FOCUSING ON THE EFFECT OF TIME:
A CONDITIONAL PROCESS ANALYSIS APPROACH TO ANALYZING 2 (WITHIN) X 2 (BETWEEN) DESIGNS

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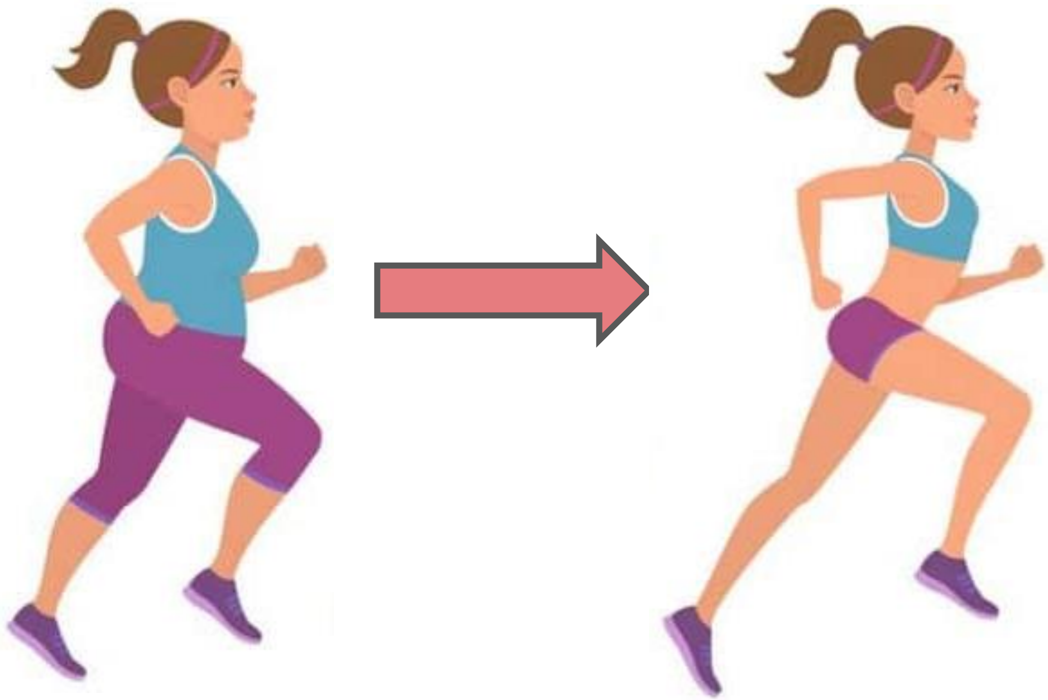
Slides available at github.com/akmontoya/SESP2019

How do we experience change?

Imagine you are interested in losing weight, so you go to a local WeightWatchers. As part of the meeting you are asked to visualize:

“How you will know if this program has been effective?”

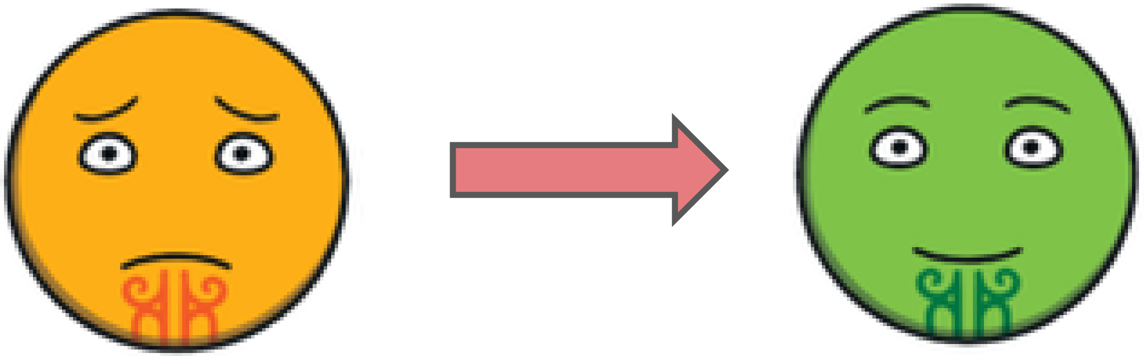


Lose weight, more energy, able to do more physically

How do we experience change?

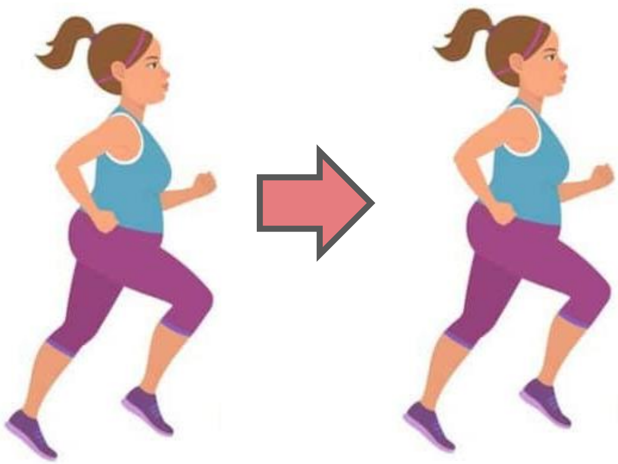
Consider now that you are a patient seeking help for depression through therapy.

