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The Use of Discrete Latent Variables in Dyadic Data Analysis

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Psychology

by

Jacob Gray

June 2018

Dissertation Committee:
Dr. Daniel J. Ozer, Chairperson
Dr. Chandra A. Reynolds
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The Dissertation of Jacob Gray is approved:

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Acknowledgements

"One of these days,
I'm gonna sit down and write a long letter
To all the good friends I've known
And I'm gonna try
To thank them all for the good times together"
-Neil Young

It's an odd feeling to actually write out an official version of one of those letters. This is my best attempt to acknowledge those that have helped along the way to this dissertation, whether they were aware of the impact they had on me, or not. I first want to thank my dissertation committee of Dan Ozer, Chandra Reynolds, and Keith Widaman. Dan put up with my constantly shifting research interests and supported the current iteration of my dissertation, even if it took some convincing. Dan also provided me with a template of the type and amount of knowledge I aspired to reach. When I started grad school I barely knew what a standard deviation was, and I like to think I've come along a bit since then. I would also like to thank everyone else who has served on my committees before now: Megan Robbins, David Funder, and Liz Davis. Additionally, a special shout out goes to Will Dunlop who has been a steady sourcing of collaboration, gossip, and guidance.

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ABSTRACT OF THE DISSERTATION

The Use of Discrete Latent Variables in Dyadic Data Analysis

by

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Dr. Daniel J. Ozer, Chairperson

Two topics of methodological research topics in the social sciences that have garnered recent attention are dyadic data analysis and the use of discrete latent variables. Dyadic data refers to data that were collected from two interdependent sources, such as data from identical twins or romantic partners. Data collected in this fashion violate the traditional independence assumption underlying many common statistical techniques. Discrete latent variables come in many commonly used models, such as the latent class, latent profile, and latent transition models. All these models share the goal of explaining observed relationships between variables using discrete categories (i.e. classifications) in which observations are statistically similar to those in the same category, and dissimilar from those in separate categories. While both dyadic data analysis and categorical latent variables have seen countless articles (and even entire textbooks) written about their usage, these two techniques have been developed as independent procedures. This dissertation will briefly review the conceptual and statistical details of both modeling

techniques and then provide two substantive examples of how dyadic data and discrete latent variables can profitably be used together. The first example combines growth mixture modeling with the use of the common fate growth model to identify distinct trajectories of marital satisfaction among couples. The oft-observed decline in satisfaction in the years following marriage can largely be attributed to a sub-population that reports a large decrease in marital satisfaction. The second substantive example combines the latent profile, latent transition, and actor-partner interdependence model into a model examining the cross-lagged association of couple members' political beliefs. The goal of this dissertation is to demonstrate how dyadic data analysis and discrete latent variables techniques can be used together with the hopes that these two modeling techniques will begin to be researched, applied, and referenced together.

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Chapter 1:

Introduction

To date, methods to apply categorical latent variables to dyadic data analysis are not available. Many of the actions or decisions involved in dyads reflect a dichotomous/categorical nature such as the decision to get married (or divorced), the decision to seek couples therapy, or even the decision of who to form a relationship with. This is also reflected in the historic practice in the marital literature of distinguishing between "distressed" and "non-distressed" couples (Bradford, Hawkins, & Acker, 2015; Jacobson, Follette, & McDonald, 1982). Given the salience of categories in research on dyads (and couples in particular), it is somewhat perplexing that the literatures on dyadic data and discrete latent variables have not come into contact before. This purpose of this dissertation is to provide such a common ground. What unites the following two studies is the methodology. Both studies represent novel applications of existing statistical methodologies. While the substantive question is different, and the methodologies being used may look quite different as well, the following two studies are the first in what is hopefully a large literature uniting these two topics. Just as there have been volumes written about both topics (Kenny, Kashy, & Cook, 2006; Collins & Lanza, 2013), there are countless opportunities for integrating dyadic data and discrete latent variables. The present studies are merely two such applications, but will hopefully give researchers an idea of the potential opportunities available to them.

Dyadic data analysis

Nonindependence

Data collected in psychology and other social sciences often demonstrate some degree of nesting. Nested observations occur when scores or values for one observation can provide information about other observations. The classic nesting paradigm in the behavioral sciences is the use of students within classrooms, where information about students in a particular classroom may give information about the values of other students in that same classroom (Raudenbush & Bryk, 2002; Vaughn, 2008). Nesting can lead to overly optimistic estimates of the model degrees of freedom, influencing the standard errors and therefore significance tests (Kenny, 1995; Kenny & Judd, 1985).

One area of research in which nested data are more or less built into the research questions is the analysis of dyadic data. Dyads are common in psychological research, as many relationships be formulated as a relationship between two people. For instance, dyads can include parent-child, identical and fraternal twins, or both members of a romantic relationship (Campbell & Kashy, 2002; Kenny & Cook, 1999; Peugh, DiLillo, & Panuzio, 2013; Kenny & Cook, 1999). While dyadic data can give insight into dynamics of close relationships, they also present challenges for accounting for the non-independence of dyadic data. For instance, research that focuses on the relationship between romantic partner personality and one's own relationship satisfaction would have to account for probable scenario that relationship satisfaction of romantic partners is likely to be highly related (Dyrenforth, Kashy, Donnellan & Lucas, 2010).

One metric of the level of nesting in data is the intraclass correlation (ICC). The ICC is a metric of the proportion of variance that is within dyads versus between dyads. The equation for the ICC (Shrout & Fleiss, 1979) is given as:

$$\frac{MS_{between} - MS_{within}}{MS_{between} + MS_{within}(n-1)} \tag{1.1}$$

Where *n* is the sample size per cluster. Because dyadic data paradigms involve cluster sizes of two, Equation (1.1) reduces to:

$$\frac{MS_{between} - MS_{within}}{MS_{between} + MS_{within}} \tag{1.2}$$

As more variance is between cluster, relative to within, the ICC increases.

Conceptual Models of Nonindependence

Given that dyad members likely share some degree of similarity and some degree of influence over each other, a crucial aspect of the modeling of dyadic data is adequately mapping out the processes that give rises to interdependence. Relevant to the current discussion of dyadic data are two models of interdependence. The first model, the Actor-Partner Interdependence Model (APIM), treats the dyad members as distinct units, and their interdependence arises via dyad members having an influence on each other. The second relevant model is the Common Fate Model (CFM), which treats the dyad as a singular unit, in attempt to model dyad-level processes (Kenny, 1996).

The APIM (Figure 1.1; Cook & Kenny, 2005; Kenny & Cook, 1999; Kenny & Ledermann, 2010) is model for assessing the relationship between some predictor and

some outcomes across dyad members. In this model, each dyad member has a score for the predictor (X), and the outcome (Y). The path from one's own predictor, to one's own outcomes is known as the "actor effect." The path from one's predictor the other dyad members outcomes is called the "partner effect" (Campbell & Kashy, 2002). The interdependence between dyads in this context is modeled with the use of partner effects. These paths indicate the extent to which partners exert an influence on each other (Cook & Kenny, 1999). The APIM has been applied to a variety of substantive research questions the relationship between partner attachment and relationship satisfaction and intimate partner violence and alcohol use (Campbell, Simpson, & Kashy, & Rholes, 2001; Lambe, Mackinnon, & Stewart, 2015)

The Common Fate Model (CFM, Figure 1.2; Galovan, Kramer, Proulx, 2017; Ledermann & Kenny, 2012) treats dyadic processes differently. Interdependence in this model is treated as arising from some dyadic level process. This means that each dyad member's score is an indicator of the latent variable of the dyad. This suggests that interdependence of couple members arises not because of partners influencing each (as in the APIM), but rather some process influences both together (Iida, Seldman, & Shrout, 2017. In a sense, both members are simply along for the dyadic ride (hence their "common fate"). The CFM has been studied and utilized less extensively than the APIM, but has been successfully applied to research questions involving the relationship between commitment and dyadic coping and the association between self-esteem and relationship satisfaction (Erol & Orth, 2014; Landis et al., 2014)

Analyzing dyadic data

Relationship researchers have been cognizant for some time about the issues inherent in studying dyads. While researchers are not likely anymore to ignore the problem of nesting, one still used practice is to analyze dyad members separately (i.e. analyze men and women in heterosexual relationships separately). There are several issues inherent in this approach. Not all dyads are "distinguishable", meaning that not all dyads have a variable that would provide a convenient split with which to separately analyze dyad members (e.g. identical twins). This approach fails when dyad members are not distinguishable.

As is typical with nested data, multilevel modeling can be used to account for the effect of nesting on statistical tests (Kenny & Cook, 1999; Kenny & Kashy, 2011). Using multilevel modeling with dyadic data requires one major restriction. In a typical multilevel model, both intercepts and slopes are treated as random effects. This means that both the overall means of the outcomes, as well as the relationship between predictor and outcomes, are allowed to differ across nesting units (see Appendix A for a simulation addressing this issue).

In addition to multilevel modeling, structural equation modeling can be used to analyze dyadic data. The APIM presented in Figure 1.1 is a good example of a model that can be assessed using SEM. One situation that often precludes the use of SEM with the APIM is the case of indistinguishable variables (e.g. same-sex couples). Because the paths in the APIM are separated by the distinguishing variables, modifications must be

made to SEM model. Specifically, phantom variables need to be specified in order to analyze the APIM with indistinguishable dyads (Macho & Ledermann, 2011; Rindskopf, 1984) The CFM model is analyzed using SEM almost exclusively (because of the need to incorporate latent variables). Under most circumstances, using the APIM with SEM or multilevel models will yield very similar results (Ledermann & Kenny, 2017).

One common practice in the analysis of dyadic data is to test for differences in effects based on the distinguishing variable (Garcia, Kenny, Ledermann, 2015). In a multilevel model context, this is achieved by modeling an interaction between the distinguishing variable and the actor and partner effects. In a SEM context, this is achieved by placing the constraint that the actor and partner effects are equal for the two dyad groups.

Longitudinal models of dyadic data

An additional complication in the analysis of dyadic data is assessing dyadic data in a longitudinal context. Many of the concepts of dyadic data have been applied to assessing change and consistency in the context of couples (Bolger & Shrout, 2007). Both the APIM and CFM have been applied to respective longitudinal models. The longitudinal APIM assesses the cross lagged influence of couple members on each. The Common Fate Growth Model again treats the couple as the unit of analysis, while measuring growth in some dyadic level process (Ledermann & Macho, 2014).

The longitudinal APIM (see Figure 1.3) is simply a cross lagged version of the APIM previously discussed (Kenny, Kashy, & Cook, 2006). There are again both actor and

partner effects, this time warranting different conceptual interpretations. The actor effects in the longitudinal APIM represent individual stability in the variables. The partner effect represents the degree of across time association holding constant initial status. For instance, positive partner effects indicate that as a dyadic relationship progresses, there is some degree of convergence in the variable in question (Perry et al., 2017). Such a model was utilized by Caspi, Herbener, & Ozer (1992) to identify the presence of shared environment effects.

The Common Fate Growth Model (Figure 1.4, Ledermann & Macho, 2014) is a model for assessing change at the dyadic level. As with the standard CFM, the couple is treated as the unit of analysis. The goal of this model is to identify the trajectory of some dyadic process. For instance, relationship satisfaction may change at the dyadic, rather than the individual level (Gray & Ozer, in prep.). This model was successfully used to identify the relationship between self-esteem of individual couple members and the trajectory of marital satisfaction at the couple level (Erol & Orth, 2014). The decision of when to treat couples or individuals as the unit of analysis is fundamentally a statistical question, but can be informed on conceptual and theoretical grounds (see Ledermann & Macho, 2014 for more details).

Discrete latent variables

Latent variables

Many research questions in psychology involve the explanation of why particular items or responses are correlated. The use of latent variables aims to explain the

covariation between a set of responses (Thurstone, 1947). Latent variable models posit a real variable that exists in the world, but is not directly measurable (Boorsboom, Mellenbergh, & Van Heerden, 2003; Bollen, 2002). One of the traditional paradigms of a latent variable model is intelligence. Intelligence is an attribute that exists in people, but is not directly measurable. We can best infer intelligence on the basis of indicators of intelligence (e.g. scores on a block design task; Spearman, 1927). The latent variable of intelligence explains the observed correlations between indicators of intelligence. The technique is contrasted with a dimensionality reduction technique, such as principal components analysis, which aims to explain variation in the items themselves (Fabrigar, Wegener, MacCallum, & Strahan, 1999; Floyd & Widaman, 1995)

Two key questions in the use of latent variables regard the nature of posited latent variable and the nature of the responses. Common factor analysis posits a continuous latent variable, indicated by continuous (or approximately continuous) items. This technique is ubiquitous in fields such as personality, where continuous latent variables and indicators are the norm (Briggs & Cheek, 1986; Ozer & Reise, 1994). When the hypothetical latent variable is continuous in nature, but the indicators are categorical or ordinal, item-response theory may be used (Embretson, 1996). Item response theory has become a popular methodology in domains in which indicators are dichotomous, such as the presence or absence of symptoms or correct/incorrect responses (Reise & Waller, 2009).

The nature of the analysis changes when the hypothetical latent variable is categorical rather than continuous. The classes of models that use categorial latent

variables are broadly known as latent class and latent profile analysis. Latent profile analysis is the categorical analog of the common factor model. Observations are grouped into discrete profiles that differ in the observed continuous variables (Muthén, 2002; Oberski, 2016). Latent class analysis is the broad term used to refer to latent variable models that feature both a latent categorical variable, with categorical indicators (McCutcheon, 2002). Table 1.1, from Collins and Lanza (2013), helps to illustrate the differences between these models.

Despite the conceptual and statistical differences between these models, they all share the same overarching goal of attempting to model observed correlations between latent variable indicators (Gibson, 1959). The models all share common features. For instance, all models demonstrate a relationship between the latent variable and the observed indicators. The factor loadings in a common factor analysis are akin to the probabilities of responses given class membership that is discussed in a latent class framework (Muthén, 2002; Nylund, Asparouhov & Muthén, 2007). Another common component is the idea of model testing. While all models are wrong (Box, 1976), they can show enough correspondence to reality to be useful. Each of the aforementioned models can be tested for their overall fit, and constraints such as measurement invariance, equal factor loadings, group means (or proportions for categorical latent variables) can be placed on all them. The similarities are not merely conceptual, but statistical as well. In fact, under the right circumstances common factor and latent class models can show the exact same fit to the data (McLachlan & Peel, 2004).

The focus of this dissertation will be on models that posit discrete latent variables. The models will be integrated with the previous discussion on dyadic data analysis, erstwhile unpaired techniques. Before a discussion of how these models can be integrated with dyadic data, a discussion of the some of the extensions of discrete latent variables, is warranted. Namely relevant to the current dissertation are growth mixture modeling and latent transition analysis. Both are longitudinal extensions of latent variable models just discussed. The immediately preceding discussion is conceptual in nature, some of the relevant mathematical details are deferred until later sections of this dissertation

Growth Mixture Modeling

Latent growth curves are widely used models that describe change at the population level (Bollen & Curran, 2006; Rovine & McDermott, 2018). These models describe average levels of change, with interindividual differences described as the random effects (i.e. the variance terms) associated with these growth parameters. These models may be misspecified when the growth parameters in the population do not follow a single Gaussian distribution, but are sampled from multiple distributions (Bauer, & Curran, 2003). Growth mixture modeling seeks to remedy violations of this assumption by estimating growth patterns for distinct groups in the population (Jung & Wickarama, 2008; Muthén & Muthén, 2002).

Growth mixture modeling is a particular form of the more general mixture modeling technique. Mixture modeling attempts to explain observed population heterogeneity using unobserved groups (Lubke & Muthén, 2005). The goal of growth

mixture modeling is to identify, or model, distinct sub-trajectories in the population (Muthén & Muthén, 2002; Nagin & Odgers, 2010; Nagin & Tremblay, 2001). This form of modeling allows researchers to identify particular individuals that have a higher propensity to increase or decrease on the outcome of interest. For example, Orcutt, Erickson, and Wolfe (2004) identified two classes of change among Gulf War veterans, one group that showed consistently low levels of PTSD symptoms, and one groups that started high and increased in their PTSD symptoms.

The popularity of growth mixture modeling has led to the development of extensions that make it more applicable in a variety of circumstances. Extensions include higher order growth mixture modeling, which incorporates second order latent growth curves (Grimm & Ram, 2009). In addition, models including covariates predicting class membership have been proposed (Asparhouv & Muthén, 2014). The particular application of growth mixture modeling featured in this dissertation will involve a dyadic extension of the second order growth mixture model.

