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Latent Growth Curves

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Studying change lies at the heart of community-based research and program evaluation. Community-based researchers frequently need to examine whether interventions did, in fact, create change and, if so, whether the change was sustainable. At times, they may also examine the natural fluctuation of community phenomena over time in order to understand how social problems and community assets unfold naturally. Yet all too often, the statistical models that are employed are much more simplistic than the ways in which we would actually expect changing community phenomena to behave. As a result, some advanced longitudinal statistical methods have received increased attention from the field (e.g., survival analysis, time-series analysis; Jason & Glenwick, 2012); however, thus far, latent growth curves (LGCs) have received less attention. LGCs are a tool that can capture more of the complexity of changing community phenomena. Therefore, the purpose of this chapter is to (a) provide a conceptual introduction to the use of LGC models in community-based research, including the models' contributions and drawbacks, and (b) present a case example of community-based research employing LGCs.

AN INTRODUCTION TO LATENT GROWTH CURVE MODELS

Growth curves are typically used to analyze longitudinal data in which the same construct is measured at multiple time points (i.e., repeated measures data). Rather than studying change in sample means over time, growth models are well suited to understanding within-person change as well as variability between people in within-person change. Growth curves analyses can be conducted within a structural equation modeling (SEM) or a multilevel modeling (MLM) framework (Bollen & Curran, 2006; Chou, Bentler, & Pentz, 1998; Curran, Obeidat, & Losardo, 2010). In both approaches, growth curves models have similar applications for community-based research. However, when discussing the construction of LGC models in the next paragraph, terms will be consistent with LGC models within an SEM framework (Bollen & Curran, 2006).

In an LGC model, the repeated measures data are used to create latent variables that capture two properties of the construct of interest, namely, a level and a slope. The level (or intercept) represents the baseline amount of the construct (Duncan & Duncan, 2004; McArdle, 2009). This baseline is typically set to be equal to participants' Time 1 scores. The slope, on the other hand, represents within-person change in the construct over time, or how much individuals changed (Duncan & Duncan, 2004; McArdle, 2009). There are different ways of creating the slope variable; this allows the analyst to test out different patterns of change (by modeling different *basis coefficients* that specify the weighting of each measurement occasion on the latent slope variable; Duncan & Duncan, 2004; McArdle, 2009). In this chapter, the term *pattern of change* refers to patterns related to the amount and direction of change across different time intervals within the same study (e.g., is the amount and direction of change always consistent across all time intervals?). This issue is discussed in more detail later in the chapter.

The level and the slope are modeled to have a mean and variance (McArdle, 2009). The mean of the level is the average baseline score in the sample. The variance of the level represents the amount that participants in the sample vary in their baseline scores, with some participants having higher baselines than others (between-person variability). Like the level, the slope is also modeled to have a mean and a variance (McArdle, 2009). The mean of the slope gives the average within-person change. The variance of the slope represents the variation among individual participants in how much they change, with some participants changing more than others over the course of the study (between-person variability) (McArdle, 2009). The researcher may also test whether baseline scores are related to how much change occurs over time (i.e., whether the level and the slope covary). Often, there is such a relationship—participants with high baseline scores tend to increase less than participants with low baseline scores—which is why it is important to consider this question for inclusion in the model.

Latent Growth Curves as Part of a Larger Model: What Relates to the Changing Variable?

Typically, the first step in an LGC analysis is to create the basic model of the level and slope and identify the model that best captures the pattern of change over time. Then, the researcher can add additional variables to the model to test whether they are related to participants' baseline scores (which becomes an intercept when it is a dependent variable) and their within-person change (the slope). In LGCs, there are a variety of options for examining relationships between the changing variable and other variables; the next section provides an overview of the basic options. Note that different options can be combined in the same model.

Growth as a Predictor of a Static Outcome Variable

Within-person change (i.e., the slope of the LGC) can be modeled as an independent variable that predicts a static (i.e., unchanging) dependent variable. An example of a research question would be, "Does within-person change in delinquency scores influence future substance abuse at one time point?"

Time-Invariant Predictors of Growth

A *time-invariant covariate* is defined as a variable that does not change in value as a function of time (Curran et al., 2010). These unchanging variables can be modeled as predictors of change (i.e., the slope of the LGC is the dependent variable). Conceptually, these variables may be of substantive interest or simply act as control variables (e.g., Does an intervention predict amount of change in delinquency scores?)