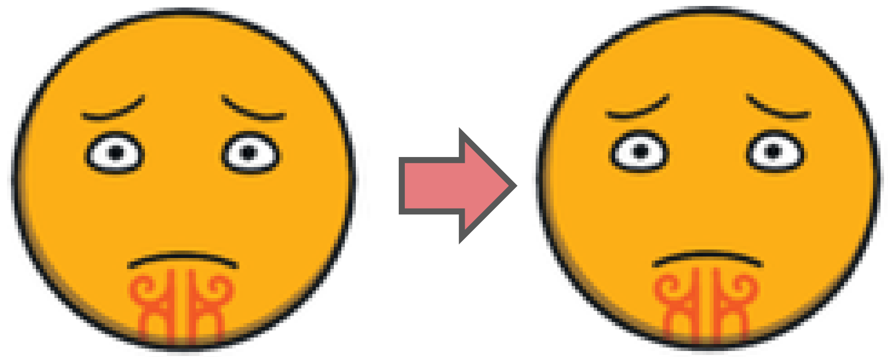
“How you will know if the therapy has been effective?”



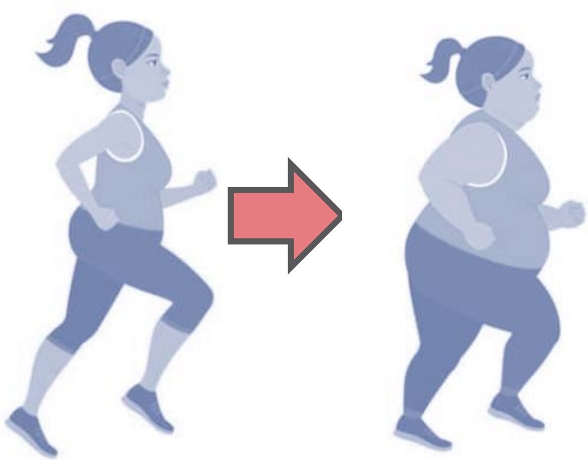
Improved mood, able to enjoy activities, increased ability to cope

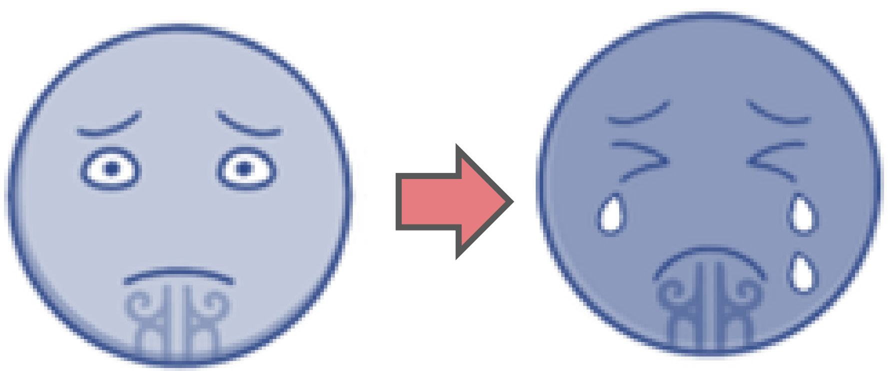
Can you "change" if you stay the same?





Scientists treat *staying the same* as "effective" if the alternative is that one would get worse



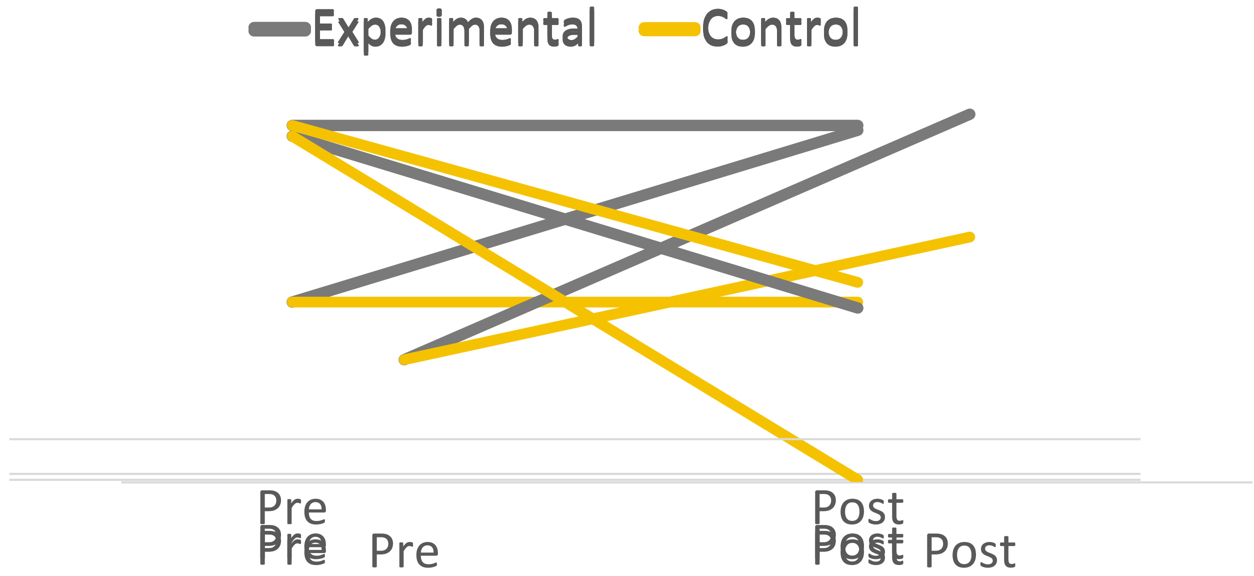


Understanding Change

- **Scientists** know that an effective treatment is one in which the change in the outcome is more beneficial for a treatment vs. control group

- **Individuals** experience an effective treatment as something that changes an outcome over time in a positive (beneficial) way.

