Survival Analysis of Corporal Punishment Bans

Andy Grogan-Kaylor

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Introduction

Corporal punishment is associated with a number of deleterious outcomes for children, including increases in behavior problems and mental health problems.

A number of countries have instituted country wide bans upon the use of corporal punishment with children.

Below, we employ a variety of empirical strategies to explore the institution of these bans.

Get The Data

```
. use "../CPBans_w_AllCountries.dta", clear // data with ALL Countries; not just bans
```

> NB It is important to have data with the *correct risk set* which includes *all countries*, not just *countries that eventually ban corporal punishment*.

In web versions of this tutorial, click the tabs below to access different sections of the tutorial.

Setup

Parametric Survival Models

Cox Model

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Discrete Time Survival Analysis

Setup

`stset` The Data

```
. generate current_year = year(today()) // variable with current year

. replace year_of_prohibition = current_year if year_of_prohibition == . // replace missing w/ current year
(186 real changes made)

. generate f = type == "CP Ban" // "failure" variable

. stset year_of_prohibition, failure(f = 1) // stset the data with time and failure variables
Survival-time data settings
         Failure event: f==1
Observed time interval: (0, year_of_prohibition]
     Exit on or before: failure
--------------------------------------------------------------------------
        248  total observations
          0  exclusions
--------------------------------------------------------------------------
        248  observations remaining, representing
         62  failures in single-record/single-failure data
```

```
    500,452  total analysis time at risk and under observation
                                                At risk from t =         0
                                     Earliest observed entry t =         0
                                          Last observed exit t =     2,021
```

Data Wrangling

```
. encode continent, generate(continent_NUMERIC) // numeric version of continent
```

Graphs

Survival Function

```
. sts graph, scheme(michigan) tmin(1970) // Kaplan-Meier Survivor Function
        Failure _d: f==1
  Analysis time _t: year_of_prohibition

. graph export mysurvival.png, width(500) replace
file mysurvival.png saved as PNG format
```

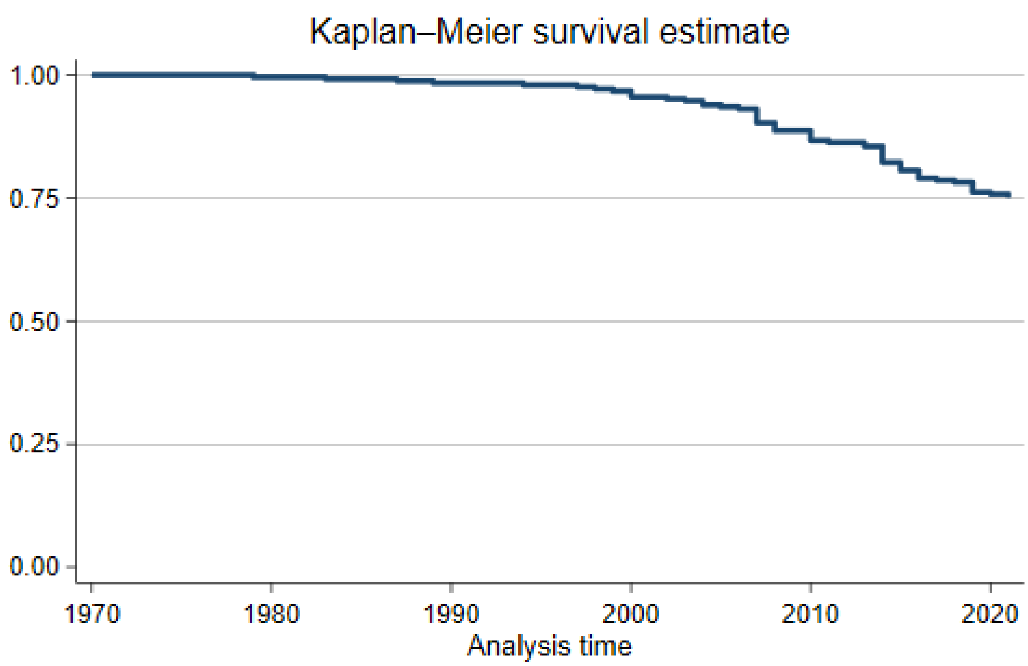

Figure 1: Kaplan-Meier Survivor Function

Failure Function

```
. sts graph, failure scheme(michigan) tmin(1970) // Kaplan-Meier Failure Function
        Failure _d: f==1
  Analysis time _t: year_of_prohibition

. graph export myfailure.png, width(500) replace
file myfailure.png saved as PNG format
```

Parametric Survival Models

Unlike other regression commands in Stata, survival analysis commands seem to require covariates. Since Europe is where these bans started, we will use Europe (category 4) as the reference category.

