Spring 5-14-2021

Individual Mobility Across Clusters: The Impact of Ignoring Cross-Classified Data Structures in Discrete-Time Survival Analysis

Christopher Cappelli

ACCEPTANCE

This dissertation, INDIVIDUAL MOBILITY ACROSS CLUSTERS: THE IMPACT OF IGNORING CROSS-CLASSIFIED DATA STRUCTURES IN DISCRETE-TIME SURVIVAL ANALYSIS, by CHRISTOPHER J. CAPPELLI, was prepared under the direction of the candidate's Dissertation Advisory Committee. It is accepted by the committee members in partial fulfillment of the requirements for the degree, Doctor of Philosophy, in the College of Education & Human Development, Georgia State University.

The Dissertation Advisory Committee and the student's Department Chairperson, as representatives of the faculty, certify that this dissertation has met all standards of excellence and scholarship as determined by the faculty.

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INDIVIDUAL MOBILITY ACROSS CLUSTERS: THE IMPACT OF IGNORING CROSS-CLASSIFIED DATA STRUCTURES IN DISCRETE-TIME SURVIVAL ANALYSIS

by

CHRISTOPHER J. CAPPELLI

Under the Direction of Dr. Audrey Leroux

ABSTRACT

In the social and behavioral sciences, it is common for event-history data to have a multilevel structure, such that individuals (e.g., students) in a lower-level are clustered into some higher-level context (e.g., schools). However, little work has explored the common situation that such data are not purely clustered, as in the situation where some students may have attended more than one school during the course of a study. In those cases, the use of a cross-classified discrete-time survival model may be needed to appropriately account for individual mobility across clusters. The purpose of this research was to understand the impact of ignoring a cross-classified data structure due to individual mobility across clusters in a discrete-time survival analysis and to examine how the baseline hazard function, variability of the cluster random effect, mobility rate, and within- and between-cluster sample size impact the performance of a cross-classified discrete-time survival model. A Monte Carlo simulation study was used to specifically examine the performance of a discrete-time survival model, a multilevel discrete-time survival model, and a cross-classified discrete-time survival model. Simulation factors included the value of the between-clusters variance, cluster size, within-cluster size, Weibull scale parameter, and mobility rate. The generating parameters for the simulation study were based on a review of the applied literature. The results indicated that substantial relative parameter bias and unacceptable coverage of the 95% confidence intervals is possible for all model parameters when a discrete-time survival model is used that does not account for either clustering or individual mobility across clusters, and to a lesser extent, when using a multilevel discrete-time survival model that does not account for mobility. Across nearly all simulation conditions and for all parameters, use of the cross-classified discrete-time survival model resulted in little to no relative parameter bias and acceptable coverage of the 95% confidence intervals. These findings will be useful for methodologists and practitioners in educational research, public health, and other social sciences where discrete-time survival analysis is a common methodological technique for the analysis of event-history data.

INDEX WORDS: Multilevel modeling, Discrete-time survival analysis, Cross-classified random effects model, Monte Carlo simulation, Mobility

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A Dissertation

Presented in Partial Fulfillment of Requirements for the

Degree of

Doctor of Philosophy

in

Educational Policy Studies

in

The College of Education & Human Development
Georgia State University

Atlanta, GA
2021

DEDICATION

This dissertation is dedicated to my wife, Jennifer Cappelli. Thank you for standing by me when I needed to talk, for taking on all of the responsibility with the kids while I was huddled in the shed for hours at a time writing, and for always being there when the going got rough. Your support was one of the few things that got me through to the end of this program. Also to my kids, Logan and Amelia Cappelli. The innocence of childhood, the laughter, and the time we spend togethers always provides me with all the happiness I can ask for in life.

I also dedicate this dissertation to my parents, Sandy and Joe Cappelli, and my sisters, Nicole Chaudhrey and Lauren Sullivan. One day, I'll make sure you all read this, instead of just telling me that you will. And lastly, to my late mother, Lynn Beaumier, who always stressed the importance of education, and always pushed me to do my best.

ACKNOWLEDGMENTS

I would be remiss to say I would have made it through this program without the support of many people.

A big thank you to my advisor and chair, Dr. Audrey Leroux, who has always pushed me to make my work the absolute best it could be. While I took coursework, she took care to introduce me to many potential areas for my dissertation research, she invited me to work with her on multiple manuscripts and academic presentations, and coached me through the long process of writing a dissertation that I can be proud of. Her feedback, coaching, and academic prowess have all contributed to my success, and I am grateful for the time I have spent learning from her. Thank you also to my committee members, who all contributed in a unique way to my journey. Thank you to Dr. Katherine Masyn, whose careful review, questions, and comments in all things survival analysis helped to make this dissertation methodologically sound. Thank you to Dr. Hongli Li, who as my assigned advisor when I entered this program, coached me through the potential directions I might take with my interests and skills, and guided me through the first couple of years in this program. And to Dr. Chris Oshima for masterfully introducing me to quantitative methods when I began my doctoral studies as Georgia State.

I owe another huge debt of gratitude to Dr. Meltem Alemdar, who not only served as a committee member, but also as my mentor and supervisor at Georgia Tech. I began working with Dr. Alemdar in 2011 in my first job out of graduate school, and her guidance has directed my professional life in ways I can’t begin to describe. Without her mentorship, I would not have even begun a PhD program, but she convinced me that I was capable and provided me with support throughout the entire process. Her continuous encouragement, positive thoughts, and unrelenting support helped me to complete my journey through this program.

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LIST OF ABBREVIATIONS

CC-DTSA	Cross-classified discrete-time survival analysis
CC-DTS model	Cross-classified discrete-time survival model
CCREM	Cross-classified random effects model
DTSA	Discrete-time survival analysis
DTS model	Discrete-time survival model
ML-DTSA	Multilevel discrete-time survival analysis
ML-DTS model	Multilevel discrete-time survival model
MM-DTSA	Multiple membership discrete-time survival analysis
MM-DTS model	Multiple membership discrete-time survival model
MMREM	Multiple membership random effects model
RPB	Relative Parameter Bias
RMSE	Root Mean Square Error

CHAPTER 1

INTRODUCTION

Background

In many fields within the social and behavioral sciences, it is common for researchers to ask questions regarding the timing of an event occurrence. For example, educational researchers may be interested in if and when student dropout occurs, and the factors that influence the timing and occurrence of dropout. Epidemiologists may be interested in the factors that contribute to the timing and occurrence of the first asthma attack among urban youth, or in the timing and occurrence of some environmental exposure following a natural disaster. In these types of research, it is often the case that data are collected during measurement occasions separated by specified periods of time, and therefore, data on an event is typically measured such that the researcher only knows that an event did or did not occur during the period of time defined by a gap between measurement occasions. Such data collection methods result in discrete-time data, also referred to as grouped-time data, and are typically analyzed using discrete-time survival analysis. While discrete-time survival methods were statistically formulated decades ago and extensively described by Allison (1982), it was not until Singer and Willett (1993) provided a tutorial on discrete-time survival analysis for applied researchers that use of the method became commonplace in the applied literature.

However, the discrete-time survival analysis described by Singer and Willett (1993) may not be appropriate in situations where the data are clustered, such that individuals are nested into some larger contextual space. For example, students can be nested into classrooms, patients can be nested in nurses, and individuals can be nested in clinics. In such cases, when lower-level units are clustered into some higher-level context, the lower-level units may no longer be assumed to be independent of their associated clusters; instead, their contextual space is likely to create an environment in which, for example, students clustered into the same school are more alike to each other than students clustered into a different school. The use of a conventional discrete-time survival analysis in the presence of clustered data structures leads to a violation of the assumption of independence of observations (Raudenbush & Bryk, 2002). Additionally, traditional discrete-time survival analysis carries an assumption of no unobserved heterogeneity, which is violated if it is known that individuals are clustered into higher-level units, and that the individuals in one cluster are more alike than individuals in another cluster. Such violations result in biased estimates of the baseline risk for event occurrence, and therefore, misplaced inferences (Barber et al., 2000). Therefore, an important extension of conventional discrete-time survival analysis is multilevel discrete-time survival analysis, adding a random effect to the model and accounting for the unobserved heterogeneity present due to clustering.

Multilevel discrete-time survival analysis represents an important contribution to survival analysis, combining the benefits of using discrete-time survival methods to understand event-history data within the multilevel modeling framework. In recent decades, such models are proving more common in the applied literature. For example, in educational research, Ma and Willms (1999) present one of the earliest empirical studies that integrate multilevel modeling techniques with discrete-time survival analysis, accounting for the clustering of students within schools to explore the factors that contribute to the timing and occurrence of student drop-out from advanced mathematics. Davoudzadeh et al. (2015) used a multilevel discrete-time survival analysis to examine the hazard of grade retention among students in kindergarten through eighth grade within the context of school-readiness predictors at both the student and school levels. Multilevel discrete-time survival analysis is also common in other behavioral science disciplines, such as sociology (e.g., Henry et al., 2004), social network analysis (e.g., de Nooy, 2011), and public health (e.g., Reardon et al., 2002). These studies represent just a small sample of the use of multilevel discrete-time survival methods in the applied literature, but illustrate the extensive use of this modeling approach throughout the social and behavioral sciences.

While each of these studies accounted for clustered data structures, they also assumed that the lower-level units were purely clustered into some higher-level unit. For example, students are members of one and only one school throughout the duration of study, or patients are members of one and only one hospital during the course of their treatment. However, in the social and behavioral sciences, applied researchers may not encounter such simple multilevel data structures. Instead, data often contain complexities that mirror the real world and result in an impure nesting of lower-level units into higher-level clusters. For example, in the case of educational research, student mobility has been shown to be quite common in the U.S., where about 12%-38.5% of students switched schools or moved between 2005 and 2010 (e.g., Ihrke & Faber, 2012; U.S. Government Accounting Office, 2010). This mobility of individuals across clusters can also be found in other social and behavioral science disciplines, such as public health, psychology, or criminology. For example, individual mobility may result in individuals who are residents of more than one city, patients who visit more than one hospital, or prisoners who are held in more than one jail. In datasets that contain mobility, the data structure can be said to be cross-classified. Alternatively, data containing mobility can also be thought of as a special case of a cross-classified data structure, termed a multiple membership data structure. In cases where cross-classified or multiple membership data structures exist, conventional multilevel modeling approaches are inappropriate. Indeed, the methodological literature is increasingly demonstrating the adverse effects of incorrect model specification in the presence of such complex data structures, and has shown that incorrectly modeling this complexity has a negative impact on parameter estimates (e.g., Cappelli et al., 2020; Luo & Kwok, 2009; Luo & Kwok, 2012; Leroux & Beretvas, 2018b; Leroux et al., 2020; Meyers & Beretvas, 2006). Therefore, in the conventional multilevel modeling framework, cross-classified random effects models (CCREMs) and multiple membership random effects models (MMREMs) have been developed to appropriately model hierarchical complexity.

Research Questions

As complex data structures are common across the social and behavioral sciences, methodological research that aims to examine the efficacy of the CCREM or the MMREM for appropriately modeling complex data structures has increased. Most commonly, methodological research using the CCREM or the MMREM has focused on their use for modeling continuous outcomes, such as academic achievement scores. However, some work has also examined the performance of the CCREM and MMREM with binary outcome data, and to a lesser extent, event-history outcome data.

Previous simulation studies that examine the performance of CCREMs and MMREMs with continuous outcomes have indicated that ignoring the mobility of individuals across clustering units negatively impacts parameter estimates, especially in regards to estimates of the coefficients for the cluster-level (e.g., school) covariates and their standard errors, as well as cluster-level variance component estimates (Cappelli et al., 2020; Chung & Beretvas, 2012; Leroux & Beretvas, 2018b; Leroux et al., 2020; Luo & Kwok, 2009, 2012; Meyers & Beretvas, 2006; Wolff Smith & Beretvas, 2014a, 2017). Vassallo et al., (2017) and Ren (2011) specifically examined the use of a CCREM with a binary outcome. Vassallo et al. (2017) only examined the intercept parameter and variance components, and similar to findings in the continuous-outcome literature, found that the fixed effect representing the intercept is unaffected by sample size, while higher sample sizes are necessary to estimate variance components without bias. Ren (2011) compared a Hierarchical Generalized Linear Model (HGLM) to a CCREM with a binary outcome, and similar to the continuous-outcome literature, found that inappropriately modeling a cross-classified data structure results in biased parameter estimates, especially for the cluster-level covariates, their standard errors, and estimates of the variance components. Methodological work in the measurement literature with complex multilevel data structures and longitudinal item response data has resulted in similar findings, indicating that misspecifying the model such that mobility is not correctly modeled does not greatly affect the fixed effect estimates, but does result in bias of the cluster-level variance component estimates (Choi & Wilson, 2016). While there has been little methodological work that has expanded upon these findings for event-history outcome data, work by Cafri and Fan (2018) and Elghafghuf et al. (2014) has suggested that continuous-time survival models that account for complex nesting perform better than models that ignore such structures. Only one methodological study has investigated the use of a discrete-time survival analysis in the presence of individual mobility across clusters. Lamote et al. (2013) applied both a cross-classified and a multiple membership discrete-time survival model to data with impure clustering due to student mobility. The authors found that the cross-classified discrete-time survival model and the multiple membership discrete-time survival model resulted in different parameter estimates, both in terms of the fixed effects and variance components, than the models that ignored or deleted mobile students from the dataset; however, they also found that the cross-classified discrete-time model better fit the data than all alternative models.

Given the wealth of research that suggests that using an ad hoc approach to ignore mobility across clusters negatively impacts model estimates, it is important that researchers are able to correctly model mobility in discrete-time survival models. Therefore, this dissertation aimed to address the following research questions: (1) What is the impact of ignoring a cross-classified data structure due to individual mobility in a discrete-time survival analysis and (2) How does the baseline hazard function, variability of the cluster random effect, mobility rate, and within- and between-cluster sample size impact the performance of a cross-classified discrete-time survival model?

Statement of Purpose

To address these research questions, this dissertation used a simulation study. The simulation study manipulated five conditions that may be encountered by applied researchers, including the within-cluster sample size, cluster sample size, variance at the cluster-level, Weibull scale parameter, and overall mobility rate. The simulation study used the parameter estimates obtained from the previous empirical and methodological literature to inform the generating parameter values. Relative parameter bias, root mean square error, and coverage of the 95% confidence intervals were used to evaluate the estimation of model parameters under the various manipulated conditions for a conditional single-level discrete-time survival model, a conditional purely clustered multilevel discrete-time survival model, and a conditional cross-classified discrete-time survival model.

This study provides an important contribution to the literature for the social and behavioral sciences. Multilevel discrete-time survival models are increasingly found in the literature, but only one prior study has accounted for impure nesting in discrete-time survival analysis, and no previous work has been conducted to explore how a discrete-time survival model performs in such circumstances. Therefore, this study was necessary to understand the effects of ignoring data that contains clustering and/or mobility for empirical researchers conducting a discrete-time survival analysis.

CHAPTER 2

REVIEW OF THE LITERATURE

In this chapter, survival analysis is presented. The discussion specifically focuses on the use of discrete-time survival analysis, with an emphasis on multilevel discrete-time survival analysis. Additionally, complex multilevel data structures are described and a review of the literature is presented for both cross-classified and multiple membership random effects modeling. Subsequent sections examine the confluence of these complex data structures and survival data, concluding with a presentation of cross-classified discrete-time survival modeling.

Introduction to Survival Analysis

In the social and behavioral sciences, researchers are often interested in knowing *if* an event occurs, and if so, *when* the event occurs. For example, educational researchers may be interested in the dynamics of teacher retention, such as the timing and occurrence of teachers leaving their profession, and the factors that contribute to the risk of leaving. In the behavioral sciences, a researcher may be interested in the timing and occurrence of the first drink of an alcoholic beverage in adolescence. In criminology, researchers might be interested in the hazard of recidivism among previously jailed individuals. In each of these examples, the research interest centers on whether and when events occur, as well as the factors that influence the timing of an event occurrence (Singer & Willett, 2003). Survival analysis refers to the general set of techniques that are used to model the timing of an event occurrence.

Survival analysis, also known as event history analysis or hazard analysis, was developed in response to an ongoing interest in studying life-history, specifically in understanding the factors that contribute to the occurrence and timing of mortality (Masyn, 2014). Traditionally, researchers utilized conventional logistic regression techniques to model event occurrence, but such models do not provide information regarding the timing of events. Furthermore, two methodological challenges arise when modeling event history using traditional logistic regression methods. First, event data are typically replete with missing data (Masyn, 2014; Singer & Willett, 2003). In studies of event history, missing data occurs for a number of reasons, some of which are typical of longitudinal studies, such as participant drop-out or loss to follow-up. More specific to event history data, some participants simply may not experience the event during the study. A number of ad hoc approaches have historically been used to resolve missing data challenges, for example, by restricting data collection to include only those participants who have experienced the event, retrospectively removing participants from the dataset who have not experienced the event, imputing unknown event times (e.g., assigning "event" to all participants at the end of the study), or dichotomizing the outcome such that the event either occurred or did not occur by a specific point in time (Allison, 1982; Singer & Willett, 1993, 2003). However, such ad hoc strategies result in a loss of important information, a distortion of event times, and ultimately, substantial biases and misplaced inferences (Allison, 1982). The second methodological challenge is that researchers may often be interested in the use of time-varying covariates, or covariates that change during each measurement occasion, to explain the timing and occurrence of the event under study (Allison, 1982). Traditional linear regression techniques are not able to handle explanatory variables that change during the course of a study, and therefore, create unrealistic restrictions for model specification.

Given these methodological challenges, statisticians developed modeling techniques that are better able to model event history data. Continuous-time survival analysis was developed to alleviate these challenges, where it is assumed that the timing of an event is known exactly and can occur at any point in time. In the development of continuous-time survival methods, numerous approaches for parameter estimation were developed that impose strict assumptions often untenable in applied research (Masyn, 2003). In his seminal paper, Cox (1972) alleviated such issues by proposing a model that utilizes a partial likelihood estimation method, where the covariates in the model are estimated without placing strict distributional restrictions on the part of the model that estimates the probability of event occurrence when all predictors equal zero, otherwise referred to as the part of the model that estimates the baseline hazard (Allison, 1982). Cox's model has been transformative in event history analysis, and has readily been extended to accommodate single and repeated event histories, time-varying covariates, and also non-proportionality, broadening the modeling potential for survival data (Allison, 1982; Singer & Willett, 2003).

While influential, Cox's model treats time as continuous, which is often not appropriate for research in the social and behavioral sciences. A continuous-time model is useful for situations in which the event occurrence is measured precisely, such that few individuals will have the same event time (Allison, 1982). In contrast, in the social and behavioral sciences, longitudinal data are typically collected at measurement occasions separated by specified periods of time, and therefore, data on an event is typically measured such that the researcher only knows that an event did or did not occur during the period of time defined by a gap between measurement occasions. For example, a behavioral scientist examining the timing and occurrence of substance abuse relapse might collect data at the end of each month, on March 31 and April 31. Some participants might relapse on April 2, while others relapse on April 30, but the researcher will only know that relapse occurred sometime between March 31 and April 31 when data are collected on the April 31 measurement occasion. In other words, although study participants may experience the event at many different times, the event history data are recorded such that the event occurs for all participants at a single point in time, which here is recorded as April 31. The result is that many participants in the study are documented as experiencing the event at the same time, which is referred to as an overlapping event time or tied event histories. Such data, where a large proportion of individuals in the population are recorded as having experienced the event at the same time, is referred to as discrete-time data. As continuous-time survival methods assume that event occurrence happens at a unique, precise point in time that differs for each individual, the use of such methods for discrete-time data are incorrect (Ducrocq, 1999). As such, discrete-time survival analysis is often preferred in the social and behavioral sciences due to an inability to document precise event timing.

The following sections describe discrete-time survival analysis in the context of the social and behavioral sciences. The methodological features of the models are presented, followed by a description of a common data format used to conduct a discrete-time survival analysis and the parameterization of the model. The chapter then discusses the extension of survival analysis to the multilevel modeling framework, including situations that assume pure clustering of data, as well as more complex nesting of individuals within clusters.

Methodological Features of Discrete-Time Survival Models

While longitudinal studies can accommodate numerous types of outcome variables, the interest in studies of event history are specifically in event occurrence outcome data. There are three common methodological features necessary for any survival analysis, including the identification of a target event, the beginning of time, and a scale for time (Masyn, 2009; Singer & Willett, 2003). In order to conduct a survival analysis, an event occurrence must be identified that clearly defines the transition of an individual from one state of being to another (Singer & Willett, 2003). For example, non-smoker to smoker or high school attendee to high school dropout. Those who are at risk of experiencing the identified event during each time period are termed the risk set (Masyn, 2009). Second, the beginning of time must be identified, or the time that all individuals in the population under study become eligible to experience the event (Singer & Willett, 2003). For example, in a study of teacher retention, the beginning of employment might represent the beginning of time for a cohort of teachers, because they cannot leave teaching before the point at which they were employed as teachers. Lastly, there must be a clear measure for how time is recorded, which can consist of either actual event times or measured event times (Masyn, 2009). In some studies, time is recorded continuously, such that the researcher knows the precise moment in time that the event occurred. In other studies, the event time may be recorded discretely, such that it is only known that the event occurred between measurement occasions. For example, it is common in studies of student grade retention that time is recorded by school year because it is only known that a student is held back following the end of the school year.

There are three types of discrete-time survival data, which occur either by study design or due to the nature of the event of interest (Safarkhani & Moerbeek, 2013). First, some events may be of a continuous-time nature but are recorded in discrete time. For example, in their study of risk for early initiation of sex among American Indian youths, Mitchell et al. (2007) discretized an event, sexual initiation, that has an underlying continuous nature. In other words, sexual initiation can occur at any precise point in time, but for the purposes of this study, was discretized. The authors argued that the timing of sexual initiation is typically measured in a much more discrete metric, generally by age in years as opposed to the precise moment of the event, and therefore, a discrete-time model was more appropriate for the data. Second, some events can only occur at discrete intervals of time. For example, Davoudzadeh et al. (2015) used a multilevel discrete-time survival analysis to examine when grade retention was most likely, as well as whether school readiness predictors influenced grade retention at the child- and school-levels. Grade retention typically only occurs once per academic year, and therefore, the event itself is of a discrete-time nature. Lastly, in some cases, data collection methods may require that the researcher provide participants with large periods of time to indicate event occurrence. This is especially true in retrospective studies where research subjects are asked to recall the timing of an event that happened in the past (Safarkhani & Moerbeek, 2013). For example, it is unlikely that a participant will be able to recall the exact day that they stopped smoking if they are asked about their smoking history at a later point in time. In such cases, the researcher may choose to ask participants to select a range of time that coincides with when they stopped smoking, such as 1-2 years ago, 3-4 years ago, etc. In each of these cases, even when the underlying nature of the event may be continuous, the event is recorded in discrete intervals. Therefore, this necessitates the use of discrete-time survival analysis.

Censoring

As previously described, one of the primary challenges of survival data, like any longitudinal study, is related to the amount of missing data. In survival jargon, missing data are most broadly referred to as “censored” data, and refers to any individual in the sample with an unknown event time (Singer & Willett, 2003). Censored data can be either noninformative or informative and is most commonly distinguished as being either left- or right-censored (Singer & Willett, 2003).

The distinction between noninformative and informative censoring is of vital importance in survival analyses, as this distinction has critical implications for the validity of the inferences made from the analysis. Noninformative censoring describes the situation in which the censored data are independent of both the risk of event occurrence and actual event occurrence (Allison, 1982; Singer & Willett, 1993, 2003). Censoring that occurs due to the study design, where event occurrence is missing simply because data collection has ended at the conclusion of the study and the event of interest did not occur for a portion of the sample population is clearly noninformative censoring. However, noninformative censoring can also occur when there is a loss to follow-up due to reasons unrelated to the study. When censoring is noninformative, it corresponds most closely to the missing at random (MAR) assumption (Masyn, 2009). In studies of event-history, this means that given the measured covariates and the participant's responses during past measurement occasions, the chance that the participant misses the current assessment does not depend on the timing of the first occurrence of the event (Bacik et al., 1998). In contrast, censoring can also be informative. Informative censoring occurs when individuals are lost to follow-up, but have experienced the event or are likely to experience the event in the future (Singer & Willett, 2003). In such cases, the censored event is related to the study interest, so the non-censored individuals are systematically different from censored individuals, which can lead to false inferences. Therefore, all survival models assume that censoring is noninformative, as any informative censoring will produce biased parameter estimates (Singer & Willett, 2003).

Additionally, censoring can be categorized by how it occurs in the data, most commonly referred to as left- or right-censoring. In left-censoring, the event time is unknown because it occurred prior to the study period (Singer & Willett, 2003). If the beginning of time is incorrectly defined for a study of event-history, then some members of the population will have experienced the event before the study commenced. In other words, the study participants experienced the event sometime between the true beginning of time and the start of data collection, and the event time is therefore left-censored. In contrast, right censoring occurs when the event time is unknown because the event occurrence is not observed and occurs sometime after the final known observation point (Masyn, 2014; Singer & Willett, 2003). In the case of right-censoring, the event time is missing either by study design (i.e., the study ended prior to the event occurrence) or by loss to follow-up. As previously explained, it is vitally important that right-censored event times are noninformative, as informative censoring will lead to biased inferences.

Person-Period Data Format

As with any statistical model, the first step in model building is to properly format the data. For many discrete-time survival analyses, the data are formatted in the person-period format. The person-period format is analogous to "long-format" data used for growth curve modeling in the multilevel modeling framework, where data are entered such that each row represents a different measurement occasion and therefore, each individual in the dataset will have multiple rows of data. For example, in a survival analysis, if the risk set consists of three individuals who are each measured on five occasions for which they are considered "at risk," there will be 15 rows of data in total. In other words, for each of the three individuals, there are five rows of data representing each measurement occasion for which they remain at risk. This is in contrast to "wide" format data, which is most typically seen in cross-sectional studies or modeling within the structural equation modeling framework, where each individual is on a single row, such that all information related to that individual is spread across multiple columns.

An important distinction of the person-period dataset used for survival analysis from other statistical modeling approaches that use long-format data is that the number of rows for each individual is determined by their status as being "at risk" for the event to occur. In single-event discrete-time survival analysis, this means that an individuals' data are conditional on whether or not they have experienced the event. If an individual has experienced the event, that person is no longer at risk for the event, and therefore will not have any further rows of data for ensuing measurement occasions, or discrete time periods. Table 1 provides an example of data in the person-period format, where the column "Time" represents the discrete time period, *t*, and event, e_{ti}, represents whether an individual, *i*, in the risk set has experienced the event (e_{ti} = 1) or has not experienced the event (e_{ti} = 0) during time period, *t* (Singer & Willett, 2003). In the example provided here, the study took place over five discrete time periods. The columns $D1_{ti}$ through $D5_{ti}$ represent dummy variables for time, which are coded as 1 for the time period it represents and 0 otherwise. For example, in Table 1, data were collected on Individual 100 during each of the five discrete time periods, *t*, of study. Event occurrence for Individual 100 is coded as 0 for all time periods, indicating that this individual did not experience the event during any time period, and is therefore right-censored. This is in contrast to Persons 110 and 120, who each experienced the event during the study in time periods 2 and 3, respectively. Therefore, they have no data following event occurrence. In other words, once the individuals experienced the event, data were no longer collected because they were not considered at risk for the event in future time periods, and therefore, their data were limited to the number of rows equal to the number of periods that it took for them to experience the event.

Importantly, the person-period dataset provides information about an individual's event processes even if the exact event times are unknown, as is represented by Individual 130 (Masyn, 2009). By including these right-censored individuals in the dataset, their information can still be included in the model. This represents an important advantage in discrete-time survival modeling as opposed to using other modeling approaches, where data for right-censored individuals are excluded from the model, resulting in biased estimates and incorrect inferences (Allison, 1982).

Table 1

Person-Period Event Data

Individual i	Time t	Event e_{ti}	Dummy 1 $D1_{ti}$	Dummy 2 $D2_{ti}$	Dummy 3 $D3_{ti}$	Dummy 4 $D4_{ti}$	Dummy 5 $D5_{ti}$
100	1	0	1	0	0	0	0
100	2	0	0	1	0	0	0
100	3	0	0	0	1	0	0
100	4	0	0	0	0	1	0
100	5	0	0	0	0	0	1
110	1	0	1	0	0	0	0
110	2	1	0	1	0	0	0
120	1	0	1	0	0	0	0
120	2	0	0	1	0	0	0
120	3	1	0	0	1	0	0
130	1	0	1	0	0	0	0
130	2	0	0	1	0	0	0
130	3	0	0	0	1	0	0

The Hazard and Survival Probabilities

The survival function and the hazard function are two of the basic functions for any discrete-time survival analysis, as they describe the patterns of event occurrence among the population. Using notation from Singer and Willet (2003), the hazard probability (h_{ti}) can be expressed as:

$$h_{ti} = \Pr[T_i = t \mid T_i \geq t], \qquad (1)$$

where T_i represents the time period, t, when individual *i* experiences the event (e_{ti} = 1). For example, when an individual experiences the event in time period 2, T_i = 2. Therefore, Equation 1 represents the hazard probability, which as a conditional probability states that an individual, *i*, will experience the event in time period *t*, given that the individual did not experience the event in any previous time period. As this probability contains information regarding the timing of event occurrence for all individuals, including those who are right-censored, it is the primary quantity of interest in survival analysis (Masyn, 2014; Singer & Willett, 2003). The set of hazard probabilities, one for each time period, is known as the hazard function (Masyn, 2014).

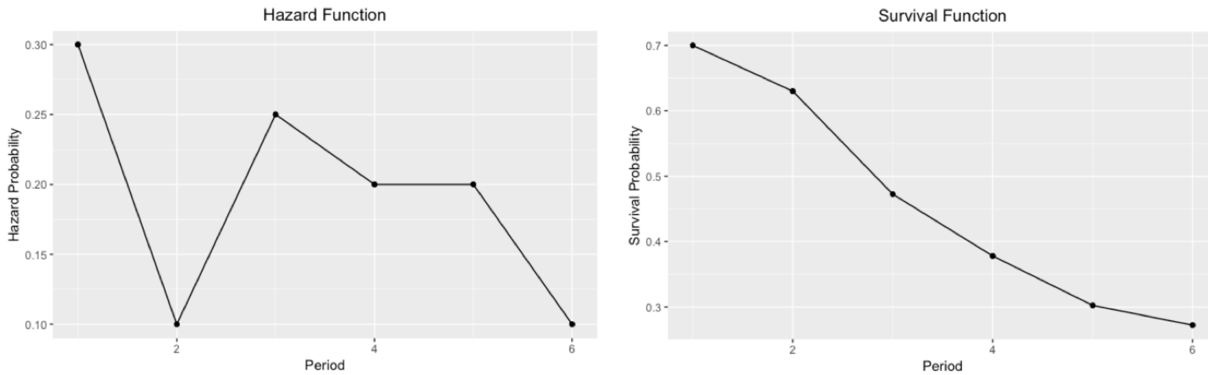
Unlike the hazard probability, the survival probability does not provide information regarding the unique risk of event occurrence in each time period. Rather, the survival probability is cumulative, and represents the proportion of the population that has not experienced the event by a given time period (Singer & Willett, 2003). In other words, it implies that an individual remains event free, or survives beyond a time period, such that the time period that an event occurs for an individual, T_i, is greater than time period t. Therefore, the survival probability, s_{ti}, is the probability that an individual, i, will remain event free beyond a time period, *t,* and is given by,

$$s_{ti} = \Pr[T_i > t]. \tag{2}$$

As a set, one for each discrete-time period, the survival probabilities are known as the survival function. Prior to estimating a discrete-time survival model, it is often useful to plot the sample hazard probabilities and survival probabilities to descriptively examine the data, as represented by Figure 1 (Singer & Willett, 2003). Plotting the hazard probabilities provides the researcher with useful information, including the ability to identify periods of high risk for event occurrence and providing information regarding the pattern of risk over time (Singer & Willett, 2003). For example, in Figure 1, it is apparent that subjects are at especially high risk for event occurrence during discrete time period 1 as compared to periods during the rest of the study. Additionally, it appears that the risk of event occurrence, overall, decreases with time.

Figure 1

Sample Hazard and Survival Functions



Although they represent different aspects of event history, the hazard and survival functions are related (Singer & Willett, 2003). The survival function is inversely related to the hazard function, such that as hazard increases, survival decreases. In other words, if a large proportion of the risk set experiences the event in a given discrete time period, the rate of survival will decrease sharply during that time period. Conversely, if the risk of event occurrence in a given discrete time period is low such that a small number of individuals experience the event, the survivor function will decrease less rapidly. When no events occur in a time period, the survival function remains level during that time. As opposed to the hazard function, the survival function is a cumulative representation of remaining event free. Therefore, it can never increase during the course of a study; rather, it will always remain stable or decrease (Singer & Willett, 2003). Figure 1 illustrates the relationship between the hazard function and the survival function. Note, for example, that between Periods 1 and 2, as the hazard probability decreases significantly from .3 to .1, the survival function has only a slight decrease, reflecting the high survival rates among the population when hazard is low. In contrast, there is a large increase in hazard between Periods 2 and 3. During the same time periods, the survival function decreases rapidly, reflecting the low survival among the population when hazard is high. As the study proceeds, the survival probabilities continually get lower as more individuals experience the event.

Note that the hazard probabilities provide useful information regarding the unique risk of event occurrence during each discrete time period among those remaining in the risk set; therefore, it provides a summary of both the timing and occurrence of events (Masyn, 2009).

Discrete-Time Survival Analysis

In discrete-time survival analysis, a researcher is interested in the if and when of event occurrence. As the outcome can only take on one of two values, $e_{ti} = 0$ or 1, it has a binomial distribution. Therefore, the outcome can be considered to represent *n* trials of 1 and is a special case of the binomial distribution called the Bernoulli distribution. Given that the hazard probabilities, as represented by Equation 1, correspond to the probability of event occurrence for each time period, which are an observed binary outcome, the discrete-time survival model is easily specified as a conventional logistic regression (Masyn, 2014). As such, an unconditional discrete-time survival model can be formulated for 5 total time periods as:

$$\log\left(\frac{h_{ti}}{1-h_{ti}}\right) = \alpha_1 D1_{ti} + \alpha_2 D2_{ti} + \alpha_3 D3_{ti} + \alpha_4 D4_{ti} + \alpha_5 D5_{ti}, \tag{3}$$

where $\log\left(\frac{h_{ti}}{1-h_{ti}}\right)$ is the log of the odds (i.e., logit) of the hazard probability for individual *i* in time period *t*, and $D1_{ti}$ through $D5_{ti}$ are dummy variables for individual *i* in time period *t* that are coded as one for the time period it represents and 0 otherwise. α_1 through α_5 are the estimated coefficients for the log hazard odds at each discrete-time period, otherwise known as the intercepts, which as a set represent the estimated logit hazard function.

Note that the hazard is preceded by a link function, here the logit link, which is a transformation of the expected outcome and links the predictors to the outcome. Although the logit link provides useful transformations of the outcome and predictor variables and is the most commonly used link function in the social and behavioral sciences, the variables are most meaningfully interpreted in the form of probabilities or odds ratios (Masyn, 2003; Singer & Willett, 2003). Given that the interest in discrete-time survival analysis is the estimated hazard probabilities for each discrete-time period, once the model parameters are estimated in the logit scale, Equation 3 can be transformed for interpretation as the hazard probability using the following:

$$\hat{h}_{ti} = \frac{1}{1+ e^{-[\hat{\alpha}_1 D1_{ti} + \hat{\alpha}_2 D2_{ti} + \hat{\alpha}_3 D3_{ti} + \hat{\alpha}_4 D4_{ti} + \hat{\alpha}_5 D5_{ti}]}}. \quad (4)$$

A discrete-time survival model can also be specified with the inclusion of covariates, which can be either time-varying or time-invariant. A conditional discrete-time survival model with one time-invariant predictor, X_i, at the individual level, such as gender, can be formulated as:

$$\log\left(\frac{h_{ti}}{1-h_{ti}}\right) = [\alpha_1 D1_{ti} + \alpha_2 D2_{ti} + \alpha_3 D3_{ti} + \alpha_4 D4_{ti} + \alpha_5 D5_{ti}] + \beta_1 X_i, \quad (5)$$

where α_1 through α_5 are the intercept coefficients for their respective time periods and represent the estimated log hazard odds of event occurrence when the predictor is equal to zero. The brackets, [ ], serve to separate the intercept parameters from the predictors entered into the model. The brackets contain the intercept parameters, which as a set represent the baseline hazard function (i.e., the value of logit hazard when the predictor is equal to 0), whereas the parameters on the right that are not inside brackets represent the predictors. Additionally, the covariate's effect on the likelihood of event occurrence is often described in terms of the hazard odds ratio (Petras et al., 2011), which represents the ratio of the odds of event occurrence for two groups. The fitted odds ratio is found by antilogging the coefficient for the predictor, X_i, such that,

$$Estimated\ odds\ ratio = e^{\hat{\beta}_1}. \quad (6)$$

Therefore, the coefficient β_1 represents the log hazard odds ratio (log hOR) of event occurrence per one-unit difference in its predictor, X_i.

Given that the discrete-time survival model is specified as a generalized linear model, they employ many of the same assumptions. For example, the model carries the linearity additivity assumption, which states that the effect of a predictor does not depend on the value of another predictor in the model and that the effect is linear. Importantly, the model also carries the assumption of no unobserved heterogeneity, which states that there is no underlying variability in individuals' baseline risk for an event that is not measured by the covariates in the model. In other words, the variation in the hazard profiles across individuals in the population is modeled as depending only on the observed variation in the covariates entered into the model (Singer & Willett, 1993, 2003). Lastly, note that in Equation 5, the covariate X_i is modeled such that its effect on the estimate of the logit hazard remains constant in each time period. This implies a common assumption in survival analysis, known as the proportionality assumption. In other words, the model is a proportional model because the change in the logit hazard per unit change in the covariate is assumed to be identical in each discrete time period. However, given that any covariate, time-variant and time-invariant alike, can result in time-varying effects, it may be necessary to specify a model that relaxes this assumption (Singer & Willett, 2003). To do so, Equation 5 can be reformulated such that,

$$\log\left(\frac{h_{ti}}{1-h_{ti}}\right) = [\alpha_1 D1_{ti} + \alpha_2 D2_{ti} + \alpha_3 D3_{ti} + \alpha_4 D4_{ti} + \alpha_5 D5_{ti}]$$

$$+\beta_1 X_i D1_{ti} + \beta_2 X_i D2_{ti} + \beta_3 X_i D3_{ti} + \beta_4 X_i D4_{ti} + \beta_5 X_i D5_{ti}, \quad (7)$$

where the terms $\beta_1 X_i$ from Equation 5 is replaced with the terms $\beta_1 X_i D1_{ti}$ through $\beta_5 X_i D5_{ti}$, allowing for a different change in the logit of the hazard probability in each discrete-time period due to the covariate, X_i. Given that the predictor is no longer assumed to result in the same change in the intercept at each period, Equation 7 relaxes the proportionality assumption, and is a nonproportional model.

As is typical of a conventional logistic regression, the discrete-time survival models presented so far additionally assume that observations, or individuals, are independent of each other. However, it is more likely that individuals who are in the same contextual space are more alike to each other, or behave in a similar way, than individuals who are in different contextual spaces; therefore, it is necessary to account for such clustering using a multilevel model.

Multilevel Discrete-Time Survival Analysis

Multilevel discrete-time survival (ML-DTS) models have become common in the applied social and behavioral sciences literature. For example, in educational research, it may be necessary to use a multilevel discrete-time survival analysis (ML-DTSA) to account for the clustering of students into schools when the research interest is in the timing of an event occurrence (for applied examples, Anderson, Howland, & McCoach, 2015; Davoudzadeh et al., 2015; Ma & Willms, 1999; Petras et al., 2011). ML-DTS models are also common in other behavioral science disciplines, such as sociology (e.g., Henry et al., 2003), social network analysis (e.g., de Nooy, 2011), and public health (e.g., Reardon et al., 2002). Just as the discrete-time survival models presented in Equations 3 and 5 are specified as a logistic regression model, a ML-DTSA can be estimated in the hierarchical generalized linear modeling (HGLM) framework. Therefore, across each of these applied studies, the use of a traditional discrete-time survival model that ignores clustering, as presented in Equations 3 and 5, can lead to a violation of the assumption of independence of observations and result in biased estimates of the standard errors, likely resulting in more frequent Type I errors and therefore misplaced inferences (Moerbeek, 2004; Raudenbush & Bryk, 2002; Steele, 2008; Steenbergen & Jones, 2002).

However, an important difference between a traditional multilevel model and a ML-DTS model is the additional assumption of no unobserved heterogeneity implicit in a conventional discrete-time survival analysis (DTSA). Importantly, one source of unobserved heterogeneity in DTSA may result from the clustering of data. For example, in the structural equation modeling framework, some methodological studies have specified an outcome of a discrete-time survival model as a latent continuous variable, and with the addition of a random effect, have examined the effects of ignoring unobserved heterogeneity in model estimates (e.g., Baker & Melino, 2000; Kang et al., 2015; Nicoletti & Rondinelli, 2006). In each of these studies, results suggest that ignoring unobserved heterogeneity by excluding a random effect from the model results in biased estimates of the hazard function. Masyn (2003), Muthén and Masyn (2005), and Moerbeek (2014) have similarly explored this issue using discrete-time survival mixture modeling, using latent classes to account for unobserved heterogeneity in DTSA.

Other studies have examined clustering beyond the individual level, where individuals are clustered into some other higher-level context. For example, if it is known that students are clustered into schools, unobserved heterogeneity may be introduced because it is likely that the students in one school are more alike to each other than they are to students in another school. Given the introduction of unobserved heterogeneity due to clustering, the consequences of ignoring a level of nesting differ in a DTSA as compared to a conventional logistic regression. Specifically, while ignoring a level of nesting will likely result in an underestimation of the standard errors, it is also expected that bias will be introduced into the point estimates of the fixed effects that represent the hazard function in a DTSA. In other words, the baseline logit hazard probability estimated using a traditional discrete-time survival model will represent the average logit hazard of students calculated over all schools without accounting for between-school differences, and is likely to result in an underestimation of the baseline hazard probability (Barber et al., 2000; Steele, 2003; Vaupel et al., 1979). Therefore, an important extension of a single-level discrete-time survival model is a ML-DTS model, adding a random effect to the clustering-level and controlling for one likely source of unobserved heterogeneity present due to the nested data structure.

A conventional ML-DTS model assumes purely clustered data. For data to be considered purely clustered, all lower-level units must be clustered within a single higher-level unit (Raudenbush & Bryk, 2002). The following sections present unconditional and conditional multilevel discrete-time survival models, and are followed by extensions of this model when presented with more complex data structures.

Unconditional Multilevel Discrete-Time Survival Models

As with any multilevel model, a multilevel discrete-time survival model can be specified where there are no covariates included in the model. An unconditional ML-DTS model can be expressed for 5 time periods as:

$$\log\left(\frac{h_{tij}}{1-h_{tij}}\right) = [\alpha_1 D1_{tij} + \alpha_2 D2_{tij} + \alpha_3 D3_{tij} + \alpha_4 D4_{tij} + \alpha_5 D5_{tij}] + u_j, \qquad (8)$$

where $\log\left(\frac{h_{tij}}{1-h_{tij}}\right)$ represents the logit of the hazard probability for individual *i* in cluster *j* during time period *t*. $D1_{tij}$ through $D5_{tij}$ are dummy variables for individual *i* in cluster *j* that are coded as 1 for the time period it represents and 0 for all other time periods. α_1 through α_5 are the corresponding intercept parameters across all level-1 and level-2 units during the respective discrete-time period. The random effect, u_j, represents the random variation in level-2 clusters across all discrete-time periods, or in other words, the effect of clustering, which is assumed to be normally distributed with a mean of 0 and variance, σ_u^2. For example, if students are clustered into schools, σ_u^2 represents the variation in the student outcome between-schools across all discrete-time periods. Note that although this model includes a single overall random effect, it is also possible to instead include random effects for the coefficient representing each discrete-time period, α_1 through α_5, which would be interpreted as the variation in logit hazard between-clusters for the respective time period.

Conditional Multilevel Discrete-Time Survival Models

A conditional ML-DTS model can also be specified by including predictors at one or both levels of the model. For example, a researcher may hypothesize that an individual-level characteristic, X_{ij}, is related to the outcome and that a cluster-level characteristic, Z_j, may explain some of the variability in the outcome. A conditional model can be expressed as,

$$\log\left(\frac{h_{tij}}{1-h_{tij}}\right) = \left[\alpha_1 D1_{tij} + \alpha_2 D2_{tij} + \alpha_3 D3_{tij} + \alpha_4 D4_{tij} + \alpha_5 D5_{tij}\right] + \beta_1 X_{ij} + \beta_2 Z_j + u_j, \quad (9)$$

where α_1 through α_5 are the intercept parameters for all individuals across clusters when the predictors are equal to 0. Together, α_1 through α_5 represent the baseline logit hazard function. β_1 represents the log hOR of event occurrence across clusters and across all discrete-time periods per unit change in X_{ij} controlling for Z_j. β_2 represents the average log hOR of event occurrence per unit change in the level-2 covariate, Z_j, controlling for X_{ij}. Note that as a proportional model, the effect of the covariates on the logit of the hazard probability is constant across all time periods. Additionally, the effect of the level-1 covariate is modeled as fixed, but could easily be modeled as random across clusters.

Methodological Research

Multilevel discrete-time survival models were developed to account for both the large number of ties resulting from grouped-time data and the effect of clustering on data analysis. Goldstein (1995) first theoretically described the integration of multilevel models with event history data. Hedeker et al. (2000) derived a random-effects grouped-time survival analysis model to account for the effects of clustering in time-to-event data. The authors derive their model where survival time is represented as both an ordered outcome (resulting in a model that is comparable to the continuous-time Cox proportional hazards model) and as a set of dichotomous predictors. Similarly, Barber et al. (2000) developed and demonstrated the use of a discrete-time multilevel hazard model, extending previous work by demonstrating how software programs capable of using maximum-likelihood estimation for HGLMs can be used to conduct a multilevel discrete-time survival analysis that incorporates time-varying covariates for two-level models. Steele (2003) extended single-level discrete time survival mixture models to clustered data by specifying a multilevel discrete-time mixture model. As opposed to previously presented multilevel discrete-time hazard models, the integration of a multilevel discrete-time survival model with mixture modeling allows for the effects of an unobserved variable at the clustering level on the probability of event occurrence at the lower-level and on the timing of event-occurrence for the at-risk population during each discrete time period. Stemming from the models proposed in this work, the methodological literature concerning discrete-time survival modeling was subsequently extended to further assess the use of such models.

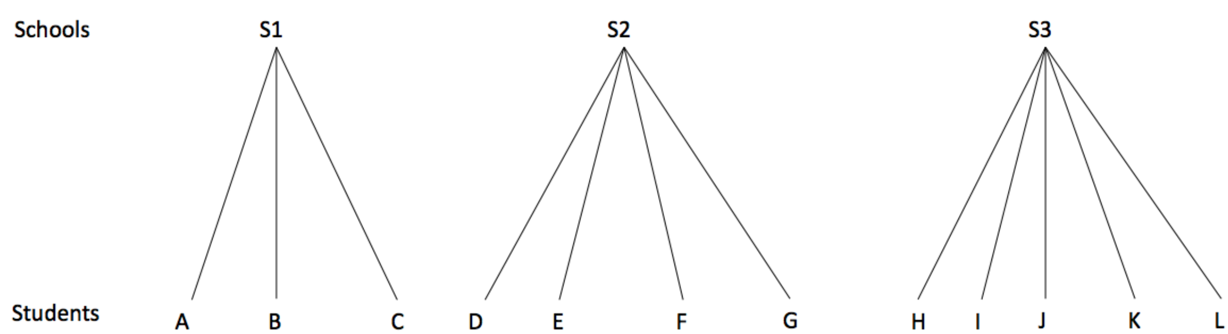
Moerbeek (2012) explored the performance of a model that incorporates a random effect at the cluster level, conducting a simulation within the context of a cluster randomized trial where families were nested within caseworkers. Here, the random effect in the ML-DTSA was placed at the clustering level to account for variability in hazard due to the clustering of families within caseworkers. The simulation varied four factors, including the number of clusters (30, 50, and 100), the within cluster sample size (5, 30, and 50), variance at the cluster level (0.25, 0.5, and 1), and survival pattern (increasing, decreasing, and constant). For all patterns, survival in the control group at the end of the study was 50%. The coefficient for the cluster-level predictor, here representing a treatment effect, was fixed to .5 on the logit scale, and 5 time periods were used for all conditions. The simulation results indicated that, on average, there was no bias associated with the fixed effect estimates or their standard errors for any of the 81 combinations of simulation conditions. However, on average, more severe negative bias was observed for the variance component estimates for conditions where there were 30 clusters with a within-cluster sample size of 5.

Impure Nesting in Multilevel Discrete-Time Survival Models

All of the studies utilizing a ML-DTSA described so far have assumed purely clustered data. In such cases, the use of an ML-DTS model accounts for the dependency that exists within the nested data structure by separating out the effects at each of the nested levels (Fielding & Goldstein, 2006). Such a pure hierarchy, where level-1 units are nested into level-2 clusters, can be depicted using a network diagram. For example, Figure 2 is a network diagram depicting a two-level purely clustered data structure where students (level-1) are nested in schools (level-2).

Figure 2

A Two-Level Pure Hierarchy Depicted as a Network Graph



However, in the social and behavioral sciences, applied researchers rarely encounter such simple multilevel data structures. Instead, data often contain complexities that mirror the real world and result in impure nesting of level-1 units into higher-level clusters.

There are many types of situations that result in multilevel data that are not purely nested. For example, one commonly referenced scenario in educational research is when students are nested within neighborhoods and within schools. If neighborhoods were nested within schools such that students within one neighborhood went to one and only one school, the data are purely clustered and can be analyzed using a conventional three-level hierarchical linear model (Raudenbush, 1993). However, in reality, it is more likely that one school consists of students from multiple neighborhoods, and a neighborhood will contain students who go to multiple schools (Raudenbush, 1993). Instead, students (level-1) are said to be cross-classified by neighborhoods (Factor A, level-2) and schools (Factor B, level-2) (Fielding & Goldstein, 2006; Meyers & Beretvas, 2006).

In educational research, student mobility also results in complex data structures. Student mobility is common in the U.S., where about 12%-38.5% of students switched schools or moved between 2005 and 2010 (e.g., Ihrke & Faber, 2012; U.S. Government Accounting Office, 2010). As such, it is often the case that large datasets have high levels of student mobility. For example, in their analysis of student drop-out between 7th and 12th grade using the Flemish 'LOSO'-project (Van Damme et al., 2002), Lamote et al. (2013) found that 27.6% of students moved schools at least one time during the course of the study.

Indeed, previous methodological studies using conventional multilevel models have demonstrated the adverse effects of incorrect model specification in the presence of such complex data structures, and show that incorrectly modeling this complexity can have a negative impact on estimates of the standard errors for the fixed effects and variance component estimates (e.g., Cappelli et al., 2020; Chung & Beretvas, 2012; Leroux & Beretvas, 2018b; Leroux et al., 2020; Luo & Kwok, 2009, 2012; Meyers & Beretvas, 2006). Additionally, within the context of discrete-time survival analysis, just as ignoring a level of clustering tends to result in unobserved heterogeneity (Barber et al., 2000; Steele, 2003), such complex data structures may also result in another source of unobserved heterogeneity. Therefore, when mobility is ignored and omitted from the model, a possible outcome is that there will be variation in the hazard function that remains unexplained due to the resulting unobserved heterogeneity; however, no prior study has explicitly examined this. As such, in contrast to conventional multilevel models that ignore complex data structures, ignoring individual mobility across clusters in a ML-DTSA may also introduce bias into the point estimates of the fixed effects representing the hazard function. It should be expected that as the data structure becomes more complex (i.e., student mobility increases), the observed bias in the parameters representing the hazard function would become more severe.

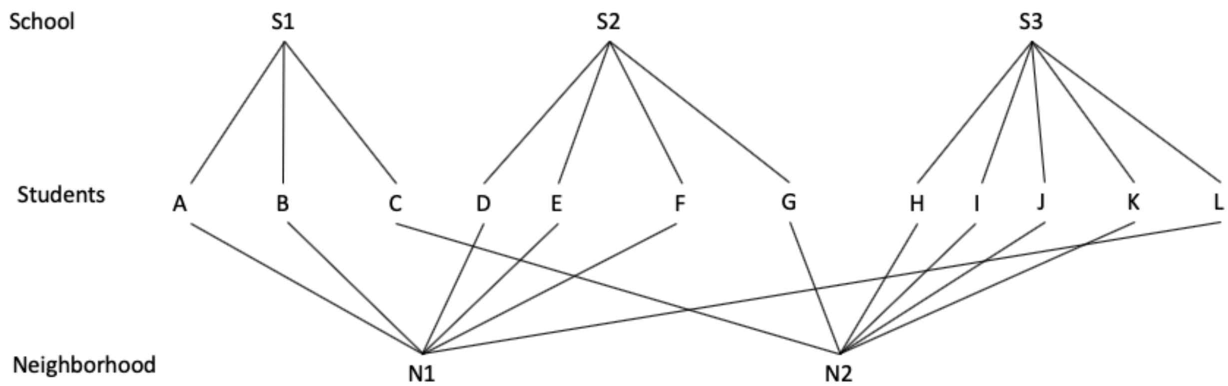
Given the negative effects on parameter estimates when such data structures are not appropriately modeled, cross-classified random effects models (CCREMs) and multiple membership random effects models (MMREMs) have been developed and can further be extended for use in a ML-DTSA.

Cross-Classified Random Effects Modeling

When higher-level units are not purely clustered within one another, such as the previous example of students cross-classified by both neighborhoods and schools, the interest may be in assessing the effect of both higher-level clusters on the outcome of interest. Figure 3 represents such a cross-classification.

Figure 3

A Cross-Classified Network Diagram



Note here that students A and C both attend School 1, but live in different neighborhoods. Therefore, students are nested in a cross-classification of neighborhoods and schools, as represented by the crossed lines in the network diagram. When data are cross-classified, the traditional multilevel modeling methods previously presented are insufficient. In fact, previous research has found that incorrectly specifying a multilevel model in the presence of cross-classified data may result in bias in the variance component estimates and in the standard error estimates of the fixed effects (Luo & Kwok, 2009, 2012; Meyers & Beretvas, 2006).

Cross-classified data structures are also seen when the interest is in modeling a dichotomous outcome variable, such as those seen in survival analysis. For example, Nuño and Katz (2019) used a CCREM to investigate the likelihood of youth joining a gang in relation to school and community level factors. Here, youth (level-1) were nested simultaneously into schools and communities (level-2). The use of a cross-classified model allowed the authors to partition the effects of schools and communities on the likelihood of gang membership. Lamote et al. (2013) extended the use of cross-classified modeling to DTSA, examining the hazard of student dropout when students are mobile. In such cases, a measurement occasion (level-1) is nested within a crossing of students (level-2, Factor A) and schools (level-2, Factor B), allowing the school indicator and corresponding school characteristics to change over time as a student moves schools.

This approach to a discrete-time survival analysis, where impure nesting results in the situation that repeated measures are nested within a cross-classification of students and schools, closely resembles the methodological work presented by Raudenbush (1993), where a cross-classified growth curve model was estimated for a continuous outcome variable. Table 2 presents a comparison of purely nested and impurely nested data structures using the illustrative data previously presented in Table 1. For example, in a purely nested data structure, student 100 is a member of school 1 for all five measurement occasions and is right-censored, and student 110 is a member of school 2 for two measurement occasions, at which time the student experienced the event. Such a data structure, where students are purely nested into schools across all measurement occasions, is conducive to the use of a purely clustered ML-DTSA. In contrast, the data structure may be considered to be cross-classified if students change schools across measurement occasions. For example, student 100 may be mobile, such that the student is a member of school 1 for 2 measurement occasions and a member of school 2 for the following 3 measurement occasions. Similarly, student 120 was a member of school 2 during the first two measurement occasions and a member of school 3 during the third measurement occasion, at which point the student was no longer a member of the risk set due to event occurrence. In this situation, where some students are mobile across clusters during the study period, the data contains an impure hierarchy and can be considered cross-classified, where measurement occasions are nested within a cross-classification of students (Factor A) and schools (Factor B).

Table 2

A Comparison of Purely Clustered Data and Cross-Classified data for a Discrete-Time Survival Analysis

	Purely Clustered DTSA			Cross-Classified DTSA		
	Clusters (Schools)			Clusters (Schools)		
Individuals (Students)	1	2	3	1	2	3
100	5			2	3	
110	2			2		
120		3			2	1
130		3			1	2

Note. The numbers inside the cells represent the number of repeated measures. For example, in the purely clustered dataset, student 100 was a member of school 1 for 5 repeated measures.

As previously presented, a cross-classified discrete-time survival analysis requires that the data be formulated in the person-period format. Table 3 extends the person-period dataset depicted in Table 1 to present the illustrative cross-classified data set from Table 2. As seen in Table 3, School *j* changes for mobile students. For example, Student 100 moves from School 1 to School 2 between measurement occasions 2 and 3, while Student 110 remains in School 1 for measurement occasions 1 and 2, at which point that student is no longer in the dataset due to event occurrence. As such, this person-period dataset can be used to appropriately model student mobility across schools using a cross-classified discrete-time survival analysis where measurement occasions are nested within a crossing of students and schools. Adapting Lamote et al.'s (2013) model specification, the parameterization of a cross-classified discrete-time survival (CC-DTS) model follows.

Table 3

Example Person-Period Dataset in the Presence of Student Mobility

Student i	Time t	Event e_{tij}	Dummy 1 $D1_{tij}$	Dummy 2 $D2_{tij}$	Dummy 3 $D3_{tij}$	Dummy 4 $D4_{tij}$	Dummy 5 $D5_{tij}$	School j
100	1	0	1	0	0	0	0	1
100	2	0	0	1	0	0	0	1
100	3	0	0	0	1	0	0	2
100	4	0	0	0	0	1	0	2
100	5	0	0	0	0	0	1	2
110	1	0	1	0	0	0	0	1
110	2	1	0	1	0	0	0	1
120	1	0	1	0	0	0	0	2
120	2	0	0	1	0	0	0	2
120	3	1	0	0	1	0	0	3
130	1	0	1	0	0	0	0	2
130	2	0	0	1	0	0	0	3
130	3	0	0	0	1	0	0	3

Unconditional Cross-Classified Discrete-Time Survival Model. A CC-DTS model can be presented using notation from Lamote et al. (2013). To facilitate model interpretation, it will be assumed here that measurement occasions are nested within a crossing of students and schools. The unconditional CC-DTS model can be presented for 5 total time periods as:

$$\log\left(\frac{h_{t(ij)}}{1-h_{t(ij)}}\right) = [\alpha_1 D1_{t(ij)} + \alpha_2 D2_{t(ij)} + \alpha_3 D3_{t(ij)} + \alpha_4 D4_{t(ij)} + \alpha_5 D5_{t(ij)}] + u_{(j)}, \qquad (10)$$

where $\log\left(\frac{h_{t(ij)}}{1-h_{t(ij)}}\right)$ represents the logit of the hazard probability at time *t* when student *i* is in school j. The subscript, (ij), indexes the cross-classified factors, students (Factor A, *i*) and schools (Factor B, *j*), where the parentheses signify cross-classification, as is commonly done in the CCREM literature (e.g., Luo & Kwok, 2009, 2012; Meyers & Beretvas, 2006). $D1_{t(ij)}$

through $D5_{t(ij)}$ are dummy variables for individual i in a school, j, that are coded as 1 for the period it represents and 0 for all other time periods. α_1 through α_5 are the intercept parameters and represent the average estimated log hazard odds across individuals and schools during the respective discrete-time period. The random effect, $u_{(j)}$, represents the random variation in the level-2 effect of clustering across all discrete-time periods while accounting for the school(s) attended by student i, and is assumed to be normally distributed with a mean of 0 and variance, σ_u^2. σ_u^2 represents the variation in the student outcome between-schools across all discrete-time periods.

Note that in a typical cross-classified model, it would be expected that each of the crossed-factors is given its own random effect; or in this example, a random student effect and a random school effect would be estimated. However, in this single-event discrete-time survival analysis, the event can occur for a student only once and the variance between students is accounted for by the Bernoulli distribution at level-1; therefore, only a random school effect is modeled (Lamote et al., 2013).

Conditional Cross-Classified Discrete-Time Survival Model. A conditional CC-DTS model can also be specified by including predictors at one or both levels of the model. For example, a researcher may hypothesize that a student-level characteristic, $X_{(ij)}$, is related to the outcome and that a school-level characteristic, $Z_{(j)}$, may explain some of the variability in the outcome. A conditional CC-DTS model can be presented using notation from Lamote et al. (2013) as,

$$\log\left(\frac{h_{t(ij)}}{1-h_{t(ij)}}\right) = \left[\alpha_1 D1_{t(ij)} + \alpha_2 D2_{t(ij)} + \alpha_3 D3_{t(ij)} + \alpha_4 D4_{t(ij)} + \alpha_5 D5_{t(ij)}\right] + \beta_1 X_{(ij)} + \beta_2 Z_{(j)} + u_{(j)}, \quad (11)$$

where α_1 through α_5 represent the average log hazard odds for all individuals across schools when $X_{(ij)}$ is equal to 0 and $Z_{(j)}$ is 0. β_1 represents the average log hOR of event occurrence across schools per unit change in $X_{(ij)}$ while holding constant other variables in the model. Additionally, β_2 represents the average log hOR of event occurrence per unit change in $Z_{(j)}$, controlling for other variables in the model. Note that here, the covariate associated with school, $Z_{(j)}$, can change for mobile students such that when a student changes schools, the school characteristic also changes accordingly. As a proportional model, it is assumed that the effect of the covariate is the same across all discrete-time periods.

Student Mobility and the CC-DTS Model

The primary difference between a ML-DTSA and a CC-DTSA lies in the way that the models, as presented here, handle the clustering of measurement occasions, students, and schools. Given the hypothetical example of Student 100 from Table 2, who switches schools once (i.e., attends schools 1 and 2) during the five measurement occasions for which the study took place, a CC-DTSA directly models the effects of school 1 and school 2, as well as their associated characteristics, on the logit of the hazard probability for the corresponding measurement occasion for that student. For example, the predicted logit of the hazard probability for Student 100 at each of the five measurement occasions, with a student- and school-level covariate included in the model, can be represented using notation from Luo & Kwok (2012) and Lamote et al. (2013), as

$$\log\left(\frac{h_{1(100,1)}}{1-h_{1(100,1)}}\right) = \alpha_1 D1_{1(100,1)} + \beta_1 X_{(100,1)} + \beta_2 Z_{(1)} + u_{(1)} \text{ at Time 1,} \quad (12)$$

$$\log\left(\frac{h_{2(100,1)}}{1-h_{2(100,1)}}\right) = \alpha_2 D2_{2(100,1)} + \beta_1 X_{(100,1)} + \beta_2 Z_{(1)} + u_{(1)} \text{ at Time 2,} \quad (13)$$

$$\log\left(\frac{h_{3(100,2)}}{1-h_{3(100,2)}}\right) = \alpha_3 D3_{3(100,2)} + \beta_1 X_{(100,2)} + \beta_2 Z_{(2)} + u_{(2)} \text{ at Time 3,} \quad (14)$$

$$\log\left(\frac{h_{4(100,2)}}{1-h_{4(100,2)}}\right) = \alpha_4 D4_{4(100,2)} + \beta_1 X_{(100,2)} + \beta_2 Z_{(2)} + u_{(2)} \text{ at Time 4, and} \quad (15)$$

$$\log\left(\frac{h_{5(100,2)}}{1-h_{5(100,2)}}\right) = \alpha_5 D5_{5(100,2)} + \beta_1 X_{(100,2)} + \beta_2 Z_{(2)} + u_{(2)} \text{ at Time 5.} \quad (16)$$

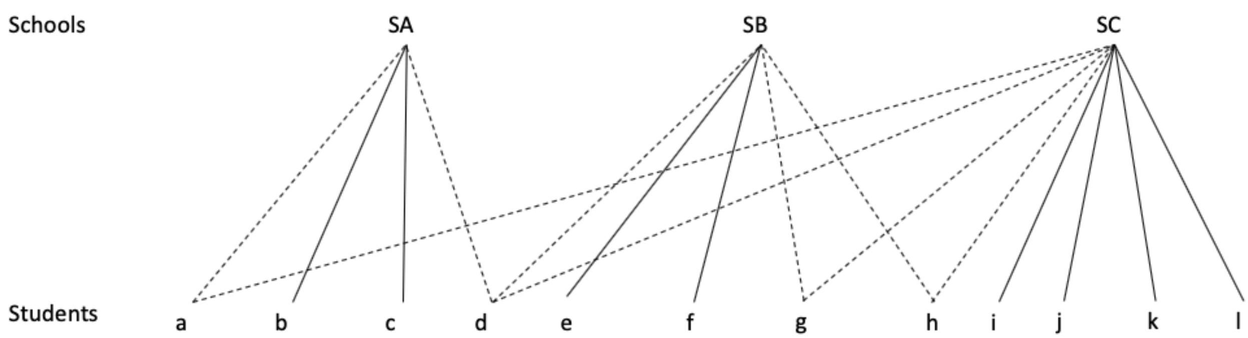
Here, $\log\left(\frac{h_{1(100,1)}}{1-h_{1(100,1)}}\right)$ through $\log\left(\frac{h_{5(100,2)}}{1-h_{5(100,2)}}\right)$ represent the logit of the hazard probability for each measurement occasion, one through five, for Student 100 who attends Schools 1 and 2. The hazard is conditional upon the value of $X_{(ij)}$ for Student 100, as well as the values of $Z_{(j)}$ and $u_{(j)}$, which are allowed to change in each measurement occasion respective to school membership at that time. Therefore, it can be seen that during each measurement occasion, the predicted logit of the hazard probability for event occurrence is estimated for Student 100 using the school and its associated characteristics that was attended by the student during a given measurement occasion. Here, during periods 1 and 2, Student 100 was a member of school 1, and therefore, during each of these measurement occasions the effect of school 1 is represented by the random effect for that school, u_1, and its associated school characteristic, Z_1 (Equations 12 through 13). When the student moves to school 2, the effect of school 2 on the predicted logit of the hazard probability for a given time period is estimated conditional on its associated school-level predictor, Z_2, and its random effect, u_2 (Equations 14 through 16).

