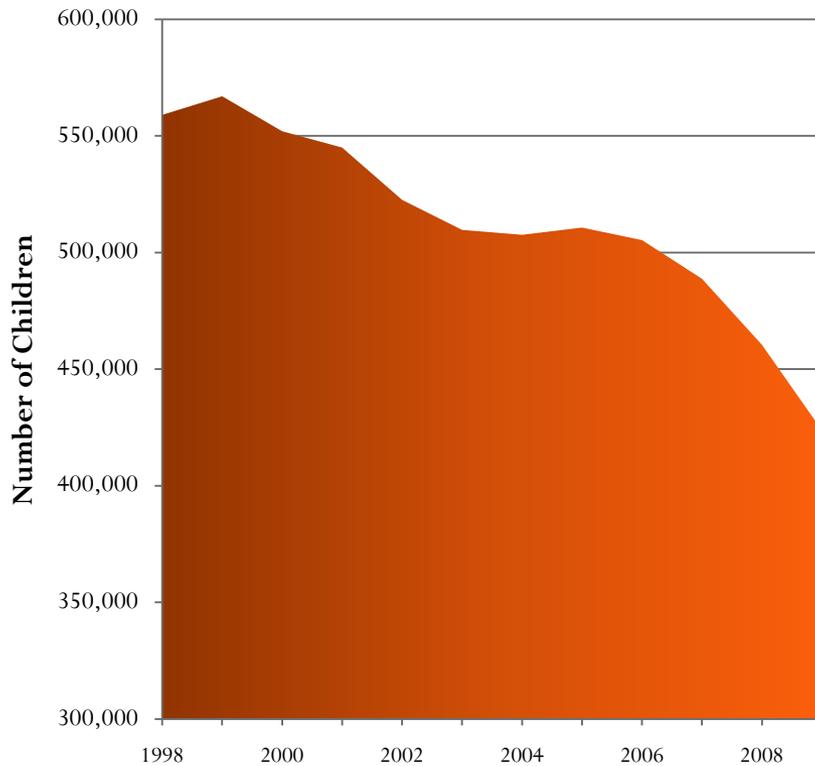


PII Overview and Evaluation Design

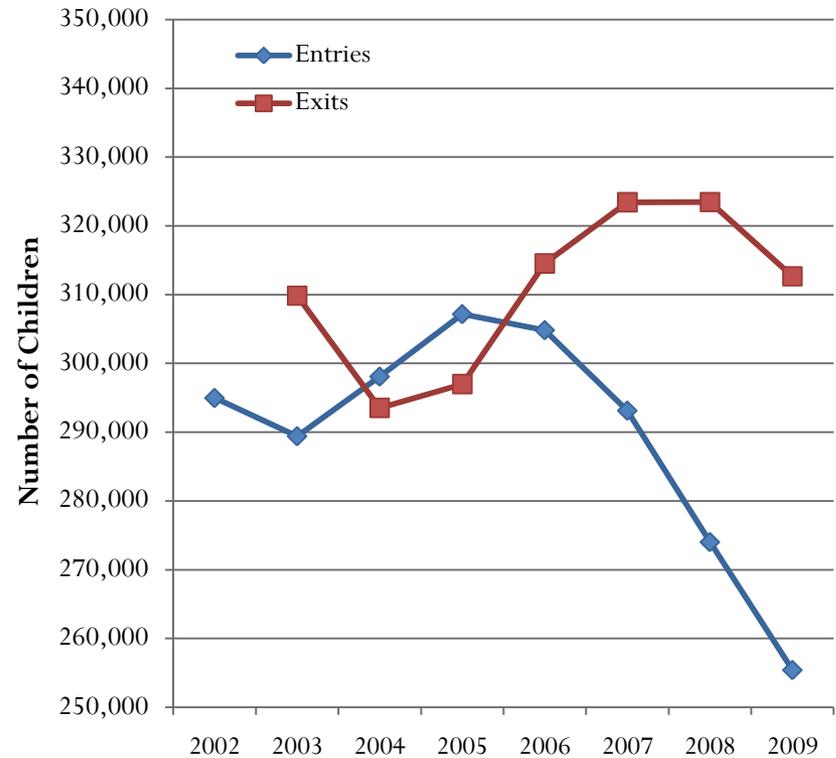


PII Background: Foster Care Trends

- Population in Foster Care



- Entries into and Exits from Foster care

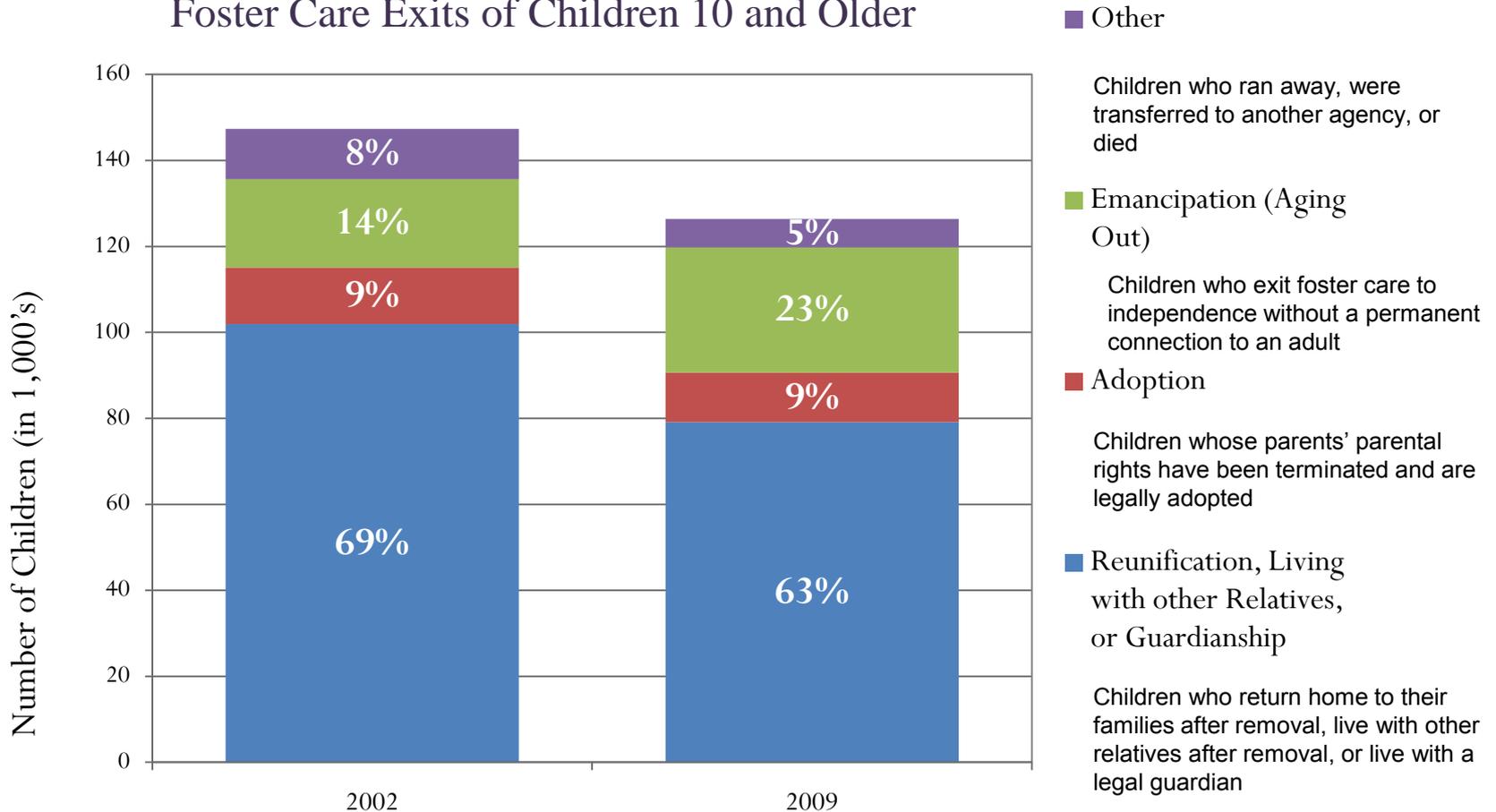


*From presentation by Bryan Samuels, Commissioner, ACYF, Emphasizing Evidence-Based Programs for Children and Youth Forum, Washington DC, April 27-28 2011.

PII Background:

Older children now more likely to age out of care

Foster Care Exits of Children 10 and Older



3

*From presentation by Bryan Samuels, Commissioner, ACYF, Emphasizing Evidence-Based Programs for Children and Youth Forum, Washington DC, April 27-28 2011.

Permanency Innovations Initiative

Presidential Initiative

The Permanency Innovations Initiative. . . is providing support . . . focused on decreasing the number of children in long-term foster care. Over the next 5 years, this program will invest \$100 million in new intervention strategies to help foster youth move into permanent homes, test new approaches to reducing time spent in foster care placements, and remove the most serious barriers to finding lasting, loving environments.*

Goal—Build Evidence for Replicable Strategies

The PII will build the evidence base for innovative interventions that improve permanency outcomes for children and youth who face serious barriers to permanency and are at high risk of long-term foster care (LTFC)

*President Barack Obama, Presidential Proclamation: National Foster Care Month, White House Office of the Press Secretary, April 29, 2011.

6 Cooperative Agreement Awards for a Planning and Design Year

- Arizona Department of Economic Security
- California Department of Social Services
- Illinois Department of Children and Family Services
- University of Kansas Center for Research, Inc.
- Los Angeles Gay and Lesbian Community Services Center
- Washoe County, Nevada, Department of Social Services

Two Contracts

Technical Assistance

Use tenets of implementation science, combined with child welfare programmatic expertise, to improve implementation, effectiveness, fidelity, and sustainability of PII interventions

JBS International (JBS)_with Center for the Support of Families (CSF),
National Implementation Research Network (NIRN)

Evaluation

Design and conduct local-level and cross-site evaluations of the interventions' ability to remove barriers and reduce long-term foster care (LTFC), design and conduct evaluations of the implementation process and cost

Westat_ with James Bell Associates (JBA),
University of North Carolina (UNC), Ronna Cook Associates (RCA)

PICO:

Well-built Evaluation Question Elements

Do children in population (P) that receive intervention (I) have a significantly better outcome (O) than children in a comparison group (C) who do not receive the I?

- Population
- Intervention
- Outcome
- Comparison

Year 1:

4 Templates and 2 Summative Plans

Template	Summative Plan(s)
Population Template	Implementation Plan and Evaluation Plan
Intervention Template	
Comparison Template	Evaluation Plan
Outcome Template	

P Template—

- *What target P(s) are at risk of LTFC or disproportionately represented in LTFC?*
- *What are the specific child, placement, and family characteristics of P that put P at risk of LTFC and what evidence shows that these are associated with LTFC?*
- *Prioritize these characteristics and summarize the results of data mining that show they are associated with risk of LTFC.*
- *What key systemic barriers especially affect P (staffing, organization support/service, leadership, other)*

Informing the Population Template

- Literature reviews
- Focus groups
- Case record reviews and data extraction
- Analyses of administrative data

Using Administrative Data

- Describe the LTFC Population
- Compare characteristics of children in LTFC with children in care for shorter periods
- Model risk characteristics known at earlier points in time that distinguish children who move into LTFC from those who exit to permanency sooner

Identifying and Refining the Target Populations for a National Initiative
to Reduce the Long-Term Foster Care Population

Survival Trees in Child Welfare
David Judkins



Cox proportional hazards models are nice but ...

