Mediation models

So one of the main kinds of models that analysts will use structural equation models for, are for mediation kinds of models. One can estimate mediation models in other modelling frameworks but SEMs are particularly well suited to mediation models. What we are talking about really here is a focus on not simply the direct effects of one variable on another which is what we are implicitly focusing on and often explicitly focusing on in a OLS context, but we want to decompose the effects of one variable on another into those direct effects but also effects that are running through other variables in the system. So we are going to be interested in the indirect as well as the direct and the total effects and this is because often times what we are interested in is understanding causal mechanisms not just whether two variables are causally related but how they are causally related. So we might for example conclude that at gaining a degree at university increases your earnings it might have a causal effect on your earnings in later life and that's a useful and interesting conclusion to be able to draw, but there might be secondary questions about how that actually happens, what is the mechanism that underlies the earnings return to gaining a degree. From a sort of a human capital perspective we might expect this to be through increasing the individuals' skill level or their productivity which would then from economic theory lead us to expect them to have higher earnings. On the other hand from a more kind of sociological perspective it might just be that the degree is just a credential and that it hasn't really endowed the individual with any greatest skill or productivity but it's just given them a certificate which enables them to get to the top of the queue, ahead of people who don't have that degree, and those kinds of mechanism questions are often very important for policy and are at the heart of what we're doing when we're fitting mediation models.

We've seen a couple of examples of path diagrams with mediation already, here we see an example where we have eta two, a latent variable which is regressed on eta one, and we have a third variable Z which is our kind of exogenous variable here and we can look at the different effects that X has on eta two. First of all the direct effects of Z on eta two is the beta weight beta 3 here the direct path, so that's what we would normally be focusing on in a regression equation that direct effect. But we can also estimate the indirect effect here because we've got the beta 1 coefficient of Eta one on Z, and the beta 2 coefficient of Eta two on Eta one. Now if we take the product of those two parameters then that will give us the indirect effect of Z on on eta two. So that's how we can algebraically recover the indirect effect of one variable on the other is taking the product of the two beta weights. And then we will perhaps be interested in the total effect, and this is the sum of the indirect and the direct effects. So we might find for example, that both direct and indirect effects are non-significant but there is still a significant total effect. So we can get different patterns of understandings of an effect of one variable on another by looking at these different effect parameters. We sometimes distinguish between partial and perfect mediation. So for example if we fitted a model that just regressed eta two on Z and we found a significant and substantial effect there, then if we add in the eta one predictor, if the effect of Z now becomes non-significant but the the indirect effect is significant then we would refer to this as perfect mediation. That all of the effect of Z on eta two flows through eta one. Where there is still a residual effect ie a significant path between Z and Eta two, that would be referred to as partial mediation.

Now as I said we can specify these kinds of models using a series of OLS models and we can recover the indirect effects by taking the product of the respective direct effects, to get the indirect and total effects. One of the advantages of doing this in a SEM framework using SEM software however is that those kind of calculations are done for you and just provided in the output and additionally and there are various ways of directly calculating the standard errors of those indirect paths. So we can either calculate the standard errors for these mediated paths using what's called the Delta method a parametric approach, which assumes multivariate normality, or more commonly now using nonparametric approach is like bootstrapping resampling from the sample data to generate an empirical sampling distribution. If we do that of course we need to have the raw data rather than the covariance matrix. So the SEM framework is very convenient for doing this kind of modelling. We can have more complex mediated paths that run not just from one variable through another to a third variable but through several variables and we can get estimates of those indirect and total effects and their standard errors.

Here's an example again using the European social survey an actual model here where we are looking at the the effective of being in a high-income group, your income on your level of social trust and breaking that down into the direct effect of income on social trust through and also the indirect effect through your level of happiness or life satisfaction. You can see here that the beta weights on the path diagram there indicate that there are these are standardized parameter estimates and so you can see there is an effect of being high-income on social trust, and there seems to be an indirect path there. So we could just take the product of the .09 and the .035 parameters to get the indirect effect. If we do that and we get a figure about .032 which if you look at this slide here you can see this is some output from Amos software and you can see there that in red the indirect effect of the column variable which is high-income on the row variable which is social trust is .032 which is the product of those two coefficients to give you the indirect effect, and you can see that all of the possible path estimates are provided, they're directly in the output. Also in SEM software you will get as I said the standard errors either through bootstrapping or parametric estimation and here we see that the the two-tailed p-value for that indirect effect of income on social trust is significant at the 95% level of confidence. So we could reject the null hypothesis that there is no indirect path between income and social trust.

So that's a very brief look at the way that we can fit mediation models and what some of the advantages are of doing this within the SEM context. It's important to remember a couple of limitations here, one is that in this kind of modelling environment we're really limited to continuous mediating variables, we very difficult to estimate these kinds of models when the mediator, when the Z variable is continuous and when we have a mix of continuous and categorical variables. It's also really not a framework for the kind of clean causal effect estimates and that we were talking about in the previous video on instrumental variables, really this is just decomposing covariances. There are other approaches that have a more of a causal estimate focus using the sort of the potential outcomes framework and that would be using G computation and so on. We won't be covering those in this video but it's important to be aware that there are other frameworks for estimating these kinds of mediation models which are a bit more modern and have a more robust causal inference behind them.