# Classical and Cooperative Suppression – Simplified

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## Suppression analysis

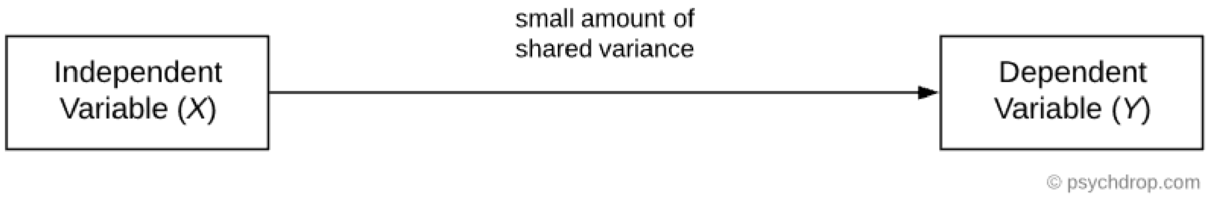
Having a good understanding of mediation helps. A bit. But for me, mediation made sense pretty quickly… Suppression did not. So, let's walk through this. Specifically, we'll talk about **classical** and **cooperative (reciprocal) suppression**. I'll also give you a basic toolkit for suppression analyses.

## It's like the opposite of a mediation effect…

Let's break down this "opposite of mediation" explanation. When there is a **mediation effect**, a third variable **decreases** the strength of the relationship between X and Y. This occurs because the mediator has taken the stage. A **suppression effect** is opposite because a third variable **increases** the relationship between *X* and *Y*.

Okay, hold on. If relationship strength **increases**, why is it called **suppression**? Well, a third variable, called a **suppressor**, suppresses *irrelevant variance* in *X*. This *enables* a stronger effect of *X* on *Y*. Suppressors **suppress error variance** in *X*. Thus, suppressors **indirectly increase** the independent variable's predictive ability of *Y*, even though **suppressors have little to no relationship with *Y***.

What we typically see **before** a third variable enters the model is that independent variables are **weakly related** to the dependent variable. In other words, we may see **little or no total effect**.