- Main effects don't always point to a suitable target population
- If factors A, B, and C are associated with longer foster care spells, this does not necessarily mean that children with all three factors have elevated risk of long-term care
- Interactions among them can reduce risk
- Also, the size of the population that has all three factors may be small – too small to be worth targeting with custom intervention

What if things were easy

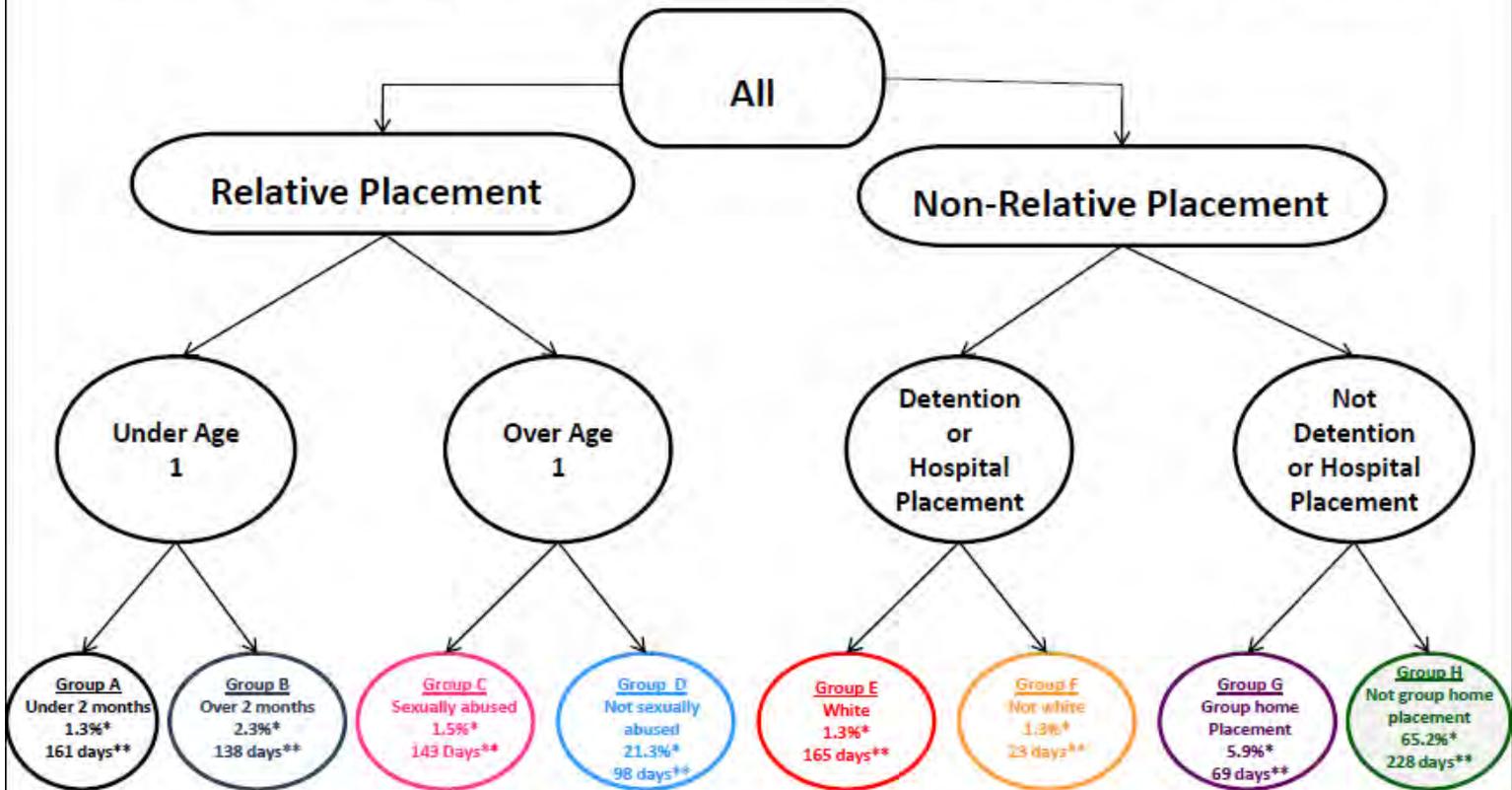
- If we had a large sample of recent cases with an indication of whether their placements became long-term placements,
- Then we could use standard interaction-detection software like SEARCH, CHAID, and CART which are designed to find interactions in models of continuous, ordered categorical and binary variables
- But much of our sample is censored
- People question the relevance of old data and the new data are not yet resolved

Extending tree models to censored survival data

- SEARCH, CHAID, and CART are all examples of tree-based regression modeling software (original idea by Morgan and Sonquist, 1963)
- They have this name because visual displays of the models strongly resemble family genealogy trees
- How to adapt them to use censored survival data?
- And to ensure that identified groups are large enough to warrant investment in custom research?

Stratification

Overview of the Flow of Uncensored Cases through the Splitting Procedure



** Percentage is of all 123,292 first placements FY1991-FY2009

*** Median days in placement is based on the 123,292 cases.

Software ideas

- A group of children who are at high risk of long-term placement should have a distinctive survival curve (where survival is defined as continuance of placement episode)
- Tree-regression modeling software makes a series of binary splitting decisions in such a manner as to maximize the differences between the resulting nodes
- If we had a way to quantify distances between survival curves, then we could set up a procedure to make a series of binary splitting decisions to maximize the differences between the survival curves between the resulting nodes

Independent Reinvention

- As I was preparing this presentation, I discovered that other have had the same broad idea:
 - Gordon and Olshen (1985)
 - Segal (1988)
 - LeBlanc and Crowley (1993)
- My ideas of how to implement are different
- Remains to be seen which are better

Back up: How do tree models work?

- Take the example of predicting nonresponse in a followup survey (Göksel, Judkins, and Mosher, 1992)
- Available predictor variables included (among others) mobility, race/ethnicity, education, income, marital status, number of visits required to obtain baseline interview
- The software considered a very large number of possible first splits
- The first split was on mobility. The followup response rate for movers was 55% compared to 79% for nonmovers

How do tree models work? (2)

- Among movers, the next split was on race/ethnicity. Response rates were 32% for Hispanic movers, 42% for black movers, and 68% for white movers.
- Among nonmovers, the next split was on also on race/ethnicity but with two rather than 3 splits. Response rates were 72% for black and Hispanic nonmovers, and 84% for white nonmovers.

How do tree models work? (3)

- Splits continued down each root with independent decisions made across nodes
- Stopped each root when too small to split further or no heterogeneity within final node could be discovered
- 30 cells were formed with response rates that varied from 32% to 95%

Who uses tree models?

- Popular among survey methodologists
- Very popular for fraud detection in credit card transactions
- In general, popular for people who need to make predictions
- Less popular for people who want to understand the contributions of various factors for some outcome
- From LeBlanc and Crowley: “Interest in tree-based methods for censored survival data usually comes from the need of clinical researchers to define interpretable prognostic classification rules both for ... and *for designing future trials.*”

Defining distances between survival curves

- Survival curves all collapse at 1 at time =0 and at 0 at time= 18 years
- Hazard curves show more interesting variation over time
- Either determines the other (hazard & survival curves)

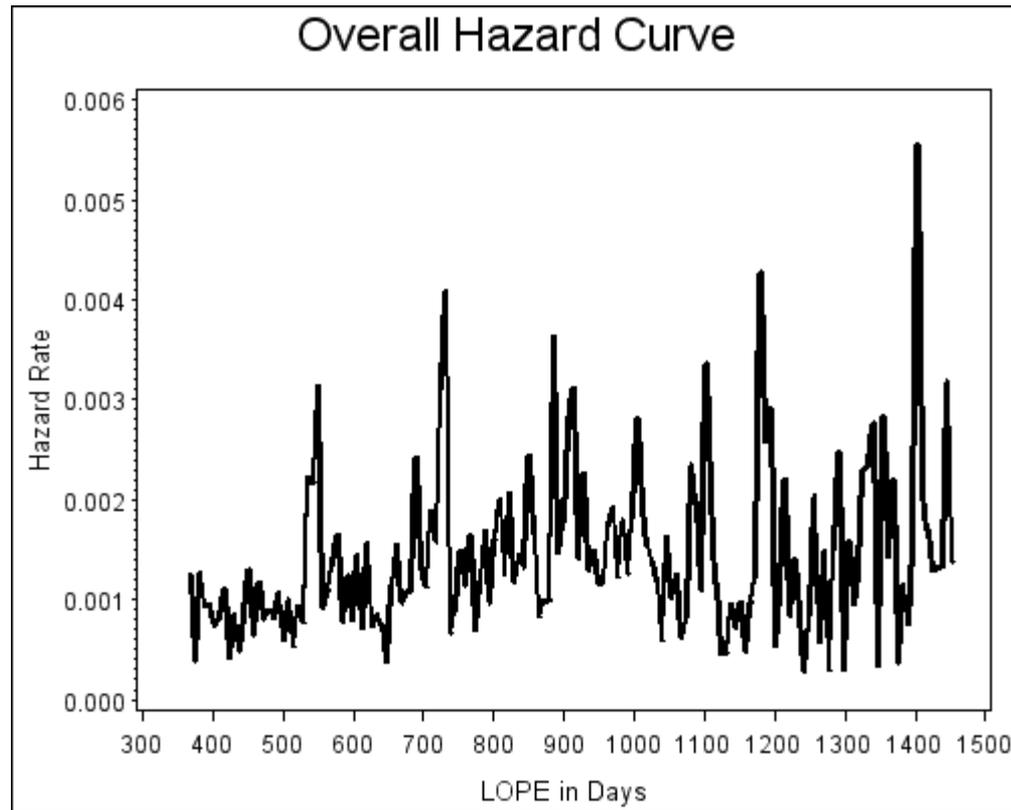
In PII Context:

- Survival curve at day t is the probability that child will still be in foster care at day t
- The hazard curve at day t is the probability that a placement will end on that day *given that the placement episode did not end sooner*
- Hazard curve is difficult to estimate well because it refers to instantaneous probabilities but foster care exits may be sparsely distributed, particularly for large values of t

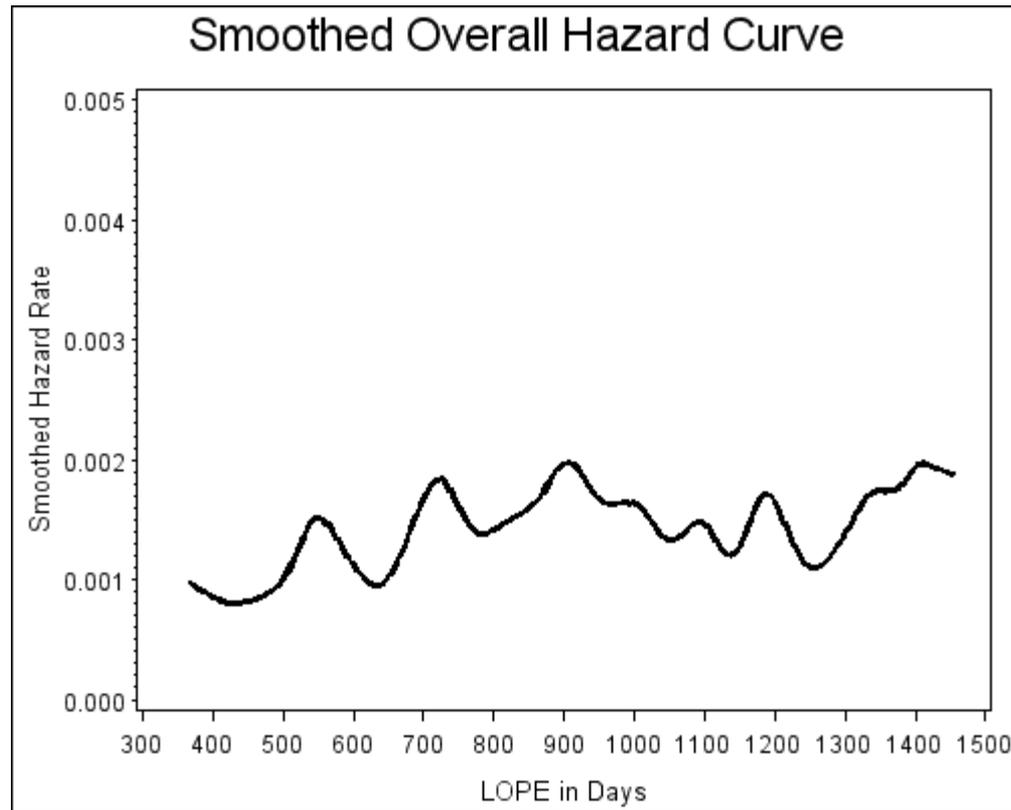
Washoe County, NV

- Children already in placement one year
- Illustrate survival curves and hazard curves from SAS PROC LIFETEST
- Hazard curves will be calculated on a weekly basis. Fairly noisy given sample sizes. Will show original and smoothed hazard curves

Overall hazard curve



Smoothed overall hazard curve



Calculating differences between hazard curves

- My software has two options
 - Max distance at any of the measured points of the (unsmoothed) two curves (inspired by the Kolmogorov-Smirnov test for the equivalence of two probability distribution functions)
 - Average distance at all of the measured points (an approximation to the area between the curves)
- Might someday try calculating differences between smoothed hazard curves