Time-Varying Covariates With Growth

The changing variable can be related to another variable that is also measured over time. The added variable is called a *time-varying covariate* when it is directly modeled as a predictor of the repeated measurement occasions (and is not a predictor of the latent slope) (Curran et al., 2010). This is appropriate when the time-varying covariate is believed to not have its own latent change process, but instead is believed to affect the measurement of the changing variable at each time point (e.g., Does English literacy at each time point affect delinquency scores on a self-administered survey at each time point?)

Covaration of Growth in One Variable With Growth in Another

In this instance, the researcher is interested in the relationship between multiple changing variables. When the second changing variable is believed to have its own latent growth process, a second LGC is added to the model and the growth curves are correlated with one another (a parallel process model) (Cheong, McKinnon, & Khoo, 2003; Curran et al., 2010; McArdle, 2009) The correlation between the two slopes tests whether change in one variable is related to change in the other. For example, does change in social support co-occur with change in delinquency? Or, in a multivariate LGC, the researcher can test whether multiple LGCs of different variables actually represent one common growth process (e.g., change in drug use and truancy as subcomponents of a second-order changing delinquency growth process) (Duncan & Duncan, 1996).

Extensions of These Basic Models

This provided an overview of the basic types of research questions about change that can be asked using LGCs. The researcher can then build from these basic types of relationships to test more complex relationships, such as mediation or moderation (Bollen, Curran, & Willoughby, 2004; Cheong et al., 2003).

THE IMPORTANCE OF NONLINEAR CHANGE IN COMMUNITY-BASED RESEARCH

Certain features of LGC models make them particularly useful for community-based research and program evaluation. One such advantage is that LGCs can capture a variety of patterns of change, including nonlinear change (McArdle, 2009; Ram & Grimm, 2007). Linear change means that the rate of change is constant over time. In other words, in any two time intervals of the same length, change occurs in the same direction and amount (see Fig. 14.1 for three examples of linear change). If a study measures sense of community every 3 months, an assumption of linear change would mean that sense of community is expected to increase or decrease in the same amount over each 3-month time interval. However, an ecological and systemic approach would suggest that, although this assumption may hold true in certain scenarios, it is too simplistic to capture many, if not most, patterns of change (Bronfenbrenner, 1979; Trickett, 2009). Instead, it is likely that, at least some of the time, the direction or rate of change over time may shift. To illustrate this, a series of patterns of nonlinear change that are likely to occur in community-based research and program evaluation will be presented.

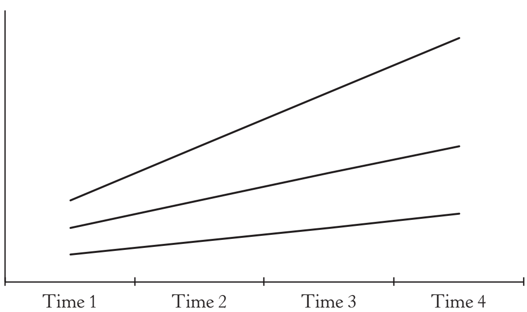

FIGURE 14.1: Three examples of linear change.

Patterns of Nonlinear Change

Incubation, or Delayed Change

One likely pattern of nonlinear change in community-based research and program evaluation is an "incubation effect" in which an intervention does not create change immediately: There is a lag between when the intervention occurs and when change begins. Such a pattern would be expected in "upstream" interventions that intervene in one part of a systemic process and are expected to create change that has to spread to another part of the system. Initially, there is no change in the targeted outcomes while the effects of the intervention flow through the system. Then, after a delay, improvement occurs (see Fig. 14.2).

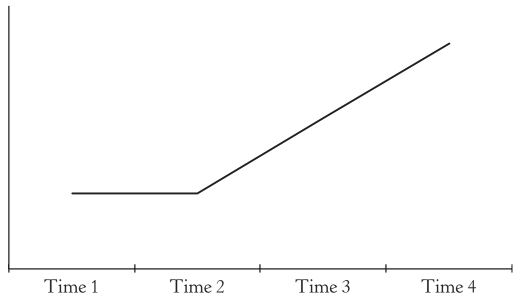

FIGURE 14.2: Delayed change.

