Summer 8-2011

The Path from Foster Care to Permanence: Does Proximity Outweigh Stability?

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THE PATH FROM FOSTER CARE TO PERMANENCE:

DOES PROXIMITY OUTWEIGH STABILITY?

by

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Under the Direction of Gengsheng (Jeff) Qin

ABSTRACT

This thesis investigates the relationship between foster care placement settings and discharges. Placement settings are where foster children live: foster homes, group homes, etc. There may be one or several placements for any individual child. In the interest of stability, federal funding to states depends in part on low numbers of placement moves. Federal reviews, however, do not consider whether the placement settings resemble permanent family life (foster homes compared to congregate care) or the direction of placement moves. Competing risks regression was used to analyze time to discharge data of foster children in Georgia. Discharges (competing risks) were compared based on the number and the direction of placement moves. Children with movement patterns that favored placements similar to permanent family life were found to have higher probabilities of discharges to safe permanence. This thesis promotes "proximity to permanence" as an important, but often overlooked, consideration in foster care placements.

INDEX WORDS: Adoption, Competing risks regression, Discharge, Foster care, Permanence, Placement, Reunification

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of

Master of Science

in the College of Arts and Sciences

Georgia State University

2011

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August 2011

ACKNOWLEDGEMENTS

Many thanks to Christopher Church, Dr. Jeff Qin, Dr. Xu Zhang, Dr. Jiaweh Liu, Dr. Yu-Sheng Hsu, Dr. Draga Vidakovic, Dr. Jun Han, Dr. Yichuan Zhao, Dr. Yixin Fang, the students of the Georgia State statistics department, Sutandra Sarkar, Rachele Ulysse, Andy Barclay, Marcy Fost, Kenneth Fost, Dan Fost, Mr. Jim Sams, Bat Walden.

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1 INTRODUCTION

1.1 Background

In the United States last year, there were over 250,000 children living in foster care (1. Administration for Children and Families). In Georgia, over 5000 children were removed from their homes and placed in foster care (15. Fostering Court Improvement). Having already endured an unhealthy environment at home, these children were separated from their families and the lives they have known.

As soon as a child is removed from his/her family, the state seeks to provide *safe*, *stable* care. Several **placement settings** are possible:

1 Trial home visit
2 Pre-adoptive home
3 Foster family home, relative
4 Foster family home, non-relative
5 Group home
6 Institution
7 Supervised independent living
8 Runaway

All except Runaway can be assigned by the state Division of Child and Family Services (DFCS). The placements are not all equivalent. Clearly, the top of the list includes entries that are more similar to - and may be more likely to lead to – discharges from foster care to family life.

Discharges from foster care also are sorted into 8 categories:

1 Reunification with parent or primary caretaker
2 Adoption by other relatives
3 Adoption by non-relatives
4 Guardianship
5 Emancipation
6 Transfer to another agency
7 Runaway
8 Death of child

The first three in the list are preferable to the rest. Runaway and death are obviously unacceptable outcomes. Emancipation and transfer also are undesirable. Guardianship is less ideal than reunification or adoption. Children who fail to unite with a permanent family of some kind are less likely to enjoy success in life, as measured by high school and college degrees, homelessness, and other indicators. (3. Courtney and Hughes, 2005).

Federal funding of state foster systems is dependent on periodic reviews called Child and Family Services Reviews (CFSR). The CFSR measures several indicators of safety, timeliness, and stability of foster care and discharges. Safety is measured by abuse rates in care, and rates of re-entry into care. Timeliness is measured by median lengths of stay in care. Stability is measured by the number of placement moves - fewer are better.

The *quality* of placements and placement moves is not often measured, and not included in the CFSR.   States that move too many children too frequently risk the loss of federal funding. The notion is well-founded, as each move disturbs the stability of the life of the child. However, the benefit of a move in the right direction may outweigh the disruption it causes. For example, moves from institutional care to a private foster home may be beneficial, yet are discouraged by the current system of review.

There may be many arguments about the suitability of one placement type or another. Psychological, emotional, educational, and financial considerations, among others, are all relevant. This thesis doesn't investigate any of those aspects.

This study focuses on the statistical probability of discharges to safe permanence, here defined as Adoption, Reunification with Family, Reunification with Other Relatives, or Guardianship, **depending on foster care placement history**. The word "permanence" refers to permanent associations with families.   "Safe" means the discharge to permanence lasts at least one year.

For foster children with only a single placement, the difference between congregate care (group homes and institutions) versus non-relative foster homes is investigated.

For children with more than one placement per foster care episode, the difference between placement histories is investigated. The list of placement settings: 1 Reunification with parent or primary caretaker, 2 Adoption by other relatives, 3 Adoption by non-relatives, 4 Emancipation, 5 Guardianship, 6 Transfer to another agency, 7 Runaway, 8 Death of child, is ordered by "**Proximity to Permanence**" (2. Andy Barclay). The lower-numbered members of the list are "nearer" to permanence. Each placement change in a foster care episode may thus be ranked as either Toward Permanence, Lateral, or Away from Permanence. Children with exactly two placements have exactly one move. The question is whether the direction of the moves is associated with lengths of stay and types of discharge. Children with more than two placements have more than one move, so their career is here categorized as Toward Permanence (no moves away from permanence, at least one move toward permanence), Lateral (all moves to the same type of placement), Forward and Backward (moves both toward and away from permanence, in any order), and Away from Permanence (no moves toward permanence, at least one move away from permanence. See Table 2.1.

Table 1.1 Summary of Placement History Types by Number of Placements

One Placement (0 Moves)	Two Placements (1 Move)	Three Placements (2 Moves)	More Than Three Placements (Latest 3 Moves Used)
Congregate Care, Foster Home (Non-relative)	Toward Permanence, Lateral, Away from Permanence	Toward Permanence, Lateral, Toward and Away from Permanence, Away from Permanence	Toward Permanence, Lateral, Toward and Away from Permanence, Away from Permanence

1.1 Purpose of the Study

This thesis investigates the probability of discharge from foster care to safe permanence based on type of placement history. For one-placement episodes, the histories examined are limited to congregate care and non-relative foster homes. For multiple placement episodes, the movement history is determined to be one of several categories (refer to Table 2.1) based on a ranking of placements that favors proximity to permanence. Placement histories with higher probability of discharge to safe permanence can be considered better than histories with lower probabilities, at least in this one aspect.

Decisions about appropriate placements or placement moves should consider the probability of favorable discharge, in addition to other more commonly discussed factors such as psychological, social, and emotional impact, financial considerations, etc.

2 Methods

2.1 Data Source

The data source is the Adoption and Foster Care Analysis and Reporting System (AFCARS). All states, as well as Puerto Rico and the District of Columbia, are required to supply foster care and adoption data twice annually. Foster care files from the state of Georgia, years from 1998 to 2008, were used for the current thesis.

Foster care files contain child-level information for up to 66 variables, including demographic information such as gender, birth date, and race, plus foster care episode information such as date and reason for removal, placement type, discharge date and type if applicable, among others.

The National Data Archive on Child Abuse and Neglect (NDACAN), located at Cornell University, distributes the AFCARS data (9. "NDACAN").

2.2 Record Linking

The AFCARS data contain some identifiers, for example birth date, race/ethnicity, and gender, of foster children. However, the data do not contain unique identifiers, and does not link the data from one 6 month period to the next. In order to create a longitudinal data set for survival analysis, the children in the semi-annual reports were linked by birth date, gender, and first removal from home. Other variables, such as race, ethnicity, age of primary caretaker, age of first foster parent, and some others were used to verify, link, or unlink records as necessary. Missing data and data errors were frequently encountered.

Each AFCARS data set only lists the latest placement setting, so if there were more than one placement within the 6 month reporting period, the earlier placements are lost. The number of placements is recorded, so it is evident when this has occurred. The direction of placement moves is essential to this analysis, so children with missing values for placements were excluded from the thesis. It is not known if the values are missing at random, so this is a potential source of bias in the analysis.

2.3 Survival Analysis Background

The goal of the analysis was to examine length of stay in foster care (for various placement histories) until discharge to safe permanence. Permanence in this sense refers to permanent associations with families. Children still in care were censored. Other children exited without permanent associations with families - to emancipation, transfer, runaway, and death. These “non-permanent” outcomes were treated as a single competing risk.

Under the competing risks model setting, it is not appropriate to use the usual Kaplan-Meier estimator to estimate the probability of discharge to permanence. The Kaplan-Meier estimator here would represent the (net) probability of discharge to permanence in a hypothetical world in which there were no discharges to non-permanence. This would overestimate the true probability of discharge to permanence (7. Klein, Rizzo, et al., 2001).

Instead, crude probabilities were utilized. Crude probabilities are probabilities of discharges from a particular cause in the real world where all other risks are acting on individuals. These probabilities can be obtained from the cumulative incidence curves created for each type of placement history for comparison. (See Table 2.1 for types of placement histories.) The cumulative incidence curve represents the probability of an event in the presence of competing risks and censored data. In this case, the event of interest was discharge to safe permanence. All other discharges were treated as a single competing risk. Those still in care at the end of the data period were censored. Unadjusted cumulative incidence curves were created for each type of placement history for comparison (Figure 2.3).

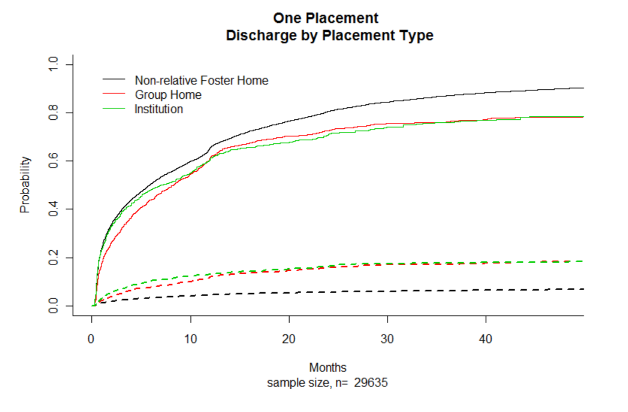

Figure 2.3a

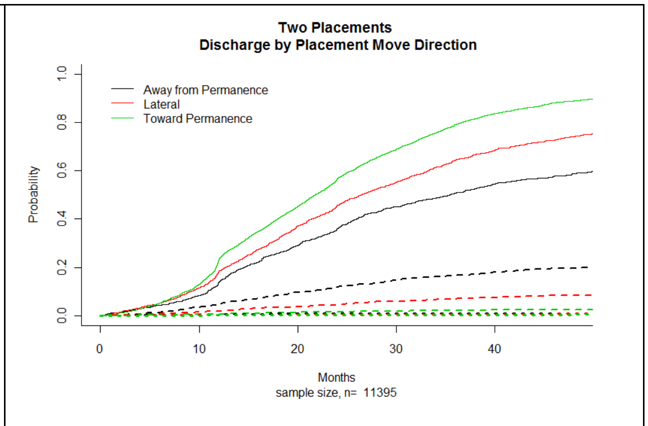

Figure 2.3b

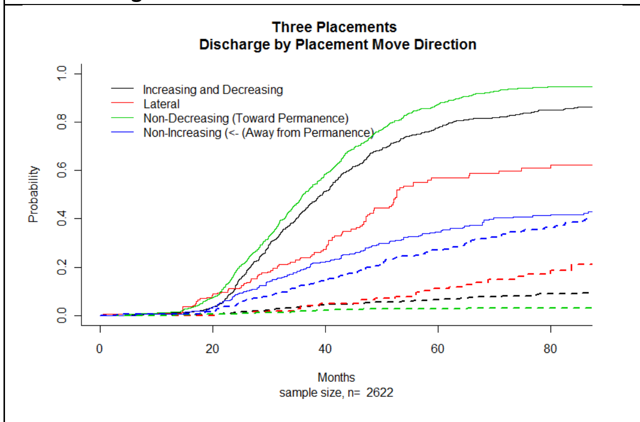

Figure 2.3c

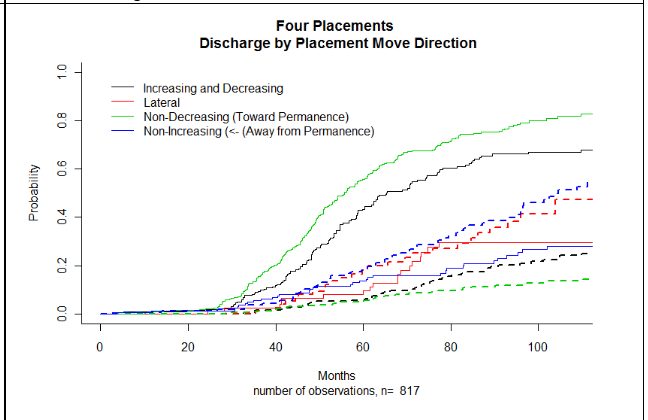

Figure 2.3d Four or More Placements: Last 3 Moves

Solid lines represent cumulative incidence curves for discharges to permanence.
Dotted lines represent cumulative incidence curves fro discharges to non-permanence.

Figure 2.3 Unadjusted Cumulative Incidence Curves by Placement Move Histories

The curve in Figure 2.3a seems to show that non-relative foster homes, compared to group homes or institutions, are associated with higher probability of discharge to permanence (solid curves), and lower probability of discharge to non-permanence (dotted curves). Likewise, Figures 2.3 b, c, and d suggest that movement histories toward permanence are associated in probability with discharges to permanence.

There are many factors that could influence time until discharge, so cumulative incidence curves should be adjusted for covariates (Section 3). In each adjusted cumulative incidence curve, the placement history was treated as one of the covariates so that tests for significance could be performed. Data were separated into sets for children with only one placement, children with two placements, children with three placements, and children with four or more placements. In addition, because the analyses were computationally expensive, some of the data were broken into different time periods to make the data sets smaller. This had the beneficial side effect of allowing evaluation of trends or differences over several years of testing.

