WELCOME TO THE NDACAN SUMMER TRAINING SERIES!

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NDACAN SUMMER TRAINING SERIES

National Data Archive on Child Abuse and Neglect

Bronfenbrenner Center for Translational Research

Cornell University

NEW HORIZONS FOR CHILD WELFARE DATA

NDACAN SUMMER TRAINING SERIES SCHEDULE

- July 1, 2020 - Introduction to NDACAN
- July 8, 2020 - Historical Data
- July 15, 2020 - Research Example using Historical Data
- July 22, 2020 - Administrative Data (NCANDS, AFCARS, NYTD)
- **August 5, 2020 - Research Example using Linked Administrative Data**
- August 12, 2020 - Linking Administrative Data in SPSS

SESSION AGENDA

- Linking AFCARS and NCANDS data
- Using AFCARS/NCANDS data to evaluate risk of child welfare events
- Evaluating inequalities in AI/AN system contact by tracing cases across systems

BACKGROUND

- American Indian / Alaska Native children have very high risk of child welfare system contact
- Family separation through fostering and adoption was historically used to force assimilation of AI/AN children into white cultural, social, and economic practices
- ICWA recognizes the harm posed by mass separation to tribal nations and families
- Despite ICWA protections, large inequalities persist

RESEARCH QUESTIONS

- Use AFCARS/NCANDS to provide estimates of relative risk of various child welfare system outcomes for AI/AN children relative to white children
- Link AFCARS/NCANDS to estimate probability of transitioning from one stage of child welfare case processing to another
  - Pr(Substantiation | Investigation)
  - Pr(Removal | Substantiation)

LINKING AFCARS AND NCANDS DATA

UNIQUE IDENTIFIERS IN AFCARS

```
> head(afcars_id)
    FY         StFCID       RecNumbr St
1 2009 AL000000003371 000000003371 AL
2 2009 AL000000005381 000000005381 AL
3 2009 AL000000011564 000000011564 AL
4 2009 AL000000013741 000000013741 AL
5 2009 AL000000015621 000000015621 AL
6 2009 AL000000017071 000000017071 AL
```

```
> head(ncands_id)
   subyr     AFCARSID StaTerr
1:  2011 458511777220      AK
2:  2011 465267777370      AK
3:  2011 466081678184      AK
4:  2011 464803276906      AK
5:  2011 465079087182      AK
6:  2011 465078887181      AK
```

```
ncands_xwalk<-ncands_xwalk%>%
  mutate(stfcid = paste(fips, afcarsid, sep=""))
```

```
afcars<-afcars%>%
  rename_all(tolower) %>%
  mutate(stfcid = paste(state, recnumbr, sep = ""))
```

```
> head(afcars_id)
          stfcid state year
1 17000220853390    17 2000
2 17000221194591    17 2000
3 17000222163792    17 2000
4 17000222803792    17 2000
5 17000222803793    17 2000
6 17000223123999    17 2000
```

```
> head(ncands_xwalk)
         chid         stfcid      rptdt subyr
1 1000009B1DBF 9401101919394 2001-08-23  2002
2 1000009B8DD8 9101101919405 2001-08-23  2002
3 1000009B5329 9501101051014 2002-04-08  2002
4 1000009BC3D0 9201100037660 2002-01-08  2002
5 1000009B2F5B 9701101980471 2002-06-23  2002
6 1000009B1E67 9401101505406 2002-02-08  2002
```

JOIN! OOPS!

```
> nrow(afcars_id)
[1] 91239944
> nrow(ncands_xwalk)
[1] 47495685
> join<-left_join(afcars_id, ncands_xwalk)
Joining, by = "stfcid"
> nrow(join)
[1] 254874376
```

CONSIDERATIONS FOR JOINING

- Each AFCARS StFCID has one entry for each reporting year that the child was in foster care (the data are at the child-year level)
- Each NCANDS AFCARSID may appear multiple times in a reporting year (the data are at the report-child level)
- Each child in AFCARS may have multiple reports across reporting years
- Think carefully about your desired data structure before joining

