The Use of Piecewise Growth Models in Evaluations of Interventions

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Abstract

In studies of interventions (e.g., remedial reading interventions), interest often centers on student academic progress, or on changes in various attitudinal and affective measures, both during and after the intervention period. By enabling us to subdivide a time series into meaningful segments, and summarize important aspects of change in each segment, piecewise growth models provide a means of addressing key questions in intervention studies. In this report, we discuss the use of piecewise models in (1) examining whether rates of progress for individuals in an intervention study, on average, slow down, remain constant or speed up during the follow-up period; (2) assessing whether there is substantially more variability among individuals in their rates of change in the intervention period or in the follow-up period; (3) identifying conditions under which we see rapid rates of progress during the intervention period, and sustained progress during the follow-up period.

In studies of interventions (e.g., preschool initiatives such as Head Start; remedial reading interventions), interest often centers on student academic progress, or on changes in various attitudinal and affective measures, both during and after the intervention period. Of particular concern is how well students fare after an intervention ends: Do rates of progress/improvement tend to hold steady (or perhaps even increase), or do they tend to decline?

Growth modeling provides a valuable framework for studying the effects of interventions over time (see, e.g., Muthén & Curran, in press; for an introduction to growth modeling, see Bryk & Raudenbush, 1992). In this paper, we wish to illustrate the value of piecewise growth models in exploring issues of the kind outlined above. As will be seen, for each time period or segment of interest in a time series (e.g., the intervention period; a post-intervention follow-up period), the piecewise model enables one to estimate, for example, a mean rate of growth/progress, and the amount of variation among individuals in their rates of growth. In addition, one can attempt to identify key correlates of growth for each time segment of interest: How do differences in implementation and student background characteristics relate to differences in rates of growth/progress during the intervention? What factors are instrumental in promoting sustained progress after the intervention has ended?

To illustrate the value and use of piecewise growth models in studies of interventions, and to discuss some of the limitations of more conventional growth modeling strategies in such settings, we focus on analyses of the data from a study of the relative effectiveness of two types of short-term psychotherapy interventions. In the course of presenting our analyses, implications for the study of school-based interventions will emerge. We will explore a number of these implications.

An Illustrative Example: The STAPP/NDP Intervention Study

The data that we will use are based on a randomized trial conducted by Svartberg, Seltzer and Stiles (in revision) comparing two forms of short-term psychotherapy. From a pool of 20 individuals referred for short-term psychotherapy, 10 were randomly assigned to a directive, psychodynamic form of therapy termed STAPP, and 10 were randomly assigned to a non-directive form of therapy (NDP). In both the STAPP and NDP interventions, patients received 20 sessions of treatment. A key outcome of interest in this intervention is level of client distress as measured by an instrument termed the Symptom Checklist-90 (SCL-90; Derogatis, 1977). Efforts were made to measure levels of distress at multiple points in time: immediately prior to the start of treatment, after 10 sessions, at termination, and 6, 12 and 24 months after termination.

The trajectories of SCL-90 scores for three clients are displayed in Figure 1. Note that on the SCL-90 scale, scores between 0 and 0.20 indicate that an individual is asymptomatic; scores between 0.20-0.40 indicate mild levels of distress; scores between 0.40-1.00 indicate moderate levels of distress; and scores exceeding 1.00 indicate severe symptomology. In Figure 1, we see that Client 4's initial SCL-90 score is approximately 0.50 and that his scores decline over the intervention period; at termination, Client 4's SCL-90 score is close to a value