The most popular method for adjusting Kaplan-Meier type survival curves is the Cox proportional hazards model. Fine and Gray (4. 1999) developed an analog to this method for cumulative incidence curves. By modeling the hazard function for the subdistribution functions for each of the competing risks, Fine and Gray created a "proportional hazards" method that could be applied to cumulative incidence curves. An advantage of the method is that the effects of covariates can be interpreted in familiar ways. A disadvantage is the requirement of proportional hazards assumptions. Non-proportional hazards can still be analyzed using Fine and Gray's model, but more elaborate methods are required.

Scheike, Zhang and Gerds (11. 2008) developed a flexible model for estimating adjusted cumulative incidence curves that includes Fine and Gray's model as a special case. The flexible model does not require any proportional hazards assumptions, and allows some covariates to have time-varying effects while others have constant effects. A disadvantage is that values of coefficients of covariates may be difficult to interpret, and the time-varying effects are estimated non-parametrically, so do not yield coefficients at all. The purpose of the regression in this thesis was to adjust the curves so that the placement histories could be compared on a "level playing field", not to determine which covariates were important or what the effects of certain covariates were (other than placement history). Scheike and Zhang (2011) provide the mathematical details:

Assuming two types of failures, k = 1; 2, the cumulative incidence function for cause 1 given a set of covariates x is given by

$$P_1(t,x) = P(T \leq t, \epsilon = 1|z) = \int_0^t \lambda_1(s;x)\exp\left[-\int_0^t \{\lambda_1(u;x) + \lambda_2(u;x)\}\,du\right] ds, \quad (1)$$

where T is the failure time, ϵ indicates the cause of failure and $\lambda_k(t; x)$ is the hazard of the k^{th} cause of failure conditional on x, which is defined as

$$\lambda_k(t;x) = \lim_{\Delta t \to 0} \frac{1}{\Delta t} P\{t \leq T \leq t + \Delta t, \epsilon = k | T \geq t\}.$$

Here, the cause-specific hazards for all causes need to be properly modeled. Cox's proportional hazards model is the most popular regression model in survival analysis and here the hazard function is given by

$$\lambda_k(t;x) = \lambda_{k0}(t) exp\{x^T \beta\}$$

where λ_{k0} is a cause-specific baseline and β are regression coefficients....

...<Scheike and Zhang> considered a class of flexible models of the form

$$h\{P_1(t; x, z)\} = x^T \alpha(t) + g(x, \gamma, t) \quad (2)$$

where h and g are known link functions and α(t) and γ are unknown regression coefficients (see Scheike et al., 2008, SZG). .. Any link function can be considered and used here. In this study we focus on ...additive models

$$-\log\{1 - P_1(t;\ x;\ z\}) = x^T\alpha(t) + (z^T\gamma)t. \quad (4)$$

The regression coefficients α(t) and γ are estimated by a simple direct binomial regression approach. We have developed a function, comp.risk(), available in the R package timereg, that implements this approach. In addition we have proposed a useful goodness-of fit test to identify whether time-varying effect is present for a specific covariate.

The Scheike and Zhang model (and its special case, the Fine and Gray model) can be relatively easily implemented using the R package timereg. The Scheike and Zhang model (4) is used throughout the analyses in this thesis.

2.4 Competing Risks Regression of the Cumulative Incidence Curves: Specifics

The topic of interest is whether the placement history influences the probability of discharge to safe permanence. Recall that the placement history examined here is defined as: 1. Congregate Care versus Non-relative Foster Home (for single placement episodes) or 2. Overall course of moves, such as Toward Permanence, Lateral, Away from Permanence, or Both Toward and Away from Permanence.

Therefore a variable was created to represent the placement history in each data set. This variable, either an indicator for Congregate Care (single placement episodes) or a dummy-coded multilevel factor called Coursematrix (multiple placement episodes) was included in all models so it could be tested. In addition, each model initially included combinations of about 24 other potential covariates. The exact number is not consistent because of dummy coding and the need to combine some variables in many cases where there were very few observations. For example, there are AFCARS variables for Reason for Removal: Alcohol Use by Parent and Reason for Removal: Alcohol Use by Child. In every data set, there were very few or 0 cases of Reason for Removal: Alcohol Use by Child, so the two variables were combined into a single Reason for Removal: Alcohol Use. See Table 2.4.1 (a, b, and c) for a list of the initial covariates.

Table 2.4.1 a Variable of Interest: Placement History

Placements	**Variable(s)**	**Values**
One	cong	1 if congregate care; 0 Otherwise
Two	coursematrix	Column 1: 1 if Away from Permanence; 0 Otherwise Column 2: 1 if Toward Permanence; 0 Otherwise baseline: Lateral (Columns 1 and 2 both equal 0)
Three or More	coursematrix	Column 1: 1 if Toward and Away from Permanence; 0 Otherwise Column 2: 1 if Toward Permanence; 0 Otherwise Column 3: 1 if Away from Permanence; 0 Otherwise baseline: Lateral (Columns 1, 2, 3 all equal 0)

Table 2.4.1 b Covariates: Child Characteristics

Column Number	Definition	Notes
85	Gender	Male versus baseline Female
86	Child has Disability	
87	Presence of Disability Unknown	
88	Child Mentally Retarded	
89	Child Visually or Hearing Impaired	Usually combined with 90 into physvishear
90	Child Physically Disabled	Usually combined with 89 into physvishear
91	Child Emotionally Disturbed	
92	Child Other Medical Conditions	
93	Total Number of Removals	Minimum 1, includes current removal. May be changed to numrem: indicator for more than 1 removal; or NumRemMat: matrix, first column indicates 2 removals; second column indicates 3 or more removals.
111	Age of Primary Caretaker	
112	Not Eligible for Federal Aid	Indicator: 1 if NOT eligible
113	Race	Usually White versus baseline Black; May be coded into wbo or wbm for White, Black, Other, or White, Black, Mixed BW
114	Child Age at Removal	Continuous variable

Table 2.4.1 c Covariates: Removal-Related Characteristics

Column Number	Definition	Notes
94	Manner of Removal	Voluntary versus baseline Court-Ordered
96	Reason for Removal: Physical Abuse	
97	Reason for Removal: Sexual Abuse	
98	Reason for Removal: Neglect	
99	Reason for Removal: Parent Alcohol Use	Usually combined with 101 into RRAlcohol
100	Reason for Removal: Parent Drug Use	Usually combined with 102 into RRDrug
101	Reason for Removal: Child Alcohol Use	Usually combined with 99 into RRAlcohol
102	Reason for Removal: Child Drug Use	Usually combined with 100 into RRDrug
103	Reason for Removal: Child Disability	Sometimes combined with 104 into blamechild
104	Reason for Removal: Child Behavior	Sometimes combined with 103 into blamechild
105	Reason for Removal: Parent Death	
106	Reason for Removal: Parent Incarceration	
107	Reason for Removal: Parent Can't Cope	
108	Reason for Removal: Abandonment	Often combined with 109 into relinqaband
109	Reason for Removal: Relinquishment	Often combined with 108 into relinqaband
110	Reason for Removal: Inadequate Housing	

Backward selection was used to create the regression models for the cumulative incidence curves. First, a full model was fit using all the possible covariates and all covariates were treated non-parametrically as time-varying. At each stage, each coefficient $\alpha(t)$ was tested, H_0: $\alpha(t) = 0$, following Scheike and Zhang (2008, 2011) and the variable with the highest p-value greater than 0.05 was removed. When there were no more variables meeting that criterion, the variables were inspected for time-varying or constant effects. The variable with the highest p-value for H_0: $\alpha(t)$ is constant, using a Cramer von Mises-type test. The R package, timereg function comp.risk() also provides Kolmogorov-Smirnov- type tests for constant effects. Cramer von Mises and Kolmogorov-Smirnov tests had close agreement with each other. At each subsequent stage, either a variable was removed from the model, or a time-varying variable was changed to constant. When no more p-values greater than 0.05 remained, the model was considered final.

Note that the variable of interest, the placement history variable, was kept in the model as time-varying in all analyses with more than one placement. That is because the time-varying behavior was of interest, and also because the variable by its own nature is time-varying (the changing course of placements over the foster care history), so it made sense to keep it as such. In most cases, the variable tested as time-varying, but not always. For models with only a single placement, the variable of interest was just the indicator for congregate care, with baseline non-relative foster home. This variable was allowed to have a constant effect in the rare cases where the math dictated it.

3 RESULTS

3.1 One Placement Setting

Data for children with exactly one placement were the most common. To make computations possible, the data were divided into 6-month periods, and evaluated for children entering foster care in Georgia between the federal fiscal years of 2005 and 2008. The variable of interest here is "cong", an indicator for congregate care, which includes group homes and institutions. "Cong" equals 1 if the child was placed in congregate care, or 0 if the child was placed in a non-relative foster home. Other placements were excluded from this part of the analysis. The reason is that the two "competing" placements, congregate care and non-relative foster home, represent conflicting ideas on foster child placement. Other placements are less disputed. Relative foster home is generally desired. Emancipation is to be avoided.

Note that the effect of congregate care on ultimate discharge may not be uniform over time, so results may vary from one data set to another, because they are separated into 6 month periods based on the two halves of federal fiscal years (FFY).

3.1.1 One Placement Setting. April 1, 2008 to September 30, 2008

Data include only children with a single placement, in a non-relative foster home, or in congregate care. There are 901 observations. The final model includes 3 time-varying covariates and 10 constant covariates (Table 3.1.1). The final model takes the form

$$-\log\{1 - P_1(t;\ x;\ z\}) \ = \ x^{T}\alpha(t) + \ (z^{T}\gamma)t, \qquad (4)$$

in which $\alpha(t)$ are time varying effects, estimated non-parametrically and γ are constant effects. The same basic model is used throughout the analyses, but the covariates included and values change for each subset of data.

Table 3.1.1 Variables in Final Regression Model, FFY 2008 Final 6 Months

Terms	Definitions	Terms	Definitions
data1$cong	Indicator : Congregate vs baseline Non-relative	const(data1[, 106])	Removal Reason: Parent Incarceration
const(data1[, 87])	Presence of Disability Not Known	const(data1[, 108])	Removal Reason: Abandonment
const(data1[, 90])	Physically Disabled	const(data1[, 110])	Removal Reason: Inadequate Housing
const(data1[, 91])	Emotionally Disturbed	data1[, 112]	dataset.EligNone
data1[, 92]	Other Medical Conditions	const(data1[, 114])	Age Latest Removal
data1[, 98]	Removal Reason: Neglect	const(wbmf)MixBW	Mixed Race BW (vs Black)
const(data1[, 105])	Removal Reason: ParentDeath	const(wbmf)White	Indicator: White (vs Black)

The variable data1$cong, the indicator for congregate care, was significant with p-value 0.036. It was marginally time-varying, with Cramer von Mises p-value 0.063 and Kolmogorov-Smirnov p-value 0.119. The data set only included children who entered care between after April 1, 2008, and the end of the report period was September 30, 2008, so there was not a lot of time to see the eventual outcomes. The summary output is included in Appendix A 3.1.1.

Figure 3.1.1 shows the cumulative incidence curves for Congregate Care and Non-relative Foster Home, with all other covariates held at baseline. Here children in congregate care had generally greater probabilities of discharge to permanence compared to children in non-relative foster homes. As will be seen, this is unusual within this thesis, and is probably because the sample is limited to a 6 month period and many foster care discharges require more than 1 year.

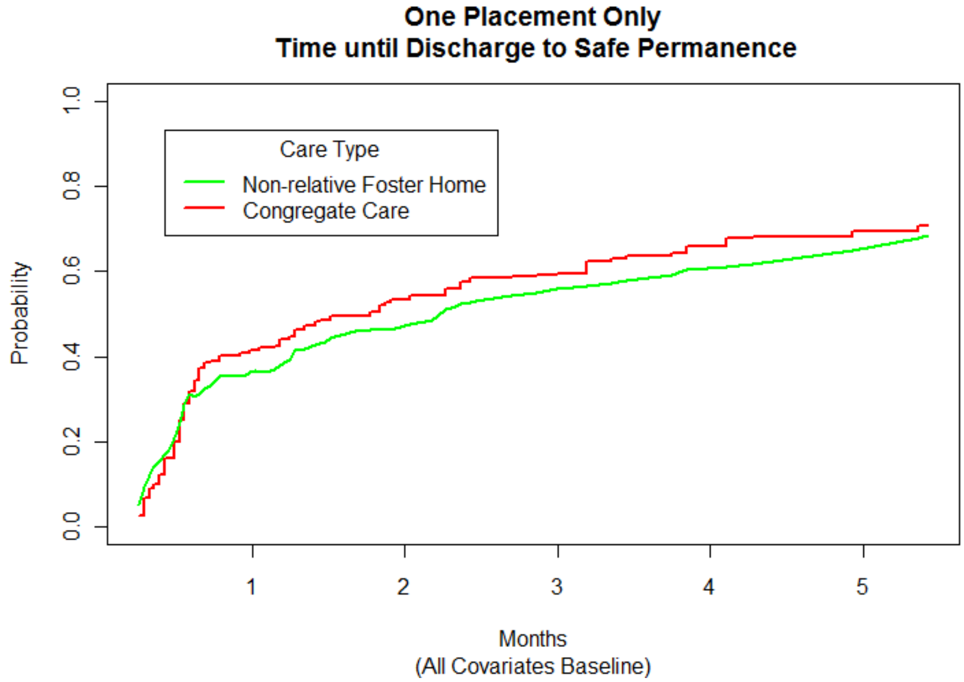

Figure 3.1.1 Cumulative Incidence Curves: FFY 2008 Final 6 Months

3.1.2 One Placement Setting. October 1, 2007 to March 31, 2008

There were 813 children in this data set. The final model included 6 time-varying and 3 constant covariates, along with the congregate care indicator. As in the last half of FFY 2008, congregate care was associated with greater probability of discharge to permanence than non-relative foster care, p=0.018. Once again, caution is advised, because these results are not typical of the thesis, and the children in question only have data for a maximum of one year, which may not be enough time to demonstrate the true effect of the placement. This view may provide insight into the time-varying nature of the placement, and it is possible that congregate care truly leads to more or faster discharges to permanence than non-relative foster homes, during the first 6 months to 1 year of foster care. The variables can be found in Table 3.1.2. The summary output is included in Appendix A 3.1.2.