Latent Transition Analysis

Latent transition analysis is a longitudinal extension of the latent class analysis, which assesses change in discrete latent variables. The model is conceptually similar to the autoregressive model, in which levels of a variable at one time point predict levels at another time point. In latent transition analysis, class membership is assessed at (at least) two time points, and subjects are allowed to switch between classes (Collins, Hyatt, &

Graham, 2000; Lanza & Collins, 2008). Transitions occur when a subject switches from one class to another a later time point.

The latent transition model is akin to multivariate extension of a latent Markov model (Böckenholt, 2005). Several of the parameters of interest include the conditional response probabilities, overall rates of latent classes, and the probabilities of transition between particular classes. Measurement invariance is a crucial aspect of latent transition analysis. Measurement invariance in this context means that at each time point, the probability of obtaining particular responses conditional class membership is the same. In the absence of invariance, it is difficult to interpret the transition between classes.

Extensions of the univariate latent transition analysis have been developed. The associate latent transition analysis assesses the longitudinal relationship between classes and transitions (Bray, Lanza, & Collins, 2010; Flaherty, 2008a). There has been limited attention paid to this multivariate extension of the latent transition analysis, but the model has been successfully used to study the association between changes in life stressors and depression and the association between changes in negative affect and changes in drinking behavior (Pettit et al., 2010; Witkiewitz & Villarroel, 2009). The present dissertation will dive further into this multivariate extension of the latent transition analysis by developing a latent transition analysis for change in two members of a dyad. This model will share superficial similarities with the longitudinal APIM that was discussed above.

The Ontology of Latent Classes

One issue that has thus far not been mentioned but is pertinent to discuss is the ontological status of latent classes. Block and Ozer (1982) note the distinction between "type-as-label" and "type-as-distinctive-form". This distinction finds two purposes in the use of types (or classes in the present context), one in which types are not necessarily veridical but make for useful communicative labels and another usage in which types are meant to exist in the real world. One example of using the type-as-label is the classification of "smart" and "dull" individuals. While intelligence is a true continuum, the classification of individuals into groups based on intelligence can serve as a useful heuristic (as in the case of deciding which children may need remedial education). An example of the type-as-distinctive-form is the classification of species, which show categorical differences. The difference between a seahorse and grizzly bear is not a mere device of communication but reflect real group differences. This distinction was echoed by Meehl (1992) who distinguished between "natural kinds" and "arbitrary classes" when discussing the presence of classes of observations.

There have been numerous attempts to statistically determine whether latent classes are best described as labels or as distinctive forms (Halpin & Maraun, 2010; Lubke & Neale, 2006; Lubke & Neale, 2008; Lubke & Tueller, 2010; Waller & Meehl, 1998). While these techniques have worked to varying success, the issue of types-as-label remains. Statistical clues may suggest that latent classes are not appropriate (or perform as well as latent factors, cf. McLachlan & Peel, 2004), the expediency and communicability of treated observations as belonging to latent classes may warrant their

discussion. The present dissertation remains agnostic as to which of these forms latent classes should take, however it is worth noting that the modeling of latent classes need not perfectly recreate a categorical structure to remain useful.

Outline

The first study will expand upon the aforementioned growth mixture model by applying higher order growth mixture modeling to dyadic trajectories. This study represents an integration of the Common Fate Growth Model and growth mixture modeling discussed previously. This study will utilize the British Household Panel Survey to identify different trajectories of marital satisfaction at the couple level. Class membership will then be predicted by covariates that have been identified as important predictors of declines in marital satisfaction. Lastly, the implications of group membership will be seen as group membership will be used to analyze the occurrence and timing of divorce among the couples in the study.

The second study will represent and integration of the longitudinal APIM and latent transition analysis. Rather than model latent transitions as an individual phenomenon, I will model the association between couple members in the latent classes over times. I will discuss the different ways in which latent transitions may be related across time, before identifying the best model to describe latent transitions between couple members. This study will also utilize the British Household Panel Survey to analyze transitions between classes of political attitudes across time.

Chapter 2:

Classes of Couples: An Application of Second-Order Growth Mixture Modeling

Abstract: Developments in the analysis of dyadic data and the modeling of longitudinal change with heterogenous populations have occurred separately from one another. The present study provides a novel application of growth mixture models to the analysis of trajectories of dyadic level marital satisfaction. Using the British Household Panel Survey (N = 2,086 couples) a model consisting of two distinct trajectories of marital satisfaction was chosen to represent the data. The majority of the sample was placed in a Stable class that showed little to no change in marital satisfaction, while a minority were classified as Declining. Covariates consisting of couple neighborhood condition, job satisfaction, financial situation, and perceived importance of one's partner were used to predict class membership. Using event history analysis, couples in the Declining class were significantly more likely to get divorced in the succeeding four years. The Declining class, while small, was consequential. The present study demonstrate how growth mixture modeling can be used to statistically identify couples most in need of marital intervention.

Class of Couples: An Application of Second-Order Growth Mixture Modeling

Data from dyads allow for the unique opportunity to model the ways in which dyad members covary and change with one another. This potential opportunity also comes with the added cost that dyadic data often require the use of quantitative methods that allow for the nonindependence of observations (Kenny & Cook, 1999; Peugh, DiLillo, & Panuzio, 2011, Steele & Ferrer, 2011). Developments have also occurred in the area of mixture modeling, which attempt to recover unobserved population heterogeneity through the use of a mixture of distributions (McLachlan & Peel, 2000). The current study seeks to integrate developments in measuring dyadic change with growth mixture modeling. The present study will seek to identify sub-trajectories of marital satisfaction at the dyadic level, while incorporating both exogenous predictors of class membership and the distal outcome of divorce.

Trajectory of Marital Satisfaction

Among the best predictors of the longevity of marriage is how satisfied the spouses feel with their marriage (Karney & Bradbury, 1995; Kelly & Conley, 1987; Solomon & Jackson, 2014). Marital satisfaction is a multi-faceted construct, with many potential causes and consequences (Dush, Taylor, & Kroeger, 2008). In addition to relationship longevity, one's satisfaction with marriage has been associated with a variety of important outcomes, such as physical health, work success and psychological well-being (Carr, Freedman, Cornman, Schwarz, 2014; Robles, Slatcher, Trombello, & McGinn, 2014; Rogers & May, 2003; South & Krueger, 2013).

Perhaps more important than marital satisfaction at a given time point, declines in marital satisfaction may prove to be consequential. Notably, declines in marital satisfaction may provide additional insight in predicting divorce (Lavner & Bradbury, 2010; Solomon & Jackson, 2014). An understanding of the consequences and antecedents of marital satisfaction requires knowledge of the trajectory of marital satisfaction. Despite the importance of a satisfying marriage, there is on average, a decline in satisfaction following marriage (Gray & Ozer, under review; Karney & Bradbury, 1995; McNulty, Wenner, & Fisher, 2016). This average decline in relationship satisfaction has often been implicated in predicting a variety of psychological outcomes (Jacobson, Dobson, Fruzzetti, Schmaling, & Salusky, 1991).

Predictors of change in marital satisfaction have been identified in both environment and personal factors. Financial strain of couple members often presages arguments over money which in turn predicts declines in marital satisfaction (Dew, 2008). Similarly, environmental strain may come from the area in which a couple lives. Couples who report worse neighborhood conditions tend also to report a poorer quality of marriage (Cutrona et al., 2003). Satisfaction in marriage also tends to be associated with satisfaction with one's job, indicating the satisfaction in one domain is associated with satisfaction in another life domain (Ford, Heinen, & Langkamer, 2007; Rogers & May, 2003). Understanding the antecedents and predictors of marital satisfaction relies on adequate modeling of the trajectory of satisfaction.

An understanding of a dyadic process such as marital satisfaction, relies on the ability to properly model the phenomenon of interest (Kashy & Kenny, 2000; Kenny &

Cook, 1999). A crucial component of modeling dyadic data properly is the distinction between whether the variable of interest represents an individual or dyadic variable (Kenny, 1996). Variables that are considered dyadic are often modeled using a "common fate" approach (Ledermann & Kenny, 2012; Kenny, 1996). The common fate approach models a phenomenon as occurring at the couple level by the use of latent variables wherein the individual couple members are used as indicators of the dyadic construct (Ledermann & Kenny, 2012).

The analysis of common fate models has been extended to the analysis of change at the dyadic level (Ledermann & Macho, 2014). Relationship satisfaction is one such variable that has been shown to change at the dyadic, rather than the individual level (Gray & Ozer, under review). The result that marital satisfaction changes at the dyadic level raises the question of if different sub-trajectories of relationship satisfaction exist.

The Growth Mixture Model

A key interest of behavioral scientists is to describe and test hypotheses about intra-individual changes. Latent growth modeling is an increasingly popular method for analyzing change. The basic latent growth model (Bollen & Curran, 2006; McArdle, 1988; 2009) is given as:

$$y_i = \Lambda\eta_i + \varepsilon_i \tag{2.1}$$

Where y_i is a t X 1 vector of repeated measures for variable y given by observation i, and t is equal to the number of repeated measures. The matrix Λ is t X q where q is the number of latent growth factors (i.e. $q = 2$ for an intercept and slope in a linear model).

This matrix defines the shape of the trajectory, and can incorporate linear and nonlinear trajectories (McArdle, 2009). η_i is q X 1 that defines the randomly varying latent variable means. η_i is assumed to be randomly varying with a q X q covariance matrix, Ψ, indicating the variance and covariance of the latent factors (Little, 2013). ε_{it} represents the disturbance term for a given observation *i,* and is assumed to be normally distributed with a mean of zero and a variance denoted by Θ.

The latent growth curve model is extremely flexible as it can accommodate changes in multiple variables, exogenous and distal covariates, and multiple groups (Bollen & Curran, 2006). A common assumption of this model is that the sample consists of observations from a single, homogenous population. However, when this assumption is violated and observations come from two or more heterogenous populations, parameters may become uninterpretable (Grimm & Ram, 2009; Nagin, 1999). The idea of multiple sub-trajectories underlying the model forms the basis and rational for growth mixture modeling.

Growth Mixture Model

Growth mixture modeling (GMM; Muthén & Asparouhov, 2007; Muthén & Shedden, 1999; Nagin, 1999) has become a popular tool in the social sciences as a method for uncovering unobserved heterogeneity in growth trajectories. In the GMM, multiple trajectories are formed based on group membership, which itself must be estimated. The above formula can be rewritten as:

$$y_{ik} = \Lambda_k \eta_{ik} + \varepsilon_{ik} \quad (2.2)$$

Where the model parameters have the same meaning, but the model is now estimated for each of the *1, 2, ...k* latent classes. This model involves the estimation of substantially more parameters than the single group latent growth model, and so some constraints are necessary to implement it. For instance, the constraint that $\Lambda_1 = \Lambda_2 ... = \Lambda_k$ is often imposed. This constraint specifies that the overall pattern of growth is the same across latent classes, but the specification that $\eta_1 \neq \eta_2 \ldots \neq \eta_k$ allows one or more elements of the mean latent variables to differ across classes (Muthén & Muthén, 2000). GMMs are essentially a multiple groups latent growth curve, with the added complication that classes are inferred rather than observed. In this way, GMMs can be understood as a longitudinal extension of the latent class model.

The GMM can be seen as a form of a multiple groups latent growth analysis (Ram and Grimm, 2009). However in a traditional multiple groups SEM mode, group membership is known and the growth model is estimated separately based on values of the grouping variable (assuming that the grouping variable is mutually exclusive and exhaustive). These separate trajectories can be compared to see if the group membership is associated with the growth parameters. The GMM differs from the traditional multiple groups analysis in the group membership is a latent variable and group membership is estimated based on the data.

An additional common constraint is to set $\Psi_k = 0$. This constraint implies that the within-class variance-covariance matrix of the latent variables is zero. Such a constraint implies that all variance (and thus, covariance) terms in the growth parameters is accounted for by class membership. This more constrained model is often referred to as a

Latent Class Growth Model (LCGM, Muthén, 1999; Wright & Hallquist, 2014). Whereas GMM assumes random effects in each latent class, Latent Class Growth Modeling assume completely fixed effects. In this sense, the GMM is a more relaxed model compared to the LCGM. Because the with-in class variances are set to zero in LCGM, the covariances between the intercepts and slopes are also implicitly set to zero (Wright & Hallquist, 2014). Both of these models can incorporate nonlinear terms (e.g. quadratic and cubic growth), though with additional latent variables converge may become an issue, especially with the GMM. The constraints of the LCGM are often placed to increase the efficiency and convergence of the model, rather than substantive hypotheses, though such constraints are testable (see Bauer & Curran, 2003).

GMM's are becoming increasingly popular in the behavioral and social sciences. For instance, many theories on human development posit that individuals follow one of a number of discrete developmental pathways (e.g. Moffitt, 1993; Brendgen, Vitaro, Bukowski, Doyle and Markiewicz, 2001). Outcomes studied using GMM have been as varied as physical aggression, alcohol use, obesity, and psychopathology (Colder, Campbell, Ruel, Richardson, & Flay, 2003; deRoon-Cassini, Mancini, Rusch, & Bonanno, 2010; Mustillo et al., 2003; Nagin & Tremblay, 1999). As mentioned above, violating the assumption that observations are sampled from a single distribution can obscure important differences and nuances in developmental trajectories (Muthén, 1999). Furthermore, GMMs have been shown to outperform simpler clustering algorithms (such as *k*-means clustering) in identifying the presence of latent classes (Martin & van Oertzen, 2015). Another important theoretical aspect of the GMM is the ability to predict

classes of growth using covariates. Class membership is often predicted as a logistic regression (with $k = 2$ classes) or as a multinomial logistic regression (with $k > 2$ classes).

There a number of conceptual and empirical issues that need to be addressed in the estimation of growth mixture models. Unlike traditional latent growth models, growth mixture models are susceptible to local solutions (Hipp & Bauer, 2006). Researchers that fail to consider the existence of local optima may be susceptible to interpreting a model that does not represent the globally optimal solution (Shireman, Steinley, & Brusco, 2016). This problem is endemic with many forms of categorical latent variable models, as local features of the model are often fit well without parameter estimates corresponding to the overall best solution. This issue can often be addressed by the use of multiple sets of starting values (Steinley et al., 2016). Another issue in the application of GMM is the interpretation of the classes. Some are skeptical that GMMs can adequately reproduce latent classes (Bauer, 2007; Bauer & Curran, 2003). Proponents of GMM have emphasized that sub-trajectories are not meant to represent literally distinct trajectories, but rather cluster individuals based on similar trajectories (Muthén, 2003; Nagin & Odgers, 2010). The clustering of individuals based on similar trajectories can be a worthwhile endeavor when the goal is to identify important predictors or consequences of certain trajectories (Nagin, 2010).

An additional extension of the GMM is to incorporate a second order latent growth model. Here the growth factors in the growth curve model are indicated by latent variables which are the exogenous variables in their own measurement models (Hancock, Luo, & Lawrence, 2001; Sayer & Cumsille, 2005). The “second order” portion of this

model comes from the modeling of latent variables as indicators of other latent variables. This situation may arise when each construct has multiple raters or multiple items indicating a latent factor. Second order growth curves can be incorporated into a GMM framework through the use of second order growth mixture models (Grimm & Ram, 2009). This model incorporates the advantages of multivariate assessment of constructs at each time point, with the flexibility and potential usefulness of GMMs. Despite this flexibility, second order growth mixture models often compound the estimation issues present with GMM, such as local solutions and convergence problems (Grimm & Ram, 2009). The use of second order growth mixture modeling would be appropriate in the context of analyzing separate growth trajectories for couples when variables change at the dyadic level.

The application of GMM to the use of marital satisfaction may be especially relevant. From a practitioner point of view, it may be more informative to view couples as consisting as those who are in need of help and those from whom therapy is not necessary (Snyder, Heyman, & Haynes, 2005). The use of GMM may then provide a statistical basis for identifying those couples most at risk for outcomes such as divorce. Additionally, many of the measures that have been developed to assess marital satisfaction include cut scores for distinguishing between couples that are distressed or non-distressed (Busby, Christensen, Crane, & Larson, 1995; Crane, Middleton & Bean, 2000; Kimmel & van der Veen, 1974; Locke & Wallace, 1959; Schumm et al., 1986; Spanier, 1976). Additionally, several previous researchers have conceptualized marital satisfaction as a categorical variable (Whisman, Beach, & Snyder, 2008). Lavner and

Bradbury (2010) applied GMMs to trajectories of marital satisfaction and modeled five sub-trajectories of satisfaction that differed in initial starting point and changes. The use of mixture modeling has the potential to provide a modern statistical technique for this historical approach to classifying those couples most in need of intervention.