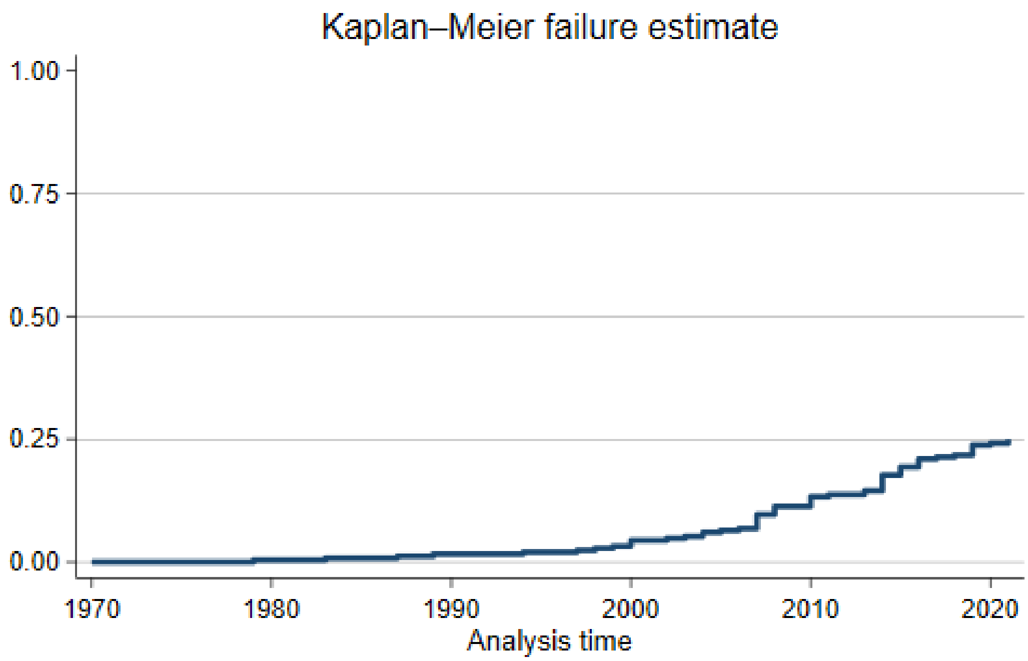

Figure 2: Kaplan-Meier Failure Function

Weibull

```
. streg ib4.continent_NUMERIC, distribution(weibull) // Weibull distribution
        Failure _d: f==1
  Analysis time _t: year_of_prohibition
Fitting constant-only model:
Iteration 0:   log likelihood =  -148.2325
Iteration 1:   log likelihood = -86.999055
Iteration 2:   log likelihood = -27.073844
Iteration 3:   log likelihood =  29.365489
Iteration 4:   log likelihood =  77.015953
Iteration 5:   log likelihood =  106.62899
Iteration 6:   log likelihood =  115.32234
Iteration 7:   log likelihood =  115.88805
Iteration 8:   log likelihood =  115.89021
Iteration 9:   log likelihood =  115.89021
Fitting full model:
Iteration 0:   log likelihood =  115.89021
Iteration 1:   log likelihood =  139.32561
Iteration 2:   log likelihood =  142.87372
Iteration 3:   log likelihood =  143.05492
Iteration 4:   log likelihood =  143.05732
Iteration 5:   log likelihood =  143.05732
Weibull PH regression
No. of subjects =      248                          Number of obs =     248
No. of failures =       62
Time at risk    = 500,452
                                                    LR chi2(5)    =   54.33
Log likelihood = 143.05732                          Prob > chi2   = 0.0000
```

