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Modeling Latent Change Score Analysis and Extensions in Mplus: A Practical Guide for Researchers

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Abstract

Many developmental and life course researchers are interested in modeling dynamic developmental processes. Latent change score (LCS) modeling is a potentially powerful modeling technique that can be used to assess complex life course processes, as well as the direction of longitudinal bivariate associations. Advances in modeling software, like Mplus, as well as widening adoption of software by researchers has made LCS modeling simpler. Thus, in the present paper, we provide 1) a theoretical overview of LCS analysis, 2) information on the interpretation of these models, 3) a practical guide for estimating these models in Mplus (including example syntax), 4) illustrative examples of LCS analysis, and 5) potential caveats for researchers.

Keywords

latent change scores; life course; growth modeling; longitudinal data analysis

Many developmental, psychological, and sociological theories describe complex, dynamic developmental processes—e.g. serial dependency, cumulative and exponential effects of early differences, the effects of exogenous life changes (Elder, 1998; Farrington, 2006). Unfortunately, many of the statistical techniques employed to assess these theories are unable to appropriately model these complex and dynamic effects. While auto-regressive cross-lagged analysis, fixed effects models, Heckman and other selection-based models, and latent growth curve analysis have all been advanced as useful techniques for analyzing change and stability in behavior over time, these techniques are often inadequate for modeling many of the important processes described life course and developmental theories. These theories address predictors of initial levels and rates of change in behavior (decreases or increases), exogenous shocks and life changes that shape trajectories, endogenous

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Conflict of Interests

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Research Ethics

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processes that amplify early vulnerability, and other complex and often nonlinear effects for which the above models are often insufficient.

Alternatively, latent change score (LCS) modeling (Barker, Rancourt, & Jelalian, 2014; Hamagami & McArdle, 2001; McArdle & Grimm, 2010) is a potentially powerful and flexible modeling technique. Based in a structural equation modeling (SEM) framework, as discussed below, this modeling technique is particularly suited to the investigation of important questions pertinent to life course and developmental processes discussed above (McArdle, Hamagami, Chang, & Hishinuma, 2014).

Particularly, researchers are often interested in the way that parallel developmental and life course processes unfold over time. That is, research is often directed at understanding how two variables affect each other across multiple time points. The models addressed in the current study specifically focus on this issue assuming that the researcher has gathered repeated measurements on at least two variables at multiple time points. In the following sections, we will discuss of several LCS models demonstrating the basic function and extension of LCS analysis. All of these models are estimated in a structural equation modeling (SEM) framework.

Latent Change Score Analysis

In this model, latent true scores are used to estimate both latent change scores—representing the change in the true score between time points—and latent growth factors—representing the constant change across all observation times. Following measurement theory, as depicted in Figure 1, we assume that a variable X for person i can be decomposed into a latent true score x and time-varying residual s at time t :

$$X_{it} = x_{it} + s_{it} \quad (1)$$

where true score variances and intercepts are fixed to 0, residuals s are allowed to vary within, but not across, time points, and manifest X s have variances fixed to 0. The true score x for the i^{th} person at time t is composed of the true score of x at time $t-1$ and the true change in x between times t and $t-1$:

$$x_{it} = x_{it-1} + \Delta x_{it} \quad (2)$$

where the intercepts and variances of latent change scores are fixed to 0. The latent change score is composed of two components (see Figure 1): a constant change across waves ($\alpha_x \cdot S_x$), and an amount proportional to the previous state ($\beta_x \cdot x_{it-1}$).

$$\Delta x_{it} = (\alpha_i \cdot G_x) + (\beta_x \cdot x_{it-1}) \quad (3)$$

where G_x is a latent variable representing slope of change across all waves with factor loadings (α_j). Slope factor loadings are typically fixed to 1 for all $t \geq 2$ and fixed to 0 for $t = 1$. This slope factor is conceptually similar to a regression intercept. It is the expected change in x at time t when the value of x at time $t-1$ is 0. In the first change score (x_2 in Figure 1), the element proportional to the previous state ($\beta_x \cdot x_{it-1}$) is replaced by an amount

equal to a latent factor representing the initial level of x (I_x). Growth factors are random effects are therefore composed of a population mean (μ_{01}) and individual variance around that mean (U_{1i}).

$$Gx = \mu_{01} + U_{1i} \quad (4)$$

In this framework, the latent change scores are typically the outcome of interest. Typically, β_x s are fixed to be equal across time intervals, both because they are assumed to be modelling a consistent underlying developmental process and to ease in model estimation. Predictors of these latent change scores and growth factors can be modeled by estimating paths between exogenous variables and latent change scores and growth factors (shown in Figure 2).