Table 3.1.2 Covariates in Final Regression Model, FFY 2008 First 6 Months

Terms	Definitions	Terms	Definitions
data1$cong	Indicator (Congregate)	data1[, 108]	Removal Reason: Abandonment
data1[, 87]	dataset.Disability.3	data1[, 109]	Removal Reason: Relinquishment
data1[, 96]	Removal Reason: Physical Abuse	data1[, 112]	Not Eligible for Aid $
data1[, 105]	Removal Reason: Parent Death	const(NumRemMat[, 2])	Indicator (removals>2)
const(data1[, 107])	Removal Reason: Caretaker Can't Cope	const(RRdrug1)	Removal Reason: Drugs, Parent or Child

Figure 3.1.2 shows the cumulative incidence curves for Congregate Care and Non-Relative Foster Home with all other covariates at baseline.

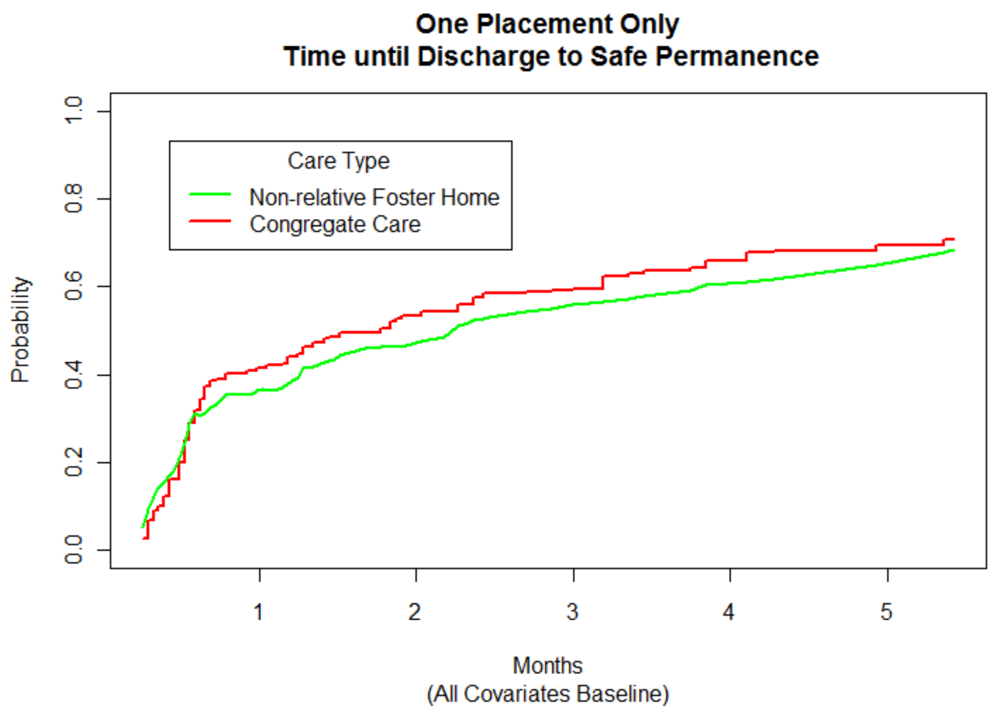

Figure 3.1.2 Cumulative Incidence Curves, FFY 2008 First 6 Months

3.1.3 One Placement Setting. April 1, 2007 to September 30, 2007

There were 1568 observations in this data set, which includes children removed from their homes during the last 6 months of FFY 2007, and placed into congregate care or non-relative foster care. The final regression model has 2 time-varying and 7 constant terms in addition to the variable of interest, the indicator for congregate care (Table 3.1.3). The summary output for the final model may be found in Appendix A 3.1.3.

Table 3.1.3 Covariates in Final Model, FFY 2007 Last 6 Months

Terms	Definitions	Terms	Definitions
data1$cong	Indicator (Congregate)	const(data1[, 108])	RR* Abandonment
data1[, 87]	Unknown If Disability	const(data1[, 109])	Relinquishment
const(data1[, 94])	Removal Voluntary (vs Court)	const(data1[, 111])	Age Primary Caretaker
data1[, 96]	RR* Physical Abuse	const(data1[, 112])	Not Eligible for Aid $
const(data1[, 98])	RR* Neglect	const(RRdrug1)	Drugs, parent or child

* RR: Reason for Removal

Figure 3.1.3 shows that non-relative foster care is associated with greater probabilities of discharge to permanence for the data set under investigation. The difference is significant, p=0.03, and the effect is time-varying, p=0.012.

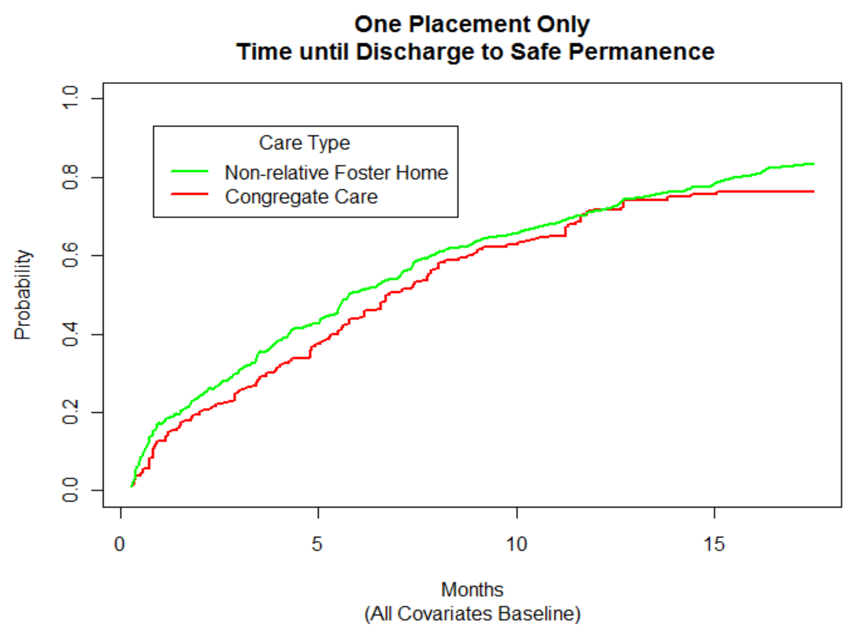

Figure 3.1.3 Cumulative Incidence Curves, FFY 2007 Last 6 Months

3.1.4 One Placement Setting. October 1, 2006 to March 31, 2007

1071 Children are included in the data set. The regression model includes 2 time-varying covariates and 5 constant covariates in addition to the indicator for congregate care (Table 3.1.4). Congregate Care is only marginally significant at p=0.05, compared to the baseline, Non-Relative Foster Family Homes. The output for the final model may be found in Appendix A 3.1.4.

Table 3.1.4 Covariates in Final Model, FFY 2007 First 6 Months

Terms	Definitions	Terms	Definitions
data1$cong	Indicator (Congregate)	const(data1[, 98])	Removal Reason: Neglect
data1[, 87]	Presence of Disability Not Known	const(data1[, 108])	Removal Reason: Abandonment
const(data1[, 94])	Removal Voluntary	const(data1[, 112])	Not Eligible for Aid $
data1[, 96]	Removal Reason: Physical	const(RRdrug1)	Removal Reason:

Figure 3.1.4 displays the cumulative incidence curves, adjusted to baseline levels of all nuisance covariates.

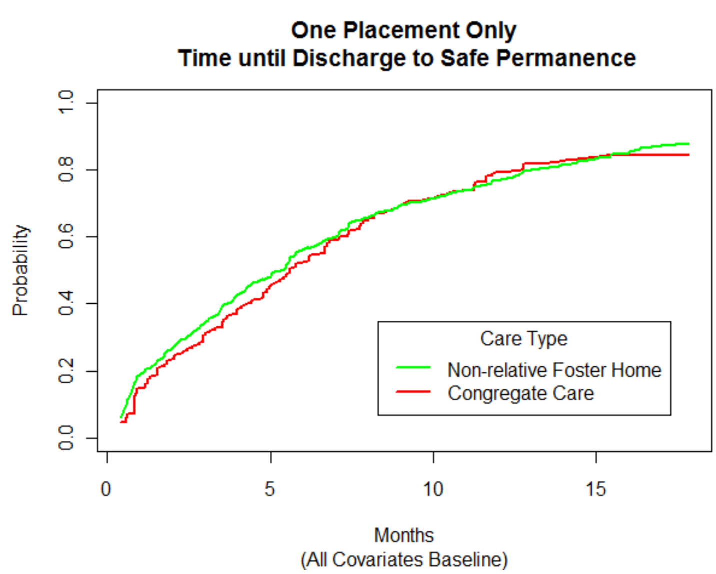

Figure 3.1.4 Cumulative Incidence Curves, FFY 2007 First 6 Months

3.1.5 One Placement Setting. April 1, 2006 to September 30, 2006

This data set includes 1164 observations. In this regression analysis, congregate care behaved as a constant effect, and it was significant at p=0.0321. The rest of the model included 4 other constant terms and four time-varying terms (Table 3.1.5). The output for the final model may be found in Appendix A 3.1.5.

Table 3.1.5 Covariates in the Final Model, FFY 2006 Last 6 Months

Terms	**Definitions**	**Terms**	**Definitions**
data1$cong	Indicator (Congregate)	data1[, 112]	Not Eligible for Aid $
data1[, 87]	Presence of Disability Not Known	const(data1[, 114])	Age at Latest Removal
const(data1[, 94])	Removal Manner: Voluntary (versus Court)	const(RRdrug1)	Removal Reason: Drugs
data1[, 96]	Removal Reason: Physical Abuse	const(RRalcohol1)	Removal Reason: Alcohol (Parents)
data1[, 97]	Removal Reason: Sexual Abuse		

Figure 3.1.5 shows the cumulative incidence curves for the Congregate Care and Non-Relative Foster Family Homes, with the rest of the covariates held at baseline.

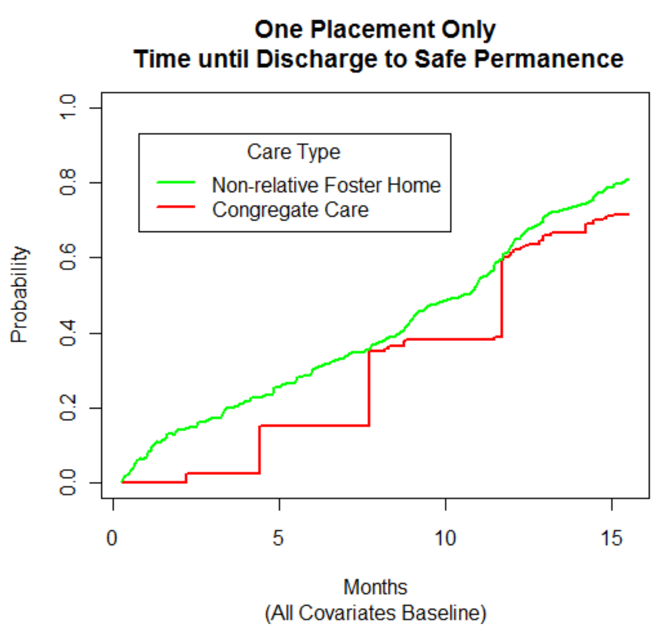

Figure 3.1.5 Cumulative Incidence Curves, FFY 2006 Last 6 Months

3.1.6 One Placement Setting. October 1, 2005 to March 31, 2006

The first half of FFY 2006 had 1309 observations. The regression model used 5 time-varying co-variates and 5 constant ones (Table 3.1.6). Congregate care appeared as a constant effect, but not significant, p=0.904. For children entering care during the period, there appeared no difference in probability of discharge to permanence for congregate care versus non-relative foster home. The output for the regression analysis may be found in Appendix A 3.1.6.

Table 3.1.6 Covariates in the Final Regression Model, FFY 2006 First 6 Months

Terms	**Definitions**	**Terms**	**Definitions**
const(data1$cong)	Indicator (Congregate)	const(data1[, 110])	Removal Reason: Inadequate Housing
data1[, 85]	Gender	data1[, 112]	Not Eligible for Aid $
data1[, 87]	Presence of Disability Not Known	const(blamechild)TRUE	Removal Reason: Child Behavior or Disability
const(data1[, 94])	Removal Manner Voluntary (vs. Court)	RR drug1	Reason for Removal: Drugs
data1[, 96]	Removal Reason: Physical Abuse	const(relinqaband)TRUE	Relinquishment or Abandonment
const(data1[, 98])	Removal Reason: Neglect		

Figure 3.1.6 shows the cumulative incidence curves are mostly overlapping for congregate care and non-relative foster homes, with all other covariates held at baseline.