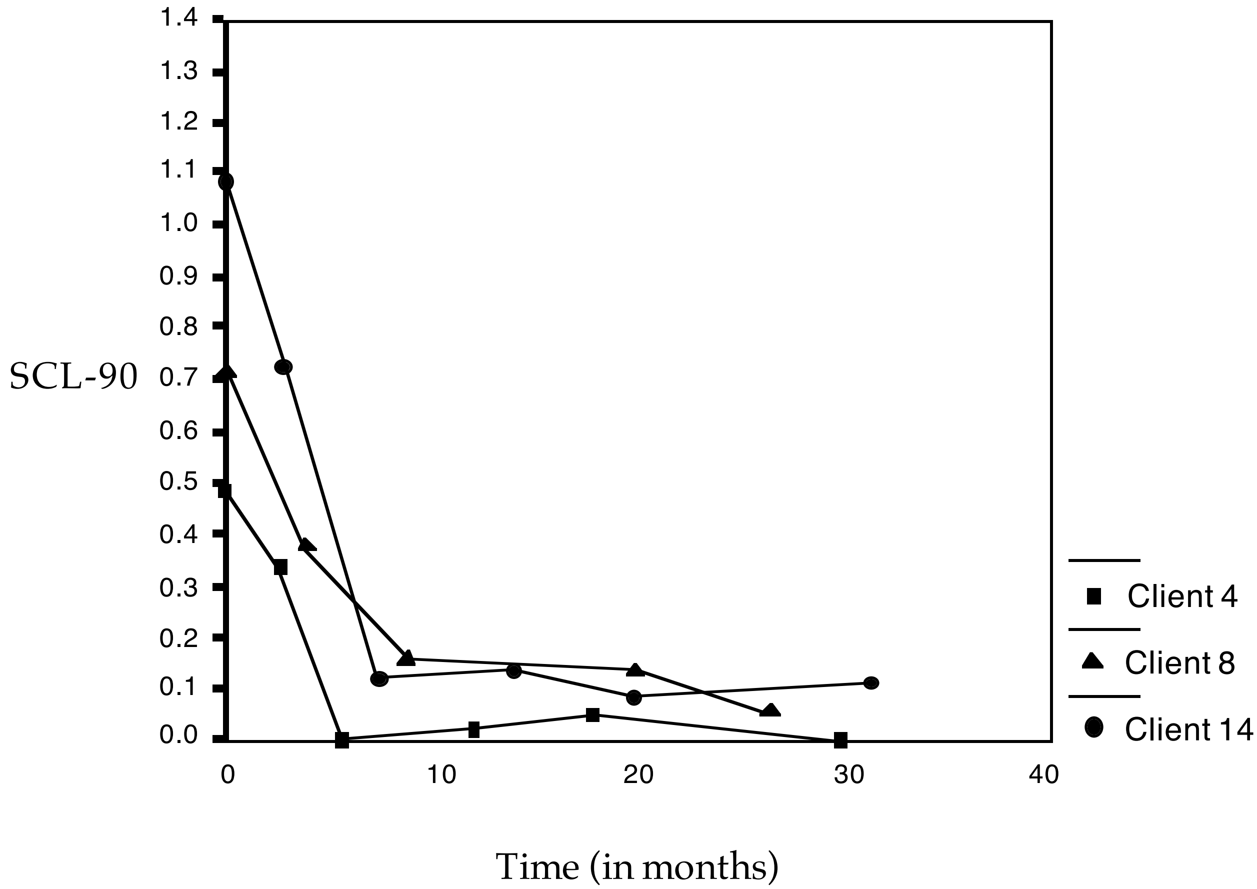

Figure 1. SCL - 90 Trajectories for Clients 4, 8 and 14. Termination occurred at 5.9 months, 8.9 months and 7.5 months for Clients 4, 8 and 12, respectively.

of 0. In the follow-up period, it can be seen that Client 4's SCL-90 scores hold fairly steady, taking on values toward the low end of the SCL-90 scale. Fairly similar patterns occur for Clients 8 and 14: We see declines in their levels of distress during the intervention period, and their scores hover in the asymptomatic range of the scale in the follow-up period.

For nearly all clients in the sample, we observe declines in levels of distress during treatment, and a flattening out of rates of change in the follow-up period. As illustrated by the 3 trajectories displayed in Figure 1, clients differ in terms of their initial levels of distress, in terms of how rapidly they improve during the treatment period, and in terms of their levels of distress at termination.

A Quadratic Model for Individual Growth

Growth modeling provides a valuable framework for studying change over time. It enables us to estimate an average growth trajectory for the individuals in a sample, estimate the extent to which individuals vary in terms of various aspects of change (e.g., in their rates of change), and identify key correlates of change (e.g., to what extent do individuals in the STAPP and NDP interventions differ in their rates of change?). Growth models consist of two models: a model for individual growth, which is often termed a within-person model, and a model that enables us to study differences in growth across individuals, which is often referred to as a between-person model.