USING AFCARS/NCANDS TO IDENTIFY CHILD WELFARE EVENT RISK

LIFE TABLES

- A life table follows a cohort of individuals over time and estimates the risk of
  - An event occurring during each year
  - And the cumulative risk of an event at each age
- A traditional life table follows a cohort over time (e.g. individuals who share a birth year)
- A period life table uses a single period of time to approximate a cohort
  - Key assumption: stability of event risk over time

year	age	race_ethn	var	pop
<dbl>	<dbl>	<chr>	<dbl>	<dbl>
2016	0	AI/AN	6660	76508
2016	1	AI/AN	2948	76634
2016	2	AI/AN	2474	77049
2016	3	AI/AN	2051	76421
2016	4	AI/AN	1974	77503
2016	5	AI/AN	1817	75837
2016	6	AI/AN	1747	77273
2016	7	AI/AN	1716	76899
2016	8	AI/AN	1577	79353
2016	9	AI/AN	1426	79873
2016	10	AI/AN	1218	78320
2016	11	AI/AN	1099	77815
2016	12	AI/AN	1081	75871
2016	13	AI/AN	1027	74777
2016	14	AI/AN	1012	74289
2016	15	AI/AN	955	74927
2016	16	AI/AN	865	76819
2016	17	AI/AN	634	74961

AGE-SPECIFIC RISK

year	age	race_ethn	var	pop	q
<dbl>	<dbl>	<chr>	<dbl>	<dbl>	<dbl>
2016	0	AI/AN	6660	76508	0.0834
2016	1	AI/AN	2948	76634	0.0377
2016	2	AI/AN	2474	77049	0.0316
2016	3	AI/AN	2051	76421	0.0265
2016	4	AI/AN	1974	77503	0.0251
2016	5	AI/AN	1817	75837	0.0237
2016	6	AI/AN	1747	77273	0.0224
2016	7	AI/AN	1716	76899	0.0221
2016	8	AI/AN	1577	79353	0.0197
2016	9	AI/AN	1426	79873	0.0177
2016	10	AI/AN	1218	78320	0.0154
2016	11	AI/AN	1099	77815	0.0140
2016	12	AI/AN	1081	75871	0.0141
2016	13	AI/AN	1027	74777	0.0136
2016	14	AI/AN	1012	74289	0.0135
2016	15	AI/AN	955	74927	0.0127
2016	16	AI/AN	865	76819	0.0112
2016	17	AI/AN	634	74961	0.00842

year	age	race_ethn	var	pop	q	p
<dbl>	<dbl>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
2016	0	AI/AN	6660	76508	0.0834	0.917
2016	1	AI/AN	2948	76634	0.0377	0.962
2016	2	AI/AN	2474	77049	0.0316	0.968
2016	3	AI/AN	2051	76421	0.0265	0.974
2016	4	AI/AN	1974	77503	0.0251	0.975
2016	5	AI/AN	1817	75837	0.0237	0.976
2016	6	AI/AN	1747	77273	0.0224	0.978
2016	7	AI/AN	1716	76899	0.0221	0.978
2016	8	AI/AN	1577	79353	0.0197	0.980
2016	9	AI/AN	1426	79873	0.0177	0.982
2016	10	AI/AN	1218	78320	0.0154	0.985
2016	11	AI/AN	1099	77815	0.0140	0.986
2016	12	AI/AN	1081	75871	0.0141	0.986
2016	13	AI/AN	1027	74777	0.0136	0.986
2016	14	AI/AN	1012	74289	0.0135	0.986
2016	15	AI/AN	955	74927	0.0127	0.987
2016	16	AI/AN	865	76819	0.0112	0.989
2016	17	AI/AN	634	74961	0.00842	0.992

year	age	race_ethn	var	pop	q	p	d	lx
<dbl>	<dbl>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
2016	0	AI/AN	6660	76508	0.0834	0.917	8342.	100000
2016	1	AI/AN	2948	76634	0.0377	0.962	3459.	91658.
2016	2	AI/AN	2474	77049	0.0316	0.968	2787.	88199.
2016	3	AI/AN	2051	76421	0.0265	0.974	2262.	85411.
2016	4	AI/AN	1974	77503	0.0251	0.975	2091.	83149.
2016	5	AI/AN	1817	75837	0.0237	0.976	1919.	81058.
2016	6	AI/AN	1747	77273	0.0224	0.978	1769.	79139.
2016	7	AI/AN	1716	76899	0.0221	0.978	1707.	77370.
2016	8	AI/AN	1577	79353	0.0197	0.980	1489.	75663.
2016	9	AI/AN	1426	79873	0.0177	0.982	1313.	74174.
2016	10	AI/AN	1218	78320	0.0154	0.985	1124.	72861.
2016	11	AI/AN	1099	77815	0.0140	0.986	1006.	71737.
2016	12	AI/AN	1081	75871	0.0141	0.986	1001.	70731.
2016	13	AI/AN	1027	74777	0.0136	0.986	951.	69730.
2016	14	AI/AN	1012	74289	0.0135	0.986	931.	68779.
2016	15	AI/AN	955	74927	0.0127	0.987	859.	67848.
2016	16	AI/AN	865	76819	0.0112	0.989	1308.	66989.
2016	17	AI/AN	634	74961	0.00842	0.992	0	65681.

