sociological science

Supplement to:

Chung, Pil H., and Peter Hepburn. 2018. “Mass Imprisonment and the Extended Family.” Sociological Science 5: 335-360.

Appendix

A1. Rate Inputs

Table A1-1. Years of admission and release data known and interpolated for each year of simulation.

Simulation Years	Year of Admission Data	Year of Release Data
1960-1963	1960; 1961-1963*	1978
1964-1969	1964; 1965-1969*	1978
1970-1973	1970; 1971-1873*	1978
1974-1978	1974-1978	1978
1979-2013	1979-2013	1979-2013
2014+	2014	2014

*Interpolated

The earliest year for which we could locate release data is 1978, and so we hold the known 1978 release rates constant for earlier years. We do not expect this methodological choice to effect this study's findings in any appreciable way for two reasons: 1) historically, imprisonment rates held steady over the period 1960-1980 – this suggests that the 1978 release rates are not an unreasonable approximation for the rates of earlier years; and 2) our study's outcomes of interest are all based on measures of *first*, rather than *current*, imprisonment status – a slight mis-specification of release rates is not likely to affect these outcomes since when and whether current prisoners are released has no bearing on when and whether any other individual in the simulation is imprisoned for the first time.

Table A1-2. Year of known and interpolated race-, sex-, and age- distributions assumed for each year of admission and release data.

Admission

Year of Data	Year of Race Distribution	Year of Sex Distribution	Year of Age Distribution
1960-1963	1960; 1961-1963*	1964	1974
1964-1973	1964; 1965-1973*	1964-1973*	1974
1974-1978	1974-1978	1974; 1975-1978*	1974; 1973-1978*
1979-2013	1979-2013	1979-2013	1979-2013
2014+	2014	2014	2014

*Interpolated

Release

Year of Data	Year of Race Distribution	Year of Sex Distribution	Year of Age Distribution
1960-1973	1974	1991	1991
1974-1990	1974; 1975-1990*	1991	1991
1991-2013	1991-2013	1991-2013	1991-2013
2014+	2014	2014	2014

*Interpolated

For years with missing race-, sex-, and age- distribution information where there is no observed data to serve as the "lower bound" for the interpolation procedure, we apply the earliest known race-, sex-, and age- distribution. Also, for years where prisoners' race information is not further disaggregated into Hispanic and non-Hispanic categories, we downwardly adjust the given proportion of black and white prisoners according to the most contemporaneously reported proportion of Hispanic prisoners (United States Bureau of Justice Statistics, 2016b, 2016b, 2016a) such that we end up with plausible approximations for the proportion of total prisoners who are non-Hispanic black and non-Hispanic white.

A2. Calibration of SOCSIM via Maximum Likelihood Estimation

In order to recover results that are consistent with observed data, we calibrate our input rates against the known distribution of family sizes and life expectancies (TFR and e_0) at each ten-year interval from 1910 to 2009. This calibration is done via two scaling factors – θ_m and θ_f – that multiplicatively adjust the levels of the age-specific mortality and fertility inputs, respectively. What is thus assumed is confidence in the general shape of the age-specific mortality and fertility curves, but uncertainty regarding their magnitudes (Figure 1).

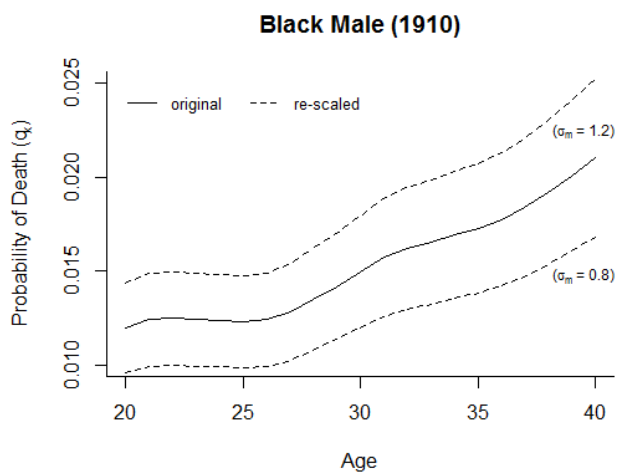

Figure A2-1. Example of re-scaled age-specific mortality curves. The area between the dashed lines demarcates the range of possible re-scaled values.