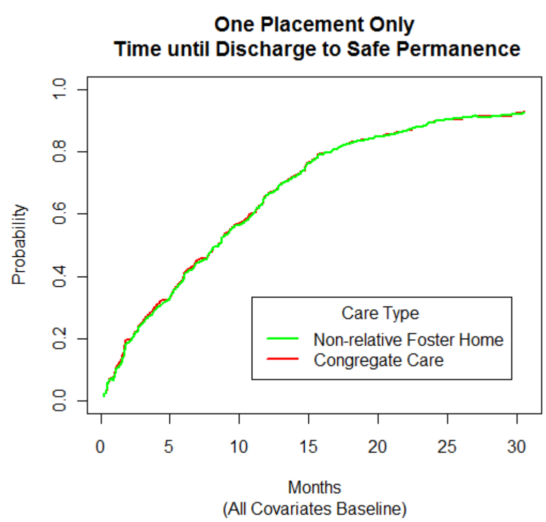

Figure 3.1.6 Cumulative Incidence Curves, FFY 2006 First 6 Months

3.1.7 One Placement Setting. April 1, 2005 to September 30, 2005

There were 1520 observations in the data set. Congregate care had a significant effect, with probability of discharge to permanence lower than that for non-relative foster family homes, p<0.001. The final model included 8 time-varying terms and 1 constant term (Table 3.1.7). The output for the regression model may be found in Appendix A 3.1.7.

Table 3.1.7 Covariates in the Final Model, FFY 2005 Last 6 Months

Terms	Definitions	Terms	Definitions
data1$cong	Indicator (Congregate)	data1[, 107]	RR Caretaker Can't Cope
data1[, 87]	Presence of Disability Unknown	data1[, 112]	Not Eligible for Aid $
const(data1[, 91])	Emotionally Disturbed	data1[, 114]	Age at Latest Removal
data1[, 94]	Removal Voluntary (vs Court)	RR* drug1	RR Drugs
data1[, 96]	RR* Physical Abuse	NumRemMat[, 2]	More than 2 Removals
data1[, 97]	RR* Sexual Abuse	wbmfWhite	Race White (vs baseline Black)
data1[, 98]	RR* Neglect		

*RR: Reason for Removal

Figure 3.1.7 shows the congregate care and non-relative foster homes cumulative incidence curves adjusted for baseline levels of all other covariates.

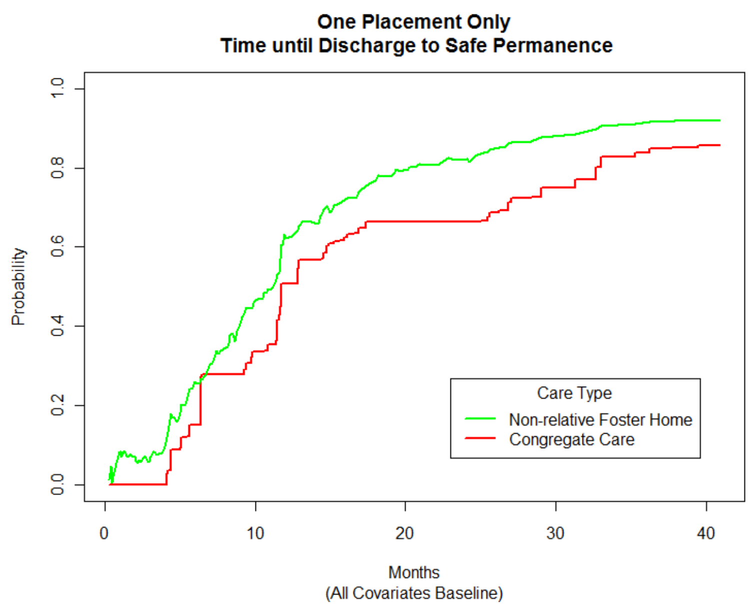

Figure 3.1.7 Cumulative Incidence Curves, FFY 2005 Last 6 Months

3.1.8 One Placement Setting. October 1, 2004 to March 31, 2005

1491 observations make up the first half of FFY 2005 data set. Congregate care had a significantly lower probability of discharge to permanence compared to non-relative foster homes, p=0.006. The final model included 4 other time-varying covariates and 2 constant covariates (Table 3.1.8). The summary output may be found in Appendix A 3.1.8.

Table 3.1.8 Covariates in Final Regression Model, FFY 2005 First 6 Months

Terms	**Definitions**	**Terms**	**Definitions**
data1$cong	Indicator (Congregate)	data1[, 112]	Not Eligible for Aid $
data1[, 87]	Presence of Disability Not Known	data1[, 114]	Age at Latest Removal
data1[, 94]	Removal Voluntary (versus Court Ordered)	const(relinqaband)	Relinquishment or Abandonment
const(data1[, 105])	Removal Reason: Parent Death		

Figure 3.1.8 displays the cumulative incidence curves for congregate care and non-relative foster family homes, adjusted for baseline levels of all nuisance covariates.

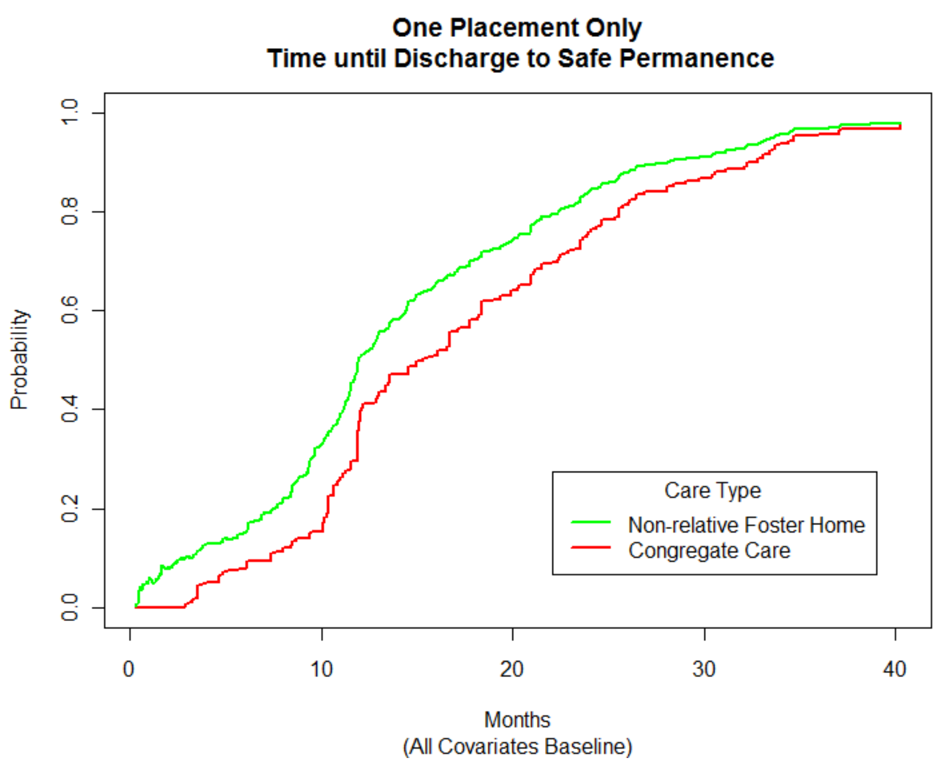

Figure 3.1.8 Cumulative Incidence Curves, FFY 2005 First 6 Months

3.2 Two Placement Settings

For children with two placements during their foster care stay, there is obviously only a single move. That move may be Toward Permanence, Lateral, or Away from Permanence. Thus, the matrix "coursematrix" was created to code two dummy variables for use in the models. The first column is an indicator equal to 1 if the move was away from permanence, 0 otherwise. The second column is an indicator equal to 1 if the move was toward permanence, 0 otherwise. Thus, if both columns are 0, the move was the baseline, lateral. In order to accommodate the large amount of data, samples were divided into calendar years.

3.2.1 Two Placements, Year 2007

The data set includes 1010 observations that entered foster care during calendar year 2007, and an additional 19 that entered care during 2008. The final regression model includes the coursematrix variables of interest, 2 other time-varying covariates, and 7 constant covariates (Table 3.2.1). The moves toward permanence were significantly different than the baseline lateral moves, p<0.001. The summary output may be found in Appendix A 3.2.1.

Table 3.2.1 Covariates in Final Regression Model, Year 2007

Terms	Definitions	Terms	Definitions
coursematrix[, 1]	Away from Permanence	const(data2[, 106])	Removal Reason: Parent Incarceration
coursematrix[, 2]	Toward Permanence	const(data2[, 107])	Removal Reason: Caretaker Can't Cope
const(data2[, 88])	Mental Retardation	const(data2[, 108])	Removal Reason: Abandonment
data4[, 96]	Removal Reason : Physical Abuse	data3[, 111]	Age Primary Caretaker
const(data2[, 98])	Removal Reason: Neglect	const(data2[, 112])	Indicator: Not Eligible for Federal Financial Aid
const(data2[, 105])	Removal Reason : Parent Death		

Figure 3.2.1 shows the cumulative incidence curves for the move histories: Toward Permanence, Lateral, Away from Permanence, with all other covariates held at baseline values.

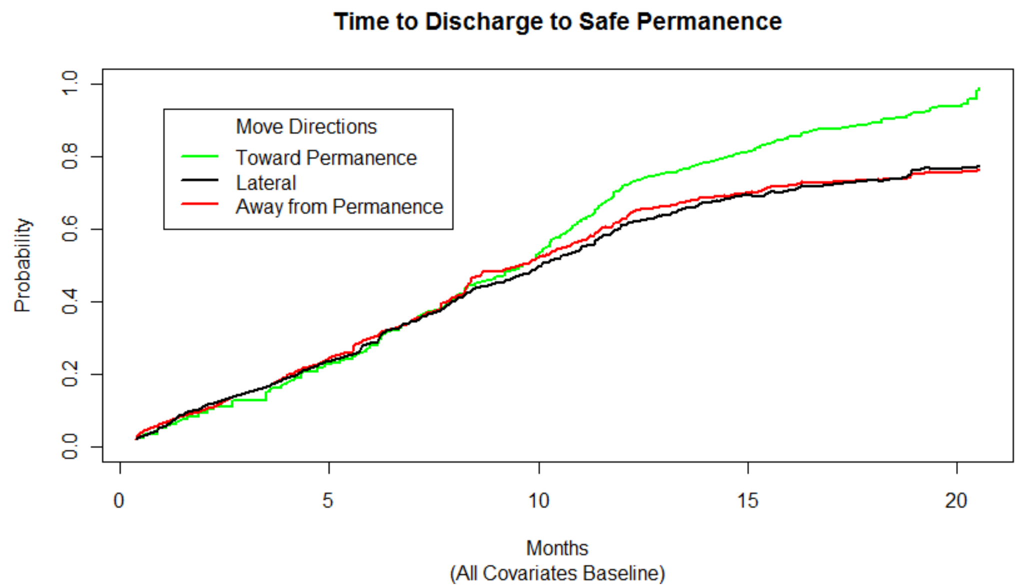

Figure 3.2.1 Cumulative Incidence Curves for Move Directions for 2007

3.2.2 Two Placements, Year 2006

The 2006 data set has 1019 observations with exactly two placements. The model has 9 constant covariates and 1 time-varying covariate in addition to the coursematrix columns (Table 3.2.2). Movements toward permanence, $p < 0.001$, and movements away from permanence, $p=0.015$, were both significantly different from lateral movements. The summary output may be found in Appendix A 3.2.2.

Table 3.2.2 Covariates in the Final Regression Model, Two Placements, Year 2006

Terms	Definitions	Terms	Definitions
coursematrix[, 1]	Away from Permanence	const(data2[, 105])	Removal Reason: Parent Death
coursematrix[, 2]	Toward Permanence	const(data2[, 109])	Removal Reason: Relinquishment
const(data2[, 88])	Mental Retardation	const(data2[, 112])	Indicator: Not Eligible for Federal Financial Aid
const(data2[, 90])	Physical Disability	const(wbmf)MixBW	Race MixBW vs baseline Black
data4[, 96]	Removal Reason: Physical Abuse	const(wbmf)White	Race White vs baseline Black
const(data2[, 98])	Removal Reason: Neglect		

Figure 3.2.2 shows the cumulative incidence curves for the move histories: Toward Permanence, Lateral, Away from Permanence, with all other covariates held at baseline values.

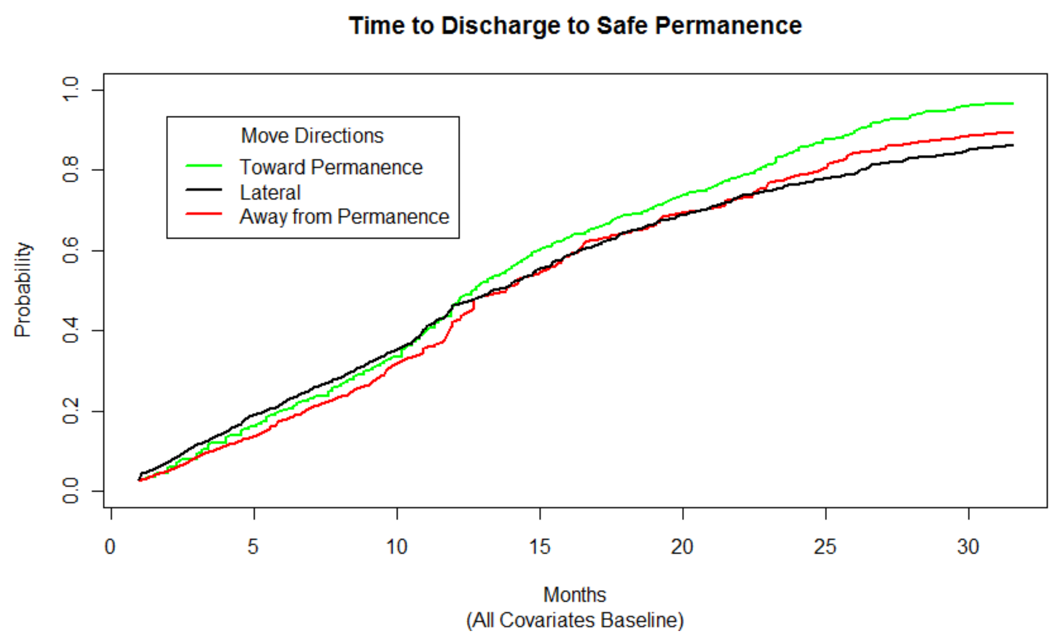

Figure 3.2.2 Cumulative Incidence Curves, Two Placements, Year 2006

3.2.3 Two Placements, Year 2005

There are 1223 observations in the year 2005 two placements data set. The final regression model includes the variables of interest, 3 time-varying covariates, and 5 constant covariates (Table 3.2.3). Movements toward permanence are significantly different from lateral moves, p<0.01, as are moves away from permanence, p=0.03. The summary output may be found in Appendix A 3.2.3.