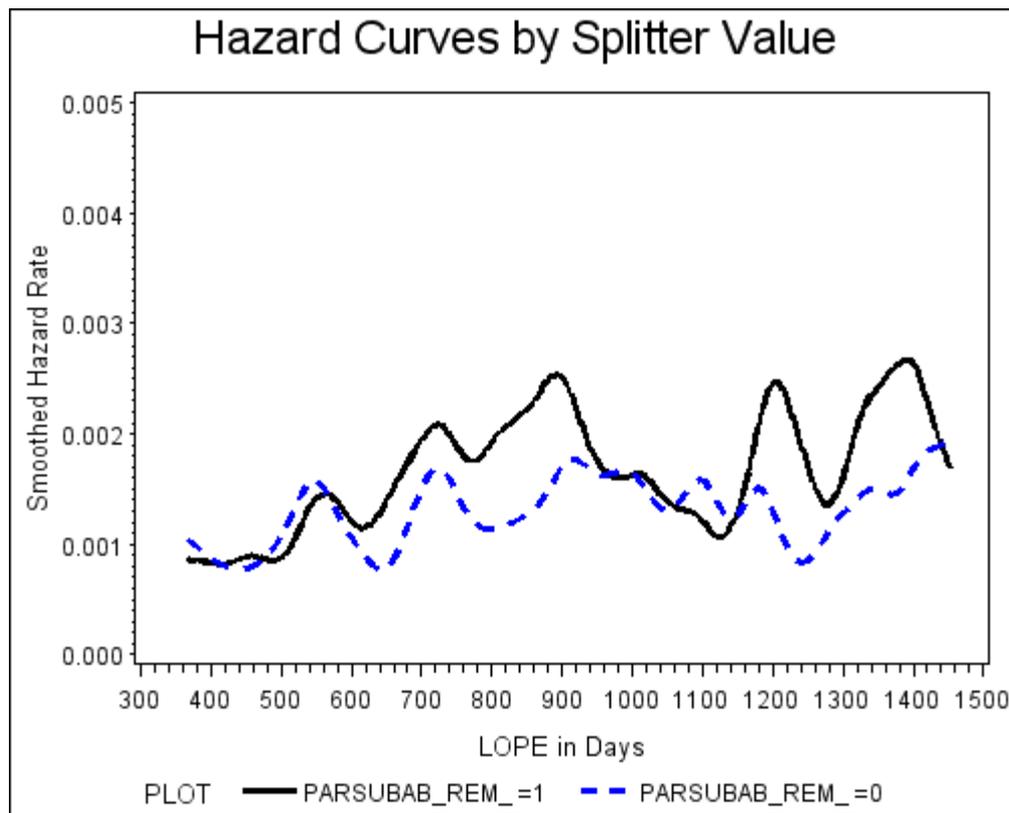
Node size limitations

- My software can only do three splits on binary variables
- So it forms at most 8 nodes and will usually form that number exactly
- Minimum size of final node under user control – in terms of number of uncensored children
- Nodes from second split must have at least 3 times that number of children
- Nodes from first split must have at least 10 times that number of children

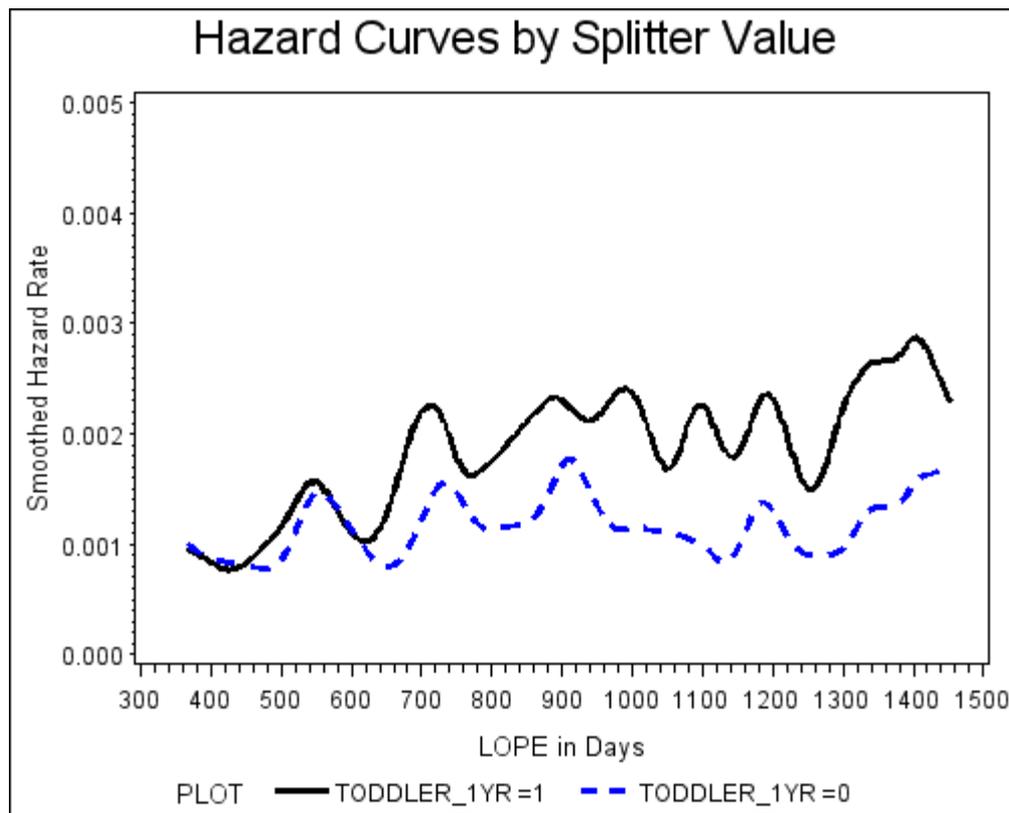
Washoe

- Given small number of children in care for at least one year,
- Set min size for third-level nodes at 50
- So min size for second-level nodes was 150
- And min size for second-level nodes was 500
- Only 6 variables eligible for first split

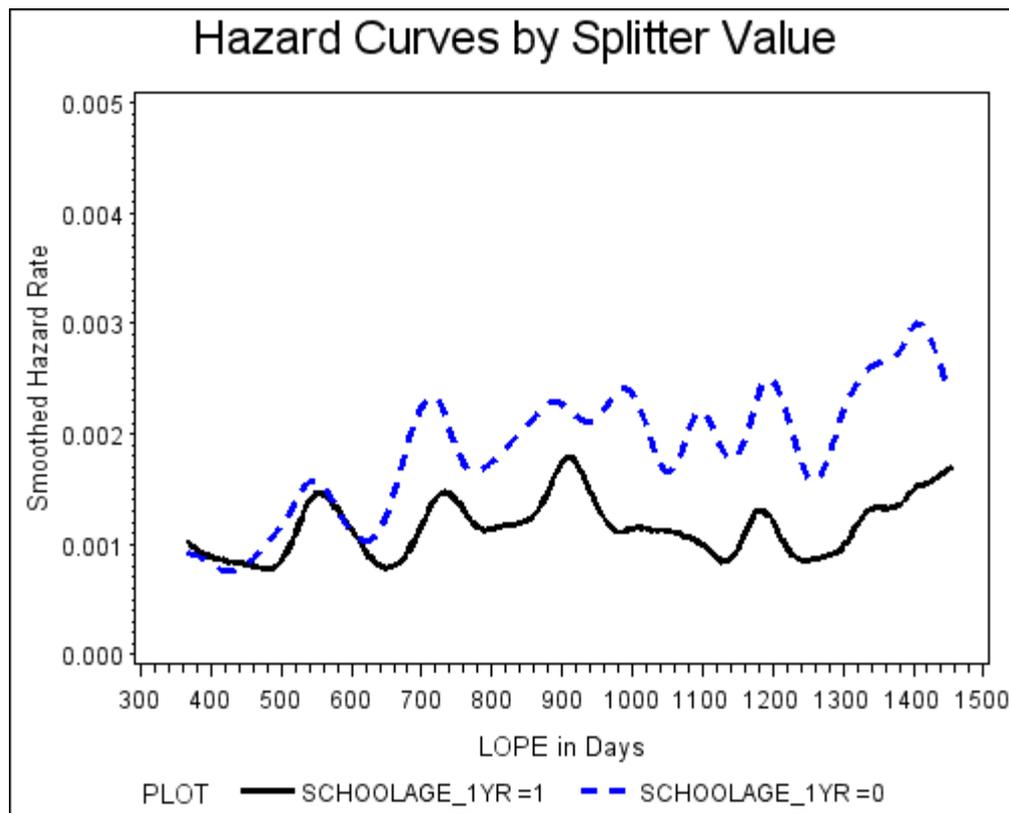
If split on removal due to parental substance abuse



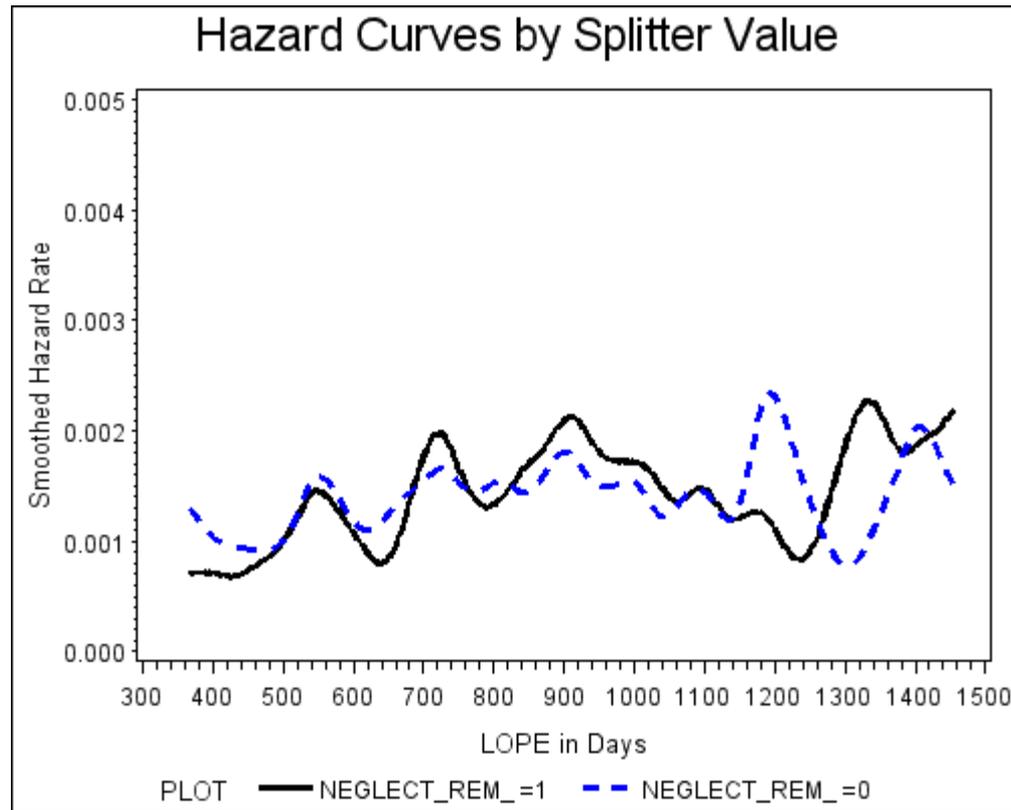
If split on whether child is toddler age at one year of placement



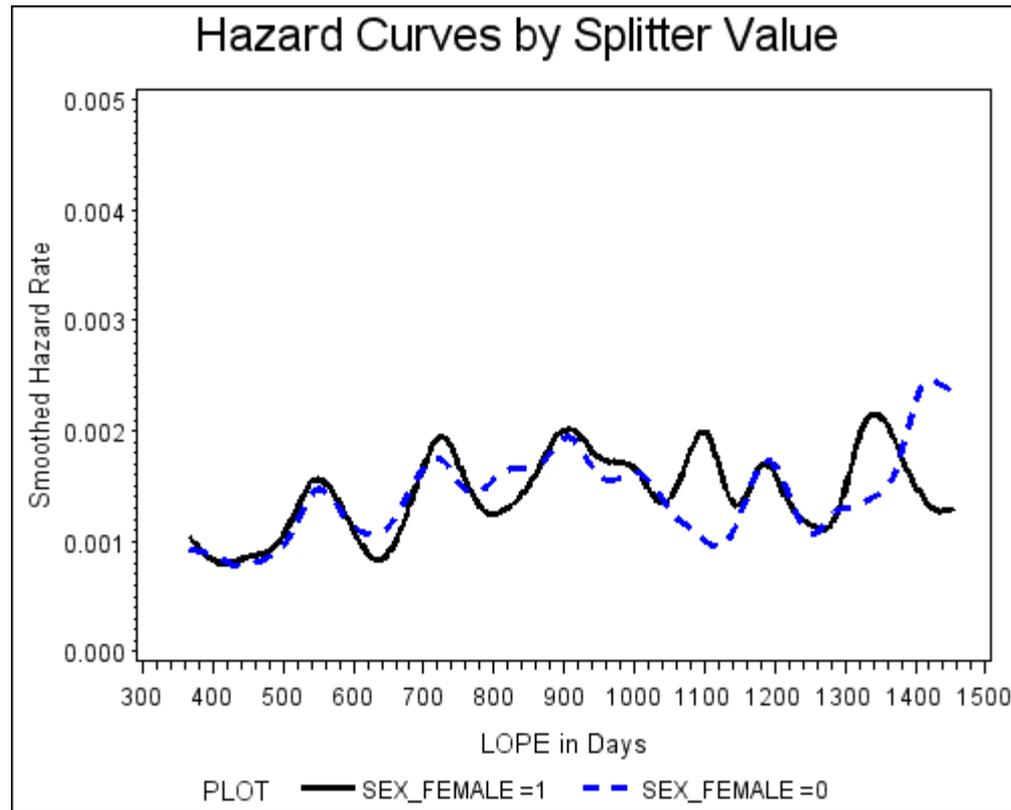
If split on whether child is school age at one year of placement