year	age	race_ethn	var	pop	q	p	d	lx	c
<dbl>	<dbl>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
2016	0	AI/AN	6660	76508	0.0834	0.917	8342.	100000	0
2016	1	AI/AN	2948	76634	0.0377	0.962	3459.	91658.	0.0834
2016	2	AI/AN	2474	77049	0.0316	0.968	2787.	88199.	0.118
2016	3	AI/AN	2051	76421	0.0265	0.974	2262.	85411.	0.146
2016	4	AI/AN	1974	77503	0.0251	0.975	2091.	83149.	0.169
2016	5	AI/AN	1817	75837	0.0237	0.976	1919.	81058.	0.189
2016	6	AI/AN	1747	77273	0.0224	0.978	1769.	79139.	0.209
2016	7	AI/AN	1716	76899	0.0221	0.978	1707.	77370.	0.226
2016	8	AI/AN	1577	79353	0.0197	0.980	1489.	75663.	0.243
2016	9	AI/AN	1426	79873	0.0177	0.982	1313.	74174.	0.258
2016	10	AI/AN	1218	78320	0.0154	0.985	1124.	72861.	0.271
2016	11	AI/AN	1099	77815	0.0140	0.986	1006.	71737.	0.283
2016	12	AI/AN	1081	75871	0.0141	0.986	1001.	70731.	0.293
2016	13	AI/AN	1027	74777	0.0136	0.986	951.	69730.	0.303
2016	14	AI/AN	1012	74289	0.0135	0.986	931.	68779.	0.312
2016	15	AI/AN	955	74927	0.0127	0.987	859.	67848.	0.322
2016	16	AI/AN	865	76819	0.0112	0.989	1308.	66989.	0.330
2016	17	AI/AN	634	74961	0.00842	0.992	0	65681.	0.343

EVALUATING INEQUALITIES IN AI/AN CHILD WELFARE SYSTEM CONTACT

MEASUREMENT (NCANDS)

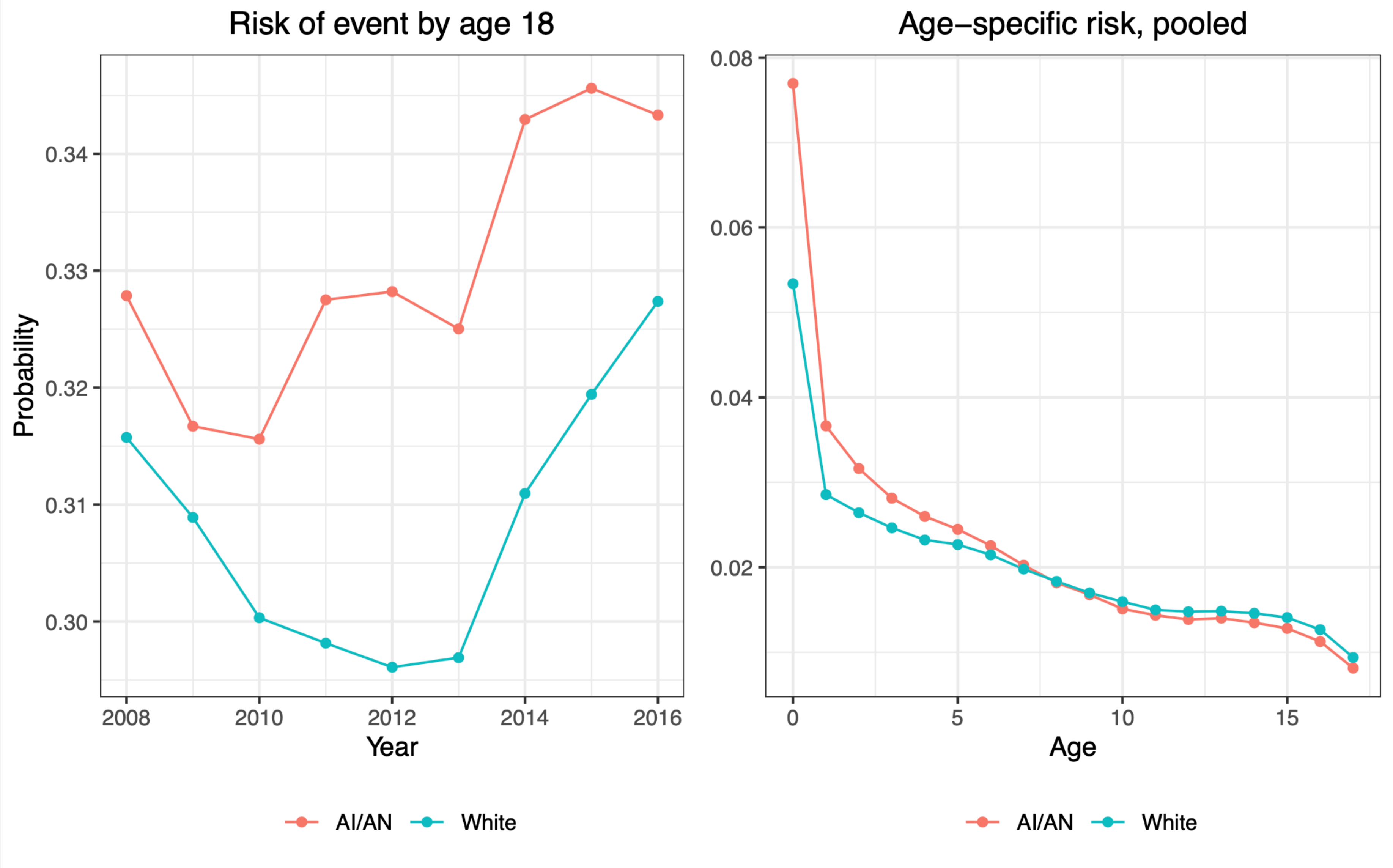
- Identify the *first* investigated maltreatment report for each child
  - Search within each NCANDS state-child ID for the earliest report date
- Identify the *first* substantiated maltreatment report for each child
  - Search within each NCANDS state-child ID for the earliest report date where rptvictim == 1