Table 3.2.3 Covariates in the Final Regression Model, Two Placements, Year 2005

Terms	Definitions	Terms	Definitions
coursematrix[, 1]	Away from Permanence	data4[, 96]	Reason for Removal Physical Abuse
coursematrix[, 2]	Toward Permanence	const(data2[, 98])	Removal Reason Neglect
data2[, 87]	dataset.Disability.3	const(data2[, 105])	Removal Reason Parent Death
const(data2[, 91])	EmotionallyDisturbed	data2[, 114]	dataset.AgeLatestRemoval
const(data2[, 94])	Removal Voluntary vs Court	const(physvishear)TRUE	

Figure 3.2.3 shows the cumulative incidence curves for the different levels of move directions, with other variables at baseline values.

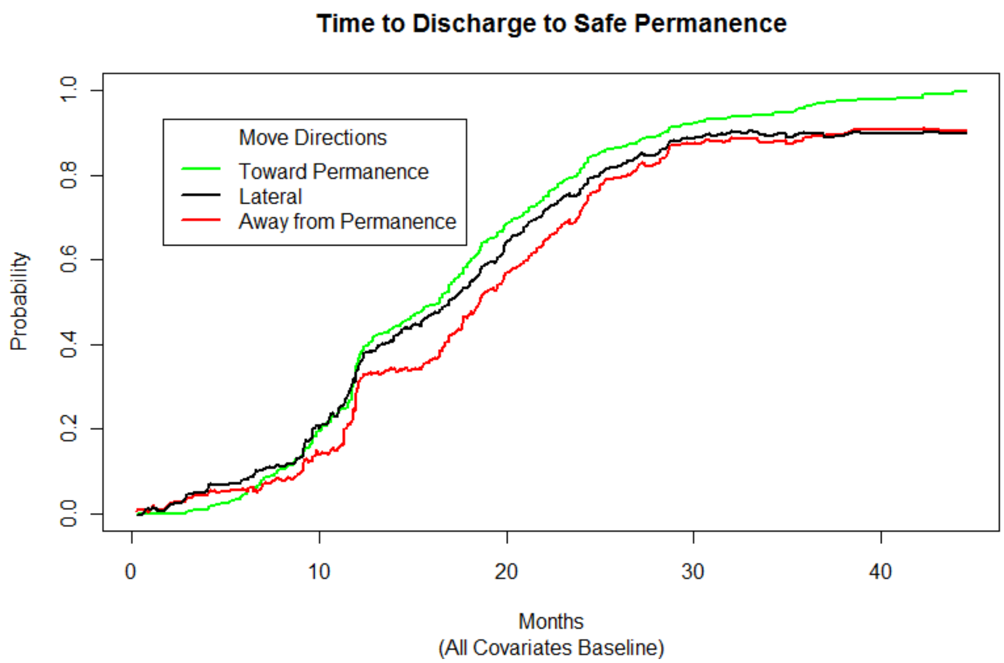

Figure 3.2.3 Covariates in the Final Regression Model, Two Placements, Year 2005

3.2.4 Two Placements, Year 2004

The year 2004 two placements data set had 1304 observations. The final model included the variables of interest, coursematrix, and 8 time-varying and 3 constant covariates (Table 3.2.4). Movements toward permanence were significantly different than lateral moves, with higher probability of permanence, p<0.01. Moves away from permanence were also significantly different from lateral moves. The summary output may be found in Appendix A 3.2.4.

Table 3.2.4 Covariates in the Final Regression Model, Two Placements, Year 2004

Terms	Definitions	Terms	Definitions
coursematrix[, 1]	Away from Permanence	data2[, 111]	Age Primary Care Taker
coursematrix[, 2]	Toward Permanence	data2[, 112]	Not Eligible for Aid $
data2[, 87]	Presence of Disability Unknown	data2[, 114]	Age at Latest Removal
const(data2[, 94])	Removal Manner Voluntary (vs Court Ordered)	abuseTRUE	Removal Reason: Physical or Sexual Abuse (combined)
data2[, 98]	Removal Reason: Neglect	const(relinqaband)TRUE	Relinquishment or Abandonment (combined)
const(data2[, 105])	Removal Reason: Parent Death	multrem	Indicator: More than one removal
data2[, 110]	Removal Reason: InadequateHousing		

Figure 3.2.4 shows the cumulative incidence curves for the different levels of move directions, with other variables at baseline values.

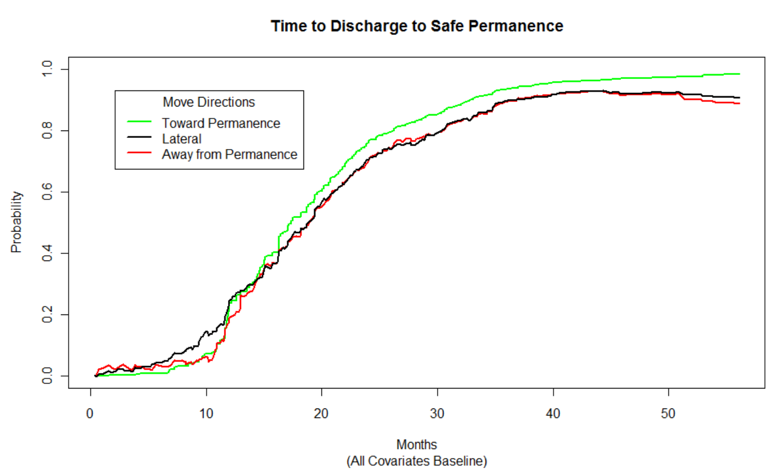

Figure 3.2.4 Cumulative Incidence Curves for Move Directions, Two Placements, Year 2004

3.3 Three Placement Settings

Data covered children entering foster care from years 2004 to 2008, with exactly three placements during their stay. There were 912 observations.

The final model includes 4 time-varying terms and 8 constant terms, in addition to the 3 terms created for coding the placement move directions (Table 3.3). The summary output may be found in Appendix A 3.3.

Table 3.3 Covariates in the Final Model, Three Placements, Years 2004-2008

Terms	Definitions	Terms	Definitions
coursemat[, 1]	Increase and Decrease	data3[, 98]	Removal Reason: Neglect
coursemat[, 2]	Toward Permanence (Non-Decreasing)	data3[, 106]	Removal Reason: Parent Incarceration
coursemat[, 3]	Away from Permanence (Non-Increasing)	data3[, 111]	Age Primary Caretaker
const(data3[, 90])	Physical Disability	data4[, 114]	Age at Latest Removal
const(data3[, 91])	Emotionally Disturbed	const(RRdrug3)	Removal Reason Drugs
data3[, 92]	OtherMedicalConditions	const(blackwhite)White	Race White vs Black
const(data3[, 94])	Manner of Removal (Voluntary vs Court Order)	const(relinqaband)TRUE	Removal Reason Relinquishment or Abandonment
const(data4[, 96])	Reason for Removal: Physical Abuse		

Figure 3.3 is a plot of the cumulative incidence curves for each placement history, with all other covariates held at baseline levels. Though it is not obvious in the graph, each course of move directions differed significantly from the baseline, Lateral. The primary variable of interest is Toward Permanence, and it can be seen that children with a history of moves toward permanence indeed achieved permanence with greater probability ($p<0.001$).

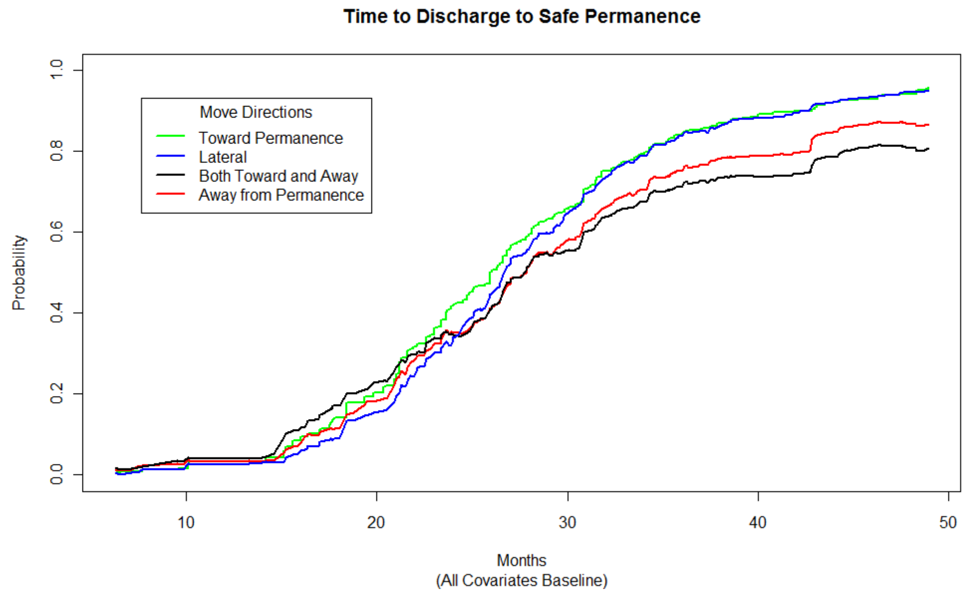

Figure 3.3 Cumulative Incidence Curves for Move Directions, Three Placements

3.4 Four or More Placement Settings

Data covered children entering foster care from years 2000 to 2008, with four or more placements during their stay. When there were more than four placements, the course history of the most recent four placements was used. There are two reasons for this: 1. With a history of many placement changes, there are likely to be few courses that are monotone moving toward or away from permanence, and 2. The earlier history was often years earlier, and may no longer have great influence on the future of the child. The sample size was 586 observations.

The final model includes 4 constant covariates, 1 time-varying covariate, and three variables for the dummy coded course variable of interest, coursemat (Table 3.4). The summary output may be found in Appendix A 3.4.

Table 3.4 Covariates in the Final Regression Model, Four Placements

Terms	Definitions	Terms	Definitions
coursemat[, 1]	Increase and Decrease	const(data4[, 90]	Physical Disability
coursemat[, 2]	Toward Permanence (Non-Decreasing)	const(multrem)	Indicator (removals>1)
coursemat[, 3]	Away from Permanence (Non-Increasing)	const(data4[, 96])	Reason for Removal Physical Abuse
data4[, 114]	Age at Latest Removal	const(data4[, 105])	Reason for Removal Parent Death

Of particular interest is coursemat[,2], a placement history moving toward permanence. This is significantly different from lateral moves ($p<0.001$). The model does not recognize the effect as significantly time-varying, Cramer von Mises $p=0.171$ and Kolmogorov-Smirnov $p=0.313$. In many cases, the effect of the movements is revealed after about 12 months of care. Here the tests are "confused" by equal weighting on time lengths. This is evident from a plot of the time-varying estimates of the coefficients:

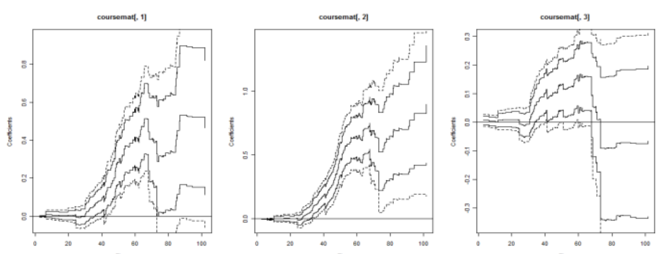

Figure 3.4.1 Time-Varying Coefficients

Plots of the test process (Figure 3.4.2) show why the overall test for time-varying effect was not significant, even though it is evident that the effect changed over time in the graphs above.

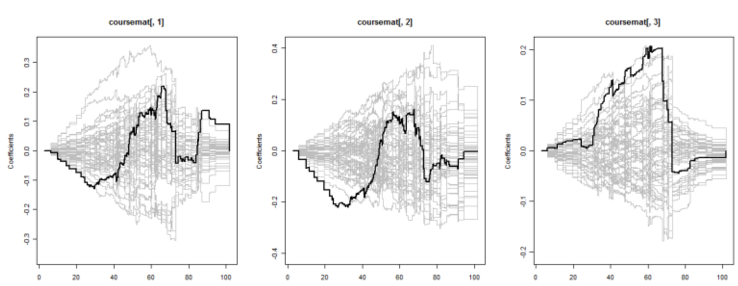

Figure 3.4.2 Test Processes Viewed Over Time

Finally, a plot of the cumulative incidence curves for each placement course history, with all other covariates at baseline, shows that movements toward permanence indeed result in greater probabilities of permanent family outcomes.

