intercept)	2.06	0.21	9.80	0.00
Depression	0.58	0.26	2.23	0.03
Prior Bereavement	0.16	0.09	1.70	0.09
Interpersonal Trauma	0.25	0.07	3.41	0.00
Number of Social Supports	-0.05	0.02	-2.68	0.01
Media Exposure	0.08	0.03	2.41	0.02

Table 4: Best Subset

	Value	Std. Error	t-stat	p-value
(Intercept)	2.26	0.18	12.62	0.00
Depression	0.62	0.26	2.35	0.02
Interpersonal Trauma	0.25	0.07	3.44	0.00
Number of Social Supports	-0.05	0.02	-2.91	0.00
Media Exposure	0.09	0.04	2.44	0.01

5 Cortisol

Here we provide simple regression tables for full and alternate models of Cortisol. We use "Prior Bereave Indic." to denote the indicator variable formed for at least one observed prior bereavement.

5.1 The Full Model

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	5.88	9.13	0.64	0.53
Female	9.60	5.21	1.84	0.09
Depression	-0.86	11.54	-0.07	0.94
Anxiety	-4.47	8.11	-0.55	0.59
Prior Bereave Indic.	-11.05	5.57	-1.98	0.07
Other Trauma	1.23	2.07	0.59	0.56
Interpersonal Trauma	3.34	9.39	0.36	0.73
Peers Known	6.44	3.77	1.71	0.11
Number of Social Supports	0.84	0.50	1.67	0.12
Media Exposure	1.13	1.37	0.82	0.42

5.2 Complete Subsets

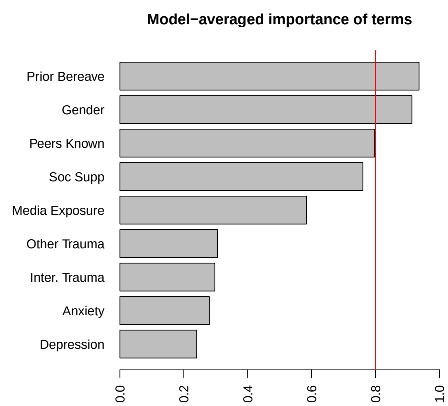

Figure 8: This plot shows the variable importance measure averaged across all possible subsets.

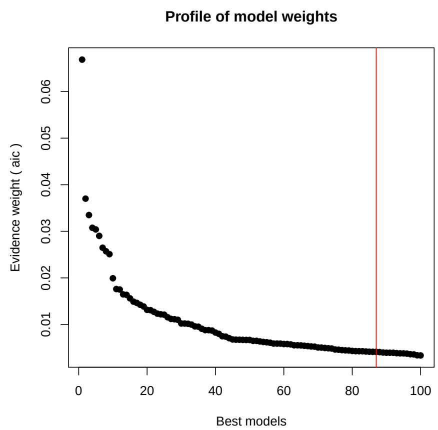

Figure 9: This plot shows the normalized AIC (model fit) across the different models, indicating in this case the dramatically improved fit of the top model.

5.3 Best Subset

This is the top performing model.

	Estimate	Std. Error	t value	p-value
(Intercept)	6.90	8.06	0.86	0.40
Female	8.44	4.29	1.97	0.06
Prior Bereave Indic.	-10.36	4.69	-2.21	0.04
Peers Known	5.67	3.20	1.77	0.09
Number of Social Supports	0.90	0.43	2.08	0.05
Media Exposure	1.73	1.01	1.70	0.11

6 Missing Data

There is some missing data in the survey both due to individuals starting the survey (online) but then not answering any questions, and other missingness due to standard non-response of specific questions. After removing four individuals who were over the age of 30 and were not undergraduates as well as those who had not filled even basic demographic information we were left with an effectively sample size of 122 observations.

If we listwise delete any observations with missingness in the regression variables we would drop from 122 observations to around 80 observations depending on the model. After further investigation it became clear that 13 individuals had not filled in most of the non-demographic portions of the survey (including omitting the entirety of the various trauma sections). We remove these individuals, noting with no information to go on beyond demographics, no imputation procedure can produce useful results for those individuals. This leaves the following missingness patterns:

	Observations Missing	Average Range
Gender	0	-
Peers Known	0	-
Other Adversity	3	2
Social Supports	1	unbounded
On-Going Distress	14	4
Interpersonal Trauma	6	1.17
Prior Bereavement	4	1.75
Media Exposure	0	-

The "Average Range" column indicates the average length on the bounds of what the missing data could be via other answered questions (most people only skipped one to 2 items on the index). In the scale of these variables, the bounds are incredibly tight. Thus, although there are a fair number of missing observations in general, very little actual information is truly missing.

We proceeded using the bounds as observation level priors and then checking that the bound were accurately maintained after the fact. Imputation was performed using the Amelia II software:

`James Honaker, Gary King, Matthew Blackwell (2011). Amelia II: A Program for Missing Data. Journal of Statistical Software, 45(7), 1-47. URL http://www.jstatsoft.org/v45/i07/.`