_t	Haz. ratio	Std. err.	z	P>|z|	[95% conf.	interval]
continent_NUMERIC						
Africa	.1684617	.0612563	-4.90	0.000	.0826011	.3435709
Americas	.1938708	.0704541	-4.51	0.000	.0950997	.395226
Asia	.1520997	.0603348	-4.75	0.000	.0698995	.3309653
NA	.0916735	.0931508	-2.35	0.019	.0125119	.6716806
Oceania	.0356574	.0362323	-3.28	0.001	.0048666	.2612621
_cons	0	0	-8.57	0.000	0	0
/ln_p	5.278967	.1166492	45.26	0.000	5.050339	5.507596

```
               p |   196.1672   22.88274                      156.0754    246.5576
             1/p |   .0050977   .0005946                      .0040558    .0064072
------------------------------------------------------------------------------
Note: _cons estimates baseline hazard.
```

Exponential

```
. streg ib4.continent_NUMERIC, distribution(exponential) // Exponential distribution
        Failure _d: f==1
  Analysis time _t: year_of_prohibition
Iteration 0:   log likelihood =  -148.2325
Iteration 1:   log likelihood = -139.40941
Iteration 2:   log likelihood = -131.58499
Iteration 3:   log likelihood = -131.55897
Iteration 4:   log likelihood = -131.55892
Iteration 5:   log likelihood = -131.55892
Exponential PH regression
No. of subjects =     248                             Number of obs =    248
No. of failures =      62
Time at risk    = 500,452
                                                      LR chi2(5)    =  33.35
Log likelihood = -131.55892                           Prob > chi2   = 0.0000
------------------------------------------------------------------------------
              _t | Haz. ratio   Std. err.      z    P>|z|     [95% conf. interval]
-----------------+------------------------------------------------------------
continent_NUMERIC |
          Africa |   .2736219    .099129    -3.58   0.000      .134516    .5565804
        Americas |   .3052592   .1105907    -3.28   0.001     .1500692    .6209345
            Asia |   .2489781   .0984172    -3.52   0.000     .1147345    .5402914
              NA |   .1586176   .1610769    -1.81   0.070     .0216746    1.160782
         Oceania |    .061017    .061963    -2.75   0.006     .0083378    .4465293
                 |
           _cons |    .000312   .0000552   -45.67   0.000     .0002206    .0004412
------------------------------------------------------------------------------
Note: _cons estimates baseline hazard.
```

Cox Proportional Hazards Model

```
. stcox ib4.continent_NUMERIC // Cox Proportional Hazards Model
        Failure _d: f==1
  Analysis time _t: year_of_prohibition
Iteration 0:   log likelihood = -333.92184
Iteration 1:   log likelihood = -317.94407
Iteration 2:   log likelihood = -308.96171
Iteration 3:   log likelihood = -308.00801
Iteration 4:   log likelihood = -308.00737
Refining estimates:
Iteration 0:   log likelihood = -308.00737
Cox regression with Breslow method for ties
No. of subjects =     248                             Number of obs =    248
No. of failures =      62
Time at risk    = 500,452
                                                      LR chi2(5)    =  51.83
Log likelihood = -308.00737                           Prob > chi2   = 0.0000
------------------------------------------------------------------------------
              _t | Haz. ratio   Std. err.      z    P>|z|     [95% conf. interval]
-----------------+------------------------------------------------------------
continent_NUMERIC |
          Africa |   .1769827   .0643396    -4.76   0.000     .0867938    .3608887
        Americas |   .2023186   .0735008    -4.40   0.000     .0992661    .4123544
            Asia |   .1610376   .0638871    -4.60   0.000     .0740009    .3504428
              NA |   .0969297   .0984941    -2.30   0.022     .0132287    .7102257
         Oceania |   .0380401    .038653    -3.22   0.001     .0051919    .2787139
------------------------------------------------------------------------------
```

Survival Curves

```
. stcurve, survival scheme(michigan) // survival curve

. graph export survival1A.png, width(500) replace
file survival1A.png saved as PNG format
```