Multiple Membership Random Effects Modeling

Mobility of individuals across clusters can also be modeled using a MMREM. The multiple membership data structure can be viewed as a special case of the cross-classified structure, where some lower level units are members of more than one higher-level unit of the same type (Fielding & Goldstein, 2006). For example, given a simple two-level data structure where students (level-1) are nested within schools (level-2), it is possible that the dataset contains some students who have attended multiple schools over time. In such cases, students who do not stay in one school can be characterized as "mobile" and result in a multiple membership data structure. Figure 4 presents a multiple membership data structure, where some students are members of more than one school. Here, it can be seen that, for example, students a, d, g, and h attend more than one school, as represented by the dashed lines. In other words, these students can be considered mobile. This resulting data structure, where some individuals (e.g., students) belong to more than one cluster (e.g., schools) is called a multiple membership data structure.

Figure 4

A Multiple Membership Network Diagram



As is the case with the previously presented CC-DTS model, multiple membership data structures can be accounted for in a multilevel discrete-time survival model. For example, in addition to specifying a cross-classified discrete-time survival model, Lamote et al. (2013) also specified a multiple membership discrete-time survival model to examine student dropout when some students attended multiple schools. Adapting Lamote et al.'s (2013) model specification, the parameterization of a multiple membership discrete-time survival model follows.

Unconditional Multiple Membership Discrete-Time Survival Model. A multiple membership discrete-time survival model can be presented using notation from Lamote et al. (2013). To facilitate model interpretation, it will be assumed here that individuals (level-1) are nested within schools (level-2). The unconditional multiple membership discrete-time survival model can be presented for 5 total time periods as:

$$\log\left(\frac{h_{ti\{j\}}}{1-h_{ti\{j\}}}\right) = \left[\alpha_1 D1_{ti\{j\}} + \alpha_2 D2_{ti\{j\}} + \alpha_3 D3_{ti\{j\}} + \alpha_4 D4_{ti\{j\}} + \alpha_5 D5_{ti\{j\}}\right] + \sum_{h\in\{j\}} w_{ih} u_h \quad (17)$$

where $\log\left(\frac{h_{ti\{j\}}}{1-h_{ti\{j\}}}\right)$ is the logit of the hazard probability for individual *i* who is a member of a set of schools $\{j\}$ during time period *t*. The subscript $\{j\}$ indexes the set of schools associated with an individual over time. $D1_{ti\{j\}}$ through $D5_{ti\{j\}}$ are dummy variables for individual *i* in a set of schools, $\{j\}$, that are coded as 1 for the period it represents and 0 for all other time periods. α_1 through α_5 represent the average log hazard odds for all individuals and all schools at their respective time periods. The weights (w_{ih}) are assigned to the student's association with each school, *h*, in the set of schools $\{j\}$, and for each student $\sum_{h\in\{j\}} w_{ih} = 1$. A brief discussion of the assignment of weights will follow, but it is important to note that the specification of weights is done *a priori* by the researcher. The random effect, u_{0h}, represents the random variation in the level-2 effect of clustering across all discrete-time periods while accounting for the set of schools attended by student *i*, and is assumed to be normally distributed with a mean of 0 and variance, σ_u^2. For example, σ_u^2 represents the variation in the student outcome between-schools across all discrete-time periods.

Conditional Multiple Membership Discrete-Time Survival Model. A conditional multiple membership discrete-time survival model can also be specified by including predictors at one or both levels of the model. For example, a researcher may hypothesize that an individual-level characteristic, $X_{i\{j\}}$, is related to the outcome and that a cluster-level characteristic, Z_h, may explain some of the variability in the outcome. A conditional multiple membership discrete-time survival model can be presented using notation from Lamote et al. (2013) as,

$$\text{Log}\left(\frac{h_{ti\{j\}}}{1-h_{ti\{j\}}}\right) = \left[\alpha_1 D1_{ti\{j\}} + \alpha_2 D2_{ti\{j\}} + \alpha_3 D3_{ti\{j\}} + \alpha_4 D4_{ti\{j\}} + \alpha_5 D5_{ti\{j\}}\right] + \beta_1 X_{i\{j\}} + \sum_{h\in\{j\}} w_{ih}(\beta_2 Z_h + u_h) \quad (18)$$

where α_1 through α_5 represent the average log hazard odds for all individuals across schools when $X_{i\{j\}}$ is equal to 0 and the average contribution of the level-2 predictor Z_h across all schools in set $\{j\}$ is 0. Note that here, the level-2 covariate, Z_h, is also weighted in the same way as the level-2 random effect, such that it is the average contribution of the set of schools, $\{j\}$. β_2 represents the average log hOR of event occurrence per unit change in Z_h, controlling for other variables in the model. Additionally, β_1 represents the average log hOR of event occurrence across schools per unit change in $X_{i\{j\}}$ while holding constant other values in the model. As a proportional model, it is assumed that the effect of the covariates on the logit scale is the same across all discrete-time periods.

A Brief Comparison of the MM-DTS and the CC-DTS Models

The MM-DTS and the CC-DTS models, as presented here, are similar in that they account for the mobility of students across schools. However, as opposed to the CC-DTS model, the MM-DTS model uses a weighting scheme where the weights (w_{ih}) are assigned to the student's association with each school in the set of schools attended by a student. The choice of weights that will be assigned in the model are objective and determined by the researcher, but are important to accurately depict what is happening in reality (Fielding & Goldstein, 2006). For example, an applied researcher might assign a weight for each school in the set of schools attended by each student such that it is proportional to the amount of time that a student was enrolled at that school (Wolff Smith & Beretvas, 2014b). Again, this can be illustrated using the person-period data for Student 100 from Table 3, who attended school 1 and school 2 for 2 periods and 3 periods, respectively, across five measurement occasions. Using the MM-DTS model, the contribution of each of the two schools and their associated characteristics could be modeled such that,

$$\log\left(\frac{h_{ti\{1,2\}}}{1-h_{ti\{1,2\}}}\right) = \left[\alpha_1 D1_{100\{1,2\}} + \alpha_2 D2_{100\{1,2\}} + \alpha_3 D3_{100\{1,2\}} + \alpha_4 D4_{100\{1,2\}} + \alpha_5 D5_{100\{1,2\}}\right] + \beta_1 X_{100\{1,2\}} + \beta_2\left(\frac{2}{5}Z_1 + \frac{3}{5}Z_2\right) + \frac{2}{5}u_1 + \frac{3}{5}u_2. \quad (19)$$

Therefore, the MM-DTS models the school(s) and their associated characteristics as a weighted set attended by a given student. This is in contrast to the CC-DTS model, where the school attended by a student is not assigned a weight, but rather, depends on the measurement occasion for which data are collected on a student. Therefore, the use of a CC-DTS model directly models the effect of changing schools and their associated characteristics, as represented by Equations 12 through 16, while the MM-DTS model indirectly models the effect of schools on student outcomes by assigning weights *a priori* to the clustering units, as represented by Equation 19.

This direct and indirect modeling of the effect of school on the outcome has important implications for the interpretation of the model estimates. Specifically, a MM-DTSA models the effect of school as cumulative, while for the CC-DTS model, the effect of school is noncumulative. When the effect of school is modeled as cumulative, all schools in the set of schools contribute to the outcome according to their assigned weight; conversely, when the effect is modeled as noncumulative, the effect of previous schools attended disappears when students move schools. For the CC-DTS model, Equations 12-16 illustrate this noncumulative effect of school. Note that in each Equation, 12-16, the effect of school depends entirely on the school that a student is a member of during a respective time period, such that measurement occasions are nested within a cross-classification of students and schools. For example, Equation 15 models the effect of School 2 attended by Student 100 on the logit of the hazard probability during time period 4. The effect of the previous school attended (i.e., School 1), does not factor into the logit of the hazard probability at Period 4. In contrast, a MM-DTSA models the effect of schools as cumulative, such that each school in the set of schools attended contributes to the associated current and subsequent logit of the hazard probability values. Note that this specification also means that schools attended at later time periods are modeled as impacting the hazard probability in earlier time periods, which may not accurately depict reality. In contrast, the non-cumulative effect of school modeled by a CC-DTSA may better represent reality in a given time period, but may not represent reality well at later time periods, where it is likely that previous schools attended contribute to proceeding student outcomes.

Methodological Research for Complex Data Structures

Methodological research for cross-classified and multiple membership data structures have been conducted using both cross-sectional and longitudinal data. In the case of cross-sectional data, methodological research has indicated that inappropriately modeling impure clustering results in biased estimates of the variance components and standard errors of the fixed effects (Chung & Beretvas, 2012; Chung et al., 2018; Dunn et al., 2015; Luo & Kwok, 2009; Meyers & Beretvas, 2006; Ren, 2011; Wolff Smith & Beretvas, 2014a, 2017). Luo and Kwok (2009) found that the direction and magnitude of bias in these estimates is influenced by the structure of cross-classification and the degree to which the data are cross-classified. In other words, as individual mobility across clusters increases in the dataset, the bias associated with the variance components and standard errors of the fixed effects will also increase. The variance redistribution observed by Luo and Kwok (2009) partly explains contrasting findings in the methodological literature for MMREMs; for example, while Chung and Beretvas (2012) and

Wolff-Smith and Beretvas (2014a) observed bias in both the individual- and cluster-level variance component estimates, Wolff Smith and Beretvas (2017) did not observe any bias in the estimate of the level-1 variance component across any model. In the case of longitudinal data, methodological studies have resulted in similar findings (Cappelli et al., 2020; Choi & Wilson, 2016; Grady, 2010; Grady & Beretvas, 2010; Leroux, 2019; Leroux & Beretvas, 2018a, 2018b; Leroux et al., 2020; Luo & Kwok, 2012). Studies using real data have found that model estimates differ between misspecified models and models that correctly account for mobility for both linear and nonlinear growth curve models (Grady & Beretvas, 2010; Leroux, 2019; Leroux & Beretvas, 2018a). Simulation studies have further examined these differences to describe the direction and magnitude of bias in both correctly specified and misspecified models, and indicate that inappropriately modeling individual-level mobility across clusters results in substantial bias in model estimates at the cluster-level, specifically in the variance components and in the impact of the covariates on growth rates (Cappelli et al., 2020; Choi & Wilson, 2016; Grady, 2010; Leroux & Beretvas, 2018b; Leroux et al., 2020; Luo & Kwok, 2012).

Importantly, this methodological research has provided insights regarding the study factors that may contribute to bias observed in model estimates when using CCREMs and MMREMs. For example, studies have indicated that cluster size is an important contributor of bias in MMREMs and CCREMS, where larger cluster sizes are more important than within-cluster sample sizes to mitigate bias in parameter estimates (Chen & Leroux, 2018; Vassallo et al., 2017; Wolff Smith & Beretvas, 2017). Even larger cluster-level sample sizes may be needed when using longitudinal data, where some methodological work has suggested that appropriately modeling mobility using longitudinal models without bias may require 100 or more clustering units (Leroux & Beretvas, 2018b; Leroux et al., 2020). In addition to these methodological findings, Moerbeek and Safarkhani (2018) conducted an analytical study to provide formulas that can be used to calculate the necessary sample size to achieve the desired level of statistical power when using cross-classified designs.

Additionally, other studies have examined the impact of the misspecification of weights used to represent the theoretical contribution of the cluster-level unit on mobile individuals when modeling mobility using an MMREM. While Wolff Smith and Beretvas (2014b) found that the MMREM is robust against the choice of weight patterns used to model the effect of multiple higher level units on a lower level unit, Galindo (2015) and Durrant et al. (2018) found that when mobility is generated more realistically, weight specification impacts the relative parameter bias of the cluster-level random effects' variance component in some simulated conditions.

Methodological Literature for Survival Analysis. Cross-classified and multiple membership modeling approaches can also be extended to incorporate both continuous-time and discrete-time survival outcomes. However, few methodological studies have been conducted in either continuous-time or discrete-time survival analysis with complex data structures.

Cafri and Fan (2018) proposed and evaluated a continuous-time survival model for cross-classified data against a model that ignored the complex data structure. Simulation results indicated that the model that accounted for the cross-classified data structure resulted in no bias in parameter estimates, while the modeling approach that ignored the complex data structure was found to result in substantial bias in estimates of the cluster-level variance component. Additionally, Elghafghuf et al. (2014) proposed and evaluated a Cox model with both cross-classified and multiple membership frailties (CMM Cox Model). Overall, it was found that the CCM Cox Model performs better when mobility is higher and when variance components are larger. Additionally, the level-3 random effect for one crossed-factor was found to be biased, although this is likely attributable to the small cluster-level sample size used in the simulation study.

Only one study has investigated the use of a discrete-time survival model in the presence of individual mobility across clusters. Lamote et al. (2013) applied both a cross-classified and multiple membership discrete-time survival model to data with impure clustering. This study served two purposes, (1) an applied study of student drop-out and (2) a methodological study of discrete-time survival modeling techniques. As an applied study, Lamote et al. (2013) examined the effect of student and school characteristics on dropout hazard among students over a six-year period, specifically interested in the timing and occurrence of student risk for dropout. As a methodological study, the authors considered the hierarchical structure of the dataset and examined the resulting estimates of different hierarchical discrete-time survival models, including models that ignore student mobility and both a MM-DTS and a CC-DTS model. Lamote et al. (2013) found that the unconditional MM-DTSA returned a higher Deviance Information Criterion value than both a model where student mobility was ignored and the CC-DTSA, indicating that the MM-DTSA yielded a poorer model fit. Additionally, model estimates, including those for the fixed effects representing the baseline hazard probability and the cluster-level variance component, differed in models that appropriately modeled mobility and alternative ad hoc approaches. While Lamote et al. (2013) integrated both multiple membership and cross-classified models into discrete-time survival modeling, their work included only a real-data analysis. As such, while differences were seen between models that accounted for student mobility and models that assumed a pure hierarchical data structure, it is not known which model estimates were estimated without bias, or if bias was present, the magnitude of that bias.

The purpose of this study was to build upon the work of Lamote et al. (2013) in discrete-time survival analysis in the presence of student mobility. Given the authors' findings that the CC-DTSA better fit the data containing student mobility than the MM-DTSA, this dissertation focused on the use of the CC-DTS model to appropriately model individual mobility across clusters. The following chapter presents the methods used to conduct a simulation study. The simulation study assessed the performance of a cross-classified discrete-time survival model under a variety of research contexts, and describes bias seen in the model estimates as compared to models that ignore individual mobility across clusters.

CHAPTER 3

METHODOLOGY

The primary purpose of this dissertation was to assess the impact of ignoring a cross-classified data structure due to individual mobility across clusters in a discrete-time survival analysis, and further, to investigate how the baseline hazard function, variability of the cluster random effect, mobility rate, and within- and between-cluster sample size impact the performance of a cross-classified discrete-time survival model. The research questions that were addressed specifically examined the performance of a correctly specified CC-DTS model against a ML-DTS model that modeled only the first cluster (i.e., school) of the set of clusters that mobile individuals were associated with during the course of the study. Under the approach that ignored individual mobility across clusters, the effects of multiple clusters were not modeled for mobile individuals who were exposed to multiple contexts. Essentially, to conduct a conventional multilevel discrete-time survival analysis (ML-DSTA), researchers modify the complex data structure to a purely hierarchical data structure by ignoring mobility. Additionally, a single-level discrete-time survival analysis (DTSA), which also ignored the hierarchical structure of the data, was compared to the multilevel and cross-classified analyses.

This chapter continues with a discussion of the simulation study procedures. First, the simulation study design, including the manipulated conditions proposed, is discussed. Following the proposed data generation procedures, the model estimation procedures are described, and finally, the analyses for examining parameter recovery are presented.

Simulation Study

Lamote et al.'s (2013) study illustrated that there were differences in parameter estimates in the model that ignored the hierarchical data structure, the single-level discrete-time survival

(DTS) model; the model that ignored mobility, the ML-DTS model; and the model that incorporated mobility, the CC-DTS model. However, while differences were observed, it is unknown which model provided estimates closest to the true values, or the magnitude and direction of bias that may exist. Therefore, a simulation study was designed to examine the magnitude and direction of bias in each model under conditions common in applied research settings. This study evaluated bias in estimates of the fixed effects for all models and in the variance component for multilevel discrete-time survival approaches that either ignored mobility or incorporated mobility. The following sections describe the design of the simulation study, including generating conditions, data generation, and model estimation procedures.

A Preparatory Step – A Review of the Literature

To ensure that the generating values chosen for this simulation study were representative of those commonly found in educational research, a review of the applied literature was conducted. Prior to beginning the literature review, it was necessary to set guidelines for the types of studies to be included; therefore, inclusion criteria were established to guide this literature review, as follows:

- Manuscript must be an applied educational research study
- Study must be related to educational research in a K-12 setting
- The primary focus of the study is related to student outcomes
- Study must use one of the following models for the analysis of binary outcome data: (1) HGLM, (2) MMREM, (3) CCREM, (4) DTS model, (5) MM-DTS model, (6) CC-DTS model

To search for this literature, multiple databases were used, such as Academic Search Complete, Education Source, PsychInfo, and ERIC (EBSCO). The databases were broadly searched, and studies that appeared to meet the inclusion criteria presented above were further reviewed. The search was not constrained by any fields (i.e., dates of publication, authors, etc.). While numerous search terms were used, the first search term used was “Discrete-time survival analysis AND Education”. This search term produced limited literature from each of the databases. For example, at the time of this writing, using this search term in the ERIC (EBSCO) database yielded 34 publications that were broadly related to education and utilized a discrete-time survival analysis, but either may not be considered educational research or did not meet the inclusion criteria for educational research defined above (i.e., student outcomes in K-12 education). For example, studies that did not meet the inclusion criteria but appeared in the search included those with primary research questions related to public health (i.e., emergence of depression, first time consuming alcohol, first time using cigarettes, etc.) rather than educational research specifically, but the research was conducted using school-based data sources. Other studies that appeared in the initial search, but were excluded, included educational research studies that took place outside of a K-12 setting, such as those in the university context. Consequently, more broad search terms were used in an attempt to capture studies that used binary outcome variables, but were not necessarily conducted using a discrete-time survival analysis. For example, the search terms included, but were not limited to, “Discrete-Time Survival Models AND Education”, “Discrete-Time Survival Analysis AND Education”, “Discrete-Time Survival Analysis AND Schools”, “Discrete-Time Survival Analysis AND Students”, “Binary Outcome AND Education”, “Dichotomous Outcome AND Education”, “Hierarchical Generalized Linear Model AND Schools”, “Hierarchical Generalized Linear Model AND Students”, “Event history model of student dropout”. Search terms also included binary outcome variables commonly seen in educational research, such as, “Discrete-Time

Survival Analysis AND Student Retention", "HGLM AND Graduation", "Discrete-Time Survival Analysis AND Dropout".

In conducting this search, abstracts were first reviewed to ensure that the study met the inclusion criteria. While many studies were found through this process, subsequent reviews of the manuscripts revealed that they did not always contain the information necessary to produce generating values. For example, in some studies, descriptive statistics for the overall sample were not included in the manuscript and could not be calculated given the provided information. In other studies, a discrete-time survival analysis was conducted, but time was constrained such that a hazard probability was not estimated for each measurement occasion, and therefore, the study could not be used to inform the generating values for hazard probabilities in this study. Therefore, a total of 14 studies were identified that met the inclusion criteria and were specifically used to choose generating values for this simulation study, which included values for level-1 and level-2 covariates, as well as values for the hazard probabilities. A summary of these studies is provided in Appendices A, B, and C. Specifically, Appendix A presents a summary of the studies used to inform generating values for the hazard probabilities on the logit scale, Appendix B provides a summary of estimated level-1 coefficient values for dichotomous covariates, and Appendix C provides a summary of studies from which the coefficient values for dichotomous level-2 covariates were culled. Further explanations for the chosen generating values resulting from this review of the literature are provided below.

Generating Conditions

In the present study, five factors were manipulated: cluster-level sample size (i.e., the number of schools), within-cluster sample size (i.e., the number of students per school), variance at the cluster-level, the overall mobility rate, and the Weibull scale parameter.

Cluster-Level Sample Size

Prior simulation studies examining models that appropriately accounted for mobility across clusters have found that the cluster-level sample size can have an important impact on bias observed in the model estimates. The methodological literature has explored the effects of cluster sizes of between 20 and 150 on model estimates for CCREMs and MMREMs. In the continuous-outcome cross-sectional literature, it has been found that smaller cluster sizes of 20-40 have resulted in biased estimates of cluster-level variance components (Chen & Leroux, 2018; Chung & Beretvas, 2012; Chung et al., 2018; Wheelis, 2017; Wolff Smith & Beretvas, 2017). Luo and Kwok (2012) used a longitudinal CCREM to model student mobility across clusters using cluster-level sample sizes of 25 and 50, and found that higher cluster sizes resulted in less bias when mobility was present in the data. While no simulation studies have been conducted to examine the effect of the cluster-level sample size on model estimates for a CC-DTS model, Lamote et al. (2013) used the CC-DTS model with a dataset that consisted of 55 schools at the cluster-level. Given previous findings in the literature for longitudinal data where individual mobility across clusters was present, it is important to examine the effect of the cluster-level sample size on model estimates for the CC-DTS model. Therefore, the cluster-level sample sizes in this study were set to 30, 50, and 100 to investigate model performance.

Within-Cluster Sample Size

In educational research, it is typical for the number of students per school to be about 30 (Maas & Hox, 2005). However, the range of the within-cluster sample size typically falls between 5 and 61 (Chung & Beretvas, 2012). Additionally, previous simulation research using models that accounted for individual mobility across clusters have explored the effects of within-cluster sample sizes between 10 (Chung et al., 2018; Wheelis, 2017) and 100 (Luo & Kwok, 2012). Commonly, it was found that the cluster-level sample size had a greater influence on parameter recovery than the individual-level sample size, although increases in the within-cluster sample size generally resulted in moderate gains in parameter precision (Chen & Leroux, 2018; Chung & Beretvas, 2012; Luo & Kwok, 2009, 2012; Meyers & Beretvas, 2006; Vassallo et al., 2017; Wolff Smith & Beretvas, 2014a, 2017). Additionally, Chung et al. (2018) found that increasing the within-cluster sample size significantly increased the coverage rate of the 95% credible intervals. Therefore, the number of students per school in this study was set to 25 and 75 at the first time period. However, note that due to the nature of the person-period dataset, the specified within-cluster sample sizes were only applicable to the first time-period. Beyond the first time-period, the within-cluster sample size in some clusters decreased as members of that cluster experienced the event.

Variance at the Cluster-Level

In educational research using multilevel discrete-time survival analysis, methodological studies have manipulated the estimated residual variance at the cluster-level, σ_u^2, to examine the impacts of the between-cluster variance on parameter estimates. The variance at the cluster-level is more interpretable when redefined as an intraclass correlation coefficient (ICC). Formally, the ICC is defined as the proportion of the total variance in the outcome that is attributable to variability among the cluster-level units. Previous methodological research using ML-DTS analysis has manipulated the variance between-clusters, and therefore, the ICC. For example, Moerbeek (2012) and Elghafghud et al. (2014) conducted simulation studies to explore the performance of survival models in the presence of clustered data structures. Findings suggested that when the ICC increases, under certain combinations of conditions fixed effect estimates may be negatively impacted, but the cluster-level variance component may be better estimated in conditions that include a larger ICC.

Although there are few applied studies that have utilized a multilevel discrete-time survival analysis approach in educational research, those that exist have reported a wide range of values for the variance between-clusters in conditional models, and therefore, a wide range of residual ICC values. For example, Davoudzadeh et al. (2015) reported ICC values that ranged from .003 to .13 and Petras et al. (2011) reported a residual ICC of .01. In the only study utilizing a CC-DTS model, Lamote et al. (2013) reported residual ICCs that ranged from .042 to .28. Therefore, in this study, the between-cluster variance component value was manipulated to be equal to 0.32 or 1.09, which are equivalent to residual ICC values of .10 and .25, defined here as small and large ICCs. Refer to Technical Appendix A for further information regarding the calculation of the residual ICC used in this dissertation, given between-cluster variance component values of 0.32 and 1.09.

Overall Mobility Rate

The interest in this study was to explore the effect of the overall mobility rate in the dataset on model estimates. Studies from the applied educational research literature that specifically examined student mobility have reported varying rates of mobility in their study samples, typically ranging from 15% to 50% mobility (Gruman et al, 2008; Nelson et al., 1996; Taniguchi, 2017). Additionally, Lash and Kirkpatrick (1990) reported that, in the United States, 19% of students move in any given year, with younger students experiencing even higher rates of mobility. For example, Kerbow (1996) stated that in studies of Chicago’s Public Schools, upwards of 62% of elementary school students switched schools during their elementary school years. These mobility rates are also supported by more recent government statistics, which suggest that in the United States, about 12%-38.5% of students switched schools or moved between 2005 and 2010 (Ihrke & Faber, 2012; U.S. Government Accounting Office, 2010). In the methodological literature, the majority of simulation studies have examined the impact of mobility rates between 10% and 35% (e.g., Cappelli et al., 2020; Chen & Leroux, 2018; Chung & Beretvas, 2012; Galindo, 2015; Leroux & Beretvas, 2018b; Leroux et al., 2020; Luo & Kwok, 2012). Additionally, Wheelis (2017) and Luo and Kwok (2012) explored the impact of mobility rates as low as 5% on bias in model estimates when complex data structures were inappropriately modeled. These studies found that mobility rates exceeding 10% typically result in bias in the estimate of the cluster-level predictor coefficient and the cluster-level variance component of the model that does not correctly account for mobility. Therefore, for this study, individual mobility rates of 10%, 20%, and 30% were explored.

Weibull Scale Parameter

In educational research utilizing discrete-time survival analysis, it is usually seen that survival at the end of the study remains relatively high; in other words, the overall rate of event occurrence among the sample is low. For example, in a study by Davoudazadeh et al. (2015) that examined the first occurrence of grade retention, 13% of the sample experienced the event by the end of the study. In a study of student dropout by Lamote et al. (2013), about 11% of the sample experienced the event, while higher occurrences of dropout of between 20% and 30% of the overall sample were seen in other studies (Bowers, 2010; Orozco, 2016). A summary of the findings from this literature can be found in Appendix A. In methodological research that varied the proportion of event occurrence, it was found that in some cases, especially when sample sizes were small, low rates event occurrence (25%) resulted in greater amounts of bias in some model parameters than higher rates of event occurrence among the sample (Moerbeek & Hesen, 2018;

Moerbeek & Schormans, 2015). Therefore, this study manipulated the survival patterns among individuals in the generated datasets using the Weibull survival function. A Weibull survival function was used to calculate the hazard probabilities at each of the five time periods generated in each dataset. As such, the hazard probability at each time period, *h(t)*, was calculated as, $h(t) = \alpha\lambda t^{(\alpha-1)}$, where α is the Weibull shape parameter, λ is a Weibull scale parameter, and t represents the time period, 1 through 5. For the purposes of this dissertation, the shape parameter, α, was always equal to 1.5. However, the scale parameter, λ, had two levels, .05 and 0.025. When the scale parameter was equal to 0.05, the survival at the end of the five time periods was equal to 51%, and when the scale parameter was equal to 0.025, the survival at the end of the five time periods was equal to 73%. The hazard probabilities can be calculated using the equation previously presented and providing the values of the shape (i.e., 1.5) and scale parameters (i.e., 0.05 or 0.025). For example, when the scale parameter was equal to 0.05, the hazard probability at the first time period was calculated as, $h(t) = (1.5)(.05)(1)^{(1.5-1)}$, which is equal to .075, or a logit hazard value of −2.51. This procedure was also conducted for each time period by changing the value of *t* to be equal to the time period, 1 through 5, resulting in hazard probabilities of .075, .106, .130, .150, and .168, which are equivalent to logit hazard values of −2.51, −2.13, −1.90, −1.74, and −1.60. Following the same procedures, but changing the scale parameter to 0.025, the hazard probabilities are equal to .038, .053, .065, .075, and .084, which are equivalent to logit hazard values of −3.25, −2.88, −2.67, −2.51, and −2.39. A further discussion of event occurrence, hazard functions, the number of time periods, and the survival pattern for the generated dataset is provided below.

In summary, the performance of the DTS model, the ML-DTS model, and the CC-DTS model were assessed using 72 simulation conditions from the combination of 5 factors in a fully crossed design (Table 4). As the aim of this study was to provide both methodological and applied researchers with insights regarding the performance of each model in the presence of individual mobility across clusters, the factors and their associated levels chosen for manipulation represent those that were common in applied research, and as described, have been commonly found to have substantial effects in models that ignore complex data structures when they are present. Additionally, although Lamote et al. (2013) conducted a real-data study that compared the CC-DTS model to other DTS models, this was the first simulation study to model a DTSA in the presence of a cross-classified data structure, and therefore, it is important to describe parameter recovery using the CC-DTS model when these factors are manipulated.

Table 4

Summary of Manipulated Simulation Conditions and Associated Levels

Manipulated Factor	Study Condition
Within-cluster sample size	25
	75
Cluster-level sample size	30
	50
	100
Mobility rate	10%
	20%
	30%
Variance at the cluster-level (ICC)	0.32 (.10)
	1.09 (.25)
Weibull scale parameter	0.050
	0.025

Data Generation

For each of the 72 simulation conditions, 1,000 cross-classified datasets were generated, resulting in a total of 72,000 simulated datasets that were estimated using a conditional DTS model, a conditional ML-DTS model, and a conditional CC-DTS model. Previous methodological and applied studies in DTSA and ML-DTSA have commonly used DTSA for longitudinal studies with between four and six discrete-time periods (e.g., Bowers, 2010; Davoudzadeh et al., 2015; Jolani & Safarkhani, 2017; Lamote et al., 2013; Moerbeek, 2012). Therefore, this study examined discrete-time survival models in the context of a study with 5 discrete-time periods. Additionally, while the pattern of the hazard probability (i.e., increasing, decreasing, or constant) varied in each of these studies, previous simulation research has indicated that the survival pattern does not have an effect on bias in the estimates of the parameters when using a ML-DTSA (Moerbeek, 2012). Given that in the types of outcomes often examined in educational research (e.g., student dropout), hazard commonly increases over time, this dissertation utilized an increasing hazard function. Therefore, for each of the levels of the Weibull scale parameter condition, the resulting hazard function was generated such that there were five discrete-time periods with hazard probabilities that increased over time, where the greatest hazard probability for event occurrence occurred in later time periods.

Mobility Generation

Student mobility was generated according to the level of the mobility condition for the sample size in the simulated dataset, as determined by the cluster sample size and within-cluster sample size conditions. For example, for the level of the mobility condition where 10% of students were mobile for a dataset generated using 100 clusters (i.e., schools) and a within-cluster sample size of 50 (i.e., 50 students per school), the total sample size in the simulated dataset was 5,000 students. Therefore, 500 students were randomly selected to be mobile. Mobility was generated such that the level of the mobility condition was applied identically in each generated dataset. In other words, the mobility rate was the rate of individual mobility in the sample generated in each of the 1,000 datasets generated per unique combination of conditions. For example, when a combination of conditions included 10% of students to be mobile, all 1,000 generated datasets were generated to randomly select 10% of students to be mobile. This procedure for mobility generation has been used in previous methodological studies (Cappelli et al., 2020; Choi & Wilson, 2016; Chung & Beretvas, 2012; Luo & Kwok, 2012; Meyers & Beretvas, 2006; Wolff Smith & Beretvas, 2017). For those students chosen to be mobile, subsequent schools attended were determined by their current School ID + 1. For example, for a dataset with 100 clusters, a mobile student in School 1 was assigned to School 2, but a mobile student in School 100 was assigned to School 1.

Additionally, given the longitudinal nature of discrete-time survival analysis, it is probable that in reality, students may move more than once. Furthermore, students may move in different time periods. In regards to the maximum number of times that a student is able to move, the existing literature regarding student mobility indicated that it is most common for mobile students to move schools only once during a study period; however, mobile students may also move schools two times, with very few moving more than two times. For example, in applied educational research, Gruman et al. (2008) and Lamote et al. (2013) reported that the majority of mobile students in their study samples moved only once (66% and 88%, respectively), and a lesser majority moved twice (25% and 27.6%, respectively). Kerbow (1996) reported that only 13% of elementary school students in Chicago's public schools attended four or more schools during a six-year period. Additionally, existing methodological research that explored the impacts of student mobility has used a variety of mobility patterns. For example, in some methodological studies, mobile students changed schools only once, such that they attended a maximum of two schools (e.g., Cappelli et al., 2020; Choi & Wilson, 2016; Grady, 2010; Leroux et al., 2020; Wolff Smith & Beretvas, 2014a). However, in other methodological research, mobile students were allowed to change schools more than once (e.g., Chung & Beretvas, 2012;

Leroux & Beretvas, 2018a; Luo & Kwok, 2012; Wolff Smith & Beretvas, 2014b, 2017). For example, in a methodological study using real data, Leroux (2019) reported that 86.7% of the study sample moved schools only once, while the remaining mobile students moved more than once. Similarly, Leroux and Beretvas (2018b) generated data for a simulation study such that only 15.5% of mobile students moved twice, while the remaining students moved only once. Therefore, for this study, the majority of mobile students moved only once and some mobile students were allowed to move two times. Specifically, 80% of mobile students were assigned to move schools once (i.e., attend 2 schools), and the remaining 20% of mobile students were assigned to move schools twice (i.e., attend 3 schools), as described in Table 5. For example, following the previously described situation where a dataset with 5,000 students and a 10% mobility rate results in 500 students being randomly assigned to be mobile, 400 students (80%) were assigned to move schools once, and the remaining 100 students (20%) were assigned to move schools two times.

As previously mentioned, due to the longitudinal nature of discrete-time survival analysis, it was also necessary to specify when those students who were randomly chosen to be mobile would move. Therefore, a set procedure was specified that was the same for each dataset, regardless of the level of the mobility condition, such that mobile students were assigned a time period in which to move. The proportion of mobile students assigned to move in each time period is outlined in Table 5. As illustrated in Table 5, the data generation procedure resulted in the majority of students being assigned to move in earlier time periods as opposed to later time periods. However, note that due to the discrete-nature of the measurement occasions, mobility was always 0% during period 1. As opposed to previous methodological research examining mobility, this CC-DTSA utilized the person-period dataset, as presented in Table 3. Therefore, as students experienced the event, they were no longer included in the dataset for subsequent time periods. Thus, the student mobility procedure described in Table 5 was specifically designed to maximize the likelihood that a mobile student would both move and experience the event; in other words, a mobile student was less likely to be removed from the dataset due to event occurrence prior to the time period in which they were assigned to be mobile.

Table 5

Mobility Procedures Adopted for the Simulation Study

Number of Times Mobile	Time Period	Percent of Mobile Students
Mobile Once	T2	40%
Mobile Once	T3	30%
Mobile Once	T4	10%
Mobile Twice	T2, T3	10%
Mobile Twice	T2, T4	10%

As illustrated in Table 5, 90% of mobile students were assigned to move either once or twice by time period 3. Additionally, the percentage of mobile students assigned to move schools decreased across time, such that mobility was highest between time periods 1 and 2 with no mobility between time periods 4 and 5. Again drawing from the example of a generated dataset that contained 500 mobile students, 400 students were assigned to move only once, of whom 200 were assigned to move during time period 2, 150 were assigned to move during time period 3, and 50 were assigned to move during time period 4. An additional 100 students were assigned to move twice, 50 of whom were assigned to move in both time periods 2 and 3, and the remaining 50 in time periods 2 and 4. Again, regardless of the level of the mobility condition, the proportion of students assigned to move once or twice and the proportion of students assigned to move during each time period always remained the same. It is important to note that individual mobility was generated independent of event occurrence in each dataset. Therefore, while the overall rates of mobility were specified to be equal to the level of the mobility conditions (10%, 20%, or 30%), and mobility in each time period was specified to occur as described in Table 5, as students were removed from the risk set, the overall mobility and mobility per time period was not exactly equal to the described procedures. The actual rates of individual mobility across clusters across the generated datasets is provided later in this dissertation.

Student mobility was not modeled using the conditional DTS or ML-DTS models; instead, the DTS model ignored the clustering of students into schools, while the ML-DTS model was estimated using only cluster-level characteristics from the first school attended by a student, resulting in a purely hierarchical data structure. However, for the CC-DTS model, mobility was modeled by structuring the data such that measurement occasions were nested within a crossing of students and schools. In other words, by modeling the cross-classified data structure with a CC-DTS model, the school identification and its corresponding characteristics were allowed to change at each measurement occasion as students moved schools.

Generating CC-DTS Model

This simulation study examined differences in parameter estimates between the conditional models for the DTS model, the ML-DTS model, and the CC-DTS model. All of the simulated datasets were designed to have a cross-classified data structure where individuals were mobile across clusters, resulting in impure nesting where measurement occasions are nested within a cross-classification of students and schools. The data generating values presented here were culled from both real-data studies and methodological studies utilizing discrete-time survival models, hierarchical generalized linear models, and complex multilevel models in the existing educational research literature.

The values for the coefficients for the student- and school-level predictors used in this simulation were also informed by the literature. The studies examined to establish realistic generating values for the student- and school-level predictors included those that utilized a multilevel discrete-time survival analysis, a single-level discrete-time survival analysis, and multilevel logistic regression, and are presented in Appendices B and C. For the student-level predictor, studies in educational research commonly used dichotomous variables or dummy-coded variables in the model. For example, demographic variables such as race, gender, socioeconomic status, language spoken at home, among others have been found to be associated with educational outcomes (e.g., Carpenter & Ramirez, 2007; Schifter, 2016; Werblow & Duesbery, 2009). In other studies, gender has been identified as an important predictor, or has been used as a control variable in the model (Cha, 2015; Ma & Willms, 1999). Consistently, gender and race were examined in applied studies in relation to binary outcome variables. Therefore, in this study, the student-level predictor, $X_{(ij)}$, was a dichotomous variable, where 50% of the sample were generated to have a value of 0 and the remaining 50% were generated to have a value of 1. This most closely resembles the proportions observed for the “Gender” variable in applied research. Additionally, as seen in the results of the studies summarized in Appendix B, the estimated coefficient on the logit scale most often indicated that males were more likely to experience the event than females. Therefore, the generating value for the coefficient of the student-level covariate used in this study was set to 0.50 on the logit scale. This corresponds to a hazard odds ratio (hOR) of 1.65, suggesting that, for example, the odds of event occurrence are greater for male students (coded 1) than they are for female students (coded 0).

Additionally, previous research was examined to generate a realistic cluster-level variable and its associated coefficient. In the educational research literature, student mobility was often found to be associated with variables such as school location and school type. For example, some researchers have argued that student mobility is most prevalent in urban schools, as compared to suburban or rural schools (Kerbow, 1996; Lash & Kirkpatrick, 1990). Indeed, the applied literature has also examined various educational outcomes in relation to variables such as school type or school location (e.g., Carpenter & Ramirez, 2007; Cha, 2015; Werblow & Duesbery, 2009). Given this research, it is likely that a study that accounts for both student mobility and has a discrete-time survival endpoint in the United States educational context will have a variable included in the model related to school type (i.e., public or private) or school location (i.e., urban, rural, suburban, etc.). In other words, a dichotomous variable at the clustering-level of the model is likely. Therefore, the cluster (i.e., school) predictor, $Z_{(j)}$, used in this study was also a dichotomous variable, where 30% of schools were generated to have a value of 1 and the remaining 70% had a value of 0. These values are similar to those reported by Cha (2015) and Taniguchi (2017) in the applied literature, who both used dummy-coded variables representing school location, where rural or suburban schools were coded as the reference category at level two in their models. Furthermore, in educational research using HGLM or ML-DTS models, it is most common for the values of the coefficients for level-2 variables to range from about −0.50 to 0.70 on the logit scale. Therefore, following Moerbeek (2012), this study utilized a value of 0.50 on the logit scale for the level-2 coefficient. This corresponds to a hOR of 1.65, suggesting that students in schools coded as 1 have a greater likelihood of event occurrence across the study period than students in schools coded as 0. Note that although the coefficient and hOR are equivalent for the level-1 and level-2 covariate, given that the proportion of the covariates generated to equal 1 or 0 differ, the variance in the population differs. As a result, the effect of the covariate on the outcome differs.

The random effect, $u_{(j)}$, was generated to be normally distributed with a mean of 0 and a variance, σ_u^2. Note that σ_u^2 changed according to the level of the manipulated condition for the cluster-level variance component value. The outcome, event occurrence, was assigned to each student by randomly drawing a 1 (event occurrence) or 0 (event does not occur) from a Bernoulli distribution, where the estimated hazard probability for each student was entered into the function as a probability, and *n* trials was equal to 1. For the data generation syntax in R, refer to Technical Appendix B.

Estimating Models

All generated data were estimated using a conditional DTS model, a conditional ML-DTS model, and a conditional CC-DTS model as specified by Equations 5, 9, and 11, respectively. The conditional CC-DTS model accounted for individual mobility across clusters, while the DTS model ignored clustering and the ML-DTS model used only the first cluster (i.e., school) and its associated covariate in the model, ignoring subsequent schools attended by mobile students and their associated characteristics. Note that the data generating procedures differed from the estimation procedures here. Specifically, the baseline hazard function was generated according to the two levels of the Weibull scale parameter condition, which used a two-parameter Weibull function to generate hazard values for each time period. In contrast, the estimating models (i.e., the CC-DTS, the ML-DTS, and the DTS models) left the hazard function unstructured, estimating each logit hazard value from the generated data, as is common in applied research. For the DTS model, the cluster-level coefficient was estimated by disaggregating the cluster-level variable, such that all students from the same school were assigned the same value at the clustering-level.

Estimation Procedure

All models were fit using R software using the *lme4* package (version 1.1-21), which fits models utilizing a Laplace Approximation (Raudenbush et al., 2000). The Laplace Approximation is known to be an efficient and good quality estimator for approximating the maximum likelihood value (Snijders & Bosker, 2012). The maximum number of allowable function evaluations (i.e., number of iterations) was specified to be 250,000, which is an increase from the default value of 10,000 function evaluations. In order for the DTS model to be estimated using the same function as the other models, the between-clusters variance was constrained to 0, and therefore, no random effect was estimated. Estimates of the fixed effects for all models, as well as the variance components for multilevel models, were recorded and examined as described below. For the model estimation syntax in R, refer to Technical Appendix C.

Analyses

The analyses for the simulation study compared differences in the estimates of the fixed effects for all models, as well as estimates of the variance component from the conditional ML-DTS model and the conditional CC-DTS model. Specifically, this simulation study examined the relative parameter bias (RPB), coverage of the 95% confidence intervals, and root mean square error (RMSE). Additionally, analysis of variance (ANOVA) was used to further understand the effects of the manipulated conditions on RPB, and logistic regression was used to further understand the effects of the manipulated conditions on coverage of the 95% confidence intervals. For all analysis syntax in R, refer to Technical Appendix D.

Relative Parameter Bias

Relative parameter bias for the fixed effects (for all models) and the random effects' variance component (for the ML-DTS and CC-DTS models) were calculated using the following formula:

$$B(\hat{\theta}_k) = \frac{\bar{\hat{\theta}}_k - \theta_k}{\theta_k}, \tag{21}$$

where θ_k is the generated true value of the k^{th} parameter and $\bar{\hat{\theta}}_k$ is the average of the estimates $\hat{\theta}_k$ for the k^{th} parameter across the 1,000 simulated datasets per simulation condition. Parameter estimates with a relative parameter bias of a magnitude between 0.05 and 0.10 were considered moderately biased, and relative parameter bias that was greater than a magnitude of 0.10 was considered to be substantially biased (Chen & Leroux, 2018; Flora & Curran, 2004; Hoogsland & Boomsma, 1998; Kaplan, 1989).

Coverage of the 95% Confidence Intervals

Coverage rates of the 95% confidence intervals (CIs) were evaluated for each of the fixed effects in the DTS, ML-DTS, and CC-DTS models. Coverage rates of the 95% CIs were defined as the proportion of the 1,000 estimated confidence intervals that contained the generated parameter value. Coverage rates of between .925 and .975 were deemed to be acceptable (Bradley, 1978).

Root Mean Square Error

RMSE was calculated for the fixed effects (for all models) and the random effects' variance component (for the ML-DTS and CC-DTS models) using the following:

$$RMSE = \sqrt{\left(\bar{\hat{\theta}}_k - \theta_k\right)^2 + sd(\widehat{\theta})_k^{\ 2}}, \tag{22}$$

where $\bar{\bar{\theta}}_k$ is the average of the estimates for the k^{th} parameter across the 1,000 simulated datasets per simulation condition, θ_k is the generated true value of the k^{th} parameter, and $sd(\widehat{\theta})_k$ is the standard deviation of the 1,000 estimates of the k^{th} parameter per simulation condition. Smaller values of the RMSE suggest less biased and varied parameter estimates.

Analysis of Variance

ANOVA was performed to explore the effects of the five manipulated conditions used in this study on RPB. ANOVAs were conducted for each analysis approach (DTSA, ML-DTSA, and CC-DTSA) and model parameter separately, where the RPB was entered as the dependent variable and the manipulated conditions were the independent variables. Main effects and all possible interactions were included in the ANOVAs. An additional ANOVA was conducted per parameter where RPB was the outcome and the manipulated conditions and model type were included as independent variables. By including model type as an independent variable, the factorial ANOVA reveals model differences above and beyond differences observed for the other manipulated conditions, and therefore, may result in different practically important effects of the manipulated conditions on the observed RPB. Given that the purpose of using ANOVA here was descriptive due to large sample sizes, only the effect size was computed and interpreted. Cohen (1977) suggested that partial eta squared (η_p^2) values of .01, .06, and .14 are equivalent to small, moderate, and large effect sizes. Therefore, for this study, η_p^2 values of greater than .01 were considered to be practically significant.

Logistic Regression

Logistic regression was used to understand the practical impact of the manipulated conditions on the coverage of the 95% CIs. Logistic regression was necessary because the outcome used for this analysis was a binary variable where 1 indicated that the 95% CI included the true value and 0 indicated that it did not. Regressions were conducted for each analysis approach (DTSA, ML-DTSA, and CC-DTSA) and model parameter separately, where coverage (1/0) was entered as the dependent variable and the manipulated conditions were the independent variables. Given that the purpose of using logistic regression here was primarily descriptive due to the large sample sizes, only an effect size was computed and interpreted. The What Works Clearinghouse (WWC) Procedures Handbook, Version 4 (2020) provides an effect size calculation for dichotomous outcome models, referred to as the Cox index, which is provided by: $d_{Cox} = \frac{LOR}{1.65}$, where the LOR is the log odds ratio. Following the WWC guidelines for the Cox Index as a measure of effect size, a value of 0.25 was considered to be substantively important.

CHAPTER 4

RESULTS

This chapter presents the results of the simulation study that investigated differences in the relative parameter bias (RPB), root mean square error (RMSE), and coverage of the 95% confidence intervals (CIs) for conditional model parameters estimated using a discrete-time survival model (DTS model), a multilevel discrete-time survival model (ML-DTS model), and a cross-classified discrete-time survival model (CC-DTS model). Additionally, the results of the one-way and factorial ANOVAs are presented for RPB, and the results of the logistic regressions are summarized for coverage of the 95% CIs. The CC-DTS model and ML-DTS model both accounted for the multilevel data structure where individuals are nested into clustering units, and the CC-DTS model additionally handled the mobility of individuals across clusters. The DTS model did not account for either the multilevel data structure or individual mobility across clusters.

The estimation procedure converged for all DTS, ML-DTS, and CC-DTS models using the 72,000 datasets simulated for this study. The following presentation of results is divided into summaries of the findings for the RPB and the associated ANOVAs, RMSE, and lastly, the 95% CIs and the associated results of the logistic regressions.

Relative Parameter Bias

RPB was computed for estimates of the fixed effect and variance component parameters, including the coefficients associated with the intercept parameters that together represent the hazard function (a_1, a_2, a_3, a_4, and a_5), the level-1 covariate (β_1), and the level-2 covariate (β_2), as well as for the between-clusters variance component, σ_u^2. In addition to the tables of results presented in this section, nested loop plots (Rücker & Schwarzer, 2014) that depict the RPB estimates across all 72 combinations of conditions in one plot for each parameter can be found in Appendix F. Each nested loop plot provides a visual examination of model performance, in terms of RPB, such that patterns of RPB related to each simulation condition can be easily identified for each model used in this simulation study.

This section presents the relative parameter bias results for each of the 72 simulation conditions for each of the parameters estimated using the DTS model, the ML-DTS model, and the CC-DTS model. Additionally, the results of the ANOVAs are reported for each of the parameters with RPB as the outcome.

Coefficient of the Intercept for Discrete-Time Period 1, α_1

Table 6 presents the RPB for the parameter that represents discrete-time period 1 of the logit hazard function, a_1, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS model, the ML-DTS model, and the CC-DTS model. For the DTS model, moderate or substantial RPB was found for all 36 manipulated conditions. When holding all other manipulated conditions constant, RPB increased slightly as the rate of mobility increased. However, RPB increased substantially when the between-clusters variance component value increased from 0.32 to 1.09, suggesting that there was greater RPB associated with greater variation in the outcome between-clusters. When the between-clusters variance component value was 0.32, moderate negative bias was observed, while substantial negative bias was observed for all combinations of conditions when the between-clusters variance component was equal to 1.09. For the ML-DTS model, eleven of the 36 conditions resulted in RPB of between −0.05 and −0.10, indicating moderate negative bias of the parameter. All of the combinations that resulted in unacceptable RPB occurred when the variance between-clusters was 1.09, and the majority occurred in generated datasets that included the 30% mobility condition. When the CC-DTS model was used to estimate the coefficient for discrete-time period 1, under all combinations of conditions RPB was close to zero, and therefore, no unacceptable RPB was observed.

Table 6

Relative Parameter Bias of the Coefficient Estimate of the Intercept for Discrete-Time Period 1

(α_1= −3.25), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***−0.050***	−0.010	−0.001
			75	***−0.052***	−0.011	0.000
		50	25	***−0.054***	−0.012	0.000
			75	***−0.051***	−0.009	0.003
		100	25	***−0.055***	−0.013	−0.001
			75	***−0.055***	−0.011	0.000
	20	30	25	***−0.056***	−0.021	0.001
			75	***−0.054***	−0.020	0.003
		50	25	***−0.054***	−0.019	0.004
			75	***−0.057***	−0.021	0.001
		100	25	***−0.058***	−0.021	0.002
			75	***−0.059***	−0.021	0.001
	30	30	25	***−0.056***	−0.027	0.004
			75	***−0.062***	−0.032	−0.001
		50	25	***−0.062***	−0.030	0.000
			75	***−0.061***	−0.030	0.001
		100	25	***−0.061***	−0.029	0.003
			75	***−0.063***	−0.030	0.000
1.09	10	30	25	***−0.147***	−0.026	0.001
			75	***−0.150***	−0.028	0.001
		50	25	***−0.156***	−0.030	−0.001
			75	***−0.151***	−0.026	0.004
		100	25	***−0.158***	−0.031	−0.002
			75	***−0.158***	−0.030	0.000
	20	30	25	***−0.155***	***−0.052***	0.001
			75	***−0.152***	***−0.050***	0.002
		50	25	***−0.154***	−0.048	0.004
			75	***−0.157***	***−0.052***	0.001
		100	25	***−0.160***	***−0.050***	0.001
			75	***−0.160***	***−0.052***	0.001
	30	30	25	***−0.153***	***−0.065***	0.005
			75	***−0.161***	***−0.074***	−0.004
		50	25	***−0.165***	***−0.072***	−0.003
			75	***−0.158***	***−0.068***	0.002
		100	25	***−0.161***	***−0.067***	0.003
			75	***−0.164***	***−0.070***	0.000

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to a baseline hazard probability in time period 1 of .038. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size. Italicized and bolded values indicate moderate or substantial relative parameter bias.

Table 7 presents the RPB for the coefficient of the intercept for discrete-time period 1, a_1, across all 36 combinations of conditions where the Weibull scale parameter was 0.05. Using the DTS model, moderate or substantial negative bias was present across all combinations of conditions, ranging from −0.062 to −0.185. When controlling for the other manipulated conditions, RPB became more negative as the rate of mobility increased. More substantial RPB was observed when the variance component value increased from 0.32 to 1.09. Using the ML-DTS model, ten of the 36 conditions resulted in a relative parameter bias of between −0.05 and −0.10, indicating moderate bias of the parameter. All of the combinations that resulted in moderate RPB occurred when the variance between-clusters was 1.09, and the majority occurred under the 30% mobility condition. Using the CC-DTS model, RPB was very close to zero.

Table 7

Relative Parameter Bias of the Coefficient Estimate of the Intercept for Discrete-Time Period 1 (α_1 = −2.51), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***−0.062***	−0.011	0.002
			75	***−0.062***	−0.011	0.002
		50	25	***−0.065***	−0.012	0.001
			75	***−0.063***	−0.010	0.003
		100	25	***−0.067***	−0.013	0.001
			75	***−0.067***	−0.013	0.000
	20	30	25	***−0.068***	−0.023	0.003
			75	***−0.066***	−0.022	0.003
		50	25	***−0.066***	−0.021	0.004
			75	***−0.069***	−0.024	0.001
		100	25	***−0.070***	−0.023	0.002
			75	***−0.072***	−0.025	0.000
	30	30	25	***−0.071***	−0.034	0.002
			75	***−0.076***	−0.037	−0.002
		50	25	***−0.075***	−0.035	0.000
			75	***−0.073***	−0.034	0.001
		100	25	***−0.073***	−0.032	0.003
			75	***−0.075***	−0.035	0.000
1.09	10	30	25	***−0.168***	−0.026	0.002
			75	***−0.171***	−0.031	−0.001
		50	25	***−0.176***	−0.030	0.000
			75	***−0.171***	−0.026	0.005
		100	25	***−0.181***	−0.032	−0.002
			75	***−0.179***	−0.030	0.000
	20	30	25	***−0.177***	***−0.055***	−0.001
			75	***−0.172***	***−0.052***	0.002
		50	25	***−0.174***	***−0.050***	0.005
			75	***−0.177***	***−0.054***	0.001
		100	25	***−0.181***	***−0.052***	0.002
			75	***−0.182***	***−0.055***	0.001
	30	30	25	***−0.175***	***−0.070***	0.005
			75	***−0.183***	***−0.079***	−0.005
		50	25	***−0.185***	***−0.075***	−0.001
			75	***−0.179***	***−0.072***	0.003
		100	25	***−0.183***	***−0.071***	0.003
			75	***−0.184***	***−0.074***	0.001

Note. λ is the Weibull scale parameter, λ = 0.05 corresponded to a baseline hazard probability in time period 1 of .075. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size. Italicized and bolded values indicate moderate or substantial relative parameter bias.

To further explore the results presented in Tables 6 and 7, a factorial ANOVA was conducted for the coefficient, a_1, where RPB was the dependent variable and the manipulated conditions were entered as independent variables for each model separately. Appendix D presents the partial eta-squared estimates for each model. For the DTS model, the ANOVA results indicated that the main effect of the Weibull scale parameter had a practically significant effect on the estimate of a_1 [$F(1, 71{,}928) = 1{,}428.54$, $p < .001$, $\eta_p^2 = 0.019$]. Specifically, when the Weibull scale parameter was equal to 0.05, the mean relative parameter bias was more negative than when the Weibull scale parameter was equal to 0.025 ($M_{.025} = -0.11$, $M_{.05} = -0.12$). Additionally, the main effect of the between-cluster variance component had a practically significant effect on the estimate of a_1 [$F(1, 71{,}928) = 56{,}340.86$, $p < .001$, $\eta_p^2 = 0.439$], such that the mean RPB was more negative when the between-cluster variance component was equal to 1.09 ($M_{0.32} = -0.06$, $M_{1.09} = -0.17$). For the ML-DTS model, the ANOVA results indicated that the main effect of mobility had a practically significant effect on the estimate of a_1 [$F(2, 71{,}928) = 1{,}664.44$, $p < .001$, $\eta_p^2 = 0.044$], where the mean RPB became more negative as the mobility rate increased ($M_{.10} = -0.02$, $M_{.20} = -0.04$, $M_{.30} = -0.05$). Additionally, the main effect of the between-clusters variance had a practically significant effect on the estimate of a_1 [$F(1, 71{,}928) = 4{,}134.64$, $p < .001$, $\eta_p^2 = 0.054$], such that the mean RPB became more negative as the variance between-clusters increased from 0.32 to 1.09 ($M_{0.32} = -0.02$, $M_{1.09} = -0.05$). For the CC-DTS model, no main effect or interaction between manipulated conditions was identified as having a significant practical effect on RPB.

Coefficient of the Intercept for Discrete-Time Period 2, α_2

Table 8 presents the RPB for the coefficient of the intercept of discrete-time period 2 of the logit hazard function, a_2, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS model, the ML-DTS model, and the CC-DTS model. For the DTS model, 33 out of 36 combinations of conditions resulted in moderate or substantial RPB. Moderate negative bias of −0.05 to −0.10 was observed when the variance between-clusters was 0.32, with bias becoming more substantially negative when the variance between-clusters was 1.09. For the ML-DTS model, eleven of 36 combinations of conditions resulted in moderate RPB. All of the combinations that resulted in moderate RPB occurred when the variance between-clusters was 1.09, and the majority occurred under the 30% mobility condition. For the CC-DTS model, RPB was close to 0 for all combinations of conditions.

Table 8

Relative Parameter Bias of the Coefficient Estimate of the Intercept for Discrete-Time Period 2 (α_2 = −2.88), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	−0.043	−0.007	0.005
			75	***−0.052***	−0.015	−0.002
		50	25	−0.049	−0.011	0.002
			75	−0.048	−0.010	0.003
		100	25	***−0.053***	−0.015	−0.002
			75	***−0.051***	−0.012	0.001
	20	30	25	***−0.051***	−0.020	0.003
			75	***−0.052***	−0.022	0.002
		50	25	***−0.051***	−0.019	0.004
			75	***−0.055***	−0.024	0.000
		100	25	***−0.055***	−0.022	0.001
			75	***−0.056***	−0.023	0.001
	30	30	25	***−0.052***	−0.026	0.006
			75	***−0.061***	−0.035	−0.003
		50	25	***−0.059***	−0.031	0.001
			75	***−0.059***	−0.032	0.001
		100	25	***−0.059***	−0.031	0.002
			75	***−0.060***	−0.032	0.001
1.09	10	30	25	***−0.123***	−0.025	0.003
			75	***−0.131***	−0.033	−0.002
		50	25	***−0.129***	−0.028	0.002
			75	***−0.127***	−0.026	0.004
		100	25	***−0.136***	−0.033	−0.004
			75	***−0.133***	−0.030	0.001
	20	30	25	***−0.132***	***−0.051***	0.003
			75	***−0.132***	***−0.053***	0.001
		50	25	***−0.131***	−0.048	0.006
			75	***−0.135***	***−0.054***	0.000
		100	25	***−0.139***	***−0.053***	0.000
			75	***−0.138***	***−0.054***	0.001
	30	30	25	***−0.133***	***−0.064***	0.007
			75	***−0.144***	***−0.079***	−0.006
		50	25	***−0.144***	***−0.073***	−0.002
			75	***−0.139***	***−0.070***	0.003
		100	25	***−0.142***	***−0.070***	0.002
			75	***−0.143***	***−0.071***	0.001

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to a baseline hazard probability in time period 2 of .053. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size. Italicized and bolded values indicate moderate or substantial relative parameter bias.

Table 9 presents the RPB for the coefficient of the intercept of discrete-time period 2 of the logit hazard function, a_2, across 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS model, the ML-DTS model, and the CC-DTS model. For the DTS model, 35 out of 36 combinations of conditions resulted in moderate or substantial RPB. Overall, RPB became more negative as the variance between-clusters increased, with substantial negative bias present under all conditions with a variance between-clusters equal to 1.09. For the ML-DTS model, twelve of 36 combinations of conditions resulted in moderate negative relative parameter bias. All of the combinations that resulted in moderate RPB occurred when the variance between-clusters was 1.09, and the majority occurred under the 30% mobility condition. Lastly, the CC-DTS model did not result in any moderate or substantial RPB, where all RPB estimates only had a non-zero digit in the thousands place.

Table 9

Relative Parameter Bias of the Coefficient Estimate of the Intercept for Discrete-Time Period 2 (α_2 = −2.13), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	−0.048	−0.010	0.003
			75	***−0.053***	−0.016	−0.002
		50	25	***−0.052***	−0.013	0.001
			75	***−0.050***	−0.011	0.003
		100	25	***−0.055***	−0.015	−0.001
			75	***−0.053***	−0.013	0.001
	20	30	25	***−0.056***	−0.025	0.002
			75	***−0.058***	−0.026	0.000
		50	25	***−0.055***	−0.023	0.004
			75	***−0.058***	−0.026	0.000
		100	25	***−0.060***	−0.026	0.000
			75	***−0.060***	−0.026	0.001
	30	30	25	***−0.061***	−0.035	0.003
			75	***−0.069***	−0.043	−0.006
		50	25	***−0.065***	−0.037	0.000
			75	***−0.063***	−0.035	0.002
		100	25	***−0.065***	−0.036	0.001
			75	***−0.065***	−0.037	0.000
1.09	10	30	25	***−0.115***	−0.027	0.003
			75	***−0.120***	−0.035	−0.002
		50	25	***−0.121***	−0.032	−0.001
			75	***−0.115***	−0.026	0.006
		100	25	***−0.125***	−0.034	−0.004
			75	***−0.122***	−0.031	0.001
	20	30	25	***−0.125***	***−0.055***	0.001
			75	***−0.124***	***−0.056***	0.001
		50	25	***−0.122***	***−0.051***	0.007
			75	***−0.126***	***−0.057***	0.001
		100	25	***−0.129***	***−0.056***	0.001
			75	***−0.129***	***−0.057***	0.002
	30	30	25	***−0.131***	***−0.074***	0.005
			75	***−0.140***	***−0.086***	−0.008
		50	25	***−0.138***	***−0.079***	−0.002
			75	***−0.134***	***−0.076***	0.002
		100	25	***−0.137***	***−0.076***	0.001
			75	***−0.137***	***−0.078***	0.001

Note. λ is the Weibull scale parameter, λ = 0.05 corresponded to a baseline hazard probability in time period 2 of .106. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size. Italicized and bolded values indicate moderate or substantial relative parameter bias.