Present study

The present study seeks to incorporate advances in the analysis of longitudinal dyadic data with advances in growth mixture modeling. The combination of these two analytic techniques will take an explicitly couple-centered approach and potentially provide useful information of sub-trajectories of relationship satisfaction. The first goal of the present study is to identify sub-trajectories to identify which groups, if any, account for the oft-observed decline in marital satisfaction. This approach will assign class membership and posterior probabilities to couples, rather than individuals as is typical when using growth mixture models (Jung & Wickarama, 2008). The use of such classes of couples can prove useful for marital practitioners and therapists in focusing resources and attention to couples that are particularly distressed. The second goal of the present study is to predict couple class membership using covariates that have traditionally been associated with marital satisfaction and changes therein. The final goal of the study will test the utility and importance of class membership. Divorce will be used as an outcome in an event history analysis, predicted by class membership. This last goal will give a clue as to the importance and implications of class membership by testing whether class are differentially susceptible to divorce.

Methods

Participants

The present data come from the British Household Panel Survey (BHPS), an ongoing panel survey that began in 1991. Selection was made using a multi-stage probability design with systematic sampling, with participation asked of those 16 and older. Questions were asked regarding various socioeconomic and interpersonal variables. Data that were collected in the 1998-2007 waves were used. Because the course of marriage was relevant to the present study, participants were included only if they reported being married at the initial time point and their spouse was included in the dataset. The final sample used across all time points was 2,086 couples. The average for participants at the first time-point was 48.7 years of age (*SD* = 14.6 years).

Measures

Relationship satisfaction was assessed and analyzed at the first 5 time points. Satisfaction was assessed via a single question item asking participants to rate "Satisfaction with: Spouse/Partner." This scale ranged from 1 ("Not at all satisfied") to 7 ("Completely satisfied"). Additional covariates to predict class membership were included at Time 1. Perceived financial situation was assessed on a five-point scale from 1 ("Living comfortably" to 5 ("Finding it very difficult"). Scores were reversed so that higher scores represent a better financial situation. Partner Importance was assessed with an item asking participants to rate the "Importance of: Good partnership" on a scale from 1 ("Not important at all") to 10 ("Very important"). Job satisfaction was assessed

similarly to marital satisfaction on a seven-point scale that ranged from 1 ("Not at all satisfied") to 7 ("Completely satisfied"). Lastly, participants rated their neighborhood on a three-point scale where a score of 1 indicated a good place to live, 2 indicated a bad place to live and 3 indicated a mixed response. This question was recoded so that a 1 indicated a bad neighborhood, 2 a mixed neighborhood and 3 represents a good neighborhood.

Modeling Strategy

Figure 2.1 shows the Common Fate Growth Mixture Model (CFGMM) used in the present study. At each time point a dyad level latent variable was created to represent couple level relationship satisfaction. This represents the "common fate" portion of the model (Kenny, 1996; Ledermann & Macho, 2014). Because dyads are treated as the unit of analysis, the problem of independence of observations is solved (though this approach still assumes that dyads are independent of one another). This modeling approach was chosen because past research has suggested that relationship satisfaction is best modeled as changing at the dyadic level (Gray & Ozer, under review). The growth parameters of intercept are then applied to couple level relationship satisfaction. Because growth parameters are influencing latent variables, this model resembles the curve-of-factors growth model (Duncan & Duncan, 1996; Hancock, et al., 2001). Though not included in Figure 2.1, autocorrelations were modeled for the same spouse member across time (i.e. husbands error at Time 1 were correlated to Times 2, 3, and 4). This autocorrelation was constrained to be equal across classes.

The growth parameters of the CFGMM are created at the couple level. Class membership is thus assigned to couples, indicating which trajectory a given couple belongs to. Additionally, the posterior probabilities are assigned to particular couples. This is in contrast with the majority of growth mixture models which assign classes and posterior probabilities at the individual level. Class membership was analyzed first, with covariates included to predict class membership using a multinomial logistic regression (Li & Hser, 2011; Nylund-Gibson & Masyn, 2016). Divorce was predicted as the distal outcome using both a logistic regression and a discrete time survival model. Class enumeration was based on the first five time points, while predicting occurrences of divorce occurred at the succeeding four time points. This means that the growth model was created, classes were enumerated, and class membership was assigned initially in the absence of covariates and the outcome of divorce. This is because the inclusion of covariates simultaneously with estimating the mixture model can obscure the meaning and results of this model (Li & Hser, 2011).

The optimal number of classes was chosen based on four criteria. Because mixture models with differing number of classes feature parameters that border on the permissible parameter space (i.e. the number in a given latent class cannot be less than zero), the traditional likelihood ratio test is not adequate. Lo, Mendell, & Rubin (2001) proposed a likelihood ratio test (LMR) that approximates the chi-square distribution and can be used effectively to distinguish whether a *k*-class model fits the data significantly better than a *k*-1 class model. An alternative to the LMR test is a parametric bootstrap procedure which estimates the empirical distribution of the likelihood ratio test, rather

than assume the likelihood ratio follows a χ^2 distribution (BLRT; McLachlan, 1987; McLachlan & Peel, 2000). Models were also selected on the basis of information criteria, the Akaike Information Criterion (Akaike, 1987) and the sample-adjusted Bayesian Information Criterion (Sclove, 1987). Both measures assess model fit of non-nested models, while imposing a parsimony parameter that attempts to strike a balance between better model fit and more parsimonious models. Both the likelihood-based tests and information criteria have been found to perform well in determining the number of classes in mixture modeling (Nylund, Asparouhov, & Muthén, 2007).

In addition to considering the fit of competing class models, two additional criteria were used to determine the optimum number of classes. The degree of entropy was used to choose the model that best distinguished between classes. Entropy values close to 1.0 indicate better class separation and values close to zero representing poor class discrimination (Celeux, Soromenho, 1996). Additionally, classes were chosen on the basis of theoretical meaningfulness. Additional classes may not necessarily represent meaningful sub-populations if they cannot be meaningfully distinguished from each other. Growth mixture modeling was conducted in Mplus Version 7.4 (Muthén & Muthén, 1998 – 2012), which employs a full-information maximum likelihood for handling missing data and model estimation.

Results

Descriptive Statistics

Table 2.1 presents the descriptive statistics of relationship satisfaction at each time point for both husbands and wives. Examination of the means of relationship satisfaction suggest declines across time. Concurrent correlations between husbands and wives ranged from $r = .43$ to $r = .51$ and autocorrelations between adjacent time points ranged from $r = .30$ to $r = .43$ (all p's $< .001$). Table 2.1 also shows the descriptive statistics of the covariates at Time 1. Results indicate that the mean financial situation was around the "Doing alright" anchor for both men and women. Both men and women also rated Good Partnership as very important. The average person rated his or her job as moderately satisfying and his or her neighborhood as close to the "Good" anchor.

Before proceeding to analyzing classes of growth, a single group latent growth model was performed to describe the average population level trends. Fit of the single group growth model was borderline, $\chi^2 (14) = 243.09$, $p < .0001$; $TLI = .87$, $RMSEA = .09$, 90% CI: [.07, .11]. A potential source of this model misfit is the possibility that a single trajectory does not adequately describe trends for the entire sample. The population trend was for marital satisfaction to decline (slope = -.071, $p = .0024$). There was significant variance around both the intercept and slope (both p's $< .01$), combined with the poor fit of the single growth curve suggests that a single population level trend may not be appropriate for the data (Grimm & Ram, 2009).

Class Enumeration

As mentioned above, the number classes was chosen based on four criteria: Model fit assessed by likelihood based tests, model fit assessed by information criteria, separation of classes, and meaningfulness of classes. Table 2.2 summarizes the results of class enumeration. Both likelihood based tests rejected the one-class model in favor of the two-class model. Entropy of this class was high (.95), indicating that the two classes were well separated. The variance of the slope terms in this model were not significant, and so the model was re-run with these variance terms fixed to zero. This constraint represents a compromise between a growth mixture model and the more constrained latent class growth model (Ram & Grimm, 2009). In addition, the model was run with 1,000 random starting values to ensure that the maximum likelihood solution was a global solution (McLachlan & Peel, 2000).

Three and four-class models were tested in addition to the two-class model. Both likelihood ratio tests and the information criteria indices favored the three-class model. This suggests that three classes may be needed to adequately describe the trajectories of relationship satisfaction. However, entropy for the three-class model was slightly lower. Perhaps more importantly, the third class was created largely by splitting the first, larger class into two classes. The newly created class was only a small deviation from the initial class. As with the two class model, the slope variance terms were not significant and so these variance terms were fixed to zero and re-run with 1,000 random starts. Lastly, the four-class model was fit to the data. None of the indices under consideration pointed to

the four-class model as a better representation of the data, and class separation was substantially poorer for the four-class model compared to the two and three class model.

The question of whether to choose the two or three class model came down to a question of interpretability of the classes. The two-class model featured well-separated classes. The first class, which accounted for the large majority of couples in the sample, represents a stable trajectory of relationship satisfaction. The slope of this class was -.04 points per year (on a seven point scale), which while significant was a very small annual decrease in relationship satisfaction. The second class represents a theoretically meaningful class that showed a substantial decrease in relationship satisfaction of -.88 units per year. This class, while small, is practically significant in that it may account for a substantial portion of the oft-found decline in marital satisfaction (i.e. Murray et al., 2013). The two trajectories are here labeled as "Stable" and "Decreasing" trajectories (see Figure 2). The three-class model featured both of these classes, plus an additional class that experienced a slightly larger decline in relationship satisfaction (-.13 units per year). Because the theoretical and practical utility seems to be in distinguishing those who experienced a large decline in satisfaction from those who did not, the two class model will form the basis of subsequent analyses.

As mentioned above, the two-class model featured a Stable class and a Decreasing class. The Decreasing class constituted only a small portion of the current sample (7.0%), but is theoretically meaningful in that this small class may explain the typical decline in relationship satisfaction this found during marriage. The slope random effects were not significant for either class, and so were constrained to zero. The random

effect for the intercept was significant for the Stable class and so these random effects were freely estimated. The quantitative distinction between classes appears to be in the slope, rather than the initial starting point of relationship satisfaction. This was corroborated by non-significant classes differences in Time 1 relationship satisfaction for both men and women ($t(2,071) = 1.27$, $p = .20$ and $t(2,069) = 1.48$, $p = .14$ respectively).

Predictors of class membership

Four covariates were used to at the first time point to predict class membership: Financial situation, Partner importance, Job satisfaction, and Neighborhood condition. These covariates were chosen because of previous research establishing them as important predictors of marital satisfaction (Bradbury, Fincham, & Beach, 2000). Each of these covariates were assessed for both husbands and wives and were included in a logistic regression model predicting class membership individually. The reference group used is the Stable class, so coefficients represent an elevated or decreased risk of belonging to the Decreasing class. Table 2.4 includes the results of predicting class membership presented as odd ratios. Couples were less likely to belong to the Decreasing group if both men and women reported a better financial situation at baseline. Wives' (but not husbands') report that good partnership is important was predictive of being in the Stable class as opposed to Decreasing class. Reporting greater importance of good partnership at baseline was associated with decreased likelihood of the Decreasing group for women, but was unrelated to men's partner importance. Both men and women's job satisfaction ratings were unrelated to class membership. Lastly, better perceived neighborhood conditions were associated with a decreased likelihood of belonging to the

Decreasing class. Overall, these results support the notion that a negative trajectory of marital satisfaction can be predicted by environmental and economic factors (Archuleta, Britt, Tonn, & Gable, 2011; Cutrona et al, 2003).

As mentioned above, just because predictors are significant for one dyad member and not the other, does not mean that there is a significant difference between dyad members. In this spirit, constraints were placed on the above models that set the coefficients equal for both dyad members and these models were compared to the unconstrained models in a series of 1 degree of freedom likelihood ratio tests. The coefficients for Financial Importance, Job Satisfaction, and Neighborhood Condition were not significantly different from each other ($\chi^2 = 3.12$, $p = .077$, $\chi^2 = 2.37$, $p = .12$, $\chi^2 = 2.52$, $p = .11$, respectively). However, the coefficients for Partner Importance were significantly different from each other ($\chi^2 = 7.92$, $p = .0048$), suggesting that the relationship between viewing good partnership as important and membership in the Declining Class is greater for women than for men.

Class membership and divorce

Levels of, and changes in, marital satisfaction have emerged as one of the largest predictors of divorce. The present study applied this common finding to using class membership of marital satisfaction trajectories to predict divorce. Divorce was assessed in the four years following the time points used for class enumeration. Because of the inherent uncertainty of assigning couples to classes, the posterior probabilities of class membership were used as predictor, as opposed to class membership (Roeder, Lynch, &

Nagin, 1999). For the sake of completeness, the analyses are reported using both class membership and posterior probability as predictors. It should be noted that more sophisticated methods for incorporation auxiliary variables into GMMs have been developed which incorporate the measurement error of latent class assignment (Asparouhov & Muthén, 2014). However at high levels of entropy (i.e. greater than .80) these methods will converge to the same results and bias will be reduced, the high entropy of the current model allowed for the use of these simpler methods (Clark and Muthén, 2009).

Initially, the occurrence of divorced was predicted in a logistic regression model. A discrete time survival model (Singer & Willett, 1993) was fit to the data using the survival package in R (Therneau, 1999). As Table 2.5 shows, couples who had a higher probability of being in the Decreasing class were significantly more at risk for divorce over the succeeding four years. The odds ratio indicates that those who had 100% chance of being in the Declining Group were nearly four times as likely to experience divorce, relative to those who had a 100% of being in the Stable group. The present results suggest that divorce can be predicted by identifying which trajectory a given couple follows. The Decreasing class represents a small portion of the sample but is consequential in predicting which couples get divorced and which couples stay married.[1]

[1] Because of the conceptual clarity, the same analysis was done with the simpler (albeit less recommended because of bias due to uncertainty) predictor of most likely class membership. This led to a discrete time survival model where the predictor is the dichotomous indicator of class membership. This left the analysis largely unaffected, as class membership was still significant predictor of divorce (Odds ratio = .43, p = .0038)

Discussion

Growth mixture modeling and dyadic data analysis have developed independently of one another. The present study utilized a unique fusion of the two approaches by applying growth mixture modeling to dyadic trajectories of relationship satisfaction. The model chosen consisted of two distinct trajectories of marital satisfaction. One large class represented a group that showed little, if any change in relationship satisfaction. A second class made up only a small portion of the present sample, but showed dramatic declines in marital satisfaction. Consistent with previous research on marital satisfaction as a continuous outcome, membership in the Declining class was predicted by a worse perceived neighborhood, a worse personal financial situation, and a lower perceived importance of one's partner. While the Declining class represented only a small portion of the couples in the sample, class membership was consequential as couples in the Declining class were at a significantly higher risk for divorce.

Classes of Couples

The approach utilized in the present study modeled sub-trajectories of dyadic level satisfaction, classifying couples into a Stable or Declining satisfaction class. This classification provides a modern update on the long running tradition in marital research of the classification of couples into "distressed" and "non-distressed" (Karney & Bradbury, 1995). A class of couples that experience a large decline in marital satisfaction may explain the consistent finding that marital satisfaction tends to decline in the years following marriage. The proportion of couples that were classified as declining in marital

satisfaction was small, but was consequential as these couples were at significantly higher risk of divorce.

The covariates of financial situation, neighborhood quality and importance of a good partner predicted whether a couple was classified as Stable or Decreasing, consistent with previous research that has identified these variables as important predictors of marital quality (Bradbury et al., 2000).

The present study demonstrated that GMMs can be utilized even when the basic unit of analysis is a couple, rather than an individual observation. As mentioned above, classes are often not seen as representing literal, distinct entities but rather serve as useful clusters of similar observations (Muthén & Asparhouhov, 2007; Nagin & Odgers, 2010). Applied to the present example, this suggests there may not be literal sub-trajectories of couples, but rather clusters of couples that are either stable in their overall levels of marital satisfaction, or experiencing a marked decline.

The results of models similar to the ones in the present study has the potential to be utilized by marital practitioners interested in identifying those couples most in need of intervention (i.e. Jacobson et al., 1991). Even in not representing literally distinct entities, latent classes can help focus the attention of resources of therapists and researchers to focus on those couples who could most benefit from intervention. Growth mixture modeling, and the broader class of finite mixture models, can provide a statistical basis for how best to partition the population in a manner most capable of aiding psychotherapists (Laurenceau, Hayes, & Feldman, 2007; Wright & Hallquist, 2014).