This model can be expanded into a bivariate model with the addition of a variable Y with latent change scores produced in the same way as described above. Change in x would now be composed of a third element, an amount proportional to the state of the other variable at the previous wave ($\gamma_y \cdot y_{it-1}$), as shown in Figure 3:

$$\Delta x_{it} = (\alpha_i \cdot G_x) + (\beta_x \cdot x_{it} - 1) + (\gamma_y \cdot y_{it} - 1) \quad (5)$$

As with β_x s, γ_y s are usually fixed to be equal across time points. The LCS model can estimate general patterns of change that are time-independent—the general stable growth factors—as well as change that is dependent on the levels of X and Y at the previous time point. This model can address questions such as, 1) after accounting for time-dependent effects (effect of the lagged level, β_x and γ_y), is the constant change in one variable (G_x) associated with the constant change in another (G_y), 2) after accounting for time-independent effects (G_x and G_y), how is the change in one variable associated with the previous level of another (γ_y), 3) which variable is the leading indicator in this dynamic process.

This model is not without its drawbacks. Researchers are restricted in their selection of growth shape, with most effects assumed to be linear. Coefficients that are typically fixed to be equal across time points can be freed to vary if there is available power in the model; however, researchers should have a plausible explanation why effects would change depending on evaluation period. Models can be cumbersome to program in available software packages. It is difficult to move this model into a multilevel or mixture modeling framework. These models need a substantial amount of statistical power. Coefficients will be most reliable with a large sample and numerous time points. In a simulation study, Usami, Haynes, and McArdle (2016) showed that marginal mean bias of estimates was more than halved when moving from four time points to eight and was substantially reduced when moving from an N of 200 to an N of 500. Additionally, they found that higher covariances between the intercept factor and slope factor (σ_{xx}) for each variable will inflate standard errors due to multicollinearity between G_x and x_{it-1} . Researchers should design studies with sample sizes that will provide sufficiently narrow confidence intervals (see for example, Lai and Kelly, 2011). Coefficients are often difficult to interpret because they are dependent on

both time-dependent and time-independent effects in variables. We explain interpretation of effects in LCS analysis below.

Fixed and Random Effects

Fixed effects.—Developmental and life course theories often describe time dependent effects that are assumed to be the same across the population. These processes are represented by effects of exogenous and endogenous variables on latent change scores. When latent change scores are regressed on exogeneous variables (β_Z in Figure 2), researchers are estimating effects of exogenous shocks on change processes. For example, a researcher could estimate a LCS model of depression in youth and regress the change score in each wave on a variable representing parental divorce. The path estimate would represent the effect of parental divorce on change in youth depression at the same wave after taking into account the general growth pattern in depression.

Similarly, the bivariate model can be used to analyze an endogenous process whereby two variables affect each other. The “coupling” effects between the variables (γ_x and γ_y in Figure 3) represent change in one variable predicted by the previous wave level of the other variable that is the same across the population. For examples, a bivariate model of change in marital satisfaction and marital conflict could be estimated. γ_x and γ_y would represent the effect of satisfaction at the previous wave on the change in conflict after accounting for individual variance in growth patterns. The direction of effect between these variables can be assessed informally by comparing the magnitude of these estimates. More formally can compare model fit (χ^2 and confirmatory fit index) between a model with all coupling effects constrained to 0 and 1) a model with only one set of coupling effect (e.g. γ_x) constrained to 0 and 2) a model with only the other set of coupling effects (e.g. γ_y) constrained to 0. If only one of the coupling models significantly improves on the model with no coupling (e.g. the model estimating and effect for γ_x , number 2 above), that is evidence that the variable with coupling estimated is the leading variable in the association (x in this example). Additionally, we can compare the unidirectional coupling models above with a model with both sets of coupling effects estimated. If this fourth model does not improve on one of the unidirectional models (e.g. the model estimating and effect for γ_x , number 2 above), that is evidence that the variable with coupling estimated in the model that is not improved on is the leading variable (again, x in this example).

Random effects.—Alternatively, many life course and developmental researchers are interested in the causes and consequences of individual differences. In this model, between person differences are, in part, represented by the latent growth factors I_x and G_x . These factors represent time-independent processes that occur across the observation period. By virtue of being random effects, these factors represent only between person effects. Predictors and outcomes of these latent factors can be modeled similarly to latent factors in any SEM. Thus, predictors of G_x (β_{WG} in Figure 2) can be understood as individual differences that affect the general growth pattern of x , or in the case of I_x (β_{WI} in Figure 2), the initial level of x .