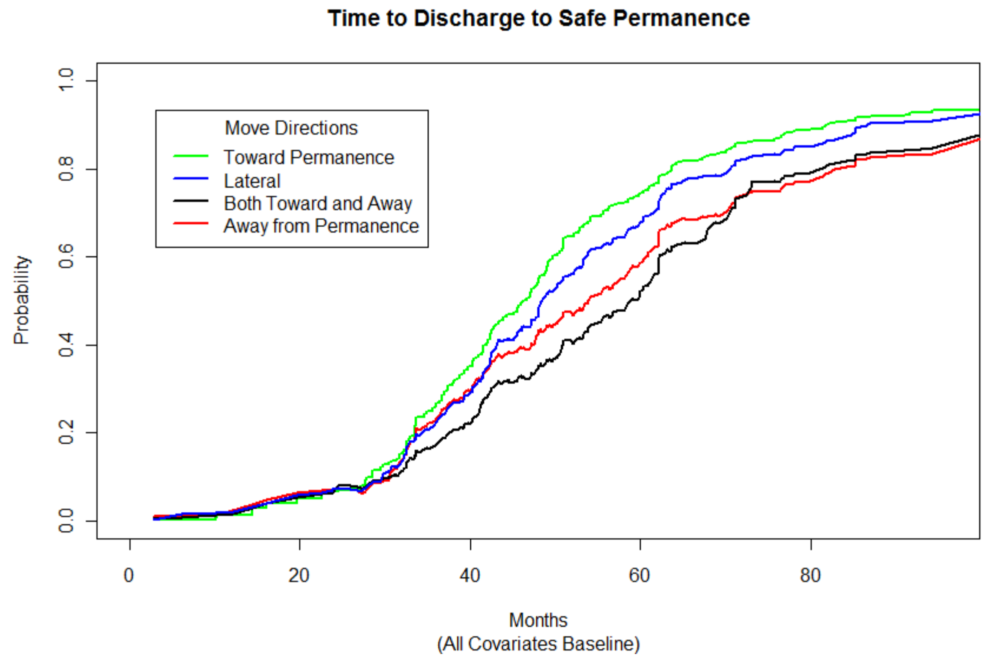

Figure 3.4.3 Cumulative Incidence Curves for Move Directions, Four Placements

4 CONCLUSIONS

Some foster care placements are more like permanent family settings than others. For example, a non-relative foster family home is more like a permanent family than an institution or group home. It is with this idea that the movement histories are categorized into: Movements Toward Permanence, Lateral Movements, Movements Away from Permanence, and Movements Toward and Away from Permanence (in any order). The question is: Do movements "toward permanence" actually result in a higher probability of permanence?

Table 4.1 and Table 4.2 summarize the results from the analyses in this thesis. The tables contain the test statistics and p-values for the variables of interest in the thesis - the movement directions. In all multi-placement analyses (Table 4.1), movements “toward permanence” were associated with statistically significant higher probabilities of discharges to permanence, relative to the baseline, lateral moves.

Table 4.1 Test Statistics and P-Values for Move Directions from Multi-Placement Models

	Number of Placements (Year)					
Movement History	**4 (2000-2008)**	**3 (2004 - 2008)**	**2 (2007)**	**2 (2006)**	**2 (2005)**	**2 (2004)**
Toward Permanence	7.72 p=0.000	6.93 p=0.000	9.20 p=0.000	7.03 p=0.000	6.56 p=0.00	5.80 p=0.00
Toward and Away from Permanence	5.47 0.000	8.11 0.000	na	na	na	na
Away from Permanence	3.09 p=0.023	4.42 p=0.001	1.79 p=0.527	3.46 p=0.015	3.31 p=0.03	3.21 p=0.03

For single placement foster care episodes, congregate care was compared to non-relative foster homes. Using FFY 2008 data, congregate care appeared to be associated with higher probabilities of discharge to permanent families. This should be interpreted with caution, as it generally disagrees with the rest of the analyses, and the data are heavily censored because the final date of the AFCARS reports used in the thesis, September 30, 2008, does not leave a full year for the children entering in FFY 2008 to discharge. Data from 2006 showed virtually no difference in discharges to permanence between congregate care and non-relative foster homes, but 2005 and 2007 data showed significantly higher probabilities for discharges to permanence from non-relative foster homes. The differences were more pronounced after one year of foster care.

Table 4.2 Test Statistics and P-Values for Congregate Care from All One Placement Models

Federal Fiscal Year (half)	2008 (2)	2008 (1)	2007 (2)	2007 (1)	2006 (2)	2006 (1)	2005 (2)	2005 (1)
Congregate Care	2.95 p=0.036*	3.18 p=0.018*	3.14 p=0.03	3.14 p=0.03	-2.14** p=0.0321	0.121** p=0.904	4.62 p=0.000	3.73 p=0.006

*in 2008, congregate care led to higher probability of discharge to permanence than foster homes.
**constant effect

Of course, statistical likelihood of discharge to permanence is only one factor to consider when a state develops plans for individual children or the foster care population in general. It is hoped that this thesis will promote the concept of “proximity to permanence” and contribute to the conversation on how best to care for foster children.

5 REFERENCES

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6 APPENDICES

Appendix A: Summary Output for Each Model in the Results Section

A 3.1.1 One Placement, April 1, 2008 to September 30, 2008

Competing risks Model

Test for nonparametric terms

Test for non-significant effects

	Supremum-test of significance	p-value H_0: B(t)=0
(Intercept)	7.23	0.000
data1[, 92]	7.46	0.000
data1[, 98]	3.54	0.004
data1[, 112]	4.60	0.000
data1$cong	2.95	0.036

Test for time invariant effects

	Kolmogorov-Smirnov test	p-value H_0:constant effect
(Intercept)	0.317	0.000
data1[, 92]	0.153	0.006
data1[, 98]	0.194	0.001
data1[, 112]	0.146	0.016
data1$cong	0.129	0.119

	Cramer von Mises test	p-value H_0:constant effect
(Intercept)	0.2100	0.000
data1[, 92]	0.0351	0.010
data1[, 98]	0.0899	0.000

```
data1[, 112]                0.0365              0.014
data1$cong                  0.0300              0.063
Parametric terms:
                    Coef.     SE Robust SE     z    P-val
const(data1[, 87])  -0.1510 0.0338    0.0338 -4.46 8.09e-06
const(data1[, 90])  -0.1580 0.0474    0.0474 -3.33 8.76e-04
const(data1[, 91])  -0.1230 0.0398    0.0398 -3.08 2.05e-03
const(data1[, 106]) -0.0366 0.0155    0.0155 -2.37 1.79e-02
const(data1[, 110]) -0.0278 0.0120    0.0120 -2.32 2.01e-02
const(wbmf)MixBW    -0.0641 0.0191    0.0191 -3.35 8.09e-04
const(wbmf)White    -0.0229 0.0122    0.0122 -1.87 6.13e-02
const(data1[, 105]) -0.0591 0.0189    0.0189 -3.12 1.80e-03
const(data1[, 108]) -0.0615 0.0166    0.0166 -3.70 2.12e-04
const(data1[, 114])  0.0055 0.0015    0.0015  3.66 2.54e-04


  Call:
comp.risk(survlos1 ~ const(data1[, 87]) + const(data1[, 90]) +
    const(data1[, 91]) + data1[, 92] + data1[, 98] + const(data1[,
    106]) + const(data1[, 110]) + data1[, 112] + const(wbmf) +
    const(data1[, 105]) + const(data1[, 108]) + const(data1[,
    114]) + data1$cong, data = data1, cause = data1$distype,
    causeS = 1, Nit = 200, gamma = 0, n.sim = 1000, weighted = 0,
    model = "additive", cens.code = 0, clusters = NULL, detail = 1,
    interval = 0.01, resample.iid = 1, cens.model = "KM")
```

A 3.1.2 One Placement, October 1, 2007 to March 31, 2008

Competing risks Model

Test for nonparametric terms

Test for non-significant effects

	Supremum-test of significance	p-value H_0: B(t)=0
(Intercept)	6.67	0.000
data1[, 87]	3.48	0.006
data1[, 96]	1.66	0.534
data1[, 112]	4.59	0.001
data1[, 105]	7.27	0.000
data1[, 108]	2.83	0.048
data1[, 109]	2.50	0.078
data1$cong	3.18	0.018

Test for time invariant effects

	Kolmogorov-Smirnov test	p-value H_0:constant effect
(Intercept)	0.137	0.496
data1[, 87]	0.148	0.507
data1[, 96]	0.347	0.279
data1[, 112]	0.151	0.038
data1[, 105]	0.162	0.000
data1[, 108]	0.202	0.338
data1[, 109]	0.124	0.584
data1$cong	0.205	0.013

	Cramer von Mises test	p-value H_0:constant effect
(Intercept)	0.0364	0.448
data1[, 87]	0.0346	0.503
data1[, 96]	0.2030	0.295
data1[, 112]	0.0378	0.037
data1[, 105]	0.0494	0.000
data1[, 108]	0.1110	0.260
data1[, 109]	0.0133	0.673
data1$cong	0.0940	0.006

Parametric terms :

	Coef.	SE	Robust SE	z	P-val
const(NumRemMat[, 2])	-0.0682	0.0444	0.0444	-1.530	0.1250
const(RRdrug1)	-0.0300	0.0135	0.0135	-2.210	0.0268
const(data1[, 107])	-0.0122	0.0158	0.0158	-0.773	0.4400

```
 Call:
comp.risk(survlos1 ~ data1[, 87] + const(NumRemMat[, 2]) + data1[,
   96] + const(RRdrug1) + const(data1[, 107]) + data1[, 112] +
   data1[, 105] + data1[, 108] + data1[, 109] + data1$cong,
   data = data1, cause = data1$distype, causeS = 1, Nit = 200,
   gamma = 0, n.sim = 1000, weighted = 0, model = "additive",
   cens.code = 0, clusters = NULL, detail = 1, interval = 0.01,
   resample.iid = 1, cens.model = "KM")
```

A 3.1.3 One Placement, April 1, 2007 to September 30, 2007

Competing risks Model

Test for nonparametric terms

Test for non-significant effects

	Supremum-test of significance	p-value H_0: B(t)=0
(Intercept)	9.84	0.00
data1[, 87]	15.70	0.00
data1[, 96]	10.50	0.00
data1$cong	3.14	0.03

Test for time invariant effects

	Kolmogorov-Smirnov test	p-value H_0:constant effect
(Intercept)	0.132	0.121
data1[, 87]	1.250	0.000
data1[, 96]	0.334	0.003
data1$cong	0.288	0.002

	Cramer von Mises test	p-value H_0:constant effect
(Intercept)	0.085	0.119
data1[, 87]	10.700	0.000
data1[, 96]	0.849	0.000
data1$cong	0.326	0.012

Parametric terms :

```
                    Coef.      SE Robust SE     z    P-val
const(data1[, 94])  -0.060300 0.01330   0.01330 -4.53 5.89e-06
const(data1[, 98])  -0.043600 0.00850   0.00850 -5.13 2.95e-07
const(RRdrug1)      -0.012200 0.00514   0.00514 -2.37 1.80e-02
const(data1[, 111])  0.000724 0.00023   0.00023  3.15 1.61e-03
const(data1[, 112])  0.012400 0.00564   0.00564  2.19 2.85e-02
const(data1[, 108]) -0.041600 0.00820   0.00820 -5.07 4.01e-07
const(data1[, 109]) -0.066000 0.01370   0.01370 -4.80 1.57e-06
```

```
  Call:
comp.risk(survlos1 ~ data1[, 87] + const(data1[, 94]) + data1[,  96] +
const(data1[, 98]) + const(RRdrug1) + const(data1[,   111]) + const(data1[, 112]) +
 const(data1[, 108]) + const(data1[,  109]) + data1$cong, data = data1,
cause = data1$distype,   causeS = 1, Nit = 200, gamma = 0, n.sim = 1000,
weighted = 0, model = "additive", cens.code = 0, clusters = NULL, detail = 1,
 interval = 0.01, resample.iid = 1, cens.model = "KM")
```

A 3.1.4 One Placement, October 1, 2006 to March 31, 2007

Competing risks Model

Test for nonparametric terms

Test for non-significant effects

	Supremum-test of significance	p-value H_0: B(t)=0
(Intercept)	13.60	0.000
data1[, 87]	15.10	0.000
data1[, 96]	7.69	0.000
data1$cong	1.82	0.545

Test for time invariant effects

	Kolmogorov-Smirnov test	p-value H_0:constant effect
(Intercept)	0.212	0.000
data1[, 87]	1.370	0.000
data1[, 96]	0.171	0.005
data1$cong	0.138	0.340

	Cramer von Mises test	p-value H_0:constant effect
(Intercept)	0.2140	0.000
data1[, 87]	15.3000	0.000
data1[, 96]	0.1290	0.018
data1$cong	0.0586	0.486

Parametric terms :

	Coef.	SE	Robust SE	z	P-val
const(data1[, 94])	-0.0264	0.01300	0.01300	-2.03	4.19e-02
const(data1[, 98])	-0.0439	0.00799	0.00799	-5.50	3.86e-08
const(RRdrug1)	-0.0159	0.00496	0.00496	-3.21	1.35e-03
const(data1[, 112])	-0.0112	0.00537	0.00537	-2.09	3.65e-02
const(data1[, 108])	-0.0496	0.00666	0.00666	-7.45	9.44e-14

Call:

```
comp.risk(survlos1 ~ data1[, 87] + const(data1[, 94]) + data1[,
   96] + const(data1[, 98]) + const(RRdrug1) + const(data1[,
   112]) + const(data1[, 108]) + data1$cong, data = data1, cause = data1$distype,
   causeS = 1, times = temptime[c(1:246, 259)], Nit = 200, gamma = 0,
   n.sim = 1000, weighted = 0, model = "additive", cens.code = 0,
   clusters = NULL, detail = 1, interval = 0.01, resample.iid = 1,
   cens.model = "KM")
```

