Table 8. Logistic Regression Estimates of the Relationship between Ever Incarcerated and Black Self-identification in 2002 Under Different Assumptions Regarding Incarceration-driven Racial Fluidity versus Random Measurement Error

Variable	Estimates controlling for the original Black in 1979 measure used to model incarceration-driven racial fluidity	Estimates controlling for a created Black in 1979 measure that is different from Black in 2002 only by 1.6% induced random error
Ever Incarcerated	0.98 (0.35)	1.18 (0.39)
Black Self-id in 1979	8.21 (0.20)	8.25 (0.20)
N	7,661	7,661

Notes: Standard errors are in parentheses. There were 57 observations with missing data on the respondent's 1979 identity (listwise deletion was used). The same percentage of the sample (1.6%) had a discrepancy in Black racial identification for 1979 vs. 2002 in both the original and the altered NLSY data. To create the altered data we first set the 1979 racial measure equal to the 2002 indicator and then switched the 0s and 1s in the new 1979 measure for a 1.6% randomly selected subset (leaving the rest of the cases with 1979 values matching those in 2002). We estimated the model 30 times and averaged the coefficients and standard errors (see the included SAS code below).[1]

Our conclusion: The strategy of controlling for racial categorization in an earlier time period is unhelpful as a means for uncovering whether incarceration changes a person's race. Finding a robust incarceration estimate does not mean that an incarceration record systematically drives racial change. An equivalent estimate for incarceration can emerge even when racial change is entirely driven by random error.

[1] Saperstein and Penner (2016:268) argue that if one injects error into the *artificial control variable* one needs to do the same for the *real dependent variable*. However, this argument makes little sense given the aim of the exercise. It is necessary to inject error into the artificial control variable because, by construction, it starts off as a perfect errorless predictor. In contrast, the dependent variable in the actual survey data is already measured with error, as is the theoretically important independent variable: incarceration record. Saperstein and Penner's recommended approach involves supplementing existing measurement error in the dependent variable with more error. Ultimately, this approach will simply tell us what we already know: randomly inverting a portion of a dependent variable's values can reduce the predictive power of a previously correlated independent variable.
Saperstein, A. and Penner, A.M. 2016. "Still Searching For A True Race? Reply to Kramer et al. and Alba et al." American Journal of Sociology 122:1, 263-285.

```
data one; set blackidentity;
brand=abs(b2002-1);
proc logistic; model b2002 (descending)= everincar black79 ;
run;
proc surveyselect data = one method = SRS rep = 1000 seed=936
  sampsize = 123 out = randb;
  id caseid brand;
  run;
data two; set randb;
/*change the replicate filter (from 1-1000) for a new randomized black in 1979*/
if replicate=1;
brand2=brand;
proc sort; by caseid;
data three; merge one two; by caseid;
if brand2=. then b1979ran=b2002;
else b1979ran=brand2;
proc logistic; model b2002 (descending)= everincar b1979ran ;
run;

/*below are the results for the first 30 equations using randomized black in 1979

incar_b   incar_se  b79_b  b79_se
1.1905    0.3925    8.2202   0.1987
1.642     0.4005    8.3729   0.214
1.1247    0.3987    8.2819   0.2047
1.8224    0.3802    8.3271   0.2093
1.4094    0.3968    8.2879   0.2053
1.8456    0.3662    8.2719   0.2036
1.3788    0.3674    8.118    0.1892
1.6542    0.3842    8.2848   0.2051
0.6294    0.376     8.2144   0.1982
1.049     0.3827    8.126    0.1899
0.9635    0.3858    8.1537   0.1925
1.1911    0.4054    8.3464   0.2112
0.8758    0.3867    8.1891   0.1958
1.3929    0.3809    8.185    0.1954
1.0126    0.3985    8.3143   0.2079
1.2564    0.3981    8.2736   0.2039
0.8613    0.3915    8.3082   0.2074
0.9635    0.3858    8.1537   0.1925
0.8758    0.3867    8.1891   0.1958
1.0218    0.39      8.1953   0.1963
1.7144    0.3728    8.2505   0.2016
1.6709    0.4032    8.3981   0.2167
0.751     0.3824    8.2004   0.1969
0.8573    0.3854    8.1749   0.1944
0.8946    0.3881    8.2042   0.1972
0.7704    0.3877    8.3726   0.214
1.234     0.3961    8.2548   0.2021
0.9446    0.3846    8.1416   0.1914
1.4594    0.4013    8.3301   0.2096
0.8613    0.3915    8.3082   0.2074 */
```