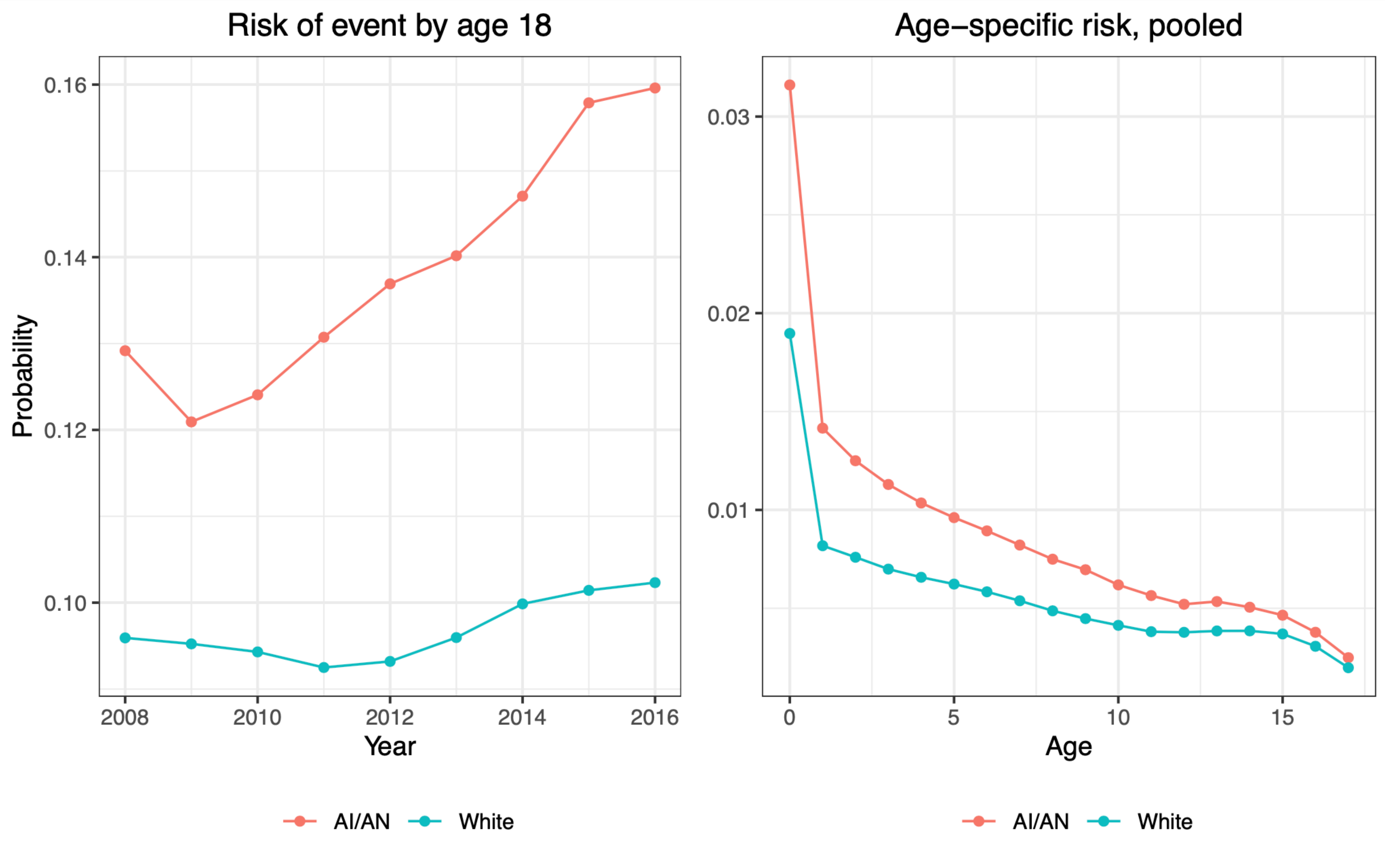
MEASUREMENT (AFCARS)