Gains Followed by Maintenance

"Gains followed by maintenance" may occur for interventions that create a period of improvement followed by maintenance of the improved outcomes. Skill- and knowledge-building interventions that result in long-term retention would follow this pattern. From pre- to postintervention, you would expect an increase in skills/knowledge. After the intervention ends, you would expect that people's skills/knowledge would stay the same; improvement would not continue, but you would also not expect skills or knowledge to be lost (see Fig. 14.3).

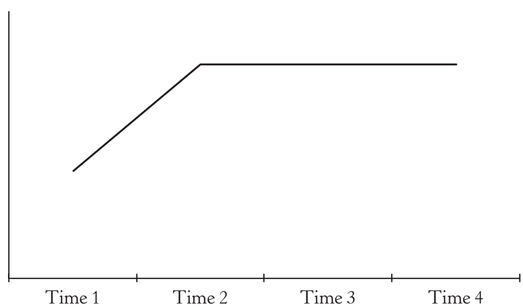

FIGURE 14.3: Gains followed by maintenance.

Lost Gains

Another pattern of nonlinear change that community-based researchers and evaluators may expect is "lost gains" in which change occurs after an intervention but is not sustained; all improvements are lost and outcomes return to preintervention levels. For example, an intervention may produce improvement only while resources are allocated to the issue, with outcomes dropping back to preintervention rates when those resources are gone (see Fig. 14.4).

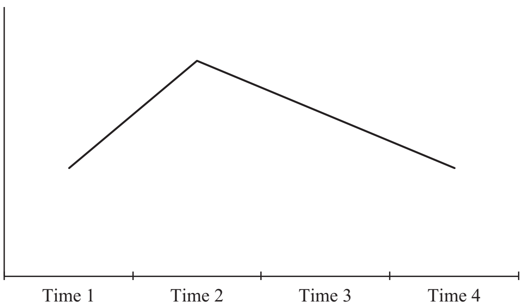

FIGURE 14.4: Lost gains.

Variation in the Rate of Change

In this pattern, the rate of change is not constant; change occurs more rapidly (acceleration) or less rapidly (deceleration; see Fig. 14.5). An example may occur in network-based adoption of innovations (Rogers, 2003). Change is initially less rapid when early adopters begin to adopt the innovation; then, as more people adopt the innovation, it spreads more rapidly to the people to whom they are connected; finally, once the network is almost saturated and there are few people in the network who have not adopted the innovation, adoption rates decelerate again.

Taken together, the different conceptual ways of thinking about change that have been presented highlight the importance of the flexibility of LGCs for community-based research and evaluation. By not being restricted to the simplistic assumption that change is linear, the analyst can choose the model that best fits the changing community phenomenon.

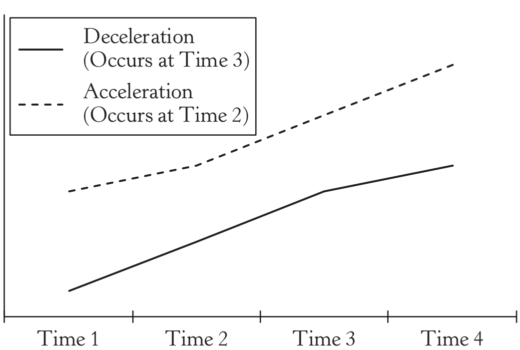

FIGURE 14.5: Variation in the rate of change.

Matching the Pattern of Change to the Appropriate Statistical Model

The literature provides some specific subtypes of LGC models that can be used to test different types of statistical models of nonlinear change. The analyst may include a linear growth slope term coupled with a polynomial slope term(s) to test for exponential growth (e.g., quadratic, cubic; Grimm & Ram, 2009; Ram & Grimm, 2007). Such models of exponential growth represent very specific types of variation in the rate of change. Spline growth curves are LGCs in which growth occurs at different rates within different periods of the study (also known as piecewise models; Ram & Grimm, 2007). Different spline models could be used to represent a wide variety of nonlinear types of change, including delayed change, gains then maintenance, lost gains, and certain forms of acceleration and deceleration. The broader latent growth curve literature provides specific guidance on how to implement these statistical models of nonlinear change appropriately (e.g., Grimm & Ram, 2009; Ram & Grimm, 2007).