Growth mixture modeling is a flexible framework that has the potential to expand beyond the application described here. One possible application is that of testing the invariance of husbands and wives across time, testing whether the contribution to dyad level marital satisfaction is equal for spouse members or across time (Ledermann & Macho, 2014). With GMM it also possible to test whether the influence of husbands and wives is equivalent across class membership. The present study assessed marital satisfaction with a single item, but higher order GMMs have the capability of assessing multivariate constructs (Sterba, 2013). While the present study was restricted to estimating a single class for each couple, sudden events (i.e. infidelity, Buss & Shackelford, 1997) may cause couples to shift from one class to another. GMM is able to accommodate the switching of classes over time (Dolan, Schmittman, Lubke, & Neale, 2005), allowing for the examination of the impact of events on sub-trajectories. The novel application of growth mixture modeling to dyad level variables present new opportunities for both applied and basic researchers in the social sciences.

Caveats

It should be noted that GMMs are exploratory, data-driven techniques. This means that in the absence of compelling theoretical hypotheses, GMMs are subject to capitalizing on chance (Bauer, 2007; Grimm & Ram, 2009). This issue is salient in the present study as the classes used in the present study are different than those in previous studies (Lavner & Bradbury, 2010). This difference may have arisen because marital satisfaction was modeled as a dyadic variable in the present study, whereas Lavner and Bradbury (2010) modeled trajectories from men and women separately.

The model expounded here is new and theoretically interesting, but as with any GMM, some cautions may be warranted. GMM is most adequately used when there is a theoretical basis for expecting certain classes to emerge and there are qualitative differences between latent classes (Bauer, 2007). In the absence of a clear theoretical basis, the function of classes in a growth mixture model may not be what the researcher intends. For instance, classes may arise simply as a function of highly skewed distributions that would otherwise violate assumptions of conventional growth modeling (Bauer & Curran, 2003). The use of growth mixture modeling with couples should not arise haphazardly, but should ideally reflect substantive hypotheses. At a minimum, researchers seeking to uncover a latent structure should seek to replicate the latent classes (Bauer, 2007).

An additional issue with in the use of growth mixture modeling with dyads is the relative complexity of the model being estimated. Because class membership is assigned at the couple level, this model is essentially a second order growth mixture model (Grimm & Ram, 2009). Higher order growth mixture models are often prone to convergence and identification issues, which can sometimes preclude their usage. Difficulties associated with higher order growth mixture modeling can often be helped with larger sample sizes, which may be impractical in a clinical setting where the distinction between Stable and Declining couples is most important. Issues with model convergence can lead to the inclusion of constraints aimed solely at improving the performance of the model and may not correspond to substantive hypotheses. When such

post-hoc constraints are added to a model, caution should be used in interpreting model parameters (Muthén, 2003; Nagin & Odgers, 2010).

Conclusions

The present study proposed a new application of growth mixture modeling to dyadic data which involved estimating sub-trajectories at the couple level. A two-class solution was used which modeled a Stable trajectory and a Decreasing trajectory. The Decreasing class of couples was small (only 7.0% of the sample), but consequential as this class was at significantly higher risk of divorce. The application of growth mixture modeling has the potential to be utilized by marital practitioners who find utility in the classification of couples most in need of marital intervention.

Chapter 3:

A Dyadic Latent Transition Analysis of Political Beliefs

Abstract: Latent transition analysis is a longitudinal extension of the latent class analysis. The central question of LTA concerns how membership in latent classes evolves over time, the stability of latent class membership, and which latent classes are likely follow which other latent classes. This technique has been used to examine the development of health risk behaviors, smoking, and emotion problems. Thus far LTA has been used to track development and change in latent classes among individuals. This study will examine the estimation of a dyadic latent transition analysis (dLTA). A dLTA differs from the traditional LTA in the class membership for any one individual at time *t* will be modeled both as predicted by own class membership at time *t -1* (as in traditional LTA), as well as predicted by the dyad member's class membership at *t -1*. The modeling of each dyad member will occur individually, leaving open the possibility the number and meaning of profiles varies within dyads. This type of model will not only give information as the process by which dyad members influence each others' latent class membership, but can also test for whether this influence is equal for both dyad members. The estimation of the model will resemble Flaherty's (2008a, 2008b) Associative LTA, in which transitions among different classes for multiple constructs are related to one another.

The Latent Class Model

Similar to the common factor model, the latent class models posits a latent variable to describe the association among manifest variables. Whereas the common factor model theorizes a continuous latent variable, the latent class model explains the covariance among indicators by creating groups of relatively homogenous observations (Collins & Lanza, 2010; Magidson & Vermunt, 2004). Both models assume local independence, meaning that the latent variable is sufficient to explain the relationship among indicators, and that there is no relationship conditional on latent variable. Latent classes are mutually exclusive and independent, meaning that:

$$\sum_{c=1}^{C} \gamma_c = 1 \tag{3.1}$$

Let *y* equal a vector of responses for individual *i* to multiple indicators of some latent class. The probability of observing a particular response pattern is:

$$P(Y = y) = \sum_{c=1}^{C} \gamma_c \prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{(j, r_j|c)}^{I(y_j = r_j)} \tag{3.2}$$

Where $P(Y = y)$ is a function of the vector of expected class probabilities γ_c, the total number of indicators *J*, and a vector of response probabilities conditional on latent class membership. This model yields two vectors of probabilities. First, a vector of probabilities for an observation belonging to each latent class is obtained, which is indicated as $P(Y = y)$. The second vector of probabilities is the probability of observing a particular response on a given indicator, conditional on latent class membership and is

given as $\rho_{(j,r_j|c)}^{I(y_j=r_j)}$ (Böckenholt, 2005). This term indicates that the probability, ρ, is unique to both the item j and the item response, r_j and is estimated for each latent class, c. $I(y_j = r_j)$ indicates whether the response is made so that when $j = r_j$, the value is equal to one, and is zero otherwise. The quantity R indicates the number of response categories for each item. A conceptual comparison to factor analysis can be made here. Just as items are "better" indicators of a latent factor with higher factor loadings, the closer the item-response probability (conditional on latent class membership), $\rho_{(j,r_j|c)}^{I(y_j=r_j)}$, is to zero or one, the better that item "indicates" the latent class.

Latent Transition Analysis

While the original intention of the latent class model was for use with cross-sectional data, research questions often involve change or stability in latent classes over time. The latent transition analysis is a repeated measures extension of the latent class model. Specification of an LTA model involves the same components as a latent class model, within each time point. This means LTA involves the calculation of class membership probabilities and response probabilities. In LTA, a third vector of probabilities is added that quantifies the probability of belong to a latent class at Time t, conditional on class membership at Time t-1. These transition probabilities give information about the stability of latent classes, as well as the most likely direction of change (Collins & Lanza, 2010). A simple two class, two timepoint transition matrix would resemble the following:

(3.3)
$$\begin{bmatrix} \tau(1t+1|1) & \tau(2t+1|1) \\ \tau(1t+1|2) & \tau(2t+1|2) \end{bmatrix}$$

Where the values represent probabilities and the diagonal indicates degree of stability in latent classes across time, and the off-diagonal values represent transitions between two latent classes

As before with latent class analysis, classes are mutually exclusive and exhaustive. Therefore at both time points, the vector of latent class probabilities must sum to 1. Change in the relative frequency of latent classes indicates that as time passes, certain latent classes are becoming more or less prevalent (latent classes can even appear or disappear as time unfolds). In the case of two timepoints, the latent transition model can be written as:

(3.4)
$$P(Y=y) = \sum_{s_1=1}^{S}\sum_{s_2=1}^{S} \delta_{s1}\, \tau_{(s_1|s_2)} \prod_{t=1}^{2}\prod_{j=1}^{J}\prod_{r_{j,t}=1}^{R} \rho_{(j,r_{j,t}|s_t)}^{I(y_{j,t}=r_{j,t})}$$

Where the probability of observing a particular response vector *y* is a function of the prevalence of latent classes (δ_s1) at times s_1 and s_2, and the probability of transitioning between latent classes, $\tau_{(s_1|s_2)}$. The probability of a particular item response conditional on latent class is given as $\rho_{(j,r_{j,t}|s_t)}^{I(y_{j,t}=r_{j,t})}$, which is then multiplied over the number of total response categories per item *R*, the number of items, *J* and the number of timepoints (*T* = 2 in this example). Traditionally, LTA has been performed with a single variable, but recent extensions of LTA have allowed for the incorporation of additional discrete latent variables (Flaherty, 2008b).

Illustrative Example

Consider the following small matrix which features 22 participants with class membership at two time points:

	Class Membership	
ID	Time 1	Time 2
1	1	1
2	1	1
3	1	1
4	1	1
5	1	1
6	1	1
7	1	1
8	1	1
9	1	1
10	1	1
11	1	2
12	1	2
13	1	2
14	1	2
15	2	1
16	2	1
17	2	2
18	2	2
19	2	2
20	2	2
21	2	2
22	2	2
Parameter		
τ_1	.64	.55
τ_2	.36	.45

At Time 1, 14 of the 22 (64%) participants are in class 1, while the remaining eight (36%) are in class two. At Time 2, the average probability of belonging to class 1 drops to 55%, while the average probability of belonging to class 2 increases to 45% Consistent with equation (3.1), these class probabilities sum to (.64 + .36 and .55 + .45) 1 at both time points. Now let's consider a transition matrix of this brief example:

(3.5)
$$\begin{bmatrix} \tau_{(1t+1|1)} = .71 & \tau_{(2t+1|1)} = .29 \\ \tau_{(1t+1|2)} = .25 & \tau_{(2t+1|2)} = .75 \end{bmatrix}$$

The diagonal demonstrates some degree of stability in class membership. In this case, 71% of the participants who were in class 1 at Time 1 remained in class 1 at Time 2. Likewise, of the participants who were in class 2 at the first time point, 75% remained in class 2 at the second time. The off-diagonal values represent instances of transition between classes. In this context, 29% of the participants in class 1 at Time 1 transitioned into the second class at Time 2. Similarly, of the participants in class 2 at Time 1, 25% transitioned into the first class.

Now imagine that each of the class indicated by five dichotomous items (e.g. yes/no answers to questions). Hypothetical response probabilities given class membership are given below:

	Class 1	Class 2
Item 1	.1	.8
Item 2	.4	.4
Item 3	.9	.2
Item 4	1.0	0.0
Item 5	.3	.9

Given these hypothetical values, we can identify which items best indicate different latent classes. For instance, those in class 1 have a 10% chance of responding in the affirmative to item 1, while those in class 2 have an 80% chance of answering in the affirmative to item 1. The item that best discriminates classes is item 4, as every participant in class 1 answered in the affirmative, while no participants in class 2 answered in the affirmative. The worst item is item 2, as the probability of answering in the affirmative was 40% -- regardless of class membership (meaning that item 4 is not informative of class membership). Using these conditional item probabilities and the probabilities of class membership, we can estimate the probabilities of affirmative responses for all items. For instance, the probability of answering a "yes" to item 1 is: $(.1 * .64) + (.8 * .36) = .352$ (at the first time point). Assuming measurement invariance across both time points, the overall item probabilities are below.

	Time 1	Time 2
Item 1	.35	.42
Item 2	.40	.40
Item 3	.65	.59
Item 4	.64	.55
Item 5	.52	.57

Using Equation 3.2, we can calculate the probability of particular response patterns. The probability of obtaining responses to the five items of [0, 0, 1, 1, 0] is calculated as:

$$P(Y = [0,0,1,1,0]) = \sum_{c=1}^{C} \gamma_c \prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{(j,r_j|c)}^{I(y_j=r_j)} \tag{3.6}$$

$$= .64 * (.9 * .6 * .9 * 1.0 * .7) + .36 * (.2 * .6 * .2 * 0.0 * .1)$$

$$= .218$$

The reason the probability of this particular response pattern is relatively high, is that [0,0,1,1,0] is the most likely response pattern of the most likely class (approximately 34% of class 1 members will have this pattern).

Using the same equation, we can also calculate a less common pattern of responses. The probability of obtaining responses to the five items of [1 1, 0, 1, 0] is calculated as:

$$= .64 * (.1 * .4 * .1 * 1.0 * .7) + .36 * (.8 * .4 * .8 * 0.0 * .1)$$

$$= .0018$$

This unlikely pattern of responses becomes even less likely at Time 2:

$$= .55 * (.1 * .4 * .1 * 1.0 * .7) + .45 * (.8 * .4 * .8 * 0.0 * .1)$$

$$= .0015$$

The reason behind these two probabilities being relatively low is that the respondent answered in the affirmative for item 4 (ensuring class 1 membership), but otherwise had a response pattern more characteristic of class 2. The goal of the maximum likelihood estimation is to estimate conditional item probabilities and class probabilities in a way that maximizes the odds of all responses in the data set. As the number of participants, classes, items, or item responses increase, the complexity of this calculation increases drastically.

Latent Profile Analysis

Similar to latent class analysis, latent profile analysis uses a categorial latent variable to explain the relationships between indicators. The difference between latent profile and latent class analysis is the distribution of the indicators. Latent profile analysis creates latent categories with continuous indicators (as opposed to the categorical nature of latent class indicators). Like all latent variable models discussed thus far, latent profile analysis carries the assumption of local independence of the indicators (Tein, Coxe, & Cham, 2013). This means that a latent profile analysis attempts to maximize between profile differences and minimize within profile differences. The procedure for deciding the number of profiles is similar to the number of classes in that adjacent class solutions (e.g. 2 vs. 3 then 3 vs. 4). The distribution of the continuous indicators is given as:

$$f(x_i|\Theta) = \sum_{1}^{k} \pi_k f_k(x_i|\Theta_k) \tag{3.7}$$

Where π_k is the probability of being in the each of the *k* profiles and $f_k(x_i|\Theta_k)$ represents the class specific solution. The observed distribution is the summation of each of the class specific distributions.

Latent profile and latent class differ in their measurement model, but not in the structural model (Gibson, 1959). Structurally both models feature categorical variables that can incorporate external variables as outcomes or predictors. Latent categories for both models can be predicted using a logistic regression (or multinomial logistic regression for more than two classes). Additionally, the logic behind a latent transition

analysis applies to latent profile analysis. Latent profile transition analysis has been used to model discrete changes in managerial commitment, sensory features, and motivation (Ausderau et al, 2014; Kam, Morin, Meyer, Topolnytsky, 2016)

Associative Latent Transition Analysis

Not only do research questions often involve changes in discrete latent variables across time, but there is often substantive interest in the co-development of multiple discrete processes (Flaherty 2008a, 2008b). There are several different avenues offered in Bray, Lanza, and Collins (2010) for how this relationship between two discrete processes can unfold. Obviously, two developmental processes can be independent of each other, in which case knowledge of one's latent class at any given time point offers no information on that observation's standing on another latent variable. There may be also baseline relationship between latent classes, but the transitions are independent and the relationship at baseline accounts for the relationship between latent classes. Concurrent relationships imply a relationship between latent classes at each time point assessed. Associate Latent Transition Analysis (ALTA) can also incorporate lagged effects where membership in a given latent class predicts membership in another latent class at a later time point. Finally, transitions can be predicted from latent class membership, or transitions in one variable can predict transitions in a separate latent variable. One limitation of the ALTA in its current form is that one variable is seen as the predictor of the other variables (i.e. transitions in Variable A predict transitions in Variable B, but not vice versa). Generalizations of the ALTA can be included to model discrete change in the same variable, for separate groups of observations (Flaherty 2008a, 2008b).

Dyadic Latent Transition Analysis

There as yet no method for assessing the association between transitions in the same discrete variable, for separate individuals. A crux of dyadic data analysis is examining the relationship between the same variable assessed by two related individuals. The present study will extend previous work on latent transition analysis, ALTA, and dyadic data by illustrating how these methodologies can complement each other and be used simultaneously. This portion of the dissertation will not only describe this novel application of ALTA, but also address the substantive issue of the transmission of social values across spouses.

The dyadic latent transition analysis (DLTA) can be used to examine the co-development of latent classes between two members of a dyad. For instance, the transition between non-drinker and regular drinker for one member of a dyad can be predicted by a similar transition (or lack thereof) by the other member of the dyad. Unlike the ALTA, there does not necessarily have to be a direction to the coefficients (i.e. Dyad member 1 predicts Dyad member 2, but not vice versa), but this a constraint that can be placed on the model. The DLTA can be used in several variations, like the ALTA. For instance, the latent class of one dyad member may be predictive of the latent class for the other dyad member, or the relationship may be longitudinal in that classes membership for a dyad at a prior timepoint predicts current latent class for the other dyad member (see Figure 3.1 for examples of this possible relationship).