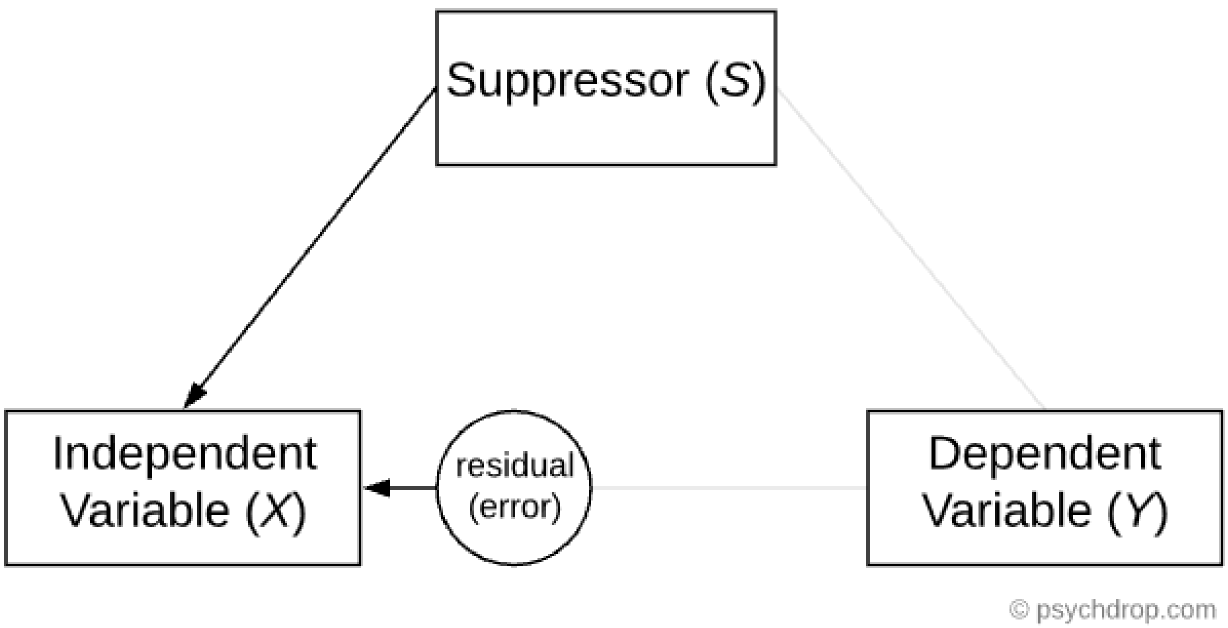



Before the **suppressor** enters the model, *X* and *Y* have a non-significant or weak relationship.

Suppression analysis comes with a lot of **relationship rules**. Very high maintenance. These rules tell us **how variables typically relate to each other in a suppression analysis.** Although rules may break down a suppression, it's difficult to simply memorise these rules. I'm going to use models to put these rules into more context. Now, let's go through classical and cooperative suppression individually.

## Classical suppression

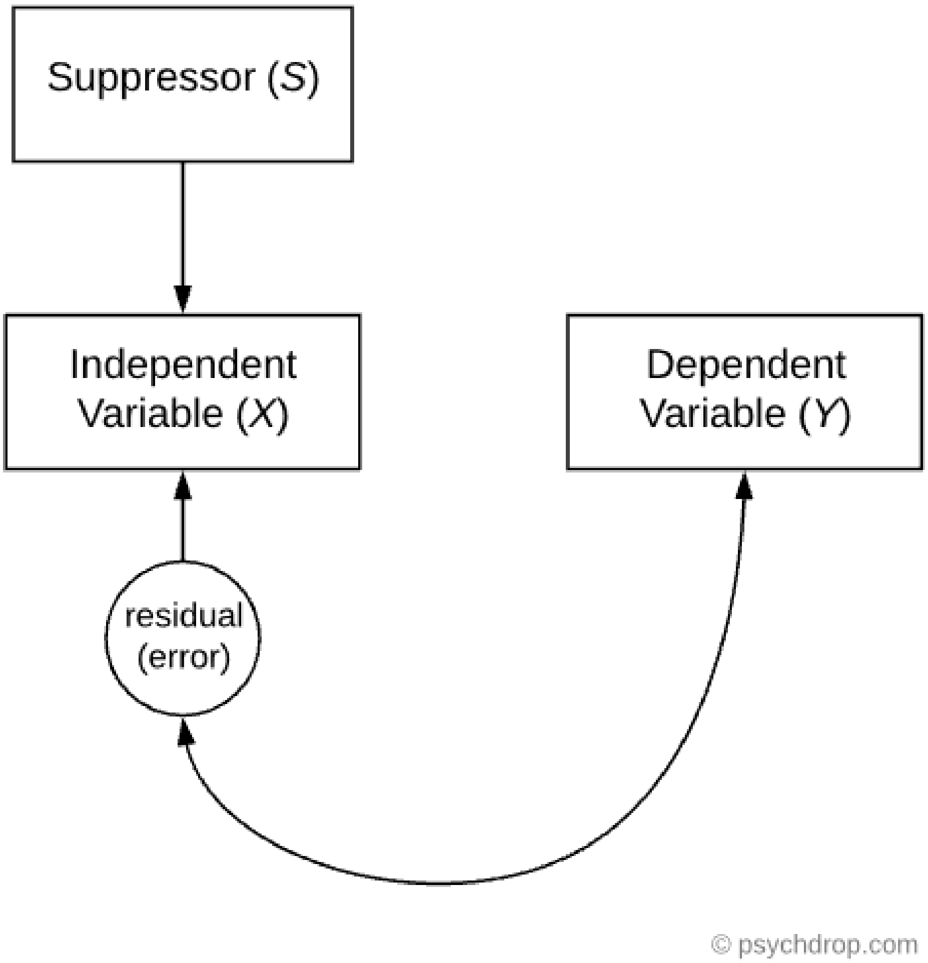
Let's try to understand classical suppression – the "opposite of mediation". Below I made a diagram to resemble a mediation path analysis. However, notice the faded, grey lines? These indicate **weak/no relationship**. There's also some **error** getting in the way of *X* and *Y*. As mentioned before, the independent variables (*X*& *S*) share some variance. The independent variables share little variance with *Y*.




