# Conscription and Military Service: Do They Result in Future Violent and Non-Violent Incarcerations and Recidivism?[i]

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## ONLINE APPENDIX

This online appendix is divided in the following sections.

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## Appendix A

## (FOR ONLINE PUBLICATION)

This appendix section contains the propositions of the nonparametric bounds explained in Section 3 of the paper, and their proofs. We use all the notations that are outlined in Section 3 of the paper.

### A1. Proposition 1 and the bounds for $LNATE_{nt}^{Z}$

To formally provide the expression for the bounds on $LNATE_{nt}^{Z}$ under A1 to A3, denote $y_{\tau}^{zd}$ as the $\tau$-th quantile of *Y* conditional on Z=*z* and D=*d*. The following proposition, adapted from FF-L (2010), presents the expressions of bounds on the objects necessary to bound $LNATE_{nt}^{Z}$.

*Proposition 1.* If Assumptions A1-A3 hold, then $L^{nt} \leq LNATE_{nt}^{Z} \leq U^{nt}$, $z = 0, 1$, where

$$L^{nt} = E[Y|Z = 1, D = 0] - U^{0,nt}; \qquad U^{nt} = E[Y|Z = 1, D = 0] - L^{0,nt}$$

$$L^{0,nt} = E\left[Y \middle| Z = 0, D = 0, Y \leq y^{00}_{\left(\frac{p_{0|1}}{p_{0|0}}\right)}\right]; \quad U^{0,nt} = E\left[Y \middle| Z = 0, D = 0, Y \geq y^{00}_{1-\left(\frac{p_{0|1}}{p_{0|0}}\right)}\right]$$

Furthermore, we have $L^{0,nt} \leq E[Y(0)|nt] \leq U^{0,nt}$; $L^{at} \leq LNATE_{at}^{Z} \leq U^{at}$, $z = 0, 1$, $L^{1,at} \leq E[Y(1)|at] \leq U^{1,at}$; $L^{0,c} \leq E[Y(0)|c] \leq U^{0,c}$ and $L^{1,c} \leq E[Y(1)|c] \leq U^{1,c}$; where

$$L^{at} = L^{1,at} - E[Y|Z = 0, D = 1]; \qquad U^{at} = U^{1,at} - E[Y|Z = 0, D = 1]$$

$$L^{1,at} = E\left[Y \middle| Z = 1, D = 1, Y \leq y^{11}_{\left(\frac{p_{1|0}}{p_{1|1}}\right)}\right]; \quad U^{1,at} = E\left[Y \middle| Z = 1, D = 1, Y \geq y^{11}_{1-\left(\frac{p_{1|0}}{p_{1|1}}\right)}\right]$$

$$L^{0,c} = E\left[Y \middle| Z = 0, D = 0, Y \leq y^{00}_{1-\left(\frac{p_{0|1}}{p_{0|0}}\right)}\right]; \quad U^{0,c} = E\left[Y \middle| Z = 0, D = 0, Y \geq y^{00}_{\left(\frac{p_{0|1}}{p_{0|0}}\right)}\right]$$

$$L^{1,c} = E\left[Y \middle| Z = 1, D = 1, Y \leq y^{11}_{1-\left(\frac{p_{1|0}}{p_{1|1}}\right)}\right]; \quad U^{1,c} = E\left[Y \middle| Z = 1, D = 1, Y \geq y^{11}_{\left(\frac{p_{1|0}}{p_{1|1}}\right)}\right].$$

Proposition 1 also presents the bounds for $LNATE_{at}^{Z}$, the direct effect of the draft lotteries on the crime outcomes of the volunteers (always-takers), and potential crime outcomes for the other strata $E[Y(1)|at]$, $E[Y(0)|c]$, and $E[Y(1)|c]$. These outcomes are necessary for us to construct the bounds for the military service effect of volunteer veterans (always-takers) and total veterans - ${LATE_{at}}^{Z}$ and *ATT*.

Proposition 1 follows the intuition provided in Section 3.3 of the paper. The relevant point identified objects under Assumption A1-A3 in Section 3.3 are as follows: $\pi_{nt} = p_{0|1}$, $\pi_{at} = p_{1|0}$, $\pi_c = p_{1|1} - p_{1|0} = p_{0|0} - p_{0|1}$, $E[Y(1)] = E[Y|Z = 1]$, $E[Y(0)] = E[Y|Z = 0]$, $E[Y(1)|nt] = E[Y|Z = 1, D = 0]$, $E[Y(0)|at] = E[Y|Z = 0, D = 1]$. The derivation of the trimming bounds for $E[Y(1)|at]$, $E[Y(0)|c]$ and $E[Y(1)|c]$ follow similar steps as in Section 3.3 with respect to the bounds for $E[Y(0)|nt]$. Specifically, the derivation of the trimming bounds for $E[Y(1)|at]$ and $E[Y(1)|c]$ use the equality $E[Y|Z = 1, D = 1] = \frac{\pi_{at}}{\pi_{at}+\pi_c} \cdot E[Y(1)|at] + \frac{\pi_c}{\pi_{at}+\pi_c} \cdot E[Y(1)|c]$ and similar steps as in Section 3.3; the derivation of the trimming bounds for $E[Y(0)|c]$ uses the equality $E[Y|Z = 0, D = 0] = \frac{\pi_{nt}}{\pi_{nt}+\pi_c} \cdot E[Y(0)|nt] + \frac{\pi_c}{\pi_{nt}+\pi_c} \cdot E[Y(0)|c]$ and similar steps as in Section 3.3.

## A2. Proposition 2 and the bounds for $LATE_c$, $LATE_{at}$, $ATT$

Under the same basic assumptions A1-A3 and the exclusion restriction, the traditional IV estimator of the effects of military service using the lottery draft as an IV identify the effect of military service on the outcome for the *c* stratum ($LATE_c$):

$$LATE_c \equiv E[Y(z,1) - Y(z,0)|D_1 - D_0 = 1]. \qquad \text{(A1.1)}$$

FF-L (2013) show that $MATE^z = E[Y(z, D_1) - Y(z, D_0)]$, for $z = 0, 1$, can be related to $LATE$. To see this, write $MATE^Z$ as follows:

$$\begin{aligned} MATE^Z &= E[Y(z, D_1) - Y(z, D_0)] \qquad \text{(A1.2)} \\ &= E\{[\mathrm{D}_1 - \mathrm{D}_0] \cdot [\mathrm{Y(z,1)} - \mathrm{Y(z,0)}]\} \\ &= \Pr(D_1 - D_0 = 1) \cdot \{\Pr(Z = 1) \cdot E[Y(1,1) - Y(1,0)|D_1 - D_0 = 1] \\ &\quad + \Pr(Z = 0) \cdot E[Y(0,1) - Y(0,0)|D_1 - D_0 = 1]\} - \Pr(D_1 - D_0 = -1) \cdot \{\Pr(Z = 1) \cdot \\ &\quad E[Y(1,1) - Y(1,0)|D_1 - D_0 = -1] + \Pr(Z = 0) \cdot E[Y(0,1) - Y(0,0)|D_1 - D_0 = -1]\}, \end{aligned}$$

for $z = 0, 1$.

In the second line of (A1.2), $MATE^Z$ is written as the expected value of the product of the effect of the draft-eligibility on veteran status times the effect from a change in the veteran status on the crime outcome. The subsequent lines use iterated expectations to make explicit the dependence on the instrument exposure. Recalling that A3 rules out defiers, such that $\Pr(D_1 - D_0 = -1) = 0$, equation (A1.2) can be related to a *LATE* that depends on the exposure status to the instrument, which we denote as $LATE_c^Z$ (FF-L, 2013):

$$LATE_c^Z \equiv E[Y(z,1) - Y(z,0)|D_1 - D_0 = 1]$$

$$= E[Y(z,1) - Y(z,0)|c] = \frac{MATE^z}{E[D_1 - D_0]}, \text{ for } z = 0,1 \qquad \text{(A1.3)}$$

Since the denominator in the last expression is point identified (it is the reduced form effect of the randomized draft-eligibility on military service), the bounds on $MATE^Z$ in FF-L (2010) can be employed to construct bounds on each of the $LATE_c^Z$ for $z=0,1$. Following FF-L (2010), we use the point identified quantities and trimming bounds above as building blocks to construct bounds on $MATE^Z$ under $z = 1$ and $z = 0$ by writing it in different ways as a function of the local effects and average potential and counterfactual outcomes of the three strata. Similar in spirit of FF-L (2010), below we write $MATE^Z$ both under and not under exposure to the IV as

$$MATE^1 = \pi_c LMATE_c^1 \qquad \text{(A1.4)}$$

$$= \pi_{nt} E[Y(0)|nt] + \pi_{at} E[Y(0)|at] + \pi_c E[Y(1)|c] - \pi_c LNATE_c^0 - E[Y(0)] \qquad \text{(A1.5)}$$

$$= E[Y(1)] - \pi_{at} E[Y(1)|at] - \pi_{nt} E[Y(1)|nt] - \pi_c E[Y(1, D_0)|c] \qquad \text{(A1.6)}$$

$$= E[Y(1)] - E[Y(0)] - \pi_{at} LNATE_{at}^Z - \pi_{nt} LNATE_{nt}^Z - \pi_c LNATE_c^0 \qquad \text{(A1.7)}$$

$$MATE^0 = \pi_c LMATE_c^0 \qquad \text{(A1.8)}$$

$$= E[Y(1)] - \pi_{nt} E[Y(1)|nt] - \pi_{at} E[Y(1)|at] - \pi_c E[Y(0)|c] - \pi_c LNATE_c^1 \qquad \text{(A1.9)}$$

$$= \pi_{at} E[Y(0)|at] + \pi_{nt} E[Y(0)|nt] + \pi_c E[Y(0, D_1)|c] - E[Y(0)] \qquad \text{(A1.10)}$$

$$= E[Y(1)] - E[Y(0)] - \pi_{at} LNATE_{at}^Z - \pi_{nt} LNATE_{nt}^Z - \pi_c LNATE_c^1 \qquad \text{(A1.11)}$$

And $MATE^Z = \Pr(Z = 1) \cdot MATE^1 + \Pr(Z = 0) \cdot MATE^0$ (A1.12).

Under Assumption A1-A5, we partially identify $MATE^Z$ by plugging in the respective point estimates or bounds estimates of the components in (A1.4)-(A1.12). We then use the estimated bounds for $MATE^Z$ and equation A1.3 to derive the bounds for $LATE_c^Z$. To make $LATE_c^Z$ estimated by bounds comparable to the traditional IV estimator that identifies (1), we average out $Z$ to obtain estimated bounds on $LATE_c$.

To derive the lower and upper bounds for $LATE_{at}$, we write $LATE_{at}$ as $LATE_{at} = \Pr(Z = 1) \cdot (E[Y(1,1)|at] - E[Y(1,0)|at]) + \Pr(Z = 0) \cdot (E[Y(0,1)|at] - E[Y(0,0)|at])$, then plug in the appropriate bounds derived into the terms that are not point identified or unobserved (i.e., $E[Y(1{,}1)|at]$, $E[Y(1{,}0)|at]$, and $E[Y(0{,}0)|at]$).

To derive the lower and upper bounds for $ATT$, we follow Chen et al. (2018) and write $ATT$ as

$$E[Y(z,1)-Y(z,0)|D=1]=\frac{\Pr(Z=1,D=1)}{\Pr(D=1)}E[Y(1,1)-Y(1,0)|Z=1,D=1]+$$
$$\frac{\Pr(Z=0,D=1)}{\Pr(D=1)}E[Y(0,1)-Y(0,0)|Z=0,D=1]. \quad \text{(A1.13)}$$

Equation A1.13 can be written as $ATT=\frac{w_1}{r_1}\Gamma(1)+\frac{w_0}{r_1}\Gamma(0)$, where $\Pr(Z=z)=w_z$ and $\Pr(D=1)=r_1$, $\Gamma(1)=p_{1|1}\bar{Y}^{11}-\pi_{at}E[Y(1,0)|at]-\pi_c E[Y(1,D_0)|c]$ and $\Gamma(0)=p_{1|0}(E[Y|Z=0,D=1]-E[Y(0,0)|at])$. We follow Chen et al. (2019) and write $\Gamma(1)$ as a function of local casual mechanism and direct effects that can be either point identified or partially identified:

$$\Gamma(1)=\pi_{at}(E[Y(1)|at]-E[Y(1,0)|at])+\pi_c LMATE_c^1 \quad \text{(A1.14)}$$
$$=\pi_{at}(E[Y(0)|at]-E[Y(1,0)|at])+E[Y|Z=1]-E[Y|Z=0]-$$
$$\pi_{nt}LNATE_{nt}^0-\pi_c LNATE_c^0 \quad \text{(A1.15)}$$
$$=p_{1|1}\bar{Y}^{11}-\pi_{at}E[Y(1,0)|at]-\pi_c E[Y(1,D_0)|c] \quad \text{(A1.16)}$$

We estimate the bounds for *ATT* by plugging in the appropriate bounds derived into the terms that are not point identified or unobserved (i.e., $E[Y(1,D_0)|c]$ and $E[Y(1,0)|at]$).

The following proposition formally presents the bounds on $LATE_c$, $LATE_{at}$, and $ATT$ under Assumptions A1-A5.

*Proposition 2.* If Assumptions A1-A5 hold, $L_M\le MATE^Z\le U_M$ and

$$\frac{L_M}{E[Y|Z=1]-E[Y|Z=0]}\le LATE_c^Z\le\frac{U_M}{E[Y|Z=1]-E[Y|Z=0]}\quad,\quad L_{at}\le LATE_{at}^Z\le U_{at}\quad,$$

$L_{ATT}\le ATT\le U_{ATT}$, where

$L_M=\Pr(Z=1)\cdot\Delta_3^1+\Pr(Z=0)\cdot\max\{\Delta_1^0,\Delta_3^0\}$

$U_M=\Pr(Z=1)\cdot\Upsilon_1^1+\Pr(Z=0)\cdot\Upsilon_1^0$

$\Delta_3^1=E[Y|Z=1]-p_{1|0}\cdot\min\{U^{1,at},E[Y|Z=1,D=0]\}-p_{0|1}\cdot E[Y|Z=1,D=0]$
$\quad -(p_{1|1}-p_{1|0})\cdot\min\{\mathrm{U}^{1,\mathrm{at}},\mathrm{E}[\mathrm{Y}|\mathrm{Z}=1,\mathrm{D}=0]\}$

$\Delta_1^0=(p_{1|1}-p_{1|0})\cdot(y^l-\min\{E[Y|Z=0,D=0],E[Y|Z=0,D=1]\})$

$\Delta_3^0=p_{1|0}\cdot E[Y|Z=0,D=1]+p_{0|1}\cdot\max\{E[Y|Z=0,D=0],E[Y|Z=0,D=1]\}$
$\quad +(p_{1|1}-p_{1|0})\cdot y^l-E[Y|Z=0]$

$\Upsilon_1^1=(p_{1|1}-p_{1|0})\cdot(E[Y|Z=1,D=1]-y^l)$

$\Upsilon_1^0=(p_{1|1}-p_{1|0})\cdot(E[Y|Z=0,D=1]-L^{0,c})$

$$L_{at} = \Pr(Z=1) \cdot (E[Y|Z=1, D=1] - E[Y|Z=1, D=0]) + \Pr(Z=0) \cdot (E[Y|Z=0, D=1] - U^{0,nt})$$

$$U_{at} = \Pr(Z=1) \cdot (\min\{E[Y|Z=1, D=0], U^{1,at}\} - y^l) + \Pr(Z=0) \cdot (E[Y|Z=0, D=1] - L^{0,c})$$

$$L_{ATT} = \frac{w_1}{r_1} \cdot \left(p_{1|1} \cdot E[Y|Z=1, D=1] - p_{1|0} \cdot E[Y|Z=1, D=0] - \left(p_{1|1} - p_{1|0}\right) \cdot \min\{\bar{U}^{1,at}, E[Y|Z=1, D=0]\}\right) + \frac{w_0}{r_1} \cdot p_{1|0} \cdot (E[Y|Z=0, D=1] - U^{0,nt})$$

$$U_{ATT} = \frac{w_1}{r_1} \cdot \begin{pmatrix} p_{1|0} \cdot E[Y|Z=0, D=1] - p_{1|0} \cdot y^l \\ +E[Y|Z=1] - E[Y|Z=0] - p_{0|1} \cdot (E[Y|Z=1, D=0] - U^{0,nt}) \\ -\left(p_{1|1} - p_{0|1}\right) \cdot (y^l - \min\{E[Y|Z=0, D=0], E[Y|Z=0, D=1]\}) \end{pmatrix} + \frac{w_0}{r_1} \cdot p_{1|0} \cdot (E[Y|Z=0, D=1] - L^{0,c})$$

and $U^{1,at}$, $U^{0,nt}$, and $L^{0,c}$ are defined as in Proposition 1.

