Online Appendix

The code to reproduce the analysis of *The Consequences of Incarceration for Mortality in the United States* is available in https://github.com/sdaza/mortality-incarceration-paper. Some of the data we use are restricted, and was obtained under special contractual arrangements to protect the anonymity of respondents. These data are not available from the authors. Those interested in obtaining PSID restricted data should contact PSIDHelp@isr.umich.edu.

1 Incarceration Measures

The incarceration indicators available in the PSID include non-response information on whether a member of a household was incarcerated at the time of the interview, and a set of questions on involvement with the criminal justice system. One of those questions asked in 1995 if respondents have been in jail or prison. Unfortunately, we cannot distinguish between prison and jail in our data. We acknowledge that prison and jail are different spaces in terms of the resources and treatment of inmates, which might have an impact on their health and mortality. However, given the limitations of our data, we use incarceration and imprisonment interchangeable.

In the case of the non-response incarceration, if a respondent in the PSID was not the only member of their family unit (FU), his incarceration status usually came from other family unit members (e.g., wife, kids). Incarcerated respondents did not get interviewed. However, they are flagged as institutionalized and followed in the next wave. Their family may still be interviewed, provided she had a family unit larger than one in the previous wave. Thus, if a respondent is the only FU member and goes to jail, there will not be an interview at all, but his extended family would be usually contacted to learn his status. If that person lives with his spouse and children, and he goes to jail, there will be an interview in which his spouse will likely be the respondent and the incarcerated respondent will be coded as in an institution for that wave. In the case of the incarceration indicator in 1995, an imprisonment question was asked only to respondents who were 13-49 years old and attended school sometime.

Although both indicators provide useful information on respondents' incarceration experiences, they have some shortcomings. In the case of *non-response incarceration*, we only have information when the household to which the respondent belongs was *interviewed*. We do not know what happened before respondents started participating in the study. Similarly, we do not know their incarceration status during periods when individuals were not interviewed. The *1995 incarceration* variable, in contrast, is retrospective, providing information from respondents' criminal justice contacts before 1996. However, that question was posed to panel members who survived until 1995 and could contaminate estimates with survivor biases. We finally combined both sources of information and adjust for survival bias.

A general concern when studying incarceration effects using survey data is that a substantial segment of the US population has been rendered invisible in many official statistics, specially incarcerated people who are very often omitted from sampling frames (Pettit, 2012). We are well aware of the potential problems posed by of missing individuals of interest for the question we pose at the outset. However, although PSID does not consider incarcerated people in the first wave, it does takes into account both retrospective and prospective incarceration events. Surely, this is not an ideal set up but, provided there are enough young respondents who are followed over time (the PSID follows new family members and the NLSY79 includes a very young sample, 12-16 year-old respondents), the estimates we obtain should be close to those we would have obtained had the first wave included those incarcerated at the time.

Figure S1 show the PSID distributions of the age of death, first imprisonment using the data available, and the difference between the age of death and first imprisonment.

2 Simulation Check

To check our data setup, we implement a simple multi-state model simulation with three transition rates (incarceration, dying without experiencing incarceration, and dying after incarceration) and three states (being born, being in prison, and dying, see Figure S2).

We use age-specific mortality rates from the US life-table, the US age population distribution, and a constant imprisonment rate of 0.007 for ages 18-45, otherwise the incarceration rate is set to 0. In our model, being in prison increases age-specific mortality rates by 1.90. Individuals enter to the observation window at different ages as in the PSID, and right censoring is defined using a uniform distribution, censoring = uniform(age_{enter}, 120). Then, we generate 1000 samples using 10,000 individuals. The average start age across simulations is 37.1.

Finally, we run 1,000 Cox models adjusting by a time-varying prison variable (coded as 1 after the incarceration transition occurs) and age (non-variant covariate). The estimated mean of mortality hazard ratios from 1,000 simulations is 1.879, pretty close to 1.90, so we conclude that our data setup is correct. The simulation results are available at https://github.com/sdaza/mortality-incarceration-paper/blob/master/simulation/simulation.ipynb.

3 Model Specifications

3.1 Time-varying covariates and attrition

By using Marginal Structural Models (MSM), we address two problematic situations pointed out by Hernán and Robins, 2006 when employing time-varying covariates: (1) There exists a time-dependent covariate that is both a risk factor for mortality and also predicts subsequent exposure (e.g., income); (2) Past exposure history (incarceration) might predicts risk factors (e.g., income or health). For instance, past income is a time-dependent confounder for the effect of incarceration on survival, because it is a risk factor for mortality and a predictor of the onset of incarceration. Additionally, prior incarceration is an independent predictor of subsequent income. Standard methods (i.e., Cox regression) that estimate mortality rates at a given time (age) using a summary measure of income or health up to that time (age) may produce biased estimates of the association of incarceration whether or not one adjusts for past income in the analysis.