Generally, researchers should use theory to inform the type of change they would expect to see in their study and then test how well that model fits the data. However, in community-based research and evaluation, there may not always be sufficient theory to determine how one would expect change to occur. For example, a researcher may expect an intervention to improve outcomes but not have a clear idea as to whether the gains would always occur at the same rate across different time intervals. In such instances, the researcher can create and test a specific type of LGC model called a *latent basis model* (McArdle, 2009; Ram & Grimm, 2007). In this model, rather than the researcher hypothesizing the pattern of change and then testing the data against his or her hypothesis, the data are used to figure out the best model of change. The results of the model reveal how rapidly change occurs in each time interval in the study.

Another feature of LGC models is useful when the researcher does not have sufficient theory to determine how exactly he or she expects change to occur. In some situations (specifically when two models are nested) the analyst can test different patterns of change against one another (using the chi-squared difference test) (McArdle, 2009). This test examines whether there is a statistically significant difference between the two models in how well the models fit the data. Suppose a researcher conducts an intervention study and believes that there has been a consistent improvement in outcomes. When the model is tested, statistical information (specifically, fit indices) will be provided to help evaluate how well the data fit the hypothesis of consistent change. However, testing this hypothesized pattern of change against other possible patterns of change provides more analytic rigor. In the same intervention study, the researcher could compare the model that represents consistent improvements (linear change) to a model that represents no improvements whatsoever (no change). A finding that the consistent (linear) change model is preferable to the no-change model would provide more statistical support for the initial hypothesis that outcomes have consistently improved. Thus, LGC models not only allow community-based researchers and evaluators to test for nonlinear change but also enable them to use their data to determine the pattern of change that appears to fit the data best.

These features of LGC are particularly important for conducting applied community-based research and evaluation. Other analyses that simply test for an effect of time, or assume that change is linear, can obscure how the process of change actually unfolds. Such an approach oversimplifies our understanding of interventions and the natural development of social problems and assets. Failing to understand the actual pattern of change may result in missing important issues related to the timing and sustainability of change; these, in turn, have significant implications for practice and future research and evaluation.

As an example, failure to capture nonlinear change could hamper the ability of a study to provide meaningful information on how to improve interventions. Suppose that an evaluation is conducted to see whether a neighborhood intervention led to significant improvements in residents' sense of community. In reality, the intervention led to an immediate improvement in sense of community scores, but the improvements were not sustained and sense of community scores slowly dropped back to preintervention levels. Testing only for linear change could lead to an erroneous conclusion that, overall, the intervention does not appear to work, when in reality it does produce improvement, but the improvement is not sustained. These two patterns of change have very different implications for program improvement and future research on similar types of programs. Concluding that there is no effect of the intervention suggests the need to seriously reconsider the intervention's design and implementation, while an intervention that is effective in the short term but the improvement is not sustainable suggests that the intervention design and implementation are generally working but the program needs adjustments to make changes sustainable in the long term. This highlights the importance of flexibility in testing for different patterns of change in applied, community-based research and evaluation.

Capturing Heterogeneity in Change

An additional advantage of LGC models for community-based research is that they allow the examination of heterogeneity in change. An ecological and diversity-oriented approach suggests that in community-based research there is likely to be heterogeneity within samples with respect to patterns of change (Trickett, 2009). Therefore, methods that capture within-person change (rather than change in means) are crucial. LGCs are such a technique. Specifically, in LGC models, rather than assuming that people change in a uniform way, participants may differ in the amount that they change. In other words, between-person variability in within-person change is captured (Duncan & Duncan, 2004; McArdle, 2009). Certain LGC models (including time-invariant covariates and parallel process models) allow the researcher to examine factors that are associated with differences in the amount of within-person change, potentially providing insight into why the heterogeneity exists. Furthermore, the researcher may use *multigroup LGCs* to test whether different groups of people differ in their patterns or trajectories of change over time (e.g., some groups may experience linear change, while others experience delayed change) (Curran et al., 2010; Ram & Grimm, 2009).

Examining heterogeneity in change has many potential applications in community-based research and evaluation. For example, researchers can use LGC models to test for differences in the amount of change and/or pattern of change between intervention and comparison groups (e.g., does the intervention group change more rapidly than the comparison group?). In a recent study, Darnell et al. (2013) employed LGC analysis to examine differences in change in counties' low infant birthweight rates over an 8-year period. They found that counties with community collaborative groups focused on low infant birthweight (the treatment group) had statistically similar baseline low infant birthweight rates in comparison to counties that did not have a community collaborative (the comparison group). Additionally, the data showed that over the 8-year period, low infant birthweight rates tended to increase, meaning that outcomes were worsening over time. However, the analyses revealed that the low infant birthweight tended to worsen less rapidly in the treatment group than in the comparison group. In other words, the intervention counties experienced less of an increase in low birthweights; although outcomes had a tendency to worsen, the intervention was effective at slowing this process. The intervention and comparison groups differed in the rate of change.