**Proof of Proposition 2.** We start by deriving bounds for the non-point identified mean potential (and counterfactual) outcomes of the three strata (*at*, *c*, *nt*) and for all the local net and mechanism average treatment effects. To simply notations, we denote $E[Y|Z=z, D=d]$ as $\bar{Y}^{zd}$, where $z = 0{,}1$ and $d = 0{,}1$.

Bounds for $E[Y(0)|nt]$: Assumption A5(c), A5(d) and $\pi_{nt} \cdot E[Y(0)|nt] + \pi_c \cdot E[Y(0)|c] = p_{0|0}\, \bar{Y}^{00}$ imply that $E[Y(0)|nt] \geq \bar{Y}^{00}$ and $E[Y(0)|nt] \geq \bar{Y}^{01}$. Since $\bar{Y}^{00}$ can be bigger than, smaller than or equal to $\bar{Y}^{01}$ thus the lower bound for $E[Y(0)|nt]$ is $\max\{\bar{Y}^{00}, \bar{Y}^{01}\}$. A5 does not provide any additional information on the upper bound for $E[Y(0)|nt]$. Therefore, the lower bound and the upper bound under Assumption A1-A5 for $E[Y(0)|nt]$ is $\max\{\bar{Y}^{00}, \bar{Y}^{01}\} \leq E[Y(0)|nt] \leq U^{0,nt}$.

Bounds for $E[Y(1)|at]$: Assumption A5(c) and the equation $\pi_{at} \cdot E[Y(1)|at] + \pi_c \cdot E[Y(1)|c] = p_{1|1}\, \bar{Y}^{11}$ implies that the lower bound for $E[Y(1)|at]$ is $\bar{Y}^{11}$; Assumption A5(d) implies that the $E[Y(1)|at] \leq E[Y(1)|nt] = \bar{Y}^{10}$. Since $\bar{Y}^{10}$ can be bigger than, smaller than or equal to $U^{1,at}$, the upper for $E[Y(1)|at]$ is $\min\{\bar{Y}^{10}, U^{1,at}\}$. Therefore, the lower bound and the upper bound under Assumption A1-A5 for $E[Y(1)|at]$ is $\bar{Y}^{11} \leq E[Y(1)|at] \leq \min\{\bar{Y}^{10}, U^{1,at}\}$.

Bounds for $E[Y(0)|c]$: Assumption A5 does not provide any additional information on the lower bound for $E[Y(0)|c]$. Assumption A5(c) and A5(d) and the equation $\pi_{nt} \cdot E[Y(0)|nt] +$

$\pi_c \cdot E[Y(0)|c] = p_{0|0}\,\bar{Y}^{00}$ imply that $E[Y(0)|c] \leq \bar{Y}^{00}$ and $E[Y(0)|c] \leq E[Y(0)|at] = \bar{Y}^{01}$. Since $\bar{Y}^{00}$ can be bigger than, smaller than or equal to $\bar{Y}^{01}$, the upper bound for $E[Y(0)|c]$ is $\min\{\bar{Y}^{00}, \bar{Y}^{01}\}$. To summarize, the lower and upper bounds for $E[Y(0)|c]$ is $L^{0,c} \leq E[Y(0)|c] \leq \min\{\bar{Y}^{00}, \bar{Y}^{01}\}$.

Bounds for $E[Y(1)|c]$: Assumption A5 does not provide any additional information on the lower bound for $E[Y(1)|c]$. Assumption A5(c), A5(d) and the equation $\pi_{nt} \cdot E[Y(1)|at] + \pi_c \cdot E[Y(1)|c] = p_{0|0}\,\bar{Y}^{11}$ imply that $E[Y(1)|c] \leq \bar{Y}^{11}$ and $E[Y(1)|c] \leq \bar{Y}^{10}$. And since $\bar{Y}^{11} \leq \bar{Y}^{10}$ by Assumption A5(c) and A5(d), the upper bound for $E[Y(1)|c]$ is $\bar{Y}^{11}$. To summarize, the lower and upper bounds for $E[Y(1)|c]$ is $L^{1,c} \leq E[Y(1)|c] \leq \bar{Y}^{11}$.

Bounds for $E[Y(1, D_0)|c]$: Assumption A4 implies that $E[Y(1, D_0)|c] \geq y^l$. Assumption A5 does not provide additional information to the lower bound for $E[Y(1, D_0)|c]$; Assumption A5(a) and A5(d) imply that $E[Y(1, D_0)|c] \leq E[Y(1)|at] \leq E[Y(1)|nt]$, and therefore $E[Y(1, D_0)|c] \leq U^{1,at}, and\ E[Y(1, D_0)|c] \leq \bar{Y}^{10}$. Since $U^{1,at}$ can be larger than, smaller than or equal to $\bar{Y}^{10}$, the upper bound for $E[Y(1, D_0)|c]$ is $\min\{U^{1,at}, \bar{Y}^{10}\}$. To summarize, the lower and upper bounds for $E[Y(1, D_0)|c]$ under Assumption A1-A5 is $y^l \leq E[Y(1, D_0)|c] \leq \min\{U^{1,at}, \bar{Y}^{10}\}$.

Bounds for $E[Y(0, D_1)|c]$: Assumption A4 implies that $E[Y(0, D_1)|c] \geq y^l$. Assumption A5 does not provide additional information to the lower bound for $E[Y(0, D_1)|c]$; Assumption A5(b) and A5(d) imply that $E[Y(0, D_1)|c] \leq E[Y(0)|at] \leq E[Y(0)|nt]$. Since $\bar{Y}^{01} \leq U^{0,nt}$, the upper bund for $E[Y(0, D_1)|c]$ is $\bar{Y}^{01}$. To summarize, the lower and upper bounds for $E[Y(0, D_1)|c]$ is $y^l \leq E[Y(0, D_1)|c] \leq \bar{Y}^{01}$.

Bounds for $LNATE_{nt}^{Z}$, for $z = 0, 1$: $E[Y(1)|nt]$ is point identified as $\bar{Y}^{10}$. Under the Assumptions A1-A5, the lower and upper bounds for $E[Y(0)|nt]$ are $\max\{\bar{Y}^{00}, \bar{Y}^{01}\} \leq E[Y(0)|nt] \leq U^{0,nt}$. By plugging in appropriate components, under Assumptions A1-A5, $\bar{Y}^{10} - U^{0,nt} \leq LNATE_{nt}^{Z} \leq \bar{Y}^{10} - \max\{\bar{Y}^{00}, \bar{Y}^{01}\}$.

Bounds for $LNATE_{at}^{Z}$, for $z = 0, 1$: $E[Y(0)|at]$ is point identified as $\bar{Y}^{01}$. By plugging in corresponding components, under Assumption A1-A5, $\bar{Y}^{11} - \bar{Y}^{01} \leq LNATE_{at}^{Z} \leq \min\{\bar{Y}^{10}, U^{1,at}\} - \bar{Y}^{01}$.

Bounds for $LNATE_c^0$: By plugging in appropriate components, under Assumptions A1-A5, $y^l - \min\{\bar{Y}^{00}, \bar{Y}^{01}\} \leq LNATE_c^0 \leq \min\{\bar{Y}^{10}, \bar{U}^{1,at}\} - L^{0,c}$.

Bounds for $LNATE_c^1$: By plugging in appropriate components, under Assumptions A1-A5, $L^{1,c} - \bar{Y}^{01} \leq LNATE_c^1 \leq \bar{Y}^{11} - y^l$.

Bounds for $LMATE_c^0$: By plugging in appropriate components, under Assumptions A1-A5, $y^l - \min\{\bar{Y}^{00}, \bar{Y}^{01}\} \leq LMATE_c^0 \leq \bar{Y}^{01} - L^{0,c}$.

Bounds for $LMATE_c^1$: By plugging in appropriate components, under Assumptions A1-A5, $L^{1,c} - \min\{\bar{Y}^{10}, U^{1,at}\} \leq LMATE_c^1 \leq \bar{Y}^{11} - y^l$.

Bounds for $E[Y(1{,}0)|at]$: Assumption A4 implies that $E[Y(1{,}0)|at] \geq y^l$. Assumption A5 does not contribute additional information to the lower bound of $E[Y(1{,}0)|at]$. Assumption A5(f) implies that $E[Y(1{,}0)|at] \leq E[Y(1)|nt]$ and therefore $E[Y(1{,}0)|at] \leq \bar{Y}^{10}$. To summarize, the lower and upper bounds for $E[Y(1{,}0)|at]$ is $y^l \leq E[Y(1{,}0)|at] \leq \bar{Y}^{10}$. And by plugging in appropriate components, $\bar{Y}^{11} - \bar{Y}^{10} \leq E[Y(1)|at] - E[Y(1{,}0)|at] \leq \min\{\bar{Y}^{10}, U^{1,at}\} - y^l$.

Bounds for $E[Y(0{,}0)|at]$: Assumption A4 implies that $E[Y(0{,}0)|at] \geq y^l$. Assumption A5(e) and A5(f) imply that $E[Y(0)|c] \leq E[Y(0{,}0)|at] \leq E[Y(0)|nt]$ and therefore $L^{0,c} \leq E[Y(0{,}0)|at] \leq U^{0,nt}$ (as $L^{0,c} \geq y^l$). And $\bar{Y}^{01} - U^{0,nt} \leq E[Y(0)|at] - E[Y(0{,}0)|at] \leq \bar{Y}^{01} - L^{0,c}$.

We now derive the bounds for *MATE*. We first use Equations A1.4-A1.7 to derive potential lower bounds for *MATE*$^l$ by plugging in the appropriate bounds derived above into the terms that are not point identified. The corresponding four lower bounds candidates are,

$$\Delta_1^1 = \pi_c \cdot (L^{1,c} - \min\{U^{1,at}, \bar{Y}^{10}\})$$

$$\Delta_2^1 = \pi_{nt} \cdot \max\{\bar{Y}^{00}, \bar{Y}^{01}\} + \pi_{at} \cdot \bar{Y}^{01} + \pi_c \cdot L^{1,c} - \pi_c \cdot [\min\{U^{1,at}, \bar{Y}^{10}\} - L^{0,c}] - E[Y|Z=0]$$

$$\Delta_3^1 = E[Y|Z=1] - \pi_{at} \cdot \min\{U^{1,at}, \bar{Y}^{10}\} - \pi_{nt} \cdot \bar{Y}^{10} - \pi_c \cdot \min\{U^{1,at}, \bar{Y}^{10}\}$$

$$\Delta_4^1 = E[Y|Z=1] - E[Y|Z=0] - \pi_{at} \cdot \min\{U^{1,at}, \bar{Y}^{10}\} + \pi_{at} \cdot \bar{Y}^{01} - \pi_{nt} \cdot [\bar{Y}^{10} - \max\{\bar{Y}^{00}, \bar{Y}^{01}\}] - \pi_c \cdot [\min\{\bar{Y}^{10}, U^{1,at}\} - L^{0,c}]$$

After some algebra, we have $\Delta_1^1 - \Delta_2^1 = \pi_{nt} \cdot U^{0,nt} - \pi_{nt} \cdot \max\{\bar{Y}^{00}, \bar{Y}^{01}\} \geq 0$ and therefore $\Delta_1^1 \geq \Delta_2^1$; $\Delta_1^1 - \Delta_3^1 = \pi_c \cdot \min\{U^{1,at}, \bar{Y}^{10}\} - \pi_c \cdot U^{1,at} \leq 0$ and therefore $\Delta_3^1 \geq \Delta_1^1$; $\Delta_1^1 - \Delta_4^1 = \pi_{at} \cdot \min\{U^{1,at}, \bar{Y}^{10}\} - \pi_{at} \cdot \bar{Y}^{11} + \pi_{nt} \cdot \bar{Y}^{00} - \pi_{nt} \cdot \max\{\bar{Y}^{00}, \bar{Y}^{01}\} + \pi_c \cdot \bar{Y}^{00} - \pi_c \cdot L^{0,c} \geq 0$ as $\pi_{at} \cdot \min\{U^{1,at}, \bar{Y}^{10}\} - \pi_{at} \cdot \bar{Y}^{11} \geq 0$, $\pi_{nt} \cdot \bar{Y}^{00} - \pi_{nt} \cdot \max\{\bar{Y}^{00}, \bar{Y}^{01}\} \geq 0$, and $\pi_c \cdot \bar{Y}^{00} - \pi_c \cdot L^{0,c} \geq 0$, and therefore $\Delta_1^1 \geq \Delta_4^1$. To summarize, the lower bound for *MATE*$^l$ is $\Delta_3^1$.

Second, for the upper bounds for *MATE*$^l$, using Equations A1.4-A1.7 we write down the four candidate upper bounds as follows.

