**1.1 Initial Data Exploration**

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| > data(Tal.Or) > psych::describe(Tal\_Or) #descriptive statistics |

**3.1 Estimation of the Average Causal Mediation Effects**

*We first fit the mediator model where the measure of anxiety (emo) is modeled as a function of the framing treatment (treat) and pre-treatment covariates (age, educ, gender, and income). Outcome variable (cong\_mesg) is binary, treatment variable (treat) is binary and the mediator (the measure of anxiety: emo) is numeric*

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| > med.fit <- lm(emo ~ treat + age + educ + gender + income, data = framing) > out.fit <- glm(cong\_mesg ~ emo + treat + age + educ + gender + income, data = framing, family = binomial("probit"))  > med.out <- mediate(med.fit, out.fit, treat = "treat", mediator = "emo", robustSE = TRUE, sims = 1000  > summary(med.out) |

In order to test for the treatment-mediator interaction

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| > med.fit <- lm(emo ~ treat + age + educ + gender + income, data = framing)  > out.fit <- glm(cong\_mesg ~ emo \* treat + age + educ + gender + income, data = framing, family = binomial("probit"))  > med.out <- mediate(med.fit, out.fit, treat = "treat", mediator = "emo", robustSE = TRUE, sims = 100)  > summary(med.out)  > test.TMint(med.out, conf.level = .95) |

We could also check assumptions (normality)

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| --- |
| > gvlma(med.fit)  > gvlma(out.fit) |

**3.2 Moderated Mediation**

One new important feature of the mediate function is the ability to study moderated mediation. Often analysts hypothesize that the magnitude of the ACME depends on (or is moderated by) a pre-treatment covariate.

*In the framing example, the ACME may be much stronger among older respondents  
than younger ones. In other words, the ACME may be moderated by age.*

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| > med.fit <- lm(emo ~ treat \* age + educ + gender + income, data = framing) > out.fit <- glm(cong\_mesg ~ emo + treat \* age + emo \* age + educ + gender + income, data = framing, family = binomial("probit"))  > med.age20 <- mediate(med.fit, out.fit, treat = "treat", mediator = "emo", covariates = list(age = 20), sims = 100) > med.age60 <- mediate(med.fit, out.fit, treat = "treat", mediator = "emo", covariates = list(age = 60), sims = 100) > summary(med.age20)  > med.init <- mediate(med.fit, out.fit, treat = "treat", mediator = "emo", sims = 2)  > test.modmed(med.init, covariates.1 = list(age = 20), covariates.2 = list(age = 60), sims = 100) |

**3.3 Non-binary Treatment Variables**

*Instead of using treat as the treatment variable, we use cond as the treatment variable which is a categorical variable with 7 levels.*

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| > med.fit <- lm(emo ~ cond + age + educ + gender + income, data = framing) > out.fit <- glm(cong\_mesg ~ emo + cond + age + educ + gender + income, data = framing, family = binomial("probit")) > med23.out <- mediate(med.fit, out.fit, treat = "cond", mediator = "emo", control.value = 2, treat.value = 3, sims = 100) > summary(med23.out) |

To compare different levels of the treatment variable: 

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| > med14.out <- mediate(med.fit, out.fit, treat = "cond", mediator = "emo", control.value = 1, treat.value = 4, sims = 100) > summary(med14.out)  > plot(medl4.out) |

**3.4. Sensitivity Analysis for Sequential Ignorability**

We conduct sensitivity analysis by checking if there is a change in the parameter (the correlation between the residuals of the mediator and outcome regressions). The key assumption is that the treatment assignment is essentially random after adjusting for observed pre-treatment covariates and that the assignment of mediator values is also essentially random once both observed treatment and the same set of observed pre-treatment covariates are adjusted for.

Therefore, the correlation parameter () between errors in the step 2 and step 3 regression equations is assumed to be 0. If there exists unobserved pre-treatment confounders that affect both the mediator and the outcome, the sequential ignorability assumption is violated and the parameter is no longer zero.

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| > med.fit <- lm(emo ~ treat + age + educ + gender + income, data = framing) > out.fit <- glm(cong\_mesg ~ emo + treat + age + educ + gender + income, data = framing, family = binomial("probit")) > med.out <- mediate(med.fit, out.fit, treat = "treat", mediator = "emo", robustSE = TRUE, sims = 100) > sens.out <- medsens(med.out, rho.by = 0.1, effect.type = "indirect", sims = 100) > summary(sens.out)  > plot(sens.out, sens.par = "rho", main = "Anxiety", ylim = c(-0.2, 0.2))  > plot(sens.out, sens.par = "R2", r.type = "total", sign.prod = "positive") |

R2M∗R2Y: the proportion of the previously unexplained variance in the mediator and outcome variables is required to be explained by an unobservable pretreatment confounder in order to render a mediation of 0.

˜R2M˜R2Y: How much of the proportion of the original variance explained by an unobserved confounder is required to render a mediation effect of 0?

--> 0.1395 . Depending on where you stand that's substantial or not.

Here, rho.by = 0.1 specifies that ρ will vary from −0.9 to 0.9 by 0.1 increments, and effect.type = "indirect" means that sensitivity analysis is conducted for the ACME. Alternatively, specifying effect.type = "direct" performs sensitivity analysis for the ADE and "both" returns sensitivity analysis for the ACME and ADE.

**4.1 Testing Significance of Mediation**

There are many ways to assess if the mediation is significant, and the ‘bootstrapping method’ is one.

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| med.out <- mediate(med.fit, out.fit, boot=TRUE, treat = "treat", mediator = "emo", robustSE = TRUE, sims = 100)  summary(med.out) |

**5.1. Causal Diagrams**

For causal diagrams,

Graphical user interface, text, application

Description automatically generated

Diagram

Description automatically generated

Text

Description automatically generated

A picture containing text, antenna

Description automatically generated