- *S* & *Y* – little to no shared variance
- *S* & *X* – moderate shared variance

- *X* & *Y* – little shared variance

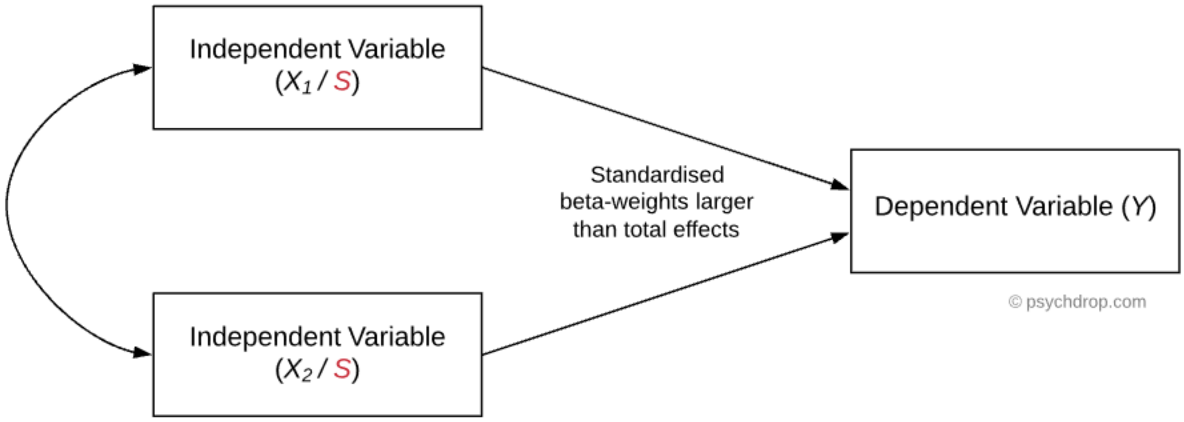
Now let's get rid of the grey lines – zero lines for a zero correlation. We'll also show a **classic suppression effect**. The suppressor **increases** *X*'s relationship with *Y*. We can use a bold line to show the *revealed* relationship for *X* and *Y*.




In **classic suppression**, a third variable leads to an **'appearance' or increase** in the strength of the relationship between *X* and *Y*. That's the work of a **suppressor**. The suppressor continues to have **no relationship** with *Y*.