Procedurally, twenty candidate values are chosen (at even intervals) between the range 0.80 to 1.20 for each θ_m and θ_f parameter. This results in 400 possible (θ_m, θ_f) pairs. Each of these pairs are applied to the simulation's 11 sets of mortality and fertility inputs, and the simulation is then run to completion 25 times (for each pair of scaling factors) producing 25 unique values of TFR and e0. The variation and average of these outcomes over the 25 runs is used to compute a likelihood estimate of observing the true values of the outcomes assuming that the simulated outcomes are normally distributed. In sum, what is produced is an estimated likelihood surface that varies by θ_m and θ_f for each of the 11 input rates used in the simulation (Figure 2). The (θ_m , θ_f) pair that generate the highest likelihood value is then chosen as the final re-scaling parameter set.

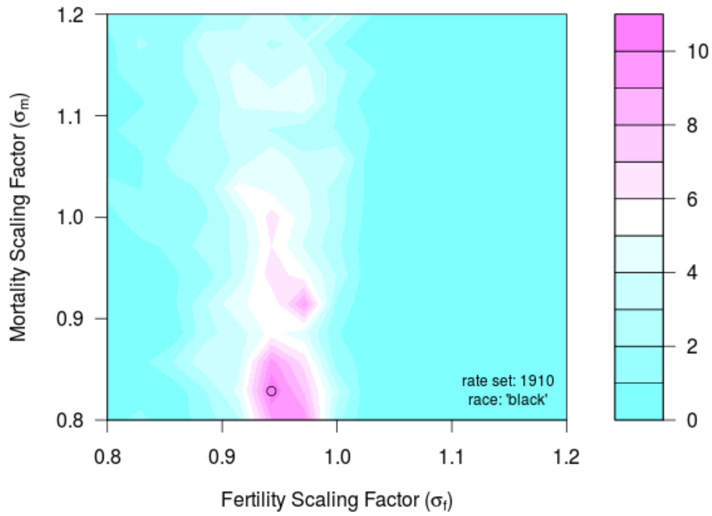

Figure A2-2. Example of estimated likelihood surface generated by the calibration procedure. The point marked by the hollow dot represents the (θ_m , θ_f) pair associated with the maximum likelihood value.

Thus in sum: (11 simulation input rate sets) x (400 re-scaling pairs) x (25 random simulations) = 110,000 calibration simulations are conducted to arrive at a final set of 11 re-scaling parameters. In concert, these 11 re-scaling parameters applied to our simulation's fertility and mortality inputs do a competent job of reproducing the expected TFR and e_0 values (Figure 3).

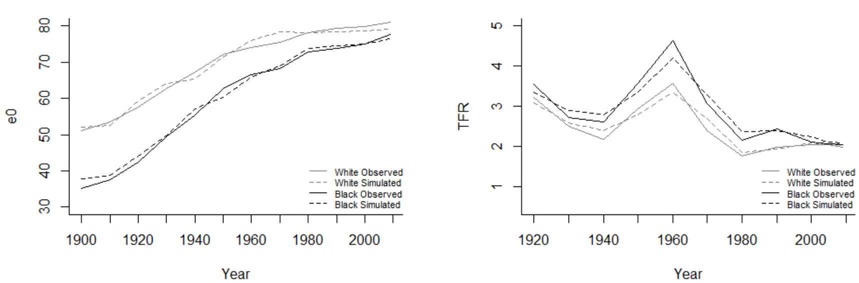

Figure A2-3. Period female life expectancy (e0) and total fertility rate (TFR): observed and simulated values.

An identical strategy is employed to calibrate the race-specific rates of prison admission and prison release to reliably re-produce observed population rates of first admission to prison (Carson & Golinelli, 2013) in simulation (Figure 4).