Following van der Wal and Geskus, 2011, we compute stabilized inverse probability weights to correct the biases related to time-varying covariates. We also adjust these weights using the association between incarceration and attrition as a way to confront informative censoring. The specification of our models are available in our online repository. The marginal structural models adjust both for the incarceration indicator and baseline covariates (i.e., time-invariant covariates) as we include them in the numerator to stabilize weights.

3.2 Goodness of fit

We explore different specifications and examine goodness of fit. We test the proportional hazard assumption of Cox models using Schoenfeld residuals (i.e., observed minus expected values of the covariates at each failure time). When we find indications of departures from proportionality, we introduce an interaction term between the covariate and the log of time. In general, that interactions are noisy and do not change the average results of the effect of imprisonment. Thus, we decide to present the simplest models in the paper.

We also estimate models adjusting for *unmeasured frailty* by introducing a random proportionality factor that modifies the hazard function of a respondent (Mills, 2011; Broström, 2012). Specifically, we estimate a shared frailty model with a gamma distribution fit (with a mean of 1 and variance θ) based on the long-term family identifier available and individual identifier in the PSID. We do not observe substantial differences in the estimates.

3.3 Sampling Weights

We estimate models with and without sampling weights. Our analytic sample includes respondents who are not PSID sample members, according to the PSID terminology. Those respondents have an unknown probability of selection. We assign sample weights to non-sample respondents using the following procedure: After defining our analytic sample, we consider only the first longitudinal sample weight available for individual i at time t_0 (i.e., the sample weight at the start of the period of observation for individual i). If the individual i did not have a sample weight, we pooled the weights from the members of his family unit u at time t_0, and compute the average. We estimate models without and with sample to assess how sensitive they are to this procedure.

3.4 Missing data

We implement two strategies to deal with missing data. First, we impute time-varying covariates (e.g., education, income, health) using the *Last Observation Carried Forward* (LSCF) procedure. This strategy is not problematic regarding stable and monotonic variables such education, but can be questionable with respect to variables such health and income where more change over time is expected. When health is poor, we should not expect much change, specially if the time between missing periods is short. Income, on the other hand, will change due to aging and structural economic factors. In addition to LSCF, we also impute backwards only when the first incarceration episode (according to the PSID) occurred after the first record of the covariate of interest. We remove respondents that do not comply with this rule. For the rest of time-invariable variables, we exclude observations with missing data and without sampling weights. Regarding our key independent variable (incarceration), we impute unobserved periods with zeros (i.e., no event). If imprisonment indeed increases mortality, our incarceration variable and imputation procedure would underestimate the association, particularly if it is unlikely that ex-inmates have lower risk of dying after their release.

Our second strategy is multiple imputation. We implement multilevel models to impute missing values using both time-invariant and time-variant covariates. For example, to impute income we specify a model such as:

$$\begin{aligned} income_j = &\alpha + year_i + male_i + race_i + age_i + \\ &edu_j + prison_j + prison95_j + health_j + dropout_j + died_j + \\ &\delta_i + \varepsilon_j \end{aligned}$$

Where j represents each observation in a long-format dataset, and i individuals. δ_i represents the random effect at the individual level. We examine the distribution of the imputed variables by age and year to check they were reasonable. Then, we pool estimates from 100 imputations. Results are displayed in Tables S1 and S2.

3.5 NLSY 79

To validate our data setup and extent the analysis by Massoglia, Pare, Schnittker, and Gagnon, 2014 using NLSY79, we estimate the association between imprisonment and mortality using the complete NLSY sample (584 deaths in total) and implement marginal structural models (MSM) to adjust by time-varying confounders.

We estimate Cox-models using sampling weights and adjusting for age (set of dummies), gender, race, income, education, work status, marriage, poor health, delinquency at the baseline, and parent's education. The number of respondents who here incarcerated and died during the observation period of the NLSY was 81, and 17 of them were women. The average number of years between the last spell and the year of death was 8.4 (median = 7), about 40% lower than the PSID. As expected, deaths occurred on average at younger ages (41, median = 43), and 42% of them occurred within the first 5 years after release at an average age of 37. This is different from the PSID, where a much smaller proportion of deaths (22%) occurred within the first 5 years.