In settings in which plots of individual growth trajectories display curvature, as in the case of the trajectories displayed in Figure 1, data analysts typically use a quadratic model to model individual growth. Thus in the case of the STAPP/NDP intervention data, we might pose a quadratic model of the following form:

$$Y_{ti} = \beta_{0i} + \beta_{1i}(Month_{ti} - c_i) + \beta_{2i}(Month_{ti} - c_i)^2 + \varepsilon_{ti} \quad (1)$$

where Y_{ti} is the observed SCL-90 score for individual i at measurement occasion t, and $Month_{ti}$ captures the number of months that have elapsed since the start of treatment for person i at measurement occasion t. Thus, for example, at the third measurement occasion (t = 3) for Client 4 (i = 4), $Month_{ti}$ takes on a value of 5.90. The parameters β_{0i} , β_{1i} , and β_{2i} are termed growth parameters. The meanings that we attach to the parameters β_{0i} and β_{1i} depend upon the term c_i in Equation 1. If we set $c_i = 0$, then β_{0i} represents the SCL-90 status for person i at the start of treatment (i.e., initial status) and β_{1i} represents the initial rate of change for person i. If we set c_i equal to the value of $Month_{ti}$ at termination (e.g., $c_4 = 5.90$ in the case of Client 4), then β_{0i} represents the SCL-90 status for person i at termination and β_{1i} represents the rate of change for person i at termination. β_{2i} captures the amount of curvature in individual i's growth trajectory; that is, the acceleration or deceleration in SCL-90 scores for person i. β_{2i} is a characteristic of the entire trajectory; its meaning, in contrast to β_{0i} and β_{1i} does not depend on c_i. Finally, ε_{ti} is an error term assumed normally distributed with mean 0 and variance σ^2.

A hallmark of growth models is that growth parameters contained in the within-person model (e.g., β_{0i}, β_{1i}, and β_{2i} in Equation 1) are treated as outcomes in a between-person model. Thus we can examine, for example, whether there are systematic differences between STAPP and NDP clients in terms of their status at termination (β_{0i}) and in terms of their acceleration or deceleration across the time frame spanned by the study.

The Need for Piecewise Models in Intervention Studies

In the above study, as in many intervention studies, we have two very distinct time periods: the intervention period and the follow-up period. As such, those factors connected with differences in change in the first period may differ substantially from those that are instrumental in the second period. That is, those factors that are related to differences in rates of change, for example, in the intervention period, may differ substantially from those that are related to rates of change in the follow-up period. In addition, rates of change may be highly variable among individuals in one period, but fairly homogeneous in another period.

The quadratic model for individual change, however, does not readily lend itself to exploring issues of this kind. In particular, the parameters β_{0i} and β_{1i} provide summaries of individual growth at a specific point in time, and β_{2i} provides a summary of the entire time series for an individual. What is needed, in contrast, is a model for individual change that explicitly captures the fact that our study spans two qualitatively distinct periods—that is, a model that contains parameters that capture or summarize important features of change in the intervention period and in the follow-up period.

Piecewise models for individual growth provide a means of dividing a time series into meaningful segments, and capturing key features of change in each segment. In our illustrative example, we employ a two-piece linear model for growth (Bryk & Raudenbush, 1992, pp. 148-151; Seltzer, Frank, & Bryk, 1994) that yields summaries of change for a client in the treatment and follow-up periods.

As outlined in the Appendix, we use the variable $Month_{ti}$ to create two predictor variables (i.e., $Monthtrt_{ti}$ and $Monthaft_{ti}$), which enable us to capture a client's rate of change in the treatment period and his or her rate of change in the follow-up period:

$$Y_{ti} = \beta_{0i} + \beta_{1i}\, Monthtrt_{ti} + \beta_{2i}\, Monthaft_{ti} + \varepsilon_{ti} \quad (2)$$

where β_{0i} now represents the rate of improvement for client i during the intervention period and β_{2i} captures the rate of improvement for client i during the follow-up period. Our coding scheme for $Monthtrt_{ti}$ and $Monthaft_{ti}$ is such that β_{0i} represents SCL-90 status for person i at termination. As in Equation 1, the ε_{ti} are errors assumed normally distributed with mean 0 and variance σ^2.