Cross level effects.—LCS models also estimate associations between random and fixed factors. Thus, developmental theories of contemporary and cumulative continuity (Caspi & Bem, 1990) can be assessed by this model. If an exogenous variable affects Ix (β_{WT} is significant) and βx is not significant, this effect represents a contemporary consequence. That is, the same factor (or constellation of factors) that affects x at time 1 also affects x at every other time point. This effect is not amplified over time, but carries through to all time points (because x at any time point is partially composed of x at $t-1$). Alternatively, if an exogenous variable affects Ix (β_{WT} is significant) and βx is significant, this effect represents a cumulative consequence. The initial difference is amplified at each wave as change in x in one wave causes further change in x at the next wave. These effects are further explicated in illustrative examples below.

Random effects represent moderators not included in the model (Usami, Hayes, and McArdle, 2015). If an exogenous variable affects the growth factor Gx , that effect represents individual differences in the fixed growth process. The estimation of this random slope factor is the principal mathematical difference between this model and simpler model; thus, the ability to model individual differences in growth is a particular faculty of this model. For example, Moffitt (1993) argues in her dual taxonomy theory that life course persistent and adolescent limited offenders will have different delinquency growth trajectories. Therefore, the individual differences that theoretically influence offender category should explain individual differences in delinquency slope. Being somewhat unfair to the theory for the sake of argument, if Moffitt's theory is correct, the exogenous individual differences she describes in her theory should fully explain the variance in the slope factor. The fixed effects portion of the model will describe the growth process that is the same for the entire population after taking into account individual differences caused by offender category. Whether these effects represent contemporary or continuous continuity again largely depends on the proportional effects as described for the initial level factor above.

Model Selection

While a variety of methods exist to assess stability and change with longitudinal data, there is no one-size-fits-all analytical model. Different techniques rely on different assumptions and can be used to evaluate different research questions. In all cases, it is essential for researchers to select their statistical model based on their particular research questions. In general, more parsimonious models are preferred; therefore, researchers should have reasonable theoretical, conceptual, practical, and/or empirical reasons to use LCS modeling. There are a number of conceptual reasons that a researcher might choose LCS modeling. For instance, researchers who are principally interested in change as an outcome could select the LCS model so long as they plausibly do not violate model assumptions (Usami, Hayes, & McArdle, 2015).

However, if a researcher is particularly interested the longitudinal association between two variables, they ought to justify using LCS analysis rather than a simpler (and often easier to interpret) auto-regressive cross-lagged (ARCL) model. The ARCL model is mathematically a special case of LCS analysis in which the variance of the slope factors are fixed to 0 (and thus assumed to be invariant across the population) and covariances among growth factors

are fixed to 0. Though there are a number of conceptual differences between these models, the principal mathematical difference is the estimation of random effects of the slope factor. If a researcher has a theoretical reason to expect individual differences in growth patterns—particularly if a researcher is interested in modeling these differences, as discussed above—they could reasonably select the LCS model. Alternatively, if a researcher is simply interested in selecting the model that best fits the data, they ought to use fit statistics to determine the ideal model. In a simulation study, Usami, Hayes, and McArdle (2016) show that the comparative fit index (CFI) and the root mean square error of approximation (RMSEA) are particularly effective for model selection. Thus, based on previous research, researchers interested in the longitudinal association between two variables who are simply trying to identify the model that best fits the data ought to choose the model with the highest CFI and lowest RMSEA (Usami, Hayes, and McArdle, 2016).

The LCS analysis is also similar to a parallel-process latent growth curve (LGC) analysis. In this type of LGC, latent factors representing the initial level and slope of two variables are freed to covary. Thus, LGC analysis allows researchers to test for longitudinal association in change between these two variables but does not allow researchers to assess the direction of this effect. Thus, we can examine whether, but not how, these variables are associated (Barker, Rancourt, & Jelalian, 2014).

Illustrative Examples

As an illustrative example, we explore how delinquency and deviant peers are associated over time. The direction and strength of this association has a storied tradition in criminology and often represent the key differences between theoretical models (Akers, 1998; Gottfredson & Hirschi, 1990). Whether youth “flock” together with similarly delinquent friends, or whether they “feather” (i.e. are influenced by deviant friends and engage in more delinquent behaviors), has been a constant question in criminological literature, and therefore serves as a potentially useful heuristic to explore these models.

Additionally, to illustrate the particularly valuable functions of LCS analysis, we illustrate how several hypotheses from particularly popular life course and developmental models in criminology can be assessed in this model. Moffitt (1993) argues that infant health problems may indicate biological vulnerability that is then amplified across the life course; Moffitt (1993) also argues that poor parenting may create similar social vulnerabilities. Broadly, these vulnerabilities sort individuals into a “life course persistent” offender category (Farrington, 2006). We therefore assess how these early adverse life experiences are associated with interindividual differences in delinquency. Additionally, substantial research has indicated that school environment is an important influence on youth delinquency (Payne, 2009; Wilson, Gottfredson, & Najaka, 2001). Thus, we expect that youth in schools with more problems will engage in more delinquency. Substantial changes in school environment may represent an important “turning point” in youths’ lives (Sampson & Laub, 1993). We therefore assess how school environment affects intraindividual changes in delinquency. These models are not intended to act as exhaustive tests of these hypotheses, but rather as illustrations of the capacity of LCS analysis to answer questions relevant to life course and developmental research. Note that in all conceptual models in figures below, all

unlabeled paths are fixed to 1. The data used for analyses below are available through the Inter-university Consortium for Political and Social Research (ICPSR: <https://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/26721>).