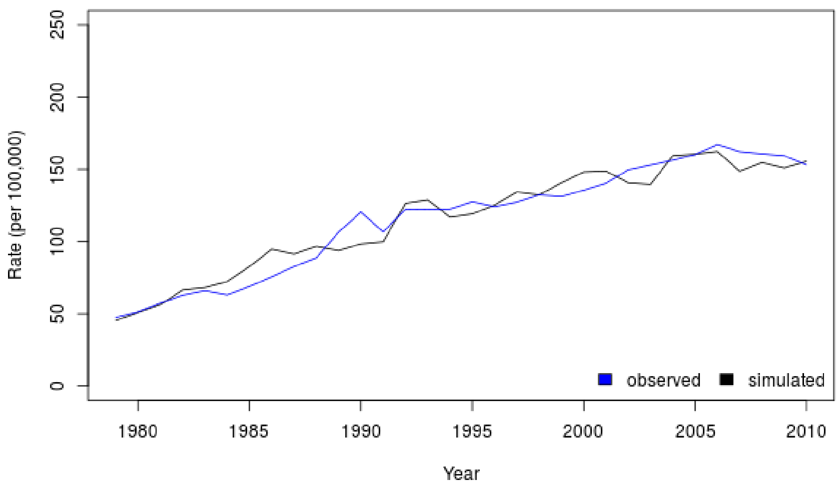

Figure A2-4. Period male first imprisonment rate (per 100,000): observed and simulated values. Race-specific rates are aggregated to allow comparison to observed rates (which are not reported separately by race).

Traditionally, calibration of this sort has been done via an informed trial-and-error methodology, but advances in computational power allow for more systematic optimization procedures, such as the one presented here (for similar applications see: Ševčíková, Raftery, & Waddell (2007); Zagheni (2011)). That being said, the need for these calibration steps should alert the reader to the danger of placing too much confidence in the exact magnitudes of effect being reported here (or in any other microsimulation study). These concerns, however, should be much less pronounced when considering the relative differences between two identically-configured simulations that vary only in their initial inputs as is the case in the present study.

A3. Replication of Prior Findings

To check the overall credibility of our fully calibrated microsimulation model, we attempt to replicate measures of own and family imprisonment reported by three prominently cited studies:

1. Western & Wildeman (2009): The cumulative probability of imprisonment for black and white men by age 30-34 (for 5-year birth cohorts over the period 1960-1979[1]).
2. Wildeman (2009): The cumulative probability of imprisonment of parents (fathers and mothers) for black and white children by age 14 (born 1978 and 1990).
3. H. Lee et al. (2015): The proportion of black and white Americans in 2006 who have at least one family member in prison and the average number of imprisoned family members.

The following tables gives the results of our replication exercises:

[1] Western & Wildeman (2009) reports cumulative probabilities for cohorts born as early as 1945, but our simulation starts in 1960 and so we compare results for only those cohorts for which we are able to generate estimates.

Table A3-1. Cumulative probability of imprisonment for black and white men by age 30-34 (for 5-year birth cohorts over the period 1960-1979: original values and simulated values.

	Birth Cohort			
	1960-1964	1965-1969	1970-1974	1975-1979
Western & Wildeman (2009)				
1. Black	15.2%	20.3%	22.8%	20.7%
2. White	2.2%	2.8%	2.8%	3.3%
Simulation				
1. Black	14.6%	20.2%	23.9%	23.4%
2. White	1.8%	3.0%	3.3%	3.4%

Table A3-2. Cumulative probability of imprisonment of parents (mothers and fathers) for black and white children by age 14 (born 1978 and 1990): original values and simulated values.

	Birth Year			
	1978		1990	
	Mother	Father	Mother	Father
Wildeman (2009)				
1. Black	1.4%	13.4%	3.2%	24.5%
2. White	0.2%	2.1%	0.6%	3.6%
Simulation				
1. Black	1.9%	11.1%	3.3%	25.1%
2. White	0.5%	1.9%	0.7%	4.1%

Table A3-3. The proportion of black and white Americans 18-years or older in 2006 who have at least one family member in prison and the average number of imprisoned family members: original values and simulated values.