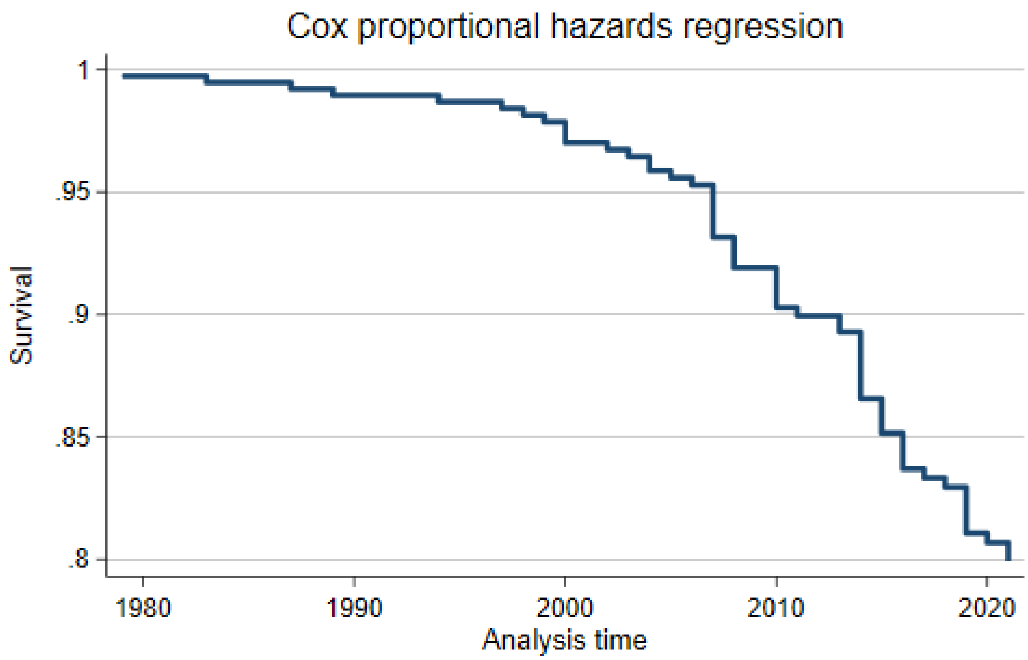

Figure 3: Survival Curve

```
. stcurve, failure scheme(michigan) // failure curve

. graph export survival1B.png, width(500) replace
file survival1B.png saved as PNG format

. stcurve, failure at(continent_NUMERIC= (1 2 3 4 5 6)) ///
> legend(order(1 "Africa" 2 "Americas" 3 "Asia" ///
> 4 "Europe" 5 "NA" 6 "Oceania")) ///
> scheme(michigan) // survival curve by continent

. graph export survival2.png, width(500) replace
file survival2.png saved as PNG format
```

Proportional Hazards Assumption

```
. estat phtest // formal test of PH assumption
Test of proportional-hazards assumption
Time function: Analysis time
```

	chi2	df	Prob>chi2
Global test	6.20	5	0.2870

```
. stphplot, by(continent_NUMERIC) scheme(michigan) // graphical test of PH assumption
        Failure _d: f==1
  Analysis time _t: year_of_prohibition

. graph export ph.png, width(500) replace
file ph.png saved as PNG format
```