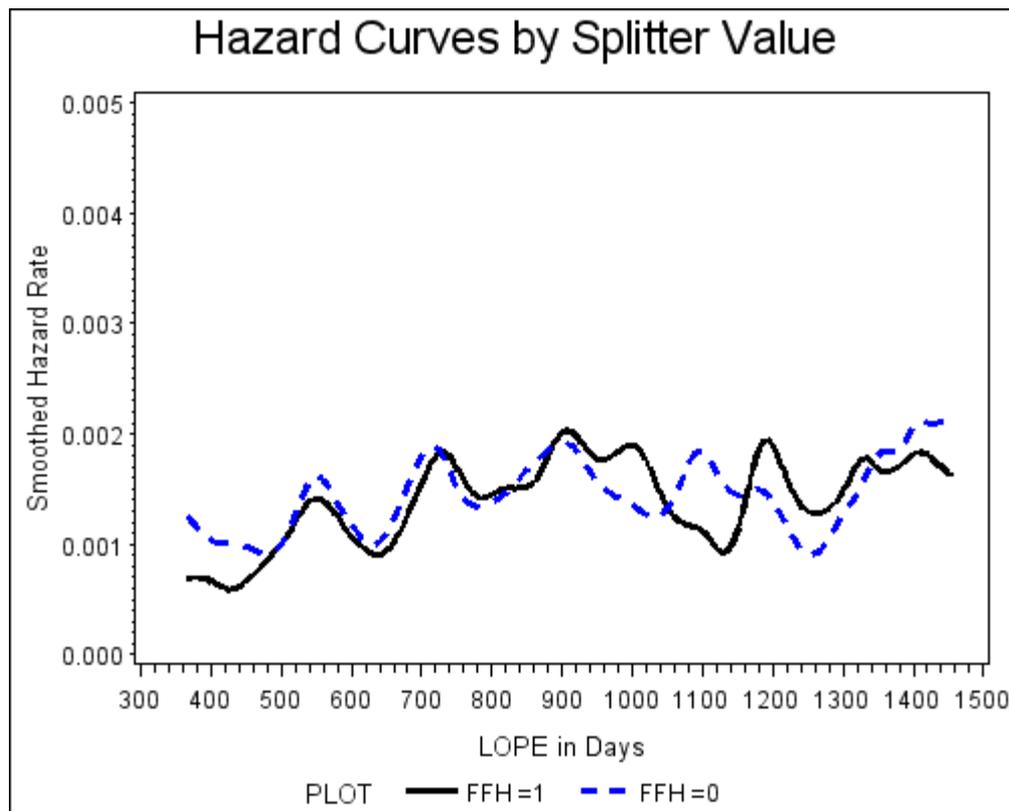
If split on removal due to neglect



If split on sex of child



If split on resource group at one year of placement is foster family home

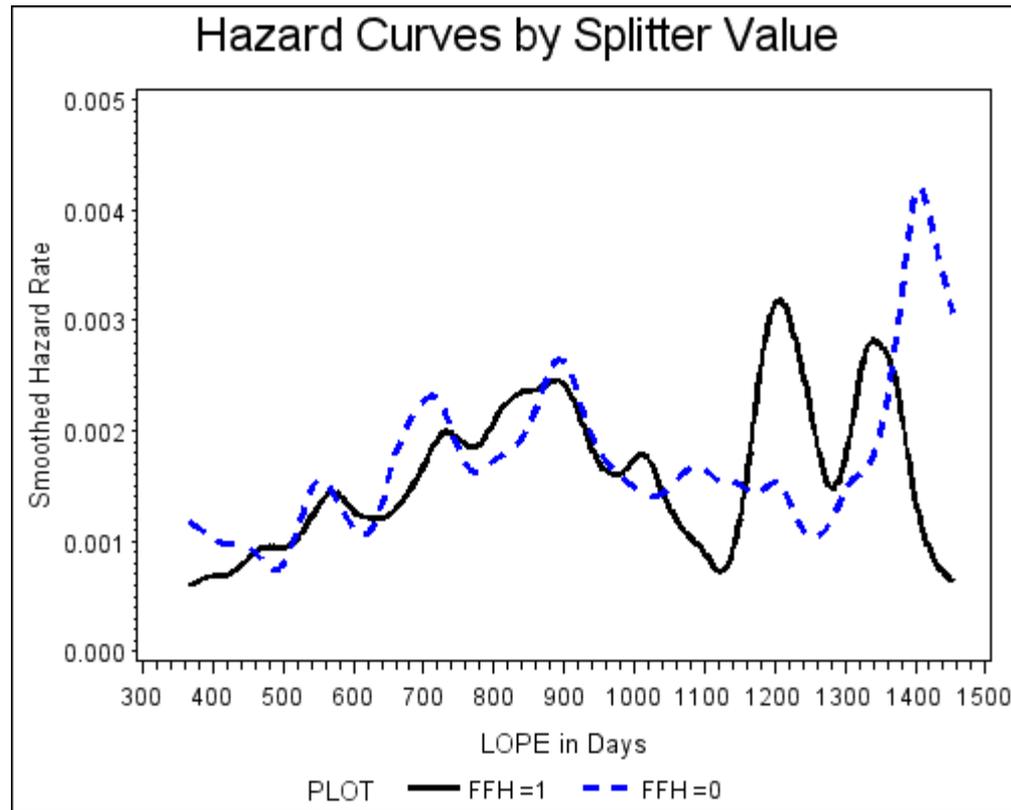


Distances

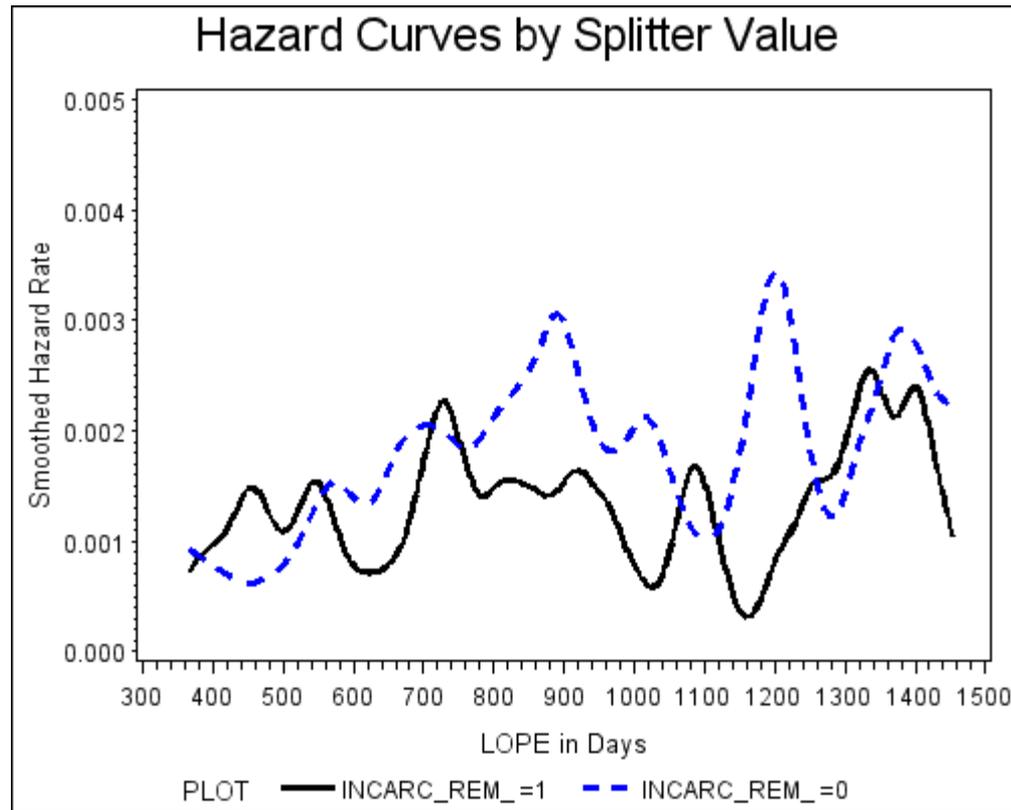
Splitter	Max rule	Average rule
Removal due to parental substance abuse	0.00630	0.00107
Child aged 1-4 after one year of placement	0.00614	0.00105
Child aged 5 to 18 after one year of placement	0.00609	0.00109
Female child	0.00548	0.00078
Removal due to neglect	0.00469	0.00097
Child in foster family home after one year of placement	0.00460	0.00102

Second splits

Splitting children removed for parental substance abuse by foster family home at one year

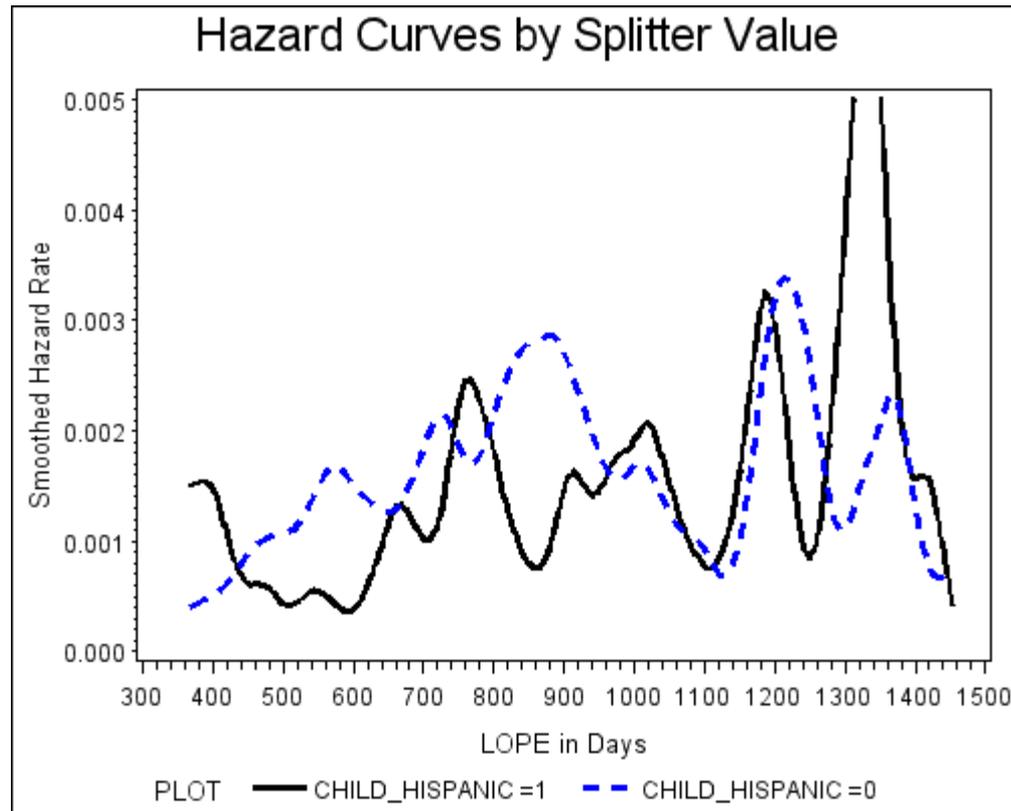


Splitting children *not* removed for parental substance abuse by removal due to parental incarceration