$\Upsilon_1^1 = \pi_c \cdot (\bar{Y}^{11} - y^l)$

$\Upsilon_2^1 = \pi_{nt} \cdot U^{0,nt} + \pi_{at} \cdot \bar{Y}^{01} + \pi_c \cdot \bar{Y}^{11} - \pi_c \cdot [0 - \min\{\bar{Y}^{00}, \bar{Y}^{01}\}] - E[Y|Z=0]$

$\Upsilon_3^1 = E[Y|Z=1] - \pi_{at} \cdot \bar{Y}^{11} - \pi_{nt} \cdot \bar{Y}^{10} - y^l$

$\Upsilon_4^1 = E[Y|Z=1] - E[Y|Z=0] - \pi_{at} \cdot [\bar{Y}^{11} - \bar{Y}^{01}] - \pi_{nt} \cdot [\bar{Y}^{10} - \mathrm{U}^{0,\mathrm{nt}}] - \pi_c \cdot (0 - \min\{\bar{Y}^{00}, \bar{Y}^{01}\})$

After some algebra, we have $\Upsilon_1^1 - \Upsilon_2^1 = \pi_c \cdot L^{0,c} - \pi_c \cdot \min\{\bar{Y}^{00}, \bar{Y}^{01}\} \leq 0$ and therefore $\Upsilon_1^1 \leq \Upsilon_2^1$; $\Upsilon_1^1 - \Upsilon_3^1 = \pi_c \cdot \bar{Y}^{11} - E[Y|Z=1] + \pi_{at} \cdot \bar{Y}^{11} + \pi_{nt} \cdot \bar{Y}^{10} = 0$ and therefore $\Upsilon_1^1 = \Upsilon_3^1$; $\Upsilon_1^1 - \Upsilon_4^1 = \pi_c \cdot L^{0,c} - \pi_c \cdot \min\{\bar{Y}^{00}, \bar{Y}^{01}\} \leq 0$ and therefore $\Upsilon_1^1 \leq \Upsilon_4^1$. Therefore the upper bound for *MATE*$^l$ is $\Upsilon_1^1$ or $\Upsilon_3^1$.

We then move on to *MATE*$^0$, using Equations A1.8-A1.11 and by plugging in the appropriate bounds derived into the terms that are not point identified, we have the following candidate for the lower bounds.

$\Delta_1^0 = \pi_c \cdot (y^l - \min\{\bar{Y}^{00}, \bar{Y}^{01}\})$

$\Delta_2^0 = E[Y|Z=1] - \pi_{nt} \cdot \bar{Y}^{10} - \pi_{at} \cdot \min\{\bar{Y}^{10}, U^{1,at}\} - \pi_c \cdot \min\{\bar{Y}^{00}, \bar{Y}^{01}\} - \pi_c \cdot (\bar{Y}^{11} - y^l)$

$\Delta_3^0 = \pi_{at} \cdot \bar{Y}^{01} + \pi_{nt} \cdot \max\{\bar{Y}^{00}, \bar{Y}^{01}\} + \pi_c \cdot y^l - E[Y|Z=0]$

$\Delta_4^0 = E[Y|Z=1] - E[Y|Z=0] - \pi_{at} \cdot (\min\{U^{1,at}, \bar{Y}^{10}\} - \bar{Y}^{01}) - \pi_{nt} \cdot (\bar{Y}^{10} - \max\{\bar{Y}^{00}, \bar{Y}^{01}\}) - \pi_c \cdot [\bar{Y}^{11} - y^l]$

After some algebra, we have $\Delta_1^0 - \Delta_2^0 = \pi_{at} \cdot \min\{\bar{Y}^{10}, U^{1,at}\} - \pi_{at} \cdot \bar{Y}^{11} \geq 0$, and therefore $\Delta_1^0 \geq \Delta_2^0$; $\Delta_3^0 - \Delta_4^0 = \pi_{at} \cdot \min\{\bar{Y}^{10}, U^{1,at}\} - \pi_{at} \cdot \bar{Y}^{11} \geq 0$, and therefore $\Delta_3^0 \geq \Delta_4^0$;

$\Delta_1^0 - \Delta_3^0 = \pi_c \cdot \bar{Y}^{00} - \pi_c \cdot \min\{\bar{Y}^{00}, \bar{Y}^{01}\} + \pi_{nt} \cdot \bar{Y}^{00} - \pi_{nt} \cdot \max\{\bar{Y}^{00}, \bar{Y}^{01}\}$. Since $\pi_c \cdot \bar{Y}^{00} - \pi_c \cdot \min\{\bar{Y}^{00}, \bar{Y}^{01}\} \geq 0$ and $\pi_{nt} \cdot \bar{Y}^{00} - \pi_{nt} \cdot \max\{\bar{Y}^{00}, \bar{Y}^{01}\} \leq 0$, therefore, $\Delta_1^0$ can be larger than, equal to and smaller than $\Delta_3^0$. To summarize, the lower bound for *MATE*$^0$ under Assumptions A1-A5 is $\max\{\Delta_1^0, \Delta_3^0\}$.

Last, we derive the upper bounds candidates for *MATE*$^0$ using Equations A1.8-A1.11. They are.

$\Upsilon_1^0 = \pi_c \cdot (\bar{Y}^{01} - L^{0,c})$

$\Upsilon_2^0 = E[Y|Z = 1] - \pi_{nt} \cdot \bar{Y}^{10} - \pi_{at} \cdot \bar{Y}^{11} - \pi_c \cdot \mathrm{L}^{0,\mathrm{c}} - \pi_c \cdot (L^{1,c} - \bar{Y}^{01})$

$\Upsilon_3^0 = \pi_{at} \cdot \bar{Y}^{01} + \pi_{nt} \cdot \mathrm{U}^{0,\mathrm{nt}} + \pi_c \cdot \bar{Y}^{01} - E[Y|Z = 0]$

$\Upsilon_4^0 = E[Y|Z = 1] - E[Y|Z = 0] - \pi_{at} \cdot [\bar{Y}^{11} - \bar{Y}^{01}] - \pi_{nt} \cdot [\bar{Y}^{10} - \mathrm{U}^{0,\mathrm{nt}}] - \pi_c \cdot (L^{1,c} - \bar{Y}^{01})$

After some algebra, we have $\Upsilon_1^0 - \Upsilon_2^0 = \pi_c \cdot L^{1,c} - \pi_c \cdot \bar{Y}^{11} \leq 0$, and therefore $\Upsilon_1^0 \leq \Upsilon_2^0$; $\Upsilon_1^0 - \Upsilon_3^0 = 0$, and therefore $\Upsilon_1^0 = \Upsilon_3^0$; $\Upsilon_1^0 - \Upsilon_4^0 = \pi_c \cdot L^{1,c} - \pi_c \cdot \bar{Y}^{11} \leq 0$, and therefore $\Upsilon_1^0 \leq \Upsilon_4^0$. To summarize, the upper bound for *MATE*$^0$ under Assumptions A1-A5 is $\Upsilon_1^0$ or $\Upsilon_3^0$.

In summary from above, the lower bound for $MATE^Z$ under Assumptions A1-A5 is $\Pr(Z = 1) \cdot \Delta_3^1 + \Pr(Z = 0) \cdot \max\{\Delta_1^0,\ \Delta_3^0\}$; the upper bound for $MATE^Z$ under Assumptions A1-A5 is $\Pr(Z = 1) \cdot \Upsilon_1^1 + \Pr(Z = 0) \cdot \Upsilon_1^0$ ( $\Upsilon_1^1$ and $\Upsilon_1^0$ can be replaced by $\Upsilon_3^1$ and $\Upsilon_3^0$ respectively).

Following Equation 9 in the main text, the lower bound for $LATE_c^Z$ is $\frac{\Pr(Z=1)\cdot\Delta_3^1 + \Pr(Z=0)\cdot\max\{\Delta_1^0,\Delta_3^0\}}{E[D|Z = 1] - E[D|Z = 0]} \leq LATE^Z \leq \frac{\Pr(Z=1)\cdot\Upsilon_1^1 + \Pr(Z=0)\cdot\Upsilon_1^0}{E[D|Z = 1] - E[D|Z = 0]}$.

Next, we derive bounds for $LATE_{at}^Z$ in Proposition 2 by plugging in appropriate bounds and point estimates that we derived earlier. The bounds for $LATE_{at}^Z$ is $\Pr(Z = 1) \cdot (\bar{Y}^{11} - \bar{Y}^{10}) + \Pr(Z = 0) \cdot (\bar{Y}^{01} - U^{0,nt}) \leq LATE_{at}^Z \leq \Pr(Z = 1) \cdot (\min\{\bar{Y}^{10}, U^{1,at}\} - y^l) + \Pr(Z = 0) \cdot (\bar{Y}^{01} - L^{0,c})$.

Finally, we derive bounds for *ATT*. We start by bounding $\Gamma(1)$ in $ATT = \frac{w_1}{r_1}\Gamma(1) + \frac{w_0}{r_1}\Gamma(0)$.

We first use Equations A1.14-A1.16 to derive potential lower bounds for $\Gamma(1)$ by plugging in the appropriate bounds derived above into the terms that are not point identified. The corresponding three lower bounds candidates for $\Gamma(1)$ are,

$lb_\alpha^1 = p_{1|0} \cdot (\bar{Y}^{11} - \bar{Y}^{10}) + (p_{1|1} - p_{1|0}) \cdot (L^{1,c} - \min\{U^{1,at}, \bar{Y}^{10}\})$

$lb_\beta^1 = p_{1|0} \cdot (\bar{Y}^{01} - \bar{Y}^{10}) + E[Y|Z=1] - E[Y|Z=0] - p_{0|1} \cdot (\bar{Y}^{10} - \max\{\bar{Y}^{00}, \bar{Y}^{01}\}) - (p_{1|1} - p_{1|0}) \cdot (\min\{U^{1,at}, \bar{Y}^{10}\} - L^{0,c})$

$lb_\gamma^1 = p_{1|1} \cdot \bar{Y}^{11} - p_{1|0} \cdot \bar{Y}^{10} - (p_{1|1} - p_{1|0}) \cdot \min\{\bar{U}^{1,at}, \bar{Y}^{10}\}$

Since $L^{1,c} \leq \bar{Y}^{11}$, we have $lb_\alpha^1 - lb_\gamma^1 = (p_{1|1} - p_{1|0}) \cdot (L^{1,c} - \bar{Y}^{11}) \leq 0$. thus, $lb_\alpha^1 \leq lb_\gamma^1$.

Since $\max\{\bar{Y}^{00}, \bar{Y}^{01}\} \leq U^{0,nt}$, we have $lb_\beta^1 - lb_\gamma^1 = p_{0|1} \cdot \max\{\bar{Y}^{00}, \bar{Y}^{01}\} - p_{0|1} \cdot U^{0,nt} \leq 0$. Thus $lb_\beta^1 \leq lb_\gamma^1$.

Therefore, the lower bound for $\Gamma(1)$ is
$lb_\gamma^1 = p_{1|1} \cdot \bar{Y}^{11} - p_{1|0} \cdot \bar{Y}^{10} - (p_{1|1} - p_{1|0}) \cdot \min\{\bar{U}^{1,at}, \bar{Y}^{10}\}$.

The corresponding three upper bounds candidates for $\Gamma(1)$ are,

$ub_\alpha^1 = p_{1|0} \cdot \min\{\bar{Y}^{10}, U^{1,at}\} - p_{1|0} \cdot y^l + (p_{1|1} - p_{1|0}) \cdot (\bar{Y}^{11} - y^l)$

$$ub_\beta^1 = p_{1|0} \cdot \bar{Y}^{01} - p_{1|0} \cdot y^l + E[Y|Z=1] - E[Y|Z=0] - p_{0|1} \cdot (\bar{Y}^{10} - U^{0,nt}) - (p_{1|1} - p_{0|1}) \cdot (y^l - \min\{\bar{Y}^{00}, \bar{Y}^{01}\})$$

$ub_\gamma^1 = p_{1|1} \cdot \bar{Y}^{11} - p_{1|0} \cdot y^l - (p_{1|1} - p_{1|0}) \cdot y^l$

Since $\min\{\bar{Y}^{10}, U^{1,at}\} \geq \bar{Y}^{11}$, $U^{0,nt} \geq \bar{Y}^{00}$, and $\bar{Y}^{00} \geq \min\{\bar{Y}^{00}, \bar{Y}^{01}\}$, we can obtain that
$ub_\alpha^1 - ub_\beta^1 = p_{1|0} \cdot \min\{\bar{Y}^{10}, U^{1,at}\} - p_{1|0} \cdot \bar{Y}^{11} + p_{0|1} \cdot U^{0,nt} - p_{0|1} \cdot \bar{Y}^{00} + (p_{1|1} - p_{0|1}) \cdot \bar{Y}^{00} - (p_{1|1} - p_{0|1}) \cdot \min\{\bar{Y}^{00}, \bar{Y}^{01}\} \geq 0$
and thus $ub_\alpha^1 \geq ub_\beta^1$.

We can also obtain that $ub_\beta^1 - ub_\gamma^1 = (p_{1|1} - p_{0|1}) \cdot (\min\{\bar{Y}^{00}, \bar{Y}^{01}\} - \bar{Y}^{00}) \leq 0$, as $\min\{\bar{Y}^{00}, \bar{Y}^{01}\} \leq \bar{Y}^{00}$. Hence $ub_\beta^1 \leq ub_\gamma^1$.

Therefore, the upper bound for $\Gamma(1)$ is

$$ub_\beta^1 = p_{1|0} \cdot \bar{Y}^{01} - p_{1|0} \cdot y^l + E[Y|Z=1] - E[Y|Z=0] - p_{0|1} \cdot (\bar{Y}^{10} - U^{0,nt}) - (p_{1|1} - p_{0|1}) \cdot (y^l - \min\{\bar{Y}^{00}, \bar{Y}^{01}\}$$

To construct bounds for $\Gamma(0) = p_{1|0} \cdot (E[Y|Z = 0, D = 1] - E[Y(0,0)|at])$, we plug in the lower and upper bounds for $E[Y(0,0)|at]$. $\Gamma(0)$ is bounded by
$p_{1|0} \cdot (\bar{Y}^{01} - U^{0,nt}) \leq \Gamma(0) \leq p_{1|0} \cdot (\bar{Y}^{01} - L^{0,c})$.

We finish deriving the bounds for $ATT$ in Proposition 2 by plugging in the lower and upper bounds for $\Gamma(1)$ and $\Gamma(0)$ in $ATT = \frac{w_1}{r_1}\Gamma(1) + \frac{w_0}{r_1}\Gamma(0)$ to have $L_{ATT}$ and $U_{ATT}$ in Proposition 2,

$$L_{ATT} = \frac{w_1}{r_1} \cdot \left(p_{1|1} \cdot \bar{Y}^{11} - p_{1|0} \cdot \bar{Y}^{10} - \left(p_{1|1} - p_{1|0}\right) \cdot \min\{\bar{U}^{1,at}, \bar{Y}^{10}\}\right) + \frac{w_0}{r_1} \cdot p_{1|0} \cdot (\bar{Y}^{01} - U^{0,nt})$$

$$\begin{aligned} U_{ATT} = \frac{w_1}{r_1} \cdot \Big(&p_{1|0} \cdot \bar{Y}^{01} - p_{1|0} \cdot y^l + E[Y|Z = 1] - E[Y|Z = 0] - p_{0|1} \cdot (\bar{Y}^{10} - U^{0,nt}) \\ &- \left(p_{1|1} - p_{0|1}\right) \cdot (y^l - \min\{\bar{Y}^{00}, \bar{Y}^{01}\}\Big) \\ &+ \frac{w_0}{r_1} \cdot p_{1|0} \cdot (\bar{Y}^{01} - L^{0,c}). \end{aligned}$$

References*:*


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## Appendix B. Estimation and Inference

**(FOR ONLINE PUBLICATION)**

In Appendix A, we have presented the bounds for the military service of the always-takers and compliers, $LATE_{at}$ and $LATE_c$, that contain maximum (max) and minimum (min) operators. The concavity and convexity of the min and max operators cause the sample analog estimates of this type of bounds narrower than the true bounds. Moreover, Hirano and Porter (2012) showed that there exist no locally asymptotically unbiased estimators and no regular estimators for parameters that are nonsmooth functionals of the underlying data distribution, such as those involving min or max operators. In this paper, we follow Flores and Flores-Lagunes (2013) and use the method proposed by Chernozhukov, Lee and Rosen (2013; hereafter CLR) to obtain confidence regions for the true parameter value and half-median unbiased estimators for these upper and lower bounds. (The half-median unbiasedness property means that the upper bound estimator exceeds the true value of the upper bound with probability at least one half asymptotically, while the reverse holds for the lower bound.) In this appendix, we briefly describe CLR's procedure as applied to our setting.