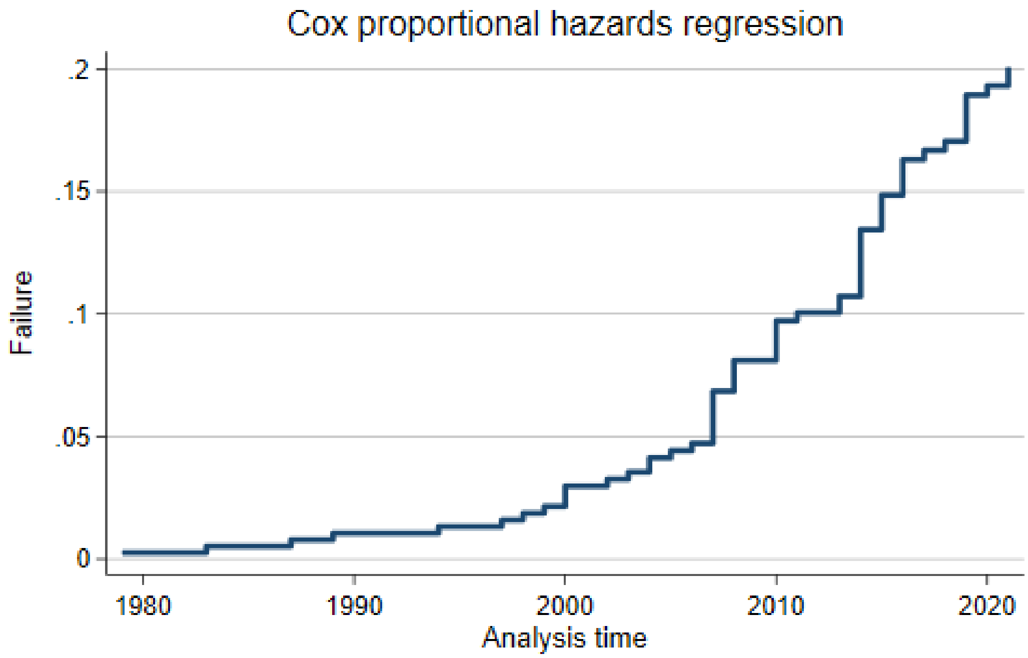

Figure 4: Failure Curve

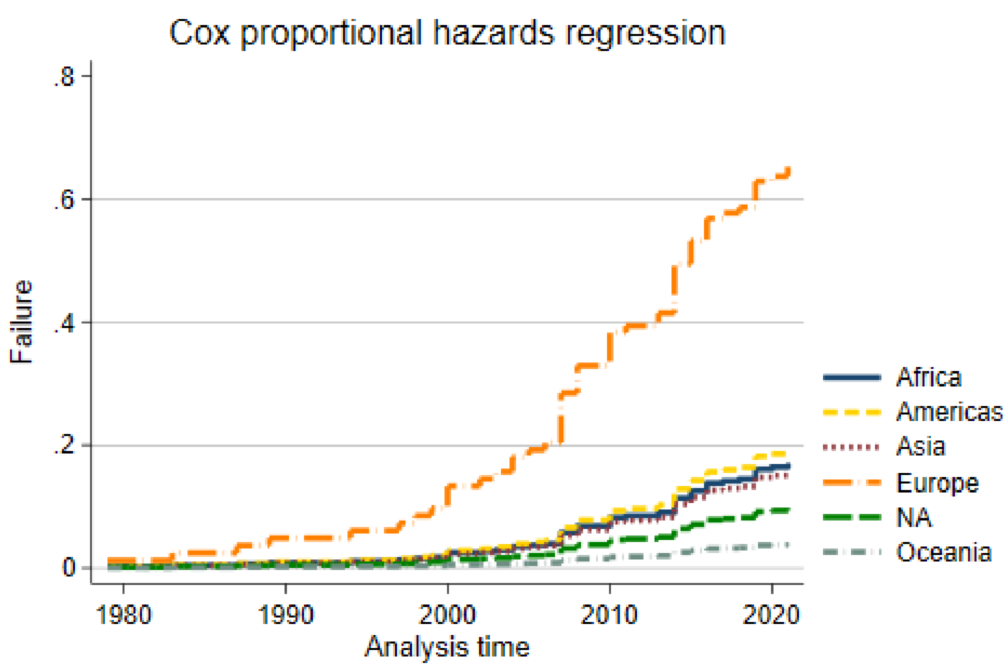

Figure 5: Failure Curve By Continent

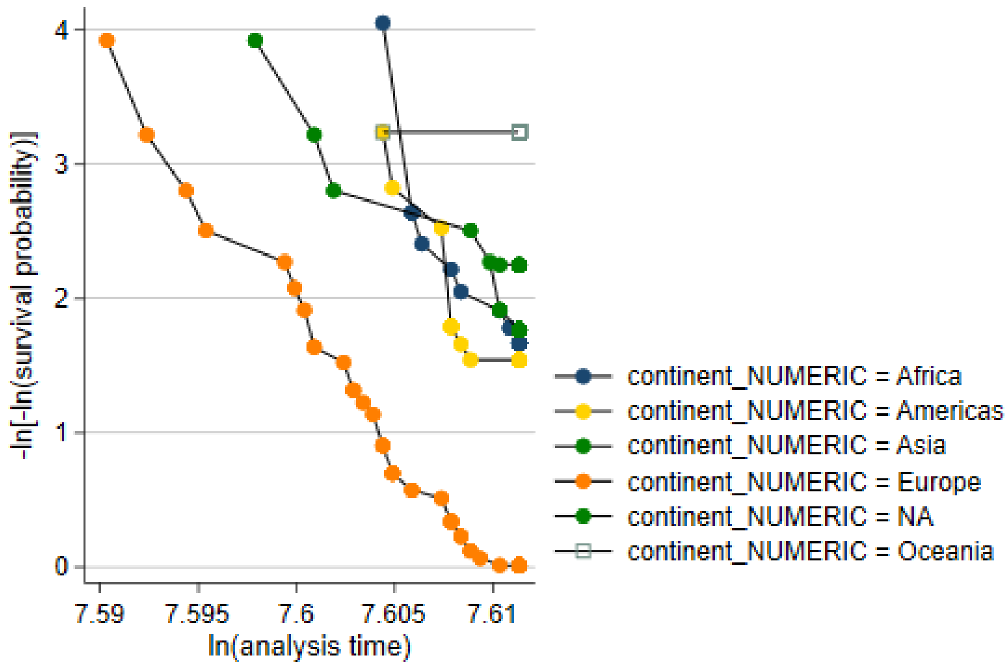

Figure 6: Graphical Test of Proportional Hazards Assumption

Life Table

```
. ltable year_of_prohibition f, graph failure scheme(michigan) // lifetable
```

Interval		Beg. Total	Deaths	Lost	Cum. Failure	Std. Error	[95% Conf. Int.]	
1979	1980	248	1	0	0.0040	0.0040	0.0006	0.0283
1983	1984	247	1	0	0.0081	0.0057	0.0020	0.0319
1987	1988	246	1	0	0.0121	0.0069	0.0039	0.0370
1989	1990	245	1	0	0.0161	0.0080	0.0061	0.0424
1994	1995	244	1	0	0.0202	0.0089	0.0084	0.0478
1997	1998	243	1	0	0.0242	0.0098	0.0109	0.0531
1998	1999	242	1	0	0.0282	0.0105	0.0136	0.0583
1999	2000	241	1	0	0.0323	0.0112	0.0163	0.0635
2000	2001	240	3	0	0.0444	0.0131	0.0248	0.0787
2002	2003	237	1	0	0.0484	0.0136	0.0278	0.0836