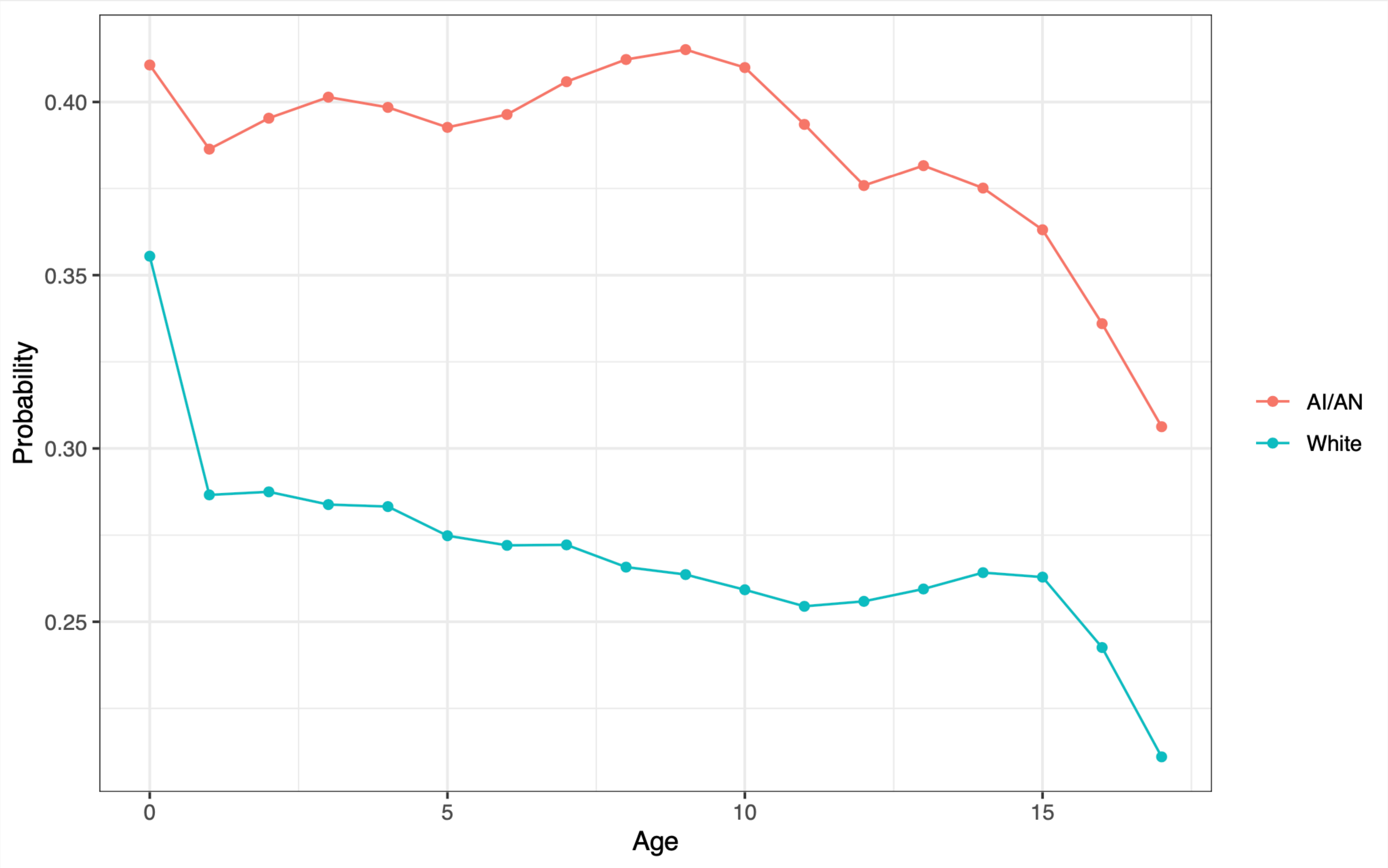
- Identify the first foster care entry for each child
  - Include only records where Entered == 1 and TotalRem == 1
- Identify non-native non-kin foster caregivers for AI/AN children
  - If curplset == 2, or rf1makn / rf2amakn == 1, True, otherwise False