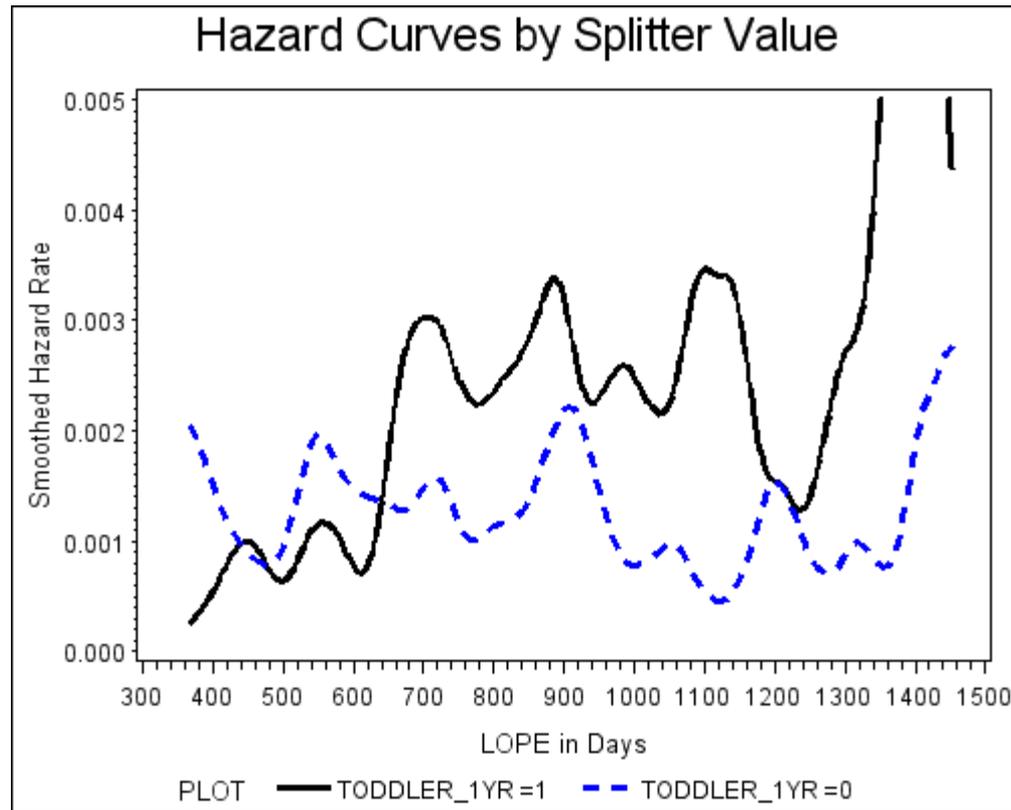


Third splits

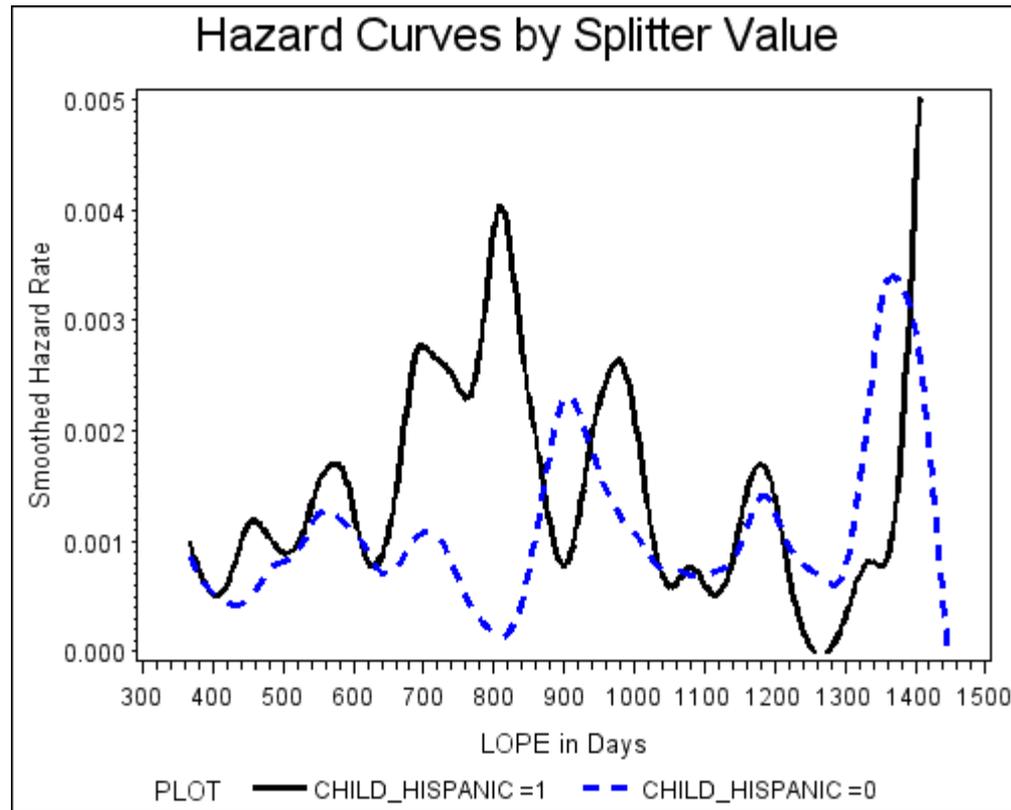
Splitting children removed for parental substance abuse and living in foster family home at one year by ethnicity



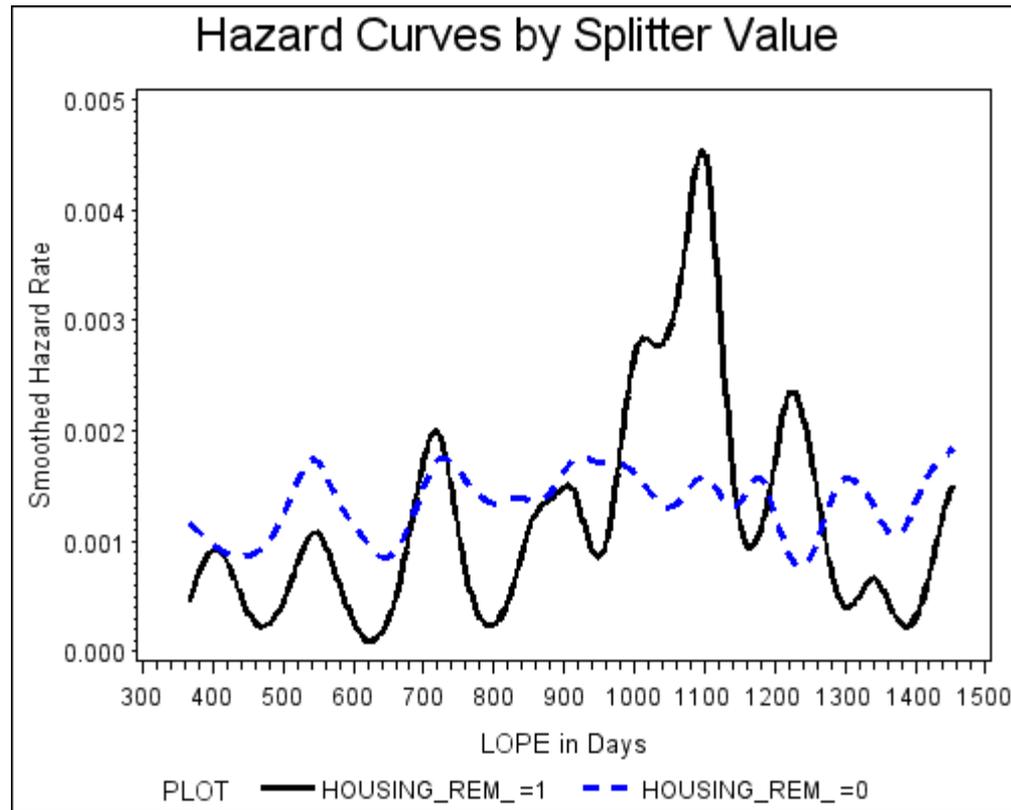
Splitting children removed for parental substance abuse and *not* living in foster family home at one year by age

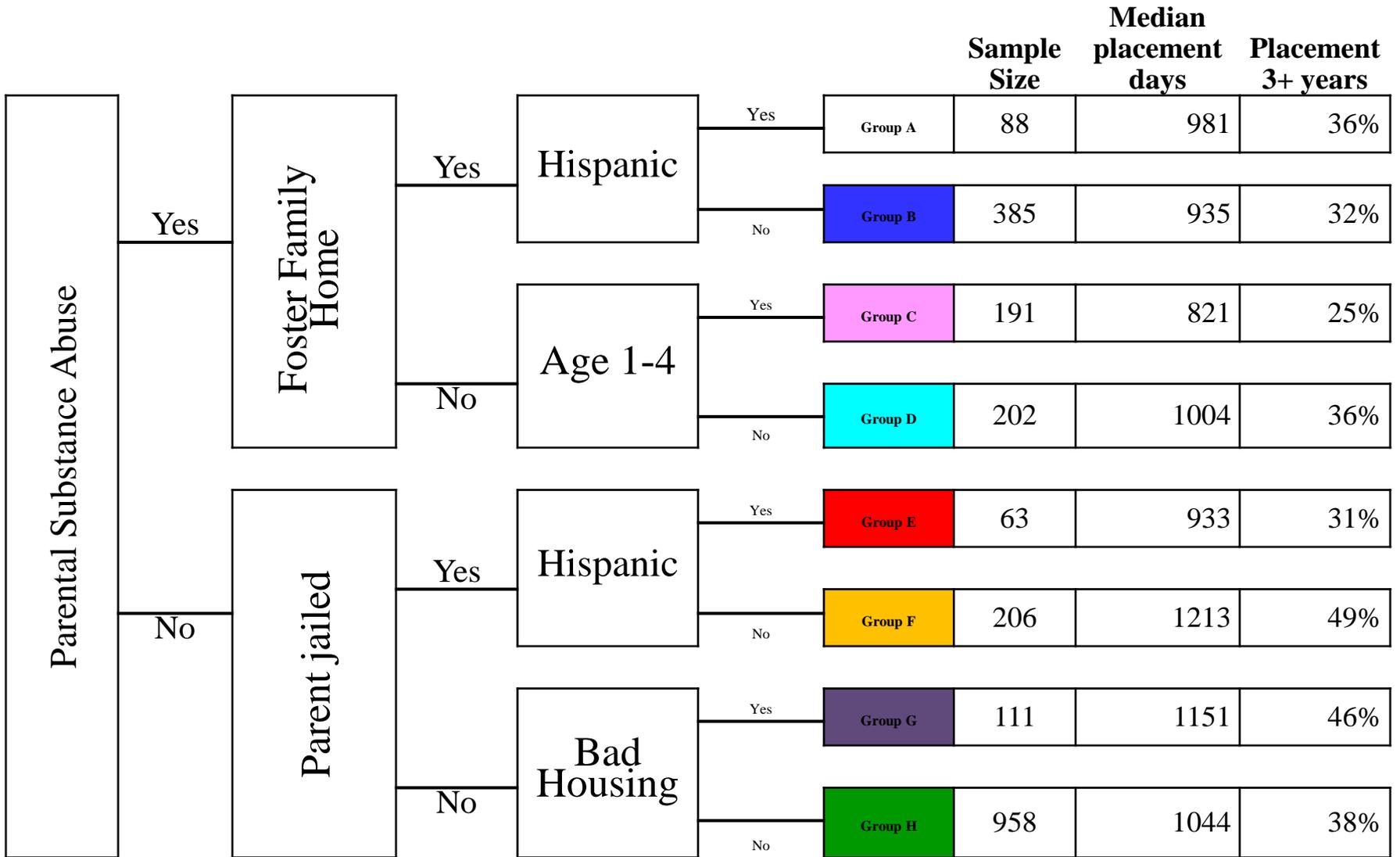


Splitting children removed for parental incarceration by ethnicity

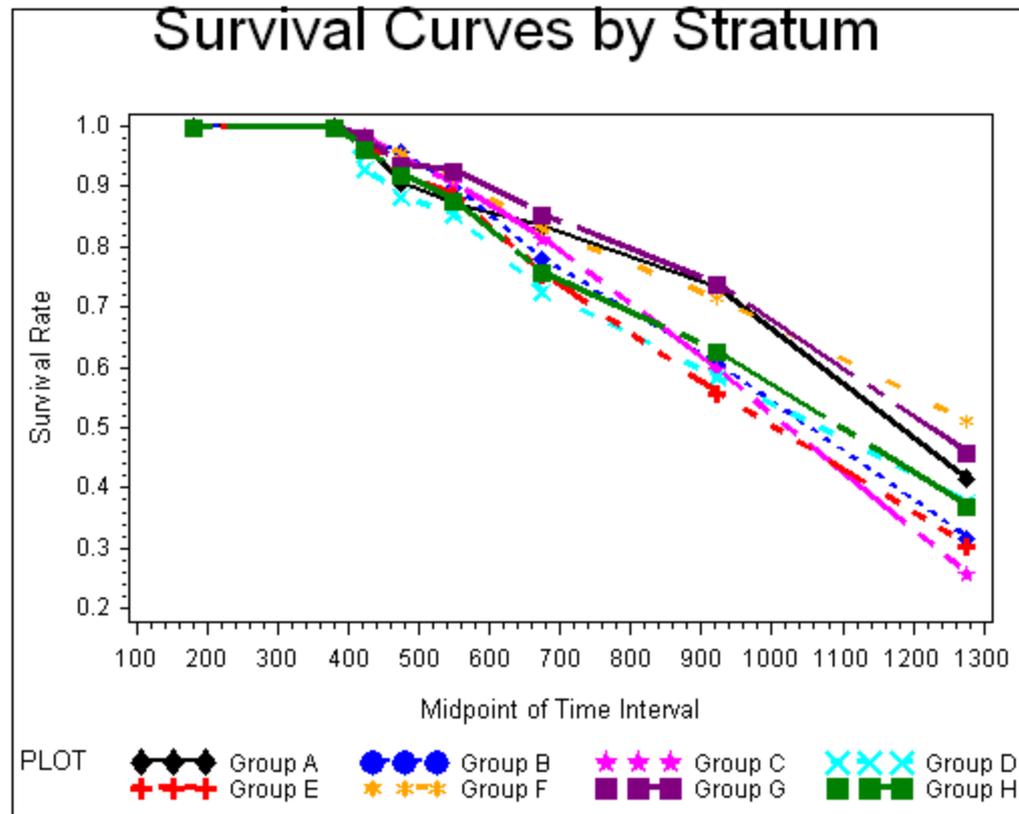


Splitting children *not* removed for either parental substance abuse or parental incarceration by removal due to housing