2003	2004	236	1	0	0.0524	0.0142	0.0308	0.0886
2004	2005	235	2	0	0.0605	0.0151	0.0369	0.0983
2005	2006	233	1	0	0.0645	0.0156	0.0400	0.1032
2006	2007	232	1	0	0.0685	0.0160	0.0432	0.1080
2007	2008	231	7	0	0.0968	0.0188	0.0659	0.1409
2008	2009	224	4	0	0.1129	0.0201	0.0794	0.1593
2010	2011	220	5	0	0.1331	0.0216	0.0965	0.1820
2011	2012	215	1	0	0.1371	0.0218	0.1000	0.1865
2013	2014	214	2	0	0.1452	0.0224	0.1069	0.1955
2014	2015	212	8	0	0.1774	0.0243	0.1352	0.2309
2015	2016	204	4	0	0.1935	0.0251	0.1496	0.2484
2016	2017	200	4	0	0.2097	0.0258	0.1641	0.2658
2017	2018	196	1	0	0.2137	0.0260	0.1677	0.2701
2018	2019	195	1	0	0.2177	0.0262	0.1713	0.2745
2019	2020	194	5	0	0.2379	0.0270	0.1897	0.2960
2020	2021	189	1	0	0.2419	0.0272	0.1934	0.3002
2021	2022	188	2	186	0.2579	0.0289	0.2062	0.3196

```
. graph export myltable.png, width(500) replace
file myltable.png saved as PNG format
```