Using husbands and wives as the most illustrative example, the Figure 3.2 shows the dyadic latent transition analysis. The dyadic components are shown as dashed lines. The model can be seen as the most "saturated" model. Here, there are covariances between the concurrent classes (at both time points), the cross-lagged paths between classes, and the classes predicting transitions are included as well. Constraints can be placed on all of these parameters.

Models of Dyadic Latent Transition Analysis

Figure 3.1 demonstrates many of the basic dyadic paths that can potentially be used in a DLTA. Most of these models are simplified versions of potential processes across time. While they are presented as separate models, it is worth noting that many of these models (with the exception of Figure 1a) are not mutually exclusive, and we will also discuss a model in which all of these paths are included. One of the common practices when assessing a dyadic model such as this, is to test for gender effects. This can also be done in the context of a DLTA by constraining paths to be equal across genders. For the sake of simplicity, and because it reflects the substantive example to follow, the dyad members are labeled as husband and wife. The latent variables in this series of figures represent a multicategorical latent variable, in which the number of classes will be derived empirically.

Complete independence between husbands and wives is demonstrated in Figure 1a. Here both the concurrent and longitudinal relationship between dyad members is zero. This model is unlikely to reflect true processes in the population as husbands and wives

are correlated on a wide variety of psychological outcomes (Watson, Beer, McDade-Montez, 2014). However, this model can provide an initial baseline model against which more complex models can be compared.

Figure 1b shows a model in which husbands and wives are correlated at each time point. This model features no longitudinal associations between dyad members. This is a model that posits that similarity between husband and wife is due to initial similarity, plus a shared environment that promoting similarity between couple members (not unlike the results presented in Caspi, Herbener & Ozer, 1992). This model lacks any direct effects between spousal members.

Figure 1c shows a DLTA with cross-lagged relationships. This model posits that husbands and wives are correlated because of direct effects on each other. There is no initial similarity between couple members, but couple members exert a direct effect on each other so that the classes at Time 2 are correlated across dyad members. Unlike the concurrent relationship model, this model implies that couple members have more than an initial similarity, similar to the longitudinal APIM (Kenny, Kashy, & Cook, 2006).

The association between couple members and transitions is shown in Figure 1d. This model doesn't imply that this is a direct relationship between couple members. However, class membership at Time 1 predicts the transition of the other dyad members. This implies that no initial similarity, but that initial status influences change in class membership.

The most veridical representation of dyadic processes most likely involves the composition of more than one of the models discussed above. Figure 3.2 shows the complete DLTA. The model represents every way in which initial class status in related longitudinally across dyad members. Whereas the independent model can be used as the baseline model to test fit, this model represents the model with the most complexity, and thus the best overall fit. A model of dyadic latent transitions that adequately balances model fit and parsimony would likely reflect some sort of compromise between these two models.

Present Study

The goal of the present study is to demonstrate how the DLTA can be analyzed in practice. This methodology is demonstrated using a substantive example from the political attitudes literature. As in Study One, the data used in the present investigation come from the British Household Panel Survey. Participants were selected form the larger study on the basis of being married, with their spouse also being included in the data set. This ensures that each participant has a dyad to be paired with. In the years of 2007 and 2010 participants answered questions about their attitudes towards certain political issues.

At each timepoint, participants were asked six questions about their political attitudes. Each question was answered on a one to five scale, with five indicating less endorsement and one indicating higher levels of agreement. To facilitate interpretation of item level means, items were recoded so that greater numbers indicate higher

endorsement. The six political items ask participants to rate the extent to which they agree with the following: “Ordinary people should share in a nation’s wealth”, “There should be one law for the rich and the poor”, “Private enterprise solves economic problems”, “Public services ought to be state-owned”, “Government has an obligation to provide jobs”, and “Strong trade unions protect employees.”

Modeling Strategy

For both men and women at each timepoint, latent profiles were tested. This meant that the latent profile procedure was conducted four separate times (for two genders at two time points). This involved building up the number of latent profiles until there was statistical agreement about the number of profiles. As with Study 1, nested models that differ in the number of profiles cannot be analyzed using the traditional likelihood ratio test. This is because when the parameters on the boundary of acceptable values (e.g. class membership of zero) the resulting difference in likelihood does not follow a central chi-squared distribution (Stoel, Garre, Dolan, & van der Wittenboer, 2006). This meant that the latent profile procedure was conducted four separate times (for two genders at two time points). Once the number of profiles was determined, the next step was tests of invariance in the means of latent profiles to test whether profiles had the same meaning. A lack of measurement invariance would not necessarily preclude looking at the longitudinal association of profiles across time (or across gender).

Once the measurement models are determined for each time point, I will proceed with the structural component of the model, examining the probabilities of transitioning

from and to various latent profiles (a univariate latent transition analysis) to determine the degree of individual change in political profiles (Nylund-Gibson, Grimm, Quirk, & Furlong, 2014). Lastly, I will incorporate the novel contribution of this study by examining the degree of dyadic interdependence in class membership by comparing the various dyadic models shown above. The measurement component of the model will be assessed using Stata version 15 (Statacorp, 2017) and the structural component will be assessed using Mplus version 7.4 (Muthén & Muthén, 2012). As is recommended when analyzing latent categorical variables, a large number of random starts will be used to make sure that the program does not merely settle upon a local versus global solution (Hipp & Bauer, 2006).

Measurement Model(s)

Four different profile solutions were tried for females at Time 1. The two profile solution showed significantly better fit to the data, as compared to a one profile solution (BLRT p-value < .00001). Entropy for the two profile solution was high. The three profile solution showed significantly better fit to the data than the two profile solution (BLRT p-value < .00001). The entropy was slightly lower for the three profile solution, but both the AIC and BIC showed improvement over the two profile solution. While the BLRT and AIC indicated that a four profile solution was slightly preferable, the BIC disagreed, and there was a sizable drop in entropy (from .87 to .77). Across the board, the results suggested that the improvement in model fit was not sufficient to warrant the extra parameters. Weighing fit and profile separation statistics, as well as profile interpretability (see Table 3.1), the three profile solution was chosen.

Again, four different profile solutions were tried for females at Time 2. The two profile solution showed significantly better fit to the data, as compared to a one profile solution (BLRT p-value < .00001). Entropy for the two profile solution was again high. The three profile solution showed significantly better fit to the data than the two profile solution (BLRT p-value < .00001). The entropy was slightly lower for the three profile solution, but both the AIC and BIC showed improvement over the two profile solution. The four profile solution was unanimously worse than the three profile solution. The AIC, BIC, and entropy all suggested that a four profile solution was not preferable, and the BLRT was not significant. The picture was even worse for the five profile solution, as the BLRT was not close to being significant, entropy continued to decline and the AIC and BIC continued to rise. Again the three profile solution was chosen.

Initially, the same four different profile solutions were tried for males at Time 1. The two profile solution showed significantly better fit to the data, as compared to a one profile solution (BLRT p-value < .00001). Entropy for the two profile solution was again high. The three profile solution showed significantly better fit to the data than the two profile solution (BLRT p-value < .00001). The entropy was slightly lower for the three profile solution, but both the AIC and BIC showed improvement over the two profile solution. Unlike profile enumeration for females, the four profile solution did not show a decrease in entropy, and in fact showed better fit to the data according to the BLRT and both the AIC and BIC. The five profile solution did not demonstrate significantly better fit to the data, as the BLRT was not significant and both the AIC and BIC increased relative to the four profile solution. To be sure that the profile solution was adequately

probed, a new six profile solution was tested. This solution was uniformly worse than the five profile solution. Weighing parsimony and model fit led to the choice to proceed with the four profile solution for males.

Because four profiles were chosen at Time 1, when assessing the men's profile solution at Time 2, six profiles were also tested. As before, the two profile solution was significantly better than the one profile solution with acceptable entropy. The three profile solution showed a small decrease in entropy, but an improvement in the AIC and BIC and a significant BLRT. As with Time 1, the four profile solution also demonstrated an increase in model performance as the AIC and BIC continued to decrease, with a significant BLRT. The model stopped improving with the addition of fifth and sixth profiles (including substantial decreases in model entropy). Unfortunately (for the sake of conceptual and computational clarity), at both time points four profiles of political attitudes were chosen for males, differing from the three profile solution for females.

Invariance and Interpretation of Profiles

Tests for measurement invariance were conducted to ensure that the same latent profiles were present across time. Across both timepoints, the means and variances of the indicators for each class were constrained to equality, but the proportion of individuals classified into the different profiles was allowed to differ.

Table 3.5 shows the means of the six indicators across the three latent profiles. To aid in the interpretation of the latent profiles, each profile was named after (to varying success) a prominent British (reflecting where the data were collected) politician. The

first latent profile reflects an above average tendency to endorse the notion that the poor should share in a nation's wealth, but otherwise appear skeptical of government action, being below average on endorsement of items about state ownership of public services, government obligation to provide jobs, and believing that labor unions protect their employees. This first profile is termed the "Theresa May" profile. The second profile is characterized by a below average endorsement of wealth redistribution, above average endorsement of the notion of their being one law for the rich and the poor, but a close to average endorsement of the remaining items. The profile is named after Tony Blair, for his concern of economic equality, but relative moderation on many positions (Glyn & Wood, 2001). The third class is characterized by relatively progressive concerns, reflecting a strong belief that labor unions protect their employees, a moderate belief in wealth equality and an above average endorsement of state ownership of public services. This profile will be named after Leader of the Labour Party, Jeremy Corbyn. The largest latent profile at both timepoints was the May profile, followed by the Blair profile. At both assessments the Corbyn profile was the least common. Two models were compared in which latent profile means were constrained to equality across both assessments, and a model in which means were freely estimated. A likelihood ratio test of the two models was not significant, $\chi^2(18) = 22.34$, $p = .22$, therefore latent profile means will be constrained to equality in subsequent analyses.

Table 3.6 shows the means for the four latent profiles for men. Three of the profiles map well onto the three profiles for women. The fourth class that appears to be unique to men is characterized by a general mistrust in the government, and an

appreciation for private enterprise. This profile will be classified as the "Thatcher profile." As with women, the May profile is the most common profile at both time points. The Blair and Corbyn profiles have approximately the same frequency at both time points, with the Corbyn profile becoming slightly more prevalent at the second assessment. The Thatcher profile that appears to be unique to men is the least common profile at both time points. A likelihood ratio test was conducted to test if latent profile means were invariant across. Again, this test was not significant, $\chi^2(24) = 31.76$, $p = .13$, and so profile means will be constrained to equality in subsequent analyses.

Because three of the political profiles show relatively close correspondence between men and women, tests of measurement invariance were conducted between men and women across both timepoints. Because the number of profiles differed between men and women, the proportion of women in the Thatcher profile was set to zero. Again, the likelihood ratio test was used to assess significantly worse model fit. This time model fit decreases significantly when imposing measurement invariance between genders, $\chi^2(36) = 55.31$, $p = .021$. This suggests that while the profiles have the same conceptual interpretation, the means are subtly different.

Univariate Latent Transitions

Before examining the dyadic components of the DLTA model, I examined individual transitions in the form of a univariate latent transition analysis. This will allow for the modeling of change at the individual level. Considering the invariance of latent profiles across time, we can interpret profiles that share the same means as representing

the same latent profile across time points. Profile means were constrained to equality in Mplus to ensure this invariance.

Table 3.7 shows the transition matrix for women. The diagonal element of the matrix represents stability in latent profiles. To the extent that this diagonal is filled with 1's, profiles are stable over time. The off-diagonal elements represent change in latent profiles across time. About 81% of the women who classified with the "May" profile at Time 1 were still classified as the May profile at Time 2. There was also substantial stability in the Blair profile, as nearly 78% of those classified as Blair at Time 1 were in the same profile at Time 2. Lastly, 86.5% of the Time 1 Corbyn profiles were in the same profile at Time 2. Of the women who were in the May condition at Time 1, 13.7% of them transitioned into the Blair profile, while the remained 5.4% transitioned in the Corbyn profile. Those who were in the Blair profile at Time 1 had a 22.4% change of transitioning into the May profile at Time 2. The only transition that did not occur was the transition from the Blair profile to the Corbyn profile. Thirteen percent of those in Corbyn profile at Time 1 transitioned into the May profile, while only .4% transitioned into the Corbyn profile.

Table 3.8 shows the transition matrix for men. As with women, there was a substantial degree of stability in political profiles. About 78% of those in the May profile at Time 1 were still in the May profile at the second time point. Over 80% of those in the Blair profile at Time 1 remained in the Blair profile at Time 2. There was slight less stability in the Corbyn and Thatcher profiles as 69.3% and 62.2%, respectively, remained in those profiles. Of those who were in the May profile at the first assessment, the largest

transition was to the Corbyn profile (18.6%), followed by 3.1% transitioning to the Thatcher profile and a mere .1% transitioning to the Blair profile. Those who transitioned from the Blair profile were most likely to transition to the Thatcher profile (13.5%), while 6.4% transitioned to the Corbyn profile. No participants transitioned from the Blair profile to the May profile. By the far the most common transition from the Corbyn profile was to the Thatcher profile, which encompassed 25.1% of those in the Corbyn profile, while 3.5% and 2.0% transitioned to the May and Blair profiles, respectively. Lastly, a large portion of Time 1 Thatcher profiles transitioned to the May profile (37.6%), while no participants transitioned to the Corbyn profile and only .2% transitioned to Blair profile.

The DLTA Model

The process of choosing the best model proceeded as a series of nested models. The baseline model chosen was the independence model shown in Figure 3.1a. Dyadic portions of the model were added individually and models increased in complexity. The first dyadic model was one that allowed profile membership to be related across couple members at a single a timepoint, but lacked any cross-lagged effects (Figure 3.1b). Next, cross-lagged effects were added such that profile membership at Time 2 was predicted by one's own profile and one's partner's profile at Time 1 (Figure 3.1c). The next model was one in which initial profile status predicted instances of transition for one's partner (Figure 3.1d). Then combinations of these models were tested, until the most complex model, the Fully Dyadic Model featured in Figure 3.2, was tested. Because not all of these models were nested in a fashion that made the likelihood ratio test plausible to use,

models were compared using the AIC and Sample-adjusted BIC (Lin & Dayton, 1997). It should also be noted that considerations other than model fit are pertinent, such as the theoretical tenability of given pathways (Little, 1997). One particularly relevant issue with models as complex as the DLTA is computation time. Apart from the independence model, each model took at least several hours to converge, and the fully dyadic model took just under 10 hours and 40 minutes to converge. Mplus code for the chosen model is provided in Appendix C.

Table 3.9 summarizes the model building process. The worst fitting model, as expected, was the baseline Independence model. The best fitting model was the model in which there was a concurrent relationship between couple member classes, and a crossed-lagged relationship between couple member profiles (a combination of Figures 3.1b and 3.1c). This suggests that profile membership is related between couple members both at a given time point and longitudinally. However, profile membership did not predict the actual transition between profiles for couple members.

The covariances between latent profiles at concurrent times was estimated using the PARAMETIZATION = LOGLINEAR argument in Mplus (Kankaraš, & Vermunt, 2014). This covariance between profiles indicates the extent to which membership in a given profile for one couple member is related to the profile for the other couple member. The result that fixing this covariance to zero results in worse model fit indicates that profiles are not independent across couple members. As Table 3.10 shows, there was a tendency for couple members to be classified in the same profile as their spouse. The positive covariances between the same class represents the positive tendency to be

classified similarly. The negative covariances indicate that being in that particular profile is associated with a decreased likelihood of a spouse being in the subsequent profile. For example, the negative covariance between May profiles for women and the Corbyn profiles for men indicate that women in the May profile tend *not* to have husbands in the Corbyn profile. Indeed it seems that partisan politics are inescapable even in latent profiles, as the profiles similar to Labour Party leaders are positively correlated to each other and the profiles similar to Conservative Party leaders are also correlated with each other.

The cross-lagged association of latent profiles represents the extent to which couple members can impact each other over time. The restriction of these paths to zero resulted in worse model fit, indicating that there is a significant cross-lagged association between profiles. Table 3.11 shows the results of predicting women's latent profile membership at Time 2 from men's Time 1. There was a noticeable trend that men who were in a given profile at Time 1 were more likely to be married to women with the same profile at Time 2. One transition probability worth noting is that the men in the male-only profile, the Thatcher profile, tended to have wives who were in the May profile at Time 2 and were especially less likely to have wives in the Corbyn condition at Time 2.

The cross-lagged prediction of men's profile at Time 2 from women's profile at Time 1 is presented in Table 3.12. Again, the trend that couple members tend to belong in similar profiles was found. Women who were in the Corbyn and Blair profiles were more likely to have husbands who were in these profiles at Time 2. Women who were in the May profile at Time 1 were more likely than any other profile to be associated with men

in the Thatcher profile at Time 2. This indicates that not only is there a cross-sectional association, but also a longitudinal relationship between couple members political beliefs.