Let the bounds for a parameter $\theta_0$ ($LATE_{at}$) be given by $[\theta_0^l, \theta_0^u]$, where $\theta_0^l = \max_{v \in \mathcal{V}^l = \{1,\dots,m^l\}} \theta^l(v)$ and $\theta_0^u = \min_{v \in \mathcal{V}^u = \{1,\dots,m^u\}} \theta^u(v)$. CLR refer to $\theta^l(v)$ and $\theta^u(v)$ as bounding functions. While $v$ indexes the bounding functions, $m^l$ and $m^u$ give, respectively, the number of terms inside the max and min operators. In our setting, for example, the upper bound for $LATE_{at}$ in Proposition 2 can be written as $\theta^u(1) = \Pr(Z=1) \cdot (E[Y|Z=1, D=0] - y^l) + \Pr(Z=0) \cdot (E[Y|Z=0, D=1] - L^{0,c})$ and $\theta^u(2) = \Pr(Z=1) \cdot (U^{1,at} - y^l) + \Pr(Z=0) \cdot (E[Y|Z=0, D=1] - L^{0,c})$. In the case of this paper, sample analog estimators of the bounding functions $\theta^l(v)$ and $\theta^u(v)$ are known to be consistent and asymptotically normally distributed, as they are simple functions of proportions, conditional means, and trimmed means (Newey and McFadden 1994; Lee 2009).

CLR address the issues related to estimation and inference for the bounds $[\theta_0^l, \theta_0^u]$ by employing prevision-corrected estimates of the bounding functions before applying the min and max operators. The precision adjustment consists of adding to each estimated bounding function its pointwise standard error times an appropriate critical value, $\kappa(p)$, so that estimates with higher standard errors receive larger adjustments. Depending on the choice of $\kappa(p)$, it is possible to obtain confidence regions for either the identified set or the true parameter value, and half-median unbiased estimators for the lower and upper bounds.

CLR select $\kappa(p)$ based on a standardized Gaussian process $Z_n^*(v)$. For any compact set $V \in \mathcal{V}$, they approximate by simulation the $p$-th quantile of $\sup_{v \in \mathcal{V}} Z_n^*(v)$, denoted by $\kappa_{n,V}(p)$, and use it in place of $\kappa(p)$. Since setting $V \in \mathcal{V}^u$ for the upper bound leads to asymptotically valid but conservative inference, CLR propose a preliminary set estimator $\hat{V}_n^u$ of $V_0^u = \arg\min_{v \in \mathcal{V}^u} \theta^u(v)$, which they call an adaptive inequality selector. Intuitively, $\hat{V}_n^u$ selects those bounding functions that are close enough to binding to affect the asymptotic distribution of the estimator of the upper bound. For the same reason, a preliminary set estimator $\widehat{V}_n^l$ of $V_0^l = \arg\max_{v\in\mathcal{V}^u} \theta^l(v)$ is used for the lower bound.

The precision-corrected estimator of the upper bound $\theta_0^u$ is given by

$$\hat{\theta}^u(p) = \min_{v\in\mathcal{V}^u}[\hat{\theta}^u(v) + \kappa^u_{n,\widehat{V}_n^u}(p)s^u(v)], \qquad \text{(A.2.1)}$$

where $\hat{\theta}^u(v)$ is the sample analog estimator of $\theta^u(v)$ and $s^u(v)$ is its standard error. Let $\gamma_n = [\theta_n^u(1) \ldots \theta_n^u(m^u)]'$ be the vector of bounding functions and let $\hat{\gamma}_n = [\theta_n^u(1) \ldots \theta_n^u(m^u)]'$ be the vector of bounding functions and let $\hat{\gamma}_n$ be its sample analog estimator. The steps we follow to compute the set estimator $\widehat{V}_n^u$ and the critical value $\kappa^u_{n,\widehat{V}_n^u}(p)$ in (A.2.1) are:

(1) We obtain by bootstrapping a consistent estimate $\widehat{\Omega}_n$ of the asymptotic variance of $\sqrt{n}(\hat{\gamma}_n - \gamma_n)$. Let $\hat{g}_n(v)'$ denote the v-th row of $\widehat{\Omega}_n^{1/2}$ and let $s_n^u(v) = \left|\left| \hat{g}_n(v)\right|\right| / \sqrt{n}$.

(2) We simulate R draws from $N(0,I_{m^u})$, denoted $Z_1, \ldots, Z_R$, where $I_{m^u}$ is the $m^u \times m^u$ identity matrix, and we calculate $Z_r^*(v) = \hat{g}_n(v)'Z_r / \left|\left| \hat{g}_n(v)\right|\right|$ for $r = 1, \ldots, R$.

(3) Let $Q_p(X)$ denote the p-th quantile of a random variable X and, following CLR, let $c_n = 1 - (.1/\log n)$. We compute $\kappa^u_{n,\mathcal{V}^u}(c_n) = Q_{c_n}(\max_{v\in\mathcal{V}^u} Z_r^*(v), r = 1, \ldots, R)$; that is, for each replication $r$ we calculate the maximum of $Z_r^*(1), \ldots, Z_r^*(m^u)$ and take the c-th quantile of those R values. We then use $\kappa^u_{n,\mathcal{V}^u}(c_n)$ to compute $\widehat{V}_n^u = \{v \in \mathcal{V}^u : \hat{\theta}^u(v) \leq \min_{\tilde{v}\in\mathcal{V}^u}\left[\hat{\theta}^u(\tilde{v}) + \kappa^u_{n,\mathcal{V}^u}(c_n)s_n^u(\tilde{v})\right] + 2\kappa^u_{n,\mathcal{V}^u}(c_n)s_n^u(v)\}$.

(4) We compute $\kappa^u_{n,\widehat{V}_n^u}(p) = Q_p(\max_{v\in\widehat{V}_n^u} Z_r^*(v), r = 1, \ldots, R)$, so that the critical value is based on $\widehat{V}_n^u$ instead of $\mathcal{V}^u$.

Follow similar steps above, we have the precision- corrected estimator of the lower bound $\theta_0^l$.

$$\hat{\theta}^l(p) = \max_{v\in\mathcal{V}^u}[\hat{\theta}^l(v) - \kappa^l_{n,\widehat{V}_n^u}(p)s^l(v)] \qquad \text{(A.2.2)}$$

where $\hat{\theta}^l(v)$ is the sample analog estimator of $\theta^l(v)$ and $s^l(v)$. To compute $\kappa^l_{n,\widehat{V}_n^u}(p)$, we follow same steps above but in step (3) we replace $\widehat{V}_n^u$ by $\widehat{V}_n^l = \{v \in \mathcal{V}^l : \hat{\theta}^l(v) \geq \max_{\tilde{v}\in\mathcal{V}^l}\left[\hat{\theta}^l(\tilde{v}) - \kappa^l_{n,\mathcal{V}^l}(c_n)s_n^l(\tilde{v})\right] - 2\kappa^l_{n,\mathcal{V}^l}(c_n)s_n^l(v)\}$. Because of the symmetry of the normal distribution, no changes are needed when computing the quantities in step 3 and step 4.

Half-median-unbiased estimators of the upper and lower bounds are obtained by setting $p = 1/2$ in the steps above and using equations A.2.1 and A.2.2 to compute, respectively, $\hat{\theta}^l(1/2)$ and $\hat{\theta}^u(1/2)$.

To construct confidence intervals for the parameter $\theta_0$, it is important to take into account the length of the identified set. Following CLR, let $\widehat{\Gamma}_n = \hat{\theta}_n^u(1/2) - \hat{\theta}_n^l(1/2)$, $\widehat{\Gamma}_n^+ = \max(0, \widehat{\Gamma}_n)$, $\rho_n = \max\{\hat{\theta}_n^u\left(\frac{3}{4}\right) - \hat{\theta}_n^u\left(\frac{1}{4}\right), \hat{\theta}_n^u\left(\frac{1}{4}\right) - \hat{\theta}_n^u\left(\frac{3}{4}\right)\}$, $\tau_n = 1/(\rho_n \log n)$ and $\hat{p}_n = 1 -$

$\Phi(\tau_n \hat{\Gamma}_n^+)\alpha$, where $\Phi(\cdot)$ is the standard normal CDF. Note that $\hat{p}_n \in [1-\alpha, 1-\alpha/2]$, with $\hat{p}_n$ approaching $1-\alpha$ when $\hat{\Gamma}_n$ grows large relative to sampling error and $\hat{p}_n = 1-\alpha/2$ when $\hat{\Gamma}_n = 0$. An asymptotically valid $1-\alpha$ confidence interval for $\theta_0$ is given by $[\hat{\theta}_n^l(\hat{p}_n), \hat{\theta}_n^u(\hat{p}_n)]$.

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Newey, W., and McFadden, D. (1994), "Large Sample Estimation and Hypothesis Testing," in *Handbook of Econometrics* (Vol. 4), eds. R. Engle and D. McFadden, Amsterdam: North Holland, pp. 2111–2245.

## Appendix C. Subpopulation Strata Proportion from Wang, Flores, and Flores-Lagunes (2019)

**(FOR ONLINE PUBLICATION)**

The population strata proportions needed to compute the bounds (see Sections 3.3 and 4.2 in the paper), have been borrowed from Wang, Flores and Flores-Lagunes (2019; WFF-L hereafter). They used a restricted version of the National Health Interview Survey (NHIS) to obtain these proportions. NHIS, given that it is a principal cross-sectional data source on health, is representative of the civilian population of the United States. The two key variables in NHIS to obtain these proportion estimates are the draft-eligibility and the Vietnam war veteran status.

To obtain the Vietnam War draft lotteries eligibilities $Z_i$, WFF-L used the restricted-use birth dates variables of each respondent. These birth dates variables are the day of birth, the month of birth, and the year of birth. The data was accessed through the Research Data Center of National Center for Health Statistics and the Federal Statistics Research Data Center at Ithaca, New York. The authors then used the exact birth date information in the NHIS and the lottery numbers obtained from the Selective Service System (SSS) website to construct the Random Sequence Number (RSN) from 1 to 366 of each respondent. They then define the binary draft-eligibility with the value of 1 (draft-eligible) for an individual who received a lottery number under the draft-eligibility cutoff and 0 (draft-ineligible) for an individual who received a lottery number above the draft-eligibility cutoff.

To construct the Vietnam War military service status variable $D_i$, WFF-L used the indicator measures that an individual served in the Vietnam Era in the military based on the survey questions "Did {Person} ever serve on active duty in the Armed Forces of the United States?" and "When did {Person} serve (Vietnam Era, August 1964-April 1975)".

In Table A C.1, we present the proportion estimates from WFF-L using the NHIS 1982-1996 by birth cohort and race. Each column, from left to the right, is the total observation, draft eligible sample estimates ($E[Z_i]$), veteran status sample estimates ($E[D_i]$), never-takers ($\pi_{nt} = \Pr(D_i = 0|Z_i = 1)$), always-takers ($\pi_{at} = \Pr(D_i = 1|Z_i = 0)$), and compliers ($\pi_c = (\Pr(D_i = 1|Z_i = 1) - \Pr(D_i = 1|Z_i = 0))$).

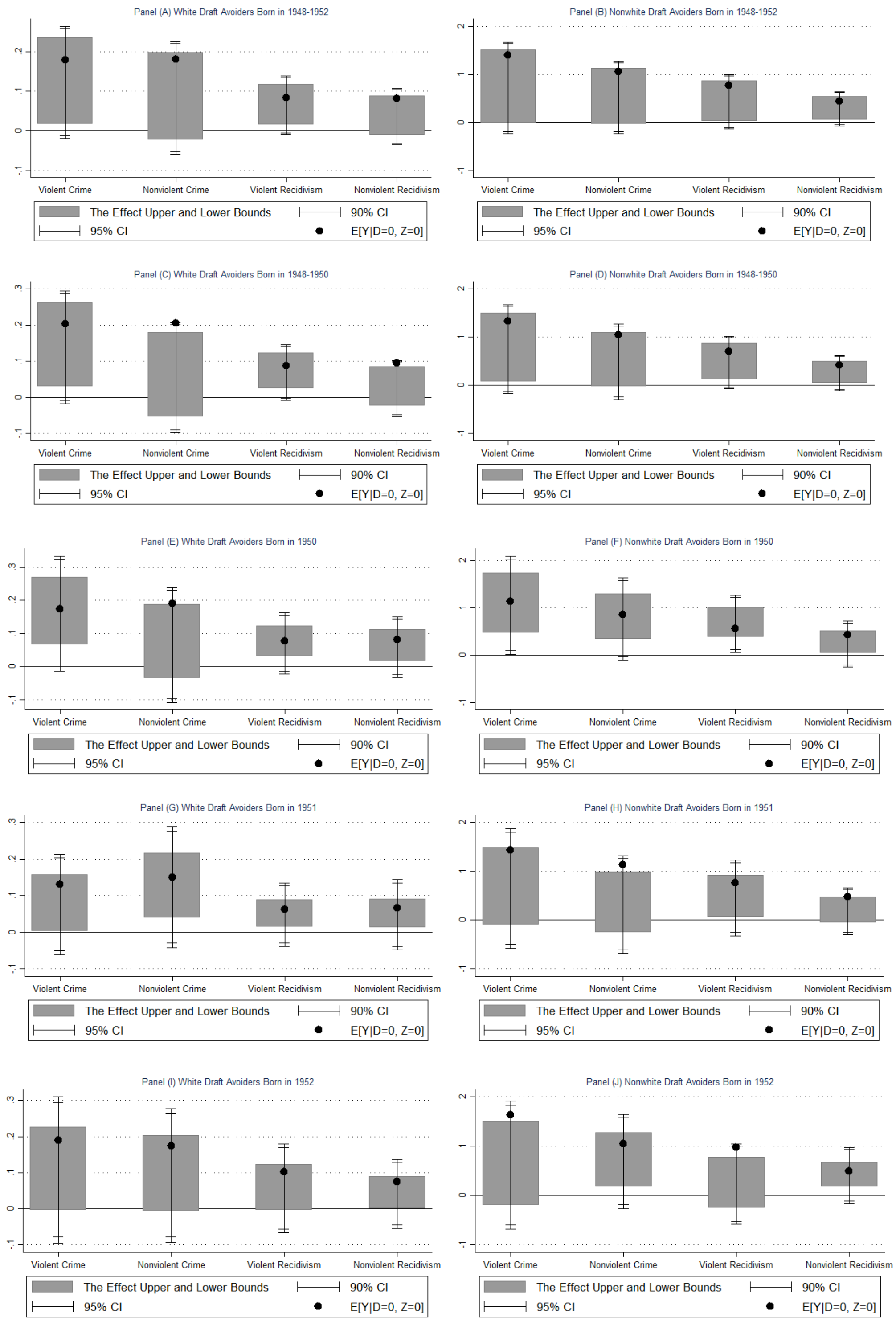
**Table A C.1 Mean Statistics of Draft-eligibility, Veteran Status, and Strata Proportions from the NHIS 1982-1996**