This scientific definition allows us to account for many patterns of change across the treatment groups. But the **subjective experience** is important.

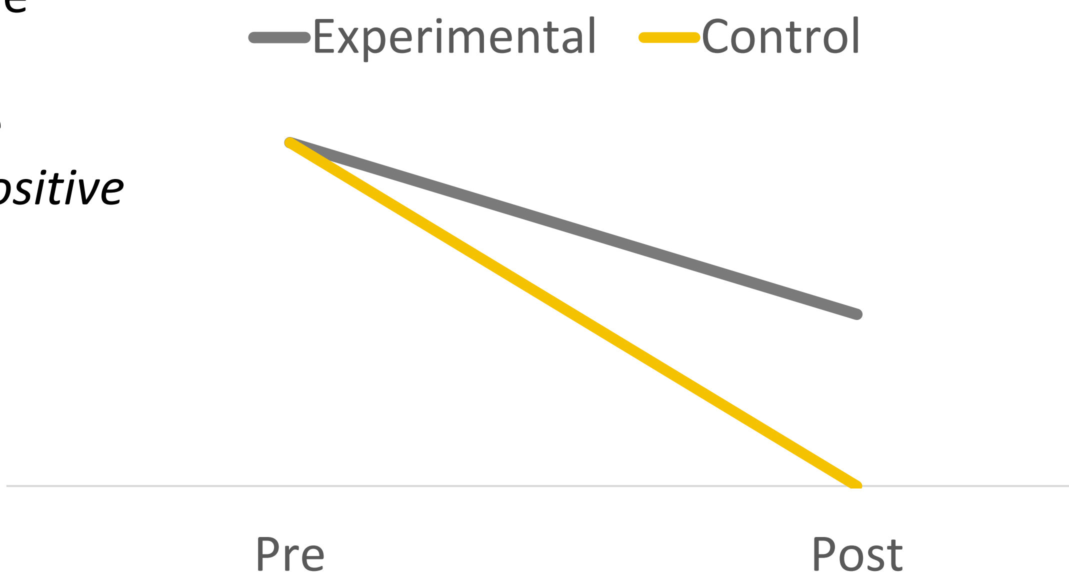


Differences in Slopes

Statistical methods for evaluating effectiveness of a treatment focus on the difference in the slopes across time

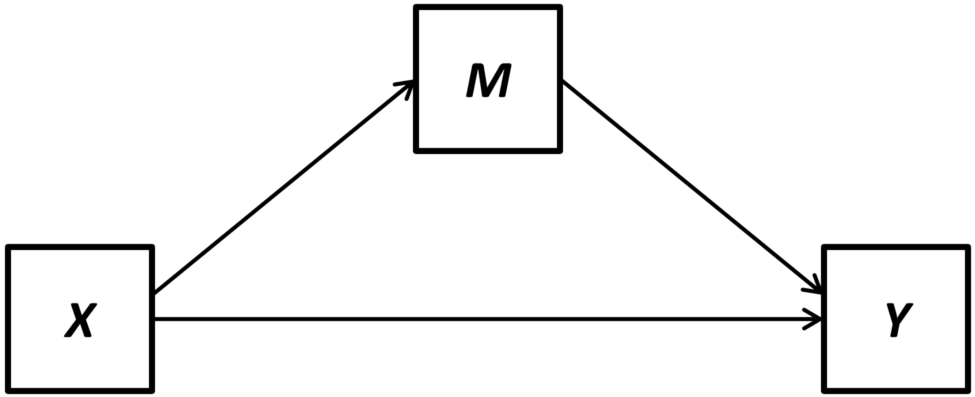
When the change over time in the **experimental** condition is *more positive* than change over time in the **control** condition, treatment is effective.

(Even if both slopes are negative)



Knowledge about the **individual slopes** in each condition is very important to understanding each individual's subjective experience of the treatment.

Why is a treatment effective?



Mediation analysis is a statistical approach to evaluating questions about **processes**.

A simple mediation model connects an **assumed** causal variable (*X*) to an **assumed** outcome variable (*Y*), through some **assumed** mechanism (*M*).

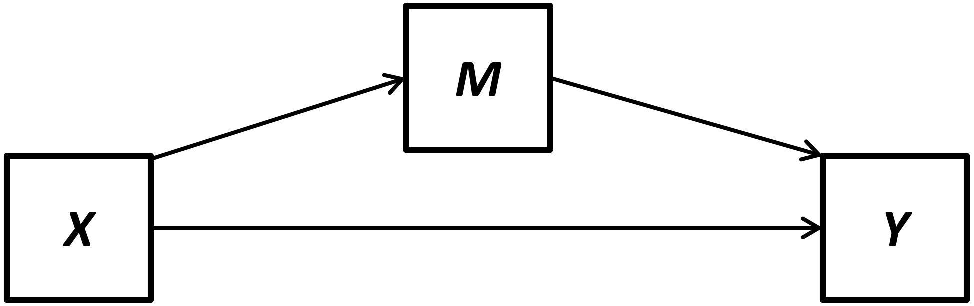
The goal is to determine if there is an effect of *X* on *Y* through *M*. This is typically done by estimating the ***indirect effect*** and testing if it is different than zero.