A 3.1.5 One Placement, April 1, 2006 to September 30, 2006

Competing risks Model

Test for nonparametric terms

Test for non-significant effects

	Supremum-test of significance	p-value H_0: B(t)=0
(Intercept)	10.90	0.000
data1[, 87]	15.20	0.000
data1[, 96]	7.61	0.000
data1[, 97]	4.09	0.000
data1[, 112]	3.68	0.004

Test for time invariant effects

	Kolmogorov-Smirnov test	p-value H_0:constant effect
(Intercept)	0.440	0
data1[, 87]	1.060	0
data1[, 96]	0.362	0
data1[, 97]	0.661	0
data1[, 112]	0.300	0

	Cramer von Mises test	p-value H_0:constant effect
(Intercept)	1.040	0
data1[, 87]	8.210	0
data1[, 96]	0.764	0
data1[, 97]	2.270	0
data1[, 112]	0.734	0

Parametric terms :

	Coef.	SE	Robust SE	z	P-val
const(data1[, 94])	-0.04890	0.014500	0.014500	-3.37	0.000763
const(RRdrug1)	-0.02890	0.007600	0.007600	-3.80	0.000144
const(RRalcohol1)	-0.02640	0.011400	0.011400	-2.33	0.019900
const(data1[, 114])	0.00238	0.000742	0.000742	3.20	0.001350
const(data1$cong)	-0.02600	0.012100	0.012100	-2.14	0.032100

Call:

comp.risk(survlos1 ~ data1[, 87] + const(data1[, 94]) + data1[, 96] + data1[, 97] + const(RRdrug1) + const(RRalcohol1) + data1[, 112] + const(data1[, 114]) + const(data1$cong), data = data1, cause = data1$distype, causeS = 1, times = temptime[c(1:195, 257)], Nit = 200, gamma = 0, n.sim = 1000, weighted = 0, model = "additive", cens.code = 0, clusters = NULL, detail = 1, interval = 0.01, resample.iid = 1, cens.model = "KM")

A 3.1.6 One Placement, October 1, 2005 to March 31, 2006

Competing risks Model

Test for nonparametric terms

Test for non-significant effects

	Supremum-test of significance	p-value H_0: B(t)=0
(Intercept)	13.60	0.000
data1[, 85]	3.46	0.013
data1[, 87]	16.00	0.000
data1[, 96]	7.45	0.000
RRdrug1	3.73	0.008
data1[, 112]	5.50	0.000

Test for time invariant effects

	Kolmogorov-Smirnov test	p-value H_0:constant effect
(Intercept)	0.228	0.015
data1[, 85]	0.287	0.000
data1[, 87]	1.520	0.000
data1[, 96]	0.268	0.002
RRdrug1	0.389	0.018
data1[, 112]	0.704	0.001

	Cramer von Mises test	p-value H_0:constant effect
(Intercept)	0.380	0.021
data1[, 85]	0.575	0.001
data1[, 87]	24.200	0.000
data1[, 96]	0.708	0.000
RRdrug1	1.520	0.017
data1[, 112]	3.520	0.004

Parametric terms :

	Coef.	SE	Robust SE	z	P-val
const(data1[, 94])	-0.043700	0.00713	0.00713	-6.130	8.97e-10
const(data1[, 98])	-0.026800	0.00549	0.00549	-4.880	1.04e-06
const(blamechild)TRUE	-0.022900	0.01000	0.01000	-2.290	2.22e-02
const(data1[, 110])	-0.015200	0.00673	0.00673	-2.260	2.38e-02
const(relinqaband)TRUE	-0.036700	0.00573	0.00573	-6.410	1.50e-10
const(data1$cong)	0.000892	0.00737	0.00737	0.121	9.04e-01

Call:

```
comp.risk(survlos1 ~ data1[, 85] + data1[, 87] + const(data1[,
   94]) + data1[, 96] + const(data1[, 98]) + RRdrug1 + const(blamechild) +
   const(data1[, 110]) + data1[, 112] + const(relinqaband) +
   const(data1$cong), data = data1, cause = data1$distype, causeS = 1,
   Nit = 200, gamma = 0, n.sim = 1000, weighted = 0, model = "additive",
   cens.code = 0, clusters = NULL, detail = 1, interval = 0.01,
   resample.iid = 1, cens.model = "KM")
```

A 3.1.7 One Placement, April 1, 2005 to September 30, 2005

Competing risks Model

Test for nonparametric terms

Test for non-significant effects

	Supremum-test of significance	p-value H_0: B(t)=0
(Intercept)	9.21	0.000
data1[, 87]	16.80	0.000
NumRemMat[, 2]	5.63	0.000
data1[, 94]	4.26	0.001
data1[, 96]	5.02	0.000
data1[, 97]	4.50	0.001
data1[, 98]	3.57	0.010
RRdrug1	3.81	0.004
data1[, 107]	4.67	0.000
data1[, 112]	5.37	0.000
wbmfMixBW	3.21	0.020
wbmfWhite	4.54	0.000
data1[, 114]	4.30	0.000
data1$cong	4.62	0.000

Test for time invariant effects

	Kolmogorov-Smirnov test	p-value H_0:constant effect
(Intercept)	0.4070	0.047
data1[, 87]	1.5500	0.000
NumRemMat[, 2]	0.5840	0.008
data1[, 94]	0.4460	0.022
data1[, 96]	0.9190	0.000
data1[, 97]	0.9920	0.006
data1[, 98]	0.3410	0.005
RRdrug1	0.3680	0.011
data1[, 107]	0.3430	0.015
data1[, 112]	0.3980	0.001
wbmfMixBW	0.3090	0.428
wbmfWhite	0.2620	0.049
data1[, 114]	0.0435	0.000
data1$cong	0.3520	0.024

	Cramer von Mises test	p-value H_0:constant effect
(Intercept)	2.1400	0.017
data1[, 87]	27.6000	0.000
NumRemMat[, 2]	3.5200	0.008
data1[, 94]	1.7000	0.031
data1[, 96]	8.8400	0.000
data1[, 97]	12.0000	0.005
data1[, 98]	1.1900	0.005

RRdrug1	0.8820	0.028
data1[, 107]	1.4300	0.003
data1[, 112]	1.5700	0.000
wbmfMixBW	0.8580	0.346
wbmfWhite	0.6670	0.041
data1[, 114]	0.0258	0.000
data1$cong	1.3000	0.011

Parametric terms :

```
                   Coef.    SE Robust SE    z  P-val
const(data1[, 91]) -0.0185 0.0072    0.0072 -2.56 0.0103
```

Call:

comp.risk(survlos1 ~ data1[, 87] + const(data1[, 91]) + NumRemMat[, 2] + data1[, 94] + data1[, 96] + data1[, 97] + data1[, 98] + RRdrug1 + data1[, 107] + data1[, 112] + wbmf + data1[, 114] + data1$cong, data = data1, cause = data1$distype, causeS = 1, times = temptime[c(seq(1, 321, 2), 322)], Nit = 200, gamma = 0, n.sim = 1000, weighted = 0, model = "additive", cens.code = 0, clusters = NULL, detail = 1, interval = 0.01, resample.iid = 1, cens.model = "KM")

A 3.1.8 One Placement, October 1, 2004 to March 31, 2005

The summary output for the regression model follows.

Competing risks Model

Test for nonparametric terms

Test for non-significant effects

	Supremum-test of significance	p-value H_0: B(t)=0
(Intercept)	12.80	0.000
data1[, 87]	19.50	0.000
data1[, 94]	6.39	0.000
data1[, 112]	4.26	0.001
data1[, 114]	5.26	0.000
data1$cong	3.73	0.006

Test for time invariant effects

	Kolmogorov-Smirnov test	p-value H_0:constant effect
(Intercept)	0.660	0.020
data1[, 87]	1.980	0.000
data1[, 94]	0.378	0.011
data1[, 112]	0.298	0.012
data1[, 114]	0.075	0.000
data1$cong	0.242	0.073

	Cramer von Mises test	p-value H_0:constant effect
(Intercept)	8.640	0.005
data1[, 87]	44.600	0.000
data1[, 94]	2.300	0.003
data1[, 112]	0.689	0.039
data1[, 114]	0.104	0.000
data1$cong	0.859	0.023

Parametric terms :

```
                    Coef.      SE Robust SE     z    P-val
const(data1[, 105])    -0.0301 0.00527   0.00527 -5.72 1.08e-08
const(relinqaband)TRUE -0.0118 0.00500   0.00500 -2.35 1.87e-02
```

Call:

```
comp.risk(survlos1 ~ data1[, 87] + data1[, 94] + data1[, 112] +
   const(data1[, 105]) + const(relinqaband) + data1[, 114] +
   data1$cong, data = data1, cause = data1$distype, causeS = 1,
   Nit = 200, gamma = 0, n.sim = 1000, weighted = 0, model = "additive",
   cens.code = 0, clusters = NULL, detail = 1, interval = 0.01,
   resample.iid = 1, cens.model = "KM")
```

A 3.2.1 Two Placements, Year 2007

Competing risks Model

Test for nonparametric terms

Test for non-significant effects

	Supremum-test of significance	p-value H_0: B(t)=0
(Intercept)	10.90	0.000
coursematrix[, 1]	1.79	0.527
coursematrix[, 2]	9.20	0.000
data2[, 96]	7.34	0.000

Test for time invariant effects

	Kolmogorov-Smirnov test	p-value H_0:constant effect
(Intercept)	0.128	0.026
coursematrix[, 1]	0.111	0.026
coursematrix[, 2]	1.840	0.399
data2[, 96]	0.183	0.003

	Cramer von Mises test	p-value H_0:constant effect
(Intercept)	0.0784	0.025
coursematrix[, 1]	0.0597	0.023
coursematrix[, 2]	35.7000	0.296
data2[, 96]	0.1520	0.008

Parametric terms :

	Coef.	SE	Robust SE	z	P-val
const(data2[, 88])	-0.01690	0.003860	0.003860	-4.37	1.23e-05
const(data2[, 98])	-0.02750	0.005980	0.005980	-4.59	4.37e-06
const(data2[, 106])	-0.00854	0.003140	0.003140	-2.72	6.60e-03
const(data2[, 107])	-0.00676	0.003130	0.003130	-2.16	3.10e-02
const(data2[, 111])	-0.00042	0.000096	0.000096	-4.37	1.22e-05
const(data2[, 112])	0.00700	0.002660	0.002660	2.63	8.50e-03
const(data2[, 105])	-0.02200	0.004660	0.004660	-4.72	2.32e-06
const(data2[, 108])	-0.00950	0.003800	0.003800	-2.50	1.26e-02

Call:

comp.risk(survlos2 ~ coursematrix[, 1] + coursematrix[, 2] + const(data2[, 88]) + data2[, 96] + const(data2[, 98]) + const(data2[, 106]) + const(data2[, 107]) + const(data2[, 111]) + const(data2[, 112]) + const(data2[, 105]) + const(data2[, 108]), data = data2, cause = data2$distype, causeS = 1, Nit = 200, gamma = 0, n.sim = 1000, weighted = 0, model = "additive", cens.code = 0, clusters = NULL, detail = 1, interval = 0.01, resample.iid = 1, cens.model = "KM")

A 3.2.2 Two Placements, Year 2006

Competing risks Model

Test for nonparametric terms

Test for non-significant effects

	Supremum-test of significance	p-value H_0: B(t)=0
(Intercept)	15.40	0.000
coursematrix[, 1]	3.46	0.015
coursematrix[, 2]	7.03	0.000
data2[, 94]	6.41	0.000

Test for time invariant effects

	Kolmogorov-Smirnov test	p-value H_0:constant effect
(Intercept)	0.156	0.012
coursematrix[, 1]	0.214	0.150
coursematrix[, 2]	0.754	0.000
data2[, 94]	0.605	0.000

Cramer von Mises test p-value H_0:constant effect

(Intercept)	0.184	0.023
coursematrix[, 1]	0.425	0.076
coursematrix[, 2]	6.550	0.000
data2[, 94]	4.000	0.000

Parametric terms :

	Coef.	SE	Robust SE	z	P-val
const(data2[, 88])	-0.01180	0.00529	0.00529	-2.24	2.53e-02
const(data2[, 90])	-0.01010	0.00304	0.00304	-3.32	9.04e-04
const(data2[, 96])	-0.02320	0.00217	0.00217	-10.70	0.00e+00
const(data2[, 98])	-0.02200	0.00332	0.00332	-6.62	3.54e-11
const(data2[, 112])	-0.01130	0.00197	0.00197	-5.70	1.17e-08
const(wbmf)MixBW	-0.00592	0.00280	0.00280	-2.11	3.45e-02
const(wbmf)White	0.00564	0.00206	0.00206	2.74	6.14e-03
const(data2[, 105])	-0.02840	0.00975	0.00975	-2.91	3.62e-03
const(data2[, 109])	-0.02350	0.00569	0.00569	-4.14	3.51e-05

Call:

comp.risk(survlos2 ~ coursematrix[, 1] + coursematrix[, 2] + const(data2[, 88]) + const(data2[, 90]) + data2[, 94] + const(data2[, 96]) + const(data2[, 98]) + const(data2[, 112]) + const(wbmf) + const(data2[, 105]) + const(data2[, 109]), data = data2, cause = data2$distype, causeS = 1, times = temptime[c(1:332,337)], Nit = 200, gamma = 0, n.sim = 1000, weighted = 0, model = "additive", cens.code = 0, clusters = NULL, detail = 1, interval = 0.01, resample.iid = 1, cens.model = "KM")

A 3.2.3 Two Placements, Year 2005

The summary output follows.