Mplus has been a very popular statistical program for SEM analysis. While a past Teacher's Corner paper has addressed the modeling of latent change score models in R (Ghisletta & McArdle, 2012), the current study uses Mplus, a flexible and user-friendly program that will be familiar to many who use SEM in their research. Mplus makes multiple valuable functions (e.g. WLSMV estimation, multilevel modeling, mixture modeling, survival modeling) available in a single package. It is relatively simple to use modern modeling techniques like robust standard errors that allow researchers to relax modeling assumptions and Bayesian modeling which allows for estimation of complex models that would not converge in maximum likelihood models. This previous Teacher's Corner focused primarily on modeling univariate LCS models in various packages in R. We build on previous studies by offering practical guidance on the various functions of LCS analysis including, 1) univariate models, 2) models with exogenous predictors, 3) bivariate models estimating direction of effect, and 4) special cases of these models.

Modeling LCS in Mplus

Univariate Model

To estimate an LCS model (shown in Figure 1) we first create latent true scores using manifest variables with loadings fixed to 1. We fix the intercepts for all manifest indicators to 0 and to ease estimation fix all of their residuals to be equal to each other. Means and variances of true scores are fixed to 0. This will create true scores as described in equation 1 above. We next estimate latent change scores for each of the latent true scores after time 1 as described in equation 2. Factor loadings for each change score are fixed to 1. Means and variances for latent change scores are fixed to 0. Next, true scores at each wave after time 1 are regressed the true score from the preceding time point. These autoregressions are fixed to 1, so that any difference between waves is now fully contained in the latent change score. We next estimate within individual proportional change effects by regressing each change score on the prior wave true score. To ease estimation, regression coefficients are constrained to be equal across time intervals. This regression represents change in x that is proportional to the level of x at the previous wave. Finally, we estimate between person level constant change effects. We estimate a latent slope variable using all latent change scores (Gx) with loading fixed to 1 and a latent initial level variable (Ix) using the true score at time 1 with the loading fixed to 1. We estimate the means and variances of these factors and estimate the covariances between them. The complete syntax for a generic univariate LCS model would be:

Data:

File is example.dat;

Variable:

Names are

xmanifest1 xmanifest2 xmanifest3 xmanifest4;

Missing are all (-999);

Model:

!true scores

x1 by xmanifest1@1; x2 by xmanifest2@1;

x3 by xmanifest3@1; x4 by xmanifest4@1;

[xmanifest1-xmanifest4@0];

xmanifest1-xmanifest4(s2);

[x1-x4@0]; x1-x4@0;

!diff scores

xd2 by x2@1; xd3 by x3@1;

xd4 by x4@1;

[xd2@-xd4@0];

xd-xd4@0;

!autoregressions

x2 on x1@1; x3 on x2@1;

x4 on x3@1;

!proportional change

xd2 on x1(b);

xd3 on x2(b);

xd4 on x3(b);

!constant change

gx by xd2-xd4@1;

gx; [gx];

ix by x1@1;

ix; [ix];

Special Cases.—The above generic syntax describes a situation in which all four time points in the study are equidistant and the proportional within person growth effects are assumed to be constant. However, researchers may have data with waves that are unevenly spaced, or they may want to model a process they would expect to change over the study period. In the first case, non-informative change scores for missing waves. Thus, if a year took place between Waves 1 and 2 and between Waves 2 and 3, but two years took place

between Waves 3 and 4, we could create a non-informative true score with a single indicator fixed at 0 for the gap year between Waves 3 and 4 by modifying the Model command above.

Model:

!true scores

x1 by xmanifest1@1; x2 by xmanifest2@1;

x3 by xmanifest3@1; **x4 by xmanifest1@0;**

x5 by xmanifest4@1;

[xmanifest1-xmanifest4@0];

xmanifest1-xmanifest4(s2);

[x1-x5@0]; x1-x5@0;

!diff scores

xd2 by x2@1; xd3 by x3@1;

xd4 by x4@1; xd5 by x5@1;

[xd2@-xd5@0];

xd2-xd5@0;

!autoregressions

x2 on x1@1; x3 on x2@1;

x4 on x3@1; x5 on x4@1;

!proportional change

xd2 on x1(b);

xd3 on x2(b);

xd4 on x3(b);

xd5 on x4(b);

!constant change

gx by xd2-xd5@1;

gx; [gx];

ix by x1@1;

ix; [ix];

Because the proportional change effects are fixed to be equal, the temporal distance between waves should be equal; therefore, we created a non-informative wave in the gap between Waves 3 and 4.