| | Total Observation | Draft-eligible | Veteran | Never-takers | Always-takers | Compliers |
|---|---|---|---|---|---|---|
| ***White and Nonwhite males born in 1948-1952*** | | | | | | |
| **Mean** | 56137 | 0.4458 | 0.2674 | 0.6616 | 0.2102 | 0.1283 |
| **SE** | -- | [0.0023] | [0.0020] | [0.0032] | [0.0025] | [0.0041] |
| ***White males born in 1948-1952*** | | | | | | |
| **Mean** | 47018 | 0.4439 | 0.2789 | 0.6439 | 0.2172 | 0.1388 |
| **SE** | -- | [0.0025] | [0.0022] | [0.0035] | [0.0027] | [0.0045] |
| ***Nonwhite sample born in 1948-1952*** | | | | | | |
| **Mean** | 9119 | 0.4565 | 0.2040 | 0.7560 | 0.1704 | 0.0736 |
| **SE** | -- | [0.0057] | [0.0046] | [0.0074] | [0.0058] | [0.0094] |
| ***White and Nonwhite males born in 1948-1950*** | | | | | | |
| **Mean** | 32946 | 0.5449 | 0.3310 | 0.6336 | 0.2886 | 0.0778 |
| **SE** | -- | [0.0030] | [0.0028] | [0.0039] | [0.0040] | [0.0056] |
| ***White males born in 1948-1950*** | | | | | | |
| **Mean** | 27612 | 0.5419 | 0.3468 | 0.6147 | 0.3012 | 0.0842 |
| **SE** | -- | [0.0032] | [0.0031] | [0.0042] | [0.0044] | [0.0061] |
| ***Nonwhite sample born in 1948-1950*** | | | | | | |
| **Mean** | 5334 | 0.5617 | 0.2434 | 0.7350 | 0.2157 | 0.0493 |
| **SE** | -- | [0.0074] | [0.0065] | [0.0090] | [0.0092] | [0.0128] |
| ***White and Nonwhite males born in 1950*** | | | | | | |
| **Mean** | 11223 | 0.5495 | 0.2532 | 0.6939 | 0.1887 | 0.1175 |
| **SE** | -- | [0.0051] | [0.0044] | [0.0064] | [0.0059] | [0.0087] |
| ***White males born in 1950*** | | | | | | |
| **Mean** | 9350 | 0.5460 | 0.2644 | 0.6801 | 0.1975 | 0.1225 |
| **SE** | -- | [0.0055] | [0.0049] | [0.0070] | [0.0065] | [0.0096] |
| ***Nonwhite sample born in 1950*** | | | | | | |
| **Mean** | 1873 | 0.5680 | 0.1939 | 0.7645 | 0.1393 | 0.0963 |
| **SE** | -- | [00126] | [0.0104] | [0.0150] | [0.0132] | [0.0200] |
| **White and nonwhite males born in 1951** | | | | | | |
| **Mean** | 11383 | 0.3351 | 0.1913 | 0.7275 | 0.1503 | 0.1221 |
| **SE** | -- | [0.0048] | [0.0040] | [0.0078] | [0.0044] | [0.0089] |
| ***White males born in 1951*** | | | | | | |
| **Mean** | 9533 | 0.3340 | 0.1965 | 0.7171 | 0.1531 | 0.1298 |
| **SE** | -- | [0.0052] | [0.0044] | [0.0085] | [0.0048] | [0.0098] |
| ***Nonwhite sample born in 1951*** | | | | | | |
| **Mean** | 1850 | 0.3408 | 0.1630 | 0.7830 | 0.1350 | 0.0820 |
| **SE** | -- | [0.0122] | [0.0094] | [0.0184] | [0.0106] | [0.0212] |
| ***White and nonwhite males born in 1952*** | | | | | | |
| **Mean** | 11808 | 0.2779 | 0.1641 | 0.7373 | 0.1261 | 0.1366 |
| **SE** | -- | [0.0044] | [0.0037] | [0.0084] | [0.0038] | [0.0092] |
| ***White males born in 1952*** | | | | | | |
| **Mean** | 9873 | 0.2770 | 0.1692 | 0.7183 | 0.1261 | 0.1556 |
| **SE** | -- | [0.0048] | [0.0040] | [0.0094] | [0.0041] | [0.0102] |
| ***Nonwhite sample born in 1952*** | | | | | | |
| **Mean** | 1935 | 0.2827 | 0.1366 | 0.8381 | 0.1266 | 0.0353 |
| **SE** | -- | [0.0113] | [0.0086] | [0.0168] | [0.0101] | [0.0196] |

**Note:** Standard errors in parentheses.

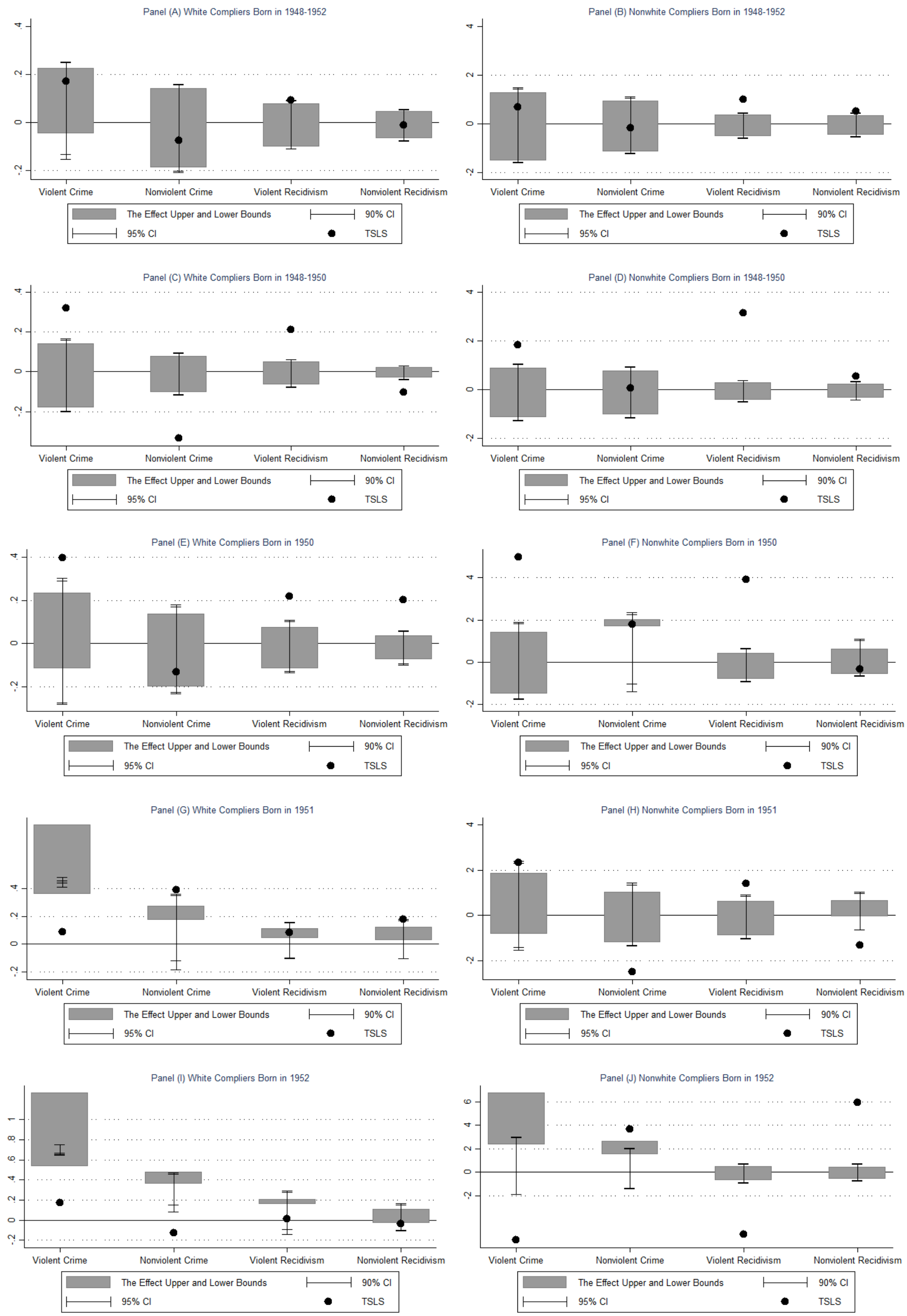
# Appendix D Results for All Subsamples

## Table D. 1 The Direct Effect of Draft Lotteries on Draft Avoiders



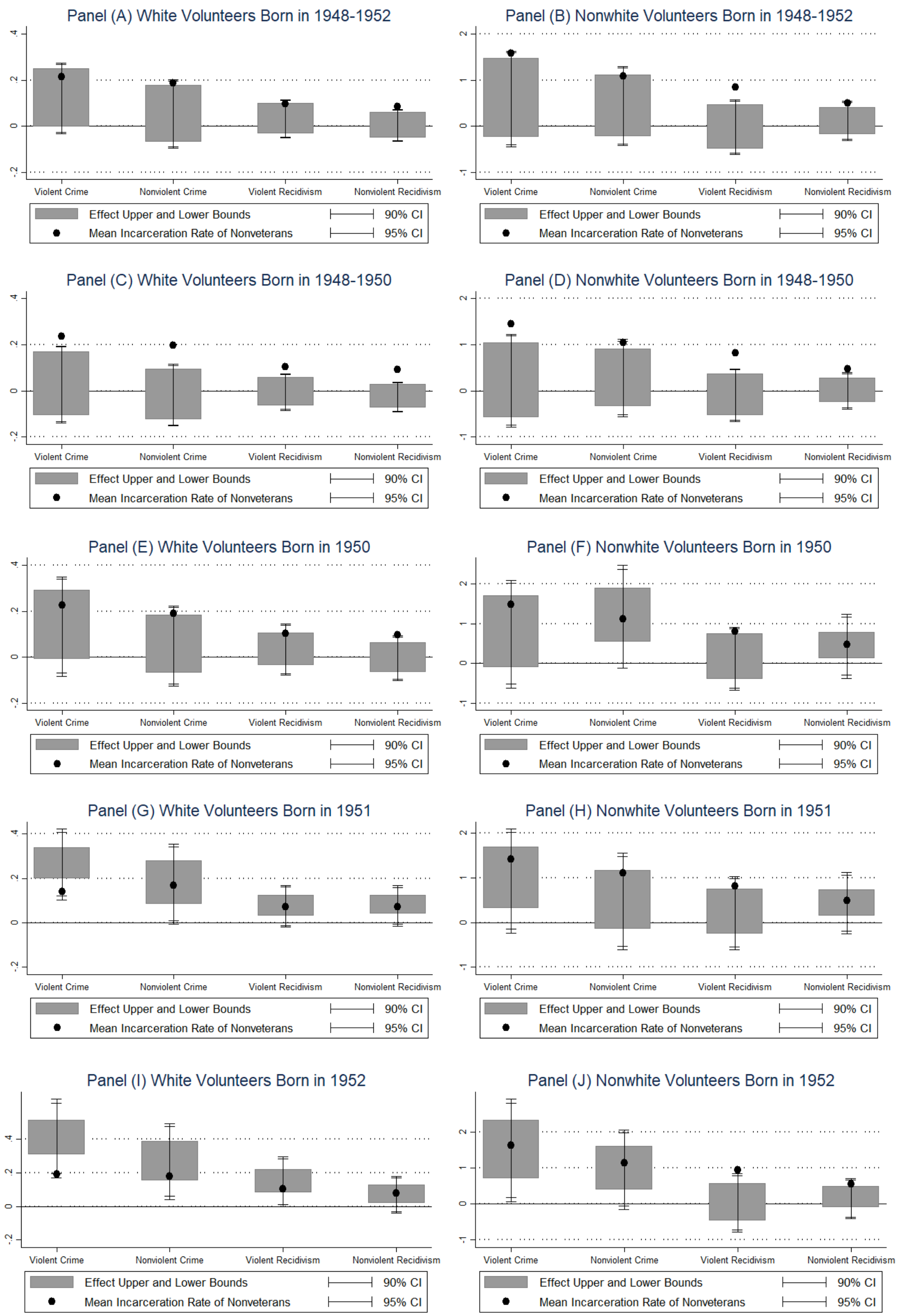

Note: The vertical axes in the figures are in the unit of percentage points.

Table D. 2 The Effect of Military Service on Draft Compliers



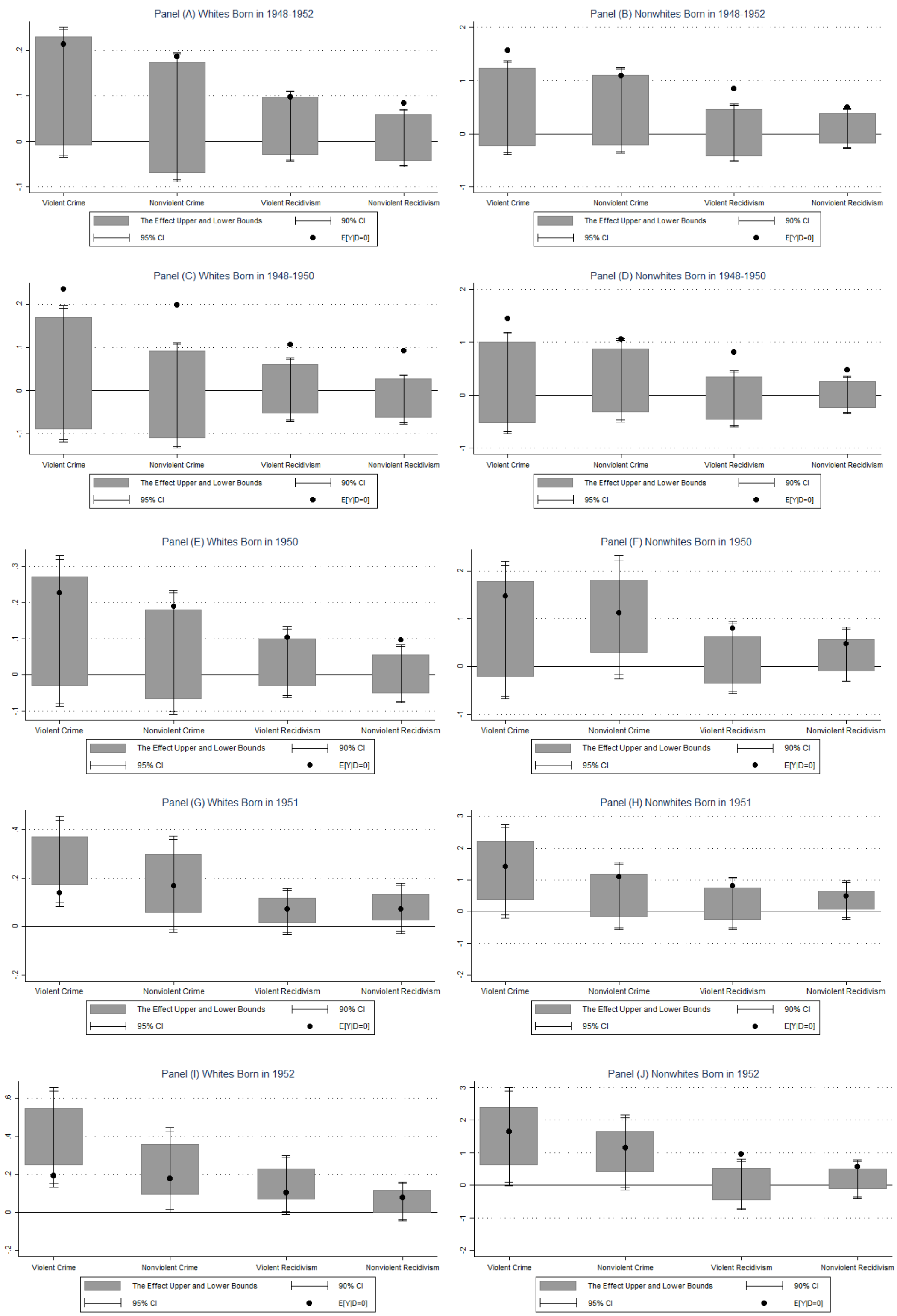

Note: The vertical axes in the figures are in the unit of percentage points.