Tables S3 and S4 display Cox models using both unweighted and weighted NLSY samples and four model specifications: adjusting or not by poor health and estimation or not of MSMs. Unweighted imprisonment coefficients are close to zero with large uncertainty bounds for the size of the effects. Weighted point estimates, on the other hand, are negative and also uncertain. The other covariates are properly signed: males have a higher risk of mortality; income, education, working status, and married are associated with lower risks; and, finally, poor (self-reported) health is a strong predictor of mortality. Our marginal structural models, in contrast, show positive and more consistent coefficients for imprisonment, with hazard ratios ranging from 1.73 to 1.77. In summary, we are able to reproduce key results from PSID when using marginal structural models and dealing with time-covariate adjustments (Hernán & Robins, 2006).

References

Broström, G. (2012). *Event history analysis with R*. CRC Press.

Hernán, M. A. & Robins, J. M. (2006). Estimating causal effects from epidemiological data. *Journal of Epidemiology and Community Health (1979-)*, *60*(7), 578–586.

Massoglia, M., Pare, P.-P., Schnittker, J., & Gagnon, A. (2014). The relationship between incarceration and premature adult mortality: Gender specific evidence. *Social Science Research*, *46*, 142–154.

Mills, M. (2011). *Introducing survival and event history analysis*. Sage Publications.

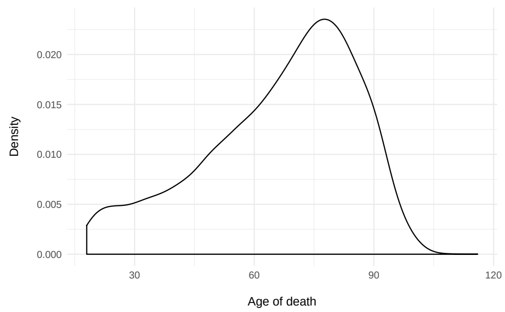
Pettit, B. (2012). *Invisible Men: Mass Incarceration and the Myth of Black Progress* (First Edition). New York: Russell Sage Foundation.

van der Wal, W. M. & Geskus, R. B. (2011). Ipw: An R package for inverse probability weighting. *Journal of Statistical Software*, *43*(13), 1–23.

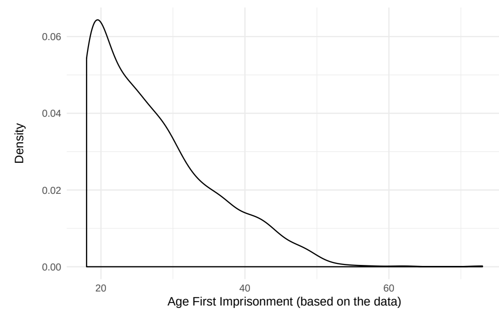
4 Figures and Tables

Figure S1: PSID Distribution Age of Death an Imprisonment

(a) Distribution Age of Death



(b) Distribution Age First Imprisonment



(c) Difference Age of Death and Imprisonment

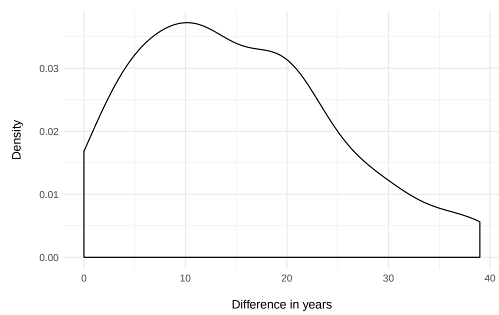


Figure S2: Simulated State Transitions

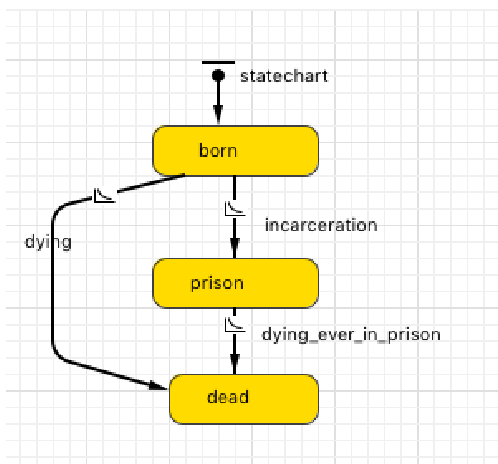


Table S1: Cox Survival Models on the effect of Imprisonment on Mortality, 100 Imputations, Unweighted, PSID 1968-2013

	M1	M1 MSM	M2	M2 MSM
Prison	0.71	0.63	0.71	0.62
	(0.16)	(0.26)	(0.15)	(0.26)
Age	0.08	0.08	0.07	0.08
	(0.00)	(0.00)	(0.00)	(0.00)
Male	0.44	0.42	0.45	0.42
	(0.04)	(0.04)	(0.04)	(0.04)
Race (ref. White)				
Black	0.37	0.48	0.33	0.48
	(0.05)	(0.05)	(0.05)	(0.05)
Other race + Unknown	0.06	0.14	0.03	0.14
	(0.10)	(0.11)	(0.10)	(0.11)
Log Income, centered	−0.04		−0.02	
	(0.02)		(0.02)	
Education (ref. $<$ HS)				
High school	−0.08		−0.03	
	(0.05)		(0.05)	
Some college	−0.34		−0.26	
	(0.07)		(0.07)	
College	−0.73		−0.63	
	(0.07)		(0.07)	
Poor health			0.53	
			(0.07)	
Person-years	633519	633519	633519	633519
Deaths	2803	2803	2803	2803

Robust standard errors in parenthesis.