Discussion

The goal of the present study was to demonstrate how two previously independent models, the latent transition and actor-partner interdependence models can fruitfully be used together. The series of models considered here were categorical extensions of the longitudinal APIM and a dyadic extension of the associative latent transition analysis (Bray et al., 2010; Kenny et al., 2006). The model that best balanced model fit and model parsimony was a model where there were both concurrent and cross-lagged associations between profile membership for various couples. Substantively, this indicated that couple members started out with similar political profiles, and were also similar to each over time.

Many variables in the literature on romantic couples either naturally fall into categories or are treated as such (Bradford et al, 2015; Busby et al., 1995). Previously, there was no method for assessing longitudinal associations between couple members on categorical latent variables. Previous research has solely focused on the use of categorical manifest variables (Spain, Jackson, & Edmonds, 2012). The DLTA provides a general framework for methodological and substantive researchers to model the over time association between couple members. The ALTA model itself has seen a limited application, but has usually applied when researchers generally believe the longitudinal association flows from one variable to another (but not vice versa, Bray et al., 2010). The

DLTA generalizes the ALTA to the situation in which paths can go in both directions (e.g. both husbands and wives exert an influence on each other).

While the DLTA is meant as a general framework, there are modifications and extensions that can be applied to make this model even more general. The DLTA as applied here focused solely on two timepoints, but can be applied to three or more repeated measures. The computational burden of a model of this size may be prohibitive, however, as the present relatively simple example of two time-points still took several hours to run. The present application of the DLTA is also most appropriate for use with distinguishable dyads, as it clearly delineates paths for separate dyad members (Gonzales & Griffin, 1999). In the case of indistinguishable dyads (e.g. identical twins), one would have to utilize random effects models, such as the multilevel latent transition analysis (Kaplan, Kim, & Kim, 2009). An additional concern reflects a common practice in the use of APIMs, and that is to test for equivalent paths across dyad members. This type of constraint would have been rather nonsensical in the present study as the actual number of latent profiles differed for men and women, and so there was a lack of equivalence in the latent variables themselves. However in future research, if invariance of the latent profiles (or classes) holds, paths from dyad members at Time 1 to Time 2 can be tested for equality. An additional extension of the present model can also incorporate covariates into the prediction of latent classes and transitions across time (Humphreys & Janson, 2000). Covariates could be useful in an applied context if one wishes to know the factors that predict transitioning between classes, such as the effect of marital conflict on transition from non-distressed to distressed classes of marital satisfaction.

Substantively, the present study corroborates previous research on couple similarity. Previous research has identified political attitudes and values as one of the strongest sources of similarity between couple members (Caspi et al., 1992; Gaunt, 2006). At the first time point under consideration, couple members evidenced significant initial similarity, akin to results on assortative mating that finds that couple members tend to pair with those who have similar political beliefs (Gaunt, 2006; Kanlder, Bleidorn, & Riemann, 2012). Couple members also tend to influence each others' political beliefs over time, as evidence by the finding that model fit decreased significantly when cross-lagged paths were taken out of the DLTA model. This too supports previous research that finds that couple members exert an influence on each other over time (Caspi et al., 1992).

The present study found that there not merely initial similarity in political profiles, but also a degree of convergence in political thought. Convergence in political beliefs has not traditionally been found in research on marriage and political beliefs (Feng & Baker, 1994; Watson et al., 2004). Convergence in the present study was seen in the transition of couple members into political profiles that more closely match those of their partner. Future research should attempt to remedy the discrepancy in the convergence found in the present study and the lack of convergence that is typically found in political attitudes.

An additional factor to consider is the shared environment that couple members experience. A shared environment can influence two couple members because they experience the same political events and climate together. For instance, the resignation of Tony Blair in 2007, the recession in 2008, and the growing visibility of Nigel Farage and

the United Kingdom Independence Party, are all events that can cause couple members to become more similar over time in their political beliefs. Future research on couple similarity would be well-informed to consider the influence of the shared environment on couple member similarity (cf. Caspi et al. 1992; Anderson, Keltner, & John, 2003).

Chapter 4:

Dissertation Conclusion

Conclusion

The preceding set of two studies utilized dyadic data and discrete latent variables in two novel ways. The first novel application was to apply growth mixture modeling to the context of dyadic growth curves. A two-class solution was chosen to represent growth at the dyadic level. The larger of the two classes showed very little change over time, while the smaller of the classes showed a dramatic decline in marital satisfaction. Previous methods of classifying couples based on satisfaction have often relied upon simple cut scores on a marital satisfaction scale, while this study used a statistically more rigorous approach by classifying couples on change in satisfaction. Group membership was associated with substantive consequeces, as the couples in the declining group were significantly more likely to get divorced in the following three years.(

The second novel application was an extension of the associative latent transition and actor-partner interdependence models to examine the mutual impact that couples members have on their partner's political beliefs over time. This combination of the ALTA and APIM models represent a new way in which researchers can examine the cross-lagged relationship of couple members using discrete latent variables. This model suggested that profiles of political attitudes show a significant relationship between dyad members both concurrently and longitudinally.

These two applications merely scratch the surface on the types of modeling that can be done in this context. The literature on marriage and relationships has long relied on classification. While relationship researchers have done well to remedy the issues

associated with having naturally nested data (Kenny et al., 2006), utilizing more sophisticated categorical latent variable techniques in relationship research is long overdue. There is now ample literature on both dyadic data and discrete latent variables to warrant their mutual inclusion in research projects. Hopefully this dissertation provides the starting point for this utilization.

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Table 1.1

Taxonomy of Models

		Latent Variables	
		Continuous	Categorical
Indicators	Continuous	Factor Analysis	Latent Profile Analysis
	Categorical	Item Response Theory	Latent Class Analysis

Table 2.1

Descriptive Statistics of Relationship Satisfaction and Covariates

Variable	Men	Women
Relationship Satisfaction		
Time 1	6.83 (.37)	6.57 (.47)
Time 2	6.69 (.68)	6.58 (.85)
Time 3	6.66 (.70)	6.52 (.83)
Time 4	6.57 (.86)	6.45 (.80)
Time 5	6.52 (.80)	6.40 (.88)
Covariates		
Financial Situation	1.94 (.92)	1.87 (.87)
Partner Importance	9.76 (.62)	9.58 (.58)
Job Satisfaction	5.26 (1.25)	5.58 (1.24)
Neighborhood Condition	1.22 (.57)	1.19 (.56)

Note. All covariates assessed at first time point

Table 2.2

Results of Class Enumeration

Fit Statistics	2 Classes	3 Classes	4 Classes
-2LL	29560.18	29044.38	28739.89
LMR (*p*)	< .00001	.0002	.270
BLRT (*p*)	< .00001	< .00001	.389
Entropy	.953	.902	.795
BIC	29705.396	29212.53	29289.56
AIC	29598.179	29088.39	29036.45
SSABIC	29645.032	29142.64	29341.54
Class size (%) C1	1941 (93.0%)	1815 (87.0%)	1806 (86.5%)
C2	145 (7.0%)	150 (7.2%)	122 (5.8%)
C3	-	121 (5.8%)	120 (5.7%)
C4	-	-	38 (1.8%)

Table 2.3

Parameters of Two Class Model

Class	Intercept			Slope	
	Estimate	S.E.	Variance (SE)	Estimate	S.E.
Stable	6.83	.008	.006 (.004)	-.04	.005
Decreasing	6.88	.027	.030 (.012)	-.88	.063

Note. Variance terms of the slope were fixed to zero.

Table 2.4

Predicting Class membership from Time 1 Covariates

Variable	Odds Ratio	95% CI	*p*-value
Financial Situation (Male)	1.41	1.16, 1.70	.00037
Financial Situation (Female)	1.50	1.24, 1.80	< .0001
Partner Importance (Male)	.85	.66, 1.12	.22
Partner Importance (Female)	.60	.48, .73	< .0001
Job Satisfaction (Male)	1.08	.88, 1.35	.46
Job Satisfaction (Female)	.94	.79, 1.15	.51
Neighborhood Condition (Male)	1.34	1.08, 1.86	.0081
Neighborhood Condition (Female)	1.44	1.02, 1.73	.037

Note. N = 2,086

Table 2.5

Predicting Proportional Hazard from posterior probability

Parameter	Estimate	S.E.	z-value	OR
Intercept	-3.22	.24	-13.44	
Slope of Stable Class Probability	-1.36	.27	-5.06	.26

Table 3.1

Profile Enumeration, Females at Time 1

	BLRT	Parameters	Entropy	AIC	BIC
Two Profile	< .00001	19	.93	58644.8	58763.33
Three Profile	< .00001	26	.87	58345.94	58508.14
Four Profile	.028	33	.77	58343.37	58532.12
Five Profile	.346	40	.76	59001.76	59162.38

Table 3.2

Profile Enumeration, Females at Time 2

	BLRT	Parameters	Entropy	AIC	BIC
Two Profile	< .00001	19	.90	54414.28	54531.77
Three Profile	< .00001	26	.88	54138.53	54299.31
Four Profile	.092	33	.82	54141.75	54302.73
Five Profile	.281	40	.64	54202.90	54207.82

Table 3.3

Profile Enumeration, Males at Time 1

	BLRT	Parameters	Entropy	AIC	BIC
Two Profile	< .00001	19	.92	60642.45	60760.00
Three Profile	< .00001	26	.89	60099.31	60260.17
Four Profile	.0031	33	.89	59800.36	60004.54
Five Profile	.14	40	.77	59806.54	60012.85
Six Profile	.632	47	.63	59813.76	60059.43

Table 3.4

Profile Enumeration, Males at Time 2

	BLRT	Parameters	Entropy	AIC	BIC
Two Profile	< .00001	19	.88	58185.33	58275.48
Three Profile	< .00001	26	.85	57675.80	57818.11
Four Profile	.00053	33	.84	57381.64	57628.28
Five Profile	.27	40	.72	57453.7	57657.17
Six Profile	.48	47	.59	57782.32	57903.19

Table 3.5

Summary of Latent Profiles for Women

	Class Means		
	May	Blair	Corbyn
Share in nation's wealth	4.01	3.06	3.54
One law for rich and poor	2.00	3.57	2.76
Private Enterprise solves problems	3.25	3.11	3.08
Public services state owned	2.74	3.05	3.03
Government obligated to provide jobs	2.55	3.15	3.15
Unions protect employees	1.98	2.74	3.58
Class Proportions			
Time 1	.524	.274	.202
Time 2	.511	.285	.204

Table 3.6

Summary of Latent Profiles for Men

	Class Means			
	May	Blair	Corbyn	Thatcher
Share in nation's wealth	4.07	3.17	3.76	2.23
One law for rich and poor	1.97	3.61	2.88	2.33
Private Enterprise solves problems	3.16	3.21	2.96	4.56
Public services state owned	2.78	3.09	3.13	1.95
Government obligated to provide jobs	2.75	3.04	3.18	1.78
Unions protect employees	2.21	2.79	3.67	2.21
Class Proportions				
Time 1	.375	.220	.224	.180
Time 2	.439	.181	.227	.153

Table 3.7

Probabilities of Transition for Women

$$\begin{bmatrix} & May_{t2} & Blair_{t2} & Corbyn_{t2} \\ May_{t1} & .809\ (.023) & .137\ (.044) & .054\ (.039) \\ Blair_{t1} & .224\ (.019) & .776\ (.041) & .000\ (.034) \\ Corbyn_{t1} & .130\ (.021) & .004\ (.032) & .865\ (.037) \end{bmatrix}$$

Table 3.8

Probabilities of Transition for Men

	May_{t2}	$Blair_{t2}$	$Corbyn_{t2}$	$Thatcher_{t2}$
May_{t1}	.782 (.034)	.001 (.029)	.186 (.042)	.031 (.045)
$Blair_{t1}$	.000 (.027)	.801 (.031)	.064 (.040)	.135 (.042)
$Corbyn_{t1}$	.035 (.028)	.020 (.027)	.693 (.040)	.251 (.044)
$Thatcher_{t1}$	.376 (.041)	.002 (.030)	.000 (.039)	.622 (.048)

Table 3.9

Summary of DLTA Model-Building

	AIC	SABIC
Independence	117761.53	117971.67
Concurrent relationship	98756.49	98834.23
Cross lagged effects	99876.45	99901.51
Baselines predict transition	101431.29	101598.42
Concurrent & cross-lagged	96076.11	96142.18
Concurrent & baseline predicting transition	98102.95	98201.58
Fully dyadic model	98204.54	98302. 87

Table 3.10

Covariance of Initial Latent Profiles

	Mayw	Blairw	Corbynw
$Thatcher_M$	.37***	-.09	-.56***
May_M	.76***	-.42***	-.22**
$Blair_M$	-.12*	.65***	.43***
$Corbyn_M$	-.45***	.31***	.52***

Table 3.11

Transition Matrix of Probabilities Predicting Women's Profile at Time 2 from Men at Time 1

$$\begin{bmatrix} & May_{Ft2} & Blair_{Ft2} & Corbyn_{Ft2} \\ May_{Mt1} & .505\ (.078) & .203\ (.081) & .292\ (.080) \\ Blair_{Mt1} & .177\ (.077) & .532\ (.084) & .291\ (.077) \\ Corbyn_{Mt1} & .126\ (.081) & .272\ (.079) & .602\ (.081) \\ Thatcher_{Mt1} & .476\ (.079) & .322\ (.085) & .202\ (.079) \end{bmatrix}$$

Table 3.12

Transition Matrix of Probabilities Predicting Men's Profile at Time 2 from Women at Time 1

	May_{Mt2}	$Blair_{Mt2}$	$Corbyn_{Mt2}$	$Thatcher_{Mt2}$
May_{Ft1}	.427 (.079)	.121 (.080)	.146 (.077)	.306 (.069)
$Blair_{Ft1}$	.051 (.081)	.478 (.085)	.276 (.079)	.195 (.082)
$Corbyn_{Ft1}$	.115 (.077)	.301 (.083)	.503 (.077)	.073 (.075)