To further explore the results presented in Tables 8 and 9, a factorial ANOVA was conducted for the coefficient, a_2, where RPB was the dependent variable and the manipulated conditions were entered as independent variables for each model separately. Refer to Appendix D for tables that present the partial eta-squared estimates for each model. For the DTS model, the main effect of the between-cluster variance component had a practically significant effect on the estimate of a_2, [$F(1, 71{,}928) = 25{,}646.58$, $p < .001$, $\eta_p^2 = 0.263$], where the mean RPB was more negative when the between-cluster variance component was equal to 1.09 ($M_{0.32} = -0.06$, $M_{1.09} = -0.13$). For the ML-DTS model, the ANOVA results indicated that the main effect of mobility had a practically significant effect on the estimate of a_2,[$F(2, 71{,}928) = 1{,}426.09$, $p < .001$, $\eta_p^2 = 0.038$], where the mean RPB became more negative as the mobility rate increased ($M_{.10} = -0.02$, $M_{.20} = -0.04$, $M_{.30} = -0.05$). Additionally, the main effect of the between-clusters variance had a practically significant effect on the estimate of a_2,[$F(1, 71{,}928) = 3{,}362.80$, $p < .001$, $\eta_p^2 = 0.045$], such that the mean RPB again became more negative as the variance between-clusters increased from 0.32 to 1.09 ($M_{0.32} = -0.02$, $M_{1.09} = -0.05$). No practically substantial impacts of the manipulated conditions on RPB were observed using the CC-DTS model.

Coefficient of the Intercept for Discrete-Time Period 3, α_3

Table 10 presents the RPB for the coefficient of the intercept of discrete-time period 3 of the logit hazard function, a_3, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS model, the ML-DTS model, and the CC-DTS model. For the DTS model, 23 combinations of conditions resulted in unacceptable levels of RPB. The RPB was moderate or substantial for all conditions when the variance component was equal to 1.09, but when the variance component was equal to 0.32, only combinations of conditions that included the 30% mobility condition were found to have unacceptable RPB. For the ML-DTS model, moderate negative RPB was present for 8 out of 36 combinations of conditions, and only for conditions where the variance between-clusters was 1.09 and under the 30% mobility condition. For the CC-DTS model, no moderate or substantial RPB was observed for any combination of conditions.

Table 10

Relative Parameter Bias of the Coefficient Estimate of the Intercept for Discrete-Time Period 3 (α_3= −2.67), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	−0.036	−0.008	0.003
			75	−0.042	−0.013	−0.001
		50	25	−0.042	−0.012	0.000
			75	−0.039	−0.009	0.003
		100	25	−0.043	−0.013	−0.001
			75	−0.043	−0.012	0.000
	20	30	25	−0.044	−0.020	0.002
			75	−0.045	−0.021	0.002
		50	25	−0.041	−0.016	0.007
			75	−0.047	−0.023	0.000
		100	25	−0.047	−0.021	0.002
			75	−0.048	−0.022	0.001
	30	30	25	−0.047	−0.026	0.006
			75	***−0.055***	−0.035	−0.003
		50	25	***−0.051***	−0.030	0.002
			75	***−0.052***	−0.031	0.002
		100	25	***−0.052***	−0.030	0.002
			75	***−0.054***	−0.032	0.000
1.09	10	30	25	***−0.090***	−0.022	0.004
			75	***−0.098***	−0.031	−0.002
		50	25	***−0.099***	−0.030	−0.002
			75	***−0.093***	−0.024	0.005
		100	25	***−0.102***	−0.031	−0.004
			75	***−0.099***	−0.029	0.000
	20	30	25	***−0.103***	−0.048	0.001
			75	***−0.102***	***−0.050***	0.000
		50	25	***−0.098***	−0.043	0.008
			75	***−0.103***	−0.049	0.001
		100	25	***−0.106***	−0.048	0.001
			75	***−0.106***	***−0.050***	0.001
	30	30	25	***−0.107***	***−0.062***	0.006
			75	***−0.117***	***−0.075***	−0.007
		50	25	***−0.115***	***−0.069***	−0.002
			75	***−0.111***	***−0.065***	0.003
		100	25	***−0.113***	***−0.065***	0.002
			75	***−0.116***	***−0.069***	−0.001

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to baseline hazard probability in time period 3 of .065. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size. Italicized and bolded values indicate moderate or substantial relative parameter bias.

Table 11 presents the RPB for the coefficient of the intercept of discrete-time period 3 of the logit hazard function, a_3, across 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS model, the ML-DTS model, and the CC-DTS model. For the DTS model, moderate or substantial negative RPB was observed for 16 combinations of conditions, all of which had a variance component value equal to 1.09. Additionally, RPB tended to become more substantial as mobility increased. For the ML-DTS model, moderate RPB was observed for 7 combinations of conditions, all of which had a variance component value equal to 1.09 and the majority of which occurred under the 30% mobility condition. In all cases, bias was negative. For the CC-DTS, no moderate or substantial RPB was observed for any combination of conditions.

Table 11

Relative Parameter Bias of the Coefficient Estimate of the Intercept for Discrete-Time Period 3 (α_3= −1.90), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	−0.026	−0.009	0.003
			75	−0.031	−0.015	−0.002
		50	25	−0.031	−0.013	0.000
			75	−0.027	−0.009	0.004
		100	25	−0.033	−0.015	−0.003
			75	−0.030	−0.012	0.001
	20	30	25	−0.034	−0.021	0.004
			75	−0.036	−0.023	0.001
		50	25	−0.033	−0.019	0.006
			75	−0.037	−0.024	0.001
		100	25	−0.037	−0.023	0.001
			75	−0.040	−0.026	−0.001
	30	30	25	−0.044	−0.033	0.003
			75	−0.048	−0.039	−0.004
		50	25	−0.046	−0.035	−0.001
			75	−0.043	−0.032	0.004
		100	25	−0.045	−0.033	0.001
			75	−0.047	−0.036	0.000
1.09	10	30	25	−0.046	−0.023	0.002
			75	***−0.052***	−0.032	−0.004
		50	25	***−0.052***	−0.031	−0.004
			75	−0.043	−0.021	0.007
		100	25	***−0.054***	−0.032	−0.006
			75	−0.049	−0.028	0.000
	20	30	25	***−0.057***	−0.045	0.004
			75	***−0.058***	−0.048	0.002
		50	25	***−0.054***	−0.042	0.008
			75	***−0.059***	−0.049	0.002
		100	25	***−0.061***	−0.049	0.001
			75	***−0.061***	***−0.051***	0.001
	30	30	25	***−0.073***	***−0.067***	0.001
			75	***−0.078***	***−0.077***	−0.008
		50	25	***−0.075***	***−0.070***	−0.004
			75	***−0.070***	***−0.065***	0.005
		100	25	***−0.073***	***−0.066***	0.002
			75	***−0.074***	***−0.070***	0.000

Note. λ is the Weibull scale parameter, λ = 0.05 corresponded to baseline hazard probability in time period 3 of .130. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size. Italicized and bolded values indicate moderate or substantial relative parameter bias.

To further explore the results presented in Tables 10 and 11, a factorial ANOVA was conducted for the coefficient, a_3, where RPB was the dependent variable and the manipulated conditions were entered as independent variables for each model separately. Appendix D presents the partial eta-squared estimates for each model. For the DTS model, the main effect of the mobility rate had a practically significant effect on the estimate of a_3 [$F(2, 71{,}928) = 382.02$, $p < .001$, $\eta_p^2 = 0.011$], such that as the mobility rate increased, the mean RPB became more negative ($M_{.10} = -0.05$, $M_{.20} = -0.06$, $M_{.30} = -0.07$). Additionally, the interaction of the between-cluster variance component and the Weibull scale parameter had a practically significant effect on RPB for the estimate of a_3 [$F(1, 71{,}928) = 1{,}210$, $p < .001$, $\eta_p^2 = 0.017$]. Specifically, the interaction indicated that the mean relative parameter bias was more negative when the Weibull scale parameter was 0.025 and the between-clusters variance was equal to 1.09, and the difference in the mean RPB between the Weibull scale parameters was greatest when the between-clusters variance was 1.09. For the ML-DTS model, the ANOVA results indicated that the main effect of mobility had a practically significant effect on the estimate of a_3 [$F(2, 71{,}928) = 984.44$, $p < .001$, $\eta_p^2 = 0.027$], such that as the mobility rate increased, the RPB became more negative ($M_{.10} = -0.02$, $M_{.20} = -0.03$, $M_{.30} = -0.05$). Additionally, the main effect of the between-clusters variance had a practically significant effect on the estimate of a_3 [$F(1, 71{,}928) = 2{,}118.58$, $p < .001$, $\eta_p^2 = 0.029$], where RPB became more negative as the variance between-clusters increased from 0.32 to 1.09 ($M_{0.32} = -0.02$, $M_{1.09} = -0.05$). For the CC-DTS, the ANOVA results indicated that no manipulated conditions had a practically important impact on RPB.

Coefficient of the Intercept for Discrete-Time Period 4, α_4

Table 12 presents the RPB for the coefficient of the intercept of discrete-time period 4 of the logit hazard function, a_4, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS model, the ML-DTS model, and the CC-DTS model. For the DTS model, 18 combinations of conditions were found to have unacceptable RPB, all of which were associated with a variance component value of 1.09. The magnitude of RPB was less than 0.10 in all cases where RPB was observed, but became more negative as mobility increased. For the ML-DTS model, moderate RPB was present for 5 out of 36 combinations of conditions, and only for conditions where the variance between-clusters was 1.09 and under the 30% mobility condition. For the CC-DTS, no moderate or substantial bias was observed, with all RPB estimates nearing 0.

Table 12

Relative Parameter Bias of the Coefficient Estimate of the Intercept for Discrete-Time Period 4 (α_4 = −2.51), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	−0.024	−0.005	0.005
			75	−0.030	−0.011	0.000
		50	25	−0.032	−0.012	−0.002
			75	−0.028	−0.008	0.003
		100	25	−0.033	−0.013	−0.002
			75	−0.030	−0.010	0.001
	20	30	25	−0.033	−0.018	0.002
			75	−0.033	−0.018	0.002
		50	25	−0.034	−0.018	0.003
			75	−0.036	−0.021	0.000
		100	25	−0.035	−0.018	0.002
			75	−0.036	−0.019	0.001
	30	30	25	−0.037	−0.023	0.006
			75	−0.043	−0.031	−0.002
		50	25	−0.044	−0.030	−0.002
			75	−0.042	−0.028	0.001
		100	25	−0.043	−0.029	0.000
			75	−0.042	−0.028	0.002
1.09	10	30	25	***−0.055***	−0.018	0.003
			75	***−0.060***	−0.025	−0.001
		50	25	***−0.062***	−0.025	−0.003
			75	***−0.055***	−0.019	0.005
		100	25	***−0.063***	−0.026	−0.003
			75	***−0.060***	−0.023	0.000
	20	30	25	***−0.064***	−0.037	0.003
			75	***−0.065***	−0.039	0.002
		50	25	***−0.066***	−0.037	0.004
			75	***−0.068***	−0.041	0.001
		100	25	***−0.068***	−0.039	0.001
			75	***−0.068***	−0.040	0.002
	30	30	25	***−0.072***	−0.049	0.007
			75	***−0.080***	***−0.061***	−0.005
		50	25	***−0.082***	***−0.059***	−0.005
			75	***−0.076***	***−0.054***	0.002
		100	25	***−0.079***	***−0.055***	0.000
			75	***−0.078***	***−0.055***	0.001

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to baseline hazard probability in time period 4 of .075. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size. Italicized and bolded values indicate moderate or substantial relative parameter bias.

Table 13 presents the RPB for the coefficient of the intercept of discrete-time period 4 of the logit hazard function, a_4, across 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS model, the ML-DTS model, and the CC-DTS model. For the DTS model, no unacceptable RPB was observed for any combination of conditions. For the ML-DTS model, moderate RPB was observed for only one combination of conditions, when the between-clusters variance component was 1.09, the mobility condition was 30%, the cluster size was 30, and the within-cluster sample size was 75. For the CC-DTS model, no moderate or substantial RPB was observed for any combination of conditions.

Table 13

Relative Parameter Bias of the Coefficient Estimate of the Intercept for Discrete-Time Period 4 (α_4= −1.74), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.004	−0.004	0.004
			75	−0.001	−0.011	−0.001
		50	25	−0.003	−0.012	−0.002
			75	0.003	−0.006	0.004
		100	25	−0.003	−0.012	−0.003
			75	0.001	−0.009	0.001
	20	30	25	−0.007	−0.016	0.002
			75	−0.007	−0.016	0.002
		50	25	−0.009	−0.018	0.001
			75	−0.008	−0.017	0.002
		100	25	−0.008	−0.017	0.001
			75	−0.009	−0.018	0.001
	30	30	25	−0.016	−0.024	0.004
			75	−0.021	−0.031	−0.004
		50	25	−0.023	−0.033	−0.006
			75	−0.017	−0.026	0.002
		100	25	−0.017	−0.026	0.001
			75	−0.017	−0.026	0.001
1.09	10	30	25	0.034	−0.013	0.002
			75	0.029	−0.021	−0.004
		50	25	0.031	−0.020	−0.004
			75	0.039	−0.010	0.007
		100	25	0.029	−0.022	−0.006
			75	0.035	−0.017	0.000
	20	30	25	0.019	−0.029	0.001
			75	0.018	−0.031	0.000
		50	25	0.022	−0.026	0.006
			75	0.019	−0.030	0.002
		100	25	0.021	−0.029	0.002
			75	0.020	−0.031	0.002
	30	30	25	0.006	−0.039	0.005
			75	−0.004	***−0.053***	−0.010
		50	25	0.000	−0.048	−0.007
			75	0.005	−0.042	0.003
		100	25	0.003	−0.042	0.001
			75	0.005	−0.043	0.001

Note. λ is the Weibull scale parameter, λ = 0.05 corresponded to baseline hazard probability in time period 4 of .150. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size. Italicized and bolded values indicate moderate or substantial relative parameter bias.

To further explore the practical implications of the results presented in Tables 12 and 13, a factorial ANOVA was conducted for the coefficient, a_4, where RPB was the dependent variable and the manipulated conditions were entered as independent variables for each model separately. Appendix D presents the partial eta-squared estimates for each model. For the DTS model, the main effect of the mobility rate had a practically significant effect on the estimate of a_4, [$F(2, 71{,}928) = 460.63$, $p < .001$, $\eta_p^2 = 0.013$], such that as the mobility rate increased, the mean RPB became more negative ($M_{.10} = -0.01$, $M_{.20} = -0.02$, $M_{.30} = -0.03$). Additionally, the interaction of the between-cluster variance component and the Weibull scale parameter had a practically significant effect on the estimate of a_4 [$F(2, 71{,}928) = 3{,}027.15$, $p < .001$, $\eta_p^2 = 0.040$]. When the between-clusters variance was 0.32, the mean RPB was more substantial when the Weibull scale parameter was 0.025 than when it was 0.05. In contrast, when the between-clusters variance was 1.09, the mean RPB was more substantial when the Weibull scale parameter was 0.05 than when it was 0.025. Again, when the between-clusters variance was 1.09, the difference in mean RPB by the Weibull scale parameter values was much more substantial than when it is 0.32. For the ML-DTS model, the main effect of mobility had a practically significant effect on the estimate of a_4 [$F(2, 71{,}928) = 524.96$, $p < .001$, $\eta_p^2 = 0.014$], such that as the mobility rate increased, the mean RPB became more negative ($M_{.10} = -0.01$, $M_{.20} = -0.03$, $M_{.30} = -0.04$). Additionally, the main effect of the between-clusters variance had a practically significant effect on the estimate of a_4 [$F(1, 71{,}928) = 697.83$, $p < .001$, $\eta_p^2 = 0.010$], where the RPB became more negative as the variance between-clusters increased from 0.32 to 1.09 ($M_{0.32} = -0.02$, $M_{1.09} = -0.03$). For the CC-DTS model, no practically significant main effects or interactions were apparent.

Coefficient of the Intercept for Discrete-Time Period 5, α_5

Table 14 presents the RPB for the coefficient of the intercept of discrete-time period 5 of the logit hazard function, a_5, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS model, the ML-DTS model, and the CC-DTS model. No moderate or substantial RPB was observed for any combination of conditions using any of the estimating models. Although no substantial RPB was observed, the CC-DTS model consistently performed better than the DTS and the ML-DTS models, with RPB close to 0 in all cases.

Table 14

Relative Parameter Bias of the Coefficient Estimate of the Intercept for Discrete-Time Period 5 (α_5= −2.39), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	−0.012	−0.004	0.003
			75	−0.018	−0.010	−0.002
		50	25	−0.016	−0.008	−0.001
			75	−0.012	−0.005	0.003
		100	25	−0.016	−0.008	−0.001
			75	−0.015	−0.007	0.001
	20	30	25	−0.020	−0.014	0.001
			75	−0.022	−0.016	−0.001
		50	25	−0.019	−0.013	0.003
			75	−0.021	−0.014	0.001
		100	25	−0.021	−0.014	0.001
			75	−0.021	−0.015	0.001
	30	30	25	−0.022	−0.017	0.006
			75	−0.030	−0.026	−0.004
		50	25	−0.026	−0.021	0.000
			75	−0.026	−0.021	0.002
		100	25	−0.026	−0.020	0.002
			75	−0.026	−0.021	0.001
1.09	10	30	25	−0.014	−0.010	0.002
			75	−0.019	−0.017	−0.003
		50	25	−0.015	−0.012	0.001
			75	−0.013	−0.010	0.005
		100	25	−0.019	−0.016	−0.003
			75	−0.016	−0.014	0.000
	20	30	25	−0.023	−0.022	0.001
			75	−0.024	−0.024	0.000
		50	25	−0.019	−0.018	0.007
			75	−0.023	−0.023	0.001
		100	25	−0.023	−0.022	0.001
			75	−0.023	−0.023	0.002
	30	30	25	−0.029	−0.029	0.005
			75	−0.037	−0.040	−0.008
		50	25	−0.035	−0.036	−0.005
			75	−0.031	−0.032	0.002
		100	25	−0.030	−0.029	0.004
			75	−0.031	−0.032	0.002

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to baseline hazard probability in time period 5 of .084. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size. Italicized and bolded values indicate moderate or substantial relative parameter bias.

Table 15 presents the RPB for the coefficient of the intercept of discrete-time period 5 of the logit hazard function, a_5, across 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS model, the ML-DTS model, and the CC-DTS model. For the DTS model, moderate or substantial RPB was observed for 16 combinations of conditions. Specifically, when all other conditions were held constant, moderate or substantial positive bias was observed when the between-clusters variance component was equal to 1.09, where the magnitude of the RPB ranged from 0.092 to 0.126. For the ML-DTS and CC-DTS model, no moderate or substantial RPB was observed for any combination of conditions.

Table 15

Relative Parameter Bias of the Coefficient Estimate of the Intercept for Discrete-Time Period 5 (α_5 = −1.60), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.040	0.002	0.005
			75	0.035	−0.004	−0.002
		50	25	0.037	−0.002	0.000
			75	0.040	0.000	0.003
		100	25	0.038	−0.003	0.000
			75	0.039	−0.002	0.001
	20	30	25	0.032	−0.002	0.005
			75	0.030	−0.004	0.001
		50	25	0.031	−0.003	0.004
			75	0.031	−0.003	0.002
		100	25	0.033	−0.003	0.003
			75	0.030	−0.006	0.000
	30	30	25	0.020	−0.010	0.002
			75	0.013	−0.018	−0.008
		50	25	0.020	−0.013	−0.003
			75	0.024	−0.007	0.003
		100	25	0.024	−0.008	0.003
			75	0.022	−0.010	0.001
1.09	10	30	25	***0.126***	0.007	0.004
			75	***0.123***	0.000	−0.002
		50	25	***0.126***	0.000	−0.003
			75	***0.131***	0.009	0.007
		100	25	***0.126***	−0.001	−0.004
			75	***0.130***	0.003	0.000
	20	30	25	***0.116***	0.009	0.004
			75	***0.114***	0.006	0.001
		50	25	***0.117***	0.008	0.006
			75	***0.116***	0.006	0.003
		100	25	***0.120***	0.007	0.003
			75	***0.117***	0.004	0.001
	30	30	25	***0.102***	0.006	0.004
			75	***0.092***	−0.007	−0.012
		50	25	***0.103***	0.002	−0.004
			75	***0.104***	0.006	0.004
		100	25	***0.107***	0.007	0.004
			75	***0.105***	0.004	0.002

Note. λ is the Weibull scale parameter, λ = 0.05 corresponded to baseline hazard probability in time period 5 of .168. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size. Italicized and bolded values indicate moderate or substantial relative parameter bias.

To further explore the practical implications of the results presented in Tables 14 and 15, a factorial ANOVA was conducted for the coefficient, a_5, where RPB was the dependent variable and the manipulated conditions were entered as independent variables for each model separately. The ANOVA results are presented in Appendix D. For the DTS model, the interaction of the between-cluster variance component and the Weibull scale parameter had a practically significant effect on the estimate of a_5 [$F(2, 71{,}928) = 5{,}604.57$, $p < .001$, $\eta_p^2 = 0.072$], where RPB was more negative when the Weibull scale parameter was 0.025 and the between-clusters variance was equal to 1.09. The difference in the mean RPB between the Weibull scale parameters was greatest when the between-clusters variance was 1.09. For the ML-DTS model, the partial Eta-Squared indicated a practically significant effect of the main effect of the Weibull scale parameter [$F(1, 71{,}928) = 714.73$, $p < .001$, $\eta_p^2 = 0.010$]. The average RPB across all conditions when the Weibull scale parameter was 0.05 was estimated with virtually no bias, while some negative bias was observed when the Weibull scale parameter was 0.025 ($M_{0.025} = -0.02$, $M_{0.05} = 0.00$). There were no practically significant impacts of the manipulated conditions on the RPB for the CC-DTS model.

Summarizing the Coefficient of the Intercepts of the Logit Hazard Function, α_1 through α_5. The results suggest that for the coefficients representing the logit hazard function, a_1 through a_5, the most substantial RPB occurred for the DTS model, which did not account for either the multilevel data structure or individual mobility across clusters. Some moderate RPB was also apparent for the ML-DTS model, which accounted for the multilevel data structure but did not model mobility. For the ML-DTS model, moderate RPB was especially evident in the logit hazard function under the 30% mobility condition and with larger variation between-clusters. The CC-DTS model accounted for both mobility in the dataset and the multilevel data structure. When the CC-DTS model was used, no moderate or substantial relative parameter bias was found for any parameter representing the logit hazard function.

Given the differences between models in RPB for the coefficients representing the logit hazard function, an additional factorial ANOVA was conducted where RPB was entered as the dependent variable and each of the manipulated conditions, in addition to model type (i.e., DTS, ML-DTS, and CC-DTS models), were entered as independent variables for each parameter in the hazard function. By including model type as an independent variable, the factorial ANOVA reveals model differences above and beyond differences observed for the other manipulated conditions, and therefore, may result in different practically important effects of the manipulated conditions on the observed RPB. Appendix E presents the results of all factorial ANOVAs when model type was included as a factor along with each of the manipulated conditions. The results indicated that for a_1, the interaction of the between-cluster variance component and model type had a practically significant effect on the RPB [$F(2, 215{,}784) = 13{,}905.54$, $p < .001$, $\eta_p^2 = 0.114$], where the mean RPB was more negative when the variance between-clusters was 1.09 for both the DTS and the ML-DTS models ($M_{DTS} = -0.17$, $M_{ML\text{-}DTS} = -0.05$) than when it was 0.32 ($M_{DTS} = -0.06$, $M_{ML\text{-}DTS} = -0.02$), but was identical for the CC-DTS model regardless of the variance-between clusters condition ($M_{0.32} = 0.00$, $M_{1.09} = 0.00$). Similar results were observed for a_2, where the interaction of the between-cluster variance component and model type had a practically significant effect on the RPB [$F(2, 215{,}784) = 5{,}524.54$, $p < .001$, $\eta_p^2 = 0.049$], where the mean RPB was more negative when the variance between-clusters was 1.09 for both the DTS and the ML-DTS models ($M_{DTS} = -0.13$, $M_{ML\text{-}DTS} = -0.05$) than when it was 0.32 ($M_{DTS} = -0.06$, $M_{ML\text{-}DTS} = -0.02$), but was identical for the CC-DTS model regardless of the variance-between clusters condition ($M_{0.32} = 0.00$, $M_{1.09} = 0.00$). Again, similar results were observed for a_3. Here, the interaction of the between-cluster variance component and model type had a practically significant effect on the RPB [$F(2, 215{,}784) = 1{,}330.79$, $p < .001$, $\eta_p^2 = 0.012$], where the mean RPB was more negative when the variance between-clusters was 1.09 for both the DTS and the ML-DTS models ($M_{DTS} = -0.08$, $M_{ML\text{-}DTS} = -0.05$) than when it was 0.32 ($M_{DTS} = -0.04$, $M_{ML\text{-}DTS} = -0.02$), but was identical for the CC-DTS model regardless of the variance-between clusters condition ($M_{0.32} = 0.00$, $M_{1.09} = 0.00$). For a_4, the interaction of the Weibull scale parameter and model type had a practically significant effect on the RPB [$F(2, 215{,}784) = 2{,}673.92$, $p < .001$, $\eta_p^2 = 0.024$], where the mean RPB was more negative when the Weibull scale parameter was equal to 0.025 than when it was equal to 0.05 for the DTS model ($M_{.025} = -0.05$, $M_{.05} = 0.00$), but was nearly identical regardless of the Weibull scale parameter for both the ML-DTS ($M_{.025} = -0.02$, $M_{.05} = -0.02$) and CC-DTS models ($M_{.025} = 0.00$, $M_{.05} = 0.00$). For a_5, a three-way interaction between model type, Weibull scale parameter, and variance between-clusters was found to have a practically significant effect on the RPB [$F(2, 215{,}784) = 1{,}242.52$, $p < .001$, $\eta_p^2 = 0.011$]. Table 16 presents the mean RPB values by condition and model for this three-way interaction effect. For the CC-DTS model, no RPB was observed regardless of the level of the variance between-clusters or the Weibull scale parameter condition. However, for the DTS model, the mean RPB was identical for each level of the variance between-clusters condition when the Weibull scale parameter was 0.025, but was much more positive when the variance between-clusters was equal to 1.09 than when it was 0.32 when the Weibull scale parameter was 0.05. For the ML-DTS model, slight differences in RPB were observed between levels of the variance between-clusters condition when the Weibull scale parameter was 0.025, but no RPB was observed regardless of the level of the variance between-clusters condition when the Weibull scale parameter was 0.05.

Table 16

Mean Relative Parameter Bias for Each Combination of Conditions Represented by the Three-Way Interaction Effect for a_5

Weibull Scale Parameter	Variance Between-Clusters	Estimating Model DTS	ML-DTS	CC-DTS
0.025	0.32	−0.02	−0.01	0.00
	1.09	−0.02	−0.02	0.00
0.05	0.32	0.03	0.00	0.00
	1.09	***0.12***	0.00	0.00

Note. Italicized and bolded values indicate moderate or substantial relative parameter bias.

Coefficient of the individual-level predictor, β_1

Table 17 presents the relative parameter bias for the level-1 predictor's coefficient, β_1, for the DTS, ML-DTS, and CC-DTS models, respectively, for the 36 unique combinations of conditions that included a Weibull scale parameter that was equal to 0.025. Moderate or substantial bias was present under all combinations of conditions using the DTS model. When the between-clusters variance was 0.32, the coefficient was estimated with negative bias of a magnitude ranging from about 0.057 to as high as 0.074, indicating moderate bias. When the between-clusters variance was 1.09, substantial negative bias was observed, ranging from −0.182 to −0.206. For the ML-DTS model, relative parameter bias was moderate for 6 out of 36 combinations of conditions. In all cases, relative parameter bias was present when the variance between-clusters was 1.09 and the mobility rate condition was 30%. The coefficient for the level-one predictor was estimated with negative bias of a magnitude from 0.053 to 0.068 for the ML-DTS model. For the CC-DTS model, no moderate or substantial RPB was observed in any combination of conditions.

Table 17

Relative Parameter Bias of the Coefficient Estimate of the Level-One Predictor (β_1 = 0.50), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***−0.057***	0.002	0.011
			75	***−0.072***	−0.013	−0.005
		50	25	***−0.073***	−0.012	−0.003
			75	***−0.068***	−0.006	0.002
		100	25	***−0.069***	−0.007	0.002
			75	***−0.072***	−0.009	0.000
	20	30	25	***−0.058***	−0.008	0.011
			75	***−0.057***	−0.007	0.009
		50	25	***−0.064***	−0.014	0.005
			75	***−0.072***	−0.021	−0.003
		100	25	***−0.071***	−0.017	0.000
			75	***−0.070***	−0.015	0.002
	30	30	25	***−0.057***	−0.012	0.012
			75	***−0.060***	−0.017	0.006
		50	25	***−0.066***	−0.019	0.003
			75	***−0.074***	−0.029	−0.006
		100	25	***−0.066***	−0.018	0.005
			75	***−0.067***	−0.020	0.002
1.09	10	30	25	***−0.182***	−0.009	0.013
			75	***−0.195***	−0.026	−0.001
		50	25	***−0.201***	−0.023	0.003
			75	***−0.200***	−0.024	−0.001
		100	25	***−0.205***	−0.025	0.001
			75	***−0.206***	−0.025	−0.001
	20	30	25	***−0.183***	−0.035	0.016
			75	***−0.186***	−0.040	0.003
		50	25	***−0.192***	−0.043	0.006
			75	***−0.198***	−0.049	−0.003
		100	25	***−0.204***	−0.049	−0.004
			75	***−0.201***	−0.045	0.000
	30	30	25	***−0.185***	***−0.056***	0.007
			75	***−0.182***	***−0.053***	0.006
		50	25	***−0.201***	***−0.068***	−0.007
			75	***−0.195***	***−0.064***	−0.003
		100	25	***−0.194***	***−0.056***	0.006
			75	***−0.195***	***−0.058***	0.001

Note. λ is the Weibull scale parameter, β_1 = *0.50* corresponded to hazard odds ratio of 1.65. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size. Italicized and bolded values indicate moderate or substantial relative parameter bias.

Table 18 presents the relative parameter bias for the level-1 predictor's coefficient, β_1, for the DTS, ML-DTS, and CC-DTS models, respectively, for the 36 unique combinations of conditions that included a Weibull scale parameter that was equal to 0.05. Moderate or substantial bias was present under all combinations of conditions using the DTS model. When the between-clusters variance was 0.32, moderate negative bias was observed; however, when the between-clusters variance was 1.09, substantial negative bias was observed, ranging from about −0.22 to −0.25. For the ML-DTS model, relative parameter bias was moderate for 8 out of 36 combinations of conditions. For the majority of conditions where RPB was present, moderate RPB was observed when the variance between-clusters was 1.09 and the mobility rate condition was 30%. In one instance, the mobility rate condition was 20% in combination with a variance between-clusters of 1.09, a cluster-size of 100, and a within-cluster size of 75. For the CC-DTS model, no moderate or substantial RPB was observed in any combination of conditions.

Table 18

Relative Parameter Bias of the Coefficient Estimate of the Level-One Predictor (β_1 = 0.50), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***−0.082***	0.001	0.010
			75	***−0.091***	−0.009	0.003
		50	25	***−0.100***	−0.013	−0.002
			75	***−0.096***	−0.010	0.000
		100	25	***−0.097***	−0.009	0.003
			75	***−0.096***	−0.007	0.004
	20	30	25	***−0.086***	−0.014	0.010
			75	***−0.087***	−0.016	0.004
		50	25	***−0.091***	−0.018	0.004
			75	***−0.094***	−0.021	0.000
		100	25	***−0.096***	−0.020	0.001
			75	***−0.102***	−0.025	−0.004
	30	30	25	***−0.093***	−0.031	0.000
			75	***−0.087***	−0.024	0.004
		50	25	***−0.095***	−0.029	−0.001
			75	***−0.093***	−0.028	0.001
		100	25	***−0.094***	−0.025	0.003
			75	***−0.094***	−0.026	0.001
1.09	10	30	25	***−0.223***	−0.013	0.012
			75	***−0.237***	−0.033	−0.005
		50	25	***−0.247***	−0.030	−0.005
			75	***−0.238***	−0.024	0.002
		100	25	***−0.248***	−0.027	0.001
			75	***−0.245***	−0.025	0.001
	20	30	25	***−0.225***	−0.040	0.014
			75	***−0.225***	−0.042	0.004
		50	25	***−0.229***	−0.041	0.012
			75	***−0.236***	***−0.050***	0.001
		100	25	***−0.244***	***−0.051***	−0.001
			75	***−0.245***	***−0.054***	−0.002
	30	30	25	***−0.227***	***−0.064***	0.006
			75	***−0.223***	***−0.061***	0.006
		50	25	***−0.234***	***−0.066***	0.002
			75	***−0.234***	***−0.070***	−0.002
		100	25	***−0.237***	***−0.065***	0.002
			75	***−0.236***	***−0.065***	0.001

Note. λ is the Weibull scale parameter, β_1 = *0.50* corresponded to hazard odds ratio of 1.65. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size. Italicized and bolded values indicate moderate or substantial relative parameter bias.

To further explore the results presented in Tables 17 and 18, a factorial ANOVA was conducted for each model, the DTS, ML-DTS, and CC-DTS models, respectively, where RPB was the dependent variable. Appendix D presents the partial eta-squared estimates for each estimating model for the coefficient of the level-one predictor. The ANOVA results indicated that the main effect of the variance between-clusters had a practically significant effect on RPB for the coefficient of β_1 for the DTS model [$F(1, 71{,}928) = 14{,}163.86$, $p < .001$, $\eta_p^2 = 0.165$]. For the DTS model, the mean of the RPB estimates was much more negative for conditions where the variance between-clusters was 1.09 than when the variance between-clusters was 0.32 ($M_{0.32} = -0.08$, $M_{1.09} = -0.21$). For the DTS model, the main effect of the Weibull scale parameter was also found to be practically significant [$F(1, 71{,}928) = 867.03$, $p < .001$, $\eta_p^2 = 0.012$]. When the Weibull scale parameter was 0.05, the average RPB across all conditions was more negative than when it was 0.025 ($M_{.025} = -0.13$, $M_{.05} = -0.16$). No practically significant differences in RPB based on the main effects or interactions between the five independent variables were found for either the ML-DTS or the CC-DTS for the coefficient of the level-1 predictor variable.

An additional factorial ANOVA was conducted where RPB was entered as the dependent variable and each of the manipulated conditions, as well as model type (i.e., DTS, ML-DTS, and CC-DTS models), were entered as independent variables. Appendix E presents the results of all factorial ANOVAs when model type is included as a factor along with each of the manipulated conditions. The results indicated that for the coefficient of the level-one predictor, the interaction of the between-cluster variance component and model type had a practically significant effect on the RPB [$F(2, 215{,}784) = 3{,}816.38$, $p < .001$, $\eta_p^2 = 0.034$], where the mean RPB was much more negative when the variance between-clusters was 1.09 for the DTS model ($M_{0.32} = -0.08$, $M_{1.09} = -0.21$), with only a slight difference between levels of the variance between-clusters condition for the ML-DTS model ($M_{0.32}$ = −0.02, $M_{1.09}$ = −0.04). In contrast, no difference was observed for the CC-DTS model regardless of the level of the variance-between clusters condition ($M_{0.32}$ = 0.00, $M_{1.09}$= 0.00).

Coefficient of the cluster-level predictor, β_2

Table 19 presents the relative parameter bias for the level-2 predictor's coefficient, β_2, for the DTS, ML-DTS, and CC-DTS models, respectively, for the 36 unique combinations of conditions that included a Weibull scale parameter that was equal to 0.025. For both the DTS model and the ML-DTS model, the coefficient for the level-2 predictor exhibited moderate or substantial RPB under all combinations of conditions. For the DTS model, substantial negative RPB was observed for all 36 combinations of conditions. When holding all other conditions constant, RPB became more negative as mobility increased in the dataset. Additionally, holding other conditions constant, RPB was greater when the variance between-clusters was 1.09 as compared to when it was 0.32. Specifically, when the variance between-clusters was 0.32, bias ranged from −0.12 to −0.29. When the variance between-clusters was 1.09, the coefficient estimate was more substantially negative, ranging from about −0.24 to as −0.40. For the ML-DTS, although both moderate and substantial RPB was observed, it was notably less substantial than for the DTS model. Holding all other conditions constant, RPB became more negative as mobility increased. However, RPB was not as greatly affected by the variance between-clusters for the ML-DTS model as it was using the DTS model. For the CC-DTS model, no substantial RPB was observed for any combination of conditions.

Table 19

Relative Parameter Bias of the Coefficient Estimate of the Level-Two Predictor (β_2 = 0.50), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***−0.126***	***−0.068***	0.010
			75	***−0.128***	***−0.067***	0.016
		50	25	***−0.147***	***−0.087***	−0.005
			75	***−0.140***	***−0.082***	0.002
		100	25	***−0.163***	***−0.105***	−0.024
			75	***−0.153***	***−0.094***	−0.014
	20	30	25	***−0.221***	***−0.176***	−0.020
			75	***−0.211***	***−0.167***	−0.006
		50	25	***−0.198***	***−0.150***	0.013
			75	***−0.209***	***−0.163***	−0.003
		100	25	***−0.196***	***−0.146***	0.014
			75	***−0.207***	***−0.160***	0.004
	30	30	25	***−0.260***	***−0.223***	0.020
			75	***−0.293***	***−0.258***	−0.025
		50	25	***−0.268***	***−0.228***	0.000
			75	***−0.273***	***−0.236***	−0.001
		100	25	***−0.264***	***−0.224***	0.015
			75	***−0.267***	***−0.229***	0.008
1.09	10	30	25	***−0.246***	***−0.079***	0.022
			75	***−0.246***	***−0.074***	0.035
		50	25	***−0.279***	***−0.116***	−0.012
			75	***−0.265***	***−0.101***	0.007
		100	25	***−0.293***	***−0.134***	−0.036
			75	***−0.290***	***−0.132***	−0.027
	20	30	25	***−0.331***	***−0.203***	−0.012
			75	***−0.321***	***−0.201***	−0.012
		50	25	***−0.305***	***−0.170***	0.021
			75	***−0.323***	***−0.194***	0.000
		100	25	***−0.313***	***−0.176***	0.012
			75	***−0.320***	***−0.191***	0.008
	30	30	25	***−0.359***	***−0.253***	0.025
			75	***−0.405***	***−0.310***	−0.045
		50	25	***−0.382***	***−0.272***	−0.014
			75	***−0.372***	***−0.270***	−0.001
		100	25	***−0.360***	***−0.248***	0.028
			75	***−0.370***	***−0.264***	0.011

Note. λ is the Weibull scale parameter, $\beta_2 = 0.50$ corresponded to hazard odds ratio of 1.65. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size. Italicized and bolded values indicate moderate or substantial relative parameter bias.

Table 20 presents the relative parameter bias for the level-2 predictor's coefficient, β_2, for the DTS, ML-DTS, and CC-DTS models, respectively, for the 36 unique combinations of conditions that included a Weibull scale parameter that was equal to 0.05. For both the DTS model and the ML-DTS model, the coefficient for the level-2 predictor exhibited moderate or substantial RPB for all 36 combinations of conditions. For the DTS model, when holding all other conditions constant, RPB became became more negative as mobility increased in the dataset. Additionally, holding other conditions constant, RPB was greater when the variance between-clusters was 1.09 as compared to when it was 0.32. Specifically, when the variance between-clusters was 0.32, bias ranged from −0.13 to −0.29. When the variance between-clusters was 1.09, the coefficient estimate was more substantially negative, ranging from about −0.25 to −0.40. For the ML-DTS model, although both moderate and substantial RPB was observed, it was notably less substantial than for the DTS model. Holding all other conditions constant, RPB became more negative as mobility increased. RPB of the estimate using the ML-DTS model ranged from −0.05 under the 10% mobility condition to as much as −0.27 under the 30% mobility condition. For the CC-DTS model, no substantial RPB was observed for any combination of conditions.

Table 20

Relative Parameter Bias of the Coefficient Estimate of the Level-Two Predictor ($\beta_2 = 0.50$), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***−0.145***	***−0.067***	0.008
			75	***−0.133***	***−0.055***	0.021
		50	25	***−0.157***	***−0.076***	0.001
			75	***−0.155***	***−0.074***	0.004
		100	25	***−0.171***	***−0.089***	−0.014
			75	***−0.171***	***−0.090***	−0.015
	20	30	25	***−0.225***	***−0.160***	−0.006
			75	***−0.213***	***−0.150***	−0.004
		50	25	***−0.208***	***−0.143***	0.011
			75	***−0.213***	***−0.147***	0.000
		100	25	***−0.211***	***−0.142***	0.006
			75	***−0.220***	***−0.152***	0.000
	30	30	25	***−0.266***	***−0.214***	0.011
			75	***−0.295***	***−0.244***	−0.025
		50	25	***−0.278***	***−0.221***	−0.004
			75	***−0.272***	***−0.216***	0.003
		100	25	***−0.269***	***−0.210***	0.013
			75	***−0.273***	***−0.215***	0.005
1.09	10	30	25	***−0.274***	***−0.074***	0.017
			75	***−0.257***	***−0.060***	0.038
		50	25	***−0.293***	***−0.095***	−0.002
			75	***−0.289***	***−0.090***	0.006
		100	25	***−0.317***	***−0.120***	−0.031
			75	***−0.316***	***−0.123***	−0.031
	20	30	25	***−0.346***	***−0.184***	−0.013
			75	***−0.328***	***−0.173***	−0.004
		50	25	***−0.320***	***−0.160***	0.019
			75	***−0.333***	***−0.171***	0.004
		100	25	***−0.331***	***−0.159***	0.013
			75	***−0.340***	***−0.172***	0.009
	30	30	25	***−0.364***	***−0.232***	0.025
			75	***−0.402***	***−0.274***	−0.037
		50	25	***−0.390***	***−0.246***	−0.013
			75	***−0.382***	***−0.247***	−0.002
		100	25	***−0.373***	***−0.229***	0.022
			75	***−0.379***	***−0.236***	0.011

Note. λ is the Weibull scale parameter, $\beta_2 = 0.50$ corresponded to hazard odds ratio of 1.65. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size. Italicized and bolded values indicate moderate or substantial relative parameter bias.

To further explore the results presented in Tables 19 and 20, a factorial ANOVA was conducted for each model, the DTS, ML-DTS, and CC-DTS models, respectively, where RPB was the dependent variable and the simulation conditions were entered as the independent variables. Appendix D presents the partial eta-squared estimates for each estimating model for the coefficient of the level-two predictor. The ANOVA results indicated that the main effect of the variance between-clusters had a practically significant effect on RPB for the coefficient of β_2 for the DTS model [$F(1, 71{,}928) = 1{,}452.62$, $p < .001$, $\eta_p^2 = 0.020$]. Specifically, the mean of the RPB estimates was more negative for conditions where the variance between-clusters was 1.09 than when the variance between-clusters was 0.32 ($M_{0.32} = -0.21$, $M_{1.09} = -0.33$). The rate of mobility in the dataset also had a practically significant effect on the RPB of the parameter using the DTS model [$F(2, 71{,}928) = 432.89$, $p < .001$, $\eta_p^2 = 0.012$]. When RPB was examined for datasets specific to each mobility rate, it was apparent that as the rate of mobility increased in the dataset, the mean RPB became increasingly more negative ($M_{.10} = -.21$, $M_{.20} = -.27$, $M_{.30} = -.33$). For the ML-DTS model, the rate of mobility also had a practically significant effect on the RPB [$F(2, 71{,}928) = 597.08$, $p < .001$, $\eta_p^2 = 0.016$]. As was observed for the DTS model, as the rate of mobility in the dataset increased, the RPB became more negative ($M_{.10} = -.09$, $M_{.20} = -.17$, $M_{.30} = -.24$). There was no practically significant effect of simulation condition on the RPB observed for the CC-DTS model.

Given the differences in RPB observed between models, an additional factorial ANOVA was conducted where RPB was entered as the dependent variable and each of the manipulated conditions, as well as model type (i.e., DTS, ML-DTS, and CC-DTS models), were entered as independent variables. Appendix E presents the results of all factorial ANOVAs when model type is included as a factor along with each of the manipulated conditions. The results indicate that for the coefficient of the level-two predictor, only the main effect of model type had a practically significant effect on the RPB [$F(2, 215{,}784) = 5{,}603.90$, $p < .001$, $\eta_p^2 = 0.049$], where, on average, the DTS model and the ML-DTS model resulted in substantial negative bias for the coefficient of the level-2 predictor ($M_{DTS} = -0.27$, $M_{ML\text{-}DTS} = -0.17$). In contrast, on average, the CC-DTS resulted in no substantial RPB for the coefficient of the level-2 predictor ($M_{CC\text{-}DTS} = 0.00$).

Between-Clusters Variance, σ_u^2

Table 21 presents the relative parameter bias for the between-clusters variance component, σ_u^2, for the ML-DTS and CC-DTS models, respectively, for the 36 unique combinations of conditions that included a Weibull scale parameter that was equal to 0.025. For the ML-DTS model, the coefficient for the level-2 predictor exhibited substantial RPB in datasets generated using all 36 combinations of conditions presented. Holding all other conditions constant, RPB generally became less substantial as the cluster size increased. Additionally, when all other conditions were held constant, RPB became more substantial as the rate of mobility in the generated datasets increased. Therefore, in datasets generated with a small cluster size (i.e., 30) and high mobility (i.e., 30%), substantial negative bias was observed, ranging from −0.45 to −0.48. For datasets generated with a large cluster size (i.e., 100) and a low rate of mobility (i.e., 10%), bias was still negative, but to a lesser extent, ranging from about −0.18 to −0.22. For the CC-DTS model, moderate RPB was observed in 15 out of the 36 conditions, while substantial RPB was observed in 2 out of the 36 conditions. RPB appeared to become more substantial as the cluster-level sample size decreased. Specifically, the RPB indicated that unacceptable negative bias was present in all combinations of conditions that included a cluster-level sample size of 30. In some combinations of conditions that included a between-clusters variance of 0.32 and lower mobility rates, unacceptable RPB was also observed when the cluster size was 50. Although in these cases RPB was still considered to be outside of the acceptable range of -0.05 to 0.05, it was always less substantial than when using the ML-DTS model. For those two cases that had substantial RPB beyond a magnitude of 0.10 for the CC-DTS model, both included a low cluster size and low within-cluster sample size, and the magnitude of the RPB was about 0.11.

Table 21

Relative Parameter Bias of the Estimate of the Between-Clusters Variance, σ_u^2, When λ = 0.025

Manipulated Condition				Estimating Model	
VC	m%	c	n	ML-DTS	CC-DTS
0.32	10	30	25	***−0.251***	***−0.118***
			75	***−0.229***	***−0.079***
		50	25	***−0.198***	***−0.054***
			75	***−0.209***	***−0.053***
		100	25	***−0.195***	−0.039
			75	***−0.178***	−0.021
	20	30	25	***−0.345***	***−0.077***
			75	***−0.357***	***−0.087***
		50	25	***−0.331***	***−0.061***
			75	***−0.328***	***−0.050***
		100	25	***−0.304***	−0.029
			75	***−0.298***	−0.019
	30	30	25	***−0.451***	***−0.110***
			75	***−0.437***	***−0.069***
		50	25	***−0.404***	−0.044
			75	***−0.414***	−0.045
		100	25	***−0.399***	−0.036
			75	***−0.395***	−0.024
1.09	10	30	25	***−0.261***	***−0.092***
			75	***−0.262***	***−0.071***
		50	25	***−0.227***	−0.049
			75	***−0.240***	−0.048
		100	25	***−0.218***	−0.035
			75	***−0.213***	−0.018
	20	30	25	***−0.377***	***−0.065***
			75	***−0.391***	***−0.075***
		50	25	***−0.364***	***−0.050***
			75	***−0.371***	−0.048
		100	25	***−0.338***	−0.024
			75	***−0.347***	−0.021
	30	30	25	***−0.472***	***−0.078***
			75	***−0.477***	***−0.064***
		50	25	***−0.439***	−0.029
			75	***−0.458***	−0.046
		100	25	***−0.438***	−0.028
			75	***−0.440***	−0.019

Note. λ is the Weibull scale parameter, σ_u^2 is the variance at the cluster-level, and was equal to either 0.32 or 1.09. ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Italicized and bolded values indicate moderate or substantial relative parameter bias.

Table 22 presents the relative parameter bias for the between-clusters variance component, σ_u^2, for the ML-DTS and CC-DTS models, respectively, for the 36 unique combinations of conditions that included a Weibull scale parameter that was equal to 0.05. Similar to results observed when the Weibull scale parameter was 0.025, substantial RPB was observed for all 36 combinations of conditions using the ML-DTS model. RPB was most substantial as cluster size decreased and the rate of mobility in the dataset increased. Substantial negative bias ranged from -0.16 when the cluster size was 100 under the 10% mobility rate condition to -0.45 when the cluster size was 30 under the 30% mobility rate condition. Similar to the results presented in Table 21, the use of the CC-DTS model resulted in moderate RPB for all combinations of conditions that included a cluster-level sample size of 30. When the between-clusters variance was equal to 0.32 under the 20% mobility condition, there was also moderate RPB observed when the cluster size was 50. Although unacceptable RPB was observed, it was always less substantial than when the ML-DTS was used to estimate the between-clusters variance.

Table 22

Relative Parameter Bias of the Estimate of the Between-Clusters Variance, σ_u^2, When λ = 0.05

Manipulated Condition				Estimating Model	
VC	m%	c	n	ML-DTS	CC-DTS
0.32	10	30	25	***−0.222***	***−0.093***
			75	***−0.218***	***−0.077***
		50	25	***−0.189***	***−0.050***
			75	***−0.193***	−0.048
		100	25	***−0.176***	−0.030
			75	***−0.164***	−0.019
	20	30	25	***−0.319***	***−0.057***
			75	***−0.335***	***−0.077***
		50	25	***−0.315***	***−0.056***
			75	***−0.313***	***−0.052***
		100	25	***−0.289***	−0.026
			75	***−0.283***	−0.017
	30	30	25	***−0.427***	***−0.088***
			75	***−0.419***	***−0.067***
		50	25	***−0.386***	−0.031
			75	***−0.401***	−0.048
		100	25	***−0.381***	−0.028
			75	***−0.381***	−0.024
1.09	10	30	25	***−0.242***	***−0.083***
			75	***−0.248***	***−0.076***
		50	25	***−0.205***	−0.041
			75	***−0.223***	−0.048
		100	25	***−0.195***	−0.025
			75	***−0.194***	−0.017
	20	30	25	***−0.350***	***−0.061***
			75	***−0.368***	***−0.073***
		50	25	***−0.341***	−0.044
			75	***−0.346***	−0.044
		100	25	***−0.314***	−0.017
			75	***−0.323***	−0.015
	30	30	25	***−0.448***	***−0.064***
			75	***−0.451***	***−0.058***
		50	25	***−0.419***	−0.022
			75	***−0.437***	−0.044
		100	25	***−0.417***	−0.021
			75	***−0.418***	−0.018

Note. λ is the Weibull scale parameter, σ_u^2 is the variance at the cluster-level, and was equal to either 0.32 or 1.09. ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Italicized and bolded values indicate moderate or substantial relative parameter bias.

To further explore the results presented in Tables 21 and 22, a factorial ANOVA was conducted for each model, the ML-DTS and CC-DTS models, respectively, where RPB was the dependent variable and the simulation conditions were the independent variables. Appendix D presents the partial eta-squared estimates for each estimating model. The ANOVA results indicated that the main effect of the mobility rate in the dataset had a practically significant effect on RPB for σ_u^2 using the ML-DTS model [$F(2, 71{,}928) = 8{,}217.77$, $p < .001$, $\eta_p^2 = 0.186$]. When the average RPB was calculated across all conditions for each mobility rate, it was apparent that RPB became consistently more negative as the rate of mobility in the dataset increased ($M_{.10} = -.21$, $M_{.20} = -.34$, $M_{.30} = -.43$). Additionally, there was a practically significant effect of the main effect of cluster size on the RPB using the ML-DTS model [$F(2, 71{,}928) = 359.57$, $p < .001$, $\eta_p^2 = 0.010$]. Specifically, as cluster size increased, the average RPB decreased ($M_{30} = -.35$, $M_{50} = -0.32$, $M_{100} = -.30$). For the CC-DTS model, no simulation condition was found to have a practically significant effect on RPB. Although the results presented in Tables 21 and 22 indicate moderate or substantial RPB when the cluster size was 30 and no RPB in any conditions that included a cluster size of 100, the relatively low magnitude of RPB (< 0.10) for the majority of combinations of conditions is likely why no practical effect was observed.

Given that unacceptable RPB was observed in both the ML-DTS and CC-DTS models for some or all combinations of conditions, an additional factorial ANOVA was conducted where RPB was entered as the dependent variable and each of the manipulated conditions, as well as model type (i.e., ML-DTS and CC-DTS models), were entered as independent variables. Appendix E presents the results of all factorial ANOVAs when model type is included as a factor along with each of the manipulated conditions. The results indicated that the interaction of mobility and model type had a practically significant effect on the RPB [$F(2, 215{,}784) =$

3,195.48, $p < .001$, $\eta_p^2 = 0.043$]. Specifically, the ML-DTS model consistently resulted in substantial RPB that became more negative as mobility in the dataset increased ($M_{.10} = -0.21$, $M_{.20} = -0.34$, $M_{.30} = -0.43$). In contrast, when averaging across all other manipulated conditions, the CC-DTS model resulted in the same RPB regardless of the mobility condition ($M_{.10} = -0.05$, $M_{.20} = -0.05$, $M_{.30} = -0.05$).

Root Mean Square Error

The RMSE was computed for estimates of the fixed effect and variance component parameters, including the coefficients associated with the intercept parameters that together represent the hazard function (a_1, a_2, a_3, a_4, and a_5), the level-1 covariate (β_1), and the level-2 covariate (β_2), as well as for the between-clusters variance component, σ_u^2. The RMSE was computed for all fixed effect parameters in each of the three models examined in this dissertation: the DTS model, the ML-DTS model, and the CC-DTS model. Given that the DTS model does not include a random effect, the RMSE for the between-clusters variance estimate was only computed for the ML-DTS and the CC-DTS models. Smaller values of the RMSE suggest that parameter estimates may have less bias and less variation in the parameter estimates. In addition to the tables of results presented in this section, nested loop plots (Rücker & Schwarzer, 2014) that depict the RMSE estimates across all 72 combinations of conditions in one plot for each parameter can be found in Appendix G.

This section presents the RMSE values for each of the 72 simulation conditions for each of the parameters estimated using the DTS model, the ML-DTS model, and the CC-DTS model.

Coefficient for Discrete-Time Period 1 of the Logit Hazard Function, a_1

Table 23 presents the RMSE values of the coefficient for the first discrete-time period in the logit hazard function, a_1, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, when all else was equal, the RMSE was substantially lower when the between-clusters variance was 0.32. To a lesser extent, RMSE appeared to be affected by both the cluster size and within-cluster sample size, such that in both cases, larger sample sizes resulted in lower RMSE values. Lastly, holding all other simulation conditions constant, the RMSE increased slightly as the rate of mobility in the dataset increased. For the ML-DTS model, the RMSE consistently decreased with increasing sample size, with larger cluster-level sample sizes resulting in notably lower values of the RMSE. Additionally, holding all other conditions constant, when the variance between clusters was 1.09, the RMSE was greater than when it was 0.32. Lastly, mobility had a small impact on RMSE, such that holding all other conditions constant, the RMSE tended to increase slightly as mobility increased. Similar results were observed for the CC-DTS model, where sample size and between-clusters variance impacted the magnitude of the RMSE. However, in contrast to the ML-DTS model, mobility did not have a notable impact on the RMSE values obtained using the CC-DTS model.

Table 23

Root Mean Square Error of the Coefficient Estimate of the Intercept for Discrete-Time Period 1 (α_1 = −3.25), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.270	0.223	0.226
			75	0.232	0.160	0.160
		50	25	0.241	0.171	0.170
			75	0.208	0.126	0.126
		100	25	0.216	0.128	0.125
			75	0.200	0.097	0.091
	20	30	25	0.279	0.225	0.221
			75	0.238	0.175	0.172
		50	25	0.243	0.180	0.178
			75	0.219	0.135	0.121
		100	25	0.221	0.137	0.125
			75	0.210	0.109	0.088
	30	30	25	0.282	0.233	0.220
			75	0.257	0.189	0.168
		50	25	0.257	0.187	0.166
			75	0.230	0.152	0.125
		100	25	0.229	0.149	0.122
			75	0.222	0.132	0.092
1.09	10	30	25	0.556	0.302	0.302
			75	0.547	0.256	0.251
		50	25	0.550	0.238	0.227
			75	0.527	0.205	0.195
		100	25	0.535	0.184	0.163
			75	0.532	0.164	0.139
	20	30	25	0.573	0.324	0.293
			75	0.548	0.285	0.258
		50	25	0.543	0.267	0.236
			75	0.541	0.243	0.189
		100	25	0.540	0.220	0.160
			75	0.538	0.211	0.137
	30	30	25	0.570	0.350	0.302
			75	0.576	0.332	0.258
		50	25	0.574	0.310	0.222
			75	0.545	0.282	0.200
		100	25	0.544	0.263	0.160
			75	0.548	0.261	0.143

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to baseline hazard probability in time period 1 of .038. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Table 24 presents the RMSE values of the coefficient for the first discrete-time period in the logit hazard function, a_1, across 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, the value of the between-clusters variance component had the largest impact on the RMSE, where RMSE values were much larger when the between-clusters variance component was 1.09. Additionally, fewer substantial differences were seen due to mobility rate and the cluster-level sample size. Holding all else constant, when the rate of mobility increased, the value of the RMSE also increased. In contrast, when the cluster size increased, the value of the RMSE tended to decrease. For the ML-DTS model, the RMSE consistently decreased with increasing sample size, with larger cluster level sample sizes resulting in notably lower values of the RMSE. Additionally, holding all other conditions constant, when the variance between clusters was 1.09, the RMSE was greater than when it was 0.32. Lastly, mobility had a small impact on RMSE, such that holding all other conditions constant, the RMSE tended to increase slightly as mobility increased. Similar results were observed for the CC-DTS model, where sample size and between-clusters variance impacted the magnitude of the RMSE. However, in contrast to the ML-DTS model, mobility did not have a significant impact on the RMSE values obtained using the CC-DTS model. Additionally, it was apparent that for both the ML-DTS model and the CC-DTS model, the RMSE values were much lower when the Weibull scale parameter was equal to 0.05 than when it was equal to 0.025, regardless of the other conditions present in the dataset.

Table 24

Root Mean Square of the Coefficient Estimate of the Intercept for Discrete-Time Period 1 (α_1= −2.51), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.236	0.185	0.187
			75	0.212	0.145	0.145
		50	25	0.216	0.147	0.147
			75	0.193	0.115	0.115
		100	25	0.194	0.107	0.104
			75	0.186	0.085	0.081
	20	30	25	0.244	0.187	0.185
			75	0.217	0.153	0.153
		50	25	0.217	0.152	0.150
			75	0.202	0.120	0.108
		100	25	0.199	0.112	0.099
			75	0.197	0.100	0.082
	30	30	25	0.252	0.200	0.190
			75	0.236	0.169	0.153
		50	25	0.232	0.162	0.143
			75	0.213	0.138	0.118
		100	25	0.207	0.127	0.104
			75	0.205	0.117	0.084
1.09	10	30	25	0.487	0.274	0.278
			75	0.485	0.240	0.237
		50	25	0.482	0.217	0.213
			75	0.463	0.193	0.192
		100	25	0.472	0.164	0.150
			75	0.465	0.148	0.134
	20	30	25	0.504	0.286	0.271
			75	0.484	0.262	0.252
		50	25	0.476	0.234	0.215
			75	0.473	0.215	0.183
		100	25	0.471	0.185	0.144
			75	0.473	0.183	0.132
	30	30	25	0.503	0.308	0.277
			75	0.507	0.294	0.248
		50	25	0.499	0.267	0.209
			75	0.479	0.247	0.193
		100	25	0.476	0.224	0.150
			75	0.478	0.221	0.137

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to baseline hazard probability in time period 1 of .038. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Coefficient for Discrete-Time Period 2 of the Logit Hazard Function, a_2

Table 25 presents the RMSE values of the coefficient for the second discrete-time period in the logit hazard function, a_2 across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, the value of the between-clusters variance component had the largest impact on the RMSE, where RMSE values were much larger when the between-clusters variance component was 1.09. Although less notable, the RMSE was also affected by both the rate of mobility in the dataset, the cluster size, and the within-cluster sample size. Holding all other conditions constant, as mobility increased, the RMSE values increased. With few exceptions, for both the within-cluster sample size and cluster size, as the sample size increased, the RMSE values decreased. For the ML-DTS model, the cluster level sample size had the most notable impact on the values of the RMSE, such that the RMSE consistently decreased with increasing sample size. Similar impacts of the within-cluster size on the value of the RMSE were also observed, such that smaller within-cluster sample size conditions resulted in larger values of the RMSE. Additionally, holding all other conditions constant, when the variance between clusters was 1.09, the RMSE was greater than when it was 0.32. Lastly, mobility had a small impact on RMSE, such that holding all other conditions constant, the RMSE tended to increase slightly as mobility increased. The impact of mobility on the RMSE was especially pronounced when the between cluster variance was 1.09. Similar results were observed for the CC-DTS model, where sample size and between-clusters variance impacted the magnitude of the RMSE. However, in contrast to the ML-DTS model, mobility did not have a significant impact on the RMSE values obtained using the CC-DTS model.

Table 25

Root Mean Square Error of the Coefficient of the Intercept for Discrete-Time Period 2 ($\alpha_2 = -2.88$), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.236	0.208	0.212
			75	0.212	0.157	0.155
		50	25	0.209	0.162	0.162
			75	0.183	0.125	0.125
		100	25	0.188	0.119	0.115
			75	0.169	0.091	0.087
	20	30	25	0.241	0.205	0.204
			75	0.211	0.163	0.159
		50	25	0.214	0.169	0.166
			75	0.196	0.135	0.122
		100	25	0.189	0.123	0.110
			75	0.181	0.105	0.085
	30	30	25	0.247	0.212	0.206
			75	0.229	0.178	0.156
		50	25	0.226	0.176	0.160
			75	0.204	0.147	0.122
		100	25	0.203	0.143	0.117
			75	0.192	0.124	0.088
1.09	10	30	25	0.438	0.290	0.293
			75	0.439	0.256	0.248
		50	25	0.423	0.235	0.229
			75	0.404	0.201	0.196
		100	25	0.413	0.177	0.156
			75	0.401	0.158	0.138
	20	30	25	0.454	0.305	0.284
			75	0.440	0.278	0.255
		50	25	0.425	0.251	0.226
			75	0.422	0.233	0.188
		100	25	0.419	0.206	0.150
			75	0.415	0.199	0.134
	30	30	25	0.456	0.322	0.286
			75	0.469	0.320	0.254
		50	25	0.454	0.289	0.218
			75	0.432	0.265	0.194
		100	25	0.431	0.248	0.159
			75	0.428	0.243	0.140

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to baseline hazard probability in time period 2 of .053. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Table 26 presents the RMSE values of the coefficient for the second discrete-time period in the logit hazard function, a_2, across 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, the value of the between-clusters variance component had the largest impact on the RMSE, where RMSE values were much larger when the between-clusters variance component was 1.09. RMSE was also affected by both the rate of mobility in the dataset, the cluster size, and the within-cluster sample size. Holding all other conditions constant, as mobility increased, the RMSE values increased. With few exceptions, for both the within-cluster sample size and cluster size, as the sample size increased, the RMSE values decreased. For the ML-DTS model, the cluster level sample size had the most notable impact on the values of the RMSE, such that the RMSE consistently decreased with increasing sample size. Similar impacts of the within-cluster size on the value of the RMSE were also observed, such that smaller within-cluster sample size conditions resulted in larger values of the RMSE. Additionally, holding all other conditions constant, when the variance between clusters was 1.09, the RMSE was greater than when it was 0.32. Lastly, mobility had a small impact on RMSE, such that holding all other conditions constant, the RMSE tended to increase slightly as mobility increased. The impact of mobility on the RMSE was especially pronounced when the between cluster variance was 1.09. Similar results were observed for the CC-DTS model, where sample size and between-clusters variance impacted the magnitude of the RMSE. However, in contrast to the ML-DTS model, mobility did not have a significant impact on the RMSE values obtained using the CC-DTS model. Additionally, for the CC-DTS model, when the Weibull scale parameter was 0.05, the RMSE values were consistently lower than when it was 0.025. The difference in RMSE values due to the Weibull scale parameter decreased as cluster size increased.