Utilizing the Piecewise Model

We first seek to estimate a mean improvement trajectory for the individuals in our sample, and examine the extent to which individuals vary around the mean trajectory. To do this, we pose a between-person model of the following form for the 20 clients in our sample (i = 1, … , 20):

$$\beta_{0i} = \gamma_{00} + \gamma_{0i} + U_{0i} \qquad U_{0j} \sim N(0,\tau_{00})$$

$$\beta_{1i} = \gamma_{10} + \gamma_{1i} + U_{1i} \qquad U_{1j} \sim N(0,\tau_{11})$$

$$\beta_{2i} = \gamma_{20} + \gamma_{2i} + U_{2i} \qquad U_{2j} \sim N(0,\tau_{22}), \quad (3)$$

Focusing on the equation for β_{1i}, we see that individual rates of change during treatment are modeled as a function of a mean rate of change for the treatment period, i.e., γ_{10}. U_{1j} is a residual that captures the deviation of the rate of change for person i during treatment from the average rate. The U_{1i}, which are termed random effects, are assumed normally distributed with mean 0 and variance τ_{11}. Thus τ_{11} captures the variation in individual rates of improvement during the treatment period around the average rate. Similarly, γ_{20} represents the mean rate of change for the follow-up period, U_{2i} is a random effect that captures the deviation of the rate of improvement for person i during the follow-up period from the mean rate, and τ_{22} represents the variation in individual rates of improvement during the follow-up period. Finally, γ_{00} represents mean status at termination, U_{0i} captures the deviation in termination status for person i from the mean value, and τ_{00} captures the variation across individuals in termination status.

Note that in the parlance of growth models, γ_{00}, γ_{10} and γ_{20} are termed fixed effects, and τ_{00}, τ_{11}, and τ_{22} are referred to as variance components. We also specify variance components that capture the covariation between individual growth parameters (e.g., the covariance between rate of change during the treatment period and rate of change in the follow-up period [τ_{12}], and the covariance between termination status and rate of change in the follow-up period [τ_{02}]).

The growth model defined by Equations 2 and 3 (Model I) was fit to the data using a computer program called HLM/2L (Bryk et al., 1996). The program provides us with estimates of all parameters in the model. We first examine estimates of the individual growth parameters for the clients in our sample. These estimates are similar to those that one would obtain by regressing each client's SCL-90 scores on the model specified in Equation 2. As can be seen in Table 1, the estimates of the rates of improvement during treatment range between -0.001 and -0.183. Thus, for example, a rate of -0.183 for Client 7 indicates that in the case of this client, we tend to see a reduction in distress of 0.183 points per month during the intervention period. Note, in contrast, that the estimates of individual rates of change in the follow-up period tend to take on very small negative and positive values; specifically, they range from -0.006 to 0.040. The estimates of status at termination range from 0.02 to .81, with 14 of clients taking on values of 0.30 or less.

The results in Table 1 help us understand the results that we obtain for the fixed effects and variance components in the between-person model (see Table 2). As can be seen, the average rate of improvement during treatment is -0.065 (t = -6.52)—that is, on average, client SCL-90 scores are decreasing approximately 0.065 points per month. In contrast, the average rate of improvement during the follow-up period is approximately 0 (t = 0.03). Thus, as discussed earlier, levels of distress decrease during the treatment period and then essentially hold steady during the follow-up period. Furthermore, results for the variance components indicate that while clients vary substantially in their rates of improvement during treatment ($\hat{\tau}_{11}$ = 0.0013; p = 0.000) and in their SCL-90 scores at termination ($\hat{\tau}_{00}$ = 0.0500; p = 0.000), there is virtually no variability in their rates of change posttreatment ($\hat{\tau}_{22}$ = 0.0000; $p > 0.500$).[1]

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[1] Note that since $\hat{\tau}_{22}$ is approximately equal to 0, the estimate of the covariance between rates of change during and after the intervention period is extremely small ($\hat{\tau}_{12}$ = -0.00005; S.E.($\hat{\tau}_{12}$) = 0.00013).