Additionally, parameters that we fixed to be equal above can be freed to vary depending on the theoretical background of the model and the statistical power available. For example, if

part of the sample was exposed to an intervention between Waves 2 and 3, the researcher may want to estimate the residual variance for *xmanifest3* to account for the intervention effect. Additionally, if the theory guiding the study suggests that prior wave level of *x* will have less of an influence on change in *x* over the next wave, the research may want to estimate independent values for the proportional change parameters. Researchers could use model fit differences to assess whether these less constrained models fit the data better. However, as models become more complex, they also become more computationally complex. More computationally difficult models will take longer to estimate, are more likely to produce impossible solutions, and are more likely to fail to converge. Bayesian statistics could be employed to address these complex issues and reduce bias from small sample sizes discussed above. Mplus facilitates the use of Bayesian estimator in a simple and user-friendly way, making it an attractive program for this kind of analysis (van de Schoot et al., 2014; Muthén, 2010). Researchers using Bayesian statistics should pay particular attention to the influence of prior specification and should be explicit in reporting the choices and issues that arise in their analysis (Depaoli & van de Schoot, 2017).

Univariate Model with Predictors

Using the LCS framework, we can also model predictors of both between-person growth factors and within-person change scores. Thus, we can assess predictors of 1) the initial level of a variable, 2) the slope factor, which represents individual differences in the growth process, and 3) latent change scores, representing exogenous. Exogenous predictors $y_1 - y_4$ can be modeled by adding the following to the Model command in the basic model described above.

```
!!predictors
ix gx on y1;
dx2 on y2;
dx3 on y3;
dx4 on y4;
```

In this model, *y* at Wave 1 is predicting the initial level and growth factor of *x*. That is, we are testing in this model whether y_1 influences between-person differences in the initial level and rate of increase (or decrease) in *x*. $y_2 - y_4$ predict change scores of *x* at Waves 2 – 4. Thus, in this model, *y* is considered as a time-varying covariate. We are testing whether the level of *y* at a particular wave affects change in *x* at that same wave.

Bivariate Model

One of the most powerful utilities of LCS analysis is the ability to assess the leading variable in a relationship. It is often theoretically and empirically unclear which variable comes first in a longitudinal association. As shown in Figure 3, to estimate a bivariate model of the association between *x* and *y* over 4 time points, we use the following model command:

```
Model:
!!x
```

!truescores

x1 by xmanifest1@1; x2 by xmanifest2@1;
 x3 by xmanifest3@1; x4 by xmanifest4@1;
 [xmanifest1-xmanifest4@0];
 xmanifest1-xmanifest4(s1);

!diff scores

xd2 by x2@1; xd3 by x3@1;
 xd4 by x4@1;
 [x2-x4@0]; x2-x4@0;

!autoregressions

x2 on x1@1; x3 on x2@1;
 x4 on x3@1;

!proportional change

xd2 on x1(b1);
 xd3 on x2(b1);
 xd4 on x3(b1);

!constant change

gx by xd2-xd4@1;
 [xd2@0]; [x3-xd4@0];
 xd2@0; xd3-xd4@0;

gx; [gx];

ix by x1@1;
 [x1@0]; x1@0;

ix; [ix];

!!y

!truescores

y1 by ymanifest1@1; y2 by ymanifest2@1;
 y3 by ymanifest3@1; y4 by ymanifest4@1;
 [ymanifest1-ymanifest4@0];
 ymanifest1-ymanifest4(s2);

!diff scores

yd2 by y2@1; yd3 by y3@1;

yd4 by y4@1;
 [y2-y4@0]; y2-y4@0;
 !autoregressions
 y2 on y1@1; y3 on y2@1;
 y4 on y3@1;
 !proportional change
 yd2 on y1(b2);
 yd3 on y2(b2);
 yd4 on y3(b2);
 !constant change
 gy by yd2-yd4@1;
 [yd2@0]; [yd3-yd4@0];
 yd2@1; yd3-yd4@0;
 gy; [gy];
 iy by y1@1;
 [y1@0]; y1@0;
 iy; [iy];
 !!coupling
 !proportional
 yd2 on x1(g1);
 yd3 on x2(g1);
 yd4 on x3(g1);
 xd2 on y1(g2);
 xd3 on y2(g2);
 xd4 on y3(g2);
 !constant
 gy with gx;
 gy with ix;
 iy with gx;
 iy with ix;
 iy with gy;
 ix with gx;