Testing for differences in the amount of change and pattern of change is also particularly useful for studying diversity, a core value in community-based research and program evaluation. LGCs allow researchers to test for differences in the amount and pattern of change between different demographic and social identity groups (e.g., race/ethnicity, gender, or age differences). Suppose a researcher is interested in racial differences in depression. Rather than simply testing whether different racial groups have different baseline depression scores, the researcher can also examine whether certain racial groups' depression scores improved more or less than others. This can be particularly useful in testing whether an intervention is equally beneficial to all groups that participated (e.g., Did racial minorities improve the same amount as European Americans in response to an intervention?).

Farrell and Sullivan (2004) employed such an approach to look at differences in witnessing violence between adolescent boys and girls over time. The study collected students' self-report data of how often they witnessed violence across five time points spanning the sixth through ninth grades. LGC analysis revealed that at baseline (sixth grade), boys, on average, witnessed more violence than girls. Moreover, the boys tended to have greater increases in witnessing violence over time than the girls did (Farrell & Sullivan, 2004). In other words, the boys and girls experienced inequality in witnessing violence at baseline and then experienced different amounts of change over the course of the study. Ultimately, this led to an even greater gender gap in witnessing violence at the last time point. Thus, rather than imposing a uniform model of change, LGC can test whether some groups of people change differently than others do.

An ecological focus also suggests that it is useful to understand a variety of other factors that relate to how much people change, beyond the issues that have been discussed so far. Researchers could test for differences in change between people with different contextual circumstances (e.g., participants from different types of neighborhoods, participants with different levels of social support). An ecological approach would also support testing for differences in change between groups of people with different individual-level characteristics that may make them more or less susceptible to change (e.g., differences in readiness).

Thus far, in this section, the examples have focused mostly on heterogeneity in the amount of change—do some groups change more than others? Advanced LGC models also allow for heterogeneity in the patterns of change. Such multigroup LGC models can test whether different groups have different patterns of change over the course of the study (Duncan & Duncan, 2004; Duncan et al., 2006; Ram & Grimm, 2009). For example, it may be that in response to an intervention to improve sense of community, neighborhoods with adequate resources experience a steady, consistent improvement in sense of community over the course of a study, while resource-poor neighborhoods experience a slower rate of change at first that then accelerates into more rapid improvements later in the study. This type of advanced model is more complex and is also much rarer in the literature.

Advanced Extensions of Latent Growth Curvess

More advanced extensions of LGCs are also likely to be useful to this audience. Because LGCs can be conducted within an SEM approach to modeling, LGC models can capitalize on other possibilities of SEM models. These include the ability to test mediation, the ability to have multiple dependent variables in the same analysis, and the use of measurement (structural) models that account for measurement error (Kline, 2011). Growth curve analysis can also be conducted within a multilevel modeling framework, which allows for growth curve models to be conducted when data are nested (meaning that the data violate the assumption of independent error terms; cases are nested in groups or settings that cause their errors to be correlated, such as individual children nested within classrooms) (Chou et al., 1998) (see Singer & Willett, 2003, for a discussion of longitudinal analyses within a multilevel framework).

As noted earlier in the chapter, multigroup LGC models can test whether known groups differ in their pattern (or trajectory) of change. Rather than testing for differences between known (i.e., measured) group membership (e.g., race and gender differences), growth mixture models can use the data itself to identify unobserved (latent) groups/classes that differ in their patterns of change (Muthén & Muthén, 2000; Ram & Grimm, 2009). For example, when analyzing data from an intervention study using growth mixture modeling, a researcher may test whether there is support for the existence of three different (unobserved) classes with different patterns of change: one that exhibits no change, one that significantly improves, and one that significantly gets worse. Finally, autoregressive model parameters can be added to LGCs to account for measurement error at one time point that is related to measurement error at the next time point (i.e., autoregressive residuals); autoregressive parameters can also be used in parallel process models to understand covariation of two changing LGCs over time, after controlling for their correlation at Time 1 (Bollen & Curran, 2004).