Table 26

Root Mean Square Error of the Coefficient Estimate of the Intercept for Discrete-Time Period 2 (α_2 = −2.13), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.203	0.185	0.188
			75	0.178	0.145	0.145
		50	25	0.177	0.146	0.147
			75	0.151	0.113	0.115
		100	25	0.151	0.103	0.100
			75	0.135	0.082	0.079
	20	30	25	0.202	0.176	0.175
			75	0.183	0.152	0.150
		50	25	0.180	0.149	0.146
			75	0.160	0.119	0.111
		100	25	0.156	0.109	0.096
			75	0.147	0.093	0.078
	30	30	25	0.215	0.191	0.186
			75	0.200	0.166	0.151
		50	25	0.188	0.153	0.138
			75	0.168	0.129	0.113
		100	25	0.166	0.122	0.101
			75	0.158	0.110	0.082
1.09	10	30	25	0.333	0.270	0.275
			75	0.324	0.241	0.239
		50	25	0.315	0.220	0.217
			75	0.291	0.192	0.194
		100	25	0.292	0.158	0.147
			75	0.281	0.145	0.135
	20	30	25	0.338	0.266	0.259
			75	0.328	0.252	0.246
		50	25	0.311	0.225	0.214
			75	0.306	0.209	0.185
		100	25	0.298	0.176	0.140
			75	0.295	0.171	0.130
	30	30	25	0.358	0.296	0.275
			75	0.356	0.285	0.245
		50	25	0.335	0.248	0.202
			75	0.320	0.232	0.187
		100	25	0.314	0.210	0.146
			75	0.311	0.207	0.138

Note. λ is the Weibull scale parameter, λ = 0.05 corresponded to baseline hazard probability in time period 2 of .106. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Coefficient for Discrete-Time Period 3 of the Logit Hazard Function, a_3

Table 27 presents the RMSE values of the coefficient for the third discrete-time period in the logit hazard function, a_3, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, the value of the between-clusters variance component had the largest impact on the RMSE, where RMSE values were much larger when the between-clusters variance component was 1.09. Although less substantial, the RMSE was also affected by both the rate of mobility in the dataset, the cluster size, and the within-cluster sample size. Holding all other conditions constant, as mobility increased, the RMSE values increased. Additionally, for both the within-cluster sample size and cluster size, as the sample size increased, the RMSE values decreased. For the ML-DTS model, the rate of mobility and the cluster size had a clear impact on the RMSE. When the rate of mobility increased, RMSE also increased. Conversely, as the cluster size increased, the RMSE tended to decrease. Additionally, RMSE values tended to be higher for the ML-DTS model when the variance between-clusters was 1.09. For the CC-DTS model, cluster size had a clear impact on RMSE, such that when cluster size increased, the RMSE values decreased. In contrast to the ML-DTS model, mobility did not appear to have any substantial effect on the RMSE values when the CC-DTS model was used.

Table 27

Root Mean Square Error of the Coefficient Estimate of the Intercept for Discrete-Time Period 3 (α_3= −2.67), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.221	0.208	0.210
			75	0.185	0.154	0.154
		50	25	0.185	0.156	0.155
			75	0.156	0.121	0.123
		100	25	0.157	0.115	0.111
			75	0.141	0.091	0.087
	20	30	25	0.228	0.208	0.205
			75	0.189	0.161	0.160
		50	25	0.183	0.158	0.158
			75	0.167	0.129	0.119
		100	25	0.165	0.124	0.115
			75	0.151	0.101	0.085
	30	30	25	0.236	0.217	0.212
			75	0.204	0.173	0.156
		50	25	0.201	0.172	0.158
			75	0.176	0.139	0.118
		100	25	0.173	0.133	0.110
			75	0.164	0.118	0.087
1.09	10	30	25	0.348	0.292	0.296
			75	0.335	0.250	0.248
		50	25	0.324	0.227	0.222
			75	0.299	0.196	0.195
		100	25	0.300	0.168	0.152
			75	0.287	0.151	0.137
	20	30	25	0.365	0.299	0.285
			75	0.342	0.265	0.253
		50	25	0.320	0.234	0.221
			75	0.318	0.219	0.190
		100	25	0.309	0.191	0.153
			75	0.305	0.184	0.136
	30	30	25	0.377	0.316	0.293
			75	0.372	0.300	0.251
		50	25	0.355	0.271	0.218
			75	0.333	0.244	0.191
		100	25	0.327	0.224	0.153
			75	0.328	0.223	0.138

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to baseline hazard probability in time period 3 of .065. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Table 28 presents the RMSE values of the coefficient for the third discrete-time period in the logit hazard function, a_3, across 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS, ML-DTS, and CC-DTS models, respectively. When the Weibull scale parameter was 0.05, the value of the between-clusters variance component had the largest impact on the RMSE for the DTS model, where RMSE values were much larger when the between-clusters variance component was 1.09. Although less substantial, the RMSE was also affected by both the rate of mobility in the dataset, the cluster size, and the within-cluster sample size. Holding all other conditions constant, as mobility increased, the RMSE values increased. Additionally, for both the within-cluster sample size and cluster size, as the sample size increased, the RMSE values decreased. For the ML-DTS model, the rate of mobility and the cluster size had a clear impact on the RMSE. When the rate of mobility increased, RMSE tended to also increase, especially when the between clusters variance was 1.09. Conversely, as the cluster size increased, the RMSE tended to decrease. Additionally, RMSE values tended to be higher for the ML-DTS model when the variance between-clusters was 1.09. For the CC-DTS model, cluster size had a clear impact on RMSE, such that when cluster size increased, the RMSE values decreased. In contrast to the ML-DTS model, mobility did not appear to have any substantial effect on the RMSE values when the CC-DTS model was used.

Table 28

Root Mean Square Error of the Coefficient Estimate of the Intercept for Discrete-Time Period 3 (α_3 = −1.90), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.184	0.189	0.191
			75	0.143	0.141	0.142
		50	25	0.146	0.144	0.145
			75	0.118	0.114	0.116
		100	25	0.110	0.100	0.097
			75	0.092	0.081	0.080
	20	30	25	0.185	0.185	0.187
			75	0.149	0.146	0.148
		50	25	0.142	0.139	0.141
			75	0.123	0.116	0.112
		100	25	0.116	0.105	0.099
			75	0.104	0.090	0.079
	30	30	25	0.193	0.191	0.189
			75	0.160	0.155	0.148
		50	25	0.154	0.149	0.139
			75	0.127	0.119	0.110
		100	25	0.127	0.116	0.101
			75	0.114	0.101	0.080
1.09	10	30	25	0.233	0.265	0.272
			75	0.211	0.237	0.240
		50	25	0.199	0.216	0.217
			75	0.170	0.186	0.192
		100	25	0.153	0.151	0.145
			75	0.139	0.139	0.135
	20	30	25	0.241	0.264	0.267
			75	0.219	0.242	0.246
		50	25	0.192	0.208	0.208
			75	0.182	0.195	0.186
		100	25	0.163	0.164	0.146
			75	0.152	0.152	0.129
	30	30	25	0.259	0.284	0.279
			75	0.237	0.261	0.245
		50	25	0.217	0.232	0.209
			75	0.195	0.208	0.187
		100	25	0.179	0.182	0.145
			75	0.175	0.181	0.137

Note. λ is the Weibull scale parameter, λ = 0.05 corresponded to baseline hazard probability in time period 3 of .130. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Coefficient for Discrete-Time Period 4 of the Logit Hazard Function, a_4.

Table 29 presents the RMSE values of the coefficient for the fourth discrete-time period in the logit hazard function, a_4, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS, ML-DTS, and CC-DTS models, respectively. When all other conditions were held constant, the between clusters variance had a clear impact on the RMSE for the DTS model, such that RMSE values were higher when the between cluster variance was 1.09. Although less substantial, the RMSE was also affected by both the rate of mobility in the dataset, the cluster size, and the within-cluster sample size. Holding all other conditions constant, as mobility increased, the RMSE values increased. Additionally, for both the within-cluster sample size and cluster size, as the sample size increased, the RMSE values decreased. For the ML-DTS model, the rate of mobility in the dataset appeared to have the most substantial impact on RMSE values, where RMSE increased as mobility increased. In contrast, RMSE was not impacted by mobility using the CC-DTS model. For both the ML-DTS and CC-DTS models, overall sample size had a noticeable effect on RMSE values, such that as both cluster size and within-cluster sample size increased, RMSE consistently decreased. Additionally, variance between-clusters had a substantial affect on both the ML-DTS model and the CC-DTS model, such that when it was 1.09, RMSE values were generally larger than when it was 0.32.

Table 29

Root Mean Square Error of the Coefficient Estimate of the Intercept for Discrete-Time Period 4 (α_4= −2.51), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.204	0.204	0.207
			75	0.158	0.146	0.148
		50	25	0.165	0.153	0.153
			75	0.132	0.119	0.121
		100	25	0.130	0.111	0.108
			75	0.109	0.087	0.086
	20	30	25	0.213	0.207	0.207
			75	0.163	0.153	0.155
		50	25	0.174	0.163	0.162
			75	0.141	0.123	0.117
		100	25	0.136	0.118	0.113
			75	0.119	0.093	0.083
	30	30	25	0.221	0.214	0.213
			75	0.178	0.164	0.155
		50	25	0.185	0.171	0.159
			75	0.151	0.133	0.120
		100	25	0.149	0.128	0.109
			75	0.131	0.108	0.087
1.09	10	30	25	0.282	0.289	0.296
			75	0.246	0.236	0.240
		50	25	0.242	0.223	0.223
			75	0.210	0.189	0.193
		100	25	0.199	0.157	0.150
			75	0.186	0.144	0.139
	20	30	25	0.287	0.283	0.284
			75	0.256	0.246	0.250
		50	25	0.249	0.232	0.229
			75	0.226	0.201	0.189
		100	25	0.211	0.173	0.154
			75	0.201	0.159	0.134
	30	30	25	0.304	0.300	0.298
			75	0.281	0.270	0.254
		50	25	0.270	0.249	0.218
			75	0.245	0.221	0.197
		100	25	0.233	0.195	0.149
			75	0.223	0.186	0.138

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to baseline hazard probability in time period 4 of .075. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Table 30 presents the RMSE values of the coefficient for the fourth discrete-time period in the logit hazard function, a_4, across 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS, ML-DTS, and CC-DTS models, respectively. The RMSE values for all models were substantially impacted by overall sample size in the dataset, such that as sample size increased due to both increasing cluster size and increasing within-cluster sample size, the RMSE decreased. Additionally, the variance between-clusters affected all models, such that when the variance between-clusters was 0.32, the RMSE values were lower than when the variance between-clusters was 1.09. However, some differences in the pattern of the RMSE values between models were apparent due to mobility. When the variance between-clusters was 0.32, the RMSE generally increased for the DTS model and the ML-DTS model as mobility increased. Conversely, for the CC-DTS model, the pattern for the RMSE values was either inconsistent or decreased as mobility increased. When the variance between-clusters was 1.09, there was no consistency in the pattern of increasing or decreasing RMSE with mobility across models.

Table 30

Root Mean Square Error of the Coefficient Estimate of the Intercept for Discrete-Time Period 4 (α_4= −1.74), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.179	0.190	0.192
			75	0.128	0.139	0.141
		50	25	0.135	0.145	0.146
			75	0.104	0.111	0.114
		100	25	0.090	0.098	0.097
			75	0.075	0.083	0.084
	20	30	25	0.171	0.181	0.184
			75	0.133	0.143	0.148
		50	25	0.140	0.150	0.152
			75	0.101	0.110	0.111
		100	25	0.095	0.104	0.102
			75	0.072	0.081	0.079
	30	30	25	0.183	0.193	0.196
			75	0.137	0.149	0.150
		50	25	0.141	0.152	0.148
			75	0.104	0.115	0.113
		100	25	0.096	0.105	0.099
			75	0.079	0.090	0.083
1.09	10	30	25	0.232	0.271	0.279
			75	0.187	0.230	0.238
		50	25	0.180	0.212	0.218
			75	0.161	0.183	0.192
		100	25	0.125	0.145	0.145
			75	0.120	0.134	0.137
	20	30	25	0.215	0.255	0.269
			75	0.189	0.229	0.246
		50	25	0.176	0.210	0.221
			75	0.144	0.178	0.187
		100	25	0.121	0.148	0.149
			75	0.103	0.131	0.132
	30	30	25	0.224	0.270	0.287
			75	0.182	0.236	0.247
		50	25	0.166	0.214	0.216
			75	0.142	0.184	0.191
		100	25	0.114	0.154	0.147
			75	0.102	0.144	0.138

Note. λ is the Weibull scale parameter, λ = 0.05 corresponded to baseline hazard probability in time period 4 of .150. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Coefficient for Discrete-Time Period 5 of the Logit Hazard Function, a_5

Table 31 presents the RMSE values of the coefficient for the fifth discrete-time period in the logit hazard function, a_5, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, the variance between-clusters had a substantial impact on the RMSE values, such that when the variance between-clusters was equal to 1.09, the RMSE was much higher when it was 1.09 as compared to when it was 0.32. Additionally, cluster size and within-cluster size had an impact on the RMSE for the DTS model, such that as sample sizes increased, RMSE decreased commensurably. For the ML-DTS model, cluster size had a substantial impact on the RMSE, such that as cluster size increased, RMSE decreased. Other conditions had smaller impacts on the RMSE for the ML-DTS model. For the CC-DTS model, both the cluster size and within-cluster sample size influenced the RMSE values, such that they were generally lowest as sample size increased.

Table 31

Root Mean Square Error of the Coefficient Estimate of the Intercept for Discrete-Time Period 5 (α_5= −2.39), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.200	0.207	0.210
			75	0.151	0.154	0.156
		50	25	0.157	0.160	0.161
			75	0.120	0.123	0.125
		100	25	0.113	0.112	0.113
			75	0.089	0.088	0.088
	20	30	25	0.193	0.197	0.198
			75	0.151	0.153	0.156
		50	25	0.155	0.156	0.158
			75	0.119	0.118	0.119
		100	25	0.118	0.117	0.115
			75	0.091	0.087	0.083
	30	30	25	0.196	0.199	0.201
			75	0.160	0.160	0.158
		50	25	0.160	0.161	0.158
			75	0.127	0.125	0.122
		100	25	0.121	0.118	0.110
			75	0.101	0.096	0.087
1.09	10	30	25	0.249	0.287	0.298
			75	0.204	0.241	0.252
		50	25	0.193	0.220	0.226
			75	0.161	0.189	0.198
		100	25	0.133	0.152	0.153
			75	0.116	0.138	0.141
	20	30	25	0.237	0.266	0.278
			75	0.201	0.231	0.248
		50	25	0.185	0.209	0.222
			75	0.157	0.180	0.189
		100	25	0.140	0.158	0.159
			75	0.116	0.132	0.132
	30	30	25	0.249	0.277	0.295
			75	0.214	0.243	0.256
		50	25	0.197	0.221	0.221
			75	0.167	0.188	0.195
		100	25	0.144	0.158	0.154
			75	0.131	0.146	0.140

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to baseline hazard probability in time period 5 of .084. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Table 32 presents the RMSE values of the coefficient for the fifth discrete-time period in the logit hazard function, a_5, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, the variance between-clusters had a substantial impact on the RMSE values, such that when the variance between-clusters was equal to 1.09, the RMSE was much higher when it was 1.09 as compared to when it was 0.32. Additionally, cluster size and within-cluster size had an impact on the RMSE for the DTS model, such that as sample sizes increased, RMSE decreased commensurably. For the ML-DTS model, cluster size had a substantial impact on the RMSE, such that as cluster size increased, RMSE decreased. Other conditions had smaller impacts on the RMSE for the ML-DTS model. For the CC-DTS model, both the cluster size and within-cluster sample size influenced the RMSE values, such that they were generally lowest as sample size increased.

Table 32

Root Mean Square Error of the Coefficient Estimate of the Intercept for Discrete-Time Period 5 ($\alpha_5 = -1.60$), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.194	0.194	0.197
			75	0.144	0.144	0.147
		50	25	0.153	0.151	0.152
			75	0.123	0.115	0.118
		100	25	0.116	0.105	0.106
			75	0.098	0.082	0.084
	20	30	25	0.177	0.179	0.183
			75	0.146	0.146	0.153
		50	25	0.148	0.147	0.151
			75	0.110	0.106	0.110
		100	25	0.109	0.101	0.104
			75	0.086	0.077	0.080
	30	30	25	0.184	0.191	0.196
			75	0.139	0.148	0.156
		50	25	0.144	0.149	0.152
			75	0.113	0.114	0.119
		100	25	0.102	0.100	0.104
			75	0.083	0.081	0.084
1.09	10	30	25	0.308	0.279	0.288
			75	0.269	0.234	0.245
		50	25	0.265	0.209	0.217
			75	0.256	0.187	0.196
		100	25	0.235	0.148	0.153
			75	0.232	0.131	0.138
	20	30	25	0.285	0.250	0.269
			75	0.262	0.227	0.250
		50	25	0.255	0.205	0.221
			75	0.233	0.172	0.187
		100	25	0.227	0.146	0.156
			75	0.210	0.120	0.133
	30	30	25	0.281	0.268	0.293
			75	0.241	0.226	0.256
		50	25	0.239	0.202	0.222
			75	0.223	0.176	0.197
		100	25	0.208	0.138	0.150
			75	0.198	0.126	0.140

Note. λ is the Weibull scale parameter, λ = 0.05 corresponded to baseline hazard probability in time period 5 of .168. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Coefficient for the level-one predictor, $\boldsymbol{\beta_1}$

Table 33 presents the RMSE values of the coefficient of the level-one predictor, β_1, across the 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS, ML-DTS, and CC-DTS models, respectively. The RMSE for the DTS model was clearly impacted by the variance between clusters, such that RMSE was higher when the variance between clusters was 1.09 than when it was 0.32. Additionally, sample size conditions had a notable impact on the RMSE for the DTS model, where larger sample sizes resulted in lower RMSE values. For both the ML-DTS and CC-DTS models, the cluster level and within-cluster sample size conditions had the largest impacts on the RMSE, such that as the sample size increased, RMSE decreased. No other simulation conditions appeared to have substantial impacts on the RMSE values for either the ML-DTS or CC-DTS models.

Table 33

Root Mean Square Error of the Coefficient Estimate of the Level-One Predictor (β_1 = 0.50), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.132	0.133	0.133
			75	0.083	0.075	0.075
		50	25	0.102	0.098	0.098
			75	0.064	0.055	0.055
		100	25	0.079	0.072	0.072
			75	0.053	0.041	0.041
	20	30	25	0.130	0.129	0.129
			75	0.080	0.075	0.075
		50	25	0.105	0.103	0.104
			75	0.066	0.057	0.057
		100	25	0.078	0.072	0.072
			75	0.053	0.040	0.039
	30	30	25	0.130	0.129	0.129
			75	0.077	0.073	0.073
		50	25	0.102	0.098	0.098
			75	0.067	0.057	0.055
		100	25	0.075	0.070	0.070
			75	0.053	0.042	0.040
1.09	10	30	25	0.157	0.133	0.134
			75	0.122	0.074	0.074
		50	25	0.138	0.101	0.101
			75	0.115	0.059	0.058
		100	25	0.123	0.074	0.073
			75	0.110	0.042	0.040
	20	30	25	0.157	0.133	0.132
			75	0.121	0.078	0.075
		50	25	0.137	0.104	0.103
			75	0.114	0.062	0.058
		100	25	0.123	0.076	0.072
			75	0.109	0.046	0.040
	30	30	25	0.156	0.131	0.127
			75	0.116	0.076	0.072
		50	25	0.138	0.103	0.097
			75	0.113	0.066	0.058
		100	25	0.118	0.074	0.069
			75	0.106	0.051	0.042

Note. λ is the Weibull scale parameter, $\beta_1 = 0.50$ corresponded to hazard odds ratio of 1.65. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Table 34 presents the RMSE values of the coefficient of the level-one predictor, β_1, across the 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS, ML-DTS, and CC-DTS models, respectively. The RMSE for the DTS model was clearly impacted by the variance between clusters, such that RMSE was higher when the variance between clusters was 1.09 than when it was 0.32. Additionally, sample size conditions had a notable impact on the RMSE for the DTS model, where larger sample sizes resulted in lower RMSE values. For both the ML-DTS and CC-DTS models, the cluster level and within-cluster sample size conditions had the largest impacts on the RMSE, such that as the sample size increased, RMSE decreased. No other simulation conditions appeared to have substantial impacts on the RMSE values for either the ML-DTS or CC-DTS models.

Table 34

Root Mean Square Error of the Coefficient Estimate of the Level-One Predictor ($\beta_1 = 0.50$), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.113	0.107	0.107
			75	0.078	0.064	0.064
		50	25	0.097	0.085	0.086
			75	0.067	0.047	0.047
		100	25	0.075	0.059	0.059
			75	0.058	0.034	0.034
	20	30	25	0.112	0.106	0.106
			75	0.076	0.063	0.063
		50	25	0.095	0.086	0.086
			75	0.066	0.049	0.049
		100	25	0.075	0.061	0.060
			75	0.061	0.036	0.034
	30	30	25	0.119	0.112	0.112
			75	0.075	0.062	0.061
		50	25	0.095	0.086	0.084
			75	0.065	0.048	0.046
		100	25	0.075	0.061	0.060
			75	0.058	0.036	0.034
1.09	10	30	25	0.155	0.113	0.113
			75	0.136	0.067	0.065
		50	25	0.149	0.089	0.088
			75	0.129	0.051	0.049
		100	25	0.137	0.064	0.062
			75	0.127	0.037	0.035
	20	30	25	0.157	0.116	0.117
			75	0.131	0.070	0.066
		50	25	0.144	0.094	0.093
			75	0.127	0.056	0.050
		100	25	0.135	0.065	0.060
			75	0.127	0.043	0.034
	30	30	25	0.158	0.118	0.114
			75	0.129	0.071	0.065
		50	25	0.144	0.095	0.089
			75	0.127	0.060	0.050
		100	25	0.132	0.070	0.063
			75	0.123	0.048	0.035

Note. λ is the Weibull scale parameter, $\beta_1 = 0.50$ corresponded to hazard odds ratio of 1.65. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Coefficient for the level-two predictor, $\boldsymbol{\beta_2}$

Table 35 presents the RMSE values of the coefficient of the level-two predictor, β_2, across the 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS, ML-DTS, and CC-DTS models, respectively. For all models, the variance between clusters had a clear impact on the RMSE value, such that the RMSE was lower when the variance between clusters was 0.32 than when it was 1.09. Similarly, cluster size, and less notably, within-cluster sample size, had substantial impacts on the RMSE. Specifically, in all cases, RMSE became progressively lower as the sample size increased.

Table 35

Root Mean Square Error of the Coefficient Estimate of the Level-Two Predictor ($\beta_2 = 0.50$), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.239	0.248	0.261
			75	0.214	0.219	0.230
		50	25	0.192	0.195	0.200
			75	0.178	0.178	0.186
		100	25	0.148	0.143	0.142
			75	0.140	0.134	0.135
	20	30	25	0.242	0.243	0.257
			75	0.231	0.233	0.251
		50	25	0.199	0.197	0.205
			75	0.187	0.183	0.187
		100	25	0.157	0.149	0.145
			75	0.149	0.138	0.130
	30	30	25	0.252	0.253	0.263
			75	0.239	0.236	0.242
		50	25	0.209	0.204	0.200
			75	0.199	0.193	0.185
		100	25	0.173	0.163	0.139
			75	0.170	0.159	0.132
1.09	10	30	25	0.358	0.406	0.442
			75	0.341	0.381	0.417
		50	25	0.289	0.313	0.335
			75	0.283	0.304	0.331
		100	25	0.230	0.228	0.240
			75	0.232	0.226	0.240
	20	30	25	0.349	0.375	0.433
			75	0.357	0.385	0.448
		50	25	0.287	0.302	0.347
			75	0.288	0.295	0.335
		100	25	0.233	0.224	0.243
			75	0.228	0.215	0.232
	30	30	25	0.356	0.381	0.453
			75	0.352	0.365	0.431
		50	25	0.296	0.297	0.337
			75	0.287	0.288	0.331
		100	25	0.238	0.222	0.233
			75	0.243	0.226	0.235

Note. λ is the Weibull scale parameter, $\beta_2 = 0.50$ corresponded to hazard odds ratio of 1.65. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Table 36 presents the RMSE values of the coefficient of the level-two predictor, β_2, across the 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS, ML-DTS, and CC-DTS models, respectively. For all models, the variance between clusters had a clear impact on the RMSE value, such that the RMSE was lower when the variance between clusters was 0.32 than when it was 1.09. Similarly, cluster size, and less notably, within-cluster sample size, had substantial impacts on the RMSE. Specifically, in all cases, RMSE became progressively lower as the sample size increased.

Table 36

Root Mean Square Error of the Coefficient Estimate of the Level-Two Predictor ($\beta_2 = 0.50$), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	0.231	0.242	0.254
			75	0.206	0.213	0.226
		50	25	0.185	0.187	0.194
			75	0.174	0.174	0.182
		100	25	0.145	0.136	0.136
			75	0.143	0.133	0.135
	20	30	25	0.235	0.237	0.253
			75	0.227	0.229	0.248
		50	25	0.193	0.190	0.200
			75	0.183	0.178	0.185
		100	25	0.155	0.142	0.137
			75	0.150	0.134	0.127
	30	30	25	0.245	0.246	0.259
			75	0.235	0.232	0.237
		50	25	0.203	0.194	0.190
			75	0.194	0.184	0.183
		100	25	0.170	0.154	0.134
			75	0.168	0.152	0.128
1.09	10	30	25	0.342	0.395	0.427
			75	0.328	0.380	0.412
		50	25	0.283	0.314	0.336
			75	0.277	0.303	0.329
		100	25	0.233	0.228	0.239
			75	0.235	0.228	0.242
	20	30	25	0.342	0.377	0.432
			75	0.347	0.383	0.445
		50	25	0.283	0.304	0.347
			75	0.283	0.297	0.335
		100	25	0.232	0.218	0.237
			75	0.229	0.212	0.230
	30	30	25	0.345	0.376	0.443
			75	0.343	0.364	0.431
		50	25	0.290	0.290	0.332
			75	0.285	0.285	0.328
		100	25	0.238	0.216	0.230
			75	0.242	0.219	0.232

Note. λ is the Weibull scale parameter, $\beta_2 = 0.50$ corresponded to hazard odds ratio of 1.65. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Between-Clusters Variance, σ_u^2

Table 37 presents the RMSE values of the coefficient of the between-clusters variance, σ_u^2, across the 36 combinations of conditions where the Weibull scale parameter was 0.025 for the ML-DTS and CC-DTS models. For both the ML-DTS and CC-DTS models, RMSE was greatly impacted by the variance between clusters, such that RMSE was substantially higher when the variance between clusters was 1.09 than when it was 0.32. The cluster level sample size also had substantial impacts on the RMSE value for both models, and was most pronounced when the variance between clusters was 1.09. Specifically, as the cluster level sample size increased, the RMSE value decreased. For the ML-DTS model, mobility also had a notable impact on the RMSE, such that as mobility increased, the RMSE increased. Again, this was most pronounced when the variance between clusters was 1.09, although also occurred to a lesser magnitude when the variance between clusters was 0.32. In contrast, mobility did not have a notable impact on the RMSE when using the CC-DTS model.

Table 37

Root Mean Square Error of the Estimate of the Between-Clusters Variance, σ_u^2, When λ = 0.025

Manipulated Condition				Estimating Model	
VC	m%	c	n	ML-DTS	CC-DTS
0.32	10	30	25	0.131	0.122
			75	0.107	0.095
		50	25	0.103	0.094
			75	0.090	0.073
		100	25	0.083	0.064
			75	0.072	0.052
	20	30	25	0.145	0.120
			75	0.133	0.097
		50	25	0.127	0.095
			75	0.118	0.074
		100	25	0.110	0.067
			75	0.102	0.050
	30	30	25	0.165	0.116
			75	0.152	0.093
		50	25	0.144	0.088
			75	0.142	0.074
		100	25	0.136	0.065
			75	0.131	0.052
1.09	10	30	25	0.397	0.355
			75	0.368	0.310
		50	25	0.323	0.260
			75	0.316	0.233
		100	25	0.281	0.188
			75	0.267	0.166
	20	30	25	0.475	0.349
			75	0.471	0.310
		50	25	0.435	0.269
			75	0.432	0.239
		100	25	0.390	0.192
			75	0.393	0.159
	30	30	25	0.552	0.336
			75	0.546	0.297
		50	25	0.503	0.247
			75	0.519	0.238
		100	25	0.491	0.186
			75	0.490	0.165

Note. λ is the Weibull scale parameter, σ_u^2 is the variance at the cluster-level, and was equal to either 0.32 or 1.09. ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Table 38 presents the RMSE values of the coefficient of the between-clusters variance, σ_u^2, across the 36 combinations of conditions where the Weibull scale parameter was 0.05 for the ML-DTS and CC-DTS models. For both the ML-DTS and CC-DTS models, RMSE was greatly impacted by the variance between clusters, such that RMSE was substantially higher when the variance between clusters was 1.09 than when it was 0.32. The cluster level sample size also had substantial impacts on the RMSE value for both models, and was most pronounced when the variance between clusters was 1.09. Specifically, as the cluster level sample size increased, the RMSE value decreased. For the ML-DTS model, mobility also had a notable impact on the RMSE, such that as mobility increased, the RMSE increased. Again, this was most pronounced when the variance between clusters was 1.09, although also occurred to a lesser magnitude when the variance between clusters was 0.32. In contrast, mobility did not have a notable impact on the RMSE when using the CC-DTS model.

Table 38

Root Mean Square Error of the Estimate of the Between-Clusters Variance, σ_u^2, When λ = 0.05

Manipulated Condition				Estimating Model	
VC	m%	c	n	ML-DTS	CC-DTS
0.32	10	30	25	0.118	0.111
			75	0.102	0.092
		50	25	0.093	0.082
			75	0.085	0.070
		100	25	0.077	0.059
			75	0.068	0.050
	20	30	25	0.136	0.116
			75	0.127	0.094
		50	25	0.121	0.087
			75	0.113	0.072
		100	25	0.103	0.060
			75	0.097	0.048
	30	30	25	0.155	0.106
			75	0.146	0.090
		50	25	0.136	0.079
			75	0.137	0.071
		100	25	0.129	0.058
			75	0.126	0.049
1.09	10	30	25	0.371	0.330
			75	0.356	0.302
		50	25	0.301	0.248
			75	0.302	0.227
		100	25	0.257	0.175
			75	0.249	0.163
	20	30	25	0.453	0.344
			75	0.449	0.299
		50	25	0.414	0.262
			75	0.408	0.232
		100	25	0.366	0.185
			75	0.368	0.156
	30	30	25	0.526	0.322
			75	0.520	0.291
		50	25	0.481	0.234
			75	0.497	0.225
		100	25	0.468	0.174
			75	0.467	0.161

Note. λ is the Weibull scale parameter, σ_u^2 is the variance at the cluster-level, and was equal to either 0.32 or 1.09. ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size.

Coverage Rates of the 95% Confidence Intervals

The coverage rates of the 95% CIs were computed for estimates of the fixed effect parameters, including the coefficients associated with the intercept parameters that together represent the hazard function (a_1, a_2, a_3, a_4, and a_5), the level-1 covariate (β_1), and the level-2 covariate (β_2). Additionally, the results of the logistic regressions are reported for each of the fixed effects parameters for each model, where the outcome is binary and represents whether or not a CI included the true parameter value. In addition to the tables of results presented in this section, nested loop plots (Rücker & Schwarzer, 2014) that depict the coverage rates of the 95% CIs across all 72 combinations of conditions in one plot for each parameter of interest can be found in Appendix H.

Coefficient for Discrete-Time Period 1 of the Logit Hazard Function, a_1

Table 39 presents the coverage of the 95% CIs for the intercept for the first discrete-time period in the logit hazard function, a_1, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, the coverage rates were substantially below .925 for all 36 combinations of conditions that included a Weibull scale parameter of 0.025. Coverage rates were especially poor when the variance between-clusters was 1.09, where the lowest coverage rate was .001. For the DTS model, when the variance between-clusters was 0.32, coverage rates ranged from .142 to .762. For the ML-DTS model, coverage rates were outside the acceptable .925 to .975 range for the majority of combinations of conditions, with only four combinations of conditions resulting in acceptable coverage rates. Specifically, acceptable coverage rates occurred when the variance between-clusters was 0.32, the mobility rate condition was 10%, and the cluster size was either 30 or 50. Otherwise, coverage rates were outside of the acceptable range, with values between

.446 and .910. For the ML-DTS model, coverage rates became consistently worse with increasing rates of mobility in the dataset, such that coverage was lowest for any combination of conditions under the 30% mobility condition. Conversely, the CC-DTS model resulted in acceptable coverage rates for all but two of the 36 combinations of conditions presented in Table 39. For the two coverage rates found to be unacceptable, they were only very slightly below .925.

Table 39

Coverage Rates of the Coefficient Estimate of the Intercept for Discrete-Time Period 1 ($\alpha_1 = -3.25$), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***.762***	.937	.938
			75	***.541***	.930	.939
		50	25	***.681***	.925	.945
			75	***.442***	.933	.944
		100	25	***.518***	***.910***	.935
			75	***.211***	***.907***	.943
	20	30	25	***.758***	***.918***	.936
			75	***.542***	***.881***	***.922***
		50	25	***.691***	***.906***	.938
			75	***.367***	***.894***	.949
		100	25	***.463***	***.888***	.936
			75	***.179***	***.837***	.957
	30	30	25	***.744***	***.897***	.951
			75	***.461***	***.828***	.928
		50	25	***.630***	***.890***	.950
			75	***.356***	***.828***	.949
		100	25	***.476***	***.838***	.955
			75	***.142***	***.693***	.936
1.09	10	30	25	***.280***	***.895***	.934
			75	***.114***	***.898***	.925
		50	25	***.114***	***.898***	.941
			75	***.044***	***.902***	.935
		100	25	***.016***	***.877***	.941
			75	***.002***	***.850***	.943
	20	30	25	***.254***	***.854***	.945
			75	***.116***	***.822***	***.917***
		50	25	***.117***	***.825***	.941
			75	***.024***	***.784***	.946
		100	25	***.015***	***.757***	.943
			75	***.001***	***.670***	.952
	30	30	25	***.257***	***.787***	.930
			75	***.094***	***.718***	.930
		50	25	***.089***	***.726***	.954
			75	***.029***	***.650***	.936
		100	25	***.008***	***.597***	.950
			75	***.001***	***.446***	.931

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to baseline hazard probability in time period 1 of .038. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Bolded and italicized values represent unacceptable coverage of the 95% confidence intervals.

Table 40 presents the coverage of the 95% confidence intervals for the intercept for the first discrete-time period in the logit hazard function, a_1, across 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, the coverage rates were substantially below .925 for all 36 combinations of conditions that included a Weibull scale parameter of 0.05. Coverage rates were especially poor when the variance between-clusters was 1.09, where the lowest coverage rate was .000. For the DTS model, when the variance between-clusters was 0.32, coverage rates ranged from .081 to .693. For the ML-DTS model, coverage rates were outside the acceptable .925 to .975 range for the majority of combinations of conditions, with only four combinations of conditions resulting in acceptable coverage rates. Specifically, coverage rates were within or very close to the acceptable range when the mobility condition was 10%, and in some cases, when the mobility condition was 20%. Otherwise, coverage rates were outside of the acceptable range, with values overall falling between .557 and .921. For the ML-DTS model, coverage rates became consistently worse with increasing rates of mobility and cluster size, such that coverage was lowest for any combination of conditions that included the 30% mobility condition and a cluster size of 100. Conversely, the CC-DTS model resulted in acceptable coverage rates for all but one of the 36 combinations of conditions presented in Table 40. For the one coverage rate found to be unacceptable, coverage was .916, only slightly below .925.

Table 40

Coverage Rates of the Coefficient Estimate of the Intercept for Discrete-Time Period 1 ($\alpha_1 = -2.51$), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***.693***	.935	.948
			75	***.459***	***.916***	.934
		50	25	***.598***	.929	.945
			75	***.363***	.927	.940
		100	25	***.418***	.927	.947
			75	***.149***	***.921***	.953
	20	30	25	***.680***	***.920***	.952
			75	***.443***	***.886***	.926
		50	25	***.597***	***.915***	.944
			75	***.276***	***.901***	.945
		100	25	***.361***	***.887***	.957
			75	***.109***	***.827***	.946
	30	30	25	***.665***	***.879***	.951
			75	***.398***	***.831***	.926
		50	25	***.527***	***.888***	.953
			75	***.268***	***.832***	.935
		100	25	***.365***	***.818***	.950
			75	***.081***	***.711***	.933
1.09	10	30	25	***.263***	***.918***	.928
			75	***.097***	***.911***	.930
		50	25	***.114***	***.913***	.944
			75	***.043***	***.908***	.930
		100	25	***.009***	***.891***	.938
			75	***.000***	***.877***	.948
	20	30	25	***.215***	***.877***	.941
			75	***.103***	***.843***	***.916***
		50	25	***.111***	***.868***	.937
			75	***.027***	***.841***	.943
		100	25	***.011***	***.812***	.962
			75	***.001***	***.737***	.949
	30	30	25	***.216***	***.824***	.932
			75	***.094***	***.767***	.931
		50	25	***.076***	***.774***	.938
			75	***.028***	***.727***	.925
		100	25	***.006***	***.656***	.948
			75	***.002***	***.557***	.937

Note. λ is the Weibull scale parameter, λ = 0.05 corresponded to baseline hazard probability in time period 1 of .075. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Bolded and italicized values represent unacceptable coverage of the 95% confidence intervals.

To further explore the results presented in Tables 39 and 40, a logistic regression was conducted for the DTS, ML-DTS, and CC-DTS models, where the dependent variable was binary and represented whether or not the confidence interval included the true value of the parameter and the simulation conditions were entered as the independent variables. The Cox effect was recorded and is presented in tabular form in Appendix I. For the DTS model, multiple nested logistic regression models were conducted to assess model fit, and it was determined that compared to a model with higher-order interactions, the model with third-order interactions produced the best model fit, [$\chi^2(16) = 8.44$, $p = 0.93$]. The results indicated that there was a practically significant interaction between the mobility rate (dummy variable contrasting a mobility rate of 20% and a mobility rate of 10%), cluster size (dummy variable contrasting a cluster size of 50 to a cluster size of 30), and the within-cluster sample size [$\chi^2(71{,}948) = -4.15$, $p < .05$, $d_{Cox} = -0.29$]. When the cluster size was 30, the coverage rate was always greater than when it was 50 when examined in combination with the mobility rate conditions (10% or 20%) and within-cluster sample size. For example, when the cluster size was 30, the mobility rate condition was 10%, and the within-cluster size was 25, the coverage rate was greater than when the cluster size was 50, the mobility rate condition was 10%, and the within-cluster size was 75 ($\overline{CovRate}_{30,10\%,25} = .500$, $\overline{CovRate}_{50,10\%,75} = .377$). Additionally, an interaction was observed between cluster size (dummy variable contrasting a cluster size of 50 to a cluster size of 30) and variance between clusters [$\chi^2(71{,}948) = -5.92$, $p < .05$, $d_{Cox} = -0.40$]. When the variance between-clusters was 0.32, the coverage rate was greater when the cluster size was 30 as compared to when it was 50 ($\overline{CovRate}_{30} = .600$, $\overline{CovRate}_{50} = .483$). When the variance between-clusters was 1.09, the coverage rate was substantially lower than when it was 0.32 regardless of cluster size, but followed the same pattern, such that the coverage was greater when the cluster size was 30 than when it was 50 ($\overline{CovRate}_{30}$ = .175, $\overline{CovRate}_{50}$ = .068). Similarly, an interaction was observed between cluster size (dummy variable contrasting a cluster size of 100 to a cluster size of 30) and variance between clusters [χ^2(71,948) = $-$9.20, p < .05, d_{Cox}= $-$1.33]. When the variance between-clusters was 0.32, the coverage rate was greater when the cluster size was 30 as compared to when it was 100 ($\overline{CovRate}_{30}$ = .600, $\overline{CovRate}_{100}$ = .289). When the variance between-clusters was 1.09, the coverage rate was substantially lower than when it was 0.32 regardless of cluster size, but followed the same pattern, such that the coverage was greater when the cluster size was 30 than when it was 100 ($\overline{CovRate}_{30}$ = .175, $\overline{CovRate}_{100}$ = .006). For the ML-DTS model, multiple nested logistic regression models were conducted to assess model fit, and it was determined that compared to a model with higher-order interactions, the model with second-order interactions produced the best model fit, [χ^2(25) = 21.34, p = 0.67]. A practically significant interaction was observed between mobility rate (dummy variable contrasting the 30% mobility rate condition with the 10% mobility rate condition) and variance between clusters, [χ^2(71,973) = $-$9.20, p < .05, d_{Cox}= $-$0.27]. When the variance between clusters was 0.32, the coverage rate was greater when the mobility rate condition was 10% than when it was 30% ($\overline{CovRate}_{10\%}$ = .925, $\overline{CovRate}_{30\%}$ = .828). When the variance between clusters was 1.09, a similar pattern was observed, such that the coverage rate was greater when the mobility rate condition was 10% than when it was 30% ($\overline{CovRate}_{10\%}$ = .895, $\overline{CovRate}_{30\%}$ = .686). An interaction was also observed between mobility rate (dummy variable contrasting the 30% mobility rate condition with the 10% mobility rate condition) and cluster size (dummy variable contrasting a cluster size of 100 to a cluster size of 30), [χ^2(71,973) = $-$8.48, p < .05, d_{Cox}= $-$0.34]. When the mobility rate condition was 10%, the coverage rate was nearly identical regardless of cluster size ($\overline{CovRate}_{30}$ = .918, $\overline{CovRate}_{100}$ = .917). Conversely, when the mobility rate condition was 30%, coverage was greater when the cluster size was 30 than when it was 100 ($\overline{CovRate}_{30}$ = .816, $\overline{CovRate}_{100}$ = .665). For the CC-DTS model, no main effect or interaction between the independent variables was found to have a practically significant effect on the coverage of the 95% confidence intervals.

Coefficient for Discrete-Time Period 2 of the Logit Hazard Function, a_2

Table 41 presents the coverage of the 95% confidence intervals for the intercept for the second discrete-time period in the logit hazard function, a_2, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, the coverage rates were substantially below .925 for all 36 combinations of conditions that included a Weibull scale parameter of 0.025. Coverage rates were especially poor when the variance between-clusters was 1.09, where the lowest coverage rate was .005. For the DTS model, when the variance between-clusters was 0.32, coverage rates ranged from .175 to .798. For the ML-DTS model, coverage rates were outside the acceptable .925 to .975 range for the majority of combinations of conditions, with only four combinations of conditions resulting in acceptable coverage rates. Specifically, coverage rates were within or very close to the acceptable range when the mobility condition was 10%, and in some cases, when the mobility condition was 20%. Otherwise, coverage rates were outside of the acceptable range, with unacceptable coverage values ranging from .489 and .924. For the ML-DTS model, coverage rates became consistently worse when both mobility and sample size (both within-cluster and cluster sizes) increased. Conversely, the CC-DTS model resulted in acceptable coverage rates for all but one of the 36 combinations of conditions. However, for the combination of conditions that resulted in unacceptable coverage, the coverage rate was only very slightly below the acceptable .925 minimum, at .915.

Table 41

Coverage Rates of the Coefficient Estimate of the Intercept for Discrete-Time Period 2 (α_2 = −2.88), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***.798***	.932	.943
			75	***.564***	.927	.938
		50	25	***.719***	.928	.941
			75	***.496***	***.924***	.926
		100	25	***.573***	***.915***	.938
			75	***.279***	***.910***	.938
	20	30	25	***.774***	.932	.956
			75	***.567***	***.897***	.930
		50	25	***.720***	***.903***	.948
			75	***.424***	***.880***	.937
		100	25	***.536***	***.894***	.959
			75	***.218***	***.845***	.944
	30	30	25	***.786***	***.903***	.950
			75	***.504***	***.836***	.935
		50	25	***.663***	***.891***	.952
			75	***.376***	***.808***	.948
		100	25	***.495***	***.825***	.939
			75	***.175***	***.727***	.938
1.09	10	30	25	***.392***	***.910***	.930
			75	***.166***	***.904***	.933
		50	25	***.239***	***.904***	.935
			75	***.107***	***.901***	.936
		100	25	***.051***	***.880***	.938
			75	***.015***	***.862***	.941
	20	30	25	***.365***	***.847***	.939
			75	***.178***	***.834***	***.915***
		50	25	***.236***	***.836***	.940
			75	***.065***	***.804***	.947
		100	25	***.035***	***.772***	.961
			75	***.005***	***.688***	.947
	30	30	25	***.362***	***.815***	.933
			75	***.148***	***.715***	.932
		50	25	***.160***	***.750***	.944
			75	***.057***	***.688***	.946
		100	25	***.033***	***.622***	.942
			75	***.006***	***.489***	.934

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to baseline hazard probability in time period 2 of .053. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Bolded and italicized values represent unacceptable coverage of the 95% confidence intervals.

Table 42 presents the coverage of the 95% confidence intervals for the intercept for the second discrete-time period in the logit hazard function, a_2, across 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, the coverage rates were substantially below .925 for all 36 combinations of conditions that included a Weibull scale parameter of 0.05. Coverage rates were especially poor when the variance between-clusters was 1.09, where the lowest coverage rate was .033. For the DTS model, when the variance between-clusters was 0.32, coverage rates ranged from .203 to .771. For the ML-DTS model, coverage rates were outside the acceptable .925 to .975 range for the majority of combinations of conditions, with only two combinations of conditions resulting in acceptable coverage rates. Specifically, coverage rates were within or very close to the acceptable range when the mobility condition was 10%. Otherwise, coverage rates were outside of the acceptable range, with values overall falling between .600 and .924. For the ML-DTS model, coverage rates became consistently worse with increasing rates of mobility and overall sample size, such that coverage was lowest for any combination of conditions that included the 30% mobility condition and increasing sample sizes in the generated datasets. Conversely, the CC-DTS model resulted in acceptable coverage rates for all but two of the 36 combinations of conditions. However, for the two combinations of conditions that resulted in unacceptable coverage, the coverage rates were only very slightly below the .925 threshold, with both resulting in coverage rates greater than .910.

Table 42

Coverage Rates of the Coefficient Estimate of the Intercept for Discrete-Time Period 2 (α_2 = −2.13), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***.771***	***.924***	.934
			75	***.557***	***.915***	.935
		50	25	***.713***	***.918***	.934
			75	***.508***	.926	.928
		100	25	***.575***	***.924***	.945
			75	***.316***	.930	.951
	20	30	25	***.769***	***.924***	.947
			75	***.523***	***.871***	***.917***
		50	25	***.688***	***.902***	.938
			75	***.437***	***.887***	.951
		100	25	***.535***	***.900***	.957
			75	***.241***	***.856***	.945
	30	30	25	***.731***	***.899***	.937
			75	***.477***	***.824***	.929
		50	25	***.639***	***.889***	.949
			75	***.414***	***.832***	.950
		100	25	***.489***	***.826***	.950
			75	***.203***	***.745***	.945
1.09	10	30	25	***.474***	***.909***	.927
			75	***.252***	***.908***	.933
		50	25	***.350***	***.911***	.931
			75	***.186***	***.904***	.929
		100	25	***.144***	***.901***	.948
			75	***.059***	***.878***	.943
	20	30	25	***.440***	***.896***	.938
			75	***.227***	***.861***	***.912***
		50	25	***.342***	***.871***	.936
			75	***.122***	***.858***	.941
		100	25	***.109***	***.840***	.955
			75	***.037***	***.775***	.952
	30	30	25	***.429***	***.842***	.934
			75	***.209***	***.779***	.932
		50	25	***.256***	***.809***	.945
			75	***.126***	***.765***	.941
		100	25	***.089***	***.708***	.942
			75	***.033***	***.600***	.941

Note. λ is the Weibull scale parameter, λ = 0.05 corresponded to baseline hazard probability in time period 2 of .106. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Bolded and italicized values represent unacceptable coverage of the 95% confidence intervals.

To further explore the results presented in Tables 41 and 42, a logistic regression was conducted for each model, the DTS, ML-DTS, and CC-DTS models, respectively, where the dependent variable was binary and represented whether or not the confidence interval included the true value of the parameter and the simulation conditions were entered as the independent variables. The Cox Effect was recorded for each model parameter and is presented in Appendix I. For the DTS model, multiple nested logistic regression models were conducted to assess model fit, and it was determined that compared to a model with higher-order interactions, the model with third-order interactions produced the best model fit, [$\chi^2(16) = 8.95$, $p = 0.92$]. The results indicated a practically important interaction between cluster size (dummy variable contrasting a cluster size of 100 to a cluster size of 30), variance between clusters, and Weibull scale parameter, [$\chi^2(71{,}948) = 6.05$, $p < .05$, $d_{Cox} = 0.45$]. When the cluster size was 30, the coverage rate was always greater than when it was 100 when examined in combination with the variance between clusters and Weibull scale parameter. For example, when the cluster size was 30, the variance between clusters was 0.32, and the Weibull scale parameter was 0.025, the coverage rate was greater than when the cluster size was 100, the variance between clusters was 0.032, and the Weibull scale parameter was 0.025 ($\overline{CovRate}_{30,0.32,.025} = .666$, $\overline{CovRate}_{100,0.32,.025} = .379$). Additionally, the coverage was always greater when the variance between clusters was 0.32 than when it was 1.09. When the cluster size was 100 and the Weibull scale parameter was 0.05, the coverage was greater than when the Weibull scale parameter was 0.025 regardless of the value of the variance between clusters; however, when the cluster size was 30, coverage was greater when the Weibull scale parameter was 0.025 than when it was 0.05 if the variance between clusters was 0.32, but coverage was greater when the Weibull scale parameter was 0.05 if the variance between clusters was 1.09. The main effect of the within-cluster sample size was also practically significant, [χ^2(71,948) = -14.16, p < .05, d_{Cox}= -0.67], such that the coverage rate was greater when the within-cluster sample size was 25 than when it was 75 ($\overline{CovRate}$ = .458, $\overline{CovRate}$ = .258). The main effect of the cluster size (dummy variable contrasting a cluster size of 50 to a cluster size of 30) was also practically important, [χ^2(71,948) = -4.92, p < .05, d_{Cox}= -0.25], such that coverage was greater when the cluster size was 30 than when it was 50 ($\overline{CovRate}$ = .478, $\overline{CovRate}$ = .377). For the ML-DTS model, multiple nested logistic regression models were conducted to assess model fit, and it was determined that compared to a model with higher-order interactions, the model with second-order interactions produced the best model fit, [χ^2(25) = 24.12, p = 0.51]. A practically important interaction was observed between mobility rate (dummy variable contrasting the 30% mobility rate condition with the 10% mobility rate condition) and cluster size (dummy variable contrasting a cluster size of 100 to a cluster size of 30), [χ^2(71,973) = -8.50, p < .05, d_{Cox}= -0.35]. When the mobility rate condition was 10%, the coverage rate was very similar regardless of cluster size ($\overline{CovRate}_{30}$ = .916, $\overline{CovRate}_{100}$ = .883). Conversely, when the mobility rate condition was 30%, coverage was greater when the cluster size was 30 than when it was 100 ($\overline{CovRate}_{30}$ = .821, $\overline{CovRate}_{100}$ = .693). Additionally, a practically important interaction was found between mobility rate (dummy variable contrasting the 30% mobility rate condition with the 10% mobility rate condition) and within-cluster sample size, [χ^2(71,973) = -7.58, p < .05, d_{Cox}= -0.26]. Specifically, when the mobility rate condition was 10%, the average coverage was very similar regardless of the within-cluster sample size ($\overline{CovRate}_{25}$ = .913, $\overline{CovRate}_{75}$ = .907). When the mobility rate condition was 30%, the coverage rate was greater when the within-cluster sample size was 25 than when it was 75 ($\overline{CovRate}_{25}$ = .815, $\overline{CovRate}_{75}$ = .734). For the CC-DTS model, no main effect or interaction between the independent variables was found to have a practically significant effect on the coverage of the 95% confidence intervals.

Coefficient for Discrete-Time Period 3 of the Logit Hazard Function, a_3

Table 43 presents the coverage of the 95% confidence intervals for the intercept for the third discrete-time period in the logit hazard function, a_3, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, the coverage rates were substantially below .925 for all 36 combinations of conditions that included a Weibull scale parameter of 0.025. Coverage rates were especially poor when the variance between-clusters was 1.09, where the lowest coverage rate was .033. For the DTS model, when the variance between-clusters was 0.32, coverage rates ranged from .287 to .823. For the ML-DTS model, coverage rates were outside the acceptable .925 to .975 range for the majority of combinations of conditions, with only five combinations of conditions resulting in acceptable coverage rates. Specifically, coverage rates were within or only slightly below the acceptable range when the mobility condition was 10%, and in some cases, when the mobility condition was 20%. Otherwise, coverage rates were outside of the acceptable range, with unacceptable coverage values ranging from .566 and .922. For the ML-DTS model, coverage rates became consistently worse when both mobility and sample size (both within-cluster and cluster sizes) increased. For the CC-DTS model, coverage rates were found to be acceptable for the majority of conditions. However, for seven combinations of conditions, all of which included a cluster size of 30, coverage rates were found to be very slightly below the .925 minimum acceptable rate.

Table 43

Coverage Rates of the Coefficient Estimate of the Intercept for Discrete-Time Period 3 ($\alpha_3 = -2.67$), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***.823***	.925	***.924***
			75	***.646***	***.922***	.934
		50	25	***.782***	.933	.946
			75	***.600***	.928	.931
		100	25	***.673***	.929	.951
			75	***.390***	***.906***	.941
	20	30	25	***.793***	***.903***	.940
			75	***.619***	***.887***	***.922***
		50	25	***.796***	.926	.957
			75	***.533***	***.885***	.946
		100	25	***.632***	***.895***	.940
			75	***.346***	***.862***	.947
	30	30	25	***.793***	***.897***	***.921***
			75	***.547***	***.837***	.939
		50	25	***.732***	***.893***	.952
			75	***.481***	***.843***	.951
		100	25	***.585***	***.870***	.949
			75	***.287***	***.745***	.944
1.09	10	30	25	***.552***	***.907***	***.923***
			75	***.300***	***.907***	***.924***
		50	25	***.415***	***.902***	.932
			75	***.243***	***.913***	.934
		100	25	***.215***	***.899***	.951
			75	***.076***	***.883***	.935
	20	30	25	***.526***	***.862***	.926
			75	***.281***	***.852***	***.918***
		50	25	***.413***	***.870***	.941
			75	***.178***	***.841***	.950
		100	25	***.174***	***.817***	.953
			75	***.049***	***.757***	.941
	30	30	25	***.510***	***.821***	***.924***
			75	***.265***	***.754***	.944
		50	25	***.327***	***.785***	.946
			75	***.168***	***.730***	.941
		100	25	***.146***	***.696***	.948
			75	***.033***	***.566***	.940

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to baseline hazard probability in time period 3 of .065. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Bolded and italicized values represent unacceptable coverage of the 95% confidence intervals.

Table 44 presents the coverage of the 95% confidence intervals for the intercept for the third discrete-time period in the logit hazard function, a_3, across 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, the coverage rates were substantially below .925 for all 36 combinations of conditions. Coverage rates were especially poor when the variance between-clusters was 1.09, where coverage ranged from .254 to .727. For the DTS model, when the variance between-clusters was 0.32, coverage rates ranged from .436 to .833. For the ML-DTS model, coverage rates were outside the acceptable .925 to .975 range for the majority of combinations of conditions, with only four combinations of conditions resulting in acceptable coverage rates. Specifically, coverage rates were within or very close to the acceptable range when the mobility condition was 10%, regardless of other conditions present in the dataset. Otherwise, coverage rates were outside of the acceptable range, with values overall falling between .701 and .923. For the ML-DTS model, coverage rates became notably worse with increasing mobility, such that coverage was lowest for any combination of conditions that included the 30% mobility condition in the generated datasets. Cluster size appeared to have some impact on coverage as well, especially when the variance between-clusters was 1.09, such that as sample size increased, coverage rates decreased. Conversely, the CC-DTS model resulted in acceptable coverage rates for all but two of the 36 combinations of conditions. However, for the two combinations of conditions that resulted in unacceptable coverage, the coverage rates were only very slightly below the .925 threshold.

Table 44

Coverage Rates of the Coefficient Estimate of the Intercept for Discrete-Time Period 3 (α_3 = −1.90), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***.833***	***.923***	.928
			75	***.691***	.925	.941
		50	25	***.818***	***.917***	.933
			75	***.657***	.931	.941
		100	25	***.776***	.941	.957
			75	***.588***	***.922***	.943
	20	30	25	***.822***	***.912***	.937
			75	***.662***	***.893***	***.922***
		50	25	***.828***	.925	.943
			75	***.638***	***.897***	.939
		100	25	***.757***	***.910***	.954
			75	***.502***	***.877***	.949
	30	30	25	***.802***	***.883***	.928
			75	***.634***	***.853***	.935
		50	25	***.779***	***.900***	.958
			75	***.596***	***.875***	.952
		100	25	***.704***	***.872***	.943
			75	***.436***	***.786***	.948
1.09	10	30	25	***.727***	***.918***	.932
			75	***.501***	***.908***	.926
		50	25	***.654***	***.904***	.928
			75	***.493***	***.920***	.930
		100	25	***.605***	***.922***	.958
			75	***.416***	***.903***	.942
	20	30	25	***.721***	***.915***	.936
			75	***.474***	***.867***	***.919***
		50	25	***.692***	***.904***	.936
			75	***.456***	***.875***	.938
		100	25	***.553***	***.871***	.951
			75	***.363***	***.853***	.952
	30	30	25	***.663***	***.853***	.930
			75	***.427***	***.821***	.939
		50	25	***.613***	***.833***	.936
			75	***.398***	***.826***	.945
		100	25	***.492***	***.796***	.956
			75	***.254***	***.701***	.939

Note. λ is the Weibull scale parameter, λ = 0.05 corresponded to baseline hazard probability in time period 3 of .130. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Bolded and italicized values represent unacceptable coverage of the 95% confidence intervals.

To further explore the results presented in Tables 43 and 44, a logistic regression was conducted for each model, the DTS, ML-DTS, and CC-DTS models, respectively, where the dependent variable was binary and represented whether or not the confidence interval included the true value of the parameter and the simulation conditions were entered as the independent variables. The Cox Effect was recorded for each model parameter, and is presented in Appendix I. For the DTS model, multiple nested logistic regression models were conducted to assess model fit, and it was determined that compared to a model with higher-order interactions, the model with third-order interactions produced the best model fit, [$\chi^2(16) = 19.02$, p = 0.27]. The results indicated that there was a practically important interaction between cluster size (dummy variable contrasting a cluster size of 100 to a cluster size of 30), variance between clusters, and Weibull scale parameter [$\chi^2(71{,}948) = 8.65$, $p < .05$, $d_{Cox}= 0.46$]. When the cluster size was 30, the coverage rate was always greater than when it was 100 when examined in combination with the variance between clusters and Weibull scale parameter. For example, when the cluster size was 30, the variance between clusters was 0.32, and the Weibull scale parameter was 0.025, the coverage rate was greater than when the cluster size was 100, the variance between clusters was .032, and the Weibull scale parameter was 0.025 ($\overline{CovRate}_{30,0.32,0.025} = .666$, $\overline{CovRate}_{100,0.32,0.025} = .379$). Additionally, the coverage was always greater when the variance between clusters was 0.32 than when it was 1.09. Regardless of the cluster size and the variance between clusters, coverage was always greater when the Weibull scale parameter was 0.05 than when it was 0.025. The main effect of within-cluster sample size was also found to be practically important, [$\chi^2(71{,}948) = -12.13$, $p < .05$, $d_{Cox}= -0.56$], such that the coverage rate was greater when the within-cluster sample size was 25 than when it was 75 ($\overline{CovRate}_{25} = .631$, $\overline{CovRate}_{75} = .423$). For the ML-DTS model, multiple nested logistic regression models were conducted to assess model fit, and it was determined that compared to a model with higher-order interactions, the model with second-order interactions produced the best model fit, [$\chi^2(25) = 32.8, p = 0.14$]. The results indicated that there was a practically significant interaction between mobility rate (dummy variable contrasting the 10% mobility condition to the 30% mobility condition) and cluster size (dummy variable contrasting a cluster size of 100 to a cluster size of 30), [$\chi^2(71{,}973) = -6.91, p < .05, d_{Cox} = -0.29$]. When the cluster size was 30, coverage was slightly greater when the mobility rate condition was 10% than when it was 30% ($\overline{CovRate}_{10\%} = .634$, $\overline{CovRate}_{30\%} = .580$). Similarly, when the cluster size was 100, coverage was greater when the mobility rate condition was 10% than when it was 30% ($\overline{CovRate}_{10\%} = .467$, $\overline{CovRate}_{30\%} = .367$). For the CC-DTS model, no main effect or interaction between the independent variables was found to have a practically significant effect on the coverage of the 95% confidence intervals.

Coefficient for Discrete-Time Period 4 of the Logit Hazard Function, a_4

Table 45 presents the coverage of the 95% confidence intervals for the intercept for the fourth discrete-time period in the logit hazard function, a_4, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, the coverage rates were substantially below 92.5% for all 36 combinations of conditions that included a Weibull scale parameter of 0.025. Coverage rates were especially poor when the variance between-clusters was 1.09, where coverage rates ranged from .176 to .717. For the DTS model, when the variance between-clusters was 0.32, coverage rates ranged from .460 to .857. For the ML-DTS model, coverage rates were outside the acceptable .925 to .975 range for the majority of combinations of conditions, with only seven combinations of conditions resulting in acceptable coverage rates. Specifically, coverage rates were within the acceptable range when the mobility condition was 10% and the variance between-clusters was 0.32. When the variance between-clusters was 1.09, the coverage rates were within or only slightly below .925. Otherwise, coverage rates were outside of the acceptable range. The unacceptable coverage rates ranged .702 to .922, with coverage rates generally decreasing as mobility increased. For the CC-DTS model, coverage rates were found to be acceptable for all but three combinations of conditions, all of which included a cluster size of 30 and a variance between-clusters of 1.09. However, all unacceptable coverage rates for the CC-DTS model were only slightly below the acceptable range.

Table 45

Coverage Rates of the Coefficient Estimate of the Intercept for Discrete-Time Period 4 (α_4= −2.51), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***.857***	.935	.941
			75	***.744***	.935	.948
		50	25	***.849***	.939	.941
			75	***.686***	.932	.947
		100	25	***.778***	.938	.950
			75	***.569***	.926	.943
	20	30	25	***.826***	***.914***	.940
			75	***.710***	***.908***	.933
		50	25	***.798***	***.910***	.935
			75	***.627***	***.911***	.956
		100	25	***.768***	***.907***	.936
			75	***.505***	***.891***	.960
	30	30	25	***.827***	***.896***	.933
			75	***.661***	***.872***	.935
		50	25	***.778***	***.887***	.950
			75	***.571***	***.866***	.941
		100	25	***.709***	***.872***	.946
			75	***.460***	***.804***	.947
1.09	10	30	25	***.717***	***.905***	***.921***
			75	***.504***	***.913***	.934
		50	25	***.642***	.925	.940
			75	***.458***	***.922***	.949
		100	25	***.525***	***.919***	.942
			75	***.293***	***.891***	.942
	20	30	25	***.697***	***.889***	.932
			75	***.473***	***.878***	***.924***
		50	25	***.630***	***.881***	.936
			75	***.387***	***.868***	.937
		100	25	***.479***	***.875***	.949
			75	***.247***	***.826***	.957
	30	30	25	***.659***	***.859***	***.922***
			75	***.439***	***.809***	.941
		50	25	***.556***	***.834***	.944
			75	***.336***	***.799***	.935
		100	25	***.396***	***.792***	.948
			75	***.176***	***.702***	.942

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to baseline hazard probability in time period 4 of .075. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Bolded and italicized values represent unacceptable coverage of the 95% confidence intervals.