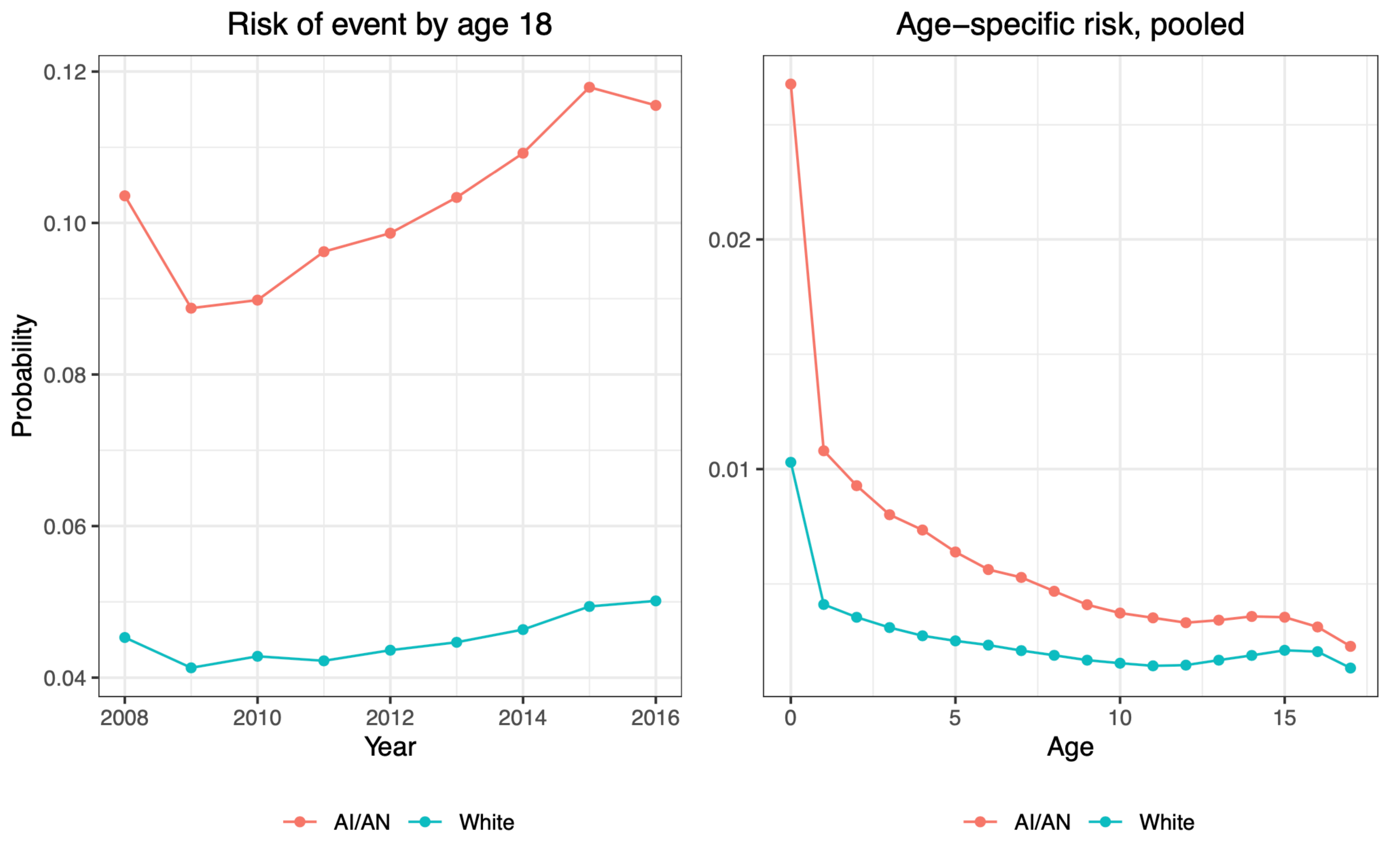
JOIN

- Marginal probabilities are calculated from a single data file: AFCARS or NCANDS
- Conditional probabilities are derived from joins of *first* NCANDS events to *first* AFCARS events by stfcid. Each child has one record
- After the joins, each variable is aggregated to an annual national count by age and race/ethnicity
- Then I compute lifetables for each group by year