	Proportion w/1 or More Family Member in Prison	Average Number of Imprisoned Kin
Lee et al. (2015)		
1. Black Men	0.320	0.84 (1.80)
2. Black Women	0.438	1.63 (3.24)
3. White Men	0.056	0.08 (0.39)
4. White Women	0.116	0.14 (0.45)
Simulation		
1. Black Men	0.348	0.65
2. Black Women	0.382	0.72
3. White Men	0.066	0.10
4. White Women	0.073	0.11

(**Note:** Values from H. Lee et al. (2015) reflect black and white Americans in 2006 who "know" at least one family member in prison. Numbers in parentheses are standard errors. Standard errors for the "Proportion" measure are not reported by H. Lee et al. (2015).)

Happily, our microsimulation returns values that are in close agreement with those reported by Western & Wildeman (2009) and Wildeman (2009). This is perhaps not surprising given that the life table methods that are used by these authors are closely related to the underlying mechanism that drives our microsimulator. Nevertheless, it is still encouraging to see agreement on these values of interest given that our estimates reflect the *joint* effect of fertility, mortality, and imprisonment input factors all operating in tandem. In sum, it seems fair to say that our microsimulation strategy performs no worse in its ability to estimate cohort-level kin imprisonment status than the estimation strategies used by Western and Wildeman.

As for the somewhat larger discrepancy between our estimates and the survey results of H. Lee et al. (2015), we can anticipate at least two factors that might account for these deviations. First, the General Social Survey (GSS) item that H. Lee et al. (2015) draw on for their estimates rely on in-the-moment respondent recall – the item in question asks: "Next, we are going to ask questions about people in your family, including relatives and in-laws. How many are currently in state or federal prison?" Thus there exists a distinct possibility of mis-reporting due to imperfect recollection (especially for more extended kin relations). Second, our simulation models are calibrated to reliably reproduce ever-imprisonment status rather than current-imprisonment status, and so some disagreement in the exact moment-to-moment imprisonment status of individuals observed in the GSS population versus in our simulated population is to be expected. Fortunately, the reliability of our study's results do not depend on the accurate estimation of *current* imprisonment status (only *ever* imprisonment status). That being said, our simulated values are all still rather close to those reported by H. Lee et al. (2015). For example, our estimates of average number of imprisoned family members fall well within a single standard deviation of these authors' estimates.

A4. Exploratory Models of Kin Imprisonment by Educational Attainment

The patterns in kin imprisonment we have described are population averages. Previous research has documented a strong class differential in the effects of mass imprisonment; the least educated face higher risks than their more-educated counterparts of being incarcerated. The correlation of educational attainment within families leads us to suspect that this burden of kin imprisonment is not evenly borne across the population. That is, families who have a greater proportion of less-educated members likely have higher rates of kin imprisonment, while those with a higher proportion of more-educated members experience less kin imprisonment.

We present here exploratory results from a sensitivity analyses in which we employ education-varying imprisonment rates and make the strong assumption of total educational homogamy within families. That is, we model kin imprisonment for blacks and whites as though each was made up of three wholly separate populations: those without a high school diploma, those with a high school diploma or equivalent, and those with some college or more. Individuals from the first population – non-high school graduates – come from families where all members are non-graduates, partner with non-graduates, and give birth to future non-graduates. All members thus face the increased imprisonment risks that come with that status. The same holds for the other groups.

Within SOCSIM, our microsimulator, we build three separate models that are specified identically to the non-stratified models we've been using so far with the exception of multiplicatively adjusted prison admission rates. These adjustment factors are derived from Pettit & Western (2004) (table 4) and are exactly equivalent to the ratio of imprisonment risk at each educational strata to the average population risk. For example: in the period 1979, white men were incarcerated at an average rate of 0.4%; however white men who never completed high school were incarcerated at a rate of 1.0%. Thus, we scale prison admission rates up by a factor of 0.4/1.0 = 2.5 for our simulation of white Americans who never completed high school in order to reflect this observed class difference in imprisonment risk.

This represents an obviously unrealistic model of the world. Parents' education is correlated with children's education, but not perfectly. Some percentage of the children of high school drop-outs will go on to earn college degrees, just as a fraction of the offspring of college graduates will never make it through high school. Educational assortative mating, likewise, is a well-documented and increasingly-common phenomenon, but it is hardly a universal practice (Greenwood, Guner, Kocharkov, & Santos, 2014; Schwartz & Mare, 2005). What this exercise helps us to establish, despite its implausibility, are the "outside bounds" of the range. The families with no high school graduates experience the worst that the system has to offer, while those in which all members have some college will be in the best position. Real-world families will fall somewhere in-between.

