Table 5. Fixed Effects Linear Probability Estimates for the Relationship Between *Ever/Never* Being Incarcerated and Racial Classification

A. Equates missing information to being interviewed in a non-prison context

Racial Classification	b	Std. Error	Probability
White	-0.00607	0.00654	.35
Black	0.00385	0.00253	.13

B. Focuses on variation in interview location by excluding incomplete histories

Racial Classification	b	Std. Error	Probability
White	-0.00254	0.00711	.72
Black	0.00152	0.00250	.54

Source: The 1979 National Longitudinal Survey of Youth.
Notes: The sample in Panel A includes 177,934 person-years with non-missing racial data. The sample in Panel B includes 158,135 person-years with non-missing racial and residence data (only cases where the respondent was, starting in 1979, continuously interviewed at known locations). All models incorporate respondent and year fixed effects. Following Saperstein and Penner, standard errors account for clustering within respondents.

Table 6. Fixed Effects Linear Probability Estimates for the Relationship Between *Ever/Never* Being Interviewed in Prison and Racial Classification for Respondents with Interview Location Data For All Years (1979-1998)

Racial Classification	b	Std. Error	Probability
White	0.00216	0.00887	.81
Black	0.00247	0.00331	.46

Source: The 1979 National Longitudinal Survey of Youth.
Notes: The sample includes 111,285 person-years with non-missing racial data and continuously non-missing residence data for all years (including 1987). The models incorporate respondent and year fixed effects. Following Saperstein and Penner, standard errors account for clustering within respondents.

Our conclusion: The lone statistically significant result for Saperstein and Penner's racial classification models with respondent fixed effects (b=.004, standard error=.002, p=.046 for black classification) is extremely fragile (2010, p. 107). It is not robust to differences in the sample or estimation procedure.

Table 7. Fixed Effects Linear Probability Estimates for the Relationship Between *Ever/Never* Being Incarcerated and Black Racial Classification

Variable	b	Std. Error	Probability
Ever incarcerated (1979-98)	0.00156	0.00242	.52
Continuous non-missing residence data	-0.00048	0.00135	.72
Non-missing residence data*ever incarcerated	-0.01074	0.00541	.05

Source: The 1979 National Longitudinal Survey of Youth.
Notes: The sample includes 177,934 person-years with non-missing racial data. The models incorporate respondent and year fixed effects. Following Saperstein and Penner, standard errors account for clustering within respondents. The more exact probability associated with the product term is .047. To account for the non-essential ill conditioning in product-term analysis, the ever incarcerated and continuous non-missing data indicator variables are centered. Because the component variables are centered, the estimated impact of the ever-incarcerated variable can be interpreted as the effect of ever being interviewed in prison at the average level of continuous non-missing residence data. Note that simply including the continuous non-missing residence data indicator without modeling the interaction would be insufficient to capture this dynamic.

Our conclusion: The use of an "ever" measure introduces additional complications in coding that were not specified in Saperstein and Penner's (2010) article. The ever-incarcerated indicator assigns a value of 1 to respondents that are currently or previously interviewed in prison and 0 to respondents that are currently/previously interviewed outside of prison *or there is no respondent residence data*. Therefore, the ever-incarcerated measure is a complicated mixture of variation related to interview context and missing information. The interaction term indicates that the coefficient on ever incarcerated shrinks for observations with continuous non-missing interview location data. Alternatively stated, including observations with missing data increases the coefficient on ever incarcerated in the black classification model. We believe that the fixed-effects estimates for current incarceration status provide the clearest gauge of "the effect on racial classification of being interviewed while incarcerated." (Saperstein, Penner, and Kizer 2014, p. 117). Still, if researchers want to use an ever-incarcerated measure to make a pre versus post distinction and/or to equate clues given by a respondent's presentation of self with the direct knowledge associated with interviewing a respondent in prison, the models need to account for "ever missing" (most easily by limiting the sample to respondents with continuously valid data for the ever variable).