Longitudinal Regression Approaches

Causality
Although regression models describe a predictive relationship in which we must choose an "independent" and "dependent" variable, concluding that there is a relationship between them is not a confirmation of a causal relationship. Mill (1843) popularized the idea that an association between $X$ and $Y$ is causal when $X$ produces $Y$ regularly ceteris paribus (when all things are equal). The general concept is isolation of the independent variable from all other potential cause of $Y$. This is the basic idea of the modern experiment, either through random assignment to groups or other methods of isolation (e.g., fully controlled manipulation of the independent variable, in say, a chemistry experiment). Kenny (1979) provides a valuable, brief summary of conditions for deciding a causal relationship exists that include: a) there is a relationship between $X$ and $Y$; b) temporal precedence ($X$ precedes $Y$); and b) nonspuriousness (third variables can be ruled out). 1 Your text (Cohen, Cohen, Aiken, & West, 2003, p. 455) adds that a "theoretically plausible mechanism" must exist. We can establish a relationship with correlation or regression analysis and we have been discussing how multiple regression can be used to try to statistically control for confounding relationships, which is one method of attempting to establish nonspuriousness, but we have not discussed establishment of temporal precedence. Without an experiment, the best way to attempt to establish temporal precedence is by collecting data over time—a longitudinal study.

Two Ways of Investigating Change over Two Waves
The focus here will be on two waves of data (e.g., pre-post test, Year 1 to Year 2), but there are many other possible designs with more time points and methods for analyzing them (see Newsom, Jones, & Hofer, 2012). With two waves, there are primarily two types of regression models used to exploring predictors of change over time. Unfortunately, the two primary methods do not always lead to the same conclusion and there is much confusion over which method is "best" and how to interpret the results. There is good reason for the confusion, because there are many subtleties and there has been enormous debate about the superiority of one method over the other (e.g., see Campbell & Kenny, 1999; MacKinnon, 2008; Finkel, 1995 for reviews). I will not try to resolve the debate, but I want to provide some clarifying information.

Difference Scores
One basic regression model is to compute a difference score for the dependent variable, by subtracting the earlier time point from the later time point, $Y_{2-1} = Y_2 - Y_1$, and then use another variable, $X_1$, to predict change in the dependent variable.

$$Y_{2-1} = B_0 + B_1X_1 + e$$

Difference scores are sometimes also referred to as "gain scores" or "change scores." The difference score captures whether a particular case has increased or decreased over the interval (e.g., one year), and the slope, $B_1$, represents the amount of change in $Y$ over each unit increment in $X$. This simple regression is a reduced form of a growth curve model, which quantifies the average difference across any two points in a longitudinal design with several time points.

Lagged Regression
An alternative is to predict the dependent variable at the second time point, $Y_2$, using both the predictor $X$ and the dependent variable measured at the previous time point, $Y_1$.

$$Y_2 = B_0 + B_1X + B_2Y_1 + e$$

1 Kenny’s is a less formal, and less complete, summary of criteria for causality than recent, more detailed discussions (see, for example, Pearl, 2008; Russo, 2010).
The concept is to take into account or control for any pre-existing differences on $Y_1$, so it is sometimes referred to as the ANCOVA approach. If $X$ was a binary predictor, representing treatment and control conditions, the model would be exactly the same as an ANCOVA.

We can represent this model with a path diagram.

$Y_1$ is the dependent variable measured at Time 1, $Y_2$ is the (exact same) dependent variable measured at Time 2, and $X_1$ is some predictor (explanatory) variable measured at Time 1. The path between the two measurements of the dependent variable represents the extent to which the two measurements are correlated. If there is a perfect relationship, the dependent variable is highly stable over time. The small arrow to the right pointing down into $Y_2$ represents the residual variance or the variance unaccounted for in $Y_2$, and, ignoring $X_1$ for a minute, that path could be interpreted as what is not stable or what is changing in the dependent variable. It then follows that another interpretation of this model (beyond controlling for initial differences) is that $X_1$ is predicting the remaining variance or the change in $Y$ over time.

Lord’s Paradox
Given the latter interpretation of the lagged regression model, one would think it is providing the same information as the difference score model—both models attempt to predict change in $Y$ with $X$. It is sometimes disconcerting to discover, however, that the two approaches do not always lead to the same result. Sometimes, $X$ will be a significant predictor of "change" using one of the regression approaches but not the other (although, often they will show the same result). Such a lack of correspondence in results from the two longitudinal regression approaches is referred to as Lord’s paradox (Lord, 1967). The explanation for this difference in the two regression models is complex and often difficult to fully grasp (Campbell & Kenny, 1999), but it comes down to two different concepts of stability and change.

Two Definitions of Stability and Change
The difference score concept of perfect stability is that the scores at Time 1 are exactly the same as the values at Time 2. In other words, $Y_2 = Y_1$ and $Y_2 - Y_1 = 0$. Change is any difference in values of $Y_2$ and $Y_1$ for an individual. In the lagged regression model, stability is defined as a perfect correlation (or autocorrelation) and perfect regression between $Y_2$ and $Y_1$. The autocorrelation will not be (or minimally be) affected if individual values change from Time 1 to Time 2, as long as they maintain the same rank in the data set at each time point. Change in the lagged regression approach, then, reflects the extent to which the autocorrelation is less than 1.0. In fact, we can see the connection between the two modeling approaches algebraically. If the difference score regression is rewritten slightly as,

$$Y_2 - Y_1 = B_0 + B_1X_1 + e$$

and, if we rearrange the terms a bit, we get:

$$Y_2 = B_0 + B_1X_1 + (1)Y_1 + e$$

And this second equation suggests that the difference score regression implies (or assumes) that the autoregression for $Y_2$ predicted by $Y_1$ is perfect (i.e., $B_2$ from the lagged regression equals 1.)

The scores may change over time without necessarily affecting the autocorrelation. For example, say you add 5 points to each score in the data set at Time 2. The mean of $Y_2$ will be increased by 5 points, but the correlation between $Y_1$ and $Y_2$ will not change. The average difference and every individual difference score will increase by 5 points, however. This example suggests one other conceptual
difference between the two definitions of stability and change. The difference score regression concerns predicting level change in the dependent variable, whereas lagged regression concerns predicting relative change in the dependent variable (for more elaborate discussion of the contrast between the two approaches to change and stability, see Newsom, 2015).

Summary
I am often asked which regression approach to the analysis of change should be used or which is "correct." My answer is that neither is incorrect. The two analysis approaches ask slightly different questions. It is certainly wrong, however, to choose one approach over the other simply because one is significant and one is not or one shows results consistent with what you would like to find. Because the difference score model concerns absolute level change in the dependent variable, it asks the question: “Whose score is most likely to increase or decrease over time?” A positive association between $X$ and the difference score, for example, tells us that individuals with a higher score on $X$ tend to increase more over time (or that those with lower values on $X$ increase less or decrease more). The difference score regression does not address pre-existing differences in the dependent variable related to $X$, because the initial values on $Y_1$ (and their relation to $X$) are not statistically controlled in the model. Lagged regression, on the other hand, because it does control for initial values of the dependent variable, is better suited addressing the question “Is $X$ a likely cause of $Y$?” (Campbell & Kenny, 1999), but it is less well-suited for describing who increases or decreases over time. The lagged regression gets at the causal precedence question, and combined with statistical control of confounding relationships, we are addressing all of the three criteria for causal inference. I should note that, even with longitudinal data, lagged regression, and control of covariates, it is still standard practice to avoid causally conclusive language in describing and interpreting the results.

References