Table 1

Growth Parameter Estimates (OLS) for Individuals in the Sample

Client i	Status at termination	Rate during treatment	Rate during follow-up
1	0.22	-0.070	-0.006
2	0.19	-0.073	0.002
3	0.05	-0.045	0.001
4	0.04	-0.080	-0.001
5	0.81	-0.097	0.003
6	0.48	-0.036	-0.005
7	0.03	-0.183	0.010
8	0.15	-0.061	-0.004
9	0.66	-0.048	0.016
11	0.30	-0.163	0.005
12	0.08	-0.111	0.040
13	0.04	-0.122	0.009
14	0.13	-0.129	-0.001
15	0.29	-0.124	0.034
16	0.02	-0.042	0.003
17	0.66	0.006	-0.001
18	0.06	-0.133	-0.002
19	0.41	-0.001	0.003
20	0.24	-0.038	0.010

Note. As can be seen, OLS growth parameter estimates for Client 10 do not appear in this table. This is due to the fact that there are no observations for Client 10 after termination.

Table 2

Results for Model I

Fixed effect	Estimate	*SE*	t ratio
Avg. status at termination γ_{00}	0.31	0.059	5.26
Avg. rate during treatment γ_{10}	-0.065	0.010	-6.52
Avg. rate after treatment γ_{20}	0.00008	0.0026	0.03

Variance estimates:

Random effect	Variance	*SD*	*df*	χ^2	*p*-value
Status at termination U_{0i}	$\hat{\tau}_{00} = 0.0500$	0.224	18	51.62	0.000
Rate during treatment U_{1i}	$\hat{\tau}_{11} = 0.0013$	0.037	18	73.94	0.000
Rate after treatment U_{2i}	$\hat{\tau}_{22} = 0.0000$	0.002	18	6.91	> 0.500
Within-person error ε_{ti}	$\hat{\sigma}^2 = 0.0356$	0.189			

Comparing the Relative Effectiveness of STAPP and NDP

We now model differences in client rates of improvement during treatment, and in termination status, as a function of treatment type. We do so by expanding the between-person model as follows:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}\,\mathrm{STAPP}_i + U_{0i} \qquad U_{0j} \sim N(0, \tau_{00})$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11}\,\mathrm{STAPP}_i + U_{1i} \qquad U_{1j} \sim N(0, \tau_{11})$$

$$\beta_{2i} = \gamma_{20}, \qquad (4)$$

where $\mathrm{STAPP}_i = 1$ if client i receives the STAPP treatment and $\mathrm{STAPP}_i = 0$ if client i receives the NDP treatment. By virtue of this coding scheme, γ_{10} represents the expected rate of change during treatment for clients who receive NDP, and γ_{11} captures the expected difference in rates of change between clients in STAPP and NDP. Similarly, γ_{00} represents the expected status at termination for NDP clients, and γ_{01} captures the expected difference in termination status between clients in STAPP and NDP. As in a regression analysis, τ_{11} represents the variation in rates of change during treatment that remains after we take into account the type of treatment received by clients, and, likewise, τ_{00} captures the variation in termination status that remains after we take into account the type of treatment received by clients. Note that in the equation for β_{2i} we have removed the random effect term (U_{2i}). We have done this because the results from the first model that we fit to the data indicate that the variance in rates of change in the follow-up period is essentially 0.

Fitting the model defined by Equations 2 and 4 to the data (Model II), we see that there is virtually no difference in rates of improvement during treatment (-0.005; t = -0.26) and in status at termination (0.037; t = 0.31) between individuals in the STAPP and NDP treatment groups (see Table 3). Thus we find that there is essentially no difference in the relativeness effectiveness of STAPP and NDP with respect to improvement in levels of distress.