Table D. 3 The Effect of Military Service on Volunteers




Note: The vertical axes in the figures are in the unit of percentage points.

Table D4. The Average Military Service Treatment Effect on Veterans (the "Treated")

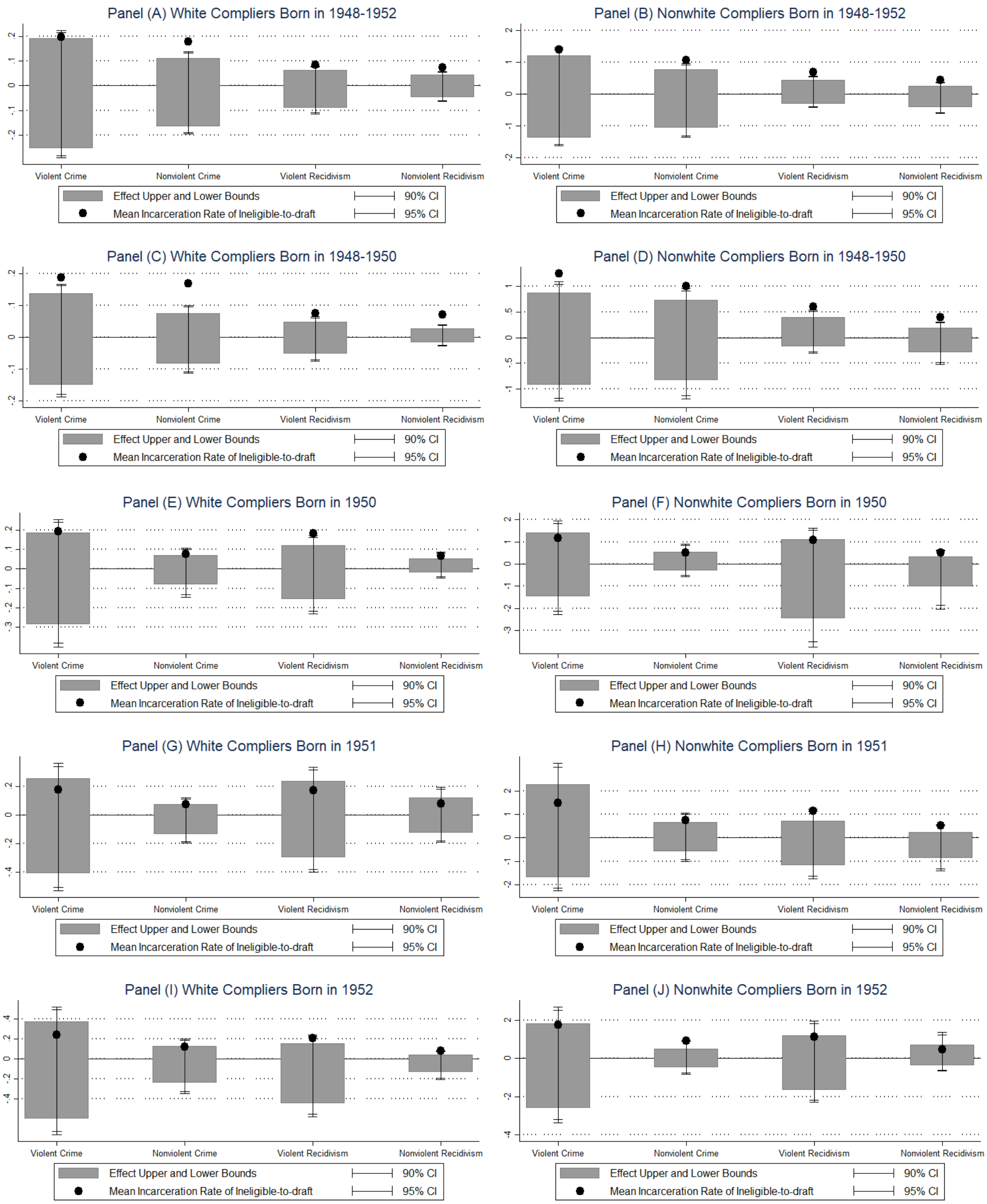



Note: The vertical axes in the figures are in the unit of percentage points.

Table D5. The Direct Effect of Draft Lotteries of Compliers Who Did Not Serve in the Military


Note: The vertical axes in the figures are in the unit of percentage points.

Table D6. The Direct Effect of Draft Lotteries of Compliers Who Served in the Military




Note: The vertical axes in the figures are in the unit of percentage points.

## Appendix E. Estimation Biases in the Pre-Draft Outcomes Analysis

**(FOR ONLINE PUBLICATION)**

Ideally, the pre-draft outcomes are computed using individual-level data representative of the U.S. male population, which includes both the incarcerated and non-incarcerated populations. Unfortunately, the individual-level data we have access to is on inmates. In this Appendix, we show the biases that arise in each of the two methods we employ to undertake the pre-draft outcomes analysis using the individual-level data on inmates. In what follows, let a pre-draft binary outcome be denoted by $X_i$ (for instance, "ever arrested before 18 years old") for each individual $i$, and let $k_j$, where $j = 1, 2, 3$, correspond to the three different subpopulation strata in the paper. We also let $incarceration_i$ be an indicator variable for the incarceration status of each individual $i$. Then, the mean of $X_i$ for a stratum, say, $k_1$, can be expressed as follows (using the law of total probability).

$$E[X_i|k_1] = 1 \cdot \Pr[incarceration_i = 1|k_1] \cdot \Pr[X_i = 1|incarceration_i = 1, k_1]$$

$$+1 \cdot \Pr[incarceration_i = 0|k_1] \cdot \Pr[X_i = 1|incarceration_i = 0, k_1]$$

$$+0 \cdot \Pr[incarceration_i = 1|k_1] \cdot \Pr[X_i = 0|incarceration_i = 1, k_1]$$

$$+0 \cdot \Pr[incarceration_i = 0|k_1] \cdot \Pr[X_i = 0|incarceration_i = 0, k_1]$$

$$= \Pr[incarceration_i = 1|k_1] \cdot \Pr[X_i = 1|incarceration_i = 1, k_1]$$

$$+ \Pr[incarceration_i = 0|k_1] \cdot \Pr[X_i = 1|incarceration_i = 0, k_1]$$

(Equation AE.1)

And the corresponding difference between two strata $k_1$ and $k_2$ can be expressed as follows.

$$E[X_i|k_1] - E[X_i|k_2] = \Pr[incarceration_i = 1|k_1] \cdot \Pr[X_i = 1|incarceration_i = 1, k_1]$$

$$+ \Pr[incarceration_i = 0|k_1] \cdot \Pr[X_i = 1|incarceration_i = 0, k_1]$$

$$- \Pr[incarceration_i = 1|k_2] \cdot \Pr[X_i = 1|incarceration_i = 1, k_2]$$

$$- \Pr[incarceration_i = 0|k_2] \cdot \Pr[X_i = 1|incarceration_i = 0, k_2] \qquad \text{(Equation AE.2)}$$

In lack of individual-level data, the **first method** to compute these pre-draft outcomes by strata and their differences consists of using the inmate individual-level data only; in other words, we use $\Pr\left[X_i = 1 \middle| incarceration_i = 1, k_j\right]$ in place of $\Pr\left[X_i = 1 \middle| incarceration_i = 0, k_j\right]$, $j = 1,2,3$ in Equation AE.2, and in all other pair-wise comparisons between strata. The estimated mean difference is estimated as,

$$\left(\widehat{E[X_i|k_1] - E[X_i|k_2]}\right)_1 = \Pr[incarceration_i = 1|k_1] \cdot \Pr[X_i = 1|incarceration_i = 1, k_1]$$
$$+ \Pr[incarceration_i = 0|k_1] \cdot \Pr[X_i = 1|incarceration_i = 1, k_1]$$
$$- \Pr[incarceration_i = 1|k_2] \cdot \Pr[X_i = 1|incarceration_i = 1, k_2]$$
$$- \Pr[incarceration_i = 0|k_2] \cdot \Pr[X_i = 1|incarceration_i = 1, k_2]$$
$$= \Pr[X_i = 1|incarceration_i = 1, k_1] - \Pr[X_i = 1|incarceration_i = 1, k_2]$$

(Equation AE.3)

The second equation in AE.3 results from $\Pr[incarceration_i = 1|k_1] + \Pr[incarceration_i = 0|k_1] = 1$ and $\Pr[incarceration_i = 1|k_2] + \Pr[incarceration_i = 0|k_2] = 1$.

The bias of the estimated mean difference using the first method is

$$\alpha_1 = \left(\widehat{E[X_i|k_1] - E[X_i|k_2]}\right) - (E[X_i|k_1] - E[X_i|k_2])$$
$$= \Pr[incarceration_i = 0|k_1]$$
$$\cdot (\Pr[X_i = 1|incarceration_i = 1, k_1] - \Pr[X_i = 1|incarceration_i = 0, k_1])$$
$$- \Pr[incarceration_i = 0|k_2]$$
$$\cdot (\Pr[X_i = 1|incarceration_i = 1, k_2] - \Pr[X_i = 1|incarceration_i = 0, k_2])$$

(Equation AE.4)

Intuitively, the bias is a function of the difference in the difference of the pre-draft outcomes' means between incarcerated and non-incarcerated males within each of the two strata $k_1$ and $k_2$.

The **second method** to compute mean pre-draft outcomes for stratum $k_j$, $j = 1,2,3$, is by estimating the first product term of the last equation in Equation AE.1 by first counting the number of inmates whose $X_i = 1$ in strata $k_j$ and dividing this by the U.S. male population who belong to $k_j$. Thus, the estimated mean difference in $X_i$ between $k_1$ and $k_2$ can be written as,

$$\left(\widehat{E[X_\iota|k_1] - E[X_\iota|k_2]}\right)_2 = \Pr[incarceration_i = 1|k_1] \cdot \Pr[X_i = 1|incarceration_i = 1, k_1]$$
$$- \Pr[incarceration_i = 1|k_2] \cdot \Pr[X_i = 1|incarceration_i = 1, k_2]$$
$$= \Pr[X_i = 1 \;\&\; incarceration_i = 1|k_1] - \Pr[X_i = 1 \;\&\; incarceration_i = 1|k_2]$$

(Equation AE.5)

And the potential bias under the second method is,

$$\alpha_2 = \left(\widehat{E[X_\iota|k_1] - E[X_\iota|k_2]}\right)_2 - (E[X_i|k_1] - E[X_i|k_2])$$

$$= \Pr[incarceration_i = 0|k_2] \cdot \Pr[X_i = 1|incarceration_i = 0, k_2] -$$
$$\Pr[incarceration_i = 0|k_1] \cdot \Pr[X_i = 1|incarceration_i = 0, k_1]$$

(Equation AE.6)

which is a function of the difference in the means of the pre-draft outcome $X_i$ for those non-incarcerated between strata $k_1$ and $k_2$.

## Appendix F – Incarceration Rate Construction and Comparison to Lindo and Stoecker (2014)

To estimate the long-term effect of Vietnam War military service on the incarceration outcomes, this paper followed the general idea in Lindo and Stoecker (2014). In this method, the total inmate counts by draft eligibility and military status are estimated using the Survey of Inmates in State of Federal Correctional Facilities 1979, 1986, and 1991; the total population by draft eligibility and military service status are estimated using the Vital Statistics of the United States 1948-1952. Then, the incarceration outcomes are constructed by dividing the inmate count estimates by the total population estimates for each draft-eligibility and military service status groups. However, this paper deviated from the data construction in the seminal paper by Lindo and Stoecker (2014). Most of the deviations result from newer information available to us. This Appendix discusses these deviations in detail.

(1) Difference in offense variables in the 1979 Survey of Inmates in State and Federal Correctional Facilities

Lindo and Stoecker (2014) used the variables "Offense V30-V33" to construct their crime outcomes. These variables have 2,247 observations with missing values for offense codes or because they are deemed observations "out of universe". After some investigation, we realized that the variables in "Current Offense V930-V933" have no missing values or "out of universe" values. Upon contacting a BJS statistician, she explained that variables V930-V933 are the actual current offense variables; while variables V30-V33 are offenses inmates were initially sentenced for before their previous probation from the prison. Thus, the justification of this departure in data construction stems from the information learned upon contacting the BJS.

(2) Difference in the treatment of "not ascertain" observations in the current offense variables in the 1979, 1986, and 1991 Surveys of Inmates in State and Federal Correctional Facilities

Lindo and Stoecker (2014) coded inmates whose offenses were not clearly ascertained as inmates with nonviolent crimes. Instead, we did not use the observations of inmates whose offense was not clearly ascertained in the survey to estimate violent crime and non-violent crime outcomes. In our analytical sample for the 1948-1952-born males in the SISFCF 1979, 1986, and 1991, there are 96 inmates with not clearly ascertained convictions out of a total of 5464 observations (1.76%). The reason for this departure in data construction is based on information learned from the same BJS statistician. The person explained that these “not ascertain” offense values “most likely mean that the literal response recorded by the interviewer did not contain enough information to be coded into one of the existing offenses (e.g., murder, burglary, etc.). This could be because the interviewer’s response was not legible or because the response the inmate provided should have been probed due to lack of clarity/specificity, but it was not.” Based on this information, we believe it is a cleaner approach to not use those observations that contain “not ascertain” for the offenses to classify inmates’ crimes as violent or nonviolent.

(3) Difference in offense variables in the 1991 Survey of Inmates in State and Federal Correctional Facilities

Lindo and Stoecker (2014) used five offense variables—“offense1-offense4” and “controlling offense”—to determine the type of crime committed by inmates (violent or nonviolent crime). Instead, we used the “Current Offense 1-5” variables to determine the type of crime committed by inmates. The reason for this departure in data construction is based on information learned from the same BJS statistician. The person clarified that the “controlling offense” is the offense with the longest sentence and is not a new offense.