Drawbacks of Latent Growth Curves

The drawbacks of the LGC approach also warrant attention. In particular, LGCs should be employed only in specific circumstances. Like all models, LGC models require a sufficient sample size; larger samples may be required when the analyst is looking at heterogeneity in the pattern of change between different groups (Duncan & Duncan, 2004; Kline, 2011). Although Bollen (2002) stated that LGCs can be adopted for use with categorical data, LGCs are typically used with continuous data. Other methods, such as latent transition analysis, may be preferable when the longitudinal variable is categorical (Collins & Lanza, 2010).

Like all longitudinal data analyses, LGC models are best when the data are collected within a rigorous longitudinal study (for in-depth discussion, see Collins, 2006). In particular, the variable of interest should be measured at time intervals that are suited to capturing meaningful change in that variable. It is also important that the variable be measured consistently over time, so that the growth curve is not inadvertently capturing change that is due to measurement error. Despite these limitations, growth models are well suited to community-based research and evaluation. To illustrate their utility, a case study using LGC analysis will be presented next.

CASE STUDY

The case study comes from a 2013 study by Adams, Greeson, Kennedy, and Tolman. The lead author's program of research focuses on understanding the associations between women's experiences of intimate partner violence (IPV) and their financial well-being. Many survivors of physical IPV also experience economic abuse in which the batterer controls and/or exploits the victim's finances (e.g., damaging credit; interfering with work and school; Adams, Sullivan, Bybee, & Greeson, 2008). Despite a growing body of research on the impact of IPV on adult women's financial well-being, very little research had been done to understand the financial impact of IPV during adolescence. In the present study, we were interested in whether experiences of IPV during adolescence may influence women's financial well-being as adults.

Conceptualization of the Longitudinal Research Question

Prior research on adults shows that many batterers interfere with their partner's education (Adams et al., 2008). Because adolescence is a key developmental stage in which girls are contemplating and completing their education, we suspected that IPV during adolescence would influence the amount of formal education that women obtained and that, in turn, this would influence their earning potential as adults. This led to the following hypotheses:

Hypothesis 1: On average, women with a history of IPV during adolescence would have completed fewer years of formal education than would women with no adolescent IPV history.

Hypothesis 2: Women who completed fewer years of formal education would tend to earn less at Time 1 (T1) than women who completed more years of formal education.

Hypothesis 3: On average, women with a history of IPV during adolescence would earn less as adults at T1 than women without a history of IPV during adolescence; this relationship would be mediated by the number of formal years of education completed.

Because of the important role that education plays in earning potential, we believed that adolescent IPV and fewer years of education would not simply hinder women's earnings at T1; instead, we believed that these factors would also be detrimental to women's ability to increase their income over time. This led to the following longitudinal hypotheses:

Hypothesis 4: Women who completed fewer years of education would experience less growth in earnings over time.

Hypothesis 5: On average, women with a history of IPV during adolescence would experience less growth in earnings over time; this relationship would be mediated by the number of formal years of education completed.

Hypotheses 4 and 5 required repeated measurement of women's earnings as adults to understand growth in earnings over time. These hypotheses made LGCs a suitable analytic technique. The hypotheses were tested using data from Tolman and Wang's (2005) study of women's employment. The sample consisted of women who were single mothers and had received cash assistance. At the first interview, women reported retrospectively on whether they had experienced IPV during adolescence (at or before the age of 17) and the number of years of formal education they had completed prior to the study. Annual earnings from employment were assessed at T1 and at two follow-up interviews, with 1 year in between interviews.

Development and Results of the Latent Growth Curve Models

Our first step was to determine which pattern of change best fit the repeated measures data on women's earnings from employment. There was not strong prior research or theory to inform a very specific hypothesis about the pattern of change. We believed that women's earned income would likely increase somewhat over time, but we were unsure whether the change would be consistent (i.e., linear) or whether change from T1 to Time 2 (T2) would be different than change from T2 to Time 3 (T3) (that is, nonlinear). First, we tested a model that suggested no change—that women's earned income did not change at all over the course of the study. As we suspected, the model did not fit the data well, suggesting that there was significant change in individual women's earned income over time. Then, we tested two different models—a linear model and a latent basis model—against one another. The linear model posited that women would experience consistent change in their earnings (i.e., a woman's change from T1 to T2 would be functionally equal to her change from T2 to T3); the latent basis model allowed changes in a woman's income to happen at different rates (a woman's change from T1 to T2 would not be equal to her change from T2 to T3). Specifically, the latent basis model used the data to determine the best way to represent patterns of change. Statistical information (in the form of a significant chi-squared difference test) indicated the latent basis model fit the data well and was a better way of capturing within-woman change over time than was the linear model.