Table 3

Results for Model II

Fixed effect	Estimate	*SE*	t ratio
Status at termination			
NDP γ_{00}	0.293	0.087	3.38
STAPP/NDP contrast γ_{01}	0.037	0.119	0.31
Rate during treatment			
NDP γ_{10}	-0.063	0.013	-4.69
STAPP/NDP contrast γ_{11}	-0.005	0.019	-0.26
Rate after treatment			
Avg. rate after treatment γ_{20}	0.00005	0.0026	0.02

Variance estimates:

Random effect	Variance	*SD*	*df*	χ^2	*p*-value
Status at termination U_{0i}	$\hat{\tau}_{00}$ = 0.0592	0.243	18	125.07	0.000
Rate during treatment U_{1i}	$\hat{\tau}_{11}$ = 0.0013	0.037	18	105.63	0.000
Within-person error ε_{ti}	$\hat{\sigma}^2$ = 0.0357	0.189			

Factors Underlying Differences in Rates of Improvement

While treatment type is unrelated to differences in rates of improvement during treatment and in termination status, are there other factors that might underlie the variability that we see in these features of growth? We now further expand the between-person model to include a measure that captures various facets of the quality of the therapist/client relationship (e.g., the extent to which the therapist creates an atmosphere in which the client feels comfortable expressing his or her feelings). The scores for this variable, which is termed *ALLIANCE*, are displayed in Table 4. As can be seen, the scores range from a low of 35 to a high of 55.

Our between-person model is now of the following form:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}\,\mathrm{STAPP}_i + \gamma_{02}\,ALLIANCE_i + U_{0i} \qquad U_{0j} \sim N(0, \tau_{00})$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11}\,\mathrm{STAPP}_i + \gamma_{12}\,ALLIANCE_i + U_{1i} \qquad U_{1j} \sim N(0, \tau_{11})$$

$$\beta_{2i} = \gamma_{20}, \tag{5}$$

Table 4

Predictors Used in Models II and III

Client	Treatment group (1 = STAPP; 0 = NDP)	ALLIANCE
1	1	53
2	1	46
3	1	49
4	1	53
5	1	51
6	1	44
7	1	49
8	1	45
9	1	47
10	1	48
11	0	49
12	0	38
13	0	55
14	0	55
15	0	54
16	0	48
17	0	35
18	0	50
19	0	35
20	0	43

where γ_{12} captures the effect of *ALLIANCE* on rates of improvement during treatment, and γ_{02} represents the effect of *ALLIANCE* on status at termination.

In fitting the growth model defined by Equations 2 and 5 to the data (Model III), we see that *ALLIANCE* is strongly related to rates of improvement during the treatment period ($\hat{\gamma}_{21}$ = -0.005; t = -4.33) (see Table 5). That is, higher levels of therapeutic alliance are associated with more rapid decreases in SCL-90 scores.

Note that upon including *ALLIANCE* in the model, the variability in rates of improvement during treatment drops from a value of 0.0013 (Table 3) to a value of 0.0005, which represents a reduction of over 60%.

Studying Change in Follow-Up Periods

In the above application, we found that there was virtually no variability in rates of change among clients in the follow-up period. Had there been variation in rates of change in this period, application of the piecewise model would have made it possible to (a) obtain an estimate of the correlation between rate of

Table 5

Results for Model III

Fixed effect	Estimate	*SE*	t ratio
Status at termination			
NDP γ_{00}	0.277	0.085	3.25
STAPP/NDP contrast γ_{01}	0.073	0.118	0.62
ALLIANCE γ_{02}	-0.014	0.010	-1.44
Rate during treatment			
NDP γ_{10}	-0.069	0.010	-7.25
STAPP/NDP contrast γ_{11}	-0.008	0.014	0.58
ALLIANCE γ_{12}	-0.005	0.001	-4.33
Rate after treatment			
Avg. rate after treatment γ_{20}	0.00026	0.0026	0.10

Variance estimates:

Random effect	Variance	*SD*	*df*	χ^2	*p*-value
Status at termination U_{0i}	$\hat{\tau}_{00} = 0.0558$	0.236	17	109.57	0.000
Rate during treatment U_{1i}	$\hat{\tau}_{11} = 0.0005$	0.022	17	36.72	0.004
Within-person error ε_{ti}	$\hat{\sigma}^2 = 0.0362$	0.190			

change during treatment and rate of change in the follow-up period (e.g., do those individuals with low rates of reduction in levels of distress during the treatment period experience increases in levels of distress in the follow-up period?); and (b) identify factors related to differences in rates of change in the follow-up period. The latter would be accomplished by specifying predictors in the equation for β_{2i} in the between-person model. Note that sets of factors that are instrumental in the intervention period may differ substantially from factors that are key in the follow-up period. The use of the piecewise model enables us to explore these possibilities.