As shown in figure 3, in this model, the growth factors of x covary with the growth factors of y . These associations represent the constant coupling between-person associations between x and y . Additionally, change in x at wave t is predicted by the level of y at wave $t-1$, and the change in y at wave t is predicted by the level of x at wave $t-1$. These associations represent the proportional coupling between x and y . That is, how much x affect the change in y after accounting for between person differences in general developmental processes. For ease of estimation, proportional coupling associations are fixed to be equal for each direction of effect. However, researchers may have theoretical reasons to expect these effects to vary over time

To assess which of these variables is the leading indicator in the association, we can compare the proportional coupling estimates (fixed at $g1$ and $g2$ in the example syntax); however, when using LCS analysis, we can estimate and compare model fit among a series of models for perform a formal test of leading indicator. We begin by estimating 1) a model with no proportional coupling, 2) a model with proportional coupling estimates where x predicts change in y (fixed at $g1$ in the example syntax), 3) a model with proportional coupling estimates where y predicts change in x (fixed at $g2$ in the example syntax), and a model with all proportional coupling included. We compare the χ^2 statistics of models 2 and 3 to model 1. If one model significantly improves on model 1, but not the other, that provides some evidence that that variable is the leader in the association. Further, we compare the χ^2 statistics of models 2 and 3 to model 4. If model 4 does not significantly improve on one of these models, that suggests that the association between x and y is driven by this variable and that it is the leading variable in the longitudinal association. These models and their interpretation are clarified in the illustrative example below.

Illustrative Example

Participants and Procedures

The data used to evaluate these models are from the Iowa Youth and Family Project (IYFP) (Conger & Elder, 1994). The IYFP began in 1989 as a study of 451 rural European American couples with children, at least one of whom was a seventh grader in 1989. Follow-up interviews were conducted in 1990, 1991, and 1992. Families meeting the selection criteria were enumerated through contacts with public and private schools and then randomly selected and recruited into the study, with 78 percent of the families agreeing to participate. The mean target ages in 1989, 1990, 1991, and 1992 were 12.6, 13.6, 14.6, and 15.6 respectively. As of 1992, 392 target youths participated in data collection, 86.9 percent of the original sample. These data represent a standard panel data set. Each observation year was coded to represent a single time point. The data are in the wide format, such that each variable at each time point for an individual respondent is represented as an additional variable in a single observation.

Measures

Delinquency.—Delinquency is a self-report measure of how many times in the past year the target youth has engaged in 23 delinquent behaviors including, “run away from home,” “taken something worth \$25 or more,” “snatched someone’s purse,” “broke in or tried to

break in to a building,” “set fire to a building or field or something like that just for fun” (1 = *yes*, 0 = *no*). Mean scores on this measure were 1.09, 0.94, 1.23, and 1.63 in 1989, 1990, 1991, and 1992 respectively. Cronbach’s alpha values range from .81 to .62.

Deviant friends.—Targets reported on their friends’ deviance using a 15-item scale developed by Elliott, Huizinga, and Ageton (1985). Items include, “during the last year, how many of your close friends have: run away from home,” “stolen something worth \$25 or more,” “hit someone with the idea of hurting them,” “used alcohol” with possible responses ranging from 1 “none of them” to 5 “nearly all of them.” Mean scores on this scale were 18.24, 18.32, 19.01, and 19.98 in 1989, 1990, 1991, and 1992 respectively. Cronbach’s alpha values range from .84 to .72.

School problems.—To assess school environment, we use a school problem index adapted for the IYFP from Elliott et al. (1985). Youths were asked to report how much of problem 8 activities were at their school, including “the use of drugs,” “poor discipline in the classroom,” and “aggressive, bossy students” with responses ranging from 1 “no problem at all” to 4 “a very serious problem.” Items were averaged to form this scale. Mean scores on this scale were 2.12, 2.13, and 2.18 in 1989, 1990, 1991, and 1992 respectively. Cronbach’s alpha values range from .85 to .81.

Infant health problems.—Fathers reported on their child’s health as an infant in 1989 using a three item scale, including “how much did he or she weigh at birth,” “did he or she have major health problems as an infant,” and “did he or she have to stay in the hospital for a week or more immediately after birth?” the first item was on a 5-point scale (1 = *9 pounds or more*, 5 = *less than 4 pounds*), the second was on a 3-point scale (1 = *no*, 3 = *yes, very much so*), and the third was dichotomous (1 = *yes*, 0 = *no*). Items were standardized and averaged to form a single scale. The mean score was 1.74, and Cronbach’s alpha score was 0.54.