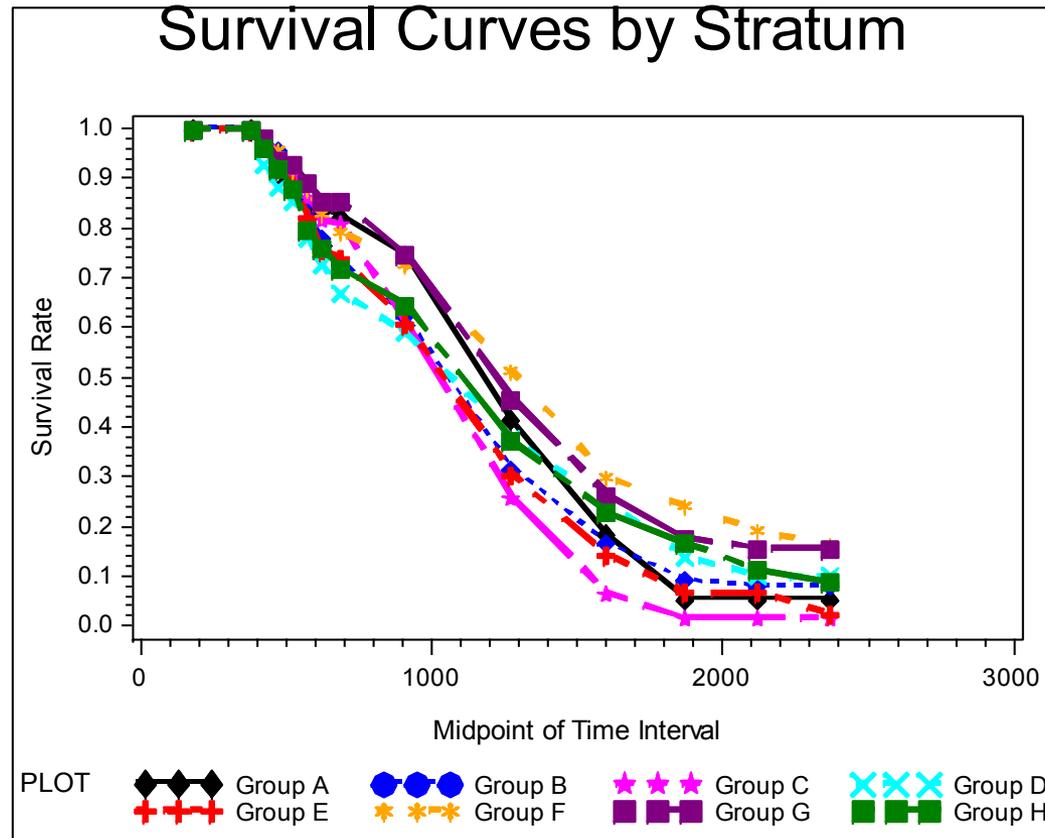




All 8 groups over medium horizon



All 8 groups over long horizon



References

- Gordon, L. and Olshen, R. (1985). Tree-structured survival analysis. *Cancer Treatment Reports*, **69**, 1065-1069.
- LeBlanc, M. and Crowley, J. (1993). Survival trees by goodness of split. *Journal of the American Statistical Association*, **88**, 457-467.
- Morgan, J. and Sonquist, J. (1963). Problems in the analysis of survey data and a proposal. *Journal of the American Statistical Association*, **58**, 415-434.
- Segal, M. (1988). Regression trees for censored data. *Biometrics*, **44**, 35-48.



Kansas Data Mining

Identifying a Target Population for the Kansas Intensive Permanency Project (KIPP)

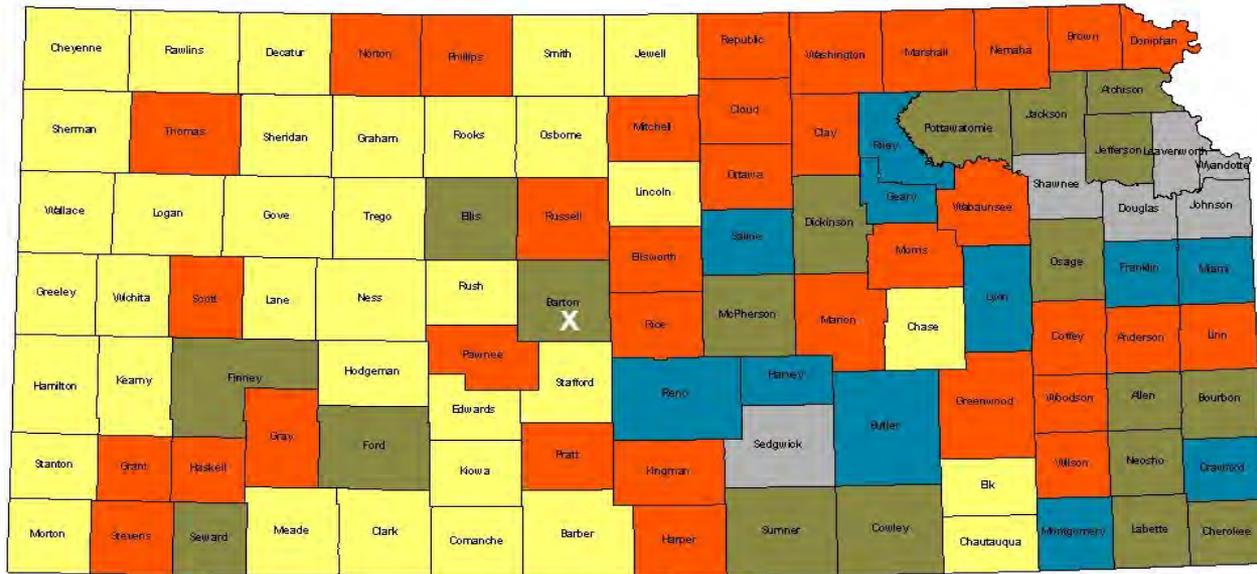


Kansas Context

- PII Project: Kansas Intensive Permanency Project (KIPP)
- Convened by
 - University of Kansas School of Social Welfare
- Key partners
 - State public child welfare agency (Kansas SRS)
 - 4 foster care providers across the state
 - KVC Behavioral Healthcare
 - St. Francis Community Services
 - TFI Family Services
 - Youthville Inc.
- Privatized foster care since 1997
- Long history of public-private-university partnership

Map of Kansas Counties by Population Density

Population Density Peer Groups for Counties in Kansas



The X in Barton County designates it as the central county of Kansas.
Source: The Geography of Kansas: Part 1: Political Geography by Walter H. Schoewe (pg. 255) Transactions of the Kansas Academy of Science (1903) copyright 1948 Kansas Academy of Science

Population Density Peer Group

- Frontier (less than 6 persons per sq. mile)
- Rural (6 to 19.9 persons per sq. mile)
- Densely-settled rural (20 to 39.9 persons per sq. mile)
- Semi-Urban (40 to 149.9 persons per sq. mile)
- Urban (150+ persons per sq. mile)

Based on 2007 U.S. Census Bureau Population Estimates using the peer group definition adopted by the Kansas Department of Health and Environment. For more information, see the following website: <http://www.socwel.ku.edu/occ/iewProject.asp?ID=76>

Brief Background of KIPP

- Target population
 - Children with severe emotional disorders (SED)
- Target of intervention
 - Parents of children with SED
 - Early in case; intensive work focused on parent
- Initial problem definition
 - Kids with SED stuck in foster care
 - Lack of dedicated parent services
 - Impact of parental trauma
 - Widening gap between parent & child with SED

Kansas Approach to Defining the Target Population

- Proposal development phase
 - Consensus process among partners
 - SED and DD emerged as issues
- Planning phase
 - What are the critical barriers to permanency?
 - What are the risk factors of LTFC?
 - Triangulation approach:
 - Would SED remain a risk factor of LTFC using multiple analyses and info sources?

4 Major Activities of Target Population Planning Phase

1. Literature review and expert consultation
2. Quantitative data analysis of child/case characteristics
3. Case record review of family risk factors
4. Electronic survey of systemic barriers

Activity 1: Literature Review & Expert Consultation

- Reviewed about 20 empirical studies
- Consulted with several national child welfare experts

Key Findings of Literature Review & Expert Consultation

- Good number of studies on permanency
- Multiple variables examined
- Single variable that consistently showed statistical significance: child mental health problems
- Current system gap: Focus on parents early on in the case

Activity 2: Quantitative Analysis

- Quantitative analysis of child/case characteristics
- N = 7,099
- Entry cohorts (FY2006 & FY2007)
- Three types of analysis
 1. Descriptive analysis of mental health diagnoses
 2. Bivariate analysis of LTFC
 - Crosstabs of all characteristics with LTFC (> 3 years OOH care)
 3. Multivariate analysis of LTFC and reunification
 - Logistic regression (outcome = LTFC, yes/no)
 - Survival analysis (outcome = time to reunification)

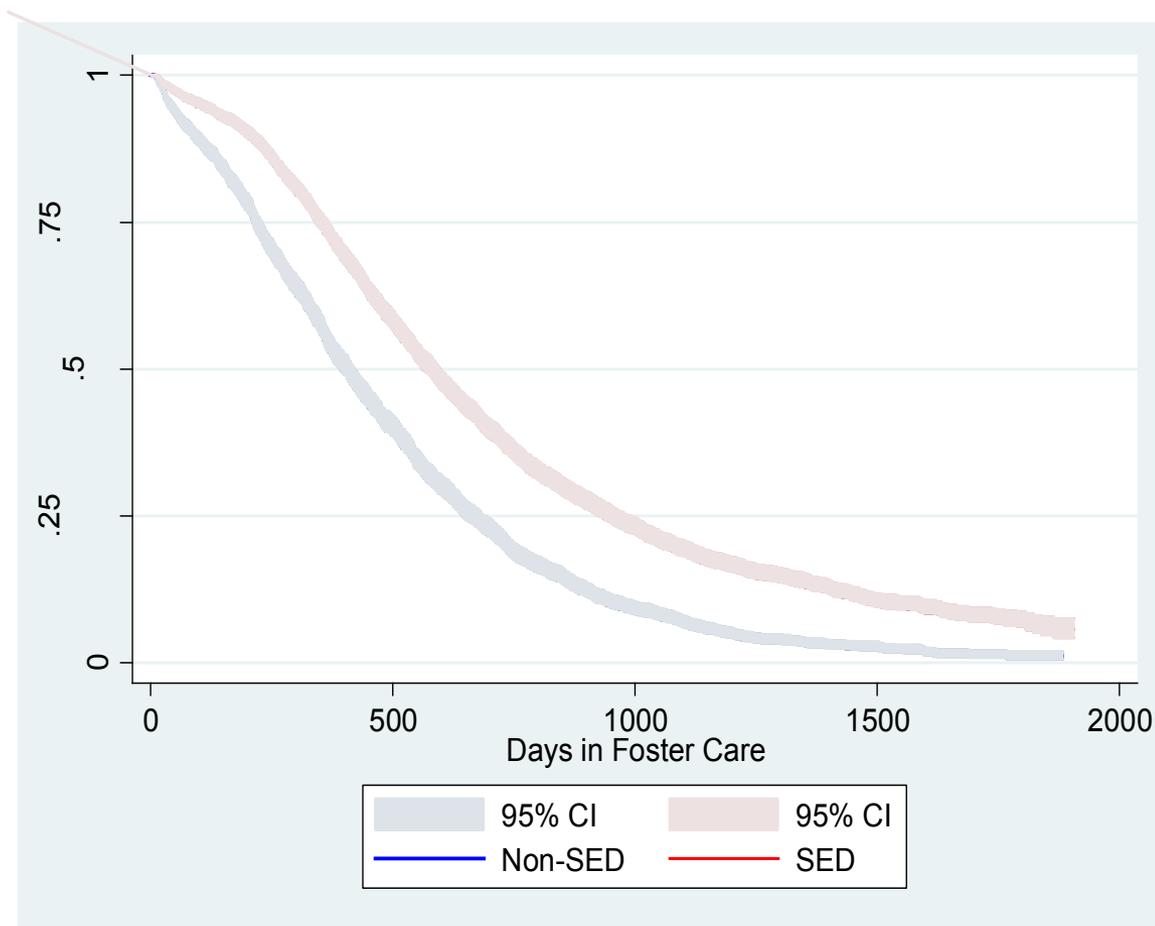
Key Findings of Descriptive Analysis of Mental Health Diagnoses