(4) Failed to replicate Lindo and Stoecker’s estimated incarceration rates in the survey year of 1991

After multiple attempts, and after reviewing the data-construction coding files kindly shared by Jason Lindo and Charles Stoecker, we were not able to replicate their estimates for the incarceration rates in the SISFCF survey year of 1991. We note that this only occurred for the 1991 survey year, as we were able to replicate the corresponding estimates in other survey years.

We looked for some external validation source that could shed some light about the incarceration rates for the 1991 survey year. We found the prisoner’s surveys published by the Bureau of Justice Statistics (BJS). Based on this source, we think that Lindo and Stoecker’s (2014) reported incarceration rates for 1991 may be too high. The incarceration rate reported by us is lower and, we argue, likely closer to the one reported by the BJS. We provide details in what follows.

Table 1 below shows the total U.S. population counts for the subjected cohorts by race and draft eligibility (from the Vital Statistics data). These figures are the same in Lindo and Stoecker (2014) and in our study. Table 2 shows the 1991 estimated incarceration rates for the same groups, which differ between Lindo and Stoecker (2014) and our study. Table 3 shows the implied count of inmates by groups, and computes the total incarcerated population.

Table 1. The Total 1948-1952-Born White and Nonwhite Population Estimates in Lindo and Stoecker (**same as ours**)

| | | |
|---|---|---|
| White | Draft Eligible | 3,556,242.5 |
| | Draft Ineligible | 4,559,703.5 |
| Nonwhite | Draft Eligible | 543,274.68 |
| | Draft Ineligible | 698,825.32 |

Table 2. The 1991 Incarceration Rates in Lindo and Stoecker and in our study

| | | Lindo and Stoecker (2014) | This paper |
|---|---|---|---|
| White | Draft Eligible | 0.0112 | 0.0052 |
| | Draft Ineligible | 0.0109 | 0.0047 |
| Nonwhite | Draft Eligible | 0.0501 | 0.0282 |
| | Draft Ineligible | 0.0429 | 0.0258 |

Table 3. The Estimated Total 1948-1952-Born White and Nonwhite Incarcerated Population Estimates in Lindo and Stoecker and in our study

| | | Lindo and Stoecker (2014) | This paper |
|---|---|---|---|
| Nonwhite | Draft Eligible | 39,830 | 15,320 |
| | Draft Ineligible | 49,701 | 18,030 |
| White | Draft Eligible | 27,218 | 18,492 |
| | Draft Ineligible | 29,980 | 21,431 |
| Total white and nonwhite | | 146,729 | 73,273 |

The implied total incarcerated population estimates can be compared to the prison Census of 1991 published by the Bureau of Justice Statistics (Bureau of Justice Statistics, 1992), after making some assumptions.

Based on the above source, in 1991 there were **730,795** male inmates nationwide who are incarcerated in state or federal correctional facilities. According to the 1991 Survey of State Prison Inmates (Bureau of Justice Statistics, 1993), about 23% state prisoners are between the ages of 35-44. Assuming that the federal inmates follow the same age ratio, we estimate that the total number of male inmates between the age of 35-44 is **168,083**.

We still need to take into account that the last number represents inmates between the ages of 35-44 whereas those born in 1948-1952 are roughly aged 39-43 in 1991. Assuming the same incarceration rate over the ages of 35-44, those aged 39-43 should not make more than 50% of inmates. Based on the estimates in Lindo and Stoecker (2014), there are 146,729 male inmates born in 1948-1952 (ages roughly 39-43 in 1991), which would imply that around 87% of the inmates between 35-44 years old were born in 1948-1952. Based on our estimates, there are 73,273 male inmates born in 1948-1952 (ages roughly 39-43 in 1991), which is about 44% of the inmates between 35-44 years old. Moreover, considering that incarceration probabilities decrease with age (Bureau of Justice Statistics, 1993), we would expect that the proportion of inmates born in 1948-1952 is somewhat below 50% relative to the inmate population in the age range of 35-44 years old. Based on the previous calculations, we place more confidence on our estimates for survey year 1991.

***References:***

Bureau of Justice Statistics. (1992) *Prisoners in 1991,* Washington, D.C.: U.S. Department of Justice, Office of Justice Program, Bureau of Justice Statistics. Accessed November 2, 2019. https://www.bjs.gov/content/pub/pdf/p91.pdf

Bureau of Justice Statistics. (1993) *Survey of State Prison Inmates, 1991,* Washington, D.C.: U.S. Department of Justice, Office of Justice Program, Bureau of Justice Statistics. Accessed November 2, 2019. https://www.bjs.gov/content/pub/pdf/SOSPI91.PDF

Lindo, J., and Stoecker, C. (2014) Drawn into Violence: Evidence on 'What Makes a Criminal' from the Vietnam Draft Lotteries. *Economic Inquiry*, 52 (1): 239-258.

## Appendix G. Estimation Results using Alternative Crime Measures

We have produced alternative sets of results using the following two alternative measures of crimes constructed with information in the SSICFC survey:

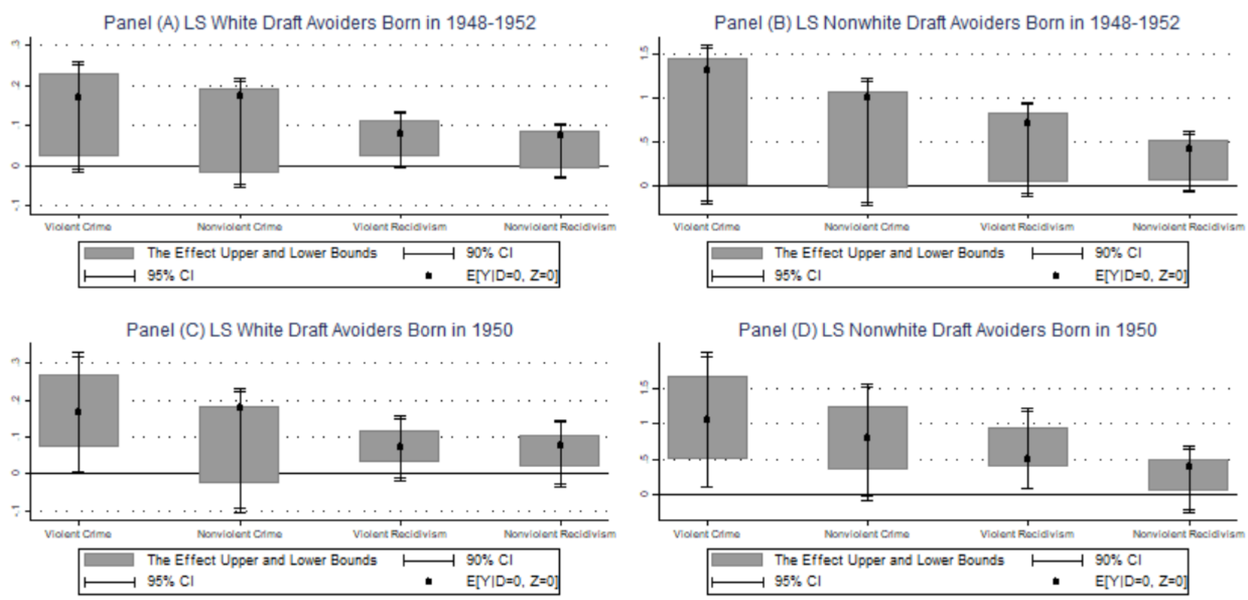
(1) defining violent/nonviolent crimes based on the inmate's original offenses, which is the same measure used by Lindo and Stoecker (2014) and which we refer to as "LS", and

(2) defining violent/nonviolent crimes based on whether the inmate ***ever*** committed a violent crime and which we refer to as "EVER".

The presentation of results follow the corresponding presentation of the results in the paper.

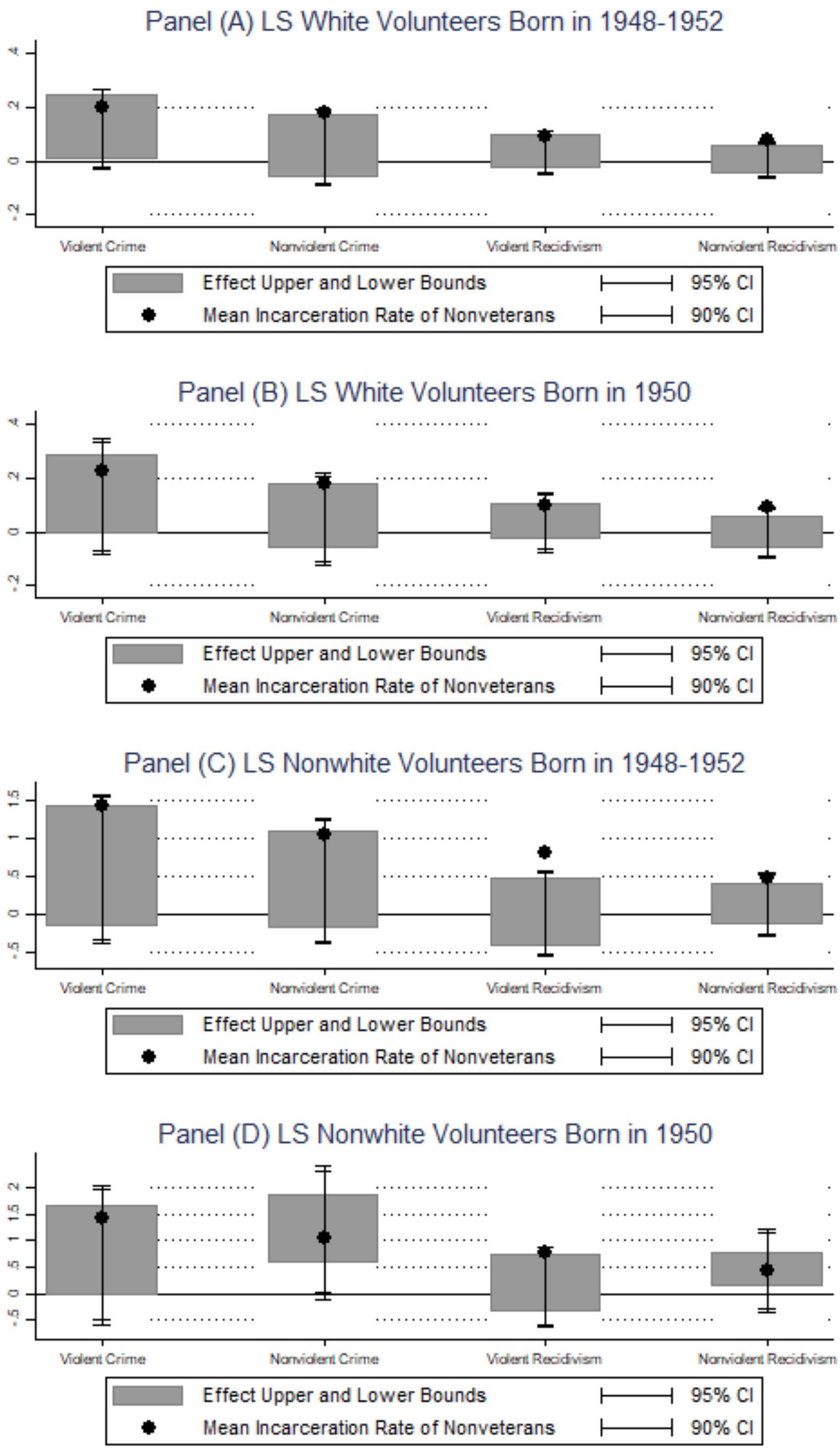
### 1. LS Measure

Figure G.1.1. Direct Effect of the Lottery Draft on Incarceration Outcomes of the Draft Avoiders



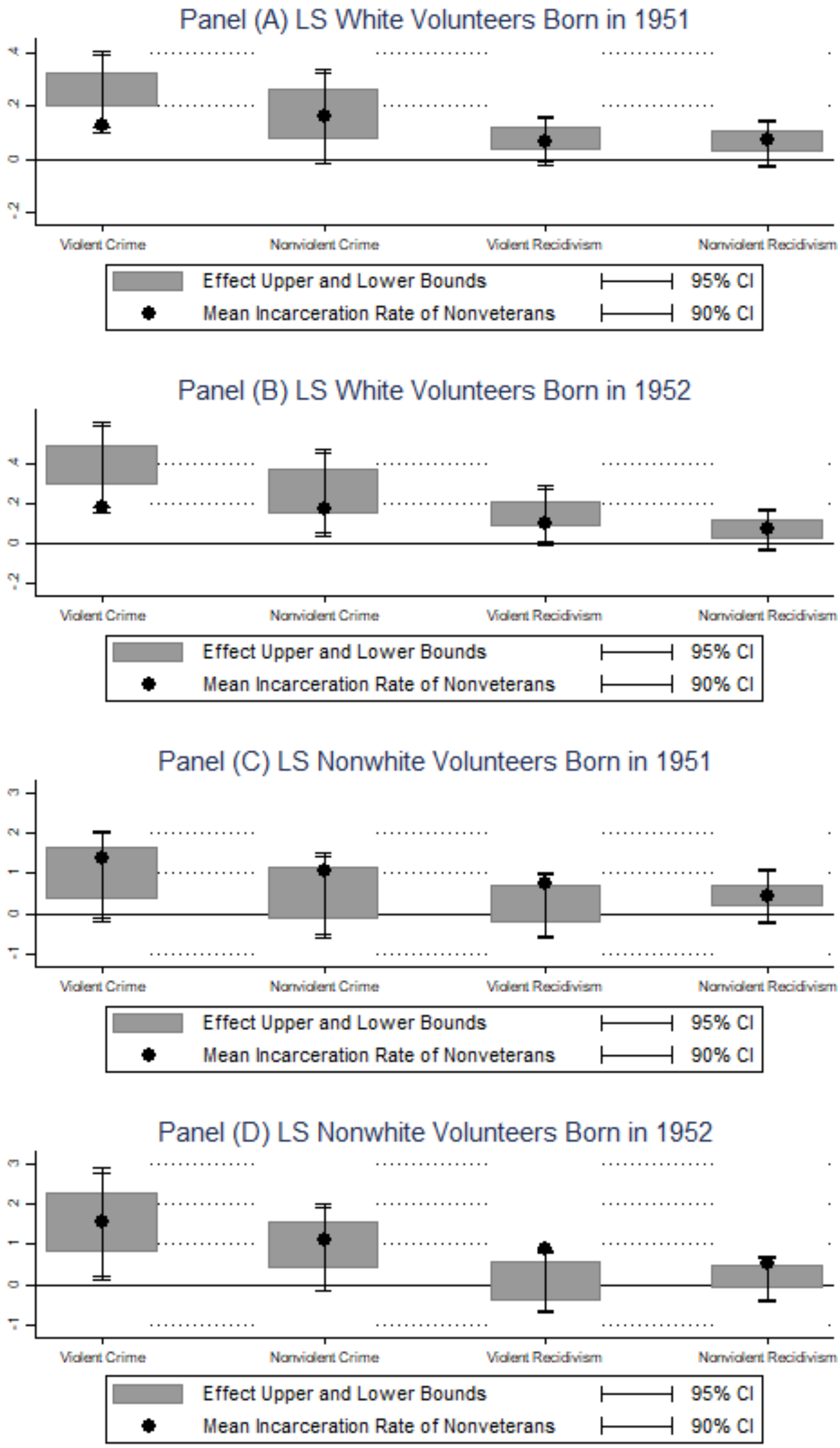

Note: The vertical axes in the figures are in the unit of percentage points.