Table 46 presents the coverage of the 95% confidence intervals for the intercept for the fourth discrete-time period in the logit hazard function, a_4, across 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, the coverage rates were substantially below .925 for all 36 combinations of conditions that included a Weibull scale parameter of 0.05. Coverage rates were especially poor when the variance between-clusters was 1.09, where coverage rates ranged from .613 to .815. For the DTS model, when the variance between-clusters was 0.32, coverage rates ranged from .697 to .897. For the ML-DTS model, coverage rates were outside the acceptable .925 to .975 range for 26 combinations of conditions. Specifically, coverage rates were within or only slightly below the acceptable range when the mobility condition was 10% or 20%, regardless of other combinations of conditions. When the variance between-clusters was 1.09, the coverage rates were within or only slightly below .925. Otherwise, coverage rates were outside of the acceptable range, ranging from .839 to .922, and generally decreased as mobility increased. For the CC-DTS model, coverage rates were found to be acceptable for all but two combinations of conditions, both of which included a cluster size of 30 and a variance between clusters of 1.09. However, both unacceptable coverage rates for the CC-DTS model were .922, and therefore, only very slightly below the acceptable range.

Table 46

Coverage Rates of the Coefficient Estimate of the Intercept for Discrete-Time Period 4 ($\alpha_4 = -1.74$), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***.867***	.934	.938
			75	***.772***	.934	.939
		50	25	***.873***	.929	.934
			75	***.747***	.938	.952
		100	25	***.897***	.944	.960
			75	***.725***	***.919***	.944
	20	30	25	***.881***	.942	.958
			75	***.754***	***.912***	.937
		50	25	***.857***	***.910***	.933
			75	***.756***	***.922***	.949
		100	25	***.881***	.927	.949
			75	***.762***	***.922***	.952
	30	30	25	***.838***	***.900***	.928
			75	***.718***	***.882***	.939
		50	25	***.847***	***.896***	.938
			75	***.720***	***.883***	.946
		100	25	***.862***	***.912***	.956
			75	***.697***	***.863***	.932
1.09	10	30	25	***.773***	***.918***	.929
			75	***.615***	.926	.933
		50	25	***.781***	***.924***	.937
			75	***.537***	.928	.939
		100	25	***.761***	.942	.948
			75	***.527***	***.915***	.943
	20	30	25	***.799***	***.917***	.944
			75	***.615***	***.900***	***.922***
		50	25	***.769***	***.916***	.940
			75	***.613***	***.914***	.935
		100	25	***.789***	***.921***	.952
			75	***.609***	***.924***	.950
	30	30	25	***.777***	***.891***	***.922***
			75	***.615***	***.864***	.933
		50	25	***.806***	***.879***	.937
			75	***.616***	***.877***	.937
		100	25	***.815***	***.886***	.952
			75	***.614***	***.839***	.939

Note. λ is the Weibull scale parameter, λ = 0.05 corresponded to baseline hazard probability in time period 4 of .150. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Bolded and italicized values represent unacceptable coverage of the 95% confidence intervals.

To further understand the practical implications of the coverage rates presented in Tables 45 and 46, a logistic regression was conducted for each model, the DTS, ML-DTS, and CC-DTS models, respectively, where the dependent variable was binary and represented whether or not the confidence interval included the true value of the parameter and the simulation conditions were entered as the independent variables. The Cox Effect was recorded for each model parameter, and is presented in Appendix I. For the DTS model, multiple nested logistic regression models were conducted to assess model fit, and it was determined that compared to a model with higher-order interactions, the model with third-order interactions produced the best model fit, [$\chi^2(16) = 23.34$, $p = 0.10$]. The results indicated a practically important interaction between cluster size (dummy variable contrasting a cluster size of 100 to a cluster size of 30), mobility rate (dummy variable contrasting the 30% mobility condition and 10% mobility condition), and the Weibull scale parameter, [$\chi^2(71{,}948) = 4.11$, $p < .05$, $d_{Cox} = 0.26$]. When the Weibull scale parameter was 0.05, coverage was always greater than when it was 0.025, regardless of the mobility rate or the cluster size. However, regardless of the mobility rate, coverage was only slightly greater when the Weibull scale parameter was 0.05 than when it was 0.025 if the cluster size was 30, while the difference was greater if the cluster size was 100. For example, when the mobility rate condition was 10%, coverage was greater when the Weibull scale parameter was 0.05 than when it was 0.025 if the cluster size was 100 ($\overline{CovRate}_{10\%,100,0.025}$ = .541, $\overline{CovRate}_{10\%,100,0.05}$ = .728), but was only slightly greater when the cluster size was 30 ($\overline{CovRate}_{10\%,30,0.025}$ = .706, $\overline{CovRate}_{10\%,30,0.05}$ = .757). A practically important interaction was also observed between mobility rate (dummy variable contrasting the 30% mobility condition and the 10% mobility condition), variance between clusters, and the Weibull scale parameter, [$\chi^2(71{,}948) = 5.32$, $p < .05$, $d_{Cox} = 0.27$]. Under the majority of combinations of conditions, coverage was greater when the mobility condition was 10%, regardless of the value of the variance between clusters and the Weibull scale parameter. However, when the variance between clusters was 1.09 and the Weibull scale parameter was 0.05, the coverage was greater when the mobility rate condition was 30% than when it was 10% ($\overline{CovRate}_{10\%,1.09,0.05}$ = .666, $\overline{CovRate}_{30\%,1.09,0.05}$ = .707). Additionally, the main effect of the within-cluster sample size was practically important, [$\chi^2(71{,}948) = -8.55, p < .05, d_{Cox} = -0.43$], such that the coverage was greater when the within-cluster sample size was 25 than when it was 75 ($\overline{CovRate}_{25}$ = .760, $\overline{CovRate}_{75}$ = .579). For the ML-DTS model, multiple nested logistic regression models were conducted to assess model fit, and it was determined that compared to a model with higher-order interactions, the model with second-order interactions produced the best model fit, [$\chi^2(25) = 19.56, p = 0.77$]. The results indicated a practically important main effect of the mobility rate (dummy variable contrasting the 30% mobility condition to the 10% mobility condition), [$\chi^2(71{,}973) = -7.17, p < .05, d_{Cox} = -0.34$], such that coverage was greater when the mobility rate condition was 10% than when it was 30% ($\overline{CovRate}_{10\%}$ = .687, $\overline{CovRate}_{30\%}$ = .646). For the CC-DTS model, multiple nested logistic regression models were conducted to assess model fit, and it was determined that compared to a model with higher-order interactions, the model with third-order interactions produced the best model fit, [$\chi^2(16) = 6.43, p = 0.98$]. A practically important interaction was found between mobility rate (dummy variable contrasting the 20% mobility rate condition to the 10% mobility rate condition), cluster size (dummy variable contrasting a cluster size of 100 to a cluster size of 30), and within-cluster sample size, [$\chi^2(71{,}948) = 3.44, p < .05, d_{Cox} = 0.40$]. Under the majority of combinations of conditions, coverage was nearly identical when the mobility rate condition was 10%, regardless of the cluster size or within-cluster sample size. However, when the mobility rate condition was 10%

and the cluster size was 100, a lower within-cluster sample size resulted in slightly greater coverage ($\overline{CovRate}_{10\%,\ 100,\ 25}$ = .950, $\overline{CovRate}_{10\%,\ 100,\ 75}$ = .943). In contrast, when the mobility rate condition was 20% and the cluster size was 100, a lower within-cluster sample size resulted in slightly lower coverage ($\overline{CovRate}_{20\%,\ 100,\ 25}$ = .947, $\overline{CovRate}_{20\%,\ 100,\ 75}$ = .955). Although there is a slight difference in coverage rates observed, the coverage rates deemed practically important here are still well within the acceptable range.

Coefficient for Discrete-Time Period 5 of the Logit Hazard Function, a_5

Table 47 presents the coverage of the 95% confidence intervals for the intercept for the fifth discrete-time period in the logit hazard function, a_5, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, undercoverage of the 95% confidence intervals was apparent for all 36 combinations of conditions. Coverage rates for the DTS model ranged from .530 to .885, and holding constant all other conditions, were lower when the variance between-clusters was 1.09 than when it was 0.32. For the ML-DTS model, coverage rates were outside the acceptable .925 to .975 range for the majority of combinations of conditions, with 12 combinations of conditions resulting in acceptable coverage rates. However, in all combinations of conditions except for those that included the 30% mobility rate condition, all coverage rates were either within or only slightly below the minimum .925 acceptable coverage rate. For the ML-DTS model, the coverage rates ranged from .841 to .937. For the CC-DTS model, coverage rates were found to be acceptable for all but one set of conditions; however, it was only very slightly below the acceptable range (.923).

Table 47

Coverage Rates of the Coefficient Estimate of the Intercept for Discrete-Time Period 5 ($\alpha_5 = -2.39$), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***.885***	.937	.935
			75	***.766***	.926	.931
		50	25	***.876***	.938	.947
			75	***.774***	***.922***	.931
		100	25	***.859***	.937	.944
			75	***.723***	.930	.937
	20	30	25	***.876***	.934	.949
			75	***.768***	***.915***	.931
		50	25	***.873***	.932	.946
			75	***.747***	***.913***	.936
		100	25	***.853***	.930	.947
			75	***.693***	***.919***	.956
	30	30	25	***.882***	.929	.945
			75	***.743***	***.871***	.928
		50	25	***.867***	***.921***	.948
			75	***.713***	***.887***	.943
		100	25	***.830***	***.904***	.951
			75	***.646***	***.849***	.938
1.09	10	30	25	***.779***	***.923***	.932
			75	***.650***	***.911***	***.923***
		50	25	***.779***	.932	.943
			75	***.630***	.925	.935
		100	25	***.798***	.934	.947
			75	***.617***	***.912***	.947
	20	30	25	***.811***	***.921***	.947
			75	***.640***	***.897***	.936
		50	25	***.814***	***.920***	.942
			75	***.637***	***.906***	.930
		100	25	***.792***	***.917***	.950
			75	***.588***	***.917***	.955
	30	30	25	***.785***	***.896***	.933
			75	***.597***	***.865***	.927
		50	25	***.793***	***.897***	.948
			75	***.587***	***.883***	.939
		100	25	***.760***	***.891***	.942
			75	***.530***	***.841***	.934

Note. λ is the Weibull scale parameter, λ = 0.025 corresponded to baseline hazard probability in time period 5 of .084. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Bolded and italicized values represent unacceptable coverage of the 95% confidence intervals.

Table 48 presents the coverage of the 95% confidence intervals for the intercept for the fifth discrete-time period in the logit hazard function, a_5, across 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, the coverage rates were below .925 for all 36 combinations of conditions that included a Weibull scale parameter of 0.05. Coverage rates were especially poor when the variance between-clusters was 1.09, where coverage rates ranged from .232 to .657. For the DTS model, when the variance between-clusters was 0.32, coverage rates ranged from .696 to .895. For the ML-DTS model, coverage rates were within the acceptable .925 to .975 range for 20 combinations of conditions. For those datasets that included conditions resulting in unacceptable rates of coverage, coverage rates were only slightly below the acceptable range for the majority of the combinations of conditions. Specifically, the range of unacceptable coverage rates was from .898 to .924. For the CC-DTS model, coverage rates were found to be acceptable for all but two combinations of conditions, both of which included a cluster size of 30. However, both unacceptable coverage rates for the CC-DTS model were greater than .920, and therefore, only very slightly below the acceptable range.

Table 48

Coverage Rates of the Coefficient Estimate of the Intercept for Discrete-Time Period 5 ($\alpha_5 = -1.60$), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***.864***	.937	.938
			75	***.749***	.938	.942
		50	25	***.857***	.929	.932
			75	***.696***	.934	.946
		100	25	***.822***	.935	.941
			75	***.630***	.940	.942
	20	30	25	***.895***	.955	.959
			75	***.731***	***.914***	.931
		50	25	***.868***	.932	.941
			75	***.754***	.934	.950
		100	25	***.845***	.940	.958
			75	***.705***	.934	.954
	30	30	25	***.876***	***.917***	.938
			75	***.747***	***.885***	***.924***
		50	25	***.872***	.925	.936
			75	***.749***	***.906***	.933
		100	25	***.880***	.942	.953
			75	***.703***	***.901***	.937
1.09	10	30	25	***.656***	***.919***	.929
			75	***.428***	***.920***	.925
		50	25	***.582***	.935	.941
			75	***.285***	***.920***	.931
		100	25	***.372***	.944	.951
			75	***.125***	.931	.938
	20	30	25	***.701***	.940	.951
			75	***.449***	***.904***	***.921***
		50	25	***.607***	.933	.939
			75	***.330***	***.918***	.940
		100	25	***.382***	***.923***	.942
			75	***.162***	.932	.947
	30	30	25	***.717***	***.902***	.929
			75	***.508***	***.898***	.928
		50	25	***.657***	***.924***	.940
			75	***.395***	***.898***	.936
		100	25	***.480***	.939	.952
			75	***.232***	***.899***	.932

Note. λ is the Weibull scale parameter, λ = 0.05 corresponded to baseline hazard probability in time period 5 of .168. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Bolded and italicized values represent unacceptable coverage of the 95% confidence intervals.

To further understand the practical implications of the coverage rates presented in Tables 47 and 48, a logistic regression was conducted for each model, the DTS, ML-DTS, and CC-DTS models, respectively, where the dependent variable was binary and represented whether or not the confidence interval included the true value of the parameter and the simulation conditions were entered as the independent variables. The Cox Effect was recorded for model parameter, and is presented in Appendix I. For the DTS model, multiple nested logistic regression models were conducted to assess model fit, and it was determined that compared to a model with higher-order interactions, the model with third-order interactions produced the best model fit, [$\chi^2(16)$ = 13.2, p = 0.66]. The results indicated that there was a practically significant interaction between the variance between clusters, cluster size (dummy variable contrasting a cluster size of 100 to a cluster size of 30), and Weibull scale parameter [$\chi^2(71{,}948) = -14.04$, $p < .05$, $d_{Cox} = -0.75$]. Regardless of the cluster size and the Weibull scale parameter, when the variance between clusters was 0.32, the coverage was nearly identical; however, when the variance between clusters was 1.09, the coverage was substantially lower when the Weibull scale parameter was 0.05 than when it was 0.025. For example, when the cluster size was 100 and the variance between clusters was 0.32, coverage was nearly identical regardless of the Weibull scale parameter ($\overline{CovRate}_{0.025}$ = .770, $\overline{CovRate}_{0.05}$ = .764); however, when the variance was 1.09, there was a substantial difference in coverage by the value of the Weibull scale parameter ($\overline{CovRate}_{0.025}$ = .680, $\overline{CovRate}_{0.05}$ = .292). Additionally, there was a practically significant interaction between the mobility rate (dummy variable contrasting the 30% mobility rate condition to the 10% mobility rate condition), cluster size (dummy variable contrasting a cluster size of 100 to a cluster size of 30), and the Weibull scale parameter [$\chi^2(71{,}948) = 4.77$, $p < .05$, $d_{Cox} = 0.30$]. When the Weibull scale parameter was 0.025, coverage was always greater than when it was 0.05, regardless of the mobility rate or the cluster size. However, regardless of the mobility rate, coverage was only slightly greater when the Weibull scale parameter was 0.05 than when it was 0.025 if the cluster size was 30, while the difference was greater if the cluster size was 100. For example, when the mobility rate condition was 10%, coverage was greater when the Weibull scale parameter was 0.025 than when it was 0.05 if the cluster size was 100 ($\overline{CovRate}_{10\%,100,0.025}$ = .750, $\overline{CovRate}_{10\%,100,0.05}$ = .487), but was only slightly greater when the cluster size was 30 ($\overline{CovRate}_{10\%,30,0.025}$ = .770, $\overline{CovRate}_{10\%,30,0.05}$ = .674). Additionally, the main effect of the within-cluster sample size was practically important, [χ^2(71,948) = -8.11, p < .05, d_{Cox}= -0.43], such that the coverage was greater when the within-cluster sample size was 25 than when it was 75 ($\overline{CovRate}_{25}$ = .773, $\overline{CovRate}_{75}$ = .595). For both the ML-DTS and CC-DTS models, no main effect or interaction between the independent variables was found to have a practically significant effect on the coverage of the 95% confidence intervals.

Coefficient of the individual-level predictor, $\boldsymbol{\beta_1}$

Table 49 presents the coverage of the 95% confidence intervals for coefficient for the individual-level predictor, β_1, across 36 combinations of conditions where the Weibull scale parameter was 0.025 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, undercoverage of the 95% confidence intervals was apparent for 28 of the 36 combinations of conditions. When the variance between-clusters was 1.09, the DTS model resulted in coverage rates outside of the acceptable range regardless of the other conditions present in the generated datasets, with coverage rates ranging from .230 to .859. When the variance between-clusters was 0.32, there was no apparent pattern that resulted in unacceptable coverage rates; however, coverage rates overall were closer to the acceptable range when the variance between-clusters was 0.32 than when it was 1.09. For the ML-DTS model, coverage rates were outside the acceptable .925 to .975 range for 5 combinations of conditions, all of which occurred when variance between-clusters was 1.09, and generally, when the mobility condition was 20% or 30% in combination with cluster sizes of 50 or greater. For the ML-DTS model, the coverage rates ranged from .869 to .950. For the CC-DTS model, coverage rates were found to be acceptable for all combinations of conditions presented in Table 49.

Table 49

Coverage Rates of the Coefficient Estimate of the Level-One Predictor ($\beta_1 = 0.50$), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	.936	.943	.941
			75	***.908***	.938	.939
		50	25	.925	.947	.944
			75	***.910***	.952	.955
		100	25	***.899***	.937	.935
			75	***.848***	.945	.946
	20	30	25	.936	.948	.945
			75	***.918***	.938	.945
		50	25	.929	.943	.941
			75	***.912***	.950	.949
		100	25	***.907***	.936	.944
			75	***.867***	.946	.947
	30	30	25	.937	.945	.948
			75	.937	.946	.953
		50	25	.935	.946	.945
			75	***.889***	.937	.955
		100	25	.928	.952	.949
			75	***.844***	.934	.951
1.09	10	30	25	***.858***	.937	.943
			75	***.704***	.943	.952
		50	25	***.813***	.955	.952
			75	***.540***	.934	.946
		100	25	***.648***	.932	.936
			75	***.230***	.935	.948
	20	30	25	***.859***	.941	.946
			75	***.684***	.942	.947
		50	25	***.803***	.941	.942
			75	***.539***	***.923***	.944
		100	25	***.631***	***.924***	.944
			75	***.265***	***.910***	.944
	30	30	25	***.858***	.934	.951
			75	***.718***	.933	.954
		50	25	***.804***	.932	.944
			75	***.558***	***.888***	.942
		100	25	***.684***	.929	.955
			75	***.282***	***.869***	.940

Note. λ is the Weibull scale parameter, $\beta_1 = 0.50$ corresponded to hazard odds ratio of 1.65. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Bolded and italicized values represent unacceptable coverage of the 95% confidence intervals.

Table 50 presents the coverage of the 95% confidence intervals for the coefficient for the individual-level predictor, β_1, across 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, undercoverage of the 95% confidence intervals was apparent for 34 of the 36 combinations of conditions. Coverage rates for the DTS model ranged from .033 to .933. For the ML-DTS model, coverage rates were outside the acceptable .925 to .975 range for 7 combinations of conditions, all of which occurred when the variance between-clusters was 1.09 and the 20% or 30% mobility conditions. For the ML-DTS model, the coverage rates ranged from .828 to .958. For the CC-DTS model, coverage rates were found to be acceptable for all combinations of conditions.

Table 50

Coverage Rates of the Coefficient Estimate of the Level-One Predictor ($\beta_1 = 0.50$), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	.933	.958	.957
			75	***.859***	.943	.940
		50	25	***.901***	.944	.939
			75	***.816***	.955	.952
		100	25	***.854***	.948	.954
			75	***.679***	.949	.952
	20	30	25	.929	.950	.959
			75	***.867***	.949	.948
		50	25	***.897***	.943	.944
			75	***.823***	.930	.940
		100	25	***.849***	.931	.944
			75	***.667***	.925	.942
	30	30	25	***.914***	.938	.938
			75	***.889***	.943	.945
		50	25	***.902***	.937	.948
			75	***.834***	.955	.963
		100	25	***.867***	.940	.944
			75	***.677***	.931	.957
1.09	10	30	25	***.786***	.945	.957
			75	***.479***	.935	.947
		50	25	***.660***	.943	.945
			75	***.289***	.946	.955
		100	25	***.410***	.945	.951
			75	***.033***	.935	.948
	20	30	25	***.786***	.936	.941
			75	***.527***	.927	.942
		50	25	***.678***	***.921***	.936
			75	***.306***	***.915***	.944
		100	25	***.430***	.930	.956
			75	***.050***	***.878***	.953
	30	30	25	***.785***	.929	.951
			75	***.530***	***.903***	.945
		50	25	***.654***	.926	.945
			75	***.284***	***.890***	.956
		100	25	***.439***	***.903***	.942
			75	***.064***	***.828***	.950

Note. λ is the Weibull scale parameter, $\beta_1 = 0.50$ corresponded to hazard odds ratio of 1.65. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Bolded and italicized values represent unacceptable coverage of the 95% confidence intervals.

To further understand the practical implications of the coverage rates presented in Tables 49 and 50, a logistic regression was conducted for each model, the DTS, ML-DTS, and CC-DTS models, respectively, where the dependent variable was binary and represented whether or not the confidence interval included the true value of the parameter and the simulation conditions were entered as the independent variables. The Cox Effect was recorded for model parameter, and is presented in Appendix I. For the DTS model, multiple nested logistic regression models were conducted to assess model fit, and it was determined that compared to a model with higher-order interactions, the model with fourth-order interactions produced the best model fit, [χ^2(4) = 2.92, p = 0.57]. The results indicated a practically important interaction between cluster size (dummy variable contrasting a cluster size of 100 to a cluster size of 30), mobility rate (dummy variable contrasting the 30% mobility condition and 10% mobility condition), the within-cluster sample size, and the variance between clusters, [χ^2(71,932) = 3.32, p < .05, d_{Cox}= 0.55]. Regardless of the other combinations of conditions, coverage was lowest when the variance between clusters was 1.09. Coverage was also lower when the cluster size and within-cluster sample sizes were greater. Additionally, the results indicated a practically important interaction between cluster size (dummy variable contrasting a cluster size of 100 to a cluster size of 30), the within-cluster sample size, the variance between clusters, and the Weibull scale parameter [χ^2(71,932) = -2.69, p < .05, d_{Cox}= -0.36]. As the cluster size and within-cluster sample size increased, the coverage decreased, regardless of the other conditions. Additionally, when the between clusters variance was 1.09 and the Weibull scale parameter was 0.05, coverage rates were always lower. However, the difference in the coverage rates by Weibull scale parameter became greater when the variance between clusters was 1.09 as compared to when it was 0.32, and increased as both the within-cluster and cluster size increased. Lastly, a practically important interaction was observed between cluster size (dummy variable contrasting a cluster size of 50 to a cluster size of 30), the within-cluster sample size, and the mobility rate (dummy variable contrasting the 30% mobility condition and 10% mobility condition), [χ^2(71,932) = -2.02, p < .05, d_{Cox}= -0.32]. The largest difference in coverage occurred due to the within-cluster sample size, such that regardless of the other variables in the interaction, coverage decreased substantially as within-cluster sample size increased. For example, when the mobility rate condition was 10% and the cluster size was 30, the coverage rate was greater when the within-cluster sample size was 25 than when it was 75 ($\overline{CovRate}_{25}$ = .878, $\overline{CovRate}_{75}$ = .738). This pattern occurred regardless of mobility rate or cluster size, although when cluster size was greater, the difference in coverage rates by within-cluster sample size also increased. For the ML-DTS model, multiple nested logistic regression models were conducted to assess model fit, and it was determined that compared to a model with higher-order interactions, the model with third-order interactions produced the best model fit, [χ^2(16) = 12.17, p = 0.73]. The results indicated a practically significant interaction between mobility rate (dummy variable contrasting the 30% mobility condition and the 10% mobility condition), cluster size (dummy variable contrasting a cluster size of 100 to a cluster size of 30), and within-cluster sample size, [χ^2(71,948) = -2.72, p < .05, d_{Cox}= -0.30]. When the mobility rate condition was 10%, the coverage rates were nearly equal regardless of the cluster size or within-cluster sample size. When the mobility rate condition was 30%, coverage was again nearly equal regardless of the within-cluster sample size when the cluster size was 30; however, when the cluster size was 100, coverage was slightly lower when the within-cluster sample size was 75 than when it was 25 ($\overline{CovRate}_{30\%,100,25}$ = .931, $\overline{CovRate}_{30\%,100,75}$ = .890). For the CC-DTS model, no main effect or interaction between the independent variables was found to have a practically significant effect on the coverage of the 95% confidence intervals.

Coefficient of the cluster-level predictor, β_2

Table 51 presents the coverage of the 95% confidence intervals for the coefficient for the cluster-level predictor, β_2, across 36 combinations of conditions where the Weibull scale parameter was .025 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, undercoverage of the 95% confidence intervals was present for all 36 combinations of conditions. Coverage rates appeared to be significantly impacted by the within-cluster sample size, where coverage was generally lower when the sample size was 75 than when it was 25. Coverage rates for the DTS model ranged from .194 to .720. For the ML-DTS model, coverage rates were outside the acceptable .925 to .975 range for 24 combinations of conditions. Generally, it appeared that the coverage rates decreased as mobility rates increased, regardless of the other conditions present in the dataset. For the ML-DTS model, the coverage rates ranged from .790 to .936, where the lowest rates of coverage occurred in datasets generated using the 30% mobility condition. For the CC-DTS model, coverage rates were found to be acceptable for all but four combinations of conditions, all of which included a cluster size of 30. However, for those conditions with unacceptable coverage rates, coverage was still greater than .910, and therefore, demonstrated only slight undercoverage.

Table 51

Coverage Rates of the Coefficient Estimate of the Level-Two Predictor ($\beta_2 = 0.50$), When λ = 0.025

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***.720***	***.923***	***.922***
			75	***.505***	.930	.942
		50	25	***.689***	.931	.946
			75	***.471***	***.923***	.931
		100	25	***.635***	.934	.943
			75	***.401***	***.918***	.934
	20	30	25	***.708***	***.916***	.940
			75	***.455***	***.887***	***.916***
		50	25	***.669***	***.912***	.949
			75	***.447***	***.902***	.929
		100	25	***.608***	***.895***	.930
			75	***.349***	***.884***	.942
	30	30	25	***.665***	***.888***	.925
			75	***.448***	***.858***	.929
		50	25	***.625***	***.883***	.955
			75	***.391***	***.855***	.938
		100	25	***.514***	***.850***	.955
			75	***.269***	***.790***	.946
1.09	10	30	25	***.522***	.936	.935
			75	***.303***	.927	.931
		50	25	***.478***	.933	.942
			75	***.291***	***.922***	.938
		100	25	***.411***	.937	.937
			75	***.238***	.930	.931
	20	30	25	***.521***	.929	.945
			75	***.297***	***.907***	***.916***
		50	25	***.472***	.925	.945
			75	***.294***	***.912***	.931
		100	25	***.421***	.925	.942
			75	***.233***	***.914***	.942
	30	30	25	***.496***	***.898***	***.915***
			75	***.312***	***.900***	.934
		50	25	***.451***	***.905***	.948
			75	***.278***	***.901***	.933
		100	25	***.367***	***.898***	.958
			75	***.194***	***.865***	.943

Note. λ is the Weibull scale parameter, $\beta_2 = 0.50$ corresponded to hazard odds ratio of 1.65. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Bolded and italicized values represent unacceptable coverage of the 95% confidence intervals.

Table 52 presents the coverage of the 95% confidence intervals for the coefficient for the cluster-level predictor, β_2, across 36 combinations of conditions where the Weibull scale parameter was 0.05 for the DTS, ML-DTS, and CC-DTS models, respectively. For the DTS model, undercoverage of the 95% confidence intervals was present for all 36 combinations of conditions. Coverage rates appeared to be significantly impacted by the within-cluster sample size, where coverage was generally lower when the sample size was 75 than when it was 25. Coverage rates for the DTS model ranged from .170 to .649. For the ML-DTS model, coverage rates were outside the acceptable .925 to .975 range for 26 combinations of conditions. Generally, the coverage rates decreased as mobility rates increased, regardless of the other conditions present in the dataset. For the ML-DTS model, the coverage rates ranged from .909 to .938, where the lowest rates of coverage were in datasets that were generated with the 30% mobility condition. For the CC-DTS model, coverage rates were found to be acceptable for all but four combinations of conditions, all of which included a cluster size of 30 and mobility rate conditions of either 20% or 30%. However, for those conditions with unacceptable coverage rates, coverage was still greater than .910, and therefore, demonstrated only slight undercoverage.

Table 52

Coverage Rates of the Coefficient Estimate of the Level-Two Predictor ($\beta_2 = 0.50$), When λ = 0.05

Manipulated Condition				Estimating Model		
VC	m%	c	n	DTS	ML-DTS	CC-DTS
0.32	10	30	25	***.649***	.928	.927
			75	***.458***	.941	.936
		50	25	***.636***	.927	.941
			75	***.408***	.930	.936
		100	25	***.573***	***.921***	.937
			75	***.346***	***.917***	.930
	20	30	25	***.633***	.925	.937
			75	***.403***	***.902***	***.917***
		50	25	***.596***	***.912***	.933
			75	***.393***	***.897***	.933
		100	25	***.547***	***.889***	.940
			75	***.278***	***.894***	.944
	30	30	25	***.611***	***.877***	***.912***
			75	***.389***	***.868***	.929
		50	25	***.554***	***.887***	.955
			75	***.324***	***.859***	.927
		100	25	***.430***	***.843***	.953
			75	***.222***	***.809***	.951
1.09	10	30	25	***.483***	.931	.937
			75	***.283***	.933	.938
		50	25	***.438***	.938	.937
			75	***.244***	***.921***	.937
		100	25	***.369***	.930	.940
			75	***.197***	***.919***	.932
	20	30	25	***.471***	.928	.931
			75	***.273***	***.904***	***.915***
		50	25	***.409***	***.924***	.933
			75	***.266***	***.913***	.936
		100	25	***.354***	***.918***	.942
			75	***.173***	***.919***	.946
	30	30	25	***.463***	***.891***	***.919***
			75	***.268***	***.905***	.935
		50	25	***.404***	***.908***	.946
			75	***.245***	***.906***	.933
		100	25	***.308***	***.900***	.957
			75	***.170***	***.903***	.946

Note. λ is the Weibull scale parameter, $\beta_2 = 0.50$ corresponded to hazard odds ratio of 1.65. DTS = discrete-time survival model, ML-DTS = multilevel discrete-time survival model, CC-DTS = cross-classified discrete-time survival model; VC = variance at the cluster-level; m% = mobility rate, c = cluster-level sample size, n = within-cluster sample size; Bolded and italicized values represent unacceptable coverage of the 95% confidence intervals.

To further understand the practical impacts of the simulation conditions on the coverage of the coefficient for the cluster-level predictor, a logistic regression was conducted for each model, the DTS, ML-DTS, and CC-DTS models, respectively, where the dependent variable was binary and represented whether or not the confidence interval included the true value of the parameter and the simulation conditions were entered as the independent variables. The Cox Effect was recorded for model parameter, and is presented in Appendix I. For the DTS model, multiple nested logistic regression models were conducted to assess model fit, and it was determined that compared to a model with higher-order interactions, the model with second-order interactions produced the best model fit, [χ^2(25) = 17.78, p = 0.85]. The main effect of the within-cluster sample size was found to be practically significant, [χ^2(71,973) = -22.83, p < .05, d_{Cox} = -0.58]. Specifically, when the within-cluster sample size was 25, the 95% confidence interval included the true parameter value more often than it did when the within-cluster sample size was 75 ($\overline{CovRate}_{25}$ = .525, $\overline{CovRate}_{75}$ = .320). Additionally, the main effect of the variance between clusters was found to have a practically important impact on the coverage rates. Specifically, when the variance between clusters was 0.32, the 95% confidence interval included the true parameter value more often than it did when it was 1.09 ($\overline{CovRate}_{0.32}$ = .500, $\overline{CovRate}_{1.09}$ = .344). For the ML-DTS model, multiple nested logistic regression models were conducted to assess model fit, and it was determined that compared to a model with higher-order interactions, the model with third-order interactions produced the best model fit, [χ^2(16) = 3.33, p = 0.99]. The results indicated a practically significant interaction between the mobility rate (dummy variable contrasting the 20% mobility condition to the 10% mobility condition), cluster size (dummy variable contrasting a cluster size of 100 to a cluster size of 30), and within-cluster sample size, [χ^2(71,948) =2.75, p < .05, d_{Cox} = 0.28]. When the mobility rate condition was 10%, the coverage rates were nearly equivalent regardless of the within-cluster sample size or cluster size. However, when the mobility rate condition was 20%, the coverage rates where nearly equivalent regardless of the within-cluster sample size if the cluster size was 100, but if the cluster size was 30, the coverage rates differed slightly by the within-cluster sample size ($\overline{CovRate}_{20\%,30,25}$ = .924, $\overline{CovRate}_{20\%,30,75}$ = .900). Additionally, the main effect of the mobility rate (dummy variable contrasting the 30% mobility condition to the 10% mobility condition) was practically important, [$\chi^2(71{,}948) = -3.88$, $p < .05$, $d_{Cox} = -0.29$]. Specifically, when the mobility rate condition was 10%, the 95% confidence interval included the true parameter value more often than it did when it was 30% ($\overline{CovRate}_{10\%}$ = .928, $\overline{CovRate}_{30\%}$ = .876). For the CC-DTS model, none of the simulation conditions were found to have a practically significant effect on the coverage of the 95% confidence intervals.

CHAPTER 5

DISCUSSION

Using a Monte Carlo simulation, this study investigates the impact of ignoring a cross-classified data structure due to individual mobility across clusters in a discrete-time survival analysis. In addition, it examines how the baseline hazard function, variability of the cluster random effect, mobility rate, and within- and between-cluster sample size impact the performance of a cross-classified discrete-time survival model. This simulation study includes datasets generated from 72 combinations of conditions by manipulating the within-cluster sample size (25 and 75), the cluster size (30, 50, 100), the between-cluster variance (0.32 and 1.09), the Weibull scale parameter (0.025 and 0.05), and the rate of individual mobility across clusters (10%, 20%, and 30%). The data generating model in this study is a cross-classified discrete-time survival model, and therefore, the CC-DTS estimating model most closely matches the data generating procedures. Model performance is assessed by examining the relative parameter bias, root mean square error, and coverage of the 95% confidence intervals for the DTS, ML-DTS, and CC-DTS models across 1,000 replications of each of the 72 unique combinations of conditions. This chapter will discuss the results of this simulation study, serving to compare and contrast the performance of each of the three models included in this simulation study. Additionally, it contains a discussion of the limitations of the current study and suggestions for future research, and lastly, the importance of the study for empirical researchers.

Summary of Results

The following section describes the notable patterns observed in the results as they pertain to the relative parameter bias (RPB), root mean square error (RMSE), and coverage rates of the 95% confidence intervals (95% CIs), and places these results within the context of the generated datasets. This section will first describe the results as they pertain to the hazard function, and then follow with results for the remaining parameters of interest: the level-1 coefficient, the level-2 coefficient, and the variance between clusters. To further illustrate the results of this study, nested-loop plots (Rücker & Schwarzer, 2014), which plot the RPB, RMSE, and coverage rates of the 95% CIs of each model for all simulation conditions in one plot per parameter, have been provided in Appendices F, G, and H, respectively.

Features of the Generated Data

This study investigates the performance of three discrete-time survival models in the presence of a cross-classified data structure that is a result of the specific situation that occurs when individuals are mobile across clusters. As such, when examining the impact of mobility on the model parameters, it is important to understand how the data generating procedures affected the specification of mobility in the dataset. Recall that discrete-time survival analysis utilizes a person-period dataset, where the risk set during each discrete-time period changes because individuals are removed from the dataset following event occurrence. Due to the person-period data format, the specified percentage of mobile individuals (10%, 20%, and 30%) does not exactly match the actual mobility present in the generated datasets. Additionally, the Weibull scale parameter condition affects event occurrence, and therefore, the proportion of individuals removed from the dataset. Table 53 presents the average overall mobility rates across the generated datasets by Weibull scale parameter. Note that the actual mobility rates are lower than the specified mobility rates due to the changing risk set. Therefore, for the remainder of this discussion, the mobility condition will be referred to as "low", "medium", and "high" levels of mobility.

Table 53

Comparison of Specified Mobility Rates to Actual Mobility Rates Observed in the Generated Datasets by Weibull Scale Parameter

Weibull Scale Parameter	Generated Overall Mobility	Actual Overall Mobility
0.025	10%	8.46%
	20%	17.08%
	30%	25.52%
0.05	10%	7.41%
	20%	14.97%
	30%	22.37%

Note. Actual overall mobility rates represent the proportion of individuals in the dataset that actually moved during the time period of study.

The Hazard Function

In discrete-time survival analysis, the hazard function is represented by a coefficient estimate, known as the intercept, for each discrete-time period to examine the likelihood of event occurrence in each discrete-time period of study. The findings indicate that the DTS model clearly has difficulty estimating the parameters representing the hazard function regardless of the combination of conditions present as compared to either the ML-DTS or the CC-DTS models. For instance, in regards to RPB, the DTS model yields moderately or substantially biased estimates for the majority of parameters representing the hazard function, regardless of the combination of simulation conditions. Indeed, the ANOVA results suggest important impacts of the Weibull scale parameter, the variance between clusters, and in some cases, mobility, on RPB for parameters representing the hazard function using the DTS model. A larger variance between-clusters, and in some cases, greater rates of mobility, result in more substantially negative RPB for the DTS model. The Weibull scale parameter sometimes interacts with the variance between-clusters, resulting in differing impacts of the Weibull scale parameter on RPB depending on the level of the variance between-clusters condition. In regards to RMSE, the within-cluster sample size plays a very important role in determining the magnitude of RMSE for the parameters representing the hazard function for the DTS model. For instance, holding all other conditions constant, the RMSE value is consistently lower when the within-cluster sample size is 75 than when it is 25. Generally, as the sample size in the dataset increases, RMSE for the DTS model decreases. Additionally, the variance between clusters consistently has a large impact on RMSE for the DTS model, where RMSE is much greater when it is 1.09 than when it is 0.32. In regard to coverage of the 95% CIs, the DTS model performs poorly for all parameters of the hazard function, never falling within the acceptable range. In almost all combinations of conditions, it performs worse than either the ML-DTS or the CC-DTS models. Indeed, the cluster size, within-cluster sample size, and variance between-clusters consistently have practically important impacts on coverage of the 95% CIs for parameters representing the hazard function for the DTS model, such that the 95% CI includes the true parameter value more often in datasets that include a lower sample size and/or a lower variance between clusters.

The performance of the ML-DTS model, in terms of RPB and coverage of the 95% CIs, is often superior to the DTS model. For instance, the ML-DTS model results in acceptable RPB for many combinations of simulation conditions. However, mobility and the variance between clusters has a clear impact on RPB for the parameters representing the hazard function for the ML-DTS model. In most cases, when the variance between clusters is 0.32, the ML-DTS model exhibits acceptable RPB, even when mobility increases. However, when the variance between clusters increases to 1.09, the magnitude of RPB for most parameters representing the hazard function becomes more substantially negative as the rate of mobility in the dataset increases, especially for medium and high rates of mobility. When unacceptable RPB is present, it is always moderate, or between a magnitude 0.05 and 0.10. Indeed, the results of the ANOVAs indicate that the main effects of both the degree of mobility and the amount of variance between-clusters have a practically important impact on the RPB for the parameters representing the hazard function for the ML-DTS model. Specifically, when the variance between-clusters or mobility increases in the dataset, RPB becomes more substantially negative. RMSE for the ML-DTS model is highly influenced by both the variance between clusters and mobility. Specifically, holding all other manipulated conditions constant, as mobility increases, the RMSE tends to increase. This is especially true when the variance between clusters is 1.09, where the RMSE values overall are larger than when it is 0.32. Comparing across models, when the variance between-clusters is 0.32 and mobility is low, the RMSE estimates for each parameter of the hazard function produced by the ML-DTS model and the CC-DTS model are nearly equal. Given that under these same conditions RPB is also similar between the ML-DTS model and the CC-DTS model, the RMSE results suggest that both models offer similar precision when estimating parameters representing the hazard function in datasets with low mobility rates and low between-cluster variance. In regard to coverage of the 95% CIs, the ML-DTS model results in undercoverage of most parameters representing the hazard function when mobility is medium or high, regardless of other combinations of conditions. This observation is further supported by the results of the logistic regressions, which indicate that coverage for the coefficients representing the hazard function using the ML-DTS model are most often affected by the mobility rate and cluster size in the generated datasets. However, overall, coverage is substantially better using the ML-DTS model than the DTS model under all combinations of conditions.

As compared to the DTS and ML-DTS models, the CC-DTS model estimates the coefficients representing the hazard function well. In all cases, RPB is clearly within the acceptable range, indicating virtually no bias (i.e., RPB was close to 0). Additionally, coverage of the 95% CIs is well within the acceptable range for all combinations of conditions using the CC-DTS model, and the results of the logistic regressions indicate no practical impact of any simulation condition on coverage of the 95% CIs. Given that the ML-DTS and CC-DTS models result in no substantial RPB when the variance between clusters is 0.32 for any parameter representing the hazard function, lower values of RMSE suggest greater precision of the estimates. As such, RMSE values indicate that most often, the CC-DTS offers greater precision in the estimates of the hazard function, especially as mobility increases, than the ML-DTS model.

Similar to the results found in a real data study by Lamote et al. (2013), the parameters representing the hazard function differ between the three models examined here. The DTS model has very different estimates of the parameters representing the hazard function than the other models, with unacceptable RPB and extremely poor coverage of the 95% CIs. A smaller difference in estimates of the hazard function exists between the ML-DTS model and the CC-DTS model, and while coverage of the 95% CIs is always found to be acceptable for the CC-DTS model, the ML-DTS model results in unacceptable coverage commensurate with increasing mobility in the dataset. This suggests that as mobility increases in the dataset, the likelihood of committing a Type I error also increases if mobility is ignored by modeling only the impact of the first cluster (e.g., school) on the hazard function.

Previous research that compares a multilevel model that ignores mobility to a model that accounts for mobility across clusters has indicated that while bias may occur in some standard error estimates for coefficients at level-1, ignoring mobility does not impact intercept estimates (see for example, Cappelli et al., 2020; Chung & Beretvas, 2012; Leroux & Beretvas, 2018b; Leroux et al., 2020; Luo & Kwok, 2009, 2012; Meyers & Beretvas, 2006). However, it should be expected that these findings would not hold true in a discrete time survival model, likely as a result of the introduction of heterogeneity to the dataset due to individual mobility across clusters. Barber et al. (2000) and Masyn (2003) described the impact of violating the assumption of no unobserved heterogeneity in discrete-time survival models, stating that when heterogeneity in the data is ignored by the estimating model, the hazard function may be negatively impacted. Barber et al. (2000) specifically stated that in the presence of clustering, excluding a random effect at the clustering level will likely result in a biased hazard function, as is apparent in this study when using a DTS model, where the hazard function is clearly biased under nearly all simulation conditions. It is likely that the low coverage rates observed using the DTS model are the result of the substantial RPB in the intercept coefficients in combination with underestimated standard errors of the intercept coefficients. It is well known that ignoring the clustering level of a nested data structure by using a single-level model, such as the DTS model, results in underestimated standard errors (Fielding & Goldstein, 2006; Moerbeek, 2004; Raudenbush & Bryk, 2002). Clark (2008) assessed the performance of a single-level generalized linear model in the presence of a clustered data structure with a specific focus on the impact of within-cluster sample sizes, and found that standard errors were underestimated by up to 40%, with standard error bias increasing as the within-cluster sample size increased to 20 individuals per cluster. The results of this study broadly follow those found by Clark (2008), although due to the combination of mobility and larger within-cluster sample sizes, more extreme undercoverage of the 95% CIs is present using the DTS model. Lamote et al. (2013) also compared a CC-DTS model to a ML-DTS model using real data, and found that the hazard functions estimated by the two models also differed. Therefore, it is likely that just as clustering results in heterogeneity in the dataset, ignoring individual mobility across clusters represents another source of possible heterogeneity.

In this study, the results indicate that the ML-DTS model has some moderate RPB under some combinations of simulation conditions, especially when the variance between clusters is high and mobility in the dataset is medium to high. Therefore, in the presence of these conditions, the results suggest that the CC-DTS model better estimates the parameters representing the hazard function.

Importantly, the data generating procedures employed in this study likely have an impact on the magnitude of the bias present in the hazard function, especially as it pertains to the moderate RPB observed in the ML-DTS model, which accounts for the clustered data structure but not mobility of individuals across clusters. As an example, one way that heterogeneity is introduced into the generated datasets is through the binary level-2 covariate (*Z*), which is specified such that students in schools coded as 1 have a greater likelihood of event occurrence across the study period than students in schools coded as 0. Additionally, mobility has an impact on *Z*, such that the true value of *Z* changes for mobile students, which remains unmodeled when using the ML-DTS model because it only takes on the value assigned to the first school. In other words, the ML-DTS model ignores the heterogeneity introduced by the impact of student mobility on the true value of the level-2 covariate, which therefore impacts the risk of event occurrence across the study (i.e., the hazard function). Furthermore, the data generation procedures for *Z* specify that 30% of clusters are coded as 1, while 70% are coded as 0; therefore, mobile students are more likely to begin in and move to a school coded 0 than they are to be in a school coded 1. If this ratio is different, for example a 50/50 ratio, mobile students would be just as likely to move into a school coded as 1 as they would be to a school coded as 0. In such a situation, it is possible that lower rates of mobility may have greater impacts on bias in the hazard function estimated using the ML-DTS model than that observed in this study, since the true variability in *Z* would be greater in such datasets. As such, the results described here offer a note of caution when using an estimating model that ignores heterogeneity, which may result in more or less substantial bias of the hazard function given different data contexts.

Coefficient of the individual-level predictor, β_1

Results indicate that the coefficient of the individual-level predictor has substantial RPB across all conditions using the DTS model, with bias becoming more substantially negative when the variance between clusters increases. This should be expected, as the DTS model does not account for the nested data structure, and therefore, violates the assumption of no unobserved heterogeneity due to clustering (Barber et al., 2000). Additionally, RPB is consistently more substantially negative for the DTS model when the Weibull scale parameter is 0.05. RMSE values are notably impacted by the within-cluster sample size, with RMSE values decreasing when the within-cluster sample size is 75 as opposed to when it is 25. Coverage of the 95% CIs most often indicates slight to substantial undercoverage using the DTS model. The results of the logistic regression indicate that the coverage rate is highly impacted by the variance between clusters and the within-cluster sample size. Specifically, coverage is extremely poor when the variance between clusters is 1.09, and generally, coverage decreases when the within-cluster sample is 75. Similar to the results observed for the hazard function, these low coverage rates are likely explained by an underestimation of the standard error for the level-1 coefficient estimate, which results in a narrowing of the 95% CIs. In combination with substantial RPB, this results in very low rates of coverage of the true parameter value. These results suggest that the DTS model consistently underestimates the individual-level coefficient, especially when the variance between clusters is high. Conversely, for the ML-DTS model, the coefficient of the individual-level predictor is estimated without bias for the majority of simulation conditions; however, the

RPB results indicate that the coefficient is moderately underestimated when the variance between clusters is high in combination with high rates of mobility. For those same combinations of conditions, coverage of the 95% CIs is also unacceptable, with the greatest undercoverage of the coefficient for the level-1 predictor occurring when mobility is high. The results indicate that the CC-DTS model, in contrast to the ML-DTS model and especially the DTS model, estimates the individual-level coefficient without bias and with acceptable coverage of the 95% CIs under all combinations of simulation conditions.

Again, the moderate RPB and undercoverage of the 95% CIs present when mobility is ignored is likely due to the impact of unmodeled heterogeneity. Importantly, previous findings in the literature for continuous and binary outcomes that examined the impact of ignoring cross-classified data structures using purely clustered multilevel models often found that there was no substantial impact of model misspecification on the individual-level fixed effect parameter estimates (see for example, Cappelli et al., 2020; Chung & Beretvas, 2012; Leroux & Beretvas, 2018b; Leroux et al., 2020; Luo & Kwok, 2009, 2012; Meyers & Beretvas, 2006). However, these findings should not be expected to remain true for a discrete-time survival model due to the additional assumption of no unobserved heterogeneity, a violation of which can negatively impact lower-level coefficient estimates and their standard errors (Barber et al., 2000; Masyn, 2003). In fact, the bias in the estimated coefficients for the level-1 covariate may occur even if the source for heterogeneity, which here is mobility across clusters, has no association with the covariate (Masyn, 2009). Specifically, for the ML-DTS model, medium to high mobility rates in combination with high variance between clusters appears to result in some RPB and undercoverage of the 95% CIs in the coefficient for the individual-level covariate. In contrast, the CC-DTS model estimates the coefficient for the level-1 covariate well, regardless of the combination of simulation conditions.

Lamote et al. (2013) is the only study that has compared the results of a cross-classified discrete-time survival model to a purely clustered discrete-time survival model, and reported that there was no substantial difference between the individual-level fixed effect estimates or their standard errors between the two models. Comparing their study results to the combination of conditions in this study that most closely match their data (i.e., 50 clusters, 75 individuals per cluster, a high mobility rate, variance between-clusters of 0.32, and Weibull scale parameter of 0.025), similar findings are apparent. Specifically, under these conditions, the magnitude of RPB is not found to be substantial for the ML-DTS or CC-DTS models, and the RMSE values and coverage of the 95% CIs are similar to those found using the CC-DTS model.

Coefficient of the cluster-level predictor, β_2

The results indicate that the coefficient of the cluster-level predictor is estimated with substantial bias for both the DTS and ML-DTS models. For the DTS model, both mobility and the variance between clusters have a substantial negative impact on RPB and RMSE, and the within-cluster sample size has a large impact on coverage of the 95% CIs. When the DTS model is used, the cluster-level coefficient is substantially underestimated, especially as compared to the ML-DTS and CC-DTS models, for all combinations of conditions. Specifically, coverage rates of the 95% CIs are extremely low and substantial negative bias is present, indicating a higher likelihood of committing a Type I error. In comparison, the ML-DTS model performs better than the DTS model, but overall, is still poor as compared to the CC-DTS model, especially when there are high rates of mobility in the dataset. The ML-DTS model also results in moderate to substantial RPB for all combinations of conditions examined, although the magnitude of the bias is always less severe than when the DTS model is used. RPB indicates only moderate underestimation of the cluster-level coefficient when overall mobility in the dataset is low, and when holding all other manipulated conditions constant, there is a clear negative impact of increasing mobility on RPB, such that substantial RPB is apparent when mobility is medium or high. Like the DTS model, the ML-DTS model results in substantial underestimation of the coefficient estimate and a high likelihood of committing a Type I error, as evidenced by the undercoverage of the 95% CIs in almost any combination of conditions that includes medium or high rates of mobility. The results of the logistic regression further support this finding, indicating that mobility has a practically important impact on coverage rates for the ML-DTS model. As opposed to the DTS and ML-DTS models, the CC-DTS model does not have substantial RPB for any combination of conditions. When the variance between clusters is 1.09, RMSE using the CC-DTS model is clearly impacted by the cluster-level sample size, such that it becomes lower as cluster size increases. In regard to coverage rates of the 95% CIs, the CC-DTS model results in acceptable coverage for the majority of combinations of conditions, with the only exceptions occurring when the cluster size is 30. Taken as a whole, these results suggest that in order to confidently estimate the cluster-level coefficient using the CC-DTS model, a cluster size greater than 30 is required.

The results of this study are consistent with the findings of previous research in the cross-classified and multiple membership literature, where model misspecification was found to have a negative impact on cluster-level coefficient estimates (e.g., Cappelli et al., 2020; Chung & Beretvas, 2012; Choi & Wilson, 2016; Grady & Beretvas, 2010; Leroux et al., 2020; Luo & Kwok, 2009, 2012; Meyers & Beretvas, 2006). In this study, it should also be expected that use of the ML-DTS or DTS models would lead to bias in the cluster-level coefficient. Note that the data generating model is a CC-DTS model, which allows for the value of the cluster level predictor, $Z_{(j)}$, to change for mobile students, such that when a student changes schools, the school characteristic also changes accordingly. In contrast, the ML-DTS model is estimated using the characteristic of only the first school attended. Therefore, for mobile students, the value of *Z* in the ML-DTS model does not match the true value of *Z*, negatively impacting the estimated coefficient. As such, as mobility increases in the dataset, RPB of the cluster-level coefficient increases using the ML-DTS model, but does not impact RPB when the CC-DTS model is used. A similar mechanism of bias has been described in previous simulation studies that examined model performance in the presence of individual mobility across clusters, which found that models that ignore mobility by using only a single school result in different coefficient estimates for the cluster-level predictor (Cappelli et al., 2020; Chung & Beretvas, 2012; Leroux et al., 2020). In a real data study using discrete-time survival analysis, Lamote et al. (2013) observed a similar pattern in the coefficient estimates, where the parameter estimates associated with school characteristics were lower when only a single school was used to estimate the cluster-level coefficient.

Between-Clusters Variance Component, σ_u^2

The between-clusters variance component, σ_u^2, is only assessed for the ML-DTS and CC-DTS models. As a single-level model, the DTS model does not account for the variance between clusters by incorporating a random component. The results indicate that the ML-DTS model results in substantial RPB regardless of the combination of conditions examined in this study. It is apparent that the most obvious pattern of RPB is related to mobility in the dataset, such that as mobility increases, the magnitude of RPB becomes larger. The ANOVA results support this finding, and indicate that mobility has a substantive impact on RPB. To a lesser extent, cluster size also has an important impact on RPB, such that the magnitude of bias becomes less severe as cluster size increases. The results indicate that even when the rate of mobility in the dataset is low, there are important negative implications for the estimation of the between-clusters variance component when using the ML-DTS model. The RMSE results also indicate that mobility has important implications for the between-clusters variance component, such that RMSE increases as mobility increases. Although not apparent when assessing RPB, RMSE for the between-clusters variance component is also clearly impacted by the amount of between-clusters variability, such that RMSE increases when variance between clusters is larger. For the CC-DTS model, the between-clusters variance component is consistently underestimated when the cluster size is 30, regardless of other combinations of simulation conditions. Additionally, especially when the variance between clusters is 0.32, RPB either approaches or slightly exceeds the magnitude of 0.05 threshold for moderate bias. In contrast to the ML-DTS model, RPB and RMSE under the CC-DTS model are not impacted by mobility. Instead, RMSE is again similarly impacted by both cluster size and variance between clusters.

These findings are supported by cross-sectional studies that examined the impact of mobility on multilevel models, which have found that ignoring mobility using a purely clustered multilevel model results in biased estimates of the cluster-level variance component (Chung & Beretvas, 2012; Wheelis, 2017; Wolff Smith & Beretvas, 2017). Additionally, methodological studies using longitudinal multilevel models have resulted in similar findings, although slightly larger cluster sizes, generally 50 or greater, were suggested when modeling mobility using a longitudinal cross-classified and/or multiple membership model to estimate cluster-level variance components without bias (Cappelli et al., 2020; Choi & Wilson, 2016; Grady, 2010; Leroux & Beretvas, 2018b; Leroux et al., 2020; Luo & Kwok, 2012). These results are also supported by the limited survival analysis literature. For example, Elghafghuf et al. (2014) used a cross-classified multiple membership Cox Model (i.e., a continuous-time, as opposed to discrete-time, survival model), and found that in terms of RPB, the CCM Cox Model performed better when mobility was higher and when variance components were larger. Similar results are seen in this study. Although the difference in RPB is only very slight, when the variance between clusters is 1.09, there is no substantial bias using the CC-DTS model when the cluster size is 50 or more, as opposed to a slight underestimation of the variance component when the cluster size is 50 and the variance between-clusters is 0.32.

Conclusions and Implications for Policy

Discrete-time survival analysis is commonly seen in the empirical literature across multiple disciplines in the social and behavioral sciences, such as education, criminology, and public health. This study examines the performance of a discrete-time survival model, a multilevel discrete-time survival model, and a cross-classified discrete-time survival model in the presence of a cross-classified data structure specifically resulting from individual mobility across clusters generated by a CC-DTS model. The results of this study suggest that in the presence of cross-classified data structures, the use of a discrete-time survival model without a random component could potentially result in severe bias for any model parameter, even when the variance between-clusters is relatively low. Therefore, under the conditions investigated in this study, a discrete-time survival model without a random component may not be appropriate to make inferences regarding the hazard function or covariates included in the model.

The multilevel and cross-classified discrete-time survival models include a random component at the clustering level, and therefore, account for the clustered data structure often present in datasets in the social or behavioral sciences. The primary difference between the models is that the CC-DTS model is specified to account for impure clustering, which in this study specifically occurs due to individual mobility across clusters, while the ML-DTS model is specified for only pure clustering of individuals within clusters. If the interest of the research is in describing the conditional hazard function, the ML-DTS model may be a comparatively simpler alternative to the CC-DTS model when overall mobility in the dataset is less than 10% in combination with an ICC of .10. However, regardless of the other conditions examined in this simulation study, as mobility increases, coverage of the 95% CIs decreases when the ML-DTS model is used, suggesting that there could potentially be an increased risk of making a Type I error, and therefore, incorrect inferences. Importantly, the extent to which the data conditions produce heterogeneity needs to be carefully considered when choosing to use the ML-DTS model in the presence of mobility, such that data conditions that result in greater heterogeneity under the same rates of mobility in this study may produce more or less bias in parameter estimates when that heterogeneity remains unmodeled. As such, caution may be necessary when employing the ML-DTS model to understand the conditional hazard function. When mobility rates are greater than 10% under the conditions investigated in this simulation, the CC-DTS model is one approach of handling mobility that could be given consideration to estimate parameters representing the hazard function to reduce parameter bias and to ensure correct inferences. Although this study employed a limited range of sample size conditions, initial findings suggest that the combination of a cluster-level sample size of 30 and within-cluster sample size of 25 may be sufficient for estimation of the hazard function using either the ML-DTS or CC-DTS models under the simulation conditions examined here. Note that the impact of sample size on these results may change when real-world conditions differ from those generated in this study. If the interest is to describe the impact of a level-1 covariate on the hazard function, the ML-DTS model and the CC-DTS model could both be considered when the ICC is .10, regardless of the proportion of mobile individuals in the dataset. A similar note of caution as described for the hazard function may also be considered here. In any case, when the ICC is .25 and the mobility rate in the dataset is greater than 10%, slight parameter bias may occur and there may be a greater likelihood of a Type I error if using the ML-DTS model. If the interest is in describing the effect of cluster-level covariates on the hazard odds of event occurrence, more caution may be necessary if using the ML-DTS model. Given the data conditions generated as a part of this simulation study, severe bias and unacceptable coverage of the 95% CIs may result when using the ML-DTS model, even when overall rates of individual mobility across clusters are less than 10% in the dataset. Although negative impacts are minimal when the cluster size is 30, the findings suggest that with data conditions that are similar to those present in this study, a minimum cluster size of 50 may be needed to accurately estimate the coefficient for a binary covariate at level 2. Lastly, if the interest is in accurately estimating the variance component at the cluster level and mobility is present in the dataset (regardless of the rate), the ML-DTS model may result in severe bias. However, to estimate the variance component without bias using the CC-DTS model under the conditions investigated in this simulation, a minimum sample size of more than 30 at the cluster level may be necessary, with increasing sample sizes at the cluster level and higher variance between clusters appearing to result in less biased estimates.

The results of this study have important implications for policy in the social and behavioral sciences. Recent educational policy interests and the resulting funding from federal agencies such as the National Science Foundation have focused on creating effective teacher preparation programs that address issues such as teacher retention (e.g., the Robert Noyce Scholarship Program). In light of these interests, discrete-time survival analysis is an important methodological approach to consider in studies of teacher retention, and indeed, has commonly been used in empirical research to understand the timing and risk of teachers leaving the profession (e.g., Donaldson, 2016; Kelly, 2004). Therefore, it is important for educational researchers to understand the impact of ignoring a level of clustering in discrete-time survival analysis, and further, the impact of ignoring mobility among students or teachers, both of which could potentially lead researchers to make incorrect inferences regarding the effect of individual- or cluster-level characteristics on the risk of event occurrence. Researchers using event-history outcomes should be especially cautious of ignoring clustering and/or mobility, regardless of whether the interest is in making inferences using parameters at the individual or clustering level. Empirical researchers are advised to take special care to understand the extent to which there is variance between clusters and mobility in their datasets if a discrete-time survival model is used to describe the timing and risk of event occurrence.

Limitations and Future Research

This study is the first exploration of the impact of ignoring individual mobility across clusters when modeling an event history outcome using discrete-time survival analysis. As the first exploration, the purpose is to establish some understanding of the performance of a DTS model, a ML-DTS model, and a CC-DTS model in the presence of mobility as generated by the CC-DTS model and other common data conditions in the social and behavioral sciences. However, there are some limitations to the current study that may be addressed in future research. One study limitation is that mobility is generated to represent the proportion of the sample to be mobile. In other words, every sample dataset generated using the 10% mobility condition was initially generated to have 10% of individuals mobile across clusters. This procedure was used in all previous studies examining mobility, and was therefore adopted here to maintain comparability. However, mobility could also be generated to be a proportion of the population, such that mobility across all datasets with the 10% mobility condition are generated to have an average of 10% mobility. Additionally, future studies may adjust the ratios of 0's and 1's in binary covariates to examine how balanced and unbalanced binary covariates may impact the results described in this study when covariate values change as a result of mobility, or add continuous covariates to the dataset. Future studies may also consider adding more than one covariate at each level of the multilevel models, and consider more complex relationships between covariates (e.g., within- and cross-level interactions).

Another limitation of this study pertains to the generation of event occurrence. Specifically, the hazard function used in this study was generated using a two-parameter Weibull function, but the analytic model leaves the hazard function unstructured. This may result in an over-identification of the model, which may introduce some slight decrease in the precision of model estimates. Although the decrease in precision should affect all models compared in this study, and therefore should not impact the substantive results, a future study should consider editing the data generation procedures to be an exact match to the analytic model explored.

As an initial exploration into the performance of discrete-time survival models when individual mobility across clusters is present in the data, this study only manipulates conditions hypothesized to likely have an important impact on model estimates based on previous research. However, there are other conditions that future research should explore to further understand how they impact the estimates from a discrete-time survival analysis. Future research may consider the impact of more extreme survival functions on parameter estimates. For example, if survival is so high at the end of the study that hazard is extremely low in certain time periods, it would be interesting to assess at what point the lack of variability in event occurrence within-clusters impacts the parameter estimates. In educational research, it is quite common to have extremely low overall event occurrence on the order of 10% to 15%, and therefore, high survival at the end of the study (e.g., Davoudazadeh et al. (2015); Lamote et al. (2013)). In this study, the lowest overall event occurrence was about 27%, meaning that about 72% of the generated sample survived through the end of the study.

Other additional conditions that future research may consider, and are specific to event history models, include the impact of manipulating the survival pattern (i.e., increasing, decreasing, and constant hazard across time), varying the widths of measurement occasions (i.e., the time between one observation and the next is not constant across individuals), or including interval-censored (missing) data in the datasets. While each of these have been explored and rarely impact parameter estimates (e.g., Moerbeek, 2012; Moerbeek & Hesen, 2018), when mobility is included in the data, it is possible that there are different impacts on model estimates. This may be especially true regarding the impact of mobility on the hazard function when the widths of measurement occasions are varied across individuals, as this may impact the timing of individual mobility.