Causality: Causal order of the variables is an **assumption** of mediation. The term “effect” is used based on this assumption. The quality of causal inference is determined by study design and theory.

Mediation for 2(Within) X 2(Between) Designs

Current approaches for understanding mediation in Pre-Post Treatment-Control designs focus solely on **the difference between the treatment and control condition.**

These methods work by focusing on the *indirect effect* of **treatment.**



Treatment

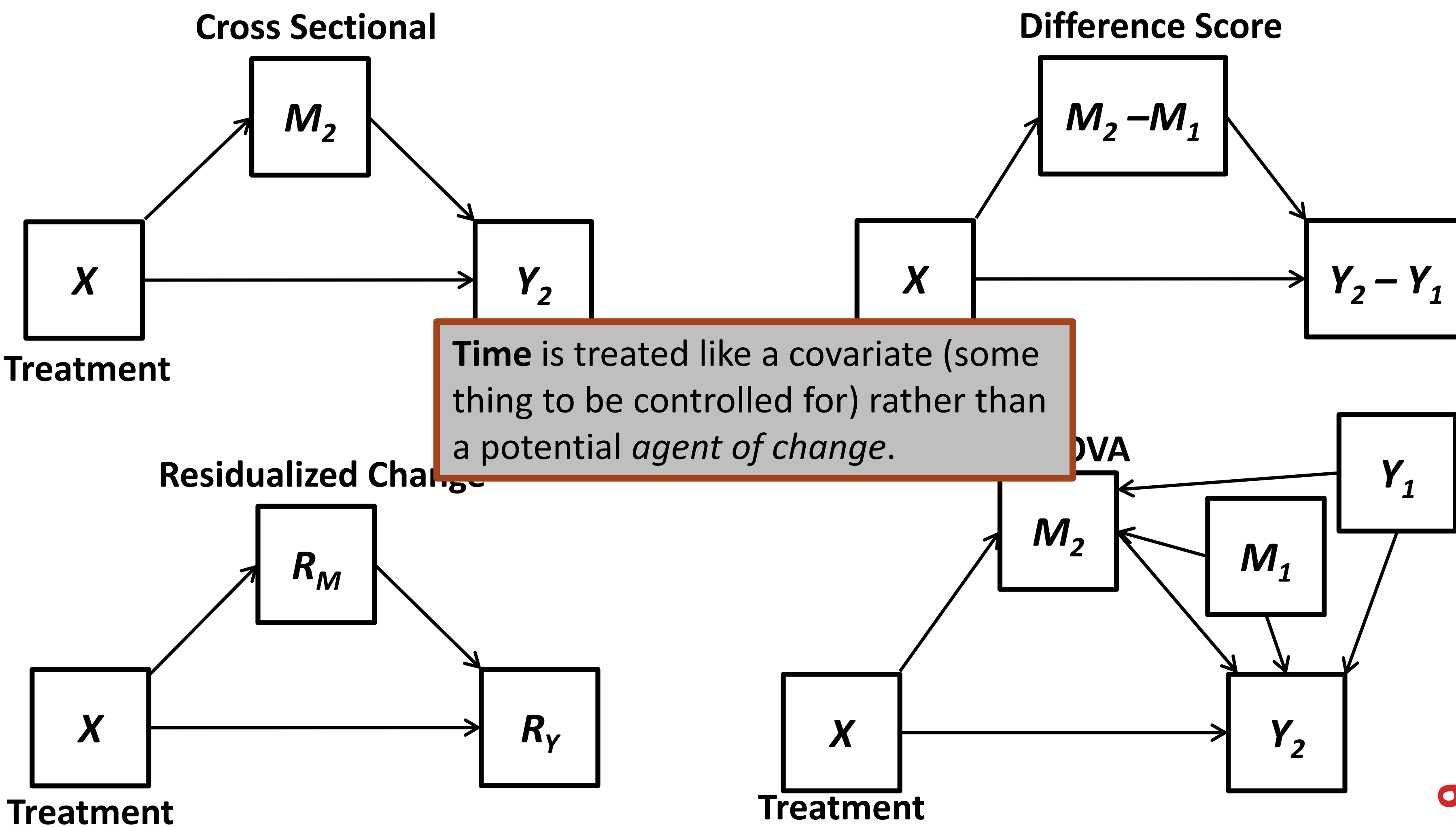
Can conclude: Treatment results in a larger change in Y through a change in M than the control condition

No idea: How much change in Y through M occurs in the treatment group and in the control group, separately.

Four Approaches (Valente & MacKinnon, 2017)

Four approaches to mediation analysis for pre-post experimental designs.

Estimate **indirect effect of treatment**, while *accounting for the premeasurements.*



Time is treated like a covariate (some thing to be controlled for) rather than a potential *agent of change*.