Figure G.1.2. Estimated Bounds for the Local Average Treatment Effect of Military Service on the Incarceration Rates of Volunteers Born in 1948-1952 and 1950



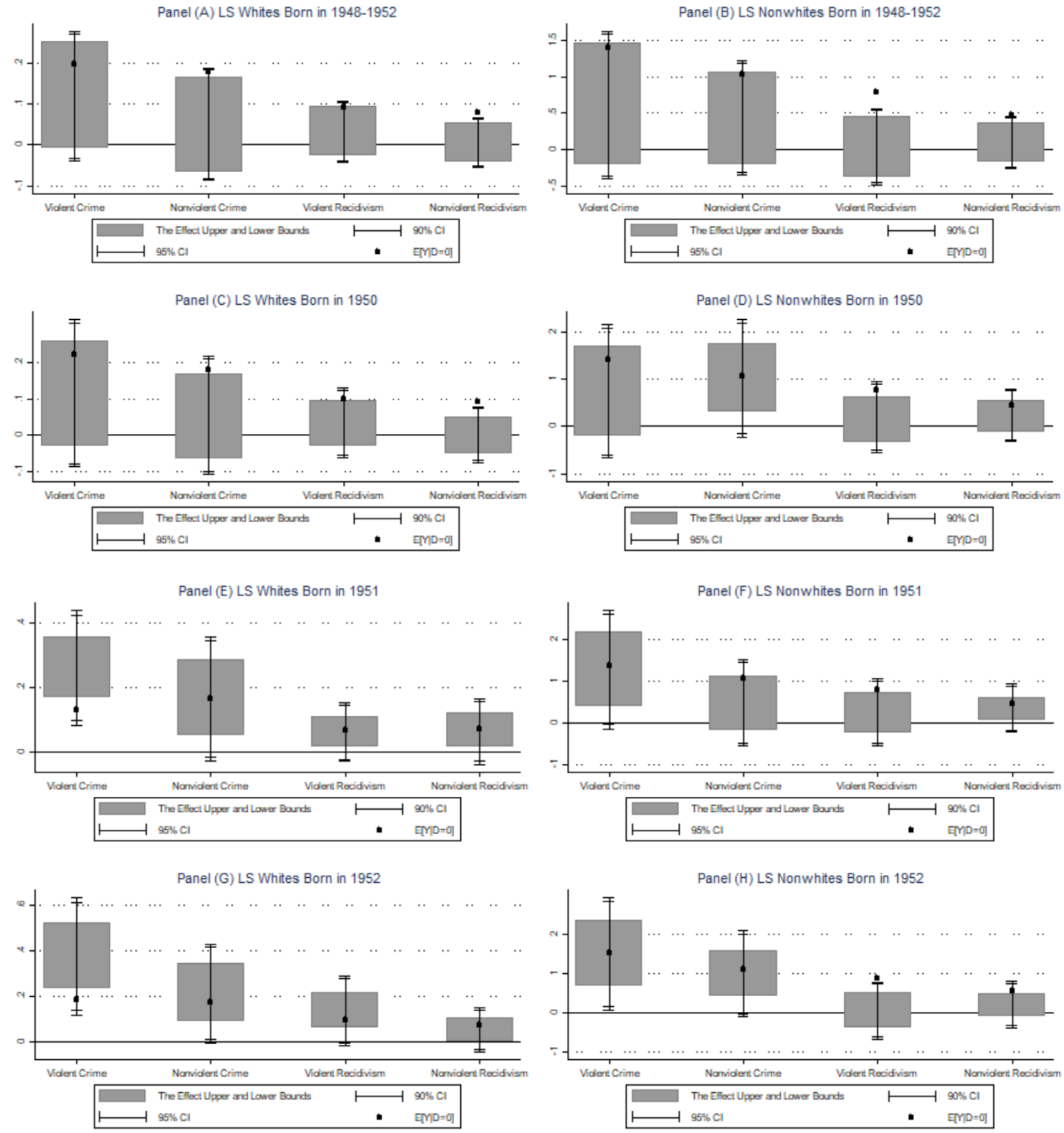

Note: The vertical axes in the figures are in the unit of percentage points.

Figure G.1.3. Estimated Bounds for the Local Average Treatment Effect of Military Service on the Incarceration Rates of Volunteers Born in 1951 and 1952




Note: The vertical axes in the figures are in the unit of percentage points.

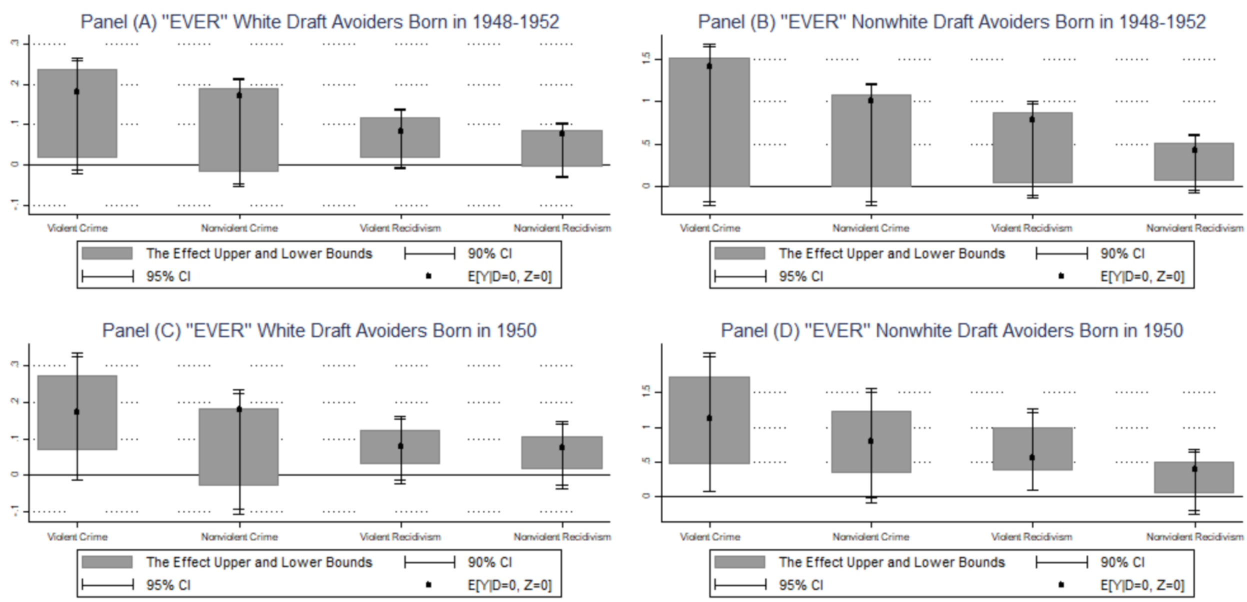
Figure G.1.4. Estimated Bounds for the Average Treatment Effect of Military Service on the Incarceration Rates of Veterans




Note: The vertical axes in the figures are in the unit of percentage points.

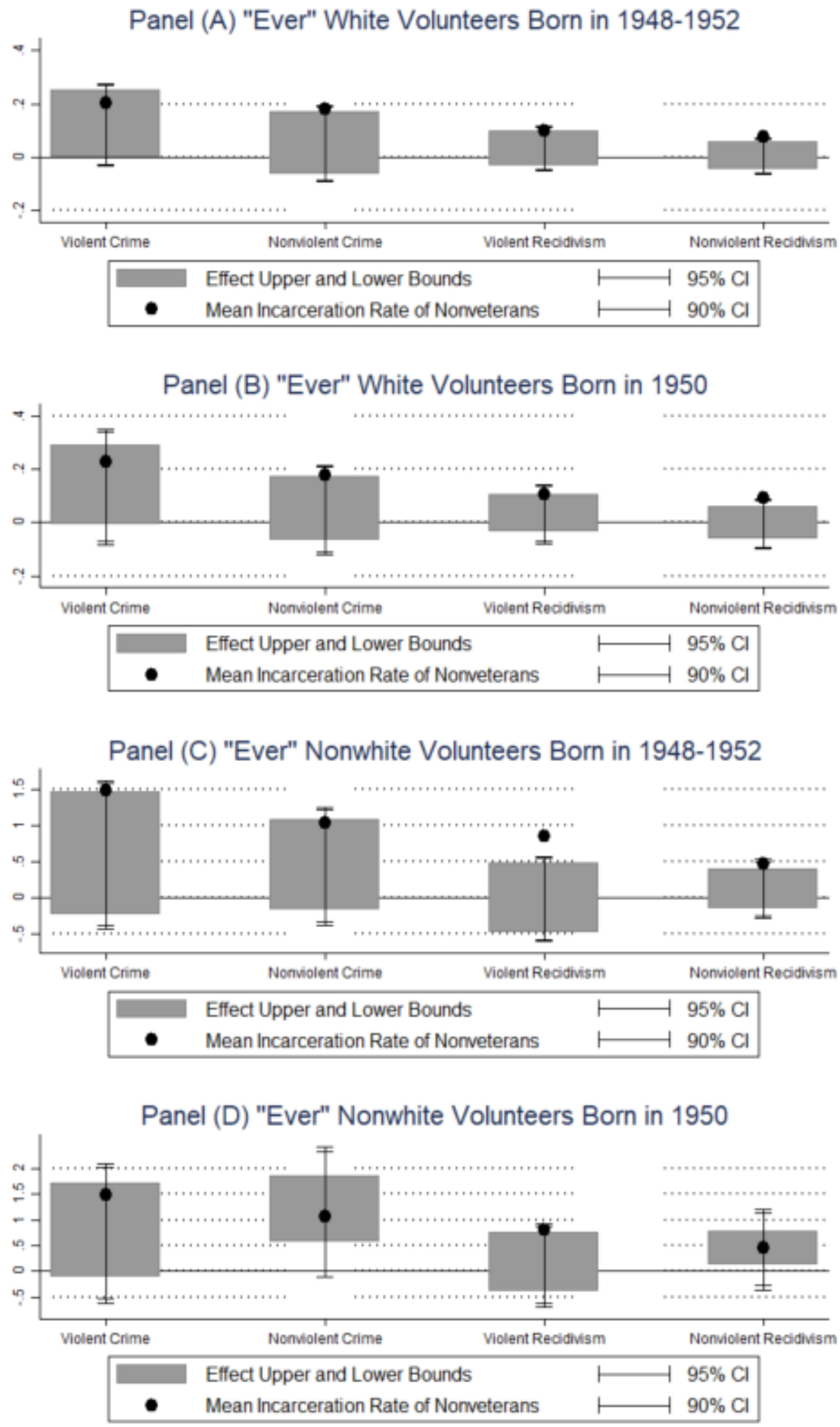
## 2. “EVER” Measure

Figure G.2.1. Direct Effect of the Lottery Draft on Incarceration Outcomes of the Draft Avoiders



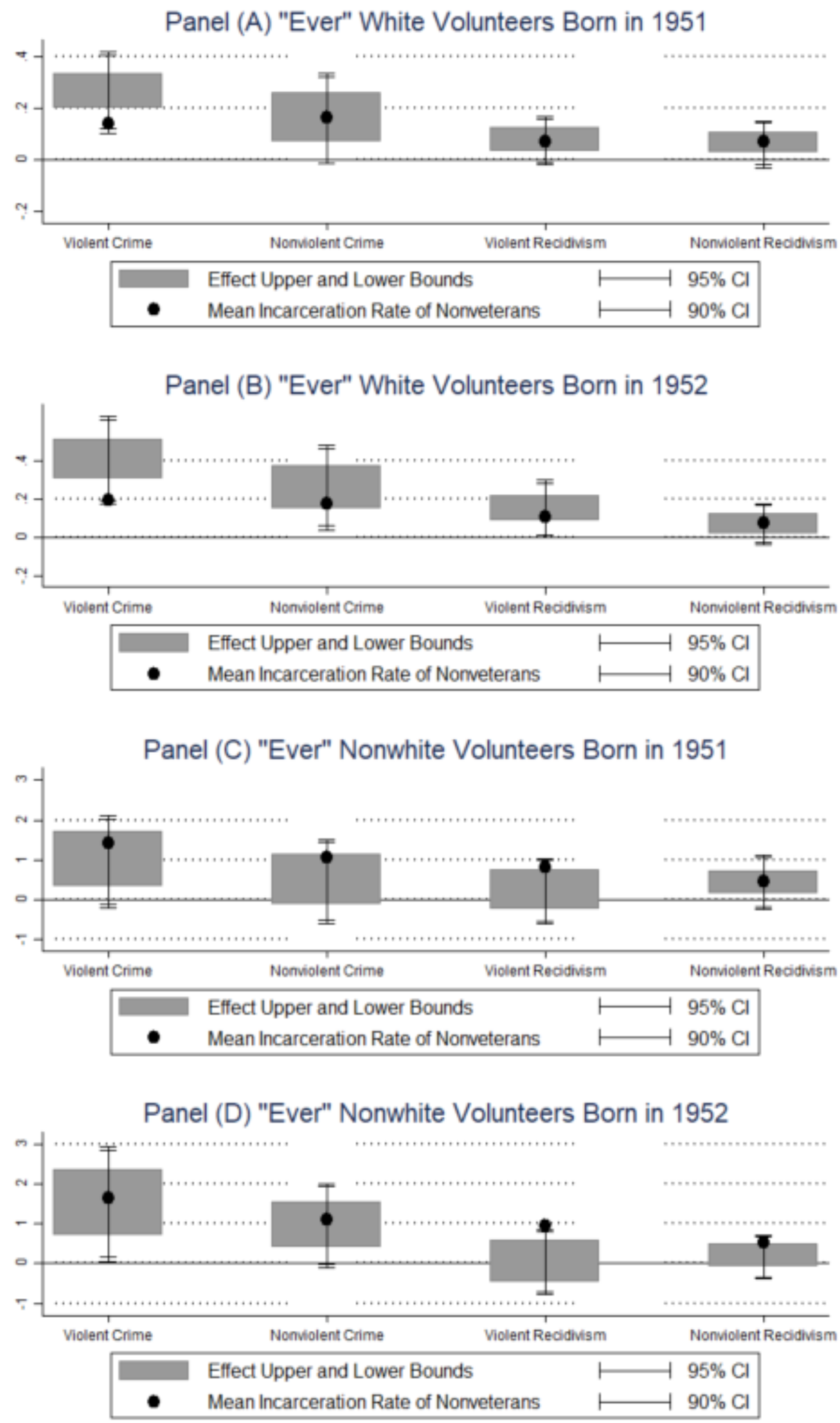

Note: The vertical axes in the figures are in the unit of percentage points.

Figure G.2.2. Estimated Bounds for the Local Average Treatment Effect of Military Service on the Incarceration Rates of Volunteers Born in 1948-1952 and 1950