Conclusions and Implications

By enabling us to subdivide a time series into meaningful segments, and summarize important aspects of change in each segment, piecewise growth models provide a means of addressing key questions in intervention studies in education and related fields, including studies of programs such as Head Start, remedial reading interventions for young children with reading difficulties, and school-based interventions targeted for children with behavioral problems. In particular, piecewise models enable us to (a) examine whether rates of change, on average, slow down, remain constant or speed up during the follow-up period; (b) assess whether there is substantially more variability in rates of change in one of the periods of interest; and (c) identify conditions under which we see rapid rates of progress during the treatment period, and sustained progress during the follow-up period. The latter is accomplished by specifying predictors in the between-person model that capture, for example, differences in the level of implementation of the intervention received by the student, in other kinds of services received by the student, in home resources and the like.

Note that the piecewise model can be further elaborated to capture curvature (i.e., acceleration/deceleration) in each period of interest. In addition, we can extend the piecewise model to situations in which each time series consists of three or more periods of substantive interest. For example, in addition to collecting observations at multiple points in time during treatment and follow-up phases, a researcher might also collect data at several points in time during a pre-treatment phase. Finally, a third-level can be added to the piecewise growth model to represent the nesting of students in different classrooms or schools. This opens opportunities to identify, for example, schools in which rates of progress in the follow-up period are particularly rapid.

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Appendix

Coding Scheme for the Piecewise Model

To illustrate the coding scheme for the time predictor variables (i.e., $Monthtrt_{ti}$ and $Monthaft_{ti}$ in the piecewise model depicted in Equation 2), we focus on Client 4. As can be seen below, the first measurement occasion for Client 4 occurred at the outset of the treatment period (*Month* = 0.0), the second measurement occasion occurred after 2.7 months elapsed, and the third measurement occasion occurred after 5.9 months elapsed, which is when treatment terminated for Client 4. The fourth measurement occasion occurred after 12.1 months elapsed (i.e., 6.2 months after termination), the fifth measurement occasion occurred after 17.9 months elapsed (i.e., 12.0 months after termination), and, finally, the sixth measurement occasion occurred after 29.9 months elapsed (i.e., 24.0 months after termination).

Note the variable *Monthtrta*. The values for *Monthtrta* are identical to the values for the *Month* variable up to and including the point at which termination occurred for Client 4, which corresponds to the third measurement occasion. For all measurement occasions following termination, *Monthtrta* takes on a value of 5.9. In contrast, *Monthaft* takes on values of 0.0 for the first 3 measurement occasions, after which it captures the number of months that have elapsed since termination; for example, at time t = 4, *Monthaft* = *Month* - *Monthtrta* = 12.1 - 5.9 = 6.2. Note, finally, the variable *Monthtrt*. *Monthtrt* is formed by simply subtracting a value of 5.9—the termination point for Client 4—from *Monthtrta*.

Table A1

Coding for Client 4

t	Month	Monthtrta	Monthaft	Monthtrt
1	0.0	0.0	0.0	-5.9
2	2.7	2.7	0.0	-3.2
3	5.9	5.9	0.0	0.0
4	12.1	5.9	6.2	0.0
5	17.9	5.9	12	0.0
6	29.9	5.9	24.0	0.0

Depending upon how much time elapses until the second observation for individual i, when termination occurs, how much time elapses until the first follow-up observation, and the like, the values for *Monthtrata* and *Monthaft* will not necessarily be identical to the values in the above Table. However, the logic for coding *Monthtrta*, *Monthaft* and *Monthtrt* is the same as described in the preceding paragraph.

Using *Monthtrta* and *Monthaft* as predictors in Equation 2, β_{1i} and β_{2i} represent, respectively, the rate of change for person i during treatment and the rate of change for person i in the follow-up period. β_{0i} represents the expected level of distress for person i (i.e., status) at termination. Note that if we were to utilize *Monthtrta* instead of *Monthtrt* in Equation 2, the meanings of the parameters β_{1i} and β_{2i} are identical to those that obtain when we use *Monthtrt* as a predictor. The only difference is that β_{0i} now represents the expected level of distress for person i at the first measurement occasion (i.e., initial status).