- Most prevalent dx of children in LTFC = behavior disorders
- Most prevalent dx of children NOT in LTFC = adjustment disorders
- Children with SED in LTFC were
 - More likely to have both externalizing and internalizing disorders
 - Also more likely to present with co-occurring developmental disorders

Key Findings of Bivariate & Multivariate Analyses

- Bivariate (one variable at a time)
 - Two variables with strongest association with LTFC:
 - Presence of an SED
 - Presence of a disability
- Multivariate (multiple variables in single statistical model)
 - LTFC – Variable with strongest relationship to LTFC:
 - SED (OR = 3.6)
 - Children with SED were 3-1/2 times more likely to experience LTFC while controlling for all other variables in model
 - Reunification – Two variables with largest effect on reunification:
 - SED (HR = .10) and early stability (HR = 7.88)
 - Children with SED were 90% less likely to reunify

Survival Curves for Children with SED and Children without SED



Activity 3: Case Record Review

- N = 30 randomly selected cases of children with SED in LTFC
- Focus on parents' needs
- Read case record
- Interviewed case manager or supervisor

Summary of Case Record Review Findings

	Family Structure			Poverty/Resources/Supports				Clinical Needs/Presenting Problems					Parenting				Home Envir/Other Stressors			
	# of CG	# of Children in OOH Care	# of Children in Home	Poverty Related Issues	Housing Not Stable	Lack of Social Supports	Multiple Services; Need Help Coordin Services	Mental Health Problems	Hx of Trauma	Parent Hx of Foster Care	AOD Issues	Devel Disab/ Cognit Probs	Medical Probs	Parent Compt	Parent Attitude	Coop Prob or Engage Prob	Prior CW Involv/ Reports/ Subst	Dom Viol	Legal Issues or Criminal Involv	Other Stress/ Caregiv Strain
Case 1	2	3	0	1	0	1	0	1	1	0	1	1	1	1	1	0	1	1	1	99
Case 2	1	3	0	1	1	1	0	1	1	99	1	0	0	1	1	1	1	1	1	99
Case 3	1	7	0	1	1	0	1	0	1	0	1	0	0	99	1	1	1	0	0	1
Case 4	1	5	0	1	0	1	0	99	99	99	1	99	99	1	1	1	1	0	1	1
Case 5	1	4	0	1	1	1	0	1	1	0	1	0	0	1	1	1	1	0	0	1
Case 6	1	3	0	1	0	1	0	1	1	0	1	0	0	1	1	1	1	1	1	1
Case 7	2	4	2	1	1	1	1	1	1	0	1	1	1	1	0	0	1	0	0	1
Case 8	1	5	0	1	1	1	0	1	1	0	1	1	0	1	1	1	1	1	1	1
Case 9	2	3	0	1	1	0	1	1	1	0	1	0	1	1	1	1	1	1	1	1
Case 10	2	1	2	1	1	1	0	1	99	99	1	0	1	1	1	1	1	1	1	0
Case 11	2	3	0	1	1	1	0	1	1	1	0	1	0	1	1	1	0	0	1	1
Case 12	2	4	0	1	1	1	0	1	1	0	1	0	0	1	1	1	1	1	1	0
Case 13	1	2	1	1	1	1	0	1	1	0	1	0	1	1	1	1	1	1	0	0
Case 14	2	3	2	0	0	1	1	1	1	1	1	0	0	1	1	1	0	0	1	1
Case 15	2	5	0	1	1	1	0	1	1	0	1	0	1	1	1	1	1	1	1	0
Case 16	2	0	1	1	0	1	0	99	1	99	1	0	1	1	1	1	1	0	0	0
Case 17	1	1	0	0	0	1	0	1	0	0	0	1	1	1	0	0	1	0	0	1
Case 18	1	2	0	1	1	0	0	1	0	0	1	1	0	1	1	0	1	0	1	0
Case 19	2	4	0	1	0	1	0	1	1	99	1	0	0	1	1	1	0	1	1	0
Case 20	2	5	0	1	1	1	0	1	1	1	0	0	0	1	0	1	1	1	0	0
Case 21	2	1	2	1	0	0	1	1	1	0	0	0	0	1	1	0	1	0	0	1
Case 22	3	2	0	1	1	1	1	1	1	0	1	0	1	1	99	1	1	99	1	99
Case 23	2	2	0	99	99	99	0	1	1	99	1	99	99	1	0	0	1	1	1	99
Case 24	1	3	0	1	0	1	1	1	1	0	1	0	0	1	0	1	1	1	1	0
Case 25	2	1	0	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	1	99
Case 26	1	7	0	1	1	1	1	1	99	0	1	0	0	1	1	0	1	1	0	1
Case 27	2	3	0	1	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0
Case 28	2	1	3	0	0	0	1	1	99	0	0	0	0	1	0	0	1	0	0	0
Case 29	1	3	0	1	1	1	1	1	1	0	1	0	1	1	1	0	1	1	1	1
Case 30	2	1	0	1	1	0	1	1	1	1	1	0	0	1	1	0	1	1	1	0
TOTAL		3.03		26	18	22	13	27	24	6	25	7	11	29	23	20	27	18	20	13
%				87%	60%	73%	43%	90%	80%	20%	83%	23%	37%	97%	77%	67%	90%	60%	67%	43%

Key Findings of Case Record Reviews

- Five risk factors were both highly prevalent and most associated with LTFC
 1. Poverty related issues (87%)
 2. Parent mental health problems (90%)
 3. Parent alcohol & other drug problems (83%)
 4. Parent history of trauma (80%)
 5. Parenting competency/attitude (97%)

Activity 4: Systemic Barriers Survey

- Electronic survey, N = 232
- Child welfare staff and stakeholders on all levels, from frontline to CEO
- Public and private agency staff

Key Findings of Systemic Barriers Survey

- 5 top systemic barriers
 - Lack of dedicated parent services (84%)
 - High caseloads (79%)
 - High caseworker turnover (77%)
 - Parent lack of transportation (76%)
 - Court system (70%)

Lessons Learned

- SED more important than other child characteristics
- Data showed children with SED are subgroup at highest risk of LTFC
 - Agencies suspected this from practice experience
 - Data confirmed it
- Children with SED in LTFC experience both externalizing *and* internalizing behaviors
- Family risk factors are critical barriers that must be addressed to expedite stable permanency

Reaction to PII Approach

- Opened our minds to the possibility of finding a different/new target population
- Provided opportunity to immerse agency administrators in data, not just university researchers
- Promoted data driven decision-making & program design
- Required resources for labor-intensive data collection, analysis, and interpretation
- Created sense of urgency for and strengthened our commitment to this subpopulation of children
- Assisted us in selecting the intervention

KIPP Co-Principal Investigators:

Becci Akin, PhD

Stephanie Bryson, PhD

Tom McDonald, PhD

Contact:

Becci Akin

Research Associate

KU School of Social Welfare

beccia@ku.edu

California Data Mining

Identifying a Target Population for the California Partners for Permanency (CAPP) Initiative

The Performance Indicators Project is a collaboration of the California Department of Social Services and the University of California at Berkeley, and is supported by the California Department of Social Services and the Stuart Foundation



California Partners for Permanency (CAPP)

- **6 early implementation sites**
 - Fresno, Humboldt, LA Pomona, LA Torrance, LA Wateridge, Santa Clara
 - Represent different regions of state
 - Comprise about 11% of children in care statewide
- **10 replication sites**
 - Contra Costa, Monterey, Napa, Orange, Sacramento, San Bernardino, SF, Santa Cruz, Solano, Yolo
- **Other partners**
 - California Tribes
 - Child Welfare Co-Investment Partnership
 - California Department of Social Services
 - County Welfare Director's Association
 - Administrative Office of the Courts
 - Philanthropy—AECF, Casey Family Programs, Stuart Foundation, Walter S. Johnson, Zellerbach Family Foundation
 - California Regional Training Academies
 - Child & Family Policy Institute of California
 - California Social Work Education Center
 - California Youth Connection
 - Center for the Study of Social Policy
 - UC Berkeley Center for Social Services Research

Approach to defining the target population

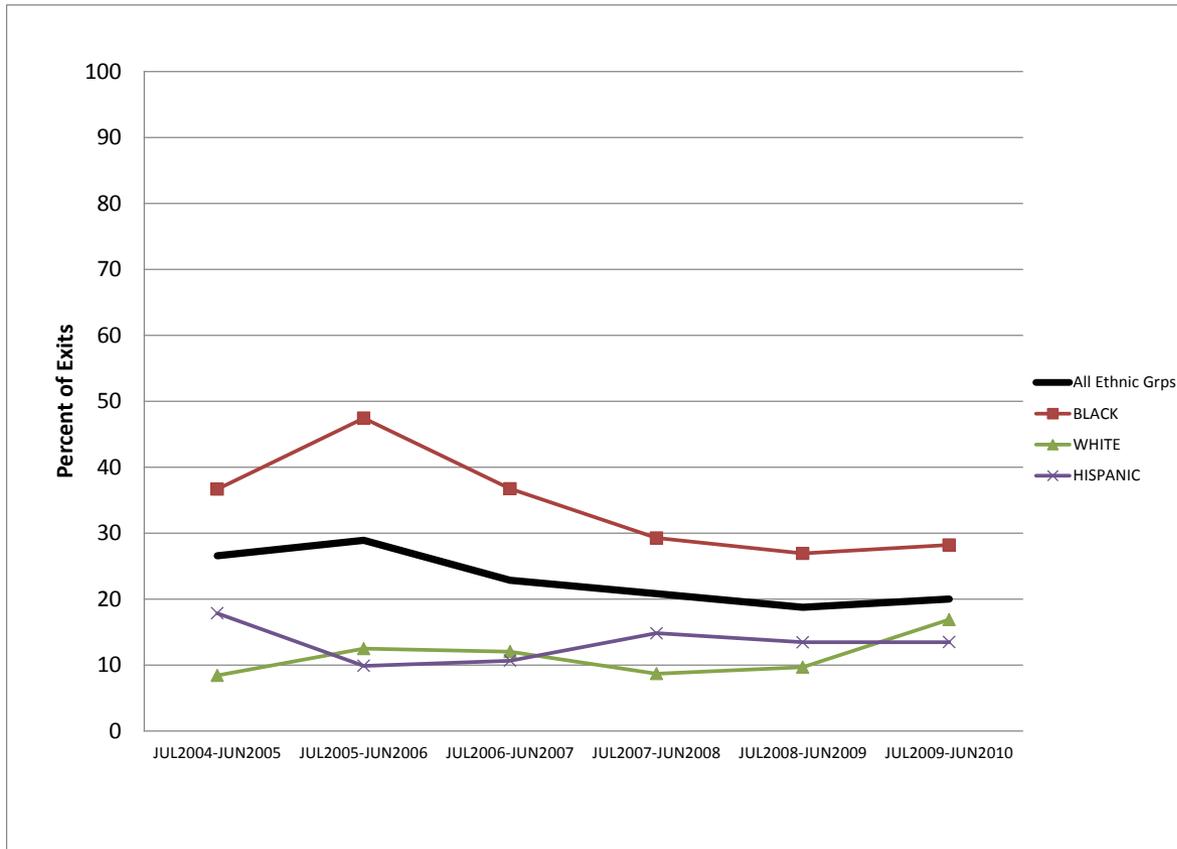
- **Examination of administrative data**
 - California Children’s Services Archive
 - Based on extracts from California’s Child Welfare Services/Case Management System (CWS/CMS)
 - Extracts configured into a longitudinal database as part of a collaboration between the California Department of Social Services (CDSS) and the Center for Social Services Research (CSSR)

- **Bivariate (exit cohort) analysis**
 - Children exiting care per year, proportion experiencing a non-permanent discharge
 - Children emancipating or turning 18 per year, proportion in care three years or more