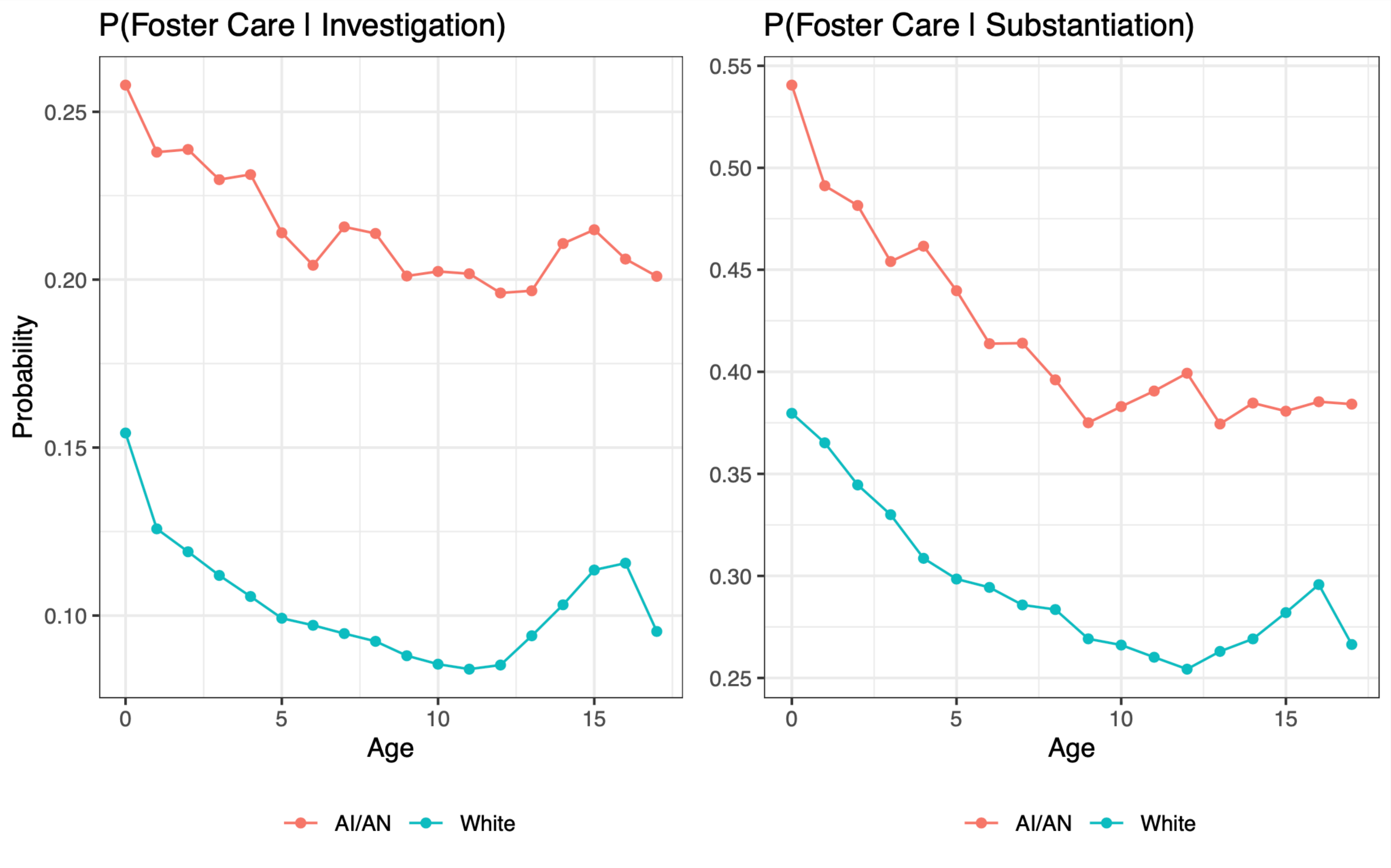

Risk of event by age 18
Probability
0.34
0.33
0.32
0.31
0.30
2008
2010
2012
2014
2016
Year
AI/AN
White
Age−specific risk, pooled
0.08
0.06
0.04
0.02
0
5
10
15
Age
AI/AN
White