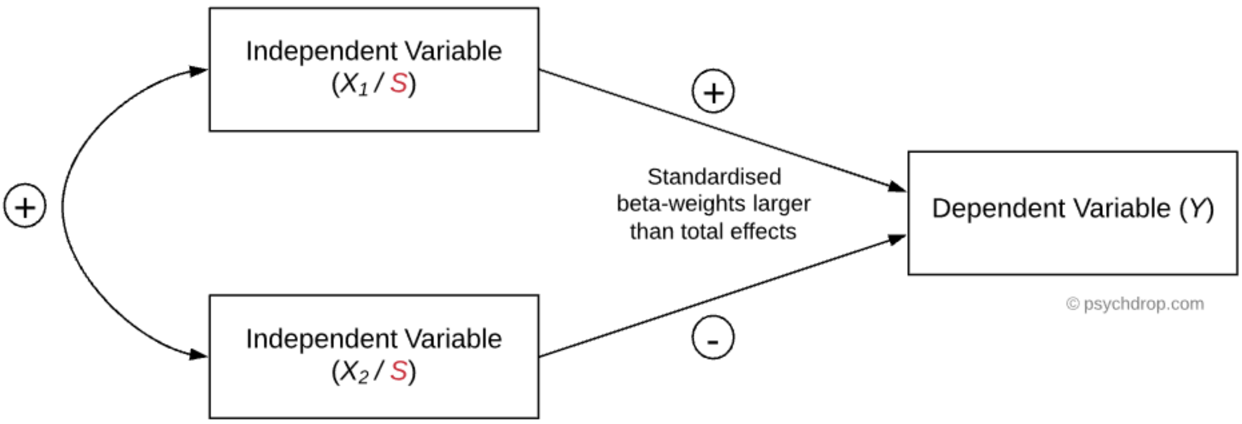
## Cooperative suppression

Cooperative or **reciprocal** suppression starts the same as classical suppression. Independent variables are weakly correlated *Y*. The difference is that **both** independent variables are **suppressors**. The suppression effect is **mutual**.

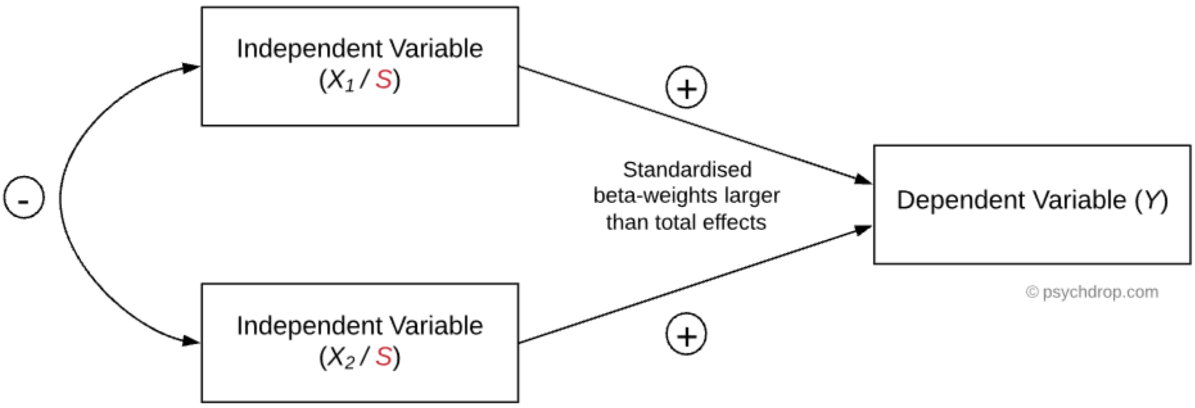



When both independent variables are in the **regression model** they **suppress each other**.

Here are some **patterns** in the correlations of **cooperative** suppression.




- *X1* & *X2* – positively correlated
- Opposite correlations with Y




- *X1* & *X2* – negatively correlated
- Positive correlations with *Y*

## Your toolkit for observing suppression effects

### Standardised beta-weights – *β*

The standardised beta-weights indicate the **strength and direction** of a relationship between two variables (e.g., *X* and *Y*). We now know that suppression leads to the '*appearance*' or strengthening of a relationship between two variables. So, if the beta-weights of the **direct effect** are **larger** than the beta-weights of the **total effect** – this suggests suppression.

### Squared Correlations

How big was our effect? To understand this, we're interested in two types of correlations. **Zero-order correlations** are **simple** correlations between two variables (e.g., bivariate regression, Pearson correlation). **Semi-partial correlations** show the **unique** effect of *X* on *Y*.

Now let's **square** these correlations. Why? Squaring a correlation gets you the **coefficient of determination**. Remember? The percentage of **shared variance** between *X* and *Y*. When you subtract the **squared zero-order correlations** from the **squared semi-partial correlations**, you can get the suppression **effect size.**

squared semi-partial correlations – squared zero-order correlations = effect size (%)

## Sources