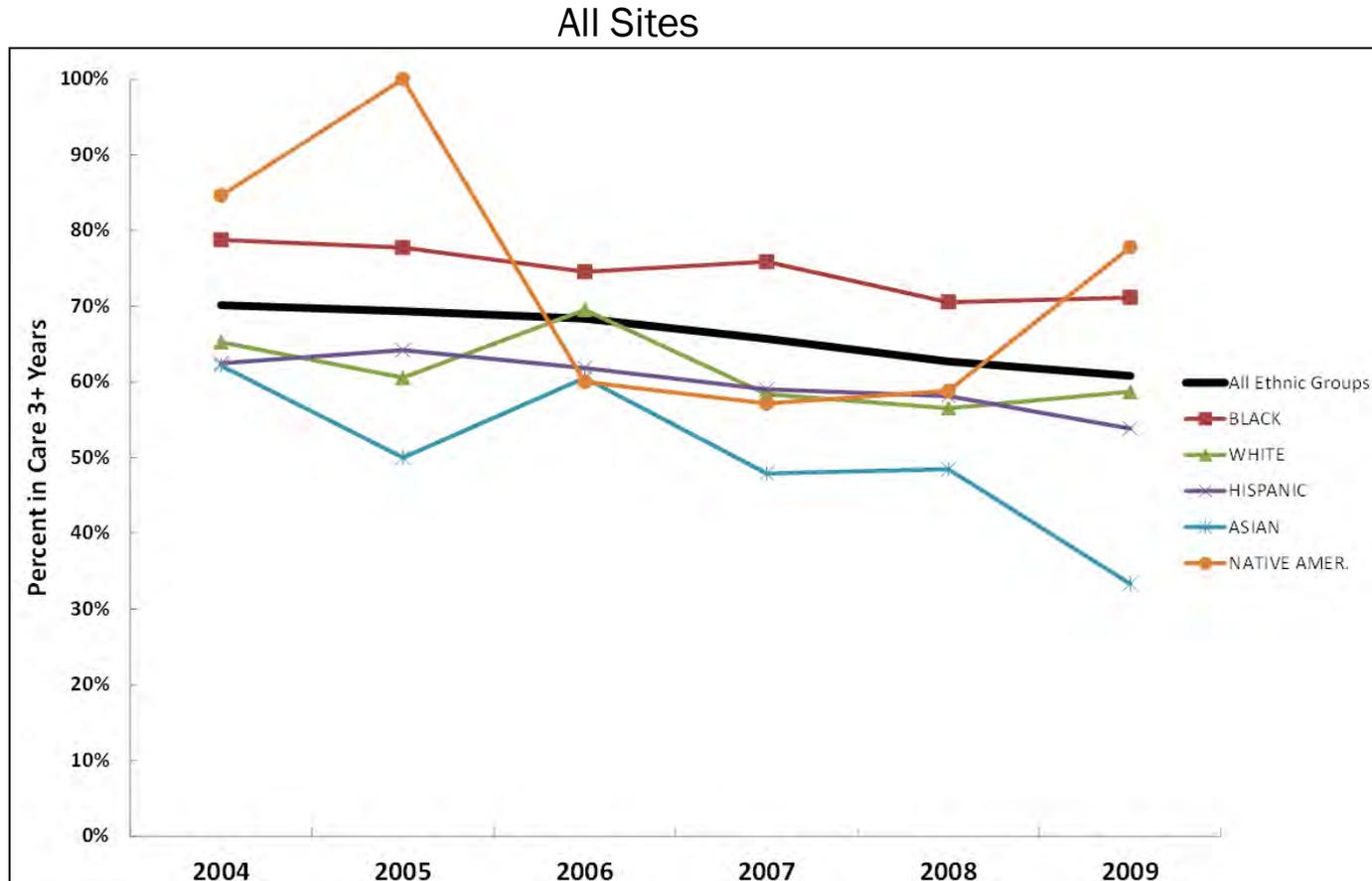
- **Multivariate (entry cohort) analysis**
 - Children entering care—likelihood of achieving a permanent discharge

Bivariate: Percent of all exits per year to a non-permanent discharge by ethnic group

LA Torrance



Bivariate: Children emancipated or turned 18 during year—percent in care three or more years



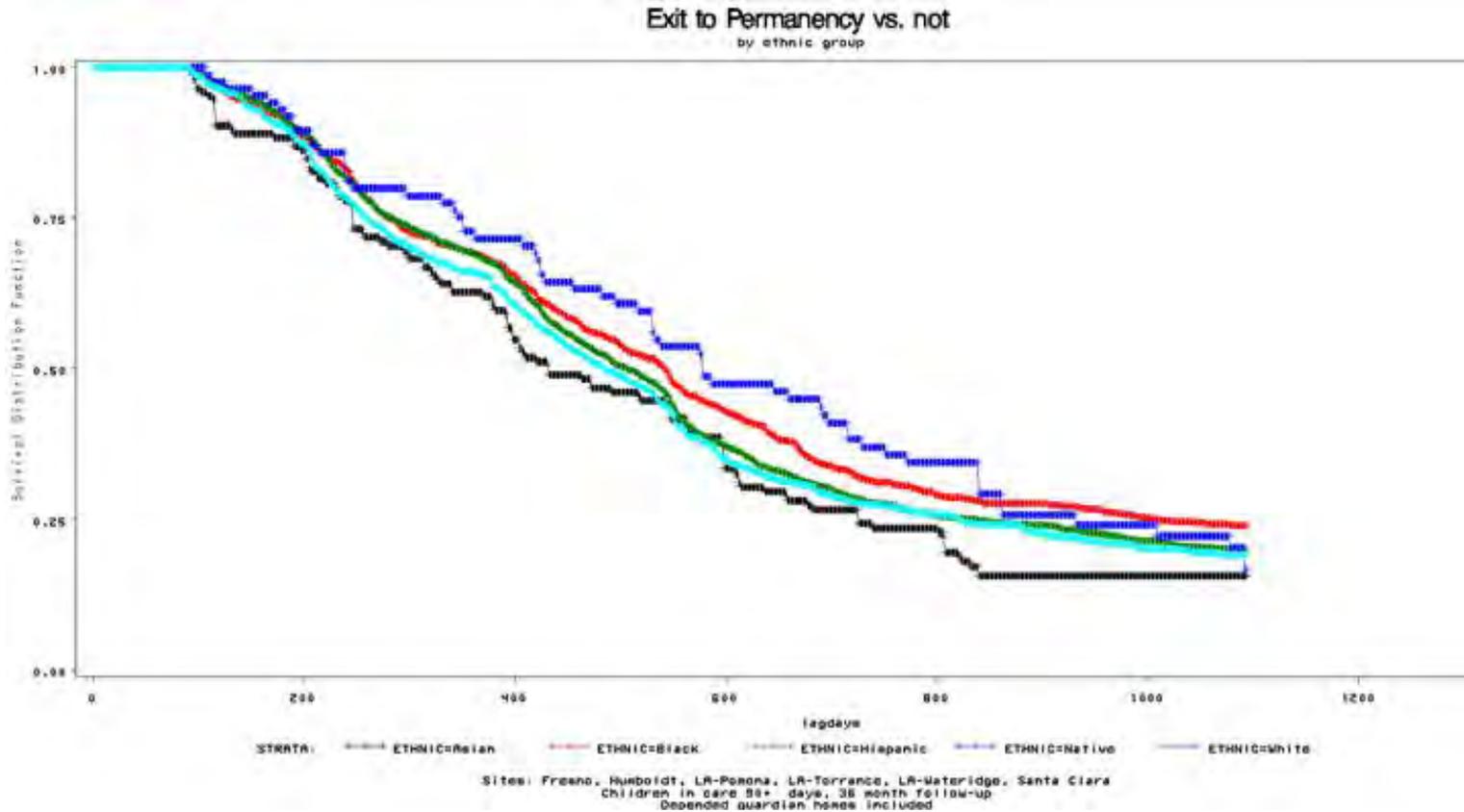
Bivariate results

- African American children were consistently discharged to non-permanent exits in higher proportions than other groups
- American Indian children (are known to be under-reported in the data yet) were also more likely than others in some sites to experience non-permanent exits
- Of those children emancipating or turning 18 in care, African American children was the group with the highest proportion who had been in care for three years or more
- American Indian children also tended more than other ethnic groups to have been in care three or more years among those emancipating or turning 18 in care

Next step taken

- Input for multivariate analysis—
 - Preliminary results were presented to county evaluation liaisons, cross-site planning, and executive management committees
 - Recommendations were taken for multivariate factors
 - Age, ethnic group, gender, removal reason, placement type, supervising county
 - Improved identification of American Indian children
 - Multiple placement moves indicator
 - Case plan goal indicator
 - Inclusion of dependent guardian homes
 - Examine children in care for at least 90 days

Survival curves for exits to permanency vs. not by ethnic group



Multivariate model for exit to permanency versus not – all sites

<u>Variable</u>	<u>Hazard Ratio</u>	<u>Probability</u>
Entry Year 2004	1	
Entry Year 2005	1.25	***
Entry Year 2006	1.37	***
White	1	
African American	0.77	***
Hispanic	0.90	0.06
Asian	1.38	**
American Indian	0.86	*
Age < 1	1	
Age_1_2		
Age_3_5		
Age_6_10		
Age_11_15		
Age_16_17	0.63	***
Male	1	
Female		
Neglect	1	
Physical	1.31	***
Sexual		
Other abuse	1.42	***
Kin	1	
Foster	1.30	***
FFA	1.15	***
Group		
Shelter		
Guardian	0.43	***
<3 placements	1	
3+ placements	0.78	***
Case goal not LTFC	1	
Case goal LTFC	0.26	***
Santa Clara	1	
Fresno	0.68	***
Humboldt	0.80	*
LA Pomona	1.21	**
LA Torrance	1.22	***
LA Wateridge	1.11	0.05

Multivariate model for exit to permanency versus not – African American children

<u>Variable</u>	<u>Hazard Ratio</u>	<u>Probability</u>
Entry Year 2004	1	
Entry Year 2005	1.25	*
Entry Year 2006	1.33	**
Age < 1	1	
Age_1_2	1.33	*
Age_3_5		
Age_6_10	1.29	*
Age_11_15		
Age_16_17	0.46	**
Male	1	
Female		
Neglect	1	
Physical		
Sexual		
Other abuse		
Kin	1	
Foster		
FFA	1.22	*
Group		
Shelter		
Guardian	0.34	***
<3 placements	1	
3+ placements	0.80	*
Case goal not LTFC	1	
Case goal LTFC	0.38	***
Santa Clara	1	
Fresno	0.65	*
LA Pomona	1.80	*
LA Torrance		
LA Wateridge		

Multivariate model for exit to permanency versus not – American Indian children

<u>Variable</u>	<u>Hazard Ratio</u>	<u>Probability</u>
Entry Year 2004	1	
Entry Year 2005		
Entry Year 2006		
Age < 1	1	
Age_1_2		
Age_3_5		
Age_6_10		
Age_11_15		
Age_16_17		
Male	1	
Female		
Neglect	1	
Physical		
Sexual		
Other abuse		
Kin	1	
Foster		
FFA		
Group		
Shelter		
Guardian		
<3 placements	1	
3+ placements	0.69	*
Case goal not LTFC	1	
Case goal LTFC	0.11	**
Humboldt	1	
Fresno		

Multivariate results

- African American and American Indian ethnic groups consistently emerged across models as the most robust predictor of non-permanent exits or remaining in long term foster care
- Some factors were significant in certain sites but not others
 - Age at entry
 - Hispanic ethnic group
 - Initial removal reason
 - Placement moves
- Other variables significant in most models but determined not to be target population constraints (due mainly to very small frequencies)
 - Guardian placement
 - Case plan goal of LTFC

Multivariate results *continued...*

- Complexity of using administrative data to isolate risk factors
- Considerable variation in factors that were statistically significant
- Important factors were not available in these models
- Nonetheless, bivariate analyses and multivariate results consistently indicated longer times to permanency for African American and American Indian children
- Past work in California suggest elevated risks for these ethnic groups

Moving forward

- Identification of systemic barriers to permanency affecting target population
 - Institutional Analysis in each site
 - Input solicited from key stakeholders and community members
- Development & installation of an integrated casework practice model to address barriers
- Issues to consider for constructing the evaluation comparison group—
 - Ongoing challenge to better identify American Indian children entering or in care
 - Potential addition of other child-specific factors
 - Risk level at intake
 - Census indicators related to removal address
 - Determination/tracking of services received by children in comparison jurisdictions

Questions ?

Daniel Webster, MSW, PhD
Center for Social Services Research
School of Social Welfare
University of California
Berkeley, CA 94720
510.290.6779

dwebster@berkeley.edu