The results of the latent basis model showed that, on average, women's earnings increased a total of $4,115 from T1 to T3. The fact that the latent basis model was preferable to the linear model indicated that growth in women's earnings was not consistent over the different time intervals in the study. Rather, the results showed that the sample experienced much more rapid growth from T1 to T2 (62.9% of the total change over the course of the study occurred from T1 to T2) and slower growth from T2 to T3 (37.1% of the total change occurred from T2 to T3). Conceptually, this represents decelerating change. It may be that growth in income was much more rapid from T1 to T2 (in comparison to growth from T2 to T3) because the sample was limited to low-income women who had received welfare assistance.

We then added variables to the model to test whether adolescent IPV history and number of formal years of education completed were related to women's earnings at T1 and change in women's

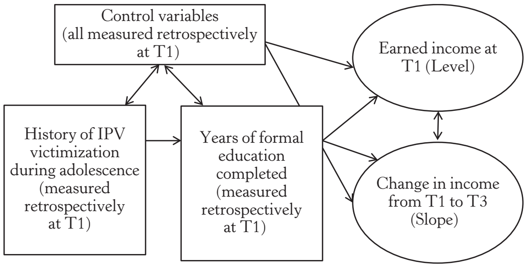

FIGURE 14.6: Case example of latent growth curve analysis to assess adolescent intimate partner violence (IPV) and education as predictors of change in women's earned income over time.

earnings from T1 to T3. The model also controlled for several covariates. Each of the covariates was measured retrospectively at T1. The conceptual model is provided in Figure 14.6.

The data supported our hypotheses. On average, women who had a history of IPV victimization during adolescence completed 0.5 fewer years of education than did women with no history of IPV during adolescence. Formal education was related to both T1 earnings (the intercept) and growth in earnings from T1 to T3 (slope). One additional year of education was associated with $855 more earnings from employment at T1 and a $664 greater increase in earnings from T1 to T3. Analysis of indirect effects (a technique used to test for mediation in SEM) suggested that a history of adolescent IPV contributed to fewer earnings at T1 (intercept) and less growth in earnings from T1 to T3 (slope) via fewer years of completed education.

Choosing LGC analysis provided several opportunities. We were able to capture the complexity of change in the earnings of these low-income women—the fact that the rate of change in income was not constant from one time interval to the next. In addition, by using LGC analysis, we were also able to capture and unpack heterogeneity in change over time. The model accounted for the fact that some groups of women had different amounts of change in their earnings than others. This variability in women's growth in earnings was partially explained by the number of formal years of education they completed and their history of IPV during adolescence. Finally, because the LGC was created in SEM, we were able to capitalize on the ability to conduct indirect effects analysis in SEM. This allowed us to test for a mediational relationship in which the dependent variable represented change over three time points.

One key limitation of this work was that we were able to analyze women's earned income at only three time points. LGC analyses are stronger when data are collected from more time points. With more data points, the analyses are able to tap into a more stable pattern of change. Although it is apparent that the rate of change was not linear, the rate at which income would continue to change is unclear. Data from additional follow-up time points would, therefore, provide a fuller picture.

Additionally, all of the control and independent variables were measured at only one time point (i.e., they were time-invariant covariates). Earned income was the only changing variable. One of the possibilities in LGC modeling is to examine covariation in two changing variables over time. The data set we analyzed did not have any relevant covariates that were measured with consistent repeated measures data. Therefore, another limitation of our study is that we could not examine whether change in a predictor variable may have related to change in our dependent variable (earned income). For example, in examining the relationship between adolescent IPV and growth in adulthood earning, it would have been helpful to control for changing adult IPV across all time points, rather than adult IPV victimization at T1 only. Future research in this area that accounts for changing covariates may be particularly beneficial.

CONCLUSION

LGC modeling is a flexible method for analyzing longitudinal data that is well suited to capturing the complexity of change in community-based research and program evaluation. The method enables evaluators and community-based researchers to capture nonlinear change and to examine heterogeneity in amount and patterns of within-person change over time. More advanced applications of this technique provide additional opportunities. These features are very well matched to the field's ecological and systems focus, interest in diversity, and use of research and evaluation to inform community practice.

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