Figure 1.1

Actor-Partner Interdependence Model

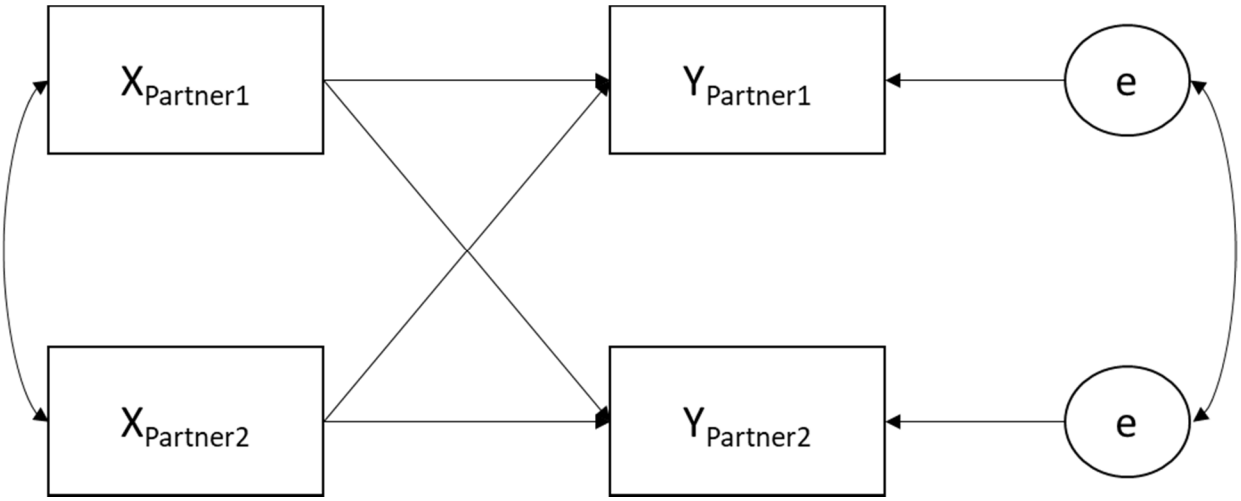


Figure 1.2

Common Fate Model

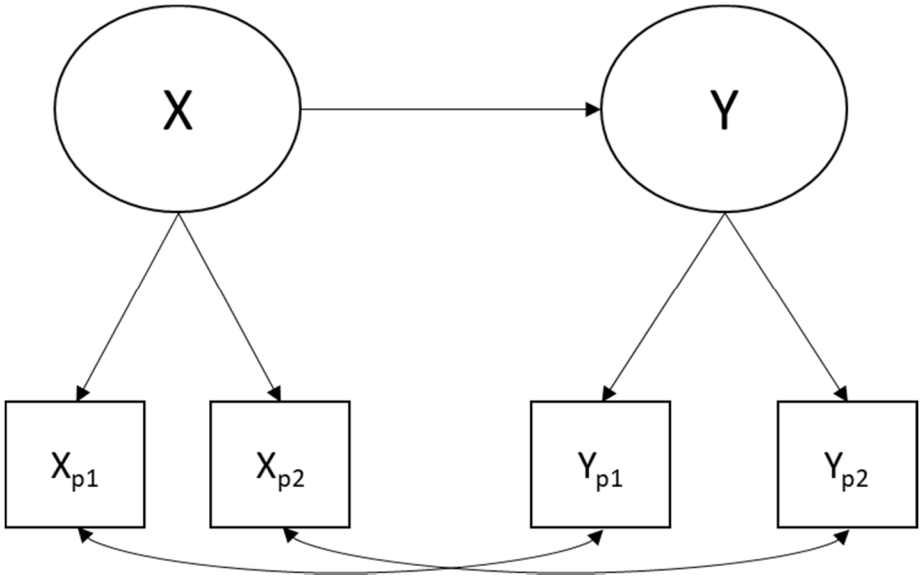


Figure 1.3

Longitudinal Actor-Partner Interdependence Model

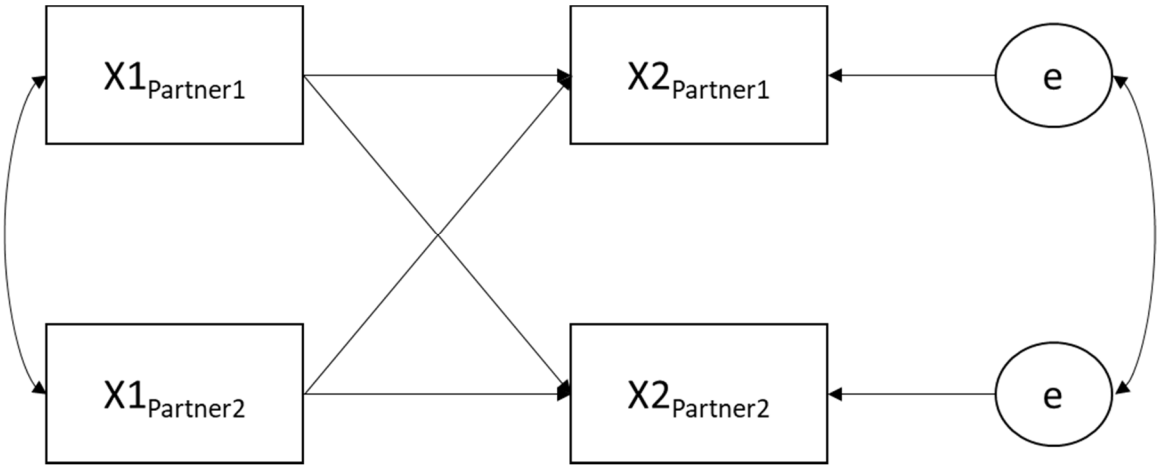


Figure 1.4

Common Fate Growth Model

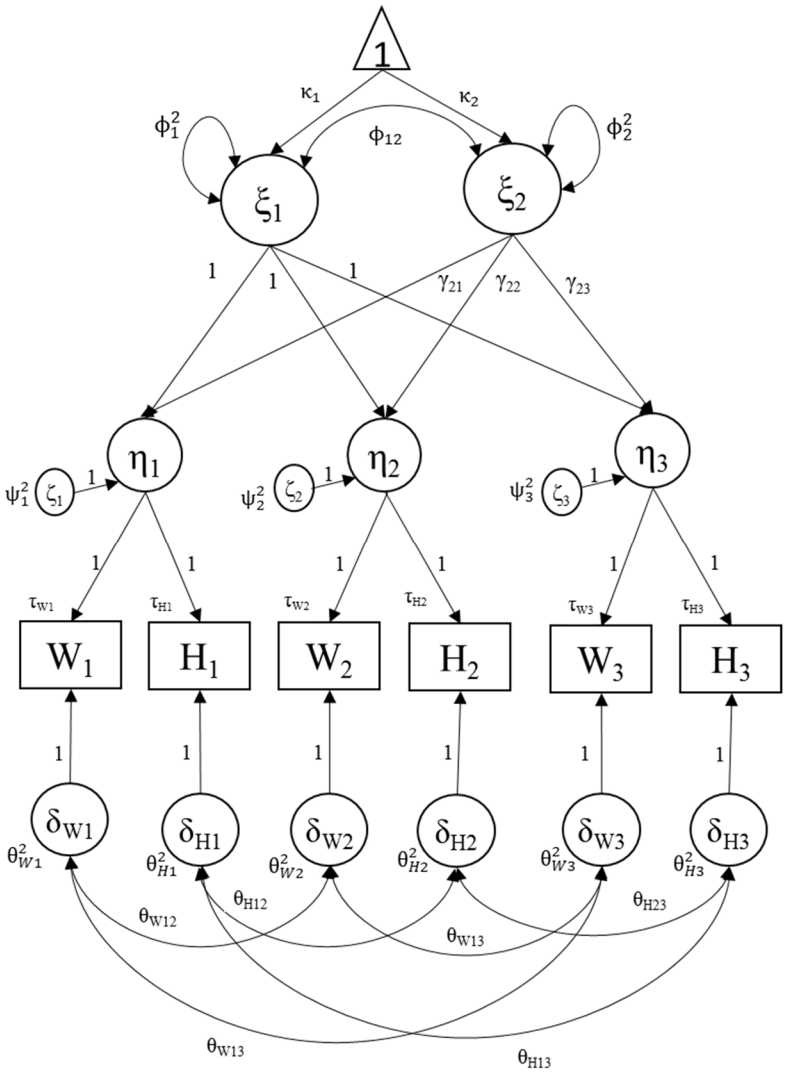
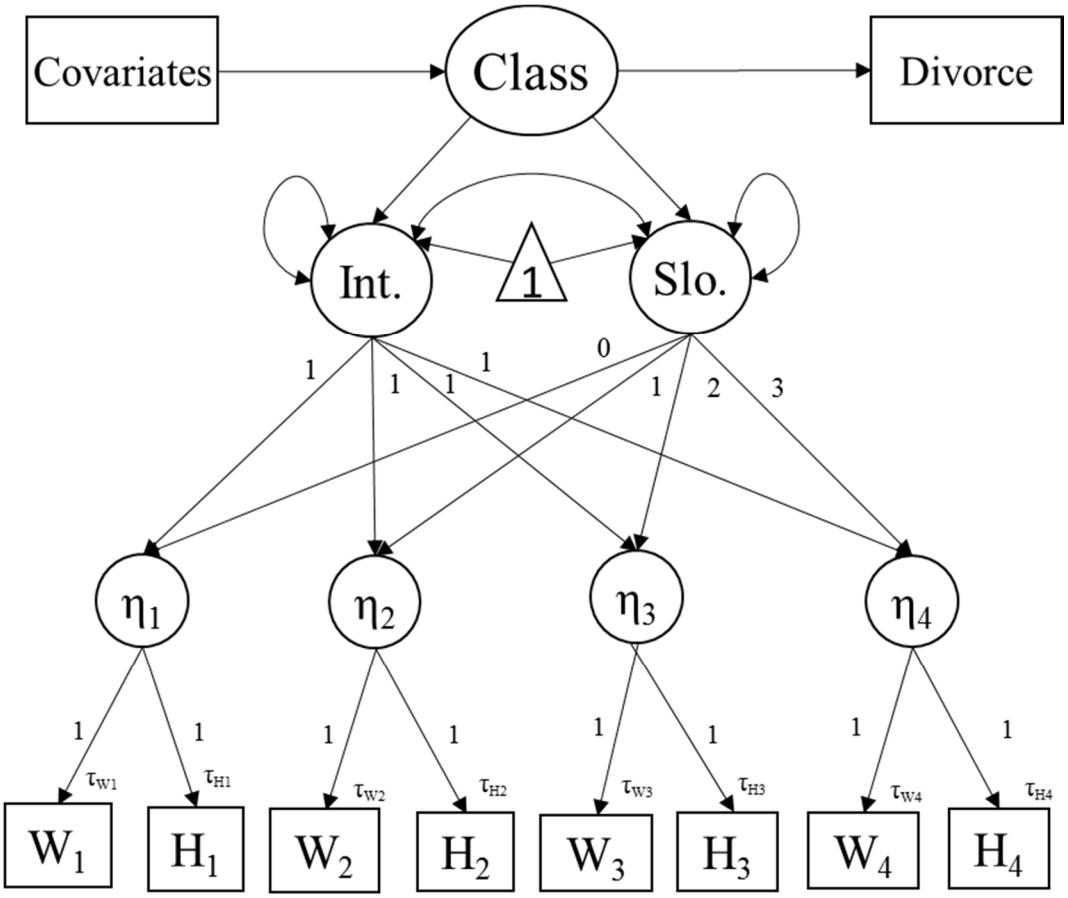


Figure 2.1

Common Fate Growth Mixture Model with Covariates



Note. Error variances and covariances omitted.

Figure 2.2

Class Trajectories

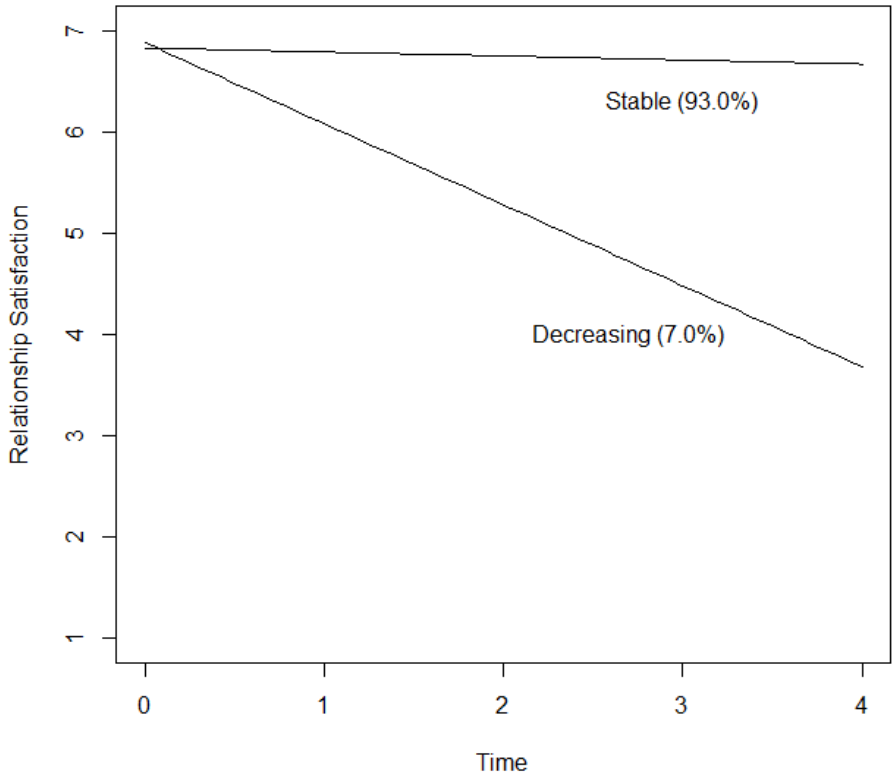
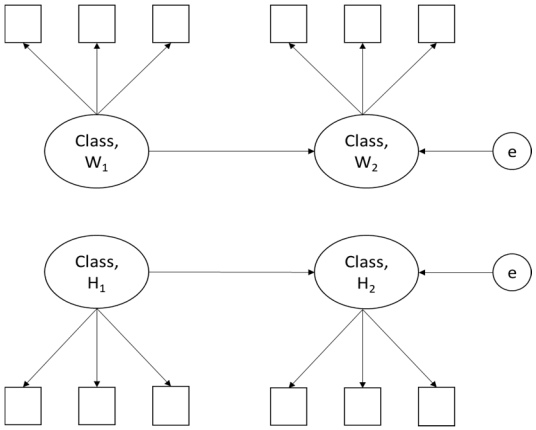
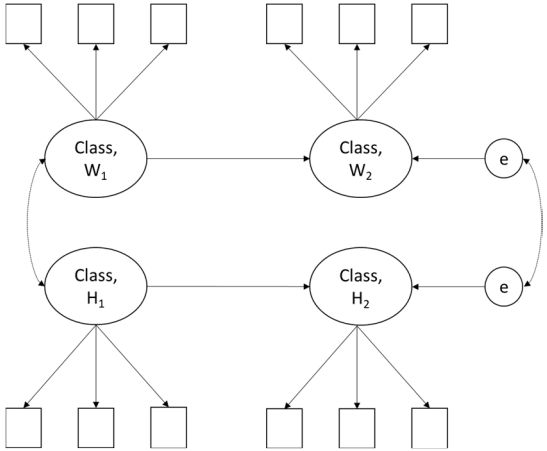


Figure 3.1

Different Models of Dyadic Latent Transition Analysis

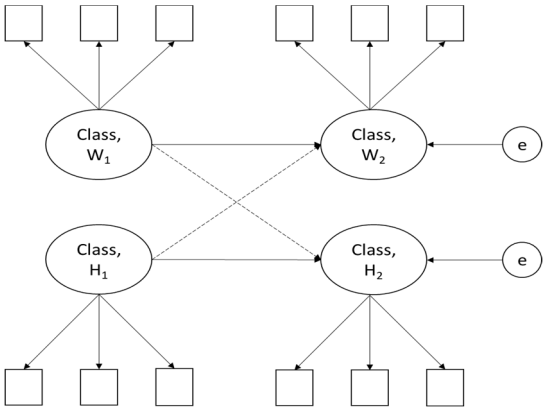


a. Independence



b. Concurrent Relationship

c. Cross-lagged Relationship



d. Baseline Predicting Transitions

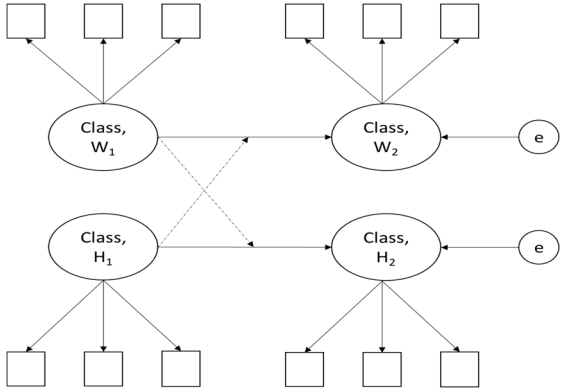
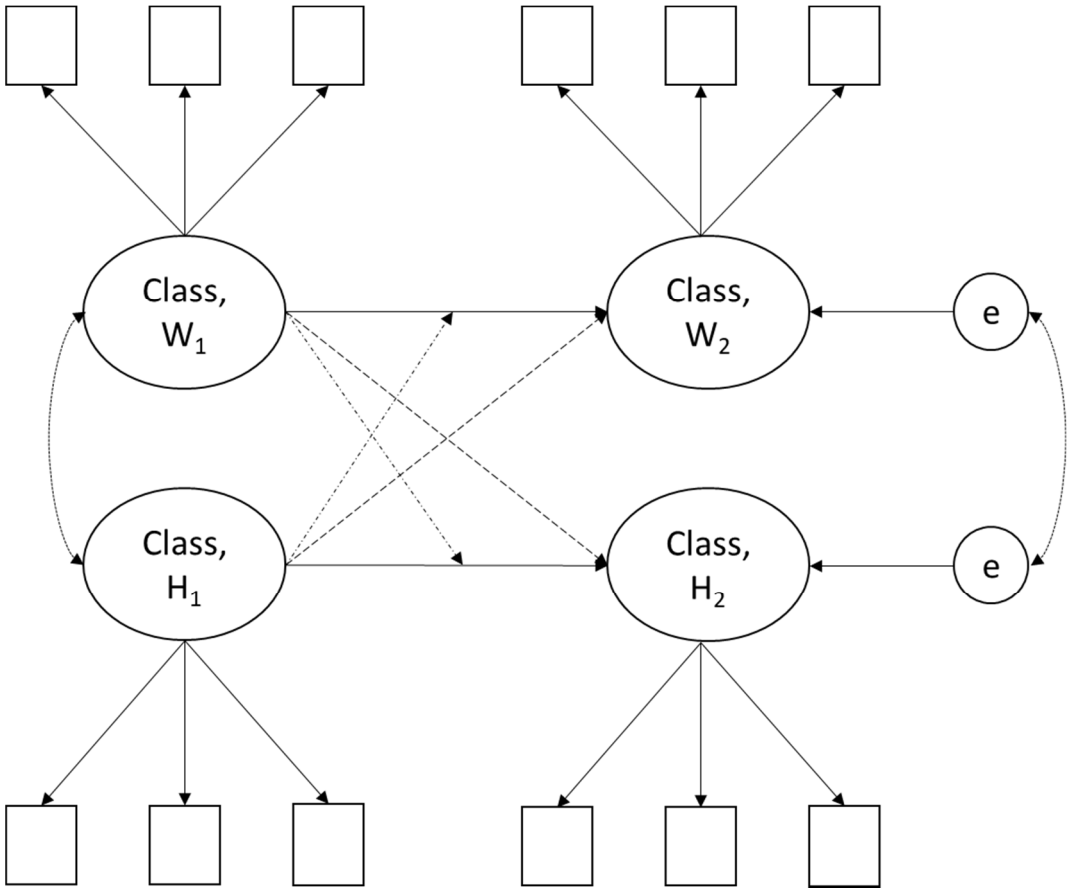