To describe the range of experience we curtail our focus to just the boom cohort (those born 1960-1970) and just to measures of the prevalence of kin imprisonment among kin of working age. Figure A4-1 replicates the plots from Figure 4, split here by family education. The top panel presents results for white families and the bottom panel for black families. Moving left to right, the figures display kin availability in families made up entirely of non-high school graduates, families in which all members have a high school diploma or equivalent, and families in which all members have some college or more.

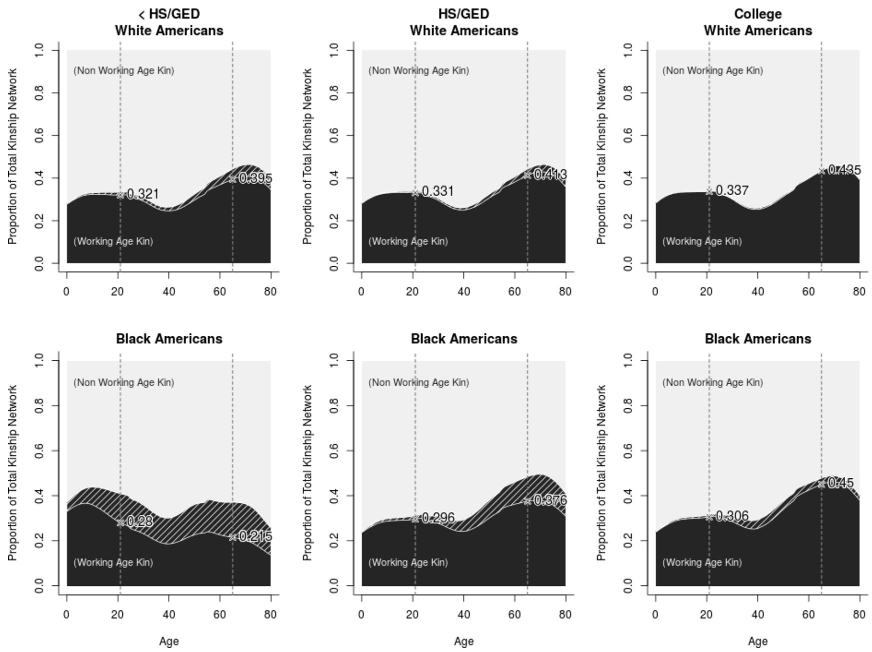

Figure A4-1. Education-specific availability of never-incarcerated, working-age (25-54 y.o.) kin in the "boom" (1960-1970) cohort. The top plots illustrate the proportions of working-age kin for white individuals; while the bottom plots illustrate the same for black individuals. The shaded regions indicate the share of working-age kin who have ever been incarcerated. Points marked by x's indicate the proportion of kin who are working age and have never been incarcerated when ego is age 21 and 65.

For both white and black populations, increasing education is associated with greater availability of never-incarcerated working-age kin. Over the course of life, white and black Americans with less than a high school education lose 7.9% and 49.3%, respectively, of their working-age kin to imprisonment. This represents a loss of 35.8 person-years of potential kin support for white Americans, and a loss of 129.8 person-years for black Americans. In contrast, white college-educated Americans lose 1.0% and black college-educated Americans 6.7% of their working-age kin to imprisonment. This translates to 5.2 person-years of potential kin support lost for whites and 40.2 person-years for blacks. Note that it takes a black family composed entirely of college-educated individuals (the theoretical "best-case" scenario for black Americans) to reach a level of familial imprisonment similar to that of a white family composed entirely of individuals with less than a high school education (the theoretical "worst-case" scenario for white Americans).

Thus, while education seems to be an important mediator of an individual's exposure to family imprisonment, race remains the dominant determinant of an individual's overall experience of familial imprisonment. This finding reinforces what has been found within close friend and family networks by previous research using empirical data (Bobo & Thompson, 2010).