Focusing on the Effect of Time

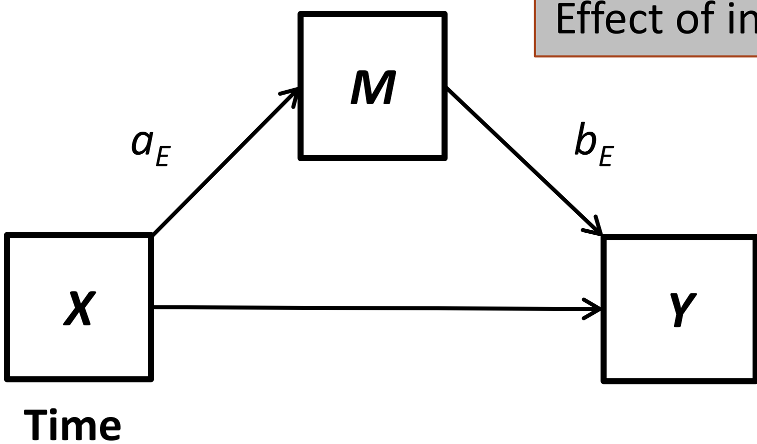
Montoya & Hayes (2017) proposed a path-analytic method for estimating mediation analysis in two-instance repeated-measures design (e.g., pre-post).

In this model the causal agent of change is **time.**

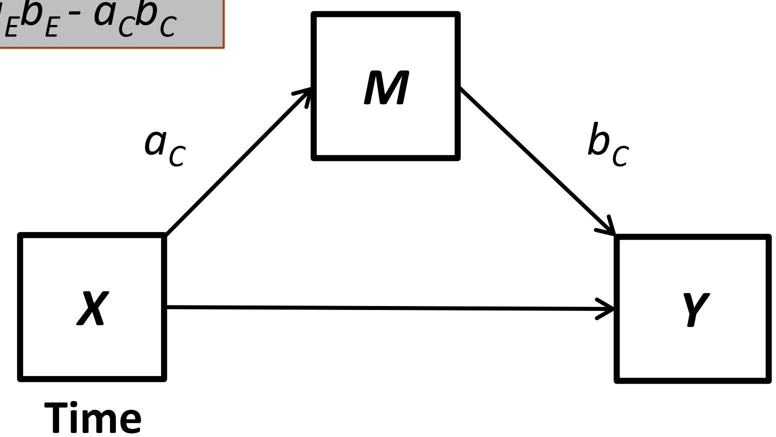
We estimate the **indirect effect of time** on the outcome through the mediator.

But what we're interested in is **Does the indirect effect of time differ across conditions?**

Effect of interest: $a_E b_E - a_C b_C$



Experimental Condition ($a_E b_E$)



Control Condition ($a_C b_C$)

One Model: Moderated Mediation

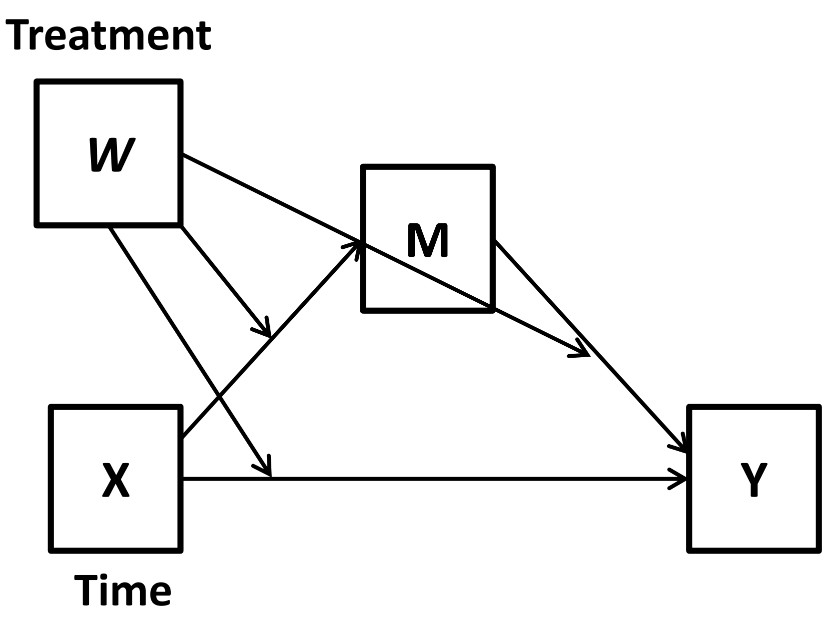
These two models can be estimated simultaneously by allowing treatment to be a moderator of all paths in the mediation model.

Now, **time** is the causal variable of interest and **treatment** is a moderator.

Conditional indirect effects: *Expected change in Y through change in M over time for a specific treatment group.*

Estimates of Interest:

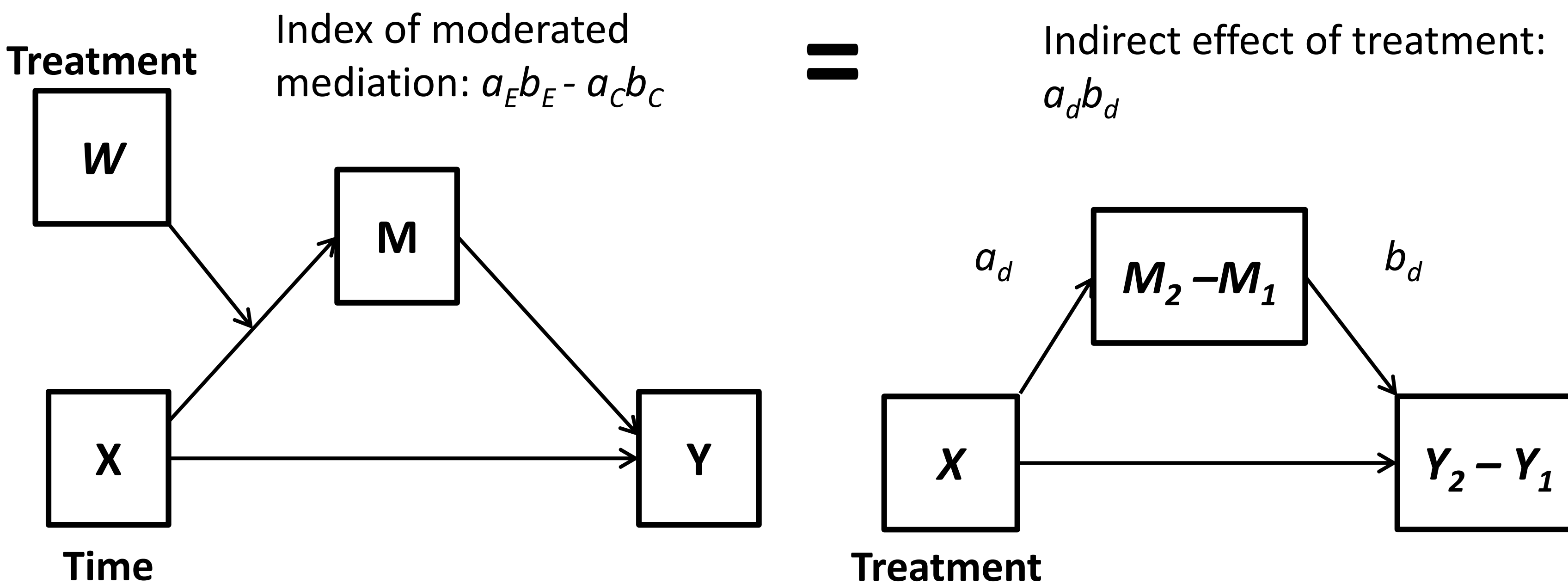
1. Conditional Indirect Effect (Experimental Condition) ($a_E b_E$)
2. Conditional Indirect Effect (Control Condition)($a_C b_C$)
3. Index of moderated mediation: $a_E b_E - a_C b_C$



A Close Connection

Our proposed model is closely related to the **difference score model** from Valente and MacKinnon (2017).

If our model only allowed moderation of the first-stage of the mediation, the index of moderated mediation from our model would be equal to the indirect effect from the difference score model



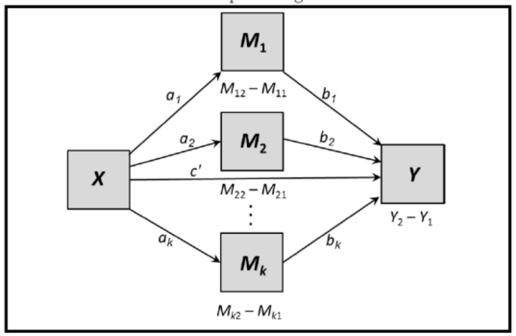
MEMORE

MEMORE is a macro available for SPSS and SAS for conducting (MEdiation and MOderation in REpeated measures designs). Documentation and download at akmontoya.com.

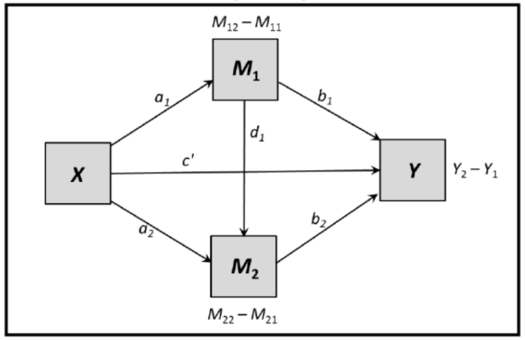
MEMORE can assess a variety of models. Find the model you are interested in in the templates file, then use that model number.

New models being released in **Version 3.0** for moderated mediation.

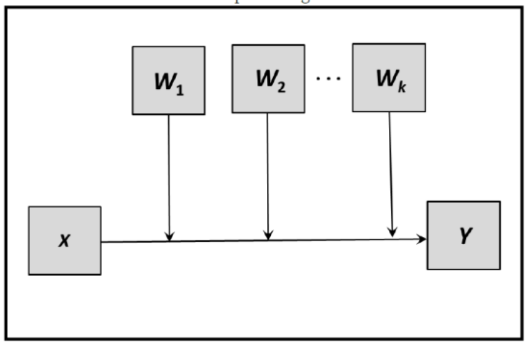
Model 1 Simple and Parallel Mediation
Conceptual Diagram



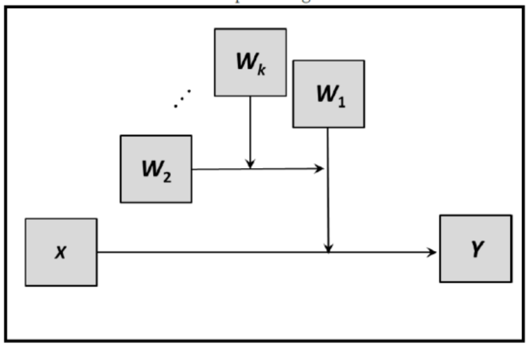
Model 1 Serial Mediation (Serial = 1)
Conceptual Diagram



Model 2 Additive Moderation
Conceptual Diagram



Model 3 Multiplicative Moderation
Conceptual Diagram



SPSS Syntax:

```
MEMORE y=y2 y1/m=m2 m1/w=group /model=4.
```

SAS Syntax:

```
MEMORE(data = filename, Y = y2 y1, M = m2 m1, w = group, model = 4);
```