Figure 3.2

Full Dyadic Latent Transition Analysis



Appendix A

Simulation

To illustrate the impact of nesting on parameter estimates, a small simulation was performed. The purpose of the simulation is to illustrate the effect of nesting on the standard errors of a linear model. The simulated model was designed to resemble a typical actor-partner interdependence model, with an intercept, two slopes, and a cluster size of 2. The mean intercept in this model is .2, the average actor effect is .5, while the average partner effect is .3. All three terms were allowed to vary randomly. The population model is in equation 1.3 as follows:

$$Y_{ij} = b_0 + b_1 * Actor_{Effect} + b_2 * Partner_{Effect} + r_{ij}$$

$$b_0 = .2 + u_{0j}$$

$$b_1 = .5 + u_{1j}$$

$$b_2 = .3 + u_{2j}$$

Where the random effects terms are all normally distributed with mean 0., One difficulty when assessing this particular model (and a problem endemic to all dyadic analyses) is the issue of degrees of freedom of the random effects. Because the size of clusters is fixed at two with dyadic data, no more than one random effect can be estimated for each multilevel model. Therefore, three separate multilevel models were assessed, one for each potential random effect. Total sample size was 1,000 (giving 500 couples). I varied the intraclass correlation, to range from no nesting in the data, to almost complete nesting to

examine how the level of nesting affects the coverage probability of the parameters. While the intraclass correlation may affect the results of multilevel models, the ICC may be a poor indicator of when to use multilevel modeling (Nezlek, 2008).

Coverage Probabilities represent the proportion of trials in which the confidence interval overlaps with the population. When parameters and standard errors are estimated correctly, the coverage probability will match the confidence intervals chosen (e.g. 95% coverage for a 95% confidence interval). As the coverage probability falls below the confidence interval level, this indicates that the standard errors are underestimated. In the rare case that the coverage probability exceeds the confidence interval, this indicates an overestimation of the standard errors. One thousand replication datasets were used, the entire simulation took just under thirty minutes to complete. Data were simulated using the mvtnorm package in R, and multilevel models were analyzed using the lme4 package (Bates, Maechler, Bolker, & Walker, 2014)

Table A.1 shows the results of the simulation. The coverage probabilities for parameters that have the random effects correctly specified indicate accurate parameters and standard errors. However, those models that did not accurately model the standard errors saw coverage probabilities dip below 95%. There is a general trend for coverage probabilities to decrease as the intraclass correlation of the variables increased. This suggests that as the level of nonindependence increases, the standard errors become increasingly underestimated. Also worth noting, the coverage probabilities are worse for the slope terms than for the intercept term. This is particularly worrisome considering the limited number of random effects to specify, and most advice regarding the actor-partner

interdependence model recommend specifying a random intercept and fixed slopes. Overall, the results of the simulation indicates the importance of accounting for nesting when analyzing dyadic data.

Recommendations on how best to estimate multilevel models revolve on the estimation of random intercepts, but fixed slopes (Kenny et al., 2006). The results of this simulation show that standard errors are typically underestimated for both intercepts and slopes, especially as the degree of nonindependence increases. The multilevel model with a random intercept, but fixed slopes still results in poor coverage probabilities of the slope parameters. The best solution to address this problem may be a piecemeal approach in which three models are estimated, one for the random intercept and two random slopes.

Table A.1

Coverage Probabilities for Dyadic Simulation

ICC	Intercept, b_0 Random	Intercept, b_1 Random	Intercept, b_2 Random	Slope 1, b_0 Random	Slope 1, b_1 Random	Slope 1, b_2 Random	Slope 2, b_0 Random	Slope 2, b_1 Random	Slope 2, b_2 Random
.00	0.951	0.969	0.947	0.829	0.95	0.836	0.889	0.865	0.945
.10	0.943	0.957	0.944	0.838	0.947	0.83	0.887	0.862	0.941
.20	0.951	0.956	0.937	0.817	0.946	0.797	0.886	0.881	0.951
.30	0.951	0.952	0.939	0.826	0.952	0.806	0.885	0.854	0.956
.40	0.95	0.935	0.928	0.839	0.957	0.803	0.867	0.853	0.951
.50	0.964	0.939	0.93	0.823	0.94	0.775	0.891	0.844	0.957
.60	0.952	0.922	0.912	0.821	0.953	0.775	0.867	0.808	0.941
.70	0.945	0.908	0.916	0.786	0.947	0.74	0.877	0.795	0.943
.80	0.95	0.895	0.894	0.794	0.936	0.763	0.893	0.77	0.962
.90	0.941	0.836	0.849	0.768	0.952	0.718	0.865	0.709	0.944
.99	0.949	0.83	0.83	0.73	0.959	0.675	0.862	0.656	0.95
Mean	.949	.918	.911	.806	.949	.774	.879	.809	.949

Note. 1,000 replications.

R code for simulation

```
library(mvtnorm)
library(lme4)

set.seed(5692)
reps <- 1000
int.est.cluster <- matrix(NA, nrow=reps, ncol=3)
slope1.est.cluster <- matrix(NA, nrow=reps, ncol=3)
slope2.est.cluster <- matrix(NA, nrow=reps, ncol=3)
se.int.cluster <- matrix(NA, nrow=reps, ncol = 3)
se.slope1.cluster <- matrix(NA, nrow=reps, ncol = 3)
se.slope2.cluster <- matrix(NA, nrow=reps, ncol = 3)
b0 <- .2
b1 <- .5
b2 <- .3
n <- 1000
iccs <- c(0,.1,.2, .3, .4, .5, .6, .7, .8, .90,.99)
nc <- 500
reps <- 1000
c.label <- rep(1:nc, each = n/nc)
icccover <- matrix(NA, nrow = length(iccs), ncol = 10)
start.time <- Sys.time()
 for (j in 1:length(iccs)){
    p <- iccs[j]
      for(i in 1:reps){
         i.sigma <- matrix(c(1.0,0.0,0,0.0,0,0.0,1-p,0,0, 0, 0, 0.0, 1-p,0,0,0, 0, 0,1-p,0,0,0,0
,0,1-p), ncol=5, byrow = TRUE)
         i.values <- rmvnorm(n = n, sigma=i.sigma)
         effect1 <- i.values[,1]
         effect2 <- i.values[,2]
         effect5 <- i.values[,3]
         effect7 <- i.values[,4]
         effect9 <- i.values[,5]
         c.sigma <- matrix(c(1.0,0.0,0,0.0,0,0.0,p,0,0, 0, 0, 0.0, p,0,0,0, 0, 0,p,0,0,0,0,0,p),
ncol=5, byrow=TRUE)
         c.values <- rmvnorm(n = nc, sigma=c.sigma)
         effect3 <- rep(c.values[,1], each = n/nc)
         effect4 <- rep(c.values[,2], each=n/nc)
         effect6 <- rep(c.values[,3], each=n/nc)
         effect8 <- rep(c.values[,4], each=n/nc)
         effect10 <-rep(c.values[,5], each=n/nc)
         X1 <- effect1 + effect3
```

```
        X2 <- effect7 + effect8
        error <- effect2 + effect4
        randerror1 <- effect5 + effect6
        randerror2 <- effect9 + effect10
        Y <- b0 + b1*X1 +b2*X2 + error + X1*randerror1 + X2*randerror2
        model.fixed <- lmer(Y~X1 + X2+ factor(1|c.label), REML=FALSE, control=lmerControl(optimizer='Nelder_Mead'))
        model.random1 <- lmer(Y~X1 +X2+ factor(0+X1|c.label), REML=FALSE, control= lmerControl(optimizer='Nelder_Mead'))
        model.random2 <- lmer(Y~X1 +X2+ factor(0+X2|c.label), REML=FALSE, control=lmerControl(optimizer='Nelder_Mead'))
        int.est.cluster[i,1] <- fixef(model.fixed)[1]
        int.est.cluster[i,2] <- fixef(model.random1)[1]
        int.est.cluster[i,3] <- fixef(model.random2)[1]
        slope1.est.cluster[i,1] <- fixef(model.fixed)[2]
        slope1.est.cluster[i,2] <- fixef(model.random1)[2]
        slope1.est.cluster[i,3] <- fixef(model.random2)[2]
        slope2.est.cluster[i,1] <- fixef(model.fixed)[3]
        slope2.est.cluster[i,2] <- fixef(model.random1)[3]
        slope2.est.cluster[i,3] <- fixef(model.random2)[3]
        vcv.fixed <- vcov(model.fixed)
        vcv.random1 <- vcov(model.random1)
        vcv.random2 <- vcov(model.random2)
        se.int.cluster[i,1] <- sqrt(diag(vcv.fixed)[1])
        se.int.cluster[i,2] <- sqrt(diag(vcv.random1)[1])
        se.int.cluster[i,3] <- sqrt(diag(vcv.random2)[1])
        se.slope1.cluster[i,1] <- sqrt(diag(vcv.fixed)[2])
        se.slope1.cluster[i,2] <- sqrt(diag(vcv.random1)[2])
        se.slope1.cluster[i,3] <- sqrt(diag(vcv.random2)[2])
        se.slope2.cluster[i,1] <- sqrt(diag(vcv.fixed)[3])
        se.slope2.cluster[i,2] <- sqrt(diag(vcv.random1)[3])
        se.slope2.cluster[i,3] <- sqrt(diag(vcv.random2)[3])
      }
    icccover[j,1] <- p
    icccover[j,2] <- coverage(int.est.cluster[,1], se.int.cluster[,1], b0,   df = 996)$cover.probability
    icccover[j,3] <- coverage(int.est.cluster[,2], se.int.cluster[,2], b0, df = 994)$cover.probability
    icccover[j,4] <- coverage(int.est.cluster[,3], se.int.cluster[,3], b0, df = 994)$cover.probability
    icccover[j,5] <- coverage(slope1.est.cluster[,1], se.slope1.cluster[,1], b1, df = 996)$cover.probability
    icccover[j,6] <- coverage(slope1.est.cluster[,2], se.slope1.cluster[,2], b1, df = 994)$cover.probability
```

```
      icccover[j,7] <- coverage(slope1.est.cluster[,3], se.slope1.cluster[,3], b1, df = 994)$c
over.probability
      icccover[j,8] <- coverage(slope2.est.cluster[,1], se.slope2.cluster[,1], b2, df = 996)$c
over.probability
      icccover[j,9] <- coverage(slope2.est.cluster[,2], se.slope2.cluster[,2], b2, df = 994)$c
over.probability
      icccover[j,10] <- coverage(slope2.est.cluster[,3], se.slope2.cluster[,3], b2, df = 994)$
cover.probability
      colnames(icccover) <- c('icc', 'Intercept, random intercept', 'Intercept, slope 1 rando
m', 'Intercept, slope 2 random','Slope 1, random intercept', 'Slope 1, slope 1 random', 'Slo
pe 1, slope 2 random','Slope 2, random intercept', 'Slope 2, slope 1 random', 'Slope 2, slop
e 2 random')
 }

end.time <- Sys.time()
end.time - start.time

## Time difference of 29.35613 mins

write.csv(icccover, 'C:/Users/Sir Jacob Gray/Documents/icccoverages.csv')
```

Appendix B

Mplus code for Second Order Growth Mixture Model

```
TITLE:      Second Order Growth Mixture Model with Two Classes
DATA:       FILE IS C:\Users\User\Documents\BHPSsat.csv;
VARIABLE:       NAMES ARE ID MT1 MT2 MT3 MT4 FT1 FT2 FT3 FT4;
usevar= ID MT1 MT2 MT3 MT4 FT1 FT2 FT3 FT4;
IDvariable is ID;
classes= c(2);
MISSING ARE ALL (99);
ANALYSIS:
Type=mixture missing;
Starts=500 10;
STITERATIONS=10;
Processors=8;
ESTIMATOR=MLR;
Model: %OVERALL%
T1 BY MT1@1 FT1@1;
T2 BY MT2@1 FT1@2
T3 BY MT3@1 FT1@3
T4 BY MT4@1 FT1@4
I S | T1@0 T2@1 T3@2 T4@3
%C#1%
[I S];
I with S@0;
I-S@0;
[MI-MS@0];
[FI-FS] (M1-M2);
 %C#2%
[I S];
I-S@0;
I with S@0;
[MI-MS@0];
[FI-FS] (M1-M2);
Savedata:
file is classtwo.txt;
save = cprob;
OUTPUT: TECH7 TECH11 TECH14;
```

Appendix C
Mplus Code for Dyadic Latent Transition Analysis

```
TITLE:      Dyadic Latent Transition Analysis
DATA:       FILE IS C:\Users\User\Documents\DLTAwide.csv;
VARIABLE:       NAMES ARE v11 v12 v13 v14 v15 v16 v21 v22 v23 v24 v25 v26 v31 v32 v33 v34 v35 v36 v41 v42 v43 v44 v45 v46;
usevariables = v11 v12 v13 v14 v15 v16 v21 v22 v23 v24 v25 v26
 v31 v32 v33 v34 v35 v36 v41 v42 v43 v44 v45 v46;
 classes = c1(3) c2(3) c3(4) c4(4);
 MISSING ARE ALL (999);
 ANALYSIS:
 Type=mixture missing;
 Starts=500 10;
 STITERATIONS=10;
 Processors=8;
PARAMETIZATION = loglinear;
 ALGORITHM=INTEGRATION;
 Model: %OVERALL%
 c2 ON c1;
 c4 ON c3;
c3 ON c2;
c4 ON c1;
c1 WITH c3;
c2 WITH c4
Model c1:
%c1#1%
[v11] (1);
[v12] (2);
[v13] (3);
[v14] (4);
[v15] (5);
[v16] (6);
%c1#2%
[v11] (7);
[v12] (8);
[v13] (9);
[v14] (10);
[v15] (11);
[v16] (12);
%c1#3%
[v11] (13);
[v12] (14);
 [v13] (15);
[v14] (16);
[v15] (17);
[v16] (18);
Model c2:
 %c2#1%
[v21] (1);
[v22] (2);
[v23] (3);
[v24] (4);
[v25] (5);
[v26] (6);
%c2#2%
[v21] (7);
[v22] (8);
 [v23] (9);
[v24] (10);
[v25] (11);
[v26] (12);
%c2#3%
[v21] (13);
[v22] (14);
 [v23] (15);
[v24] (16);
[v25] (17);
[v26] (18);
Model c3:
%c3#1%
[v31] (19);
[v32] (20);
[v33] (21);
[v34] (22);
[v35] (23);
[v36] (24);
%c3#2%
[v31] (25);
```

[v32] (26);
[v33] (27);
[v34] (28);
[v35] (29);
[v36] (30);
%c3#3%
[v31] (31);
[v32] (32);
[v33] (33);
[v34] (34);
[v35] (35);
[v36] (36);
%c3#4%
[v31] (37);
[v32] (38);
[v33] (39);
[v34] (40);
[v35] (41);
[v36] (42);
Model c4:
%c4#1%
[v41] (19);
[v42] (20);
[v43] (21);
[v44] (22);
[v45] (23);
[v46] (24);
%c4#2%
[v41] (25);
[v42] (26);
[v43] (27);
[v44] (28);
[v45] (29);
[v46] (30);
%c4#3%
[v41] (31);
[v42] (32);
[v43] (33);
[v44] (34);
[v45] (35);
[v46] (36);
%c4#4%
[v41] (37);
[v42] (38);
[v43] (39);
[v44] (40);
[v45] (41);
[v46] (42);