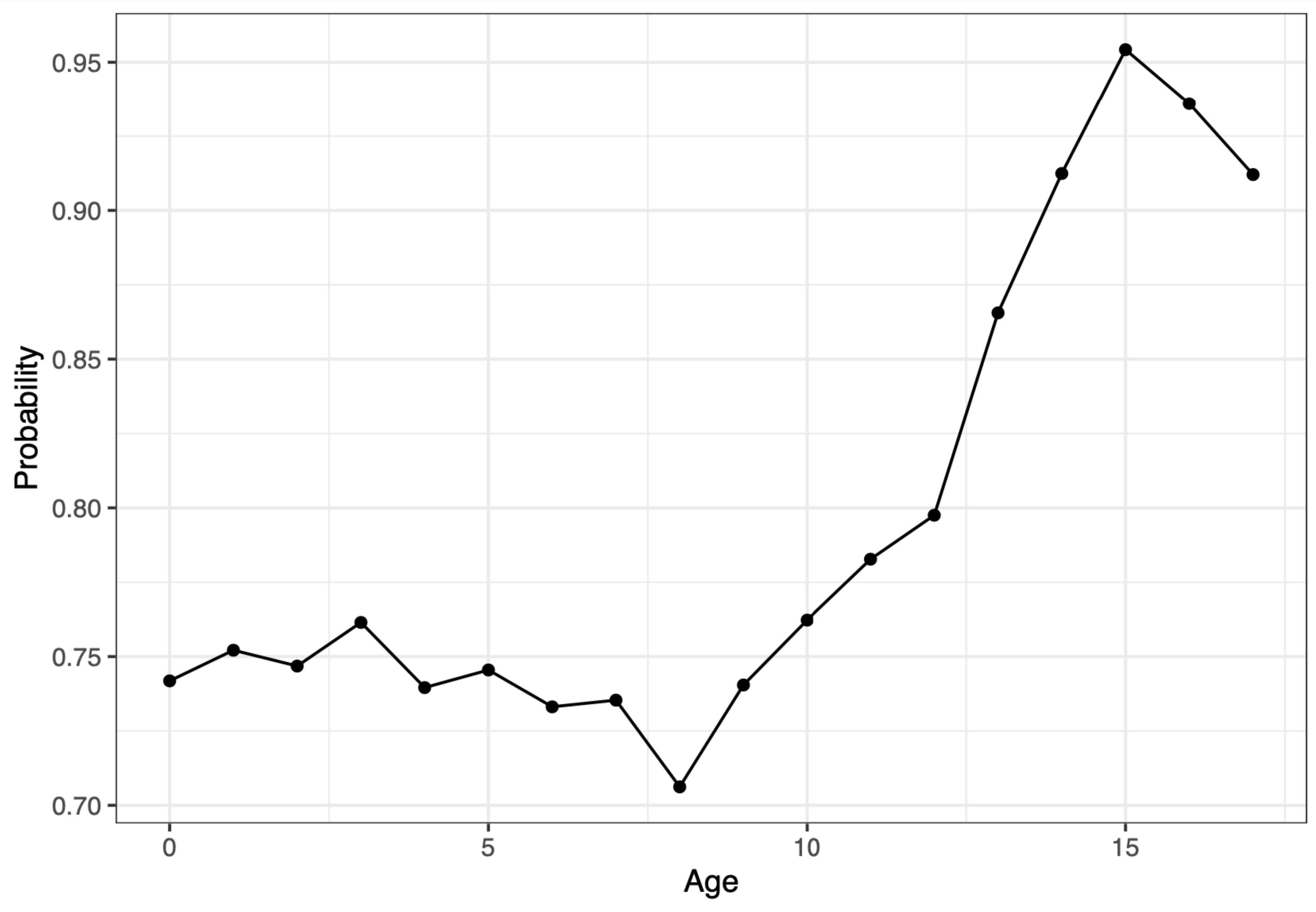

Risk of event by age 18
0.16
0.14
0.12
0.10
Probability
2008
2010
2012
2014
2016
Year
AI/AN
White
Age−specific risk, pooled
0.03
0.02
0.01
0
5
10
15
Age
AI/AN
White


Probability
0.40
0.35
0.30
0.25
0
5
10
15
Age
AI/AN
White



Risk of event by age 18
Probability
0.12
0.10
0.08
0.06
0.04
2008
2010
2012
2014
2016
Year
AI/AN
White
Age−specific risk, pooled
0.02
0.01
0
5
10
15
Age
AI/AN
White


P(Foster Care | Investigation)
P(Foster Care | Substantiation)
Probability
0.25
0.20
0.15
0.10
0.55
0.50
0.45
0.40
0.35
0.30
0.25
0
5
10
15
Age
AI/AN
White



0.95
0.90
0.85
0.80
0.75
0.70
Probability
0
5
10
15
Age

DISCUSSION

- AI/AN children have much higher exposure to child welfare system than white children
- Conditional on a screened-in case, AI/AN children are more likely than white children to enter foster care
- Conditional on a substantiated case, AI/AN children are more likely than white children to enter foster care
- The majority of AI/AN children in foster care have been in a placement in a non-kin, non-Native foster home

QUESTIONS?

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THANK YOU FOR JOINING US THIS SUMMER!
LOOK FOR A SURVEY LINK IN YOUR EMAIL