MEMORE Output

************************* TOTAL, DIRECT, AND INDIRECT EFFECTS *************************

Conditional Total effect of X on Y

group	Effect	SE	t	p	LLCI	ULCI	
.0000	.2442	1.1221	.2177	.8282	1.9896	2.4781	$\leftarrow c_0$
1.0000	4.1883	.6694	6.2567	.0000	2.8556	5.5211	$\leftarrow c_1$

Test of moderation of total effect

	coeff	SE	t	p	LLCI	ULCI	
group	3.9441	1.3066	3.0187	.0034	1.3429	6.5453	$\leftarrow c$

Conditional direct effect of X on Y

group	Effect	SE	t	p	LLCI	ULCI	
.0000	.1107	1.0858	.1020	.9191	-2.0529	2.2743	$\leftarrow c'_0$
1.0000	2.2127	.9963	2.2108	.0294	.2275	4.1980	$\leftarrow c'_1$

Test of moderation of direct effect

	coeff	SE	t	p	LLCI	ULCI	
group	2.1020	1.4737	1.4264	.1580	-.8343	5.0384	$\leftarrow c'$

Conditional indirect effect of X on Y through M

group	Effect	LLCI	ULCI	
.0000	.1335	-.4966	1.0872	$\leftarrow a_0b_0$
1.0000	1.9756	.4984	3.5770	$\leftarrow a_1b_1$

Test of moderation of indirect effect

Index	LLCI	ULCI	
1.8421	.1292	3.5538	$\leftarrow a_1b_1 - a_0b_0$

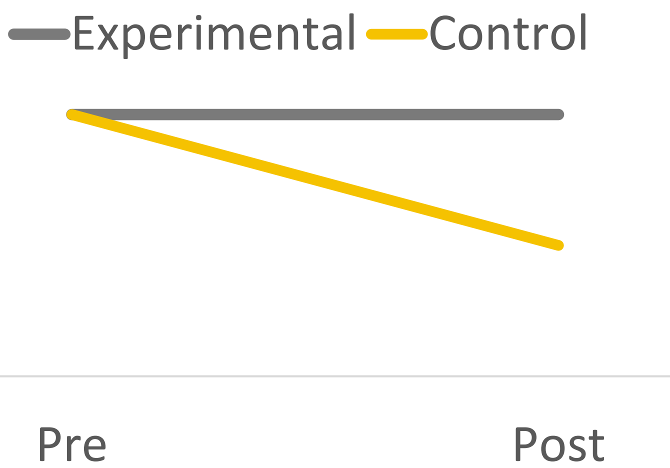
Summary

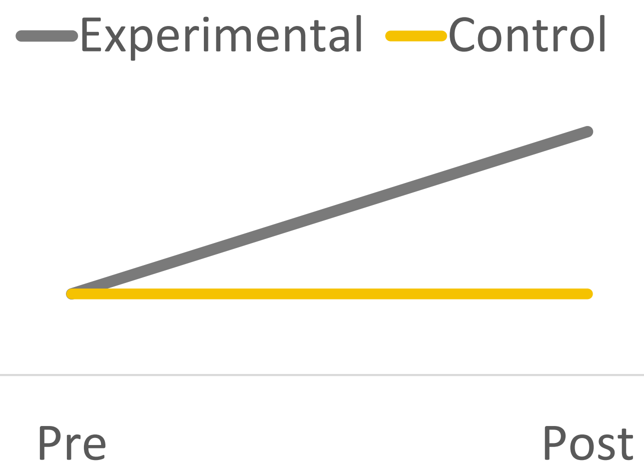
Mediation analysis with 2(Within) x 2 (Between) designs has seen new growth and development

By framing the problem as a moderated mediation model, researchers can get

(1) Information about change over time within each condition

(2) Information about differences between conditions





MEMORE is an easy to use tool for SPSS and SAS which can be used to implement this approach (and mediation and moderation separately).

Thank you!

Thank you, Dr. Andrew Hayes, Dr. Paul de Boeck, Dr. Jolynn Pek, the Quantitative Research Collaboratory, and the Mechanisms and Contingencies Lab! Thanks to the National Science Foundation Graduate Research Fellowship, for supporting my research. And thanks to all of you for attending!

Workshops available by request!

Contact: akmontoya@ucla.edu

MEMORE V2.1 can be downloaded from akmontoya.com

MEMORE V3.0 will be released with manuscript, email to Beta test.

Preprint of manuscript and Slides at github.com/akmontoya/SESP2019

Moderation in Two-Instance Repeated-Measures Designs

1. Setup two regression equations, one for each instance

$$Y_{1\mathrm{i}} = b_{10} + b_{11}W_i + \epsilon_{1i}$$

$$Y_{2\mathrm{i}} = b_{20} + b_{21}W_i + \epsilon_{2i}$$

Is b_{11} different from b_{21}?