Future studies should also examine other types of cross-classification not examined here, such as those that occur when higher-level units are not purely clustered within one another (e.g., students nested in a cross-classification of neighborhoods and schools), as well as alternative model specifications that account for individual mobility across clusters. For example, a future study may explore the performance of a multiple membership discrete-time survival (MM-DTS) model to account for mobility, which is different from the CC-DTS model investigated here in that it uses a weighting mechanism to account for mobility. Lamote et al. (2013) compared a MM-DTS model to the CC-DTS model and other models, and concluded that the CC-DTS model fit the data best. However, in other real data situations, it may not be the case that the CC-DTS model best fits the data, and the MM-DTS model could alternatively be used to account for mobility. As such, studies may also investigate the performance of a CC-DTS model when the mobility mechanism in the generated data does not exactly match the model specification, and assess the extent to which bias may occur in the CC-DTS model estimates when the impact of the multiple associated clusters, for example, is cumulative as opposed to noncumulative.

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APPENDIXES

Appendix A: Literature Informed Hazard Probabilities

Source	Analysis Used	Outcome Variable	Levels in the Model	Number of Time Periods	Range of Hazard Probability (Logit)
Ma & Willms, 1999	ML-DTSA	Student Dropout from Advanced Mathematics (Probability of math participation)	2	1	.980 (3.900)
				2	.921 (2.460)
				3	.924 (2.500)
				4	.889 (2.080)
				5	.634 (0.550)
Davoudzadeh et al., 2015	ML-DTSA	First occurrence of grade retention	2	1	.036 (−3.300)
				2	.058 (−2.786)
				3	.021 (−3.862)
				4	.017 (−4.080)
Bowers, 2010	DTSA	Student Dropout	1	1	.027 (−3.616)
				2	.043 (−3.091)
				3	.040 (−3.172)
				4	.036 (−3.283)
				5	.095 (−2.252)
				6	.036 (−3.296)
Orozco, 2016	DTSA	Student Dropout – Aggressive Students	1	1	.001 (−6.513)
				2	.003 (−5.756)
				3	.008 (−4.779)
				4	.059 (−2.769)
				5	.093 (−2.276)
				6	.044 (−3.088)
Lamote et al. (2013)[1]	CC-DTSA	Student Dropout	2	1	.000 (−7.580)
				2	.013 (−4.359)
				3	.022 (−3.784)
				4	.028 (−3.549)
				5	.031 (−3.456)
				6	.014 (−4.268)

Note. Studies were excluded that constrained the effect of time, such that hazard probabilities were not freely estimated during each time period. Only baseline hazard probabilities (logit values) are reported here. The study was excluded from this table if baseline hazard probabilities were not reported.

[1] Results represent the baseline values of the cross-classified discrete-time survival model.

Appendix B: Literature Informed Level-1 Covariate Values

Source	Model(s) Used	Outcome Variable	Levels in the Model	Example Variables (Coded as 1)	Range of Coefficient Values (logit)	Proportion Coded 1
Ma & Willms, 1999	ML-DTSA	Student Dropout from Advanced Mathematics	2	Female	0.090	Not Provided
Davoudzadeh et al., 2015	ML-DTSA	First occurrence of grade retention	2	Female	−0.547 to 0.685	.50
				Race (Multiple)	−0.352 to 0.396	.32
				Below Poverty Line	0.422 to 1.298	.16
				Non-English	−1.096 to 0.071	.13
				Special Needs	−0.166 to 0.702	.10
Bowers, 2010	DTSA	Student Dropout	1	Boys	−2.339 to −0.522	.50
				Non-European American	−1.812 to 0.277	.55
Lamote et al., 2013	CC-DTSA	Student Dropout	2	Female	−0.440 to −0.536	Not Provided
				Repeated Grade	0.987 to 1.766	Not Provided
Orozco, 2016	DTSA	Student Dropout – Aggressive Students	1	Female	0.105 to 0.330	.48
				Latino	0.405 to 0.484	.42
Randolph, Fraser, & Orthner, 2006	DTSA	Student Dropout	1	Male	−0.040	Not Provided
				African American	−0.640	Not Provided
Slama, 2014	ML-DTSA	Reclassification into mainstream classrooms	3	Spanish-Speaking	−0.579 to −0.538	.55
				Low Income	−0.245 to −0.152	.70
Schifter, 2016	DTSA	High School Graduation	1	Race (Multiple)	−0.320 to 0.255	Not Provided
				Free or Reduced Lunch	−0.388	Not Provided

Petras et al., 2011	ML-DTSA	First Occurrence of School Removal	2	African American	0.70	.34
				Male	--	.51
				Free or Reduced Lunch,	0.52	.52
Carpenter, 2007	HGLM	Likelihood of Dropout	3	Black	−0.769 to −0.309	.11
				Hispanic		.13
				White		.76
				English Spoken at Home	.069 to .382	Not Provided
Cha, 2015	HGLM	Dropout from Mathematics	2	Male	−0.287 to 0.077	.46
				Minority (Race)	−0.822 to 0.934	.54
				Free Lunch	−0.474 to 0.196	.27
Subedi & Howard, 2013	HGLM	High School Graduation and Dropout	2	English Language Learner	−0.23	Not Provided
Werblow & Duesberry, 2009	HGLM	High School Dropout	2	Female	−0.52	Not Provided
				Minority (Multiple)	−1.09 to 1.53	Not Provided

Note. If there is more than one model discussed in the source, the values reported are presented as a range. Only time-invariant covariates are reported.

Appendix C: Literature Informed Level-2 Covariate Values

Source	Model(s) Used	Outcome Variable	Levels in the Model	Example Variables Used (Coded as 1)	Range of Dichotomous Covariate Values (logit)	Proportion coded 1
Cha, 2015	HGLM	Dropout from Mathematics	2	Urban	−0.51 to 0.766	0.27
				Suburban	−0.266 to 0.397	0.42
				High minority	−0.255 to 0.898	0.26
Carpenter, 2007	HGLM	Likelihood of Dropout	2	School Type	1.36	Not Provided
				Urban	−0.989 to 0.928	Not Provided
				Rural	−0.204 to 0.680	Not Provided
Werblow & Duesberry, 2009	HGLM	High School Dropout	2	Urban	.0.07	Not Provided
				Rural	0.29	Not Provided
Taniguchi, 2017	HGLM	School Mobility	2	Semi-Urban	0.638 to 0.941	0.24

Note. If there is more than one model discussed in the source, the values reported are presented as a range. Only time-invariant covariates are reported.

Appendix D: Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias – Simulation Conditions as Independent Variables

Table D1

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Coefficient for the Intercept of Discrete-Time Period 1, α_1, For Each Estimating Model by Source of Variation

Source of Variation	Model		
	DTS	ML-DTS	CC-DTS
Mobility	0.003	***0.044***	0.000
Cluster Size	0.001	0.000	0.000
Within-Cluster	0.000	0.000	0.000
Variance	***0.439***	***0.054***	0.000
Scale	***0.019***	0.000	0.000
Mobility×Cluster Size	0.000	0.000	0.000
Mobility×Within-Cluster	0.000	0.000	0.000
Cluster Size×Within-Cluster	0.000	0.000	0.000
Mobility×Variance	0.000	0.005	0.000
Cluster Size×Variance	0.000	0.000	0.000
Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Scale	0.000	0.000	0.000
Cluster Size×Scale	0.000	0.000	0.000
Within-Cluster Size×Scale	0.000	0.000	0.000
Variance×Scale	0.001	0.000	0.000
Mobility×Cluster Size×Within-Cluster	0.001	0.000	0.000
Mobility×Cluster Size×Variance	0.000	0.000	0.000
Mobility×Within-Cluster×Student	0.000	0.000	0.000
Cluster Size×Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Cluster Size×Scale	0.000	0.000	0.000
Mobility×Within-Cluster×Scale	0.000	0.000	0.000
Cluster Size×Within-Cluster×Scale	0.000	0.000	0.000
Mobility×Variance×Scale	0.000	0.000	0.000
Cluster×Variance×Scale	0.000	0.000	0.000
Within-Cluster×Variance×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Variance×Scale	0.000	0.000	0.000
Mobility×Within-Cluster×Variance×Scale	0.000	0.000	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000	0.000	0.000
Mobility × Cluster Size × Within-Cluster × Variance × Scale	0.000	0.000	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Table D2

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Coefficient for the Intercept of Discrete-Time Period 2, α_2, For Each Estimating Model by Source of Variation

Source of Variation	Model		
	DTS	ML-DTS	CC-DTS
Mobility	0.007	***0.038***	0.000
Cluster Size	0.001	0.000	0.000
Within-Cluster	0.000	0.000	0.000
Variance	***0.263***	***0.045***	0.000
Scale	0.000	0.001	0.000
Mobility×Cluster Size	0.000	0.000	0.000
Mobility×Within-Cluster	0.000	0.000	0.000
Cluster Size×Within-Cluster	0.001	0.001	0.000
Mobility×Variance	0.000	0.005	0.000
Cluster Size×Variance	0.000	0.000	0.000
Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Scale	0.000	0.000	0.000
Cluster Size×Scale	0.000	0.000	0.000
Within-Cluster Size×Scale	0.000	0.000	0.000
Variance×Scale	0.002	0.000	0.000
Mobility×Cluster Size×Within-Cluster	0.001	0.000	0.000
Mobility×Cluster Size×Variance	0.000	0.000	0.000
Mobility×Within-Cluster×Student	0.000	0.000	0.000
Cluster Size×Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Cluster Size×Scale	0.000	0.000	0.000
Mobility×Within-Cluster×Scale	0.000	0.000	0.000
Cluster Size×Within-Cluster×Scale	0.000	0.000	0.000
Mobility×Variance×Scale	0.000	0.000	0.000
Cluster×Variance×Scale	0.000	0.000	0.000
Within-Cluster×Variance×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Variance×Scale	0.000	0.000	0.000
Mobility×Within-Cluster×Variance×Scale	0.000	0.000	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale	0.000	0.000	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Table D3

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Coefficient for the Intercept of Discrete-Time Period 3, α_3, For Each Estimating Model by Source of Variation

Source of Variation	Model		
	DTS	ML-DTS	CC-DTS
Mobility	***0.011***	***0.027***	0.000
Cluster Size	0.000	0.000	0.000
Within-Cluster	0.000	0.000	0.000
Variance	***0.084***	***0.029***	0.000
Scale	***0.037***	0.000	0.000
Mobility×Cluster Size	0.000	0.000	0.000
Mobility×Within-Cluster	0.000	0.000	0.000
Cluster Size×Within-Cluster	0.000	0.000	0.000
Mobility×Variance	0.001	0.003	0.000
Cluster Size×Variance	0.000	0.000	0.000
Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Scale	0.000	0.000	0.000
Cluster Size×Scale	0.000	0.000	0.000
Within-Cluster Size×Scale	0.000	0.000	0.000
Variance×Scale	***0.017***	0.000	0.000
Mobility×Cluster Size×Within-Cluster	0.000	0.000	0.000
Mobility×Cluster Size×Variance	0.000	0.000	0.000
Mobility×Within-Cluster×Student	0.000	0.000	0.000
Cluster Size×Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Cluster Size×Scale	0.000	0.000	0.000
Mobility×Within-Cluster×Scale	0.000	0.000	0.000
Cluster Size×Within-Cluster×Scale	0.000	0.000	0.000
Mobility×Variance×Scale	0.000	0.000	0.000
Cluster×Variance×Scale	0.000	0.000	0.000
Within-Cluster×Variance×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Variance×Scale	0.000	0.000	0.000
Mobility×Within-Cluster×Variance×Scale	0.000	0.000	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale	0.000	0.000	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Table D4

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Coefficient for the Intercept of Discrete-Time Period 4, α_4, For Each Estimating Model by Source of Variation

Source of Variation	Model		
	DTS	ML-DTS	CC-DTS
Mobility	***0.013***	***0.014***	0.000
Cluster Size	0.000	0.000	0.000
Within-Cluster	0.000	0.000	0.000
Variance	0.000	***0.010***	0.000
Scale	***0.130***	0.001	0.000
Mobility×Cluster Size	0.000	0.000	0.000
Mobility×Within-Cluster	0.000	0.000	0.000
Cluster Size×Within-Cluster	0.000	0.001	0.000
Mobility×Variance	0.001	0.001	0.000
Cluster Size×Variance	0.000	0.000	0.000
Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Scale	0.001	0.000	0.000
Cluster Size×Scale	0.000	0.000	0.000
Within-Cluster Size×Scale	0.000	0.000	0.000
Variance×Scale	***0.040***	0.001	0.000
Mobility×Cluster Size×Within-Cluster	0.000	0.000	0.000
Mobility×Cluster Size×Variance	0.000	0.000	0.000
Mobility×Within-Cluster×Student	0.000	0.000	0.000
Cluster Size×Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Cluster Size×Scale	0.000	0.000	0.000
Mobility×Within-Cluster×Scale	0.000	0.000	0.000
Cluster Size×Within-Cluster×Scale	0.000	0.000	0.000
Mobility×Variance×Scale	0.000	0.000	0.000
Cluster×Variance×Scale	0.000	0.000	0.000
Within-Cluster×Variance×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Variance×Scale	0.000	0.000	0.000
Mobility×Within-Cluster×Variance×Scale	0.000	0.000	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale	0.000	0.000	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Table D5

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Coefficient for the Intercept of Discrete-Time Period 5, α_5, For Each Estimating Model by Source of Variation

Source of Variation	Model		
	DTS	ML-DTS	CC-DTS
Mobility	0.008	0.002	0.000
Cluster Size	0.000	0.000	0.000
Within-Cluster	0.000	0.000	0.000
Variance	***0.063***	0.000	0.000
Scale	***0.263***	***0.010***	0.000
Mobility×Cluster Size	0.000	0.000	0.000
Mobility×Within-Cluster	0.000	0.000	0.000
Cluster Size×Within-Cluster	0.000	0.000	0.000
Mobility×Variance	0.000	0.000	0.000
Cluster Size×Variance	0.000	0.000	0.000
Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Scale	0.000	0.001	0.000
Cluster Size×Scale	0.000	0.000	0.000
Within-Cluster Size×Scale	0.000	0.000	0.000
Variance×Scale	***0.072***	0.003	0.000
Mobility×Cluster Size×Within-Cluster	0.000	0.000	0.000
Mobility×Cluster Size×Variance	0.000	0.000	0.000
Mobility×Within-Cluster×Student	0.000	0.000	0.000
Cluster Size×Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Cluster Size×Scale	0.000	0.000	0.000
Mobility×Within-Cluster×Scale	0.000	0.000	0.000
Cluster Size×Within-Cluster×Scale	0.000	0.000	0.000
Mobility×Variance×Scale	0.000	0.000	0.000
Cluster×Variance×Scale	0.000	0.000	0.000
Within-Cluster×Variance×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Variance×Scale	0.000	0.000	0.000
Mobility×Within-Cluster×Variance×Scale	0.000	0.000	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale	0.000	0.000	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Table D6

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Coefficient for the Level-One predictor, β_1, For Each Estimating Model by Source of Variation

Source of Variation	Model		
	DTS	ML-DTS	CC-DTS
Mobility	0.000	0.005	0.000
Cluster Size	0.001	0.000	0.000
Within-Cluster	0.000	0.000	0.000
Variance	***0.165***	0.008	0.000
Scale	***0.012***	0.000	0.000
Mobility×Cluster Size	0.000	0.000	0.000
Mobility×Within-Cluster	0.000	0.000	0.000
Cluster Size×Within-Cluster	0.000	0.000	0.000
Mobility×Variance	0.000	0.001	0.000
Cluster Size×Variance	0.000	0.000	0.000
Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Scale	0.000	0.000	0.000
Cluster Size×Scale	0.000	0.000	0.000
Within-Cluster Size×Scale	0.000	0.000	0.000
Variance×Scale	0.001	0.000	0.000
Mobility×Cluster Size×Within-Cluster	0.000	0.000	0.000
Mobility×Cluster Size×Variance	0.000	0.000	0.000
Mobility×Within-Cluster×Student	0.000	0.000	0.000
Cluster Size×Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Cluster Size×Scale	0.000	0.000	0.000
Mobility×Within-Cluster×Scale	0.000	0.000	0.000
Cluster Size×Within-Cluster×Scale	0.000	0.000	0.000
Mobility×Variance×Scale	0.000	0.000	0.000
Cluster×Variance×Scale	0.000	0.000	0.000
Within-Cluster×Variance×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Variance×Scale	0.000	0.000	0.000
Mobility×Within-Cluster×Variance×Scale	0.000	0.000	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale	0.000	0.000	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Table D7

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Coefficient for the Level-Two Predictor, β_2, For Each Estimating Model by Source of Variation

Source of Variation	Model		
	DTS	ML-DTS	CC-DTS
Mobility	***0.012***	***0.016***	0.000
Cluster Size	0.000	0.000	0.000
Within-Cluster	0.000	0.000	0.000
Variance	***0.020***	0.001	0.000
Scale	0.000	0.000	0.000
Mobility×Cluster Size	0.001	0.001	0.001
Mobility×Within-Cluster	0.000	0.000	0.000
Cluster Size×Within-Cluster	0.000	0.000	0.000
Mobility×Variance	0.000	0.000	0.000
Cluster Size×Variance	0.000	0.000	0.000
Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Scale	0.000	0.000	0.000
Cluster Size×Scale	0.000	0.000	0.000
Within-Cluster Size×Scale	0.000	0.000	0.000
Variance×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster	0.000	0.000	0.000
Mobility×Cluster Size×Variance	0.000	0.000	0.000
Mobility×Within-Cluster×Student	0.000	0.000	0.000
Cluster Size×Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Cluster Size×Scale	0.000	0.000	0.000
Mobility×Within-Cluster×Scale	0.000	0.000	0.000
Cluster Size×Within-Cluster×Scale	0.000	0.000	0.000
Mobility×Variance×Scale	0.000	0.000	0.000
Cluster×Variance×Scale	0.000	0.000	0.000
Within-Cluster×Variance×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Variance	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Variance×Scale	0.000	0.000	0.000
Mobility×Within-Cluster×Variance×Scale	0.000	0.000	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale	0.000	0.000	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Table D8

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Variance Component, σ_u^2, For Each Estimating Model by Source of Variation

Source of Variation	Model	
	ML-DTS	CC-DTS
Mobility	***0.186***	0.000
Cluster Size	***0.010***	0.008
Within-Cluster	0.000	0.000
Variance	0.008	0.000
Scale	0.003	0.000
Mobility×Cluster Size	0.000	0.000
Mobility×Within-Cluster	0.000	0.000
Cluster Size×Within-Cluster	0.000	0.000
Mobility×Variance	0.000	0.000
Cluster Size×Variance	0.000	0.000
Within-Cluster×Variance	0.000	0.000
Mobility×Scale	0.000	0.000
Cluster Size×Scale	0.000	0.000
Within-Cluster Size×Scale	0.000	0.000
Variance×Scale	0.000	0.000
Mobility×Cluster Size×Within-Cluster	0.000	0.000
Mobility×Cluster Size×Variance	0.000	0.000
Mobility×Within-Cluster×Student	0.000	0.000
Cluster Size×Within-Cluster×Variance	0.000	0.000
Mobility×Cluster Size×Scale	0.000	0.000
Mobility×Within-Cluster×Scale	0.000	0.000
Cluster Size×Within-Cluster×Scale	0.000	0.000
Mobility×Variance×Scale	0.000	0.000
Cluster×Variance×Scale	0.000	0.000
Within-Cluster×Variance×Scale	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Variance	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000	0.000
Mobility×Cluster Size×Variance×Scale	0.000	0.000
Mobility×Within-Cluster×Variance×Scale	0.000	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale	0.000	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Appendix E: Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias – Model as a Factor

Table E1

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Coefficient for the Intercept of Discrete-Time Period 1, α_1, by Source of Variation

Source of Variation	Partial Eta Squared
Mobility	0.008
Cluster Size	0.000
Within-Cluster	0.000
Variance	***0.117***
Scale	0.003
Model	***0.385***
Mobility×Cluster Size	0.000
Mobility×Within-Cluster	0.000
Cluster Size×Within-Cluster	0.000
Mobility×Variance	0.000
Cluster Size×Variance	0.000
Within-Cluster×Variance	0.000
Mobility×Scale	0.000
Cluster Size×Scale	0.000
Within-Cluster Size×Scale	0.000
Variance×Scale	0.000
Mobility×Model	0.008
Cluster Size×Model	0.000
Within-Cluster×Model	0.000
Variance×Model	***0.114***
Scale×Model	0.004
Mobility×Cluster Size×Within-Cluster	0.000
Mobility×Cluster Size×Variance	0.000
Mobility×Within-Cluster×Variance	0.000
Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Scale	0.000
Mobility×Within-Cluster×Scale	0.000
Cluster Size×Within-Cluster×Scale	0.000
Mobility×Variance×Scale	0.000
Cluster Size×Variance×Scale	0.000
Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Model	0.000
Mobility×Within-Cluster×Model	0.000
Cluster Size×Within-Cluster×Model	0.000
Mobility×Variance×Model	0.001
Cluster Size×Variance×Model	0.000
Within-Cluster×Variance×Model	0.000
Mobility×Scale×Model	0.000
Cluster Size×Scale×Model	0.000

Within-Cluster×Scale×Model	0.000
Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000
Mobility×Cluster Size×Variance×Scale	0.000
Mobility×Within-Cluster×Variance×Scale	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Model	0.000
Mobility×Cluster Size×Variance×Model	0.000
Mobility×Within-Cluster×Variance×Model	0.000
Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Scale×Model	0.000
Mobility×Within-Cluster×Scale×Model	0.000
Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Variance×Scale×Model	0.000
Cluster Size×Variance×Scale×Model	0.000
Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Cluster Size×Variance×Scale×Model	0.000
Mobility×Within-Cluster×Variance×Scale×Model	0.000
Cluster Size×Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale×Model	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Table E2

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Coefficient for the Intercept of Discrete-Time Period 2, α_2, by Source of Variation

Source of Variation	Partial Eta Squared
Mobility	0.008
Cluster Size	0.000
Within-Cluster	0.000
Variance	***0.062***
Scale	0.000
Model	***0.245***
Mobility×Cluster Size	0.000
Mobility×Within-Cluster	0.000
Cluster Size×Within-Cluster	0.001
Mobility×Variance	0.001
Cluster Size×Variance	0.000
Within-Cluster×Variance	0.000
Mobility×Scale	0.000
Cluster Size×Scale	0.000
Within-Cluster Size×Scale	0.000
Variance×Scale	0.000
Mobility×Model	0.007
Cluster Size×Model	0.000
Within-Cluster×Model	0.000
Variance×Model	***0.049***
Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster	0.000
Mobility×Cluster Size×Variance	0.000
Mobility×Within-Cluster×Variance	0.000
Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Scale	0.000
Mobility×Within-Cluster×Scale	0.000
Cluster Size×Within-Cluster×Scale	0.000
Mobility×Variance×Scale	0.000
Cluster Size×Variance×Scale	0.000
Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Model	0.000
Mobility×Within-Cluster×Model	0.000
Cluster Size×Within-Cluster×Model	0.000
Mobility×Variance×Model	0.001
Cluster Size×Variance×Model	0.000
Within-Cluster×Variance×Model	0.000
Mobility×Scale×Model	0.000
Cluster Size×Scale×Model	0.000
Within-Cluster×Scale×Model	0.000
Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000

Mobility×Cluster Size×Variance×Scale	0.000
Mobility×Within-Cluster×Variance×Scale	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Model	0.000
Mobility×Cluster Size×Variance×Model	0.000
Mobility×Within-Cluster×Variance×Model	0.000
Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Scale×Model	0.000
Mobility×Within-Cluster×Scale×Model	0.000
Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Variance×Scale×Model	0.000
Cluster Size×Variance×Scale×Model	0.000
Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Cluster Size×Variance×Scale×Model	0.000
Mobility×Within-Cluster×Variance×Scale×Model	0.000
Cluster Size×Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale×Model	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Table E3

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Coefficient for the Intercept of Discrete-Time Period 3, α_3, by Source of Variation

Source of Variation	Partial Eta Squared
Mobility	0.007
Cluster Size	0.000
Within-Cluster	0.000
Variance	***0.022***
Scale	0.003
Model	***0.106***
Mobility×Cluster Size	0.000
Mobility×Within-Cluster	0.000
Cluster Size×Within-Cluster	0.000
Mobility×Variance	0.001
Cluster Size×Variance	0.000
Within-Cluster×Variance	0.000
Mobility×Scale	0.000
Cluster Size×Scale	0.000
Within-Cluster Size×Scale	0.000
Variance×Scale	0.002
Mobility×Model	0.005
Cluster Size×Model	0.000
Within-Cluster×Model	0.000
Variance×Model	***0.012***
Scale×Model	0.007
Mobility×Cluster Size×Within-Cluster	0.000
Mobility×Cluster Size×Variance	0.000
Mobility×Within-Cluster×Variance	0.000
Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Scale	0.000
Mobility×Within-Cluster×Scale	0.000
Cluster Size×Within-Cluster×Scale	0.000
Mobility×Variance×Scale	0.000
Cluster Size×Variance×Scale	0.000
Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Model	0.000
Mobility×Within-Cluster×Model	0.000
Cluster Size×Within-Cluster×Model	0.000
Mobility×Variance×Model	0.000
Cluster Size×Variance×Model	0.000
Within-Cluster×Variance×Model	0.000
Mobility×Scale×Model	0.000
Cluster Size×Scale×Model	0.000
Within-Cluster×Scale×Model	0.000
Variance×Scale×Model	0.003
Mobility×Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000

Mobility×Cluster Size×Variance×Scale	0.000
Mobility×Within-Cluster×Variance×Scale	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Model	0.000
Mobility×Cluster Size×Variance×Model	0.000
Mobility×Within-Cluster×Variance×Model	0.000
Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Scale×Model	0.000
Mobility×Within-Cluster×Scale×Model	0.000
Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Variance×Scale×Model	0.000
Cluster Size×Variance×Scale×Model	0.000
Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Cluster Size×Variance×Scale×Model	0.000
Mobility×Within-Cluster×Variance×Scale×Model	0.000
Cluster Size×Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale×Model	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Table E4

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Coefficient for the Intercept of Discrete-Time Period 4, α_4*, by Source of Variation*

Source of Variation	Partial Eta Squared
Mobility	0.006
Cluster Size	0.000
Within-Cluster	0.000
Variance	0.002
Scale	***0.015***
Model	***0.022***
Mobility×Cluster Size	0.000
Mobility×Within-Cluster	0.000
Cluster Size×Within-Cluster	0.001
Mobility×Variance	0.000
Cluster Size×Variance	0.000
Within-Cluster×Variance	0.000
Mobility×Scale	0.000
Cluster Size×Scale	0.000
Within-Cluster Size×Scale	0.000
Variance×Scale	0.005
Mobility×Model	0.003
Cluster Size×Model	0.000
Within-Cluster×Model	0.000
Variance×Model	0.002
Scale×Model	***0.024***
Mobility×Cluster Size×Within-Cluster	0.000
Mobility×Cluster Size×Variance	0.000
Mobility×Within-Cluster×Variance	0.000
Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Scale	0.000
Mobility×Within-Cluster×Scale	0.000
Cluster Size×Within-Cluster×Scale	0.000
Mobility×Variance×Scale	0.000
Cluster Size×Variance×Scale	0.000
Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Model	0.000
Mobility×Within-Cluster×Model	0.000
Cluster Size×Within-Cluster×Model	0.000
Mobility×Variance×Model	0.000
Cluster Size×Variance×Model	0.000
Within-Cluster×Variance×Model	0.000
Mobility×Scale×Model	0.000
Cluster Size×Scale×Model	0.000
Within-Cluster×Scale×Model	0.000
Variance×Scale×Model	0.007
Mobility×Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000

Mobility×Cluster Size×Variance×Scale	0.000
Mobility×Within-Cluster×Variance×Scale	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Model	0.000
Mobility×Cluster Size×Variance×Model	0.000
Mobility×Within-Cluster×Variance×Model	0.000
Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Scale×Model	0.000
Mobility×Within-Cluster×Scale×Model	0.000
Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Variance×Scale×Model	0.000
Cluster Size×Variance×Scale×Model	0.000
Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Cluster Size×Variance×Scale×Model	0.000
Mobility×Within-Cluster×Variance×Scale×Model	0.000
Cluster Size×Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale×Model	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Table E5

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Coefficient for the Intercept of Discrete-Time Period 5, α_5, by Source of Variation

Source of Variation	Partial Eta Squared
Mobility	0.002
Cluster Size	0.000
Within-Cluster	0.000
Variance	0.006
Scale	***0.043***
Model	***0.026***
Mobility×Cluster Size	0.000
Mobility×Within-Cluster	0.000
Cluster Size×Within-Cluster	0.000
Mobility×Variance	0.000
Cluster Size×Variance	0.000
Within-Cluster×Variance	0.000
Mobility×Scale	0.000
Cluster Size×Scale	0.000
Within-Cluster Size×Scale	0.000
Variance×Scale	***0.010***
Mobility×Model	0.001
Cluster Size×Model	0.000
Within-Cluster×Model	0.000
Variance×Model	***0.012***
Scale×Model	***0.051***
Mobility×Cluster Size×Within-Cluster	0.000
Mobility×Cluster Size×Variance	0.000
Mobility×Within-Cluster×Variance	0.000
Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Scale	0.000
Mobility×Within-Cluster×Scale	0.000
Cluster Size×Within-Cluster×Scale	0.000
Mobility×Variance×Scale	0.000
Cluster Size×Variance×Scale	0.000
Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Model	0.000
Mobility×Within-Cluster×Model	0.000
Cluster Size×Within-Cluster×Model	0.000
Mobility×Variance×Model	0.000
Cluster Size×Variance×Model	0.000
Within-Cluster×Variance×Model	0.000
Mobility×Scale×Model	0.000
Cluster Size×Scale×Model	0.000
Within-Cluster×Scale×Model	0.000
Variance×Scale×Model	***0.011***
Mobility×Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000

Mobility×Cluster Size×Variance×Scale	0.000
Mobility×Within-Cluster×Variance×Scale	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Model	0.000
Mobility×Cluster Size×Variance×Model	0.000
Mobility×Within-Cluster×Variance×Model	0.000
Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Scale×Model	0.000
Mobility×Within-Cluster×Scale×Model	0.000
Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Variance×Scale×Model	0.000
Cluster Size×Variance×Scale×Model	0.000
Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Cluster Size×Variance×Scale×Model	0.000
Mobility×Within-Cluster×Variance×Scale×Model	0.000
Cluster Size×Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale×Model	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Table E6

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Coefficient for the Level-One Predictor, β_1, For Each Estimating Model by Source of Variation

Source of Variation	Partial Eta Squared
Mobility	0.000
Cluster Size	0.001
Within-Cluster	0.000
Variance	***0.030***
Scale	0.002
Model	***0.147***
Mobility×Cluster Size	0.000
Mobility×Within-Cluster	0.000
Cluster Size×Within-Cluster	0.000
Mobility×Variance	0.000
Cluster Size×Variance	0.000
Within-Cluster×Variance	0.000
Mobility×Scale	0.000
Cluster Size×Scale	0.000
Within-Cluster Size×Scale	0.000
Variance×Scale	0.000
Mobility×Model	0.001
Cluster Size×Model	0.000
Within-Cluster×Model	0.000
Variance×Model	***0.034***
Scale×Model	0.002
Mobility×Cluster Size×Within-Cluster	0.000
Mobility×Cluster Size×Variance	0.000
Mobility×Within-Cluster×Variance	0.000
Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Scale	0.000
Mobility×Within-Cluster×Scale	0.000
Cluster Size×Within-Cluster×Scale	0.000
Mobility×Variance×Scale	0.000
Cluster Size×Variance×Scale	0.000
Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Model	0.000
Mobility×Within-Cluster×Model	0.000
Cluster Size×Within-Cluster×Model	0.000
Mobility×Variance×Model	0.000
Cluster Size×Variance×Model	0.000
Within-Cluster×Variance×Model	0.000
Mobility×Scale×Model	0.000
Cluster Size×Scale×Model	0.000
Within-Cluster×Scale×Model	0.000

Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000
Mobility×Cluster Size×Variance×Scale	0.000
Mobility×Within-Cluster×Variance×Scale	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Model	0.000
Mobility×Cluster Size×Variance×Model	0.000
Mobility×Within-Cluster×Variance×Model	0.000
Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Scale×Model	0.000
Mobility×Within-Cluster×Scale×Model	0.000
Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Variance×Scale×Model	0.000
Cluster Size×Variance×Scale×Model	0.000
Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Cluster Size×Variance×Scale×Model	0.000
Mobility×Within-Cluster×Variance×Scale×Model	0.000
Cluster Size×Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale×Model	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Table E7

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Coefficient for the Level-Two Predictor, β_2, For Each Estimating Model by Source of Variation

Source of Variation	Partial Eta Squared
Mobility	0.005
Cluster Size	0.000
Within-Cluster	0.000
Variance	0.002
Scale	0.000
Model	***0.049***
Mobility×Cluster Size	0.001
Mobility×Within-Cluster	0.000
Cluster Size×Within-Cluster	0.000
Mobility×Variance	0.000
Cluster Size×Variance	0.000
Within-Cluster×Variance	0.000
Mobility×Scale	0.000
Cluster Size×Scale	0.000
Within-Cluster Size×Scale	0.000
Variance×Scale	0.000
Mobility×Model	0.003
Cluster Size×Model	0.000
Within-Cluster×Model	0.000
Variance×Model	0.003
Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster	0.000
Mobility×Cluster Size×Variance	0.000
Mobility×Within-Cluster×Variance	0.000
Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Scale	0.000
Mobility×Within-Cluster×Scale	0.000
Cluster Size×Within-Cluster×Scale	0.000
Mobility×Variance×Scale	0.000
Cluster Size×Variance×Scale	0.000
Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Model	0.000
Mobility×Within-Cluster×Model	0.000
Cluster Size×Within-Cluster×Model	0.000
Mobility×Variance×Model	0.000
Cluster Size×Variance×Model	0.000
Within-Cluster×Variance×Model	0.000
Mobility×Scale×Model	0.000
Cluster Size×Scale×Model	0.000
Within-Cluster×Scale×Model	0.000
Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000

Mobility×Cluster Size×Variance×Scale	0.000
Mobility×Within-Cluster×Variance×Scale	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Model	0.000
Mobility×Cluster Size×Variance×Model	0.000
Mobility×Within-Cluster×Variance×Model	0.000
Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Scale×Model	0.000
Mobility×Within-Cluster×Scale×Model	0.000
Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Variance×Scale×Model	0.000
Cluster Size×Variance×Scale×Model	0.000
Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Cluster Size×Variance×Scale×Model	0.000
Mobility×Within-Cluster×Variance×Scale×Model	0.000
Cluster Size×Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale×Model	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Table E8

Partial Eta Squared Values for the Factorial ANOVAs of the Relative Parameter Bias of the Variance Component, σ_u^2, For Each Estimating Model by Source of Variation

Source of Variation	Partial Eta Squared
Mobility	***0.037***
Cluster Size	0.009
Within-Cluster	0.000
Variance	0.001
Scale	0.001
Model	***0.297***
Mobility×Cluster Size	0.000
Mobility×Within-Cluster	0.000
Cluster Size×Within-Cluster	0.000
Mobility×Variance	0.000
Cluster Size×Variance	0.000
Within-Cluster×Variance	0.000
Mobility×Scale	0.000
Cluster Size×Scale	0.000
Within-Cluster Size×Scale	0.000
Variance×Scale	0.000
Mobility×Model	***0.043***
Cluster Size×Model	0.000
Within-Cluster×Model	0.000
Variance×Model	0.002
Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster	0.000
Mobility×Cluster Size×Variance	0.000
Mobility×Within-Cluster×Variance	0.000
Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Scale	0.000
Mobility×Within-Cluster×Scale	0.000
Cluster Size×Within-Cluster×Scale	0.000
Mobility×Variance×Scale	0.000
Cluster Size×Variance×Scale	0.000
Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Model	0.000
Mobility×Within-Cluster×Model	0.000
Cluster Size×Within-Cluster×Model	0.000
Mobility×Variance×Model	0.000
Cluster Size×Variance×Model	0.000
Within-Cluster×Variance×Model	0.000
Mobility×Scale×Model	0.000
Cluster Size×Scale×Model	0.000
Within-Cluster×Scale×Model	0.000
Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance	0.000
Mobility×Cluster Size×Within-Cluster×Scale	0.000

Mobility×Cluster Size×Variance×Scale	0.000
Mobility×Within-Cluster×Variance×Scale	0.000
Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Model	0.000
Mobility×Cluster Size×Variance×Model	0.000
Mobility×Within-Cluster×Variance×Model	0.000
Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Scale×Model	0.000
Mobility×Within-Cluster×Scale×Model	0.000
Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Variance×Scale×Model	0.000
Cluster Size×Variance×Scale×Model	0.000
Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Model	0.000
Mobility×Cluster Size×Within-Cluster×Scale×Model	0.000
Mobility×Cluster Size×Variance×Scale×Model	0.000
Mobility×Within-Cluster×Variance×Scale×Model	0.000
Cluster Size×Within-Cluster×Variance×Scale×Model	0.000
Mobility×Cluster Size×Within-Cluster×Variance×Scale×Model	0.000

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Italicized and bolded values indicate a practically significant effect on relative parameter bias.

Appendix F: Nested Loop Plots for Relative Parameter Bias for Each Modeled Parameter

Figure F1

Relative Parameter Bias of a_1, The Coefficient of the Intercept of the First Discrete-Time Period

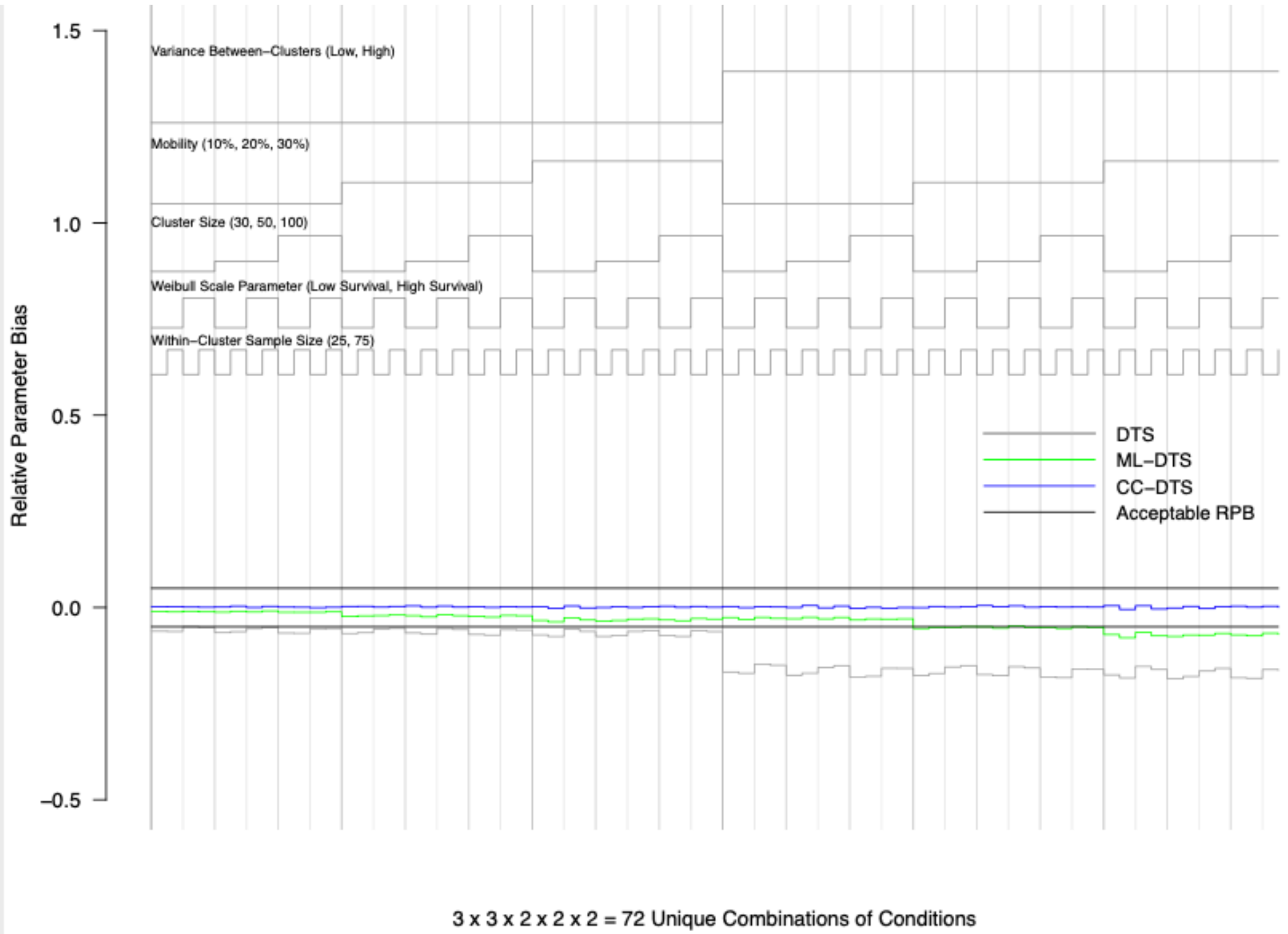


Figure F2

Relative Parameter Bias of a_2, The Coefficient of the Intercept of the Second Discrete-Time Period

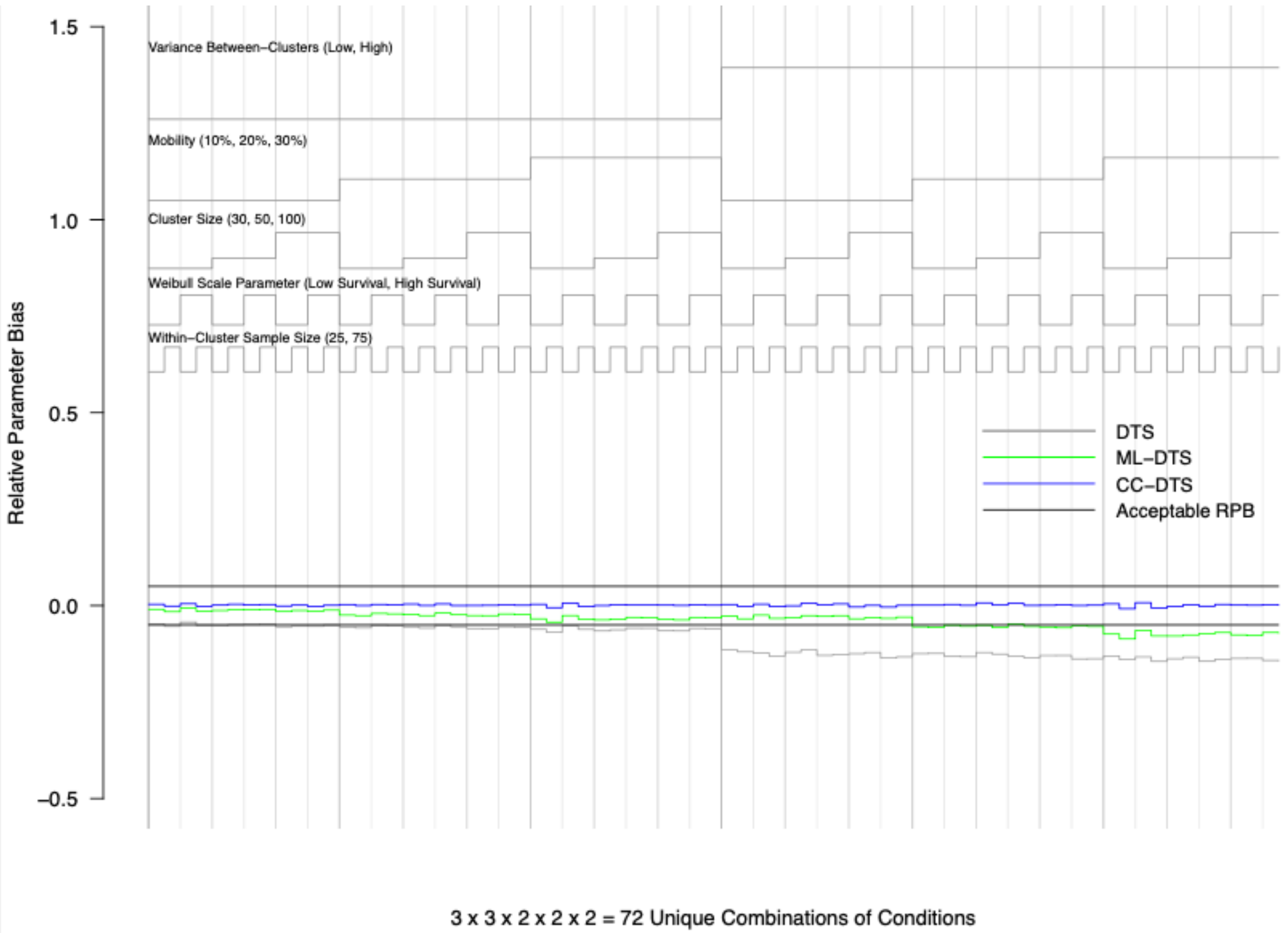


Figure F3

Relative Parameter Bias of a_3, The Coefficient of the Intercept of the Third Discrete-Time Period

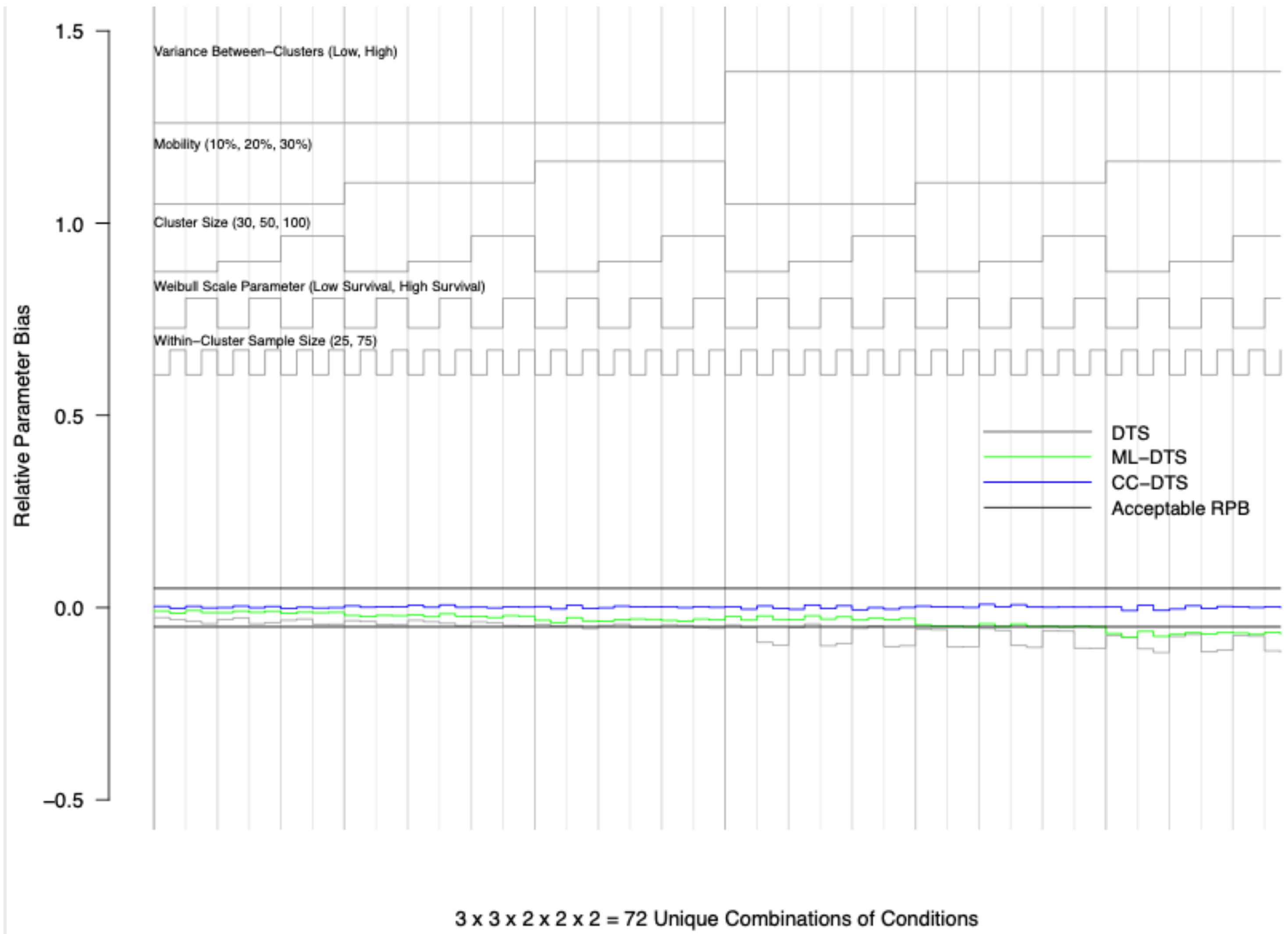


Figure F4

Relative Parameter Bias of a_4, The Coefficient of the Intercept of the Fourth Discrete-Time Period

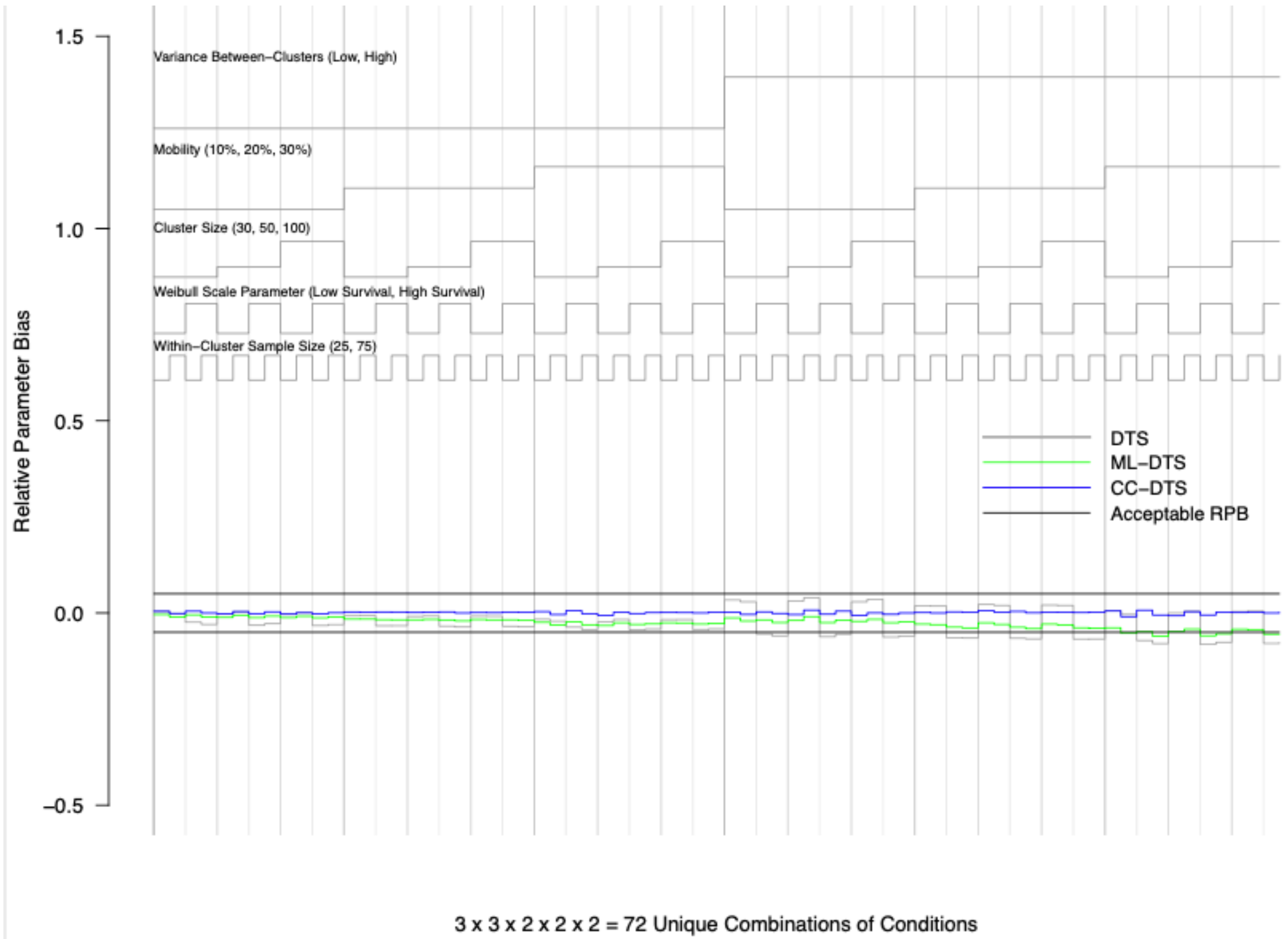


Figure F5

Relative Parameter Bias of a_5, The Coefficient of the Intercept of the Fifth Discrete-Time Period

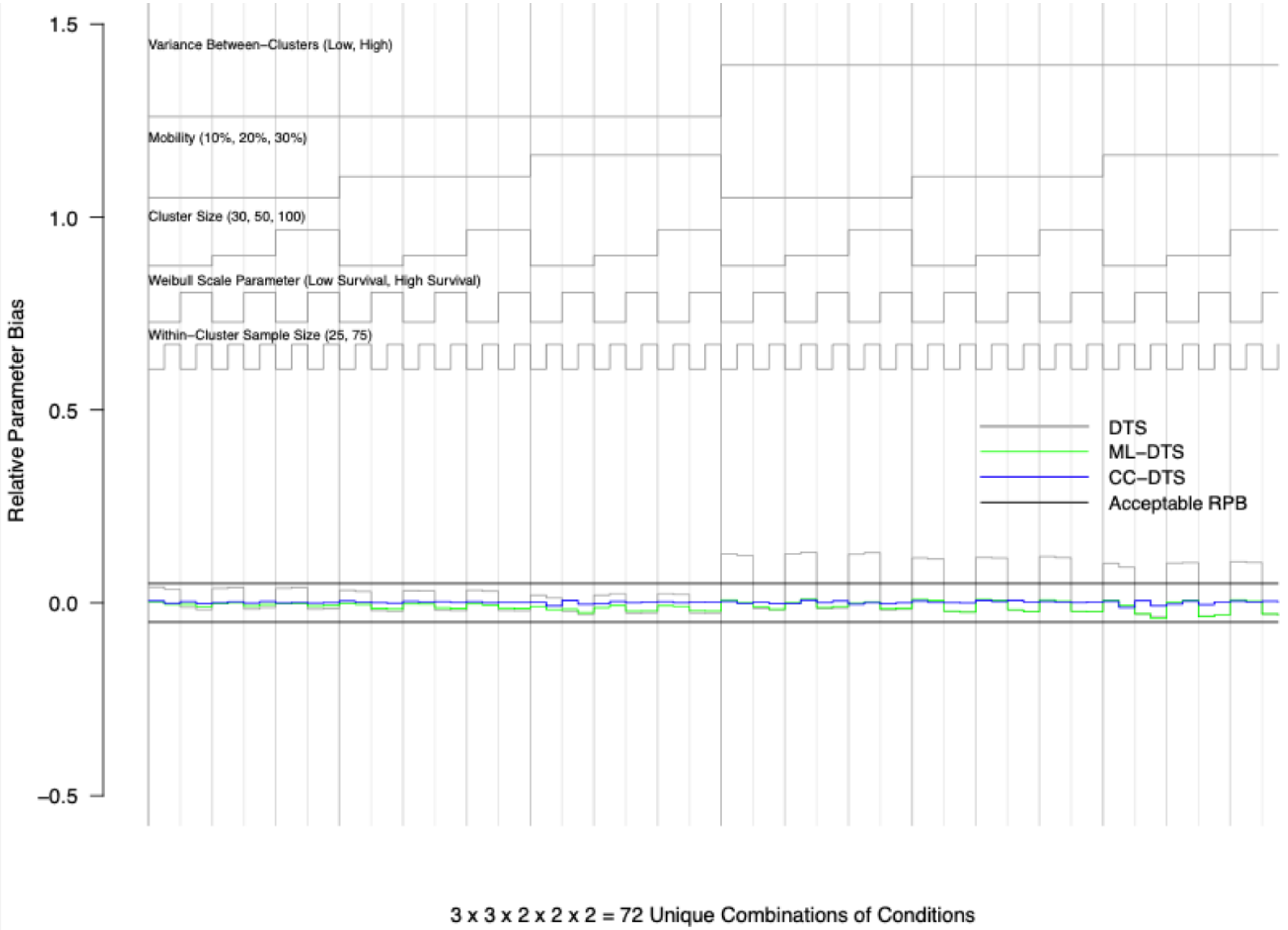


Figure F6

Relative Parameter Bias of β_1, the Coefficient of the Level-1 Covariate

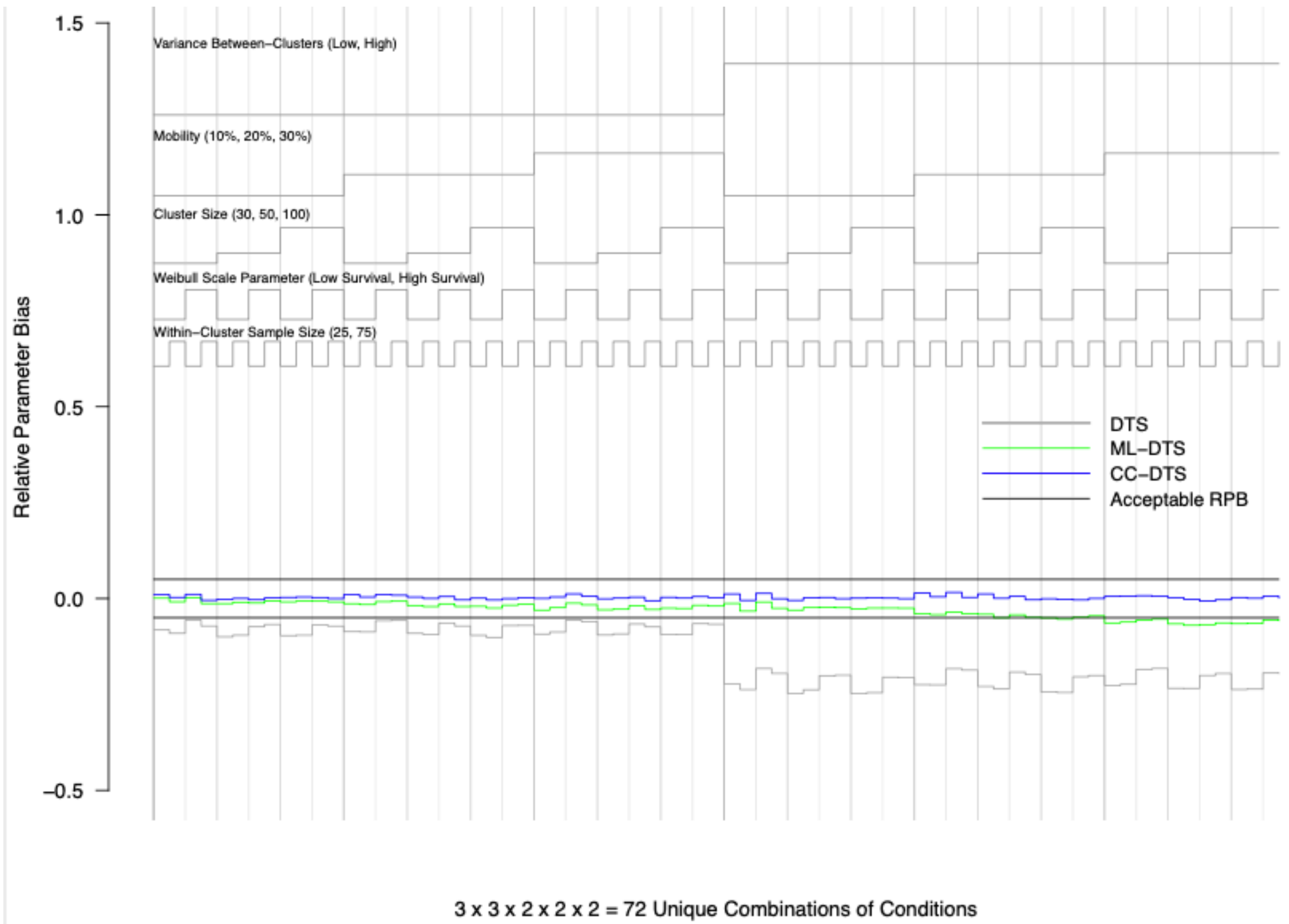


Figure F7

Relative Parameter Bias of β_2, the Coefficient of the Level-2 Covariate

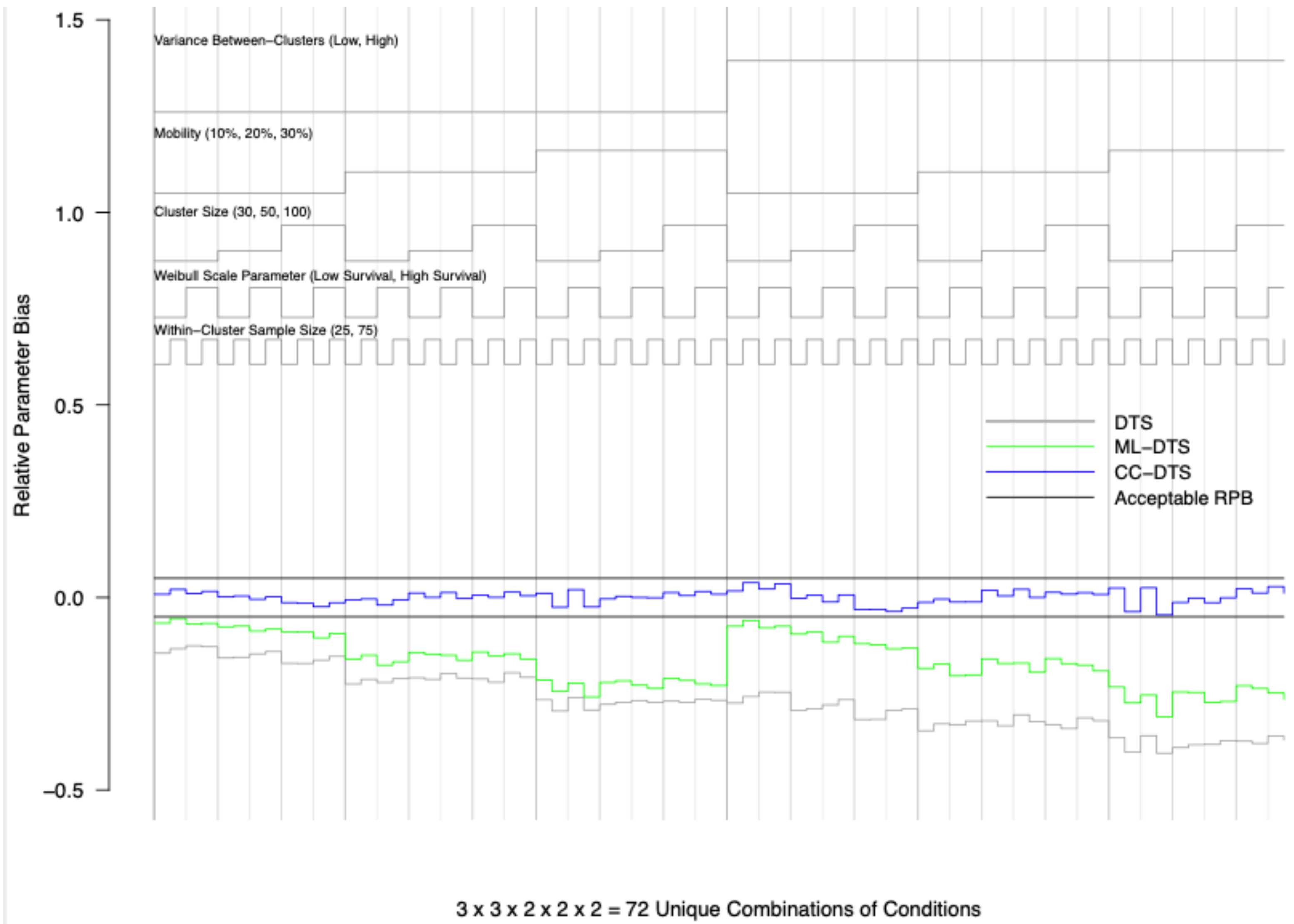
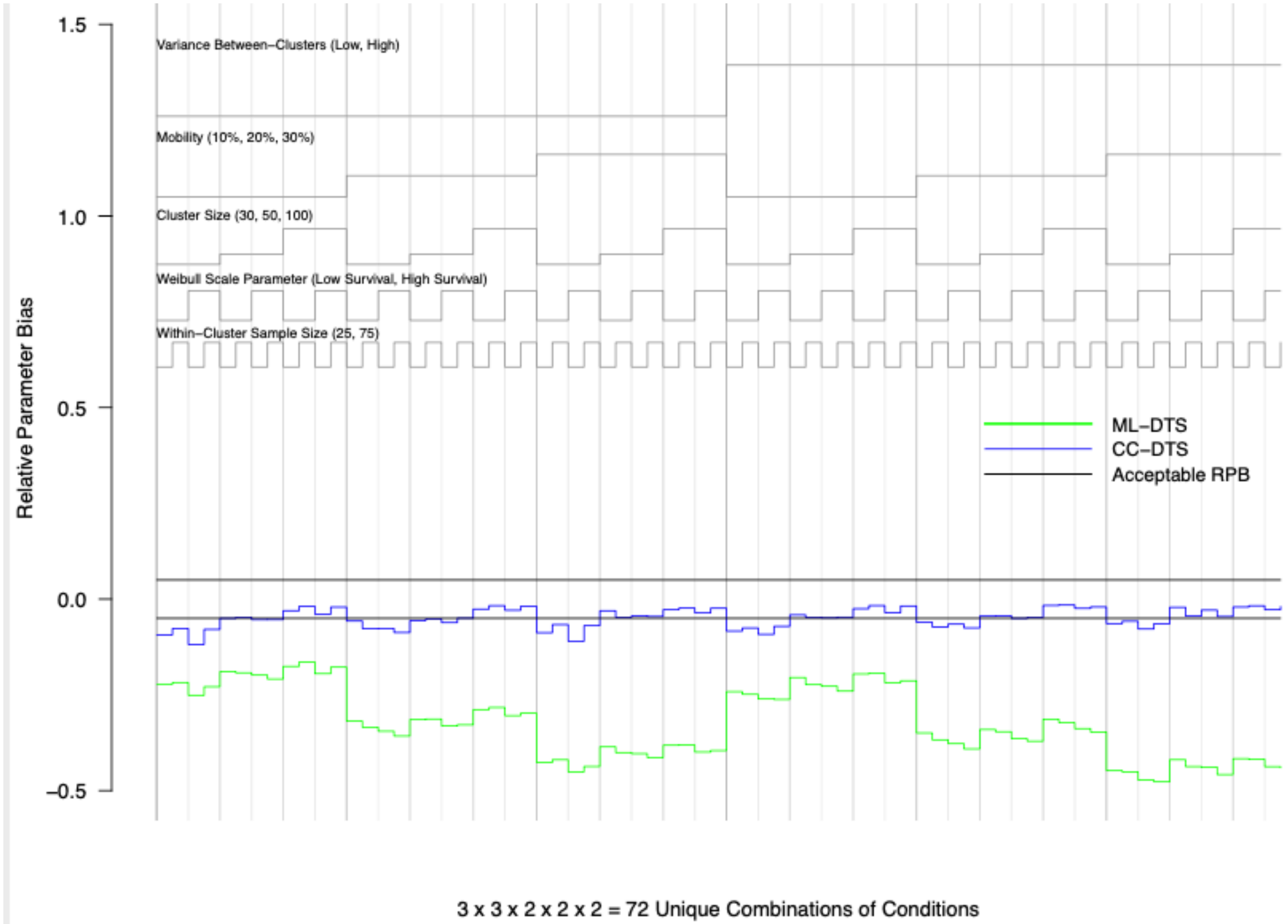