Paternal rejection.—To assess harsh parenting, we use a paternal rejection scale (Brennan, 1974). Youths were asked how much they agreed with 5 item regarding their relationship with their fathers, including “my dad finds fault with me even when I don’t deserve it,” “my father is unhappy with the things I do,” and “my father often blames me for his own problems” with responses ranging from 1 “strongly disagree” to 5 “strongly agree.” This measure is the mean score on these rejection items. The mean score was 0, and Cronbach’s alpha score was 0.79.

Plan of Analysis

We use Mplus 7.4 (Muthén & Muthén, 1998–2015) to estimate examples of each of the models described above. Missingness is accounted for with full information maximum likelihood estimation (FIML) assuming responses are missing at random (MAR); therefore, all 451 target youths were included in analyses. Maximum likelihood estimation with robust standard errors (MLR) is used for all models. The χ^2 test of model fit, root mean square error of approximation (RMSEA), and comparative fit index (CFI) were used to evaluate model fit. The Satorra-Bentler scaled χ^2 difference test corrected for MLR estimation was used to compare models.

Results

Observed values on both key variables are shown in Figure 4. The model illustrating the particular faculties of LCS analysis to model developmental and life course processes is presented as Figure 5. In this model we estimated a LCS model for delinquency. In addition, infant health problems and paternal rejection—both indicated by Moffitt's dual taxonomy theory as important influences on developmental processes (Moffitt, 1993)—are used to predict the growth factors of delinquent behavior, and school problems is used to predict change in delinquency at each wave. In this model, prior wave delinquency is positively associated with subsequent latent change, though this relationship is not significant. That is, for a one-unit increase in delinquency at time t , we would expect the change in delinquency to increase by .38 delinquent acts from time t to $t + 1$. Had this association been significant, early delinquency would be expected to increase exponentially over time as each increase in delinquency further increase the change in delinquency at the next wave.

Because Moffitt's (1993) dual taxonomy theory is principally concerned with interindividual difference, we then regress the growth factors (representing interindividual differences in development) on predictors derived from this theory. Paternal rejection is positively associated with initial delinquency rate. Thus, youth with worse relationships with their fathers are expected to engage in more delinquent acts initially in 1989. Again, had initial delinquency amplified across the life course (as discussed above), this model would suggest that the effect of this early problem behavior on initial delinquency would be exponentially increased across adolescence, or what Moffitt (1993) refers to as cumulative continuity. Because the amplification effect is not significant, this effect represents contemporary continuity. We could argue that the same constellation of factors that causes the association between paternal rejection and initial delinquency (e.g. low self-control, stable personality factors) is still affecting delinquency rate in 1992, because associations between delinquency at all waves are fixed to 1.

The general growth factor, G_d in Figure 4, represents individual differences in the growth process occurring across adolescence. The effect of infant health problems was not statistically significant in a two-tailed test (however, bias-corrected bootstrap estimates with 1000 draws produced a 95% confidence interval that did not contain 0). Were this significant, we could argue that some of the individual difference in delinquency growth patterns could be explained in terms of infant health problems, as Moffitt's theory suggests.

Finally, because we expect wave-to-wave levels of school problems to affect change in youth, we regress the latent change scores on these measures. School problems in 1991 and 1992 significantly predicted change in delinquency. That is, a one-unit difference in school problems was associated with about a .25 greater increase in problem behaviors in 1991 and 1992 across the sample.

We move now to the bivariate model shown in Figure 6. Looking at level-to-change effects, an individual's level on the deviant friends scale at time t is significantly positively associated with change in delinquency from time t to $t + 1$ ($\gamma = .42, p < .05$). Delinquency at time t is not, however, associated with change in deviant friends from time t to $t + 1$ ($\gamma = .30, p > .05$). Thus, it appears that deviant friends is potentially the leading variable in the

developmental process, though χ^2 tests will be necessary to confirm this. Both slope means are negative ($G_d = -7.33$, $p < .05$; though the slope for deviant friends, $G_f = -2.24$, is not significantly different from 0, suggesting on average there is no change in deviant friends). Predicted trajectories for both key variables for 30 randomly selected individuals are shown in Figure 7.

To assess which of these two is the leading variable in this association, we first estimate a model with cross variable couplings constrained to 0. That is, all γ s are constrained to 0 and all associations between deviant friends and delinquency are contained the between person growth variables. This model serves as the baseline model against which models with coupling can be compared. Next a model estimating the effect of prior level of delinquency on current change in deviant friends (delinquency as the leading indication), a model estimating deviant friends as the leading indicator, and finally a model with both coupling parameters. These models are able to test the degree to which prior levels of one variable affect the amount of change in the other. χ^2 differences between the baseline and comparison models can be used to estimate which construct is the leading variable. If introducing one coupling parameter significantly reduces the χ^2 compared to the baseline, and the other model does not, we can argue that the independent variable in the coupling regression is the leading variable in the relationship between these two developmental processes (Grimm, 2007).