2. Take the difference between those two regression equations

$$Y_{2i} - Y_{1i} = (b_{10} - b_{20}) + (b_{11} - b_{21})W_i + \ (\epsilon_{1i} - \epsilon_{2i}) = b_0 + b_1W_i + \epsilon_i$$

3. Regression weight for person level covariate in Step 2 tests moderation.

Estimate equation above and test if b_1 is significantly different from zero

Judd, McClelland, and Smith, 1996

CPA in Two-Instance Repeated-Measures Designs

First stage moderated mediation allows *W* to moderate the path between the within-subjects factor and the mediator.

$$M_{1i} = a_{01} + a_{11}W_i + \epsilon_{M1i}$$

$$M_{2i} = a_{02} + a_{12}W_i + \epsilon_{M2i}$$

Allowing the effect of *W* to vary by instance, which is the same as allowing the effect of instance to depend on *W*.

$$M_{2i} - M_{1i} = (a_{20} - a_{10}) + (a_{21} - a_{11})W_i + \ (\epsilon_{M2i} - \epsilon_{M1i}) = a_0 + a_1 W_i + \epsilon_{Mi}$$

How do we quantify the effect of instance on *M*?

$$\theta_{X \to M}(W) = a_0 + a_1 W_i$$

The model for the relationship between *M* and *Y* can remain the same.

$$Y_{Di} = c' + bM_{Di} + dM_{Si}^{c} + \epsilon_{Yi}$$

Montoya, *dissertation*

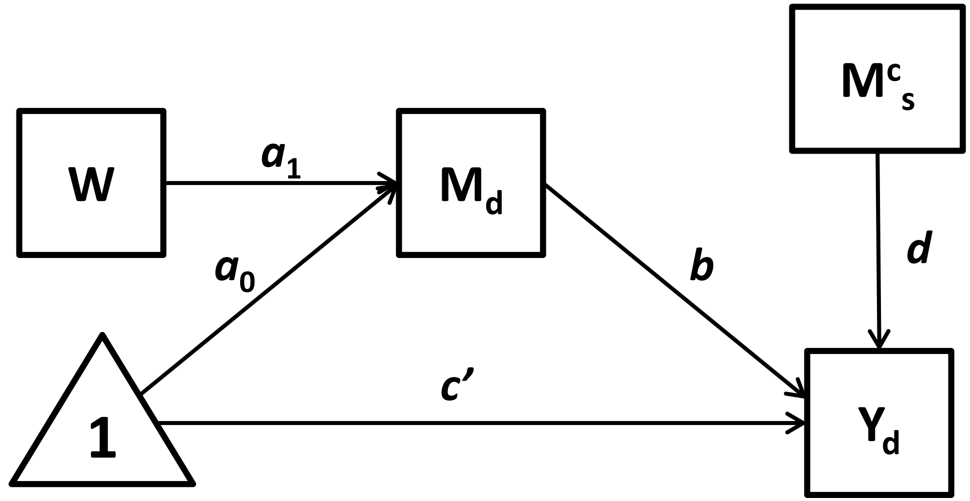
Translating to Path Model

First stage moderated mediation allows *W* to moderate the path between the within-subjects factor and the mediator.

$$M_{2i} - M_{1i} = a_0 + a_1 W_i + \epsilon_{Mi}$$

$$\theta_{X \to M}(W) = a_0 + a_1 W_i$$

$$Y_{Di} = c' + bM_{Di} + dM^c_{Si} + \epsilon_{Yi}$$



What is the indirect effect?

$$\theta_{X \to M}(W) \times b = (a_0 + a_1 W)b = a_0 b + a_1 bW$$

Indirect effect is a *function* of the moderator

Montoya, *dissertation*

Two-Condition Repeated Measures Mediation

We can quantify paths of influence in the the two condition repeated measures case.

3. Does difference in *M* predict a difference in *Y*?

$$\boldsymbol{E}(Y_{1i}) = g_{10} + g_{11}M_{1i}$$
$$\boldsymbol{E}(Y_{2i}) = g_{20} + g_{21}M_{2i}$$

$$\boldsymbol{E}(Y_{1i} - Y_{2i}) = g_{10} - g_{20} + g_{11}M_{1i} - g_{21}M_{2i}$$

Then apply a rotation to get:

$$\boldsymbol{E}(Y_{1i} - Y_{2i}) = g_{10} - g_{20} + \frac{g_{21} + g_{11}}{2}(M_{1i} - M_{2i}) + \frac{g_{11} - g_{21}}{2}(M_{1i} + M_{2i})$$

$$Y_{1i} \widehat{- Y_{2i}} = \hat{h} + \hat{b}(M_{1i} - M_{2i}) + \hat{d}\,(M_{1i} + M_{2i})$$

Judd, Kenny, and McClelland 2001

Two-Condition Repeated Measures Mediation

We can quantify paths of influence in the the two condition repeated measures case.

4. Does the difference in *M* account for all the difference in *Y*?

$$\boldsymbol{E}(Y_{1i} - Y_{2i}) = h + b(M_{1i} - M_{2i}) + d(M_{1i} + M_{2i})$$

$$\boldsymbol{E}(Y_{1i} - Y_{2i}) = h + d\frac{1}{n}\sum_{i=1}^{n}(M_{1i} + M_{2i}) + b(M_{1i} - M_{2i}) + d(M_{1i} + M_{2i} \; - \frac{1}{n}\sum_{i=1}^{n}(M_{1i} + M_{2i}))$$

Thus $h + d\frac{1}{n}\sum_{i=1}^{n}(M_{1i} + M_{2i})$ is a quantification of the direct effect. An estimate of this value could be the intercept from the following equation:

$$Y_{1i} \widehat{- Y}_{2i} = \widehat{c'} + \hat{b}(M_{1i} - M_{2i}) + \hat{d}\,(M_{1i} + M_{2i} - \frac{1}{n}\sum_{i=1}^{n}(M_{1i} + M_{2i}))$$

Judd, Kenny, and McClelland 2001