Figure F8

Relative Parameter Bias of σ_u^2, the Between-Clusters Variance Component



Appendix G: Nested Loop Plots for the Root Mean Square Error of Each Modeled Parameter

Figure G1

Root Mean Square Error of a_1, the Coefficient of the Intercept of the First Discrete-Time Period

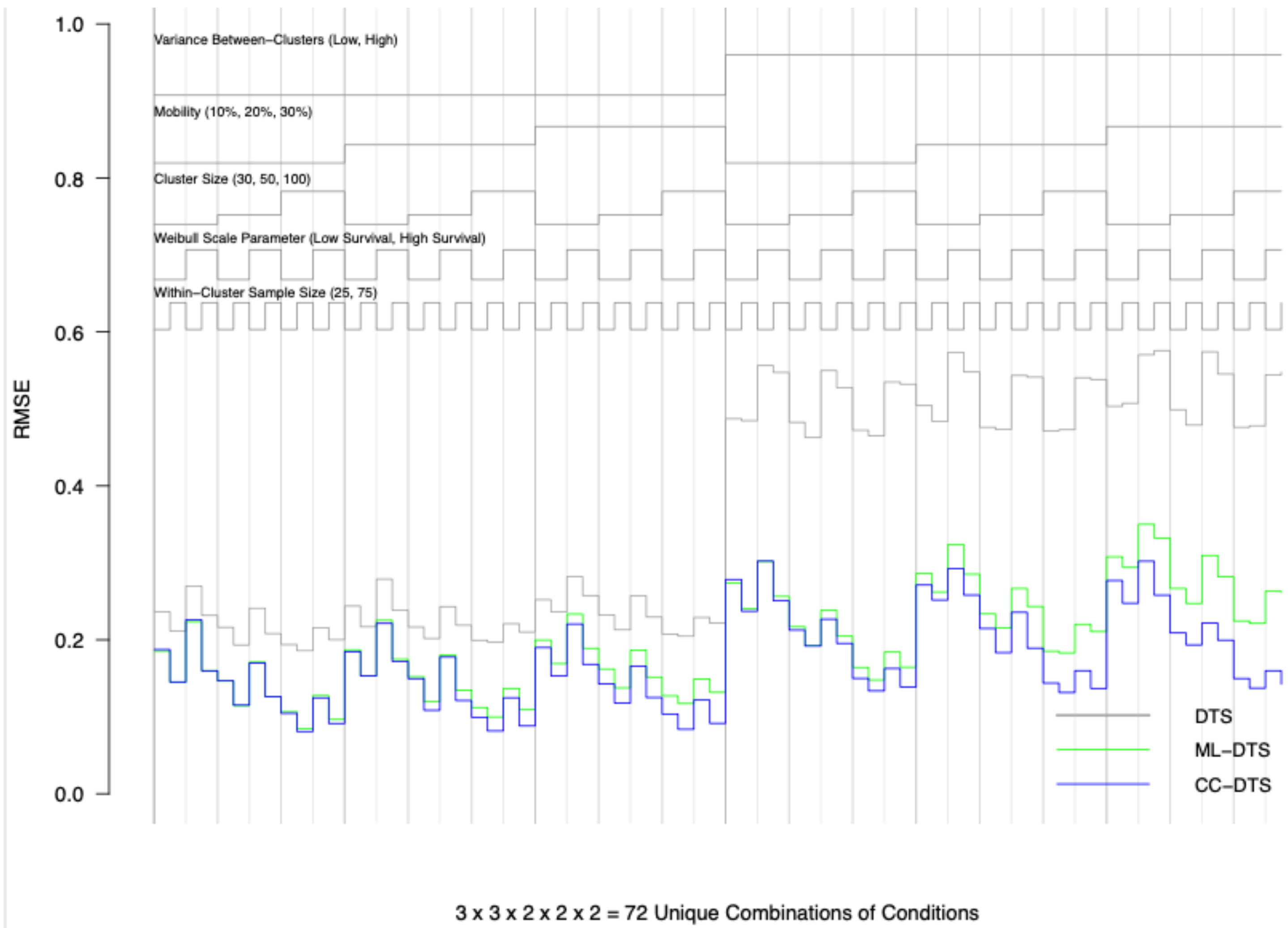


Figure G2

Root Mean Square Error of a_2, the Coefficient of the Intercept of the Second Discrete-Time Period

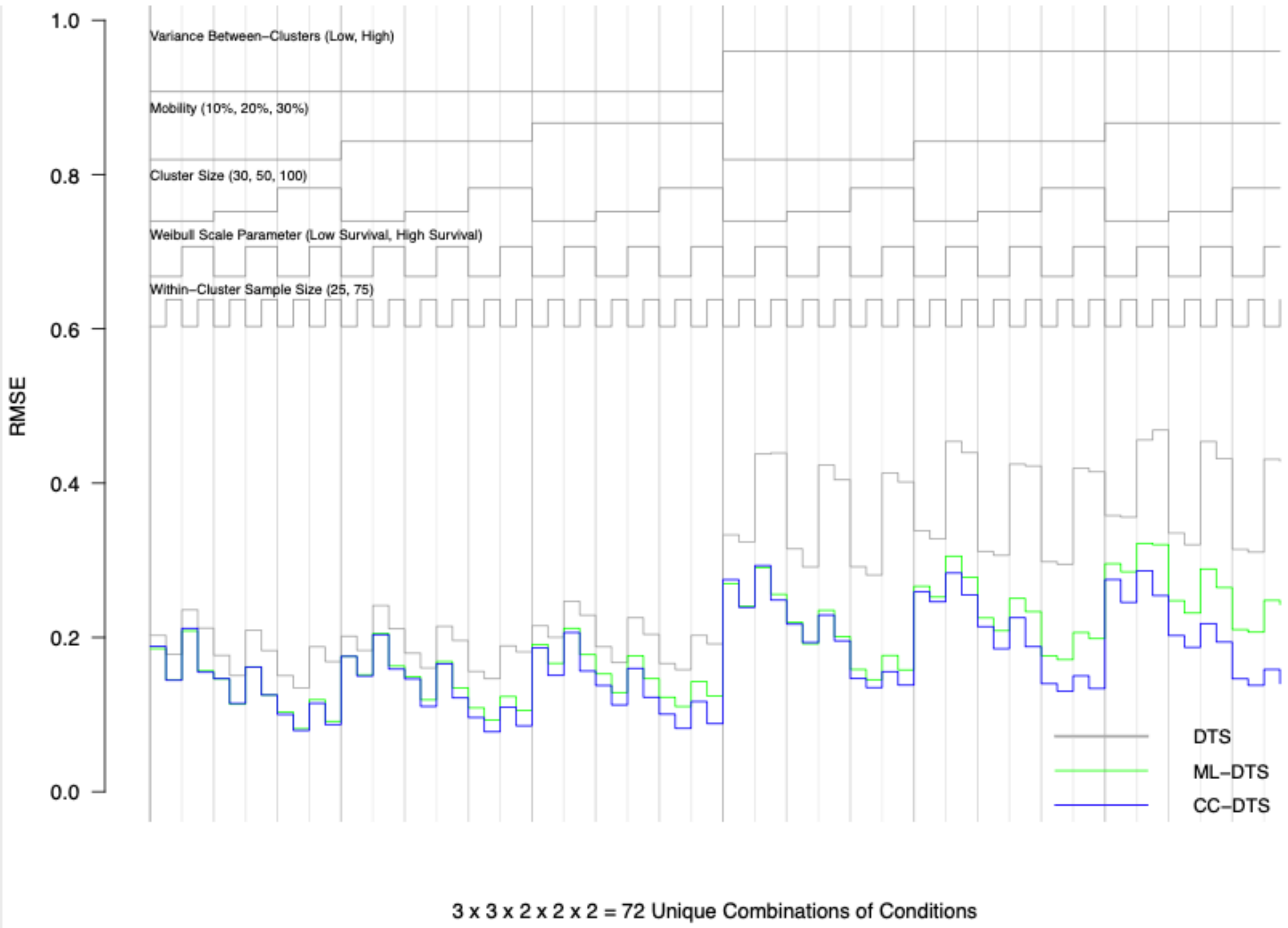


Figure G3

Root Mean Square Error of a_3, the Coefficient of the Intercept of the Third Discrete-Time Period

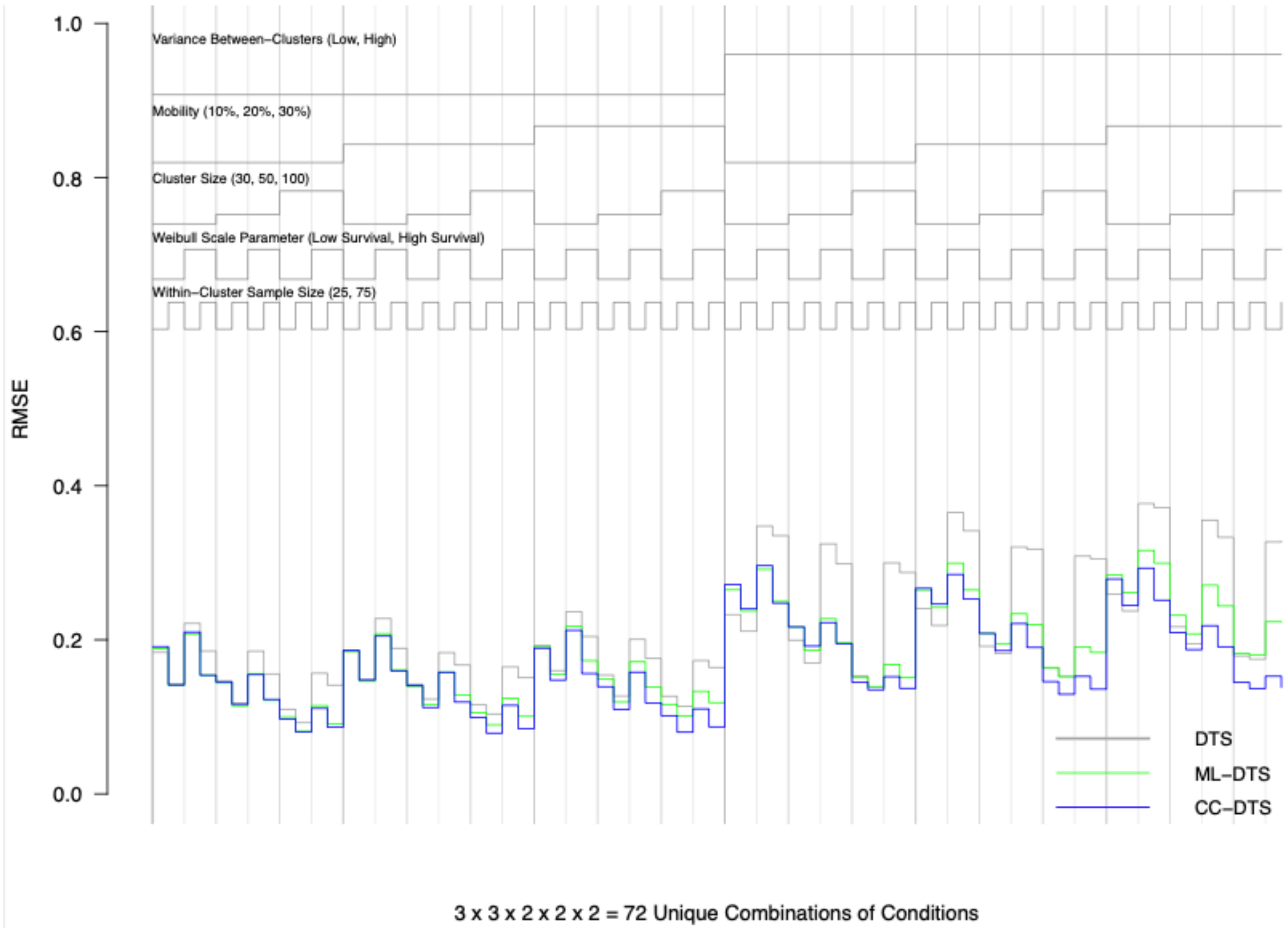


Figure G4

Root Mean Square Error of a_4, the Coefficient of the Intercept of the Fourth Discrete-Time Period

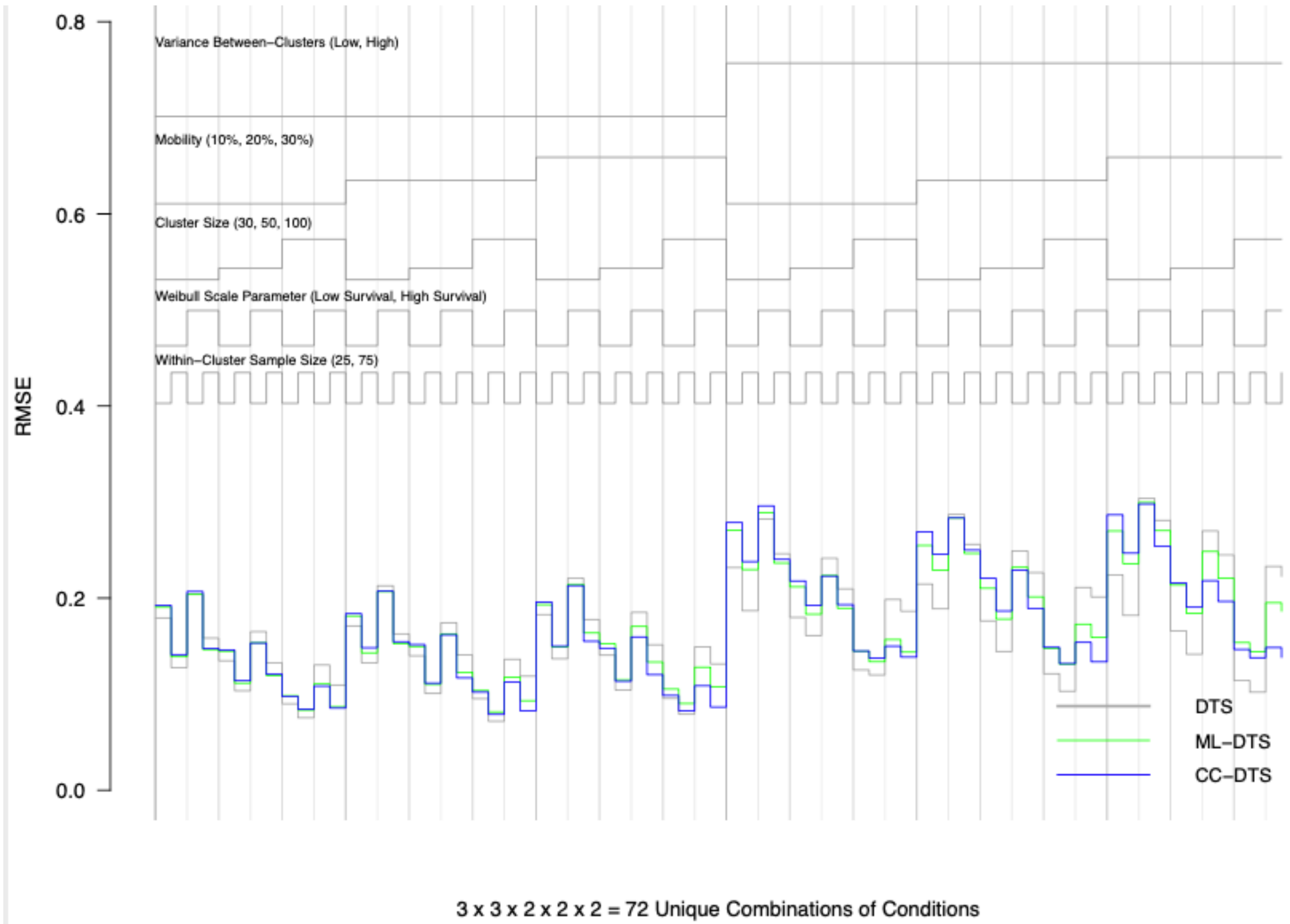


Figure G5

Root Mean Square Error of a_5, the Coefficient of the Intercept of the Fifth Discrete-Time Period

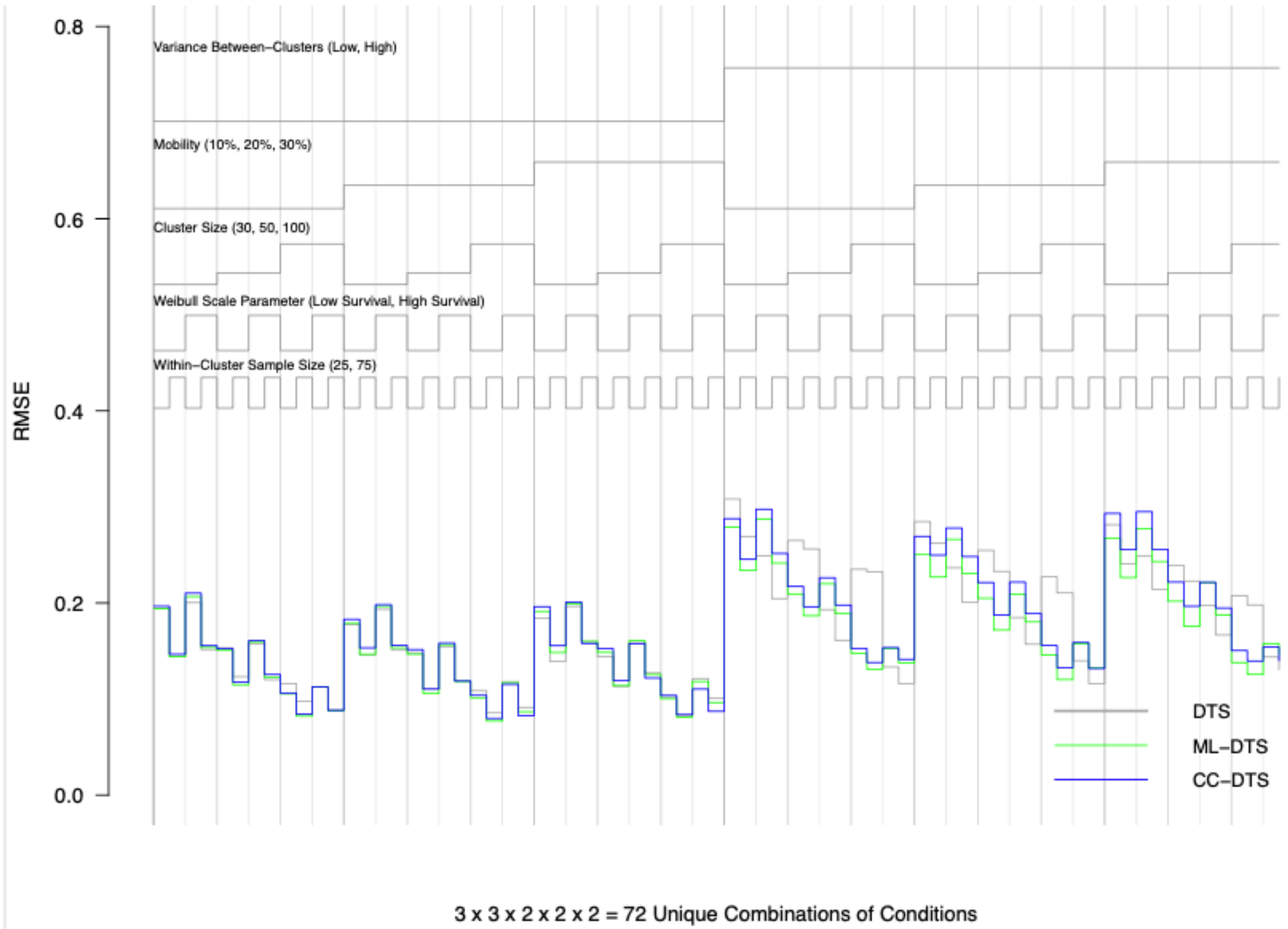


Figure G6

Root Mean Square Error of β_1, The Coefficient of the Level-1 Covariate

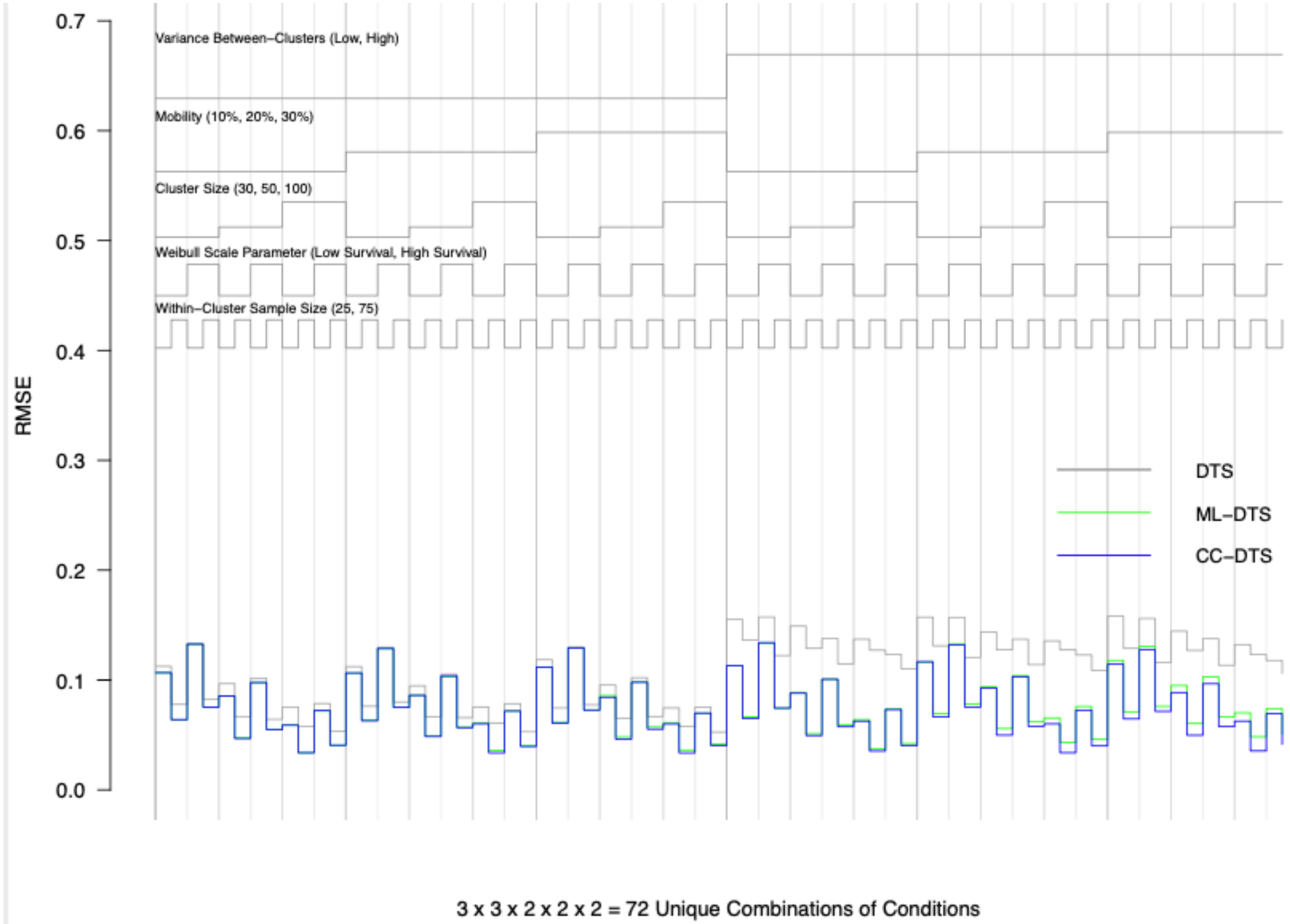


Figure G7

Root Mean Square Error of β_2, The Coefficient of the Level-2 Covariate

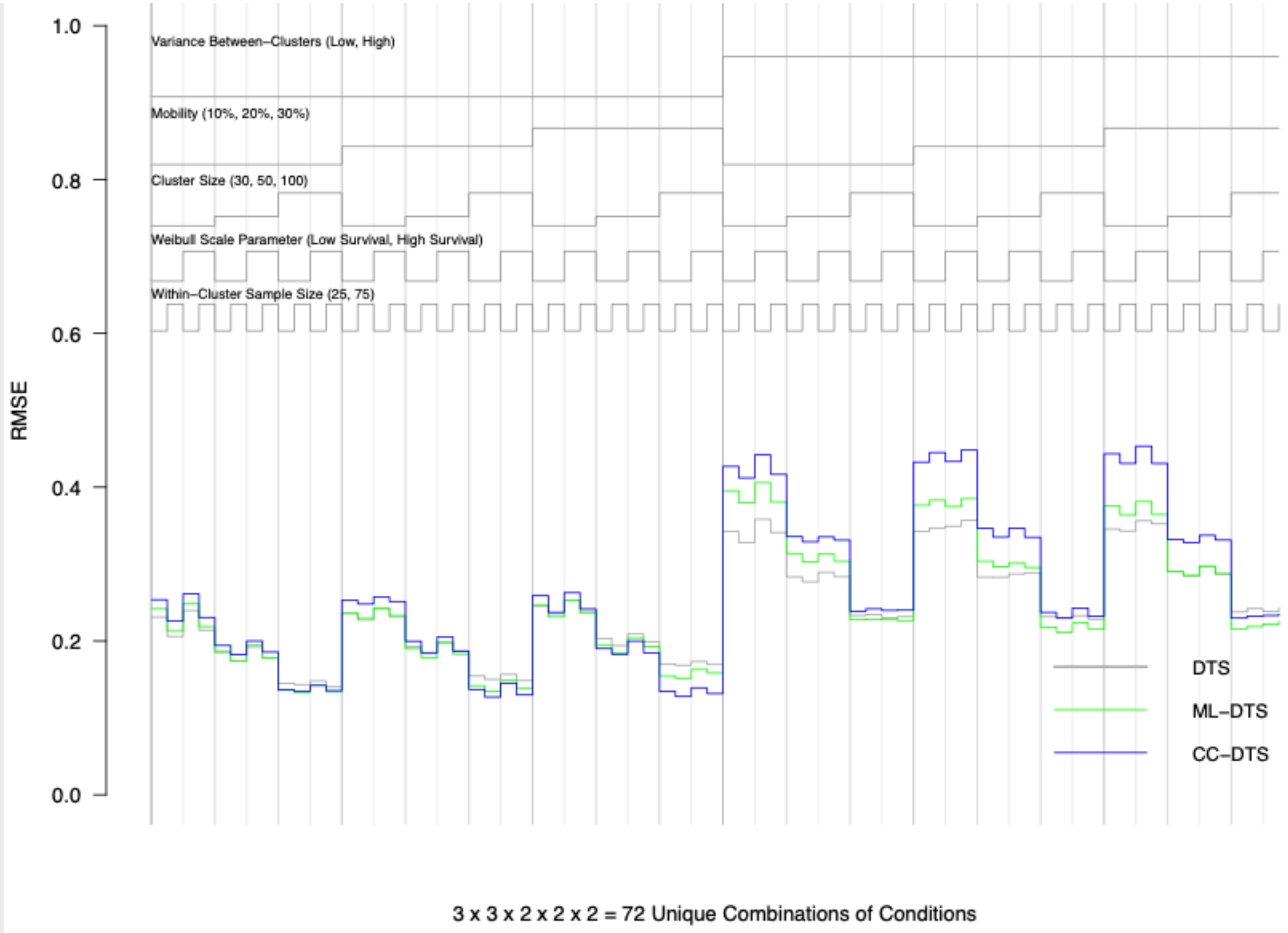
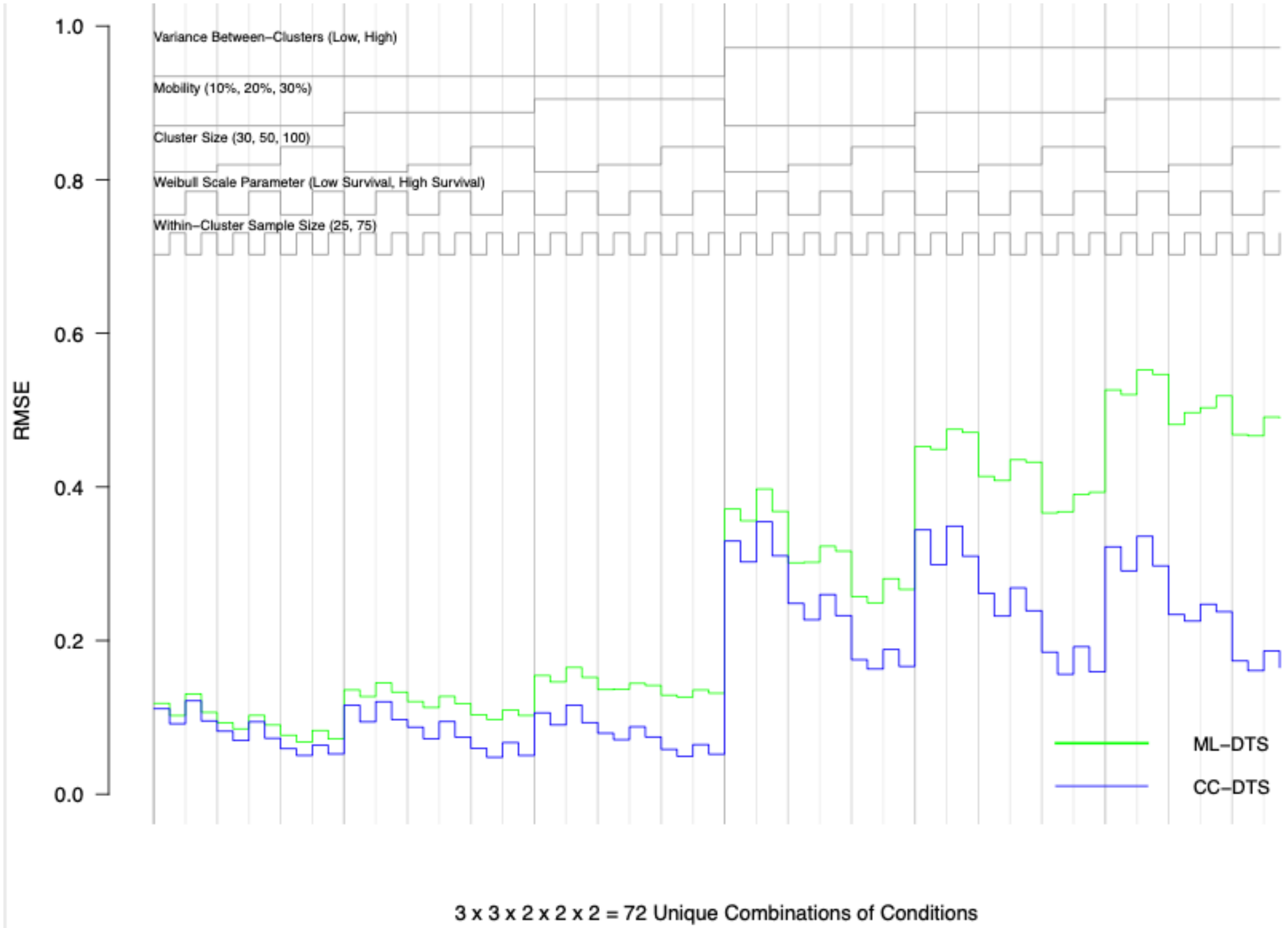


Figure G8

Root Mean Square Error of σ_u^2, The Between-Clusters Variance Component



Appendix H: Nested Loop Plots for the Coverage Rate of the 95% Confidence Intervals of Each Modeled Parameter

Figure H1

Coverage of the 95% Confidence Intervals of a_1, The Coefficient of the Intercept of the First Discrete-Time Period

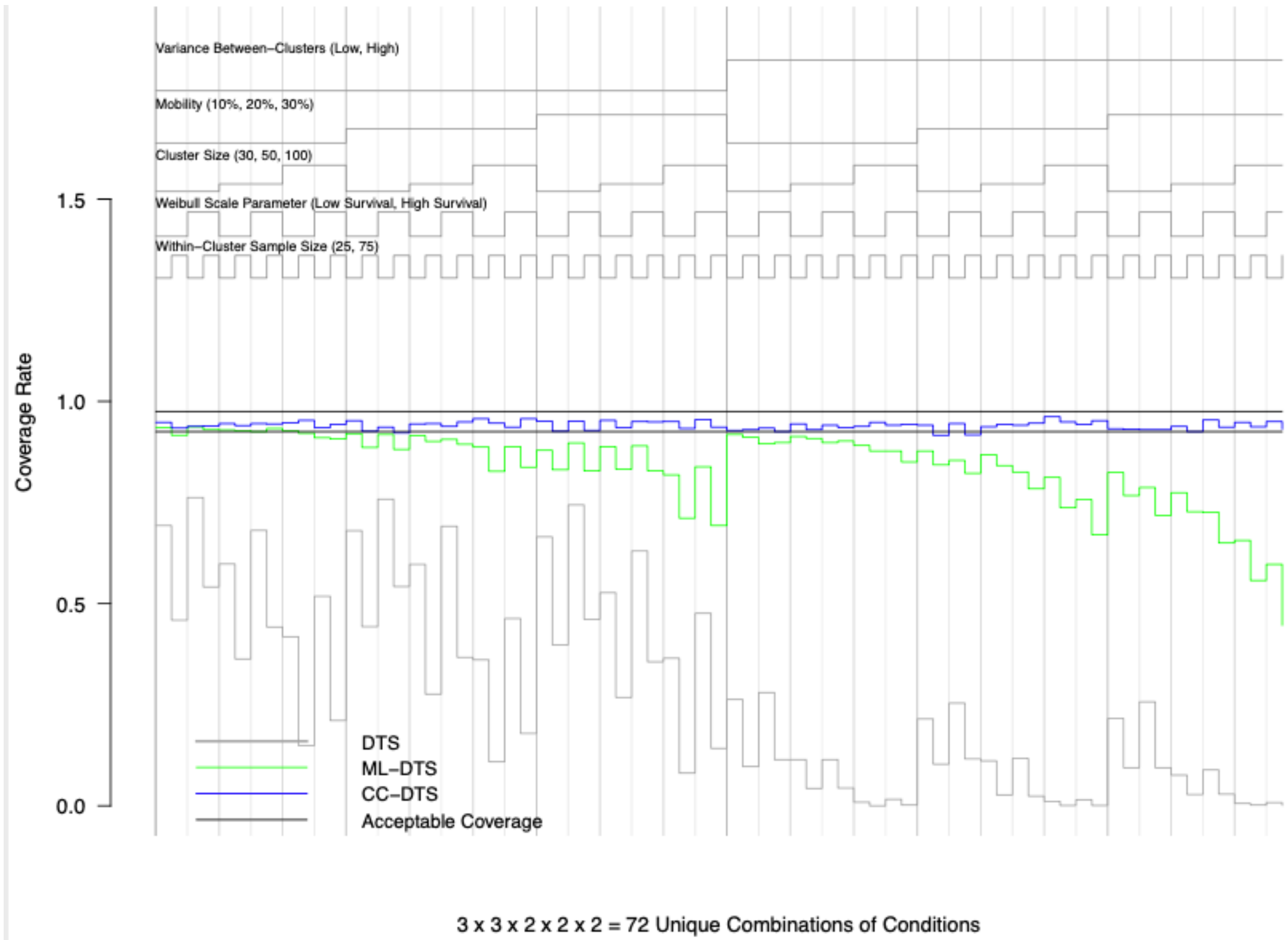


Figure H2

Coverage of the 95% Confidence Intervals of a_2, The Coefficient of the Intercept of the Second Discrete-Time Period

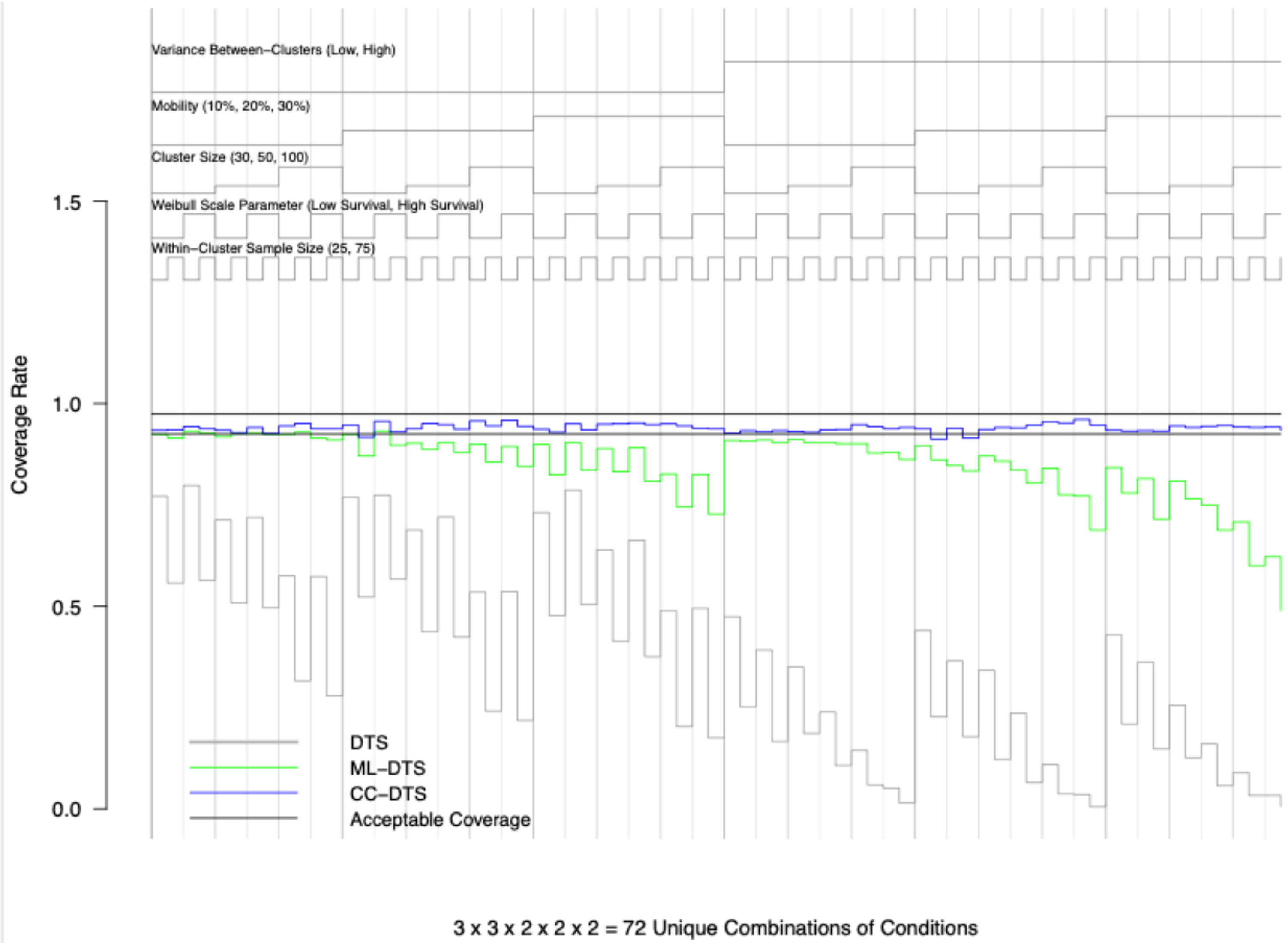


Figure H3

Coverage of the 95% Confidence Intervals of a_3, The Coefficient of the Intercept of the Third Discrete-Time Period

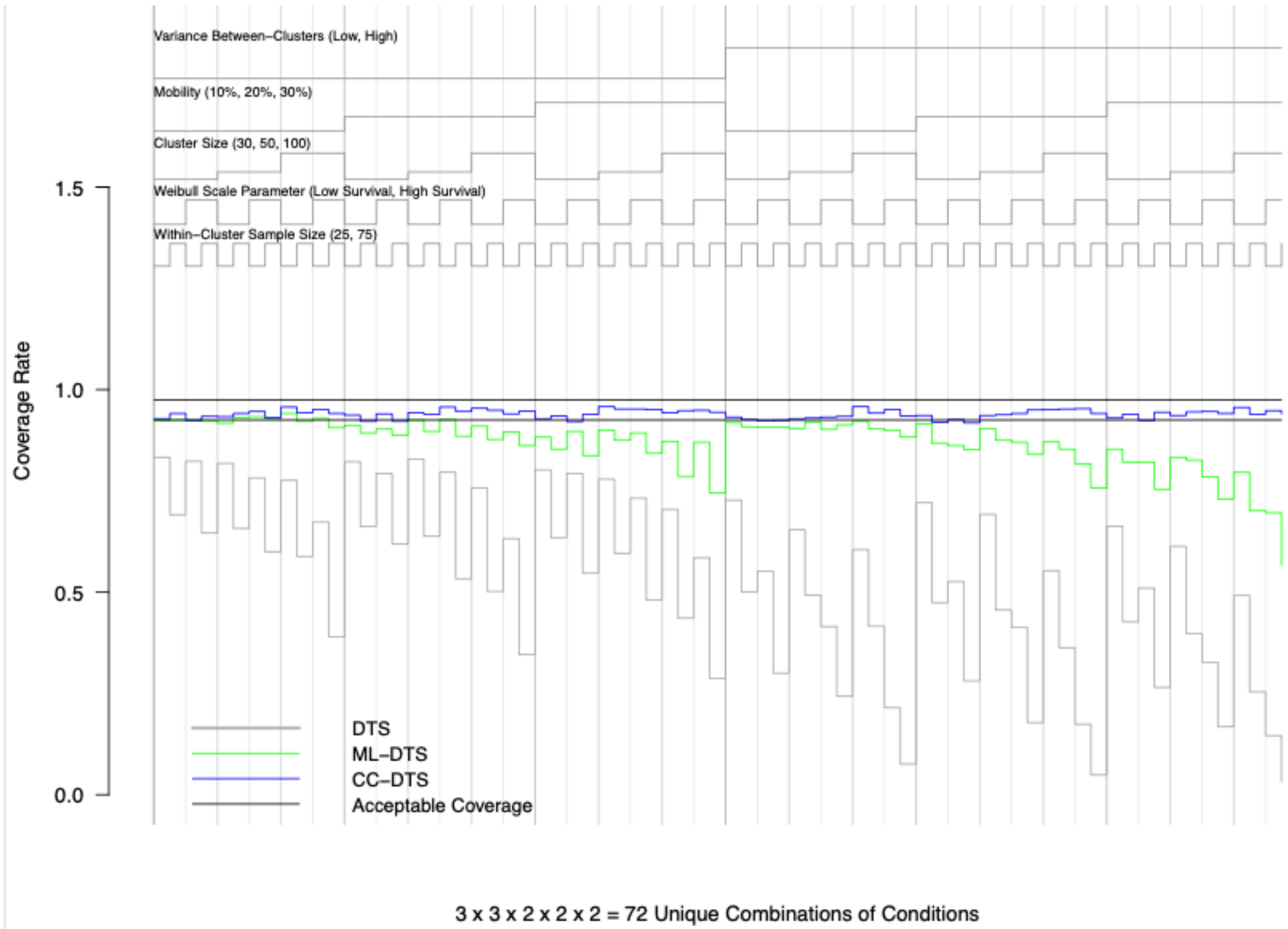


Figure H4

Coverage of the 95% Confidence Intervals of a_4, The Coefficient of the Intercept of the Fourth Discrete-Time Period

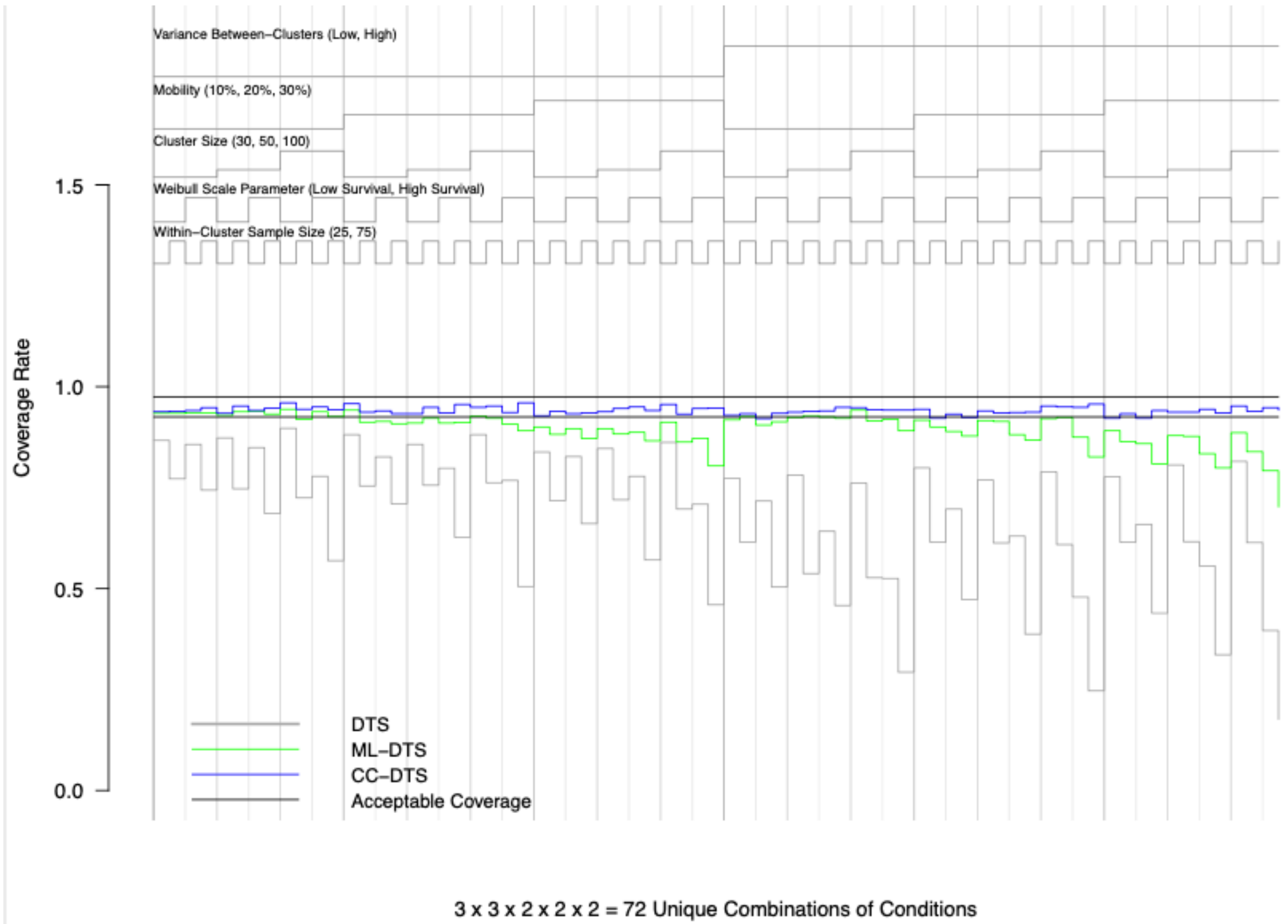


Figure H5

Coverage of the 95% Confidence Intervals of a₅, The Coefficient of the Intercept of the Fifth Discrete-Time Period

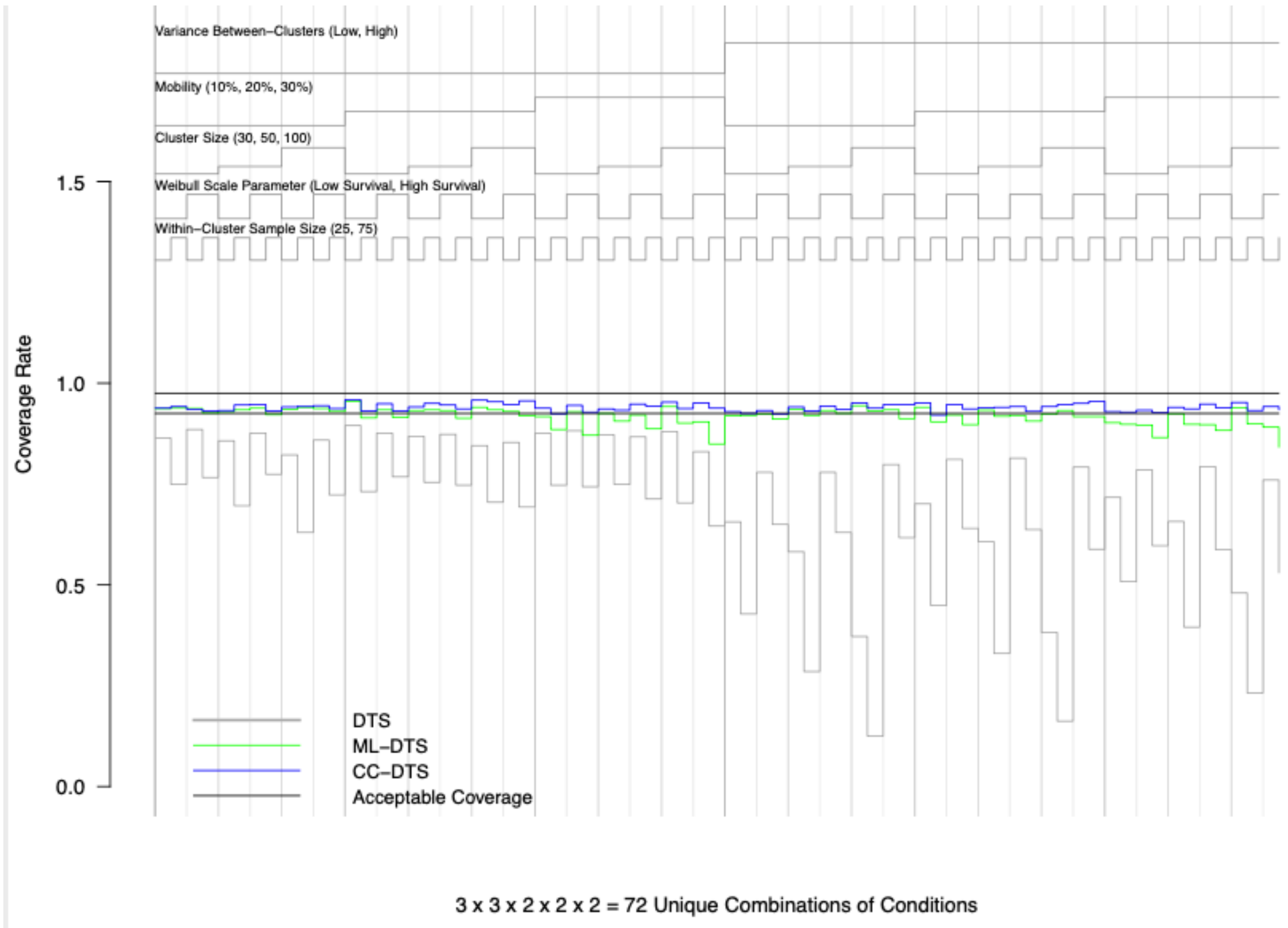


Figure H6

Coverage of the 95% Confidence Intervals of β_1, the Coefficient of the Level-1 Covariate

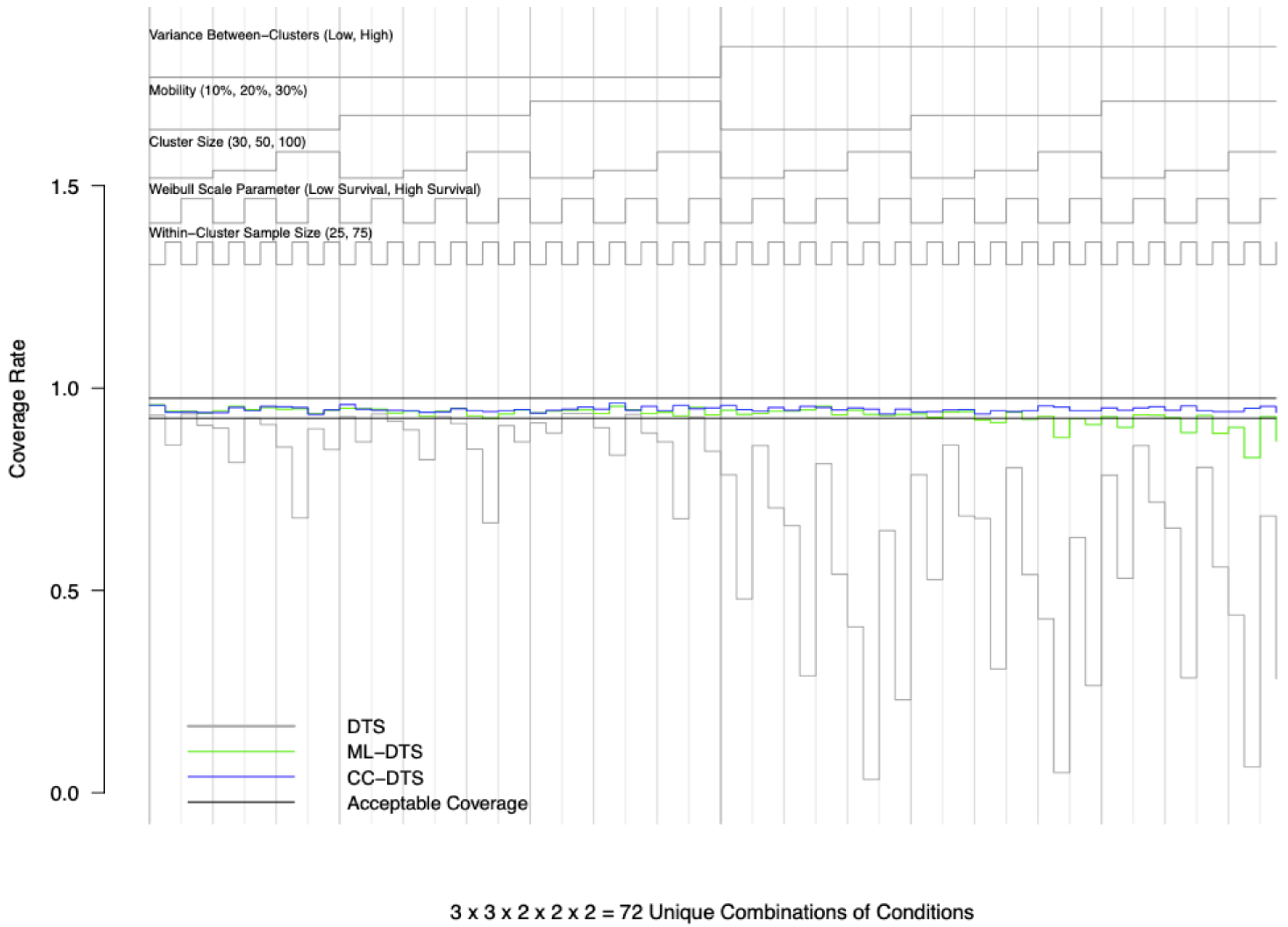
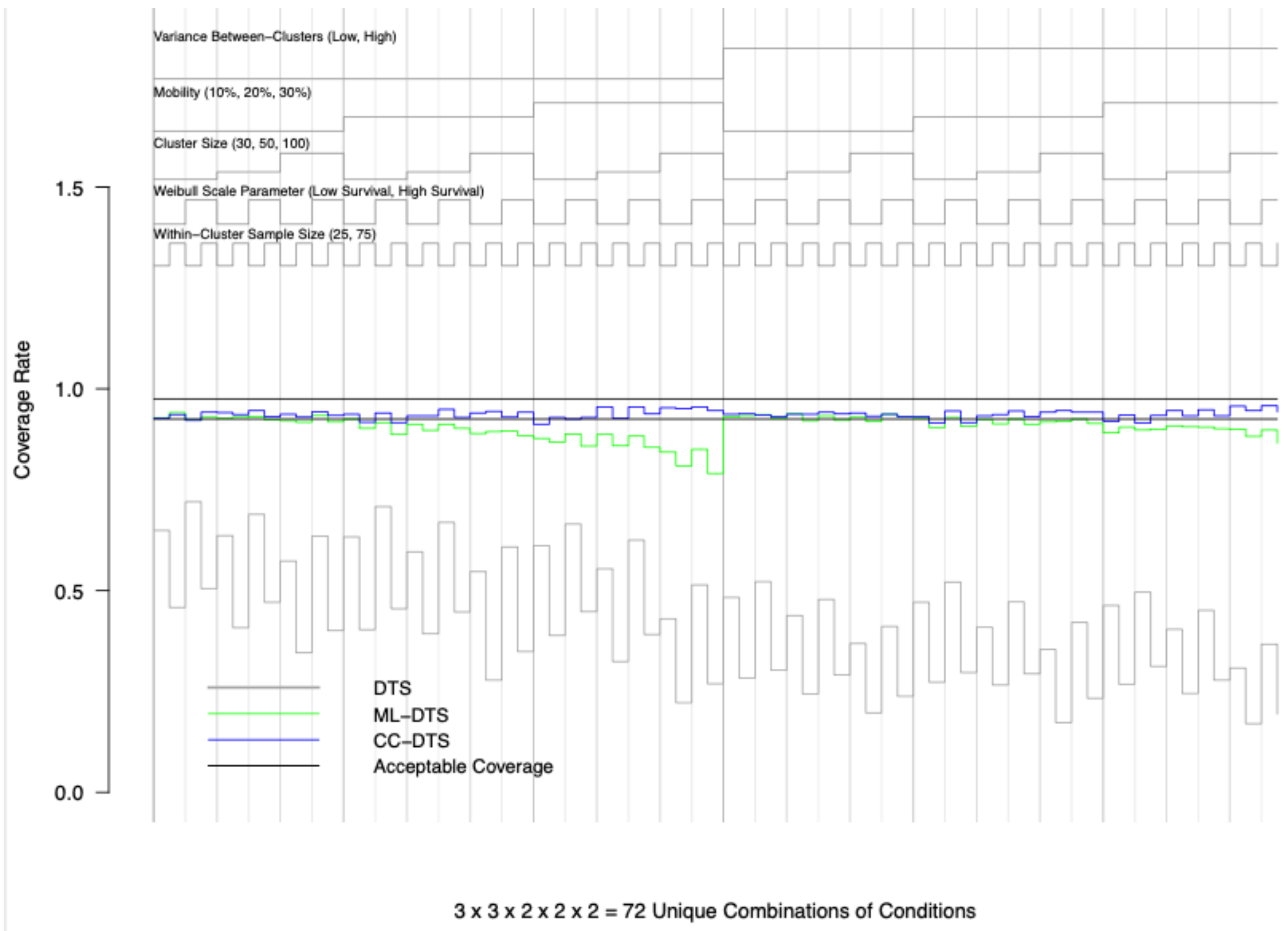


Figure H7

Coverage of the 95% Confidence Intervals of β_2, the Coefficient of the Level-2 Covariate



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Appendix I: Cox Effect for Each Main Effect and Interaction of Manipulated Conditions Entered in a Logistic Regression, by Model

Table I1

Cox effect for the Coverage of the 95% CIs of Each Main Effect and Interaction of Manipulated Conditions Entered into a Logistic Regression for the DTS Model

Source of Variation	α_1 Cox Effect	α_2 Cox Effect	α_3 Cox Effect	α_4 Cox Effect	α_5 Cox Effect	β_1 Cox Effect	β_2 Cox Effect
20% Mobility	−0.02	−0.06	−0.08	−0.04	0.05	0.03	−0.07
30% Mobility	−0.07	−0.04	−0.15	−0.11	0.04	0.03	−0.16
50 Clusters	***−0.26***	***−0.25***	−0.13	−0.05	−0.03	−0.05	−0.10
100 Clusters	***−0.67***	***−0.64***	***−0.47***	***−0.25***	−0.10	***−0.30***	−0.23
Within-Cluster	***−0.62***	***−0.67***	***−0.56***	***−0.43***	***−0.43***	−0.21	***−0.58***
Variance	***−1.27***	***−1.10***	***−0.78***	***−0.52***	***−0.45***	***−0.51***	***−0.55***
Weibull	−0.21	−0.06	0.09	0.13	−0.05	0.00	−0.14
20% Mobility×50 Clusters	0.07	0.05	0.10	−0.13	−0.06	−0.03	0.02
30% Mobility×50 Clusters	−0.05	−0.13	−0.05	−0.15	−0.07	0.00	−0.04
20% Mobility×100 Clusters	−0.10	−0.04	−0.02	−0.07	−0.11	0.03	−0.02
30% Mobility×100 Clusters	−0.02	−0.14	−0.06	−0.15	−0.15	0.23	−0.16
20% Mobility×Within-Cluster	0.04	0.07	0.00	−0.09	−0.15	0.03	−0.02
30% Mobility×Within-Cluster	−0.11	−0.10	−0.04	−0.08	−0.18	0.20	0.00
20% Mobility×Variance	−0.07	0.01	0.01	0.02	0.10	−0.04	0.07
30% Mobility×Variance	−0.03	−0.02	0.04	−0.03	−0.01	−0.04	0.15
20% Mobility×Weibull	−0.04	−0.02	0.00	0.00	0.03	−0.09	−0.02
30% Mobility×Weibull	−0.01	−0.10	0.00	−0.10	0.01	−0.21	−0.01
50 Clusters×Within-Cluster	0.04	0.08	0.02	−0.09	−0.01	0.03	0.03
100 Clusters×Within-Cluster	−0.20	−0.10	−0.14	−0.21	−0.09	−0.05	−0.03
50 Clusters×Variance	***−0.40***	−0.16	−0.21	−0.08	0.09	−0.17	0.00
100 Clusters×Variance	***−1.33***	***−0.88***	***−0.48***	−0.24	0.19	***−0.43***	0.02
50 Clusters×Weibull	0.00	0.01	0.00	0.07	−0.03	***−0.25****	−0.02
100 Clusters×Weibull	−0.02	0.05	0.21	***0.31***	−0.10	−0.23	−0.03
Within-Cluster×Variance	−0.07	0.00	−0.08	−0.05	0.05	***−0.37***	0.07

Within-Cluster×Weibull	0.01	0.03	0.04	−0.01	−0.09	***−0.32***	0.02
Variance×Weibull	0.11	***0.27***	***0.34***	0.10	***−0.28***	***−0.32***	0.04
20% Mobility×Within-Cluster×Variance	0.06	−0.04	−0.01	−0.01	−0.01	−0.07	
20% Mobility×50 Clusters×Within-Cluster	***−0.29***	−0.23	−0.18	0.10	0.10	0.02	
30% Mobility×50 Clusters×Within-Cluster	−0.01	−0.01	−0.04	0.04	0.04	***−0.32***	
20% Mobility×100 Clusters×Within-Cluster	−0.06	−0.17	−0.05	0.08	0.14	0.00	
30% Mobility×100 Clusters×Within-Cluster	−0.12	−0.09	−0.09	0.03	0.06	***−0.51***	
20% Mobility×50 Clusters×Variance	0.00	−0.04	−0.05	0.05	−0.01	0.02	
30% Mobility×50 Clusters×Variance	−0.05	−0.11	−0.05	0.04	0.03	0.01	
20% Mobility×100 Clusters×Variance	0.22	−0.12	−0.06	0.00	−0.08	−0.07	
30% Mobility×100 Clusters×Variance	−0.13	−0.11	−0.10	0.00	−0.01	−0.14	
20% Mobility×50 Clusters×Weibull	0.00	0.02	0.08	0.07	0.05	0.09	
30% Mobility×50 Clusters×Weibull	−0.05	0.10	0.10	0.21	0.10	0.24	
20% Mobility×100 Clusters×Weibull	0.01	0.04	0.00	0.12	0.14	0.00	
30% Mobility×100 Clusters×Weibull	−0.05	0.07	−0.01	***0.26***	***0.30***	−0.01	
30% Mobility×Within-Cluster×Variance	0.11	0.04	0.00	0.00	0.05	−0.14	
20% Mobility×Within-Cluster×Weibull	−0.01	−0.04	−0.01	0.12	0.10	0.09	
30% Mobility×Within-Cluster×Weibull	0.04	0.05	0.00	0.09	0.17	0.16	
20% Mobility×Variance×Weibull	0.02	0.00	0.05	0.06	−0.07	0.11	
30% Mobility×Variance×Weibull	−0.01	0.04	−0.03	***0.27***	0.12	0.23	
50 Clusters×Within-Cluster×Variance	−0.05	−0.06	0.12	0.03	−0.10	−0.22	
100 Clusters×Within-Cluster×Variance	***−0.43****	0.01	0.10	0.09	−0.09	***−0.49***	
50 Clusters×Within-Cluster×Weibull	−0.01	0.06	0.02	−0.02	−0.03	0.10	
100 Clusters×Within-Cluster×Weibull	−0.08	0.09	0.12	0.00	−0.03	−0.06	
50 Clusters×Variance×Weibull	0.09	0.09	0.16	0.02	***−0.27***	0.10	
100 Clusters×Variance×Weibull	−0.10	***0.45***	***0.46***	0.15	***−0.75***	−0.05	
Within-Cluster×Variance×Weibull	0.02	0.04	0.03	−0.03	−0.11	0.06	
30% Mobility×Within-Cluster×Variance×Weibull						−0.10	
30% Mobility×50 Clusters×Within-Cluster×Variance						***0.30***	
20% Mobility×100 Clusters×Within-Cluster×Variance						0.20	
20% Mobility×50 Clusters×Within-Cluster×Variance						0.03	
30% Mobility×100 Clusters×Within-Cluster×Variance						***0.55***	
20% Mobility×50 Clusters×Within-Cluster×Weibull						−0.13	
30% Mobility×50 Clusters×Within-Cluster×Weibull						−0.05	
20% Mobility×100 Clusters×Within-Cluster×Weibull						−0.12	
30% Mobility×100 Clusters×Within-Cluster×Weibull						0.11	

20% Mobility×50 Clusters×Variance×Weibull	−0.05
30% Mobility×50 Clusters×Variance×Weibull	***−0.29***
20% Mobility×100 Clusters×Variance×Weibull	0.08
30% Mobility×100 Clusters×Variance×Weibull	0.00
20% Mobility×Within-Cluster×Variance×Weibull	0.04
50 Clusters×Within-Cluster×Variance×Weibull	−0.05
100 Clusters×Within-Cluster×Variance×Weibull	***−0.36***

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Cluster Size = reference is 30 clusters; Mobility Rate = reference is 10%; Italicized and bolded values indicate a practically significant effect of magnitude 0.25 on coverage of the 95% confidence interval. * Represents a practical but not statistically significant finding. Blank cells represent variables not included in the logistic regression for a given model parameter based on reported model fit statistics.