> summary(comprisk2Final2005)

Competing risks Model

Test for nonparametric terms

Test for non-significant effects

	Supremum-test of significance	p-value H_0: B(t)=0
(Intercept)	13.10	0.00
coursematrix[, 1]	3.31	0.03
coursematrix[, 2]	6.56	0.00
data2[, 87]	5.49	0.00
data2[, 96]	15.00	0.00
data2[, 98]	5.59	0.00
data2[, 114]	4.26	0.00

Test for time invariant effects

	Kolmogorov-Smirnov test	p-value H_0:constant effect
(Intercept)	0.7090	0.000
coursematrix[, 1]	0.2760	0.006
coursematrix[, 2]	1.9800	0.435
data2[, 87]	1.6300	0.000
data2[, 96]	0.7180	0.000
data2[, 98]	0.4860	0.002
data2[, 114]	0.0392	0.000

	Cramer von Mises test	p-value H_0:constant effect
(Intercept)	4.860	0.000
coursematrix[, 1]	0.984	0.006
coursematrix[, 2]	72.000	0.372
data2[, 87]	25.300	0.000
data2[, 96]	5.560	0.000
data2[, 98]	2.060	0.002
data2[, 114]	0.026	0.000

Parametric terms :

	Coef.	SE	Robust SE	z	P-val
const(data2[, 88])	-0.00871	0.00286	0.00286	-3.05	0.002290
const(physvishear)TRUE	-0.00912	0.00229	0.00229	-3.99	0.000067
const(data2[, 91])	-0.00478	0.00201	0.00201	-2.38	0.017200
const(data2[, 94])	-0.00991	0.00280	0.00280	-3.53	0.000412
const(data2[, 105])	-0.01890	0.00718	0.00718	-2.63	0.008470

Call:

```
comp.risk(survlos2 ~ coursematrix[, 1] + coursematrix[, 2] +
   data2[, 87] + const(data2[, 88]) + const(physvishear) + const(data2[,
   91]) + const(data2[, 94]) + data2[, 96] + data2[, 98] + const(data2[,
   105]) + data2[, 114], data = data2, cause = data2$distype,
   causeS = 1, times = temptime, Nit = 200, gamma = 0, n.sim = 1000,
   weighted = 0, model = "additive", cens.code = 0, clusters = NULL,
   detail = 1, interval = 0.01, resample.iid = 1, cens.model = "KM")
```

A 3.2.4 Two Placements, Year 2004

Competing risks Model

Test for nonparametric terms

Test for non-significant effects

	Supremum-test of significance	p-value H_0: B(t)=0
(Intercept)	14.80	0.00
coursematrix[, 1]	3.21	0.03
coursematrix[, 2]	5.80	0.00
data2[, 87]	8.00	0.00
multrem	4.90	0.00
abuseTRUE	8.46	0.00
data2[, 98]	4.63	0.00
data2[, 110]	6.82	0.00
data2[, 111]	5.14	0.00
data2[, 112]	4.28	0.00

Test for time invariant effects

	Kolmogorov-Smirnov test	p-value H_0:constant effect
(Intercept)	0.84700	0.000
coursematrix[, 1]	0.17600	0.125
coursematrix[, 2]	0.87000	0.044
data2[, 87]	1.46000	0.000
multrem	0.31000	0.003
abuseTRUE	0.61300	0.000
data2[, 98]	0.40600	0.000

```
data2[, 110]          0.25800          0.034
data2[, 111]          0.00882          0.005
data2[, 112]          0.30000          0.005

           Cramer von Mises test p-value H_0:constant effect
(Intercept)           1.01e+01         0.000
coursematrix[, 1]     4.03e-01         0.130
coursematrix[, 2]     1.88e+01         0.021
data2[, 87]           3.54e+01         0.000
multrem               9.42e-01         0.019
abuseTRUE             4.11e+00         0.000
data2[, 98]           2.32e+00         0.000
data2[, 110]          7.42e-01         0.046
data2[, 111]          7.71e-04         0.019
data2[, 112]          1.34e+00         0.013


Parametric terms :
                      Coef.      SE Robust SE     z    P-val
const(data2[, 94])    -0.010600 0.002870  0.002870 -3.70 2.17e-04
const(data2[, 105])   -0.015200 0.003890  0.003890 -3.90 9.53e-05
const(relinqaband)TRUE -0.008140 0.003240  0.003240 -2.52 1.18e-02
const(data2[, 114])   -0.000687 0.000194  0.000194 -3.54 3.94e-04
  Call:
comp.risk(survlos2 ~ coursematrix[, 1] + coursematrix[, 2] + data2[, 87] + multrem + const(data2[, 94]) +
abuse + data2[, 98] + data2[, 110] + data2[, 111] + data2[, 112] + const(data2[, 105]) +
const(relinqaband) + const(data2[, 114]), data = data2,   cause = data2$distype, causeS = 1, times =
```

temptime[seq(1, 559, 2)], Nit = 200, gamma = 0, n.sim = 1000, weighted = 0, model = "additive", cens.code = 0, clusters = NULL, detail = 1, interval = 0.01, resample.iid = 1, cens.model = "KM")

A 3.3 Three Placements

Competing risks Model

Test for nonparametric terms

Test for non-significant effects

	Supremum-test of significance	p-value H_0: B(t)=0
(Intercept)	10.10	0.000
coursemat[, 1]	8.11	0.000
coursemat[, 2]	6.93	0.000
coursemat[, 3]	4.42	0.001
data3[, 92]	4.05	0.001
data3[, 96]	9.35	0.000
data3[, 98]	3.90	0.002
data3[, 114]	5.54	0.000

Test for time invariant effects

	Kolmogorov-Smirnov test	p-value H_0:constant effect
(Intercept)	0.2870	0.038
coursemat[, 1]	0.5900	0.001
coursemat[, 2]	0.6150	0.006
coursemat[, 3]	0.2060	0.002
data3[, 92]	0.1880	0.044
data3[, 96]	0.1780	0.023
data3[, 98]	0.1610	0.052

```
data3[, 114]                0.0298            0.001

            Cramer von Mises test p-value H_0:constant effect

(Intercept)                 1.2100            0.021

coursemat[, 1]              6.2600            0.000

coursemat[, 2]              8.1500            0.001

coursemat[, 3]              0.6120            0.001

data3[, 92]                 0.4710            0.018

data3[, 96]                 0.4340            0.005

data3[, 98]                 0.2500            0.037

data3[, 114]                0.0122            0.001


Parametric terms :

                       Coef.     SE Robust SE     z    P-val

const(data3[, 90])     -4.30e-03 1.47e-03  1.47e-03 -2.93 3.42e-03

const(data3[, 91])     -2.60e-03 1.00e-03  1.00e-03 -2.58 9.77e-03

const(data3[, 94])     -6.81e-03 1.67e-03  1.67e-03 -4.08 4.46e-05

const(RRdrug3)          4.19e-03 1.19e-03  1.19e-03  3.52 4.28e-04

const(data3[, 106])    -3.72e-03 1.56e-03  1.56e-03 -2.38 1.72e-02

const(data3[, 111])    -9.49e-05 3.23e-05  3.23e-05 -2.94 3.27e-03

const(blackwhite)White  2.79e-03 9.39e-04  9.39e-04  2.98 2.92e-03

const(relinqaband)TRUE -5.60e-03 1.60e-03  1.60e-03 -3.50 4.72e-04
```

```
Call:

comp.risk(survlos3 ~ coursemat[, 1] + coursemat[, 2] + coursemat[,
   3] + const(data3[, 90]) + const(data3[, 91]) + data3[, 92] +
   const(data3[, 94]) + data3[, 96] + data3[, 98] + const(RRdrug3) +
   const(data3[, 106]) + const(data3[, 111]) + const(blackwhite) +
   const(relinqaband) + data3[, 114], data = data3, cause = data3$distype,
   causeS = 1, times = temptime[c(1:288, 302)], Nit = 200, gamma = 0,
   n.sim = 1000, weighted = 0, model = "additive", cens.code = 0,
   clusters = NULL, detail = 1, interval = 0.01, resample.iid = 1,
   cens.model = "KM")
```

A 3.4 Four Placements

Competing risks Model

Test for nonparametric terms

Test for non-significant effects

	Supremum-test of significance	p-value H_0: B(t)=0
(Intercept)	7.58	0.000
coursemat[, 1]	5.47	0.000
coursemat[, 2]	7.72	0.000
coursemat[, 3]	3.09	0.023
data4[, 114]	6.39	0.000

Test for time invariant effects

	Kolmogorov-Smirnov test	p-value H_0:constant effect
(Intercept)	0.5880	0.003
coursemat[, 1]	0.2180	0.145
coursemat[, 2]	0.2210	0.313
coursemat[, 3]	0.2070	0.017
data4[, 114]	0.0402	0.008

	Cramer von Mises test	p-value H_0:constant effect
(Intercept)	13.9000	0.000
coursemat[, 1]	0.7980	0.155
coursemat[, 2]	1.4300	0.171
coursemat[, 3]	0.9070	0.020
data4[, 114]	0.0636	0.003

Parametric terms :

	Coef.	SE	Robust SE	z	P-val
const(data4[, 90])	-0.00331	0.001220	0.001220	-2.72	6.47e-03
const(data4[, 91])	-0.00337	0.000835	0.000835	-4.04	5.35e-05
const(multrem)	0.00194	0.000841	0.000841	2.30	2.12e-02
const(data4[, 96])	-0.00385	0.000728	0.000728	-5.29	1.25e-07
const(data4[, 105])	-0.00457	0.001050	0.001050	-4.34	1.43e-05

```
Call:
comp.risk(survlos4 ~ coursemat[, 1] + coursemat[, 2] + coursemat[,
   3] + const(data4[, 90]) + const(data4[, 91]) + const(multrem) +
   const(data4[, 96]) + const(data4[, 105]) + data4[, 114],
   data = data4, cause = data4$distype, causeS = 1, Nit = 200,
   gamma = 0, n.sim = 1000, weighted = 0, model = "additive",
   cens.code = 0, clusters = NULL, detail = 1, interval = 0.01,
   resample.iid = 1, cens.model = "KM")
```

Appendix B: Covariates Appearing in the Models

Covariate	Definition	Four Place-ments	Three Placements	Two Place-ment 2007	Two Placement 2006	Two Placement 2005	Two Placement 2004
data2[, 87]	Disability Not Deter-mined					X	X
data2[, 88]	Mental Retardation			X constant	X constant		
data 4[, 90]	Physical Disability	X constant	X constant		X constant		
data3[, 91]	Emotionally Disturbed	X constant	X constant			X constant	
data3[, 92]	Other Med Conditions		X				
data3[, 94]	Removal Voluntary		X constant		X	X constant	X constant
multrem	Indicator (removals>1)	X constant					X
data4[, 96]	**Reason for Removal Physical Abuse**	X constant	X	X	X constant	X	X (physical or sexual)
data3[, 98]	**Reason for Removal Neglect**		X	X constant	X constant	X constant	X
data4[, 105]	**Reason for Removal Parent Death**	X constant		X constant	X constant	X constant	X constant
data3[, 106]	RRParentIncarceration		X constant	X constant			
data2[, 107]	RRCaretakerCantCope			X constant			
data2[, 108]	RRAbandonment			X constant			
data2[, 109]	RRRelinquishment				X constant		
data2[, 110]	RRInadequateHousing						X
data3[, 111]	ageprimarycaretaker		X constant	X constant			X
data2[, 112]	dataset.EligNone			X constant	X constant		X
data4[, 114]	Age at Latest Removal	X	X			X	X
(physvishear) TRUE						X constant	
RRdrug			X constant				
race b or w			X constant		X constant		
race mix bw					X constant		
relinqaband			X constant				X constant

One Placement									
Covariate	**Definition**	**2008**		**2007**		**2006**		**2005**	
data1[, 85]	Gender (Male)						X		
data2[, 87]	**Disability Not Determined**	constant	X	X	X	X	X	X	X
data2[, 88]	Mental Retardation								
data 4[, 90]	Physical Disability	constant							
data3[, 91]	Emotionally Disturbed	constant						constant	
data3[, 92]	Other Med Conditions	X							
data3[, 94]	**Removal Voluntary**			constant	constant	constant	constant	X	X
multrem	Indicator (removals>1)								
data4[, 96]	**Reason for Removal Physical Abuse**		X	X	X	X	X	X	
data4[, 97]	Reason for Removal Sexual Abuse					X		X	
data3[, 98]	Reason for Removal Neglect	X		constant	constant		constant	X	
data4[, 105]	Reason for Removal Parent Death	constant	X						constant
data3[, 106]	RRParentIncarceration	constant							
data2[, 107]	RRCaretakerCantCope		constant					X	
data2[, 108]	RRAbandonment	constant	X	constant	constant				
data2[, 109]	RRRelinquishment		X	constant					
data2[, 110]	RRInadequateHousing	constant					constant		
data3[, 111]	ageprimarycaretaker			constant					
data2[, 112]	dataset.EligNone	X	X	constant	constant	X	X	X	X
data4[, 114]	Age at Latest Removal	constant				constant		X	X
NumRemMat[, 2]								X	
(physvishear)TRUE									
RRdrug	**RRdrug**		X	constant	constant	constant	X	X	
RRAlcohol						constant			
race W vs B		constant						X	
race mix bw		constant							
relinqaband							constant		constant
blamechild TRUE							constant		

Variables that appeared in most models appear in **bold** font

Appendix C: Abbreviations and Acronyms

AFCARS: Adoption and Foster Care Analysis and Reporting System

CFSR: Child and Family Services Review

DFCS: Division of Family and Child Services

FFY: Federal Fiscal Year

NDACAN: National Data Archive on Child Abuse and Neglect