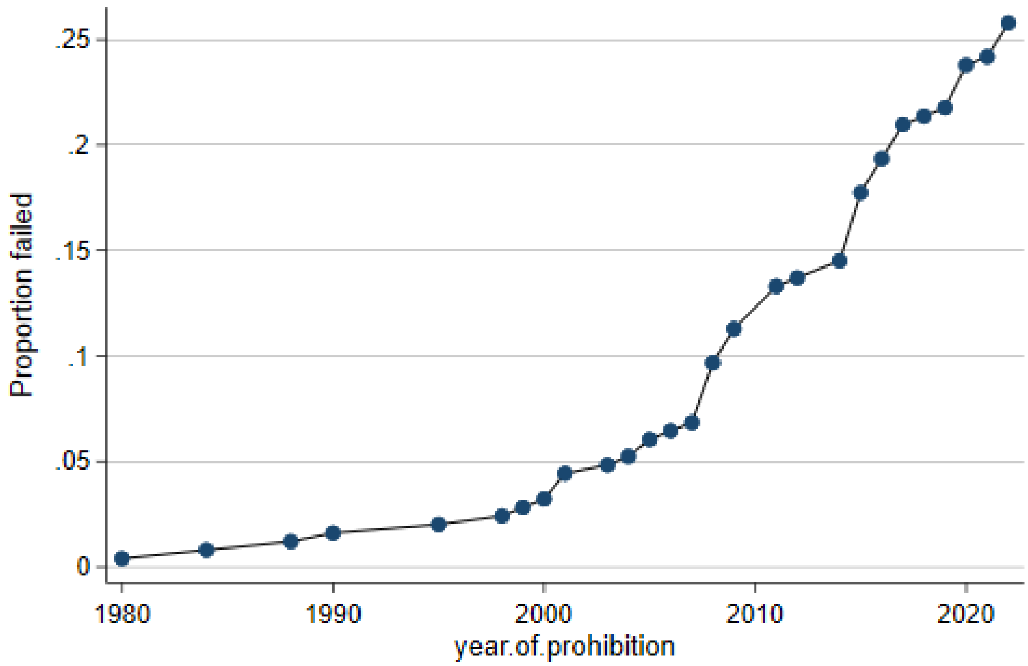

Figure 7: Graph Of Life Table

Discrete Time Survival Analysis

Discrete time survival analysis is placed at the end because it requires us to restructure the data into a long format, where every row is a *country-year*.

Restructuring the Data

We first need to generate a variable for the years during which a country was "at risk" of enacting a ban. Countries that have never enacted a ban are at risk up until the current year. Countries that enacted a ban leave the risk set once they have enacted a ban, and are thus at risk for a shorter time period.

```
. generate years_at_risk =  year_of_prohibition - 1978 + 1 // years "at risk" of enacting a ban
```

We *expand* the data to generate one row of data for every year that each country is at risk.

```
. expand years_at_risk // "expand" the data; 1 row for every year at risk
(9,908 observations created)
```

We create a year variable.

```
. bysort country_code: generate year = _n + 1977 // generate a year variable for each row
```

Lastly, we generate an indicator of the event, a `0/1`' variable, which takes the value 1 for rows in which a ban was enacted, and 0 otherwise.

```
. generate event = type == "CP Ban" & year_of_prohibition == year // generate an event indicator
```

We list out a sample of the data to make sure that the data conform to our expectations. We focus on Norway, a country that *has* enacted a ban, and Great Britain, a country that *has not* enacted a ban.

```
. list country_code year_of_prohibition event continent years_at_risk year ///
> if country_code == "NOR" | country_code == "GBR" , ab(20) // list out a sample of the data
```

	country_code	year_of_prohibition	event	continent	years_at_risk	year
3172.	GBR	2021	0	Europe	44	1978
3173.	GBR	2021	0	Europe	44	1979
3174.	GBR	2021	0	Europe	44	1980