χ^2 tests, shown in Table 1, potentially confirm our suspicion above that deviant friends is the leading indicator. Estimating the coupling parameter of delinquency predicting change in friends does not significantly improve model fit, while adding the parameter of deviant friends predicting change in delinquency significantly improves on the base line model. Adding in both coupling parameters further improves on the baseline model, suggesting a model with both coupling parameters best. Thus, while there is a high degree of longitudinal covariance, deviant friends appears to be the leading indicator.

Summary

In this paper we have discussed the particular value of the LCS analysis. Our analysis indicates that deviant peer group is the leading indicator, providing more support for social learning perspectives rather than self-control theory. Our results also illustrate the particular faculties of this model to assess life course and developmental theories. Paternal rejection was significantly associated with initial delinquency level. School problems in 1991 and 1992 were significantly associated with latent change in the same year.

Again, our goal in this study was not to provide a complete test of any theoretical perspective, but rather to address potential issues and concerns related to modeling stability and change in longitudinal models and to provide practical advice on using LCS analysis. While we argue at length about the potential value of LCS analysis, researchers should take several factors into account when selecting a modeling strategy. Researchers should use a model that is best suited to their particular research question. Parsimony is valued in scientific research; thus, researchers should not always use the most complex model for complexity's sake, particularly when a simpler model would equally or better address their

research question. We discussed above what factors researchers should take into account when selecting among longitudinal models. In particular, researchers should have an empirical and/or theoretical reason to expect substantial individual variance in individual developmental patterns (represented by G_X) when selecting LCS analysis over an ARCL model. Researchers should also use caution when analyzing a model with high covariance between growth factors for an individual variable, as this can inflate standard errors due to multicollinearity discussed above.

We advocate researchers take advantage of the high degree of flexibility in this model. Researchers should free parameters that could plausibly vary across time or across the population and compare model fit (particularly CFI and RMSEA) to identify the model that best conforms to their data. More complex models are more computationally difficult to estimate. Researchers may not be able to include as many research variables and controls into their models as would be ideal when using more complex models. For example, it is particularly difficult to assess quadratic growth terms in LCS analysis, which may be theoretically or empirically problematic. Researchers are also likely to encounter power issues when using more complex models with more estimates. We, for example were only able to detect a significant association between infant health problems and the delinquency growth factor using bootstrapped confidence intervals. As discussed above, Bayesian methods could be useful in addressing these issues; however, careful attention should be paid to influence of priors.

Because there have been relatively few simulation studies focusing on LCS analysis (for exceptions see e.g., Usami, Hayes, & McArdle, 2016; Clark, Nuttall, & Bowles, 2018), we have limited information on the influences of factors like sample size and missingness. More simulations studies are needed to evaluate the consequences of study design on this model. These models are more difficult to program, making researchers more prone to typographical errors that may distort results. More complex models are often more difficult to describe and discuss. Researchers should keep their audience in mind when selecting a modeling strategy. Generally, we would advocate for more use of the LCS analysis in longitudinal research, while keeping the above caveats in mind.

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Figure 1.
Conceptual Model of Univariate LCSGA

Figure 2.
 Modeling Predictors of Change
Note: Unlabeled paths constrained to 1

Figure 3.
Conceptual Model of Bivariate LCSGA

Figure 4. Observed longitudinal trajectories on both key variables for 30 randomly selected individuals. a) Observed longitudinal trajectories for deviant friends score. b) Observed longitudinal trajectories for delinquency.

Figure 5.

Modeling Developmental and Life Course Processes

Note: $N = 451$; $\chi^2 = 68.05^{***}$ (26), RMSEA = .04, CFI = .95; 1;

† $p < .10$, ** $p < .01$, *** $p < .001$; unstandardized results shown

Figure 6.**Bivariate LCSGA Results**

Note: $N = 451$; $\chi^2 = 74.46^{***}$ (20), RMSEA = .08, CFI = .94; unlabeled paths constrained to 1; * $p < .05$, *** $p < .001$; unstandardized results shown

Figure 7.

Expected longitudinal trajectories on both key variables for 30 randomly selected individuals (from Figure 6). a) Expected longitudinal trajectories for deviant friends score. b) Expected longitudinal trajectories for delinquency.

Table 1.

Model Comparisons

	χ^2	Degrees of Freedom	Correction Factor	Corrected	χ^2 from baseline	p-value
1. No coupling	84.17	22	1.85	-	-	-
2. Delinquency → Friends	80.57	21	1.85	3.62	3.62	0.06
3. Friends → Delinquency	72.86	21	1.71	6.50	6.50	0.01
4. All coupling	74.46	20	1.66	8.54	8.54	0.01
5. Model 3 vs. Model 4				4.51	4.51	0.03