Table I2

Cox Effect for the Coverage of the 95% CIs of Each Main Effect and Interaction of Manipulated Conditions Entered into a Logistic Regression for the ML-DTS Model

Source of Variation	α_1 Cox Effect	α_2 Cox Effect	α_3 Cox Effect	α_4 Cox Effect	α_5 Cox Effect	β_1 Cox Effect	β_2 Cox Effect
20% Mobility	−0.12	−0.10	−0.14	−0.20	−0.02	0.01	−0.06
30% Mobility	***−0.29***	***−0.28***	***−0.28***	***−0.34***	−0.22	−0.01	***−0.29***
50 Clusters	0.01	−0.07	0.03	−0.01	−0.03	0.06	0.04
100 Clusters	−0.05	−0.07	0.06	−0.02	−0.04	−0.08	0.06
Within-Cluster	−0.07	−0.09	−0.06	−0.05	−0.13	−0.07	0.03
Variance	−0.23	−0.23	−0.17	−0.21	−0.14	−0.06	0.07
Weibull	−0.07	−0.14	−0.10	−0.12	−0.04	0.15	0.04
20% Mobility×50 Clusters	−0.04	−0.07	0.01	−0.07	−0.02	−0.04	−0.08
30% Mobility×50 Clusters	−0.10	−0.08	−0.03	−0.08	0.04	−0.05	−0.03
20% Mobility×100 Clusters	−0.17	−0.18	−0.13	−0.04	−0.02	0.01	−0.23
30% Mobility×100 Clusters	***−0.34***	***−0.35***	***−0.29***	−0.17	−0.05	0.15	−0.23
20% Mobility×Within-Cluster	−0.16	−0.15	−0.13	−0.02	−0.06	0.07	−0.24
30% Mobility×Within-Cluster	−0.24	***−0.26***	−0.22	−0.13	−0.15	0.08	−0.16
20% Mobility×Variance	−0.17	−0.15	−0.08	−0.02	−0.02	−0.02	0.03
30% Mobility×Variance	***−0.27***	−0.24	−0.21	−0.07	0.02	0.01	0.03
20% Mobility×Weibull	0.04	0.09	0.10	0.16	0.06	−0.04	0.00
30% Mobility×Weibull	0.03	0.10	0.12	0.18	0.12	−0.17	−0.08
50 Clusters×Within-Cluster	0.05	0.08	0.03	0.06	0.06	0.07	−0.07
100 Clusters×Within-Cluster	−0.08	−0.02	−0.11	−0.11	0.02	0.18	−0.12
50 Clusters×Variance	−0.11	−0.03	−0.09	0.03	0.05	0.06	−0.03
100 Clusters×Variance	−0.17	−0.17	−0.15	−0.02	0.05	0.03	0.04
50 Clusters×Weibull	0.04	0.06	0.03	0.02	0.01	−0.20	−0.03
100 Clusters×Weibull	0.05	0.11	0.10	0.17	0.12	−0.03	−0.15
Within-Cluster×Variance	0.05	0.04	0.06	−0.01	0.03	0.10	−0.05
Within-Cluster×Weibull	0.02	0.02	0.05	0.04	0.04	−0.06	0.08
Variance×Weibull	0.16	0.18	0.16	0.17	0.03	−0.08	−0.06
20% Mobility×Within-Cluster×Variance						−0.04	0.07
20% Mobility×50 Clusters×Within-Cluster						−0.08	0.20

30% Mobility×50 Clusters×Within-Cluster	−0.15	0.05
20% Mobility×100 Clusters×Within-Cluster	−0.14	***0.28***
30% Mobility×100 Clusters×Within-Cluster	***−0.30***	−0.02
20% Mobility×50 Clusters×Variance	−0.06	0.03
30% Mobility×50 Clusters×Variance	−0.13	0.05
20% Mobility×100 Clusters×Variance	−0.07	0.08
30% Mobility×100 Clusters×Variance	−0.22	0.11
20% Mobility×50 Clusters×Weibull	−0.04	−0.02
30% Mobility×50 Clusters×Weibull	0.17	0.06
20% Mobility×100 Clusters×Weibull	−0.11	0.08
30% Mobility×100 Clusters×Weibull	−0.06	0.16
20% Mobility×Variance×Weibull	0.00	0.00
30% Mobility×Within-Cluster×Variance	−0.19	0.18
20% Mobility×Within-Cluster×Weibull	−0.06	−0.02
30% Mobility×Within-Cluster×Weibull	0.08	0.01
50 Clusters×Within-Cluster×Weibull	0.19	−0.06
30% Mobility×Variance×Weibull	−0.05	0.05
50 Clusters×Within-Cluster×Variance	−0.20	−0.01
100 Clusters×Within-Cluster×Variance	−0.20	−0.02
Within-Cluster×Variance×Weibull	−0.05	−0.03
100 Clusters×Within-Cluster×Weibull	0.00	0.02
50 Clusters×Variance×Weibull	0.09	0.06
100 Clusters×Variance×Weibull	0.10	0.05

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Cluster Size = reference is 30 clusters; Mobility Rate = reference is 10%; Italicized and bolded values indicate a practically significant effect of magnitude 0.25 on coverage of the 95% confidence interval. Blank cells represent variables not included in the logistic regression for a given model parameter based on reported model fit statistics.

Table I3

Cox Effect for the Coverage of the 95% CIs of Each Main Effect and Interaction of Manipulated Conditions Entered into a Logistic Regression for the CC-DTS Model

Source of Variation	α_1 Cox Effect	α_2 Cox Effect	α_3 Cox Effect	α_4 Cox Effect	α_5 Cox Effect	β_1 Cox Effect	β_2 Cox Effect
20% Mobility	−0.04	0.06	0.03	0.00	0.07	−0.02	−0.01
30% Mobility	0.10	0.04	0.05	−0.09	0.00	0.02	0.04
50 Clusters	0.04	−0.10	0.12	0.01	0.05	0.00	0.10
100 Clusters	−0.01	−0.02	0.18	0.10	0.12	0.00	0.14
Within Cluster	−0.06	−0.10	−0.03	0.04	−0.08	0.03	−0.05
Variance	−0.08	−0.09	−0.04	−0.17	−0.03	0.00	0.00
Weibull	0.07	−0.06	0.01	0.01	−0.01	0.02	−0.01
20% Mobility×50 Clusters	0.05	0.12		−0.07			
30% Mobility×50 Clusters	0.02	0.14		0.16			
20% Mobility×100 Clusters	0.11	0.14		−0.13			
30% Mobility×100 Clusters	−0.02	−0.03		0.10			
20% Mobility×Within Cluster	−0.04	−0.11		−0.10			
30% Mobility×Within Cluster	−0.13	−0.03		0.02			
20% Mobility×Variance	0.05	−0.02		0.08			
30% Mobility×Variance	0.00	−0.03		0.09			
20% Mobility×Weibull	0.01	−0.03		0.16			
30% Mobility×Weibull	−0.05	0.00		−0.03			
50 Clusters×Within Cluster	0.08	0.09		0.06			
100 Clusters×Within Cluster	0.10	0.05		−0.09			
50 Clusters×Variance	0.01	0.05		0.17			
100 Clusters×Variance	0.07	0.07		0.08			
50 Clusters×Weibull	−0.06	0.02		−0.09			
100 Clusters×Weibull	0.03	0.10		0.12			
Within Cluster×Variance	0.01	0.05		0.09			
Within Cluster×Weibull	−0.05	0.03		−0.05			
Variance×Weibull	−0.03	0.01		0.01			
20% Mobility×Within Cluster×Variance				−0.13			
20% Mobility×50 Clusters×Within Cluster				0.21			

30% Mobility×50 Clusters×Within Cluster	−0.17
20% Mobility×100 Clusters×Within Cluster	***0.40***
30% Mobility×100 Clusters×Within Cluster	−0.08
20% Mobility×50 Clusters×Variance	−0.05
30% Mobility×50 Clusters×Variance	−0.12
20% Mobility×100 Clusters×Variance	0.09
30% Mobility×100 Clusters×Variance	−0.02
20% Mobility×50 Clusters×Weibull	−0.08
30% Mobility×50 Clusters×Weibull	0.01
20% Mobility×100 Clusters×Weibull	−0.17
30% Mobility×100 Clusters×Weibull	−0.06
20% Mobility×Variance×Weibull	−0.02
30% Mobility×Within Cluster×Variance	0.00
20% Mobility×Within Cluster×Weibull	−0.09
30% Mobility×Within Cluster×Weibull	0.04
50 Clusters×Within Cluster×Weibull	0.11
30% Mobility×Variance×Weibull	0.00
50 Clusters×Within Cluster×Variance	−0.16
100 Clusters×Within Cluster×Variance	−0.04
Within Cluster×Variance×Weibull	−0.01
100 Clusters×Within Cluster×Weibull	−0.08
50 Clusters×Variance×Weibull	0.01

Note. Scale = Weibull scale parameter, Variance = variance at the cluster-level; Within-Cluster = within-cluster sample size; Cluster Size = reference is 30 clusters; Mobility Rate = reference is 10%; Italicized and bolded values indicate a practically significant effect of magnitude 0.25 on coverage of the 95% confidence interval. Blank cells represent variables not included in the logistic regression for a given model parameter based on reported model fit statistics.

Technical Appendix A: Calculation of the Residual Intra-Class Correlation Coefficient

In the discrete-time survival analysis literature, if the ICC is calculated and the method for the calculation has been reported, it is commonly calculated using the following formula: $\sigma_u^2/(\sigma_u^2 + \frac{\pi^2}{3})$. In this formulation, the individual-level error terms are assumed to follow a standard logistic distribution when the outcome is binary. For example, Moerbeek (2012) conducted a methodological study using discrete-time survival analysis, and when varying the variance-between clusters, reports the equivalent ICCs using this approach. However, this formulation of the ICC is equivalent to the ICC for the baseline model, or the model without covariates included. In this study, the generating model is a conditional model, and therefore, the between-clusters variance represents the residual variance, or the variance between-clusters after accounting for the variance described by the covariates included in the model. Therefore, the ICC was calculated to represent the residual ICC using the following equation:

$$ICC = \frac{(\beta_2^2\pi_z(1-\pi_z)+\sigma_u^2)}{(\beta_2^2\pi_z(1-\pi_z)+\sigma_u^2)+\beta_1^2\pi_x(1-\pi_x)+\frac{\pi^2}{3}} \quad ,$$

where β_1 is the coefficient for the level-1 covariate, β_2 is the coefficient for the level-2 covariate, π_z is the probability that the level-2 covariate, *Z*, is equal to 1, π_x is the probability that the level-1 covariate, *X*, is equal to 1, and $\frac{\pi^2}{3}$ is the total variance at level-1.

For example, when the variance between-clusters was equal to 0.32, the ICC can be calculated as:

$$.10 = ICC = \frac{(0.5^2 * 0.3(1-0.3) + 0.32)}{(0.5^2 * 0.3(1-0.3) + 0.32) + 0.5^2 * 0.5(1-0.5) + \frac{\pi^2}{3}}$$

Technical Appendix B: Data Generation in R

```
library(parallel)
repsPerCondition <- 1000

simulationConditions <- data.frame(
  nRATE = c(.10, .10, .10, .10, .10, .10, .20, .20, .20, .20, .20, .20, .30,
            .30, .30, .30, .30, .30, .10, .10, .10, .10, .10, .10, .20, .20,
            .20, .20, .20, .20, .30, .30, .30, .30, .30, .30, .10, .10, .10,
            .10, .10, .10, .20, .20, .20, .20, .20, .20, .30, .30, .30, .30,
            .30, .30, .10, .10, .10, .10, .10, .10, .20, .20, .20, .20, .20,
            .20, .30, .30, .30, .30, .30, .30),
  nSTU = c(25, 25, 25, 75, 75, 75, 25, 25, 25, 75, 75, 75, 25, 25, 25, 75,
           75, 75, 25, 25, 25, 75, 75, 75, 25, 25, 25, 75, 75, 75, 25, 25,
           25, 75, 75, 75, 25, 25, 25, 75, 75, 75, 25, 25, 25, 75, 75, 75,
           25, 25, 25, 75, 75, 75, 25, 25, 25, 75, 75, 75, 25, 25, 25, 75,
           75, 75, 25, 25, 25, 75, 75, 75),
  nSCH = c(30, 50, 100, 30, 50, 100, 30, 50, 100, 30, 50, 100, 30, 50, 100,
           30, 50, 100, 30, 50, 100, 30, 50, 100, 30, 50, 100,30, 50, 100,
           30, 50, 100, 30, 50, 100, 30, 50, 100, 30, 50, 100, 30, 50, 100,
           30, 50, 100, 30, 50, 100, 30, 50, 100, 30, 50, 100, 30, 50, 100,
           30, 50, 100, 30, 50, 100, 30, 50, 100, 30, 50, 100),
  nVAR = c(1.09, 1.09, 1.09, 1.09, 1.09, 1.09, 1.09, 1.09, 1.09, 1.09, 1.09,
           1.09, 1.09, 1.09, 1.09, 1.09, 1.09, 1.09, 1.09, 1.09, 1.09, 1.09,
           1.09, 1.09, 1.09, 1.09, 1.09, 1.09, 1.09, 1.09, 1.09, 1.09, 1.09,
           1.09, 1.09, 1.09, .32, .32, .32, .32, .32, .32, .32, .32, .32, .32,
           .32, .32, .32, .32, .32, .32, .32, .32, .32, .32, .32, .32, .32, .32,
           .32, .32, .32, .32, .32, .32, .32, .32, .32, .32, .32, .32),
  nLOGHAZ_T1 = c(-2.51, -2.51, -2.51, -2.51, -2.51, -2.51,-2.51, -2.51,
                 -2.51, -2.51, -2.51, -2.51,-2.51, -2.51, -2.51,-2.51, -2.51,
                 -2.51, -3.25, -3.25, -3.25, -3.25, -3.25, -3.25, -3.25, -3.25,
                 -3.25, -3.25, -3.25, -3.25, -3.25, -3.25, -3.25, -3.25, -3.25,
                 -3.25, -2.51, -2.51, -2.51, -2.51, -2.51, -2.51,-2.51, -2.51,
                 -2.51, -2.51, -2.51, -2.51,-2.51, -2.51, -2.51,-2.51, -2.51,
                 -2.51, -3.25, -3.25, -3.25,-3.25, -3.25, -3.25, -3.25, -3.25,
                 -3.25, -3.25, -3.25, -3.25, -3.25, -3.25, -3.25, -3.25, -3.25,
                 -3.25),
  nLOGHAZ_T2 = c(-2.13, -2.13,-2.13, -2.13, -2.13, -2.13, -2.13, -2.13, -2.13,
                 -2.13, -2.13, -2.13, -2.13, -2.13, -2.13, -2.13, -2.13, -2.13,
                 -2.88, -2.88, -2.88, -2.88, -2.88, -2.88, -2.88, -2.88, -2.88,
                 -2.88, -2.88, -2.88, -2.88, -2.88, -2.88, -2.88, -2.88, -2.88,
                 -2.13, -2.13,-2.13, -2.13, -2.13, -2.13, -2.13, -2.13, -2.13,
                 -2.13, -2.13, -2.13, -2.13, -2.13, -2.13, -2.13, -2.13, -2.13,
                 -2.88, -2.88, -2.88, -2.88, -2.88, -2.88, -2.88, -2.88, -2.88,
                 -2.88, -2.88, -2.88, -2.88, -2.88, -2.88, -2.88, -2.88, -2.88),
  nLOGHAZ_T3 = c(-1.90,-1.90,-1.90,-1.90,-1.90,-1.90,-1.90,-1.90,-1.90,-1.90,-1.90,
                 -1.90,-1.90,-1.90,-1.90,-1.90,-1.90,-1.90,-2.67,-2.67,-2.67,-2.67,
                 -2.67,-2.67,-2.67,-2.67,-2.67,-2.67,-2.67,-2.67,-2.67,-2.67,-2.67,
                 -2.67,-2.67,-2.67,-1.90,-1.90,-1.90,-1.90,-1.90,-1.90,-1.90,-1.90,
                 -1.90,-1.90,-1.90,-1.90,-1.90,-1.90,-1.90,-1.90,-1.90,-1.90,-2.67,
                 -2.67,-2.67,-2.67,-2.67,-2.67,-2.67,-2.67,-2.67,-2.67,-2.67,-2.67,
                 -2.67,-2.67,-2.67,-2.67,-2.67,-2.67),
  nLOGHAZ_T4 = c(-1.74, -1.74, -1.74, -1.74, -1.74, -1.74, -1.74, -1.74, -1.74,
                 -1.74, -1.74,-1.74, -1.74, -1.74, -1.74, -1.74, -1.74, -1.74,
                 -2.51, -2.51, -2.51, -2.51,-2.51, -2.51, -2.51, -2.51, -2.51,
                 -2.51, -2.51, -2.51, -2.51, -2.51, -2.51,-2.51, -2.51, -2.51,
                 -1.74, -1.74, -1.74, -1.74, -1.74, -1.74, -1.74, -1.74,-1.74,
                 -1.74, -1.74, -1.74, -1.74, -1.74, -1.74, -1.74, -1.74, -1.74,
                 -2.51,-2.51, -2.51, -2.51, -2.51, -2.51, -2.51, -2.51, -2.51,
                 -2.51, -2.51, -2.51,-2.51, -2.51, -2.51, -2.51, -2.51, -2.51),
  nLOGHAZ_T5 = c(-1.60, -1.60, -1.60, -1.60, -1.60, -1.60, -1.60, -1.60, -1.60,
                 -1.60, -1.60,-1.60, -1.60, -1.60, -1.60, -1.60, -1.60, -1.60,
                 -2.39, -2.39, -2.39, -2.39,-2.39, -2.39, -2.39, -2.39, -2.39,
                 -2.39, -2.39, -2.39, -2.39, -2.39, -2.39,-2.39, -2.39, -2.39,
                 -1.60, -1.60, -1.60, -1.60, -1.60, -1.60, -1.60, -1.60,-1.60,
                 -1.60, -1.60, -1.60, -1.60, -1.60, -1.60, -1.60, -1.60, -1.60,
                 -2.39,-2.39, -2.39, -2.39, -2.39, -2.39, -2.39, -2.39, -2.39,
                 -2.39, -2.39, -2.39,-2.39, -2.39, -2.39, -2.39, -2.39, -2.39)
)
nREP <- rep((1:repsPerCondition), each = nrow(simulationConditions))
```

```
simulateParam <- cbind(nREP, do.call(rbind, replicate(n = repsPerCondition,
                                                      simulationConditions,
                                                      simplify = FALSE)))
simulateParam$UniqueID <- 1:nrow(simulateParam)

simulateParams <- split(simulateParam, 1:nrow(simulateParam))

rm(repsPerCondition, nREP, simulateParam, simulationConditions)

UniqueIDs <- do.call(rbind, simulateParams)
write.csv(UniqueIDs, file = "E:/UniqueIDXtoX.csv")

rm(UniqueIDs)

#Simulate the data
SIM <- function(myParams) {

  library(coda)
  library(MASS)
  library(dplyr)

  nRATE <- myParams$nRATE
  nSCH <- myParams$nSCH
  nSTU <- myParams$nSTU
  nVAR <- myParams$nVAR
  nREP <- myParams$nREP
  nLOGHAZ_T1 <- myParams$nLOGHAZ_T1
  nLOGHAZ_T2 <- myParams$nLOGHAZ_T2
  nLOGHAZ_T3 <- myParams$nLOGHAZ_T3
  nLOGHAZ_T4 <- myParams$nLOGHAZ_T4
  nLOGHAZ_T5 <- myParams$nLOGHAZ_T5
  UniqueID <- myParams$UniqueID
  set.seed(nREP)

  #Generate Data#
  SCH_T1 = rep(seq(1, nSCH), each = nSTU)
  numSTU <- nSTU*nSCH

  # Generate X and Z
  X <- rep(0, numSTU)
  X[sample(1:numSTU, .5*numSTU)] <- 1
  Z <- rep(0, times = nSCH)
  Z[sample(1:nSCH, .3 * nSCH)] <- 1

  # Generate Mobility
  numMobSTU <- numSTU*nRATE
  MOB <- sample(1:numSTU, numMobSTU)
  MOB_PATTERN <- rep(0, numSTU)
  MOBSTU <- rep(0, numSTU)
  MOBSTU[MOB] <- ifelse(MOBSTU[MOB] == nSTU, 1, MOBSTU[MOB] + 1)

  # 40% Movers at T2
  MOB1 <- MOB[1:(.40*numMobSTU)]
  MOB_PATTERN[MOB1] <- 1

  # 30% Movers at T3
  MOB2 <- MOB[(.40*numMobSTU + 1):(.70*numMobSTU)]
  MOB_PATTERN[MOB2] <- 2

  # 10% Movers at T4
  MOB3 <- MOB[(.70*numMobSTU + 1):(.80*numMobSTU)]
  MOB_PATTERN[MOB3] <- 3

  # 10% Movers at T2 and T3
  MOB4 <- MOB[(.80*numMobSTU + 1):(.90*numMobSTU)]
  MOB_PATTERN[MOB4] <- 4

  # 10% Movers at T2 and T4
  MOB5 <- MOB[(.90*numMobSTU + 1):(numMobSTU)]
  MOB_PATTERN[MOB5] <- 5

  # Assign Schools
```

```
SCH_T2 <- SCH_T1
SCH_T2[MOB1] <- ifelse(SCH_T2[MOB1] == nSCH, 1, SCH_T2[MOB1] + 1)
SCH_T2[MOB4] <- ifelse(SCH_T2[MOB4] == nSCH, 1, SCH_T2[MOB4] + 1)
SCH_T2[MOB5] <- ifelse(SCH_T2[MOB5] == nSCH, 1, SCH_T2[MOB5] + 1)

SCH_T3 <- SCH_T2
SCH_T3[MOB2] <- ifelse(SCH_T3[MOB2] == nSCH, 1, SCH_T3[MOB2] + 1)
SCH_T3[MOB4] <- ifelse(SCH_T3[MOB4] == nSCH, 1, SCH_T3[MOB4] + 1)

SCH_T4 <- SCH_T3
SCH_T4[MOB3] <- ifelse(SCH_T4[MOB3] == nSCH, 1, SCH_T4[MOB3] + 1)
SCH_T4[MOB5] <- ifelse(SCH_T4[MOB5] == nSCH, 1, SCH_T4[MOB5] + 1)

SCH_T5 <- SCH_T4

# Assign mobility indicator per time period
MOB_T2 <- ifelse(SCH_T2 == SCH_T1, 0, 1)
MOB_T3 <- ifelse(SCH_T3 == SCH_T2, 0, 1)
MOB_T4 <- ifelse(SCH_T4 == SCH_T3, 0, 1)

rm(MOB,MOB1,MOB2,MOB3,MOB4,MOB5)

# Generate Z for CC-DTS
Z1 <- Z[SCH_T1]
Z2 <- Z[SCH_T2]
Z3 <- Z[SCH_T3]
Z4 <- Z[SCH_T4]
Z5 <- Z[SCH_T5]

# Bind data and convert to long format
dat <- rbind(cbind(STU = 1:numSTU, SCH = SCH_T1, Z = Z1,
                   D1 = 1, D2 = 0, D3 = 0, D4 = 0, D5 = 0, TIME = 1,
                   MOBSTU, MOB_PATTERN, MOB_T2 = 0, MOB_T3 = 0,
                   MOB_T4 = 0),
             cbind(STU = 1:numSTU, SCH = SCH_T2, Z = Z2,
                   D1 = 0, D2 = 1, D3 = 0, D4 = 0, D5 = 0,
                   TIME = 2, MOBSTU, MOB_PATTERN,
                   MOB_T2, MOB_T3 = 0, MOB_T4 = 0),
             cbind(STU = 1:numSTU, SCH = SCH_T3, Z = Z3,
                   D1 = 0, D2 = 0, D3 = 1, D4 = 0, D5 = 0,
                   TIME = 3, MOBSTU, MOB_PATTERN,
                   MOB_T2 = 0, MOB_T3, MOB_T4 = 0),
             cbind(STU = 1:numSTU, SCH = SCH_T4, Z = Z4,
                   D1 = 0, D2 = 0, D3 = 0, D4 = 1, D5 = 0,
                   TIME = 4, MOBSTU, MOB_PATTERN,
                   MOB_T2 = 0, MOB_T3 = 0, MOB_T4),
             cbind(STU = 1:numSTU, SCH = SCH_T5, Z = Z5,
                   D1 = 0, D2 = 0, D3 = 0, D4 = 0, D5 = 1, TIME = 5,
                   MOBSTU, MOB_PATTERN, MOB_T2 = 0, MOB_T3 = 0,
                   MOB_T4 = 0))

rm(Z2,Z3,Z4,Z5,SCH_T2,SCH_T3,SCH_T4,SCH_T5, MOB_T2, MOB_T3, MOB_T4,
   MOB_PATTERN, MOBSTU)

dat <- cbind(dat, SCH1 = rep(SCH_T1, time = 5), SCH0 = rep(1, numSTU),
             Z1 = rep(Z1, time = 5), X)

rm(SCH_T1,X,Z,Z1)

# Generate Random Effect
u <- rnorm(n = nSCH, mean = 0, sd = sqrt(nVAR))

# Generate Events
hlogit <-  nLOGHAZ_T1*dat[, "D1"] + nLOGHAZ_T2*dat[, "D2"] +
  nLOGHAZ_T3*dat[, "D3"] + nLOGHAZ_T4*dat[, "D4"] +
  nLOGHAZ_T5*dat[, "D5"] + .5*dat[, "X"] + .5*dat[, "Z"] +
  u[dat[, "SCH"]]

rm(u)

# Compute the event
HazProb <- exp(hlogit) / (1 + exp(hlogit))
```

```
  dat <- cbind(dat, Event = rbinom(n = numSTU*5, size = 1, prob = HazProb),
               nREP,nRATE,nSCH,nSTU,nVAR,nLOGHAZ_T1, nLOGHAZ_T2, nLOGHAZ_T3,
               nLOGHAZ_T4, nLOGHAZ_T5, DatasetID = UniqueID)

  rm(HazProb,hlogit)

  # Convert to person-period data format
  EventData <- group_by(as.data.frame(dat), STU) %>%
    mutate(first1 = min(which(Event == 1 | row_number() == n()))) %>%
    filter(row_number() <= first1) %>%
    select(-first1)

  rm(dat)

  EventData <- as.data.frame(EventData)

  # Datafile export
  myfile <- file.path("ComputerPath",
                      paste0(UniqueID, "_SimDAT", ".csv"))

  write.csv(EventData, file = myfile, row.names = FALSE)
  rm(myfile)

}

##Run Simulations
system.time({
  cl <- makeCluster(mc <- getOption("cl.cores", 6))
  simulationResults <- parLapply(cl, simulateParams, SIM)
  stopCluster(cl)
})
```

Technical Appendix C: Model Estimation in R

```
library(parallel)

SIM <- function(filename) {

library(lme4)

dat <- read.csv(file = filename, header = TRUE)

##RUN THE MODELS
# DTS Estimation
DTS <- glmer(Event ~ 0 + D1 + D2 + D3 + D4 + D5 + X + Z1 + (1 | SCH0),
             family = binomial, data = dat,
             glmerControl(check.nobs.vs.rankZ = "ignore",
                          check.nobs.vs.nRE = "ignore",
                          check.nlev.gtreq.5 = "ignore",
                          check.nlev.gtr.1 = "ignore",
                          check.conv.singular = "ignore"))

# Get results
results_DTS <- cbind(fixef(DTS), confint(DTS, parm = "beta_", method = "Wald"))
colnames(results_DTS) <- c("coef","LowerCI","UpperCI")
results_DTS <- rbind(results_DTS, var = as.data.frame(VarCorr(DTS))$vcov)
results_DTS <- cbind(results_DTS, Model = 1, Convergence = 0)
rm(DTS)

# ML-DTS Estimation
MDTS <- glmer(Event ~  0 + D1 + D2 + D3 + D4 + D5 + X + Z1 + (1 | SCH1),
              family = binomial, data = dat,
              glmerControl(optimizer = "bobyqa",
                           optCtrl = list(maxfun = 2e5)))

# Get results
results_MDTS <- cbind(fixef(MDTS), confint(MDTS, parm = "beta_", method = "Wald"))
colnames(results_MDTS) <- c("coef","LowerCI","UpperCI")
results_MDTS <- rbind(results_MDTS, var = as.data.frame(VarCorr(MDTS))$vcov)
results_MDTS <- cbind(results_MDTS, Model = 2,
                      Convergence = ifelse(any(
                        grepl("failed to converge",
                              MDTS@optinfo$conv$lme4$messages))
                        == 'TRUE', 1, 0))
rm(MDTS)

# CC-DTS Estimation
CCDTS <- glmer(Event ~  0 + D1 + D2 + D3 + D4 + D5 + X + Z + (1 | SCH),
               family = binomial, data = dat,
               glmerControl(optimizer = "bobyqa",
                            optCtrl = list(maxfun = 2e5)))

# Get results
results_CCDTS <- cbind(fixef(CCDTS), confint(CCDTS, parm = "beta_", method = "Wald"))
colnames(results_CCDTS) <- c("coef","LowerCI","UpperCI")
results_CCDTS <- rbind(results_CCDTS, var = as.data.frame(VarCorr(CCDTS))$vcov)
results_CCDTS <- cbind(results_CCDTS, Model = 3,
                       Convergence = ifelse(any(
                         grepl("failed to converge",
                               CCDTS@optinfo$conv$lme4$messages))
                         == 'TRUE', 1, 0))
rm(CCDTS)

# Bind results
Results_ALL <- rbind(results_DTS, results_MDTS, results_CCDTS)
rm(results_DTS, results_MDTS, results_CCDTS)
TrueValues <- c(nLOGHAZ_T1 = dat[1, 25], nLOGHAZ_T2 = dat[1, 26],
                nLOGHAZ_T3 = dat[1, 27], nLOGHAZ_T4 = dat[1, 28],
                nLOGHAZ_T5 = dat[1, 29], .5, .5, nVAR = dat[1, 24])
Results_ALL <- cbind(nREP = dat[1, 20], nRATE = dat[1, 21], nSCH = dat[1, 22],
                     nSTU = dat[1, 23], nVAR = dat[1, 24],
                     nLOGHAZ_T1 = dat[1, 25], UniqueID = dat[1, 30], TrueValues,
```

```
                     Results_ALL)
rm(dat, TrueValues)

return(Results_ALL)
}

#Run Simulation
filenames <- list.files(path = “ComputerPath", pattern = "csv", full.names = TRUE)

system.time({
  cl <- makeCluster(mc <- getOption("cl.cores", 6))
  simulationResults <- parLapply(cl, filenames, SIM)
  stopCluster(cl)
})

simResults <- do.call(rbind, simulationResults)
write.csv(simResults, "SimResultsXthroughX.csv")
```

Technical Appendix D: Analysis in R

```
library(plyr)
library(heplots)

numREPS <- 1000

dataSIM <- data.frame(simResults)
dataSIM$Param <- as.factor(rep(c("D1", "D2", "D3", "D4", "D5", "X", "Z1", "Var")))
rm(simResults)

#Analysis
dataSIM$cov <- ifelse(dataSIM$LowerCI <= dataSIM$TrueValues &
                        dataSIM$UpperCI >= dataSIM$TrueValues, 1, 0)
dataSIM$RPB <- (dataSIM$coef - dataSIM$TrueValues)/dataSIM$TrueValues

EstModels <- ddply(dataSIM, c("Model", "Param", "nRATE", "nSCH", "nSTU",
                              "nVAR", "nLOGHAZ_T1","TrueValues"),
                   summarize, RPBmean = mean(RPB),
                   covRate = sum(cov)/numREPS,
                   sd = sd(coef),
                   EstAverage = mean(coef))

rm(numREPS)

EstModels$RMSE <- sqrt((EstModels$EstAverage - EstModels$TrueValues)^2 +
                         (EstModels$sd)^2)

EstModels <- EstModels[-c(11:12)]

#ANOVA
dataSIM$nRATE <- as.factor(dataSIM$nRATE)
dataSIM$nSCH <- as.factor(dataSIM$nSCH)
dataSIM$nSTU <- as.factor(dataSIM$nSTU)
dataSIM$nVAR <- as.factor(dataSIM$nVAR)
dataSIM$nLOGHAZ_T1 <- as.factor(dataSIM$nLOGHAZ_T1)
dataSIM$Model <- as.factor(dataSIM$Model)

dataDTS <- subset(dataSIM, dataSIM$Model == 1)
dataMLDTS <- subset(dataSIM, dataSIM$Model == 2)
dataCCDTS <- subset(dataSIM, dataSIM$Model == 3)
dataSIM_Var <- subset(dataSIM, dataSIM$Model == 2 | dataSIM$Model == 3)

#Set contrasts
options(contrasts = c("contr.helmert", "contr.poly"))

#ANOVA for RPB with Model as IV with partial eta squared
D1 <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1*Model,
               data = subset(dataSIM, Param == "D1")),
            type = 3, anova = TRUE, partial = TRUE)

D2 <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1*Model,
               data = subset(dataSIM, Param == "D2")),
            type = 3, anova = TRUE, partial = TRUE)

D3 <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1*Model,
               data = subset(dataSIM, Param == "D3")),
            type = 3, anova = TRUE, partial = TRUE)

D4 <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1*Model,
               data = subset(dataSIM, Param == "D4")),
            type = 3, anova = TRUE, partial = TRUE)

D5 <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1*Model,
               data = subset(dataSIM, Param == "D5")),
            type = 3, anova = TRUE, partial = TRUE)

X <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1*Model,
              data = subset(dataSIM, Param == "X")),
           type = 3, anova = TRUE, partial = TRUE)
```

```
Z <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1*Model,
              data = subset(dataSIM, Param == "Z1")),
           type = 3, anova = TRUE, partial = TRUE)

Var <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1*Model,
                data = subset(dataSIM_Var, Param == "Var")),
             type = 3, anova = TRUE, partial = TRUE)

Model_Eta <- round(cbind(D1,
                         D2,
                         D3,
                         D4,
                         D5,
                         X,
                         Z,
                         Var,
                         Model = 0),
                   digits = 3)
names(Model_Eta) <- c("D1Eta", "D1SS", "D1DF", "D1F", "D1P","D2Eta",
                      "D2SS", "D2DF", "D2F", "D2P", "D3Eta", "D3SS",
                      "D3DF", "D3F", "D3P", "D4Eta", "D4SS", "D4DF",
                      "D4F", "D4P", "D5Eta", "D5SS", "D5DF", "D5F",
                      "D5P", "XEta", "XSS", "XDF", "XF", "XP", "ZEta",
                      "ZSS", "ZDF", "ZF", "ZP", "VarEta", "VarSS",
                      "VarDF", "VarF", "VarP", "Model")
rm(D1, D2, D3, D4, D5, X, Z, Var)

#ANOVA within model#
#DTS Model
D1_DTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                   data = subset(dataDTS, Param == "D1")),
                type = 3, anova = TRUE, partial = TRUE)

D2_DTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                   data = subset(dataDTS, Param == "D2")),
                type = 3, anova = TRUE, partial = TRUE)

D3_DTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                   data = subset(dataDTS, Param == "D3")),
                type = 3, anova = TRUE, partial = TRUE)

D4_DTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                   data = subset(dataDTS, Param == "D4")),
                type = 3, anova = TRUE, partial = TRUE)

D5_DTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                   data = subset(dataDTS, Param == "D5")),
                type = 3, anova = TRUE, partial = TRUE)

X_DTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                  data = subset(dataDTS, Param == "X")),
               type = 3, anova = TRUE, partial = TRUE)

Z_DTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                  data = subset(dataDTS, Param == "Z1")),
               type = 3, anova = TRUE, partial = TRUE)

DTS_ANOVA <- round(cbind(D1_DTS,
                         D2_DTS,
                         D3_DTS,
                         D4_DTS,
                         D5_DTS,
                         X_DTS,
                         Z_DTS,
                         VarEta = 0,
                         VarSS = 0,
                         VarDF = 0,
                         VarF = 0,
                         VarP = 0,
                         Model = 1),
                   digits = 3)
```

```
names(DTS_ANOVA) <- c("D1Eta", "D1SS", "D1DF", "D1F", "D1P","D2Eta",
                      "D2SS", "D2DF", "D2F", "D2P", "D3Eta", "D3SS",
                      "D3DF", "D3F", "D3P", "D4Eta", "D4SS", "D4DF",
                      "D4F", "D4P", "D5Eta", "D5SS", "D5DF", "D5F",
                      "D5P", "XEta", "XSS", "XDF", "XF", "XP", "ZEta",
                      "ZSS", "ZDF", "ZF", "ZP", "VarEta", "VarSS", "VarDF",
                      "VarF", "VarP", "Model")
rm(D1_DTS, D2_DTS, D3_DTS, D4_DTS, D5_DTS, X_DTS, Z_DTS)

#ML-DTS Model
D1_MLDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                     data = subset(dataMLDTS, Param == "D1")),
                  type = 3, anova = TRUE, partial = TRUE)

D2_MLDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                     data = subset(dataMLDTS, Param == "D2")),
                  type = 3, anova = TRUE, partial = TRUE)

D3_MLDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                     data = subset(dataMLDTS, Param == "D3")),
                  type = 3, anova = TRUE, partial = TRUE)

D4_MLDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                     data = subset(dataMLDTS, Param == "D4")),
                  type = 3, anova = TRUE, partial = TRUE)

D5_MLDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                     data = subset(dataMLDTS, Param == "D5")),
                  type = 3, anova = TRUE, partial = TRUE)

X_MLDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                    data = subset(dataMLDTS, Param == "X")),
                 type = 3, anova = TRUE, partial = TRUE)

Z_MLDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                    data = subset(dataMLDTS, Param == "Z1")),
                 type = 3, anova = TRUE, partial = TRUE)

Var_MLDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                      data = subset(dataMLDTS, Param == "Var")),
                   type = 3, anova = TRUE, partial = TRUE)

MLDTS_ANOVA <- round(cbind(D1_MLDTS,
                           D2_MLDTS,
                           D3_MLDTS,
                           D4_MLDTS,
                           D5_MLDTS,
                           X_MLDTS,
                           Z_MLDTS,
                           Var_MLDTS,
                           Model = 2),
                     digits = 3)

names(MLDTS_ANOVA) <- c("D1Eta", "D1SS", "D1DF", "D1F", "D1P","D2Eta",
                        "D2SS", "D2DF", "D2F", "D2P", "D3Eta", "D3SS",
                        "D3DF", "D3F", "D3P", "D4Eta", "D4SS", "D4DF",
                        "D4F", "D4P", "D5Eta", "D5SS", "D5DF", "D5F",
                        "D5P", "XEta", "XSS", "XDF", "XF", "XP", "ZEta",
                        "ZSS", "ZDF", "ZF", "ZP", "VarEta", "VarSS", "VarDF",
                        "VarF", "VarP", "Model")
rm(D1_MLDTS, D2_MLDTS, D3_MLDTS, D4_MLDTS, D5_MLDTS, X_MLDTS, Z_MLDTS, Var_MLDTS)

#CC-DTS Model
D1_CCDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                     data = subset(dataCCDTS, Param == "D1")),
                  type = 3, anova = TRUE, partial = TRUE)

D2_CCDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                     data = subset(dataCCDTS, Param == "D2")),
                  type = 3, anova = TRUE, partial = TRUE)
```

```
D3_CCDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                     data = subset(dataCCDTS, Param == "D3")),
                  type = 3, anova = TRUE, partial = TRUE)

D4_CCDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                     data = subset(dataCCDTS, Param == "D4")),
                  type = 3, anova = TRUE, partial = TRUE)

D5_CCDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                     data = subset(dataCCDTS, Param == "D5")),
                  type = 3, anova = TRUE, partial = TRUE)

X_CCDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                    data = subset(dataCCDTS, Param == "X")),
                 type = 3, anova = TRUE, partial = TRUE)

Z_CCDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                    data = subset(dataCCDTS, Param == "Z1")),
                 type = 3, anova = TRUE, partial = TRUE)

Var_CCDTS <- etasq(lm(RPB ~ nRATE*nSCH*nSTU*nVAR*nLOGHAZ_T1,
                      data = subset(dataCCDTS, Param == "Var")),
                   type = 3, anova = TRUE, partial = TRUE)

CCDTS_ANOVA <- round(cbind(D1_CCDTS,
                           D2_CCDTS,
                           D3_CCDTS,
                           D4_CCDTS,
                           D5_CCDTS,
                           X_CCDTS,
                           Z_CCDTS,
                           Var_CCDTS,
                           Model = 3),
                     digits = 3)
names(CCDTS_ANOVA) <- c("D1Eta", "D1SS", "D1DF", "D1F", "D1P","D2Eta",
                        "D2SS", "D2DF", "D2F", "D2P", "D3Eta", "D3SS",
                        "D3DF", "D3F", "D3P", "D4Eta", "D4SS", "D4DF",
                        "D4F", "D4P", "D5Eta", "D5SS", "D5DF", "D5F",
                        "D5P", "XEta", "XSS", "XDF", "XF", "XP", "ZEta",
                        "ZSS", "ZDF", "ZF", "ZP", "VarEta", "VarSS",
                        "VarDF", "VarF", "VarP", "Model")
rm(D1_CCDTS, D2_CCDTS, D3_CCDTS, D4_CCDTS, D5_CCDTS, X_CCDTS, Z_CCDTS,
   Var_CCDTS, dataDTS, dataMLDTS, dataCCDTS)

AnovaResults <- rbind(Model_Eta, DTS_ANOVA, MLDTS_ANOVA, CCDTS_ANOVA)
rm(Model_Eta, DTS_ANOVA, MLDTS_ANOVA, CCDTS_ANOVA)

#Logistic Regression for Coverage of the 95% CIs.

options(contrasts = c("contr.treatment", "contr.poly"))


D1_DTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^3,
          data = subset(dataDTS, Param == "D1"),
          family = binomial) #Good

D2_DTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^3,
          data = subset(dataDTS, Param == "D2"),
          family = binomial) #Good

D3_DTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^3,
          data = subset(dataDTS, Param == "D3"),
          family = binomial) #Good

D4_DTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^3,
          data = subset(dataDTS, Param == "D4"),
          family = binomial) #Good

D5_DTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^3,
          data = subset(dataDTS, Param == "D5"), #Good
          family = binomial)
```

```
DTS_Log_Haz <- round(cbind(D1Estimate = D1_DTS$coefficients,
                           D1SE = summary(D1_DTS)$coefficients[,2],
                           D1TVal = summary(D1_DTS)$coefficients[,3],
                           D1PVal = summary(D1_DTS)$coefficients[,4],
                           D1OR = exp(D1_DTS$coefficients),
                           D1_CoxEffect = D1_DTS$coefficients/1.65,
                           D2Estimate = D2_DTS$coefficients,
                           D2SE = summary(D2_DTS)$coefficients[,2],
                           D2TVal = summary(D2_DTS)$coefficients[,3],
                           D2PVal = summary(D2_DTS)$coefficients[,4],
                           D2OR = exp(D2_DTS$coefficients),
                           D2_CoxEffect = D2_DTS$coefficients/1.65,
                           D3Estimate = D3_DTS$coefficients,
                           D3SE = summary(D3_DTS)$coefficients[,2],
                           D3TVal = summary(D3_DTS)$coefficients[,3],
                           D3PVal = summary(D3_DTS)$coefficients[,4],
                           D3OR = exp(D3_DTS$coefficients),
                           D3_CoxEffect = D3_DTS$coefficients/1.65,
                           D4Estimate = D4_DTS$coefficients,
                           D4SE = summary(D4_DTS)$coefficients[,2],
                           D4TVal = summary(D4_DTS)$coefficients[,3],
                           D4PVal = summary(D4_DTS)$coefficients[,4],
                           D4OR = exp(D4_DTS$coefficients),
                           D4_CoxEffect = D4_DTS$coefficients/1.65,
                           D5Estimate = D5_DTS$coefficients,
                           D5SE = summary(D5_DTS)$coefficients[,2],
                           D5TVal = summary(D5_DTS)$coefficients[,3],
                           D5PVal = summary(D5_DTS)$coefficients[,4],
                           D5OR = exp(D5_DTS$coefficients),
                           D5_CoxEffect = D5_DTS$coefficients/1.65), digits = 2)

DTS_Log_Haz <- cbind(names = rownames(DTS_Log_Haz), DTS_Log_Haz)

X_DTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^4,
         data = subset(dataDTS, Param == "X"),
         family = binomial) #4 way is better than 3 way, but not 5 way. Go with 4 way

DTS_Log_X <- round(cbind(XEstimate = X_DTS$coefficients,
                         XSE = summary(X_DTS)$coefficients[,2],
                         XTVal = summary(X_DTS)$coefficients[,3],
                         XPVal = summary(X_DTS)$coefficients[,4],
                         XOR = exp(X_DTS$coefficients),
                         X_CoxEffect = X_DTS$coefficients/1.65),
                   digits = 2)

DTS_Log_X <- cbind(names = rownames(DTS_Log_X), DTS_Log_X)

Z_DTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^2,
         data = subset(dataDTS, Param == "Z1"),
         family = binomial) #2 way is the best fit

DTS_Log_Z <- round(cbind(ZEstimate = Z_DTS$coefficients,
                         ZSE = summary(Z_DTS)$coefficients[,2],
                         ZTVal = summary(Z_DTS)$coefficients[,3],
                         ZPVal = summary(Z_DTS)$coefficients[,4],
                         ZOR = exp(Z_DTS$coefficients),
                         Z_CoxEffect = Z_DTS$coefficients/1.65),
                   digits = 2)

DTS_Log_Z <- cbind(names = rownames(DTS_Log_Z), DTS_Log_Z)

DTS_Log <- merge(DTS_Log_Haz, DTS_Log_X, by = "names", all = TRUE, sort = FALSE)
DTS_Log <- merge(DTS_Log, DTS_Log_Z, by = "names", all = TRUE, sort = FALSE)

rm(D1_DTS, D2_DTS, D3_DTS, D4_DTS, D5_DTS, X_DTS, Z_DTS, DTS_Log_Haz, DTS_Log_X,
DTS_Log_Z)

D1_MLDTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^2,
             data = subset(dataMLDTS, Param == "D1"),
             family = binomial) # 2 way is best

D2_MLDTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^2,
```

```
              data = subset(dataMLDTS, Param == "D2"),
              family = binomial) # 2 way is best

D3_MLDTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^2,
              data = subset(dataMLDTS, Param == "D3"),
              family = binomial) # 2 way is best

D4_MLDTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^2,
              data = subset(dataMLDTS, Param == "D4"),
              family = binomial) # 2 way is best

D5_MLDTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^2,
              data = subset(dataMLDTS, Param == "D5"),
              family = binomial) # 2 way is best

MLDTS_Log_Haz <- round(cbind(D1Estimate = D1_MLDTS$coefficients,
                        D1SE = summary(D1_MLDTS)$coefficients[,2],
                        D1TVal = summary(D1_MLDTS)$coefficients[,3],
                        D1PVal = summary(D1_MLDTS)$coefficients[,4],
                        D1OR = exp(D1_MLDTS$coefficients),
                        D1_CoxEffect = D1_MLDTS$coefficients/1.65,
                        D2Estimate = D2_MLDTS$coefficients,
                        D2SE = summary(D2_MLDTS)$coefficients[,2],
                        D2TVal = summary(D2_MLDTS)$coefficients[,3],
                        D2PVal = summary(D2_MLDTS)$coefficients[,4],
                        D2OR = exp(D2_MLDTS$coefficients),
                        D2_CoxEffect = D2_MLDTS$coefficients/1.65,
                        D3Estimate = D3_MLDTS$coefficients,
                        D3SE = summary(D3_MLDTS)$coefficients[,2],
                        D3TVal = summary(D3_MLDTS)$coefficients[,3],
                        D3PVal = summary(D3_MLDTS)$coefficients[,4],
                        D3OR = exp(D3_MLDTS$coefficients),
                        D3_CoxEffect = D3_MLDTS$coefficients/1.65,
                        D4Estimate = D4_MLDTS$coefficients,
                        D4SE = summary(D4_MLDTS)$coefficients[,2],
                        D4TVal = summary(D4_MLDTS)$coefficients[,3],
                        D4PVal = summary(D4_MLDTS)$coefficients[,4],
                        D4OR = exp(D4_MLDTS$coefficients),
                        D4_CoxEffect = D4_MLDTS$coefficients/1.65,
                        D5Estimate = D5_MLDTS$coefficients,
                        D5SE = summary(D5_MLDTS)$coefficients[,2],
                        D5TVal = summary(D5_MLDTS)$coefficients[,3],
                        D5PVal = summary(D5_MLDTS)$coefficients[,4],
                        D5OR = exp(D5_MLDTS$coefficients),
                        D5_CoxEffect = D5_MLDTS$coefficients/1.65),
                      digits = 2)

MLDTS_Log_Haz <- cbind(names = rownames(MLDTS_Log_Haz), MLDTS_Log_Haz)

X_MLDTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^3,
             data = subset(dataMLDTS, Param == "X"),
             family = binomial) #3 way is best

Z_MLDTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^3,
             data = subset(dataMLDTS, Param == "Z1"),
             family = binomial) #2 way is best

MLDTS_Log_XZ <- round(cbind(XEstimate = X_MLDTS$coefficients,
                      XSE = summary(X_MLDTS)$coefficients[,2],
                      XTVal = summary(X_MLDTS)$coefficients[,3],
                      XPVal = summary(X_MLDTS)$coefficients[,4],
                      XOR = exp(X_MLDTS$coefficients),
                      X_CoxEffect = X_MLDTS$coefficients/1.65,
                      ZEstimate = Z_MLDTS$coefficients,
                      ZSE = summary(Z_MLDTS)$coefficients[,2],
                      ZTVal = summary(Z_MLDTS)$coefficients[,3],
                      ZPVal = summary(Z_MLDTS)$coefficients[,4],
                      ZOR = exp(Z_MLDTS$coefficients),
                      Z_CoxEffect = Z_MLDTS$coefficients/1.65),
                digits = 2)

MLDTS_Log_XZ <- cbind(names = rownames(MLDTS_Log_XZ), MLDTS_Log_XZ)
```

```
MLDTS_Log <- merge(MLDTS_Log_Haz, MLDTS_Log_XZ, by = "names", all = TRUE, sort =
FALSE)

rm(D1_MLDTS, D2_MLDTS, D3_MLDTS, D4_MLDTS, D5_MLDTS, X_MLDTS, Z_MLDTS, MLDTS_Log_Haz,
MLDTS_Log_XZ)

D1_CCDTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^2,
              data = subset(dataCCDTS, Param == "D1"),
              family = binomial) #2 way is best

D2_CCDTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^2,
              data = subset(dataCCDTS, Param == "D2"),
              family = binomial) #2 way is best

CCDTS_Log_D1D2 <- round(cbind(D1Estimate = D1_CCDTS$coefficients,
                         D1SE = summary(D1_CCDTS)$coefficients[,2],
                         D1TVal = summary(D1_CCDTS)$coefficients[,3],
                         D1PVal = summary(D1_CCDTS)$coefficients[,4],
                         D1OR = exp(D1_CCDTS$coefficients),
                         D1_CoxEffect = D1_CCDTS$coefficients/1.65,
                         D2Estimate = D2_CCDTS$coefficients,
                         D2SE = summary(D2_CCDTS)$coefficients[,2],
                         D2TVal = summary(D2_CCDTS)$coefficients[,3],
                         D2PVal = summary(D2_CCDTS)$coefficients[,4],
                         D2OR = exp(D2_CCDTS$coefficients),
                         D2_CoxEffect = D2_CCDTS$coefficients/1.65),
                   digits = 2)

CCDTS_Log_D1D2 <- cbind(names = rownames(CCDTS_Log_D1D2), CCDTS_Log_D1D2)

D3_CCDTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1),
              data = subset(dataCCDTS, Param == "D3"),
              family = binomial) #Main effects only

D5_CCDTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1),
                data = subset(dataCCDTS, Param == "D5"),
                family = binomial) #Main effects

X_CCDTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1),
               data = subset(dataCCDTS, Param == "X"),
               family = binomial) #Main effects

Z_CCDTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1),
               data = subset(dataCCDTS, Param == "Z1"),
               family = binomial) #Main effects

CCDTS_Log_main <- round(cbind(D3Estimate = D3_CCDTS$coefficients,
                              D3SE = summary(D3_CCDTS)$coefficients[,2],
                              D3TVal = summary(D3_CCDTS)$coefficients[,3],
                              D3PVal = summary(D3_CCDTS)$coefficients[,4],
                              D3OR = exp(D3_CCDTS$coefficients),
                              D3_CoxEffect = D3_CCDTS$coefficients/1.65,
                              D5Estimate = D5_CCDTS$coefficients,
                              D5SE = summary(D5_CCDTS)$coefficients[,2],
                              D5TVal = summary(D5_CCDTS)$coefficients[,3],
                              D5PVal = summary(D5_CCDTS)$coefficients[,4],
                              D5OR = exp(D5_CCDTS$coefficients),
                              D5_CoxEffect = D5_CCDTS$coefficients/1.65,
                              XEstimate = X_CCDTS$coefficients,
                              XSE = summary(X_CCDTS)$coefficients[,2],
                              XTVal = summary(X_CCDTS)$coefficients[,3],
                              XPVal = summary(X_CCDTS)$coefficients[,4],
                              XOR = exp(X_CCDTS$coefficients),
                              X_CoxEffect = X_CCDTS$coefficients/1.65,
                              ZEstimate = Z_CCDTS$coefficients,
                              ZSE = summary(Z_CCDTS)$coefficients[,2],
                              ZTVal = summary(Z_CCDTS)$coefficients[,3],
                              ZPVal = summary(Z_CCDTS)$coefficients[,4],
                              ZOR = exp(Z_CCDTS$coefficients),
                              Z_CoxEffect = Z_CCDTS$coefficients/1.65),
                        digits = 2)
```

```
CCDTS_Log_main <- cbind(names = rownames(CCDTS_Log_main), CCDTS_Log_main)

D4_CCDTS <- glm(cov ~ (nRATE+nSCH+nSTU+nVAR+nLOGHAZ_T1)^3,
              data = subset(dataCCDTS, Param == "D4"),
              family = binomial)#3 way is best

CCDTS_Log_D4 <- round(cbind(D4Estimate = D4_CCDTS$coefficients,
                         D4SE = summary(D4_CCDTS)$coefficients[,2],
                         D4TVal = summary(D4_CCDTS)$coefficients[,3],
                         D4PVal = summary(D4_CCDTS)$coefficients[,4],
                         D4OR = exp(D4_CCDTS$coefficients),
                         D4_CoxEffect = D4_CCDTS$coefficients/1.65),
                   digits = 2)

CCDTS_Log_D4 <- cbind(names = rownames(CCDTS_Log_D4), CCDTS_Log_D4)

CCDTS_Log <- merge(CCDTS_Log_D1D2, CCDTS_Log_main, by = "names", all = TRUE, sort =
FALSE)
CCDTS_Log <- merge(CCDTS_Log, CCDTS_Log_D4, by = "names", all = TRUE, sort = FALSE)

rm(D1_CCDTS, D2_CCDTS, D3_CCDTS, D4_CCDTS, D5_CCDTS, X_CCDTS, Z_CCDTS,
   CCDTS_Log_main, CCDTS_Log_D4, CCDTS_Log_D1D2)

#Save Results

write.csv(EstModels, "BiasResults.csv")
write.csv(AnovaResults, "RPB_AnovaResults.csv")
write.csv(DTS_Log, "CoverageResultsDTS.csv")
write.csv(MLDTS_Log, "CoverageResultsMLDTS.csv")
write.csv(CCDTS_Log, "CoverageResultsCCDTS.csv")
```

Technical Appendix E: Descriptive Statistics from the Generated Datasets

```
library(parallel)

MOBILE_STATS <- function(filename) {

  library(plyr)

  dat_MOB <- read.csv(file = filename, header = TRUE)
  MOB_STATS1 <- ddply(dat_MOB, c("MOB_PATTERN"), summarize,
                      nMOB_T2 = sum(MOB_T2),
                      nMOB_T3 = sum(MOB_T3),
                      nMOB_T4 = sum(MOB_T4))

  numSTU <- dat_MOB[1, 22]*dat_MOB[1, 23]
  numMobSTU <- numSTU*dat_MOB[1, 21]

  MOB_STATS1 <- cbind(MOB_STATS1,
                      nPROP_PATTERN1 = ifelse(MOB_STATS1$MOB_PATTERN == 1,
                                              MOB_STATS1$nMOB_T2/numMobSTU, 0),
                      nPROP_PATTERN2 = ifelse(MOB_STATS1$MOB_PATTERN == 2,
                                              MOB_STATS1$nMOB_T3/numMobSTU, 0),
                      nPROP_PATTERN3 = ifelse(MOB_STATS1$MOB_PATTERN == 3,
                                              MOB_STATS1$nMOB_T4/numMobSTU, 0),
                      nPROP_PATTERN4 = ifelse(MOB_STATS1$MOB_PATTERN == 4,
                                              MOB_STATS1$nMOB_T3/numMobSTU, 0),
                      nPROP_PATTERN5 = ifelse(MOB_STATS1$MOB_PATTERN == 5,
                                              MOB_STATS1$nMOB_T4/numMobSTU, 0),
                      PROPA_MOB = (sum(ifelse(MOB_STATS1$MOB_PATTERN == 1,
                                              MOB_STATS1$nMOB_T2, 0),
                                       ifelse(MOB_STATS1$MOB_PATTERN == 2,
                                               MOB_STATS1$nMOB_T3, 0),
                                       ifelse(MOB_STATS1$MOB_PATTERN == 3,
                                               MOB_STATS1$nMOB_T4, 0),
                                       ifelse(MOB_STATS1$MOB_PATTERN == 4,
                                               MOB_STATS1$nMOB_T3, 0),
                                       ifelse(MOB_STATS1$MOB_PATTERN == 5,
                                               MOB_STATS1$nMOB_T4,
                                              0))
                                   /numSTU))
    rm(numSTU)


  MOB_STATS1 <- as.matrix(cbind(nREP = dat_MOB[1, 20], nRATE = dat_MOB[1, 21],
                                nSCH = dat_MOB[1, 22], nSTU = dat_MOB[1, 23],
                                nVAR = dat_MOB[1, 24], nLOGHAZ_T1 = dat_MOB[1, 25],
                                UniqueID = dat_MOB[1, 30], MOB_STATS1))

  rm(numMobSTU)

  return(MOB_STATS1)
}

filenames <- list.files(path = "ComputerPath", pattern = "csv", full.names = TRUE)

system.time({
  cl <- makeCluster(mc <- getOption("cl.cores", 6))
  mobilityDescriptives <- parLapply(cl, filenames, MOBILE_STATS)
  stopCluster(cl)
})

MOB_DESC <- data.frame(do.call(rbind, mobilityDescriptives))
rm(filenames, MOBILE_STATS)
```