3175.	GBR	2021	0	Europe	44	1981
3176.	GBR	2021	0	Europe	44	1982
3177.	GBR	2021	0	Europe	44	1983
3178.	GBR	2021	0	Europe	44	1984
3179.	GBR	2021	0	Europe	44	1985
3180.	GBR	2021	0	Europe	44	1986
3181.	GBR	2021	0	Europe	44	1987
3182.	GBR	2021	0	Europe	44	1988
3183.	GBR	2021	0	Europe	44	1989
3184.	GBR	2021	0	Europe	44	1990
3185.	GBR	2021	0	Europe	44	1991
3186.	GBR	2021	0	Europe	44	1992
3187.	GBR	2021	0	Europe	44	1993
3188.	GBR	2021	0	Europe	44	1994
3189.	GBR	2021	0	Europe	44	1995
3190.	GBR	2021	0	Europe	44	1996
3191.	GBR	2021	0	Europe	44	1997
3192.	GBR	2021	0	Europe	44	1998
3193.	GBR	2021	0	Europe	44	1999
3194.	GBR	2021	0	Europe	44	2000
3195.	GBR	2021	0	Europe	44	2001
3196.	GBR	2021	0	Europe	44	2002
3197.	GBR	2021	0	Europe	44	2003
3198.	GBR	2021	0	Europe	44	2004
3199.	GBR	2021	0	Europe	44	2005
3200.	GBR	2021	0	Europe	44	2006
3201.	GBR	2021	0	Europe	44	2007
3202.	GBR	2021	0	Europe	44	2008
3203.	GBR	2021	0	Europe	44	2009
3204.	GBR	2021	0	Europe	44	2010
3205.	GBR	2021	0	Europe	44	2011
3206.	GBR	2021	0	Europe	44	2012
3207.	GBR	2021	0	Europe	44	2013
3208.	GBR	2021	0	Europe	44	2014
3209.	GBR	2021	0	Europe	44	2015
3210.	GBR	2021	0	Europe	44	2016
3211.	GBR	2021	0	Europe	44	2017
3212.	GBR	2021	0	Europe	44	2018
3213.	GBR	2021	0	Europe	44	2019
3214.	GBR	2021	0	Europe	44	2020
3215.	GBR	2021	0	Europe	44	2021
6811.	NOR	1987	0	Europe	10	1978
6812.	NOR	1987	0	Europe	10	1979
6813.	NOR	1987	0	Europe	10	1980
6814.	NOR	1987	0	Europe	10	1981
6815.	NOR	1987	0	Europe	10	1982
6816.	NOR	1987	0	Europe	10	1983
6817.	NOR	1987	0	Europe	10	1984
6818.	NOR	1987	0	Europe	10	1985
6819.	NOR	1987	0	Europe	10	1986
6820.	NOR	1987	1	Europe	10	1987

Analysis

Lastly, we analyze the data using a straightforward logistic regression model. While there is some discussion on this point, we choose not to cluster the standard errors on country, because of the argument from Singer and Willett (2003) that the rows of data are *conditionally* independent.

We ask for *odds ratios* so that our results are roughly comparable to those from the continuous time survival models.

```
. logit event ib4.continent_NUMERIC, cluster(country_code) or
Iteration 0:   log pseudolikelihood = -377.92887
Iteration 1:   log pseudolikelihood = -375.10409
Iteration 2:   log pseudolikelihood = -356.66291
Iteration 3:   log pseudolikelihood = -356.57244
```

```
Iteration 4:   log pseudolikelihood = -356.57228
Iteration 5:   log pseudolikelihood = -356.57228

Logistic regression                                     Number of obs = 10,156
                                                        Wald chi2(5)  =  51.46
                                                        Prob > chi2   = 0.0000
Log pseudolikelihood = -356.57228                       Pseudo R2     = 0.0565

                              (Std. err. adjusted for 248 clusters in country_code)
------------------------------------------------------------------------------------
                 |               Robust
           event | Odds ratio   std. err.      z    P>|z|     [95% conf. interval]
-----------------+------------------------------------------------------------------
continent_NUMERIC|
          Africa |   .2166869   .0718543    -4.61   0.000     .1131281    .4150446
        Americas |   .2442922   .0809085    -4.26   0.000     .1276425    .4675456
            Asia |   .1984237   .0731346    -4.39   0.000     .0963517    .4086277
              NA |   .1224256    .118522    -2.17   0.030     .0183574    .8164555
         Oceania |   .0473871   .0476801    -3.03   0.002     .0065947    .3405066
                 |
           _cons |   .0186916   .0027184   -27.36   0.000     .0140557    .0248566
------------------------------------------------------------------------------------
Note: _cons estimates baseline odds.
```

References

Allison, P. D. (1984). *Event History Analysis: Regression for Longitudinal Event Data.* SAGE Publications.

Singer, J. D., & Willett, J. B. (2003). *Applied longitudinal data analysis : modeling change and event occurrence.* Oxford ; New York : Oxford University Press.

StataCorp. 2021. *Stata 17 Survival Analysis Reference Manual.* College Station, TX: Stata Press