Table S2: Cox Survival Models on the effect of Imprisonment on Mortality, 100 Imputations, Weighted, PSID 1968-2013

	M1	M1 MSM	M2	M2 MSM
Prison	0.86	0.82	0.85	0.82
	(0.26)	(0.41)	(0.23)	(0.41)
Age	0.09	0.09	0.08	0.09
	(0.00)	(0.00)	(0.00)	(0.00)
Male	0.46	0.42	0.46	0.42
	(0.05)	(0.05)	(0.05)	(0.05)
Race (ref. White)				
Black	0.31	0.40	0.26	0.40
	(0.10)	(0.11)	(0.10)	(0.11)
Other race + Unknown	−0.05	0.03	−0.07	0.03
	(0.13)	(0.13)	(0.12)	(0.13)
Log Income, centered	−0.05		−0.03	
	(0.02)		(0.02)	
Education (ref. < HS)				
High school	−0.04		0.01	
	(0.07)		(0.07)	
Some college	−0.31		−0.20	
	(0.09)		(0.09)	
College	−0.68		−0.55	
	(0.09)		(0.10)	
Poor health			0.74	
			(0.07)	
Person-years	633519	633519	633519	633519
Deaths	2803	2803	2803	2803

Robust standard errors in parenthesis.

Table S3: Cox Survival Models on the effect of Imprisonment on Mortality, Unweighted, NLSY79 1980-2014

	M1	M1 MSM	M2	M2 MSM
Prison	0.00	0.57	0.03	0.57
	(0.16)	(0.17)	(0.16)	(0.17)
Male	0.54	0.50	0.54	0.50
	(0.09)	(0.09)	(0.09)	(0.09)
Race (ref. Non-Hispanics/Blacks)				
Black	0.01	0.43	0.03	0.44
	(0.10)	(0.10)	(0.10)	(0.10)
Hispanic	−0.22	0.01	−0.19	0.01
	(0.13)	(0.12)	(0.13)	(0.12)
Log Income, centered	−0.02		−0.03	
	(0.02)		(0.02)	
Education (ref. $<$ HS)				
High school	−0.16		−0.15	
	(0.11)		(0.11)	
Some college	−0.38		−0.35	
	(0.15)		(0.15)	
College	−0.43		−0.37	
	(0.18)		(0.18)	
Working	−1.06		−0.74	
	(0.10)		(0.11)	
Married	−0.87		−0.81	
	(0.10)		(0.10)	
Poor health			0.90	
			(0.11)	
Deaths	584	584	584	584
Person-years	297282	297282	297282	297282

Robust standard errors in parenthesis. Age, Delinquency at 1980 and Parent's education coefficient omitted.

Table S4: Cox Survival Models on the effect of Imprisonment on Mortality, Weighted, NLSY79 1980-2014

	M1	M1 MSM	M2	M2 MSM
Prison	−0.27	0.55	−0.25	0.55
	(0.20)	(0.19)	(0.20)	(0.19)
Male	0.54	0.49	0.55	0.49
	(0.11)	(0.11)	(0.11)	(0.11)
Race (ref. Non-Hispanics/Blacks)				
Black	−0.12	0.40	−0.09	0.40
	(0.10)	(0.09)	(0.10)	(0.09)
Hispanic	−0.34	−0.05	−0.29	−0.04
	(0.13)	(0.13)	(0.13)	(0.13)
Log Income, centered	−0.02		−0.02	
	(0.02)		(0.02)	
Education (ref. < HS)				
High school	−0.04		−0.04	
	(0.14)		(0.14)	
Some college	−0.22		−0.19	
	(0.18)		(0.18)	
College	−0.36		−0.29	
	(0.21)		(0.21)	
Working	−1.14		−0.76	
	(0.14)		(0.14)	
Married	−1.07		−1.00	
	(0.14)		(0.14)	
Poor health			0.97	
			(0.14)	
Deaths	584	584	584	584
Person-years	297282	297282	297282	297282

Robust standard errors in parenthesis. Age, Delinquency at 1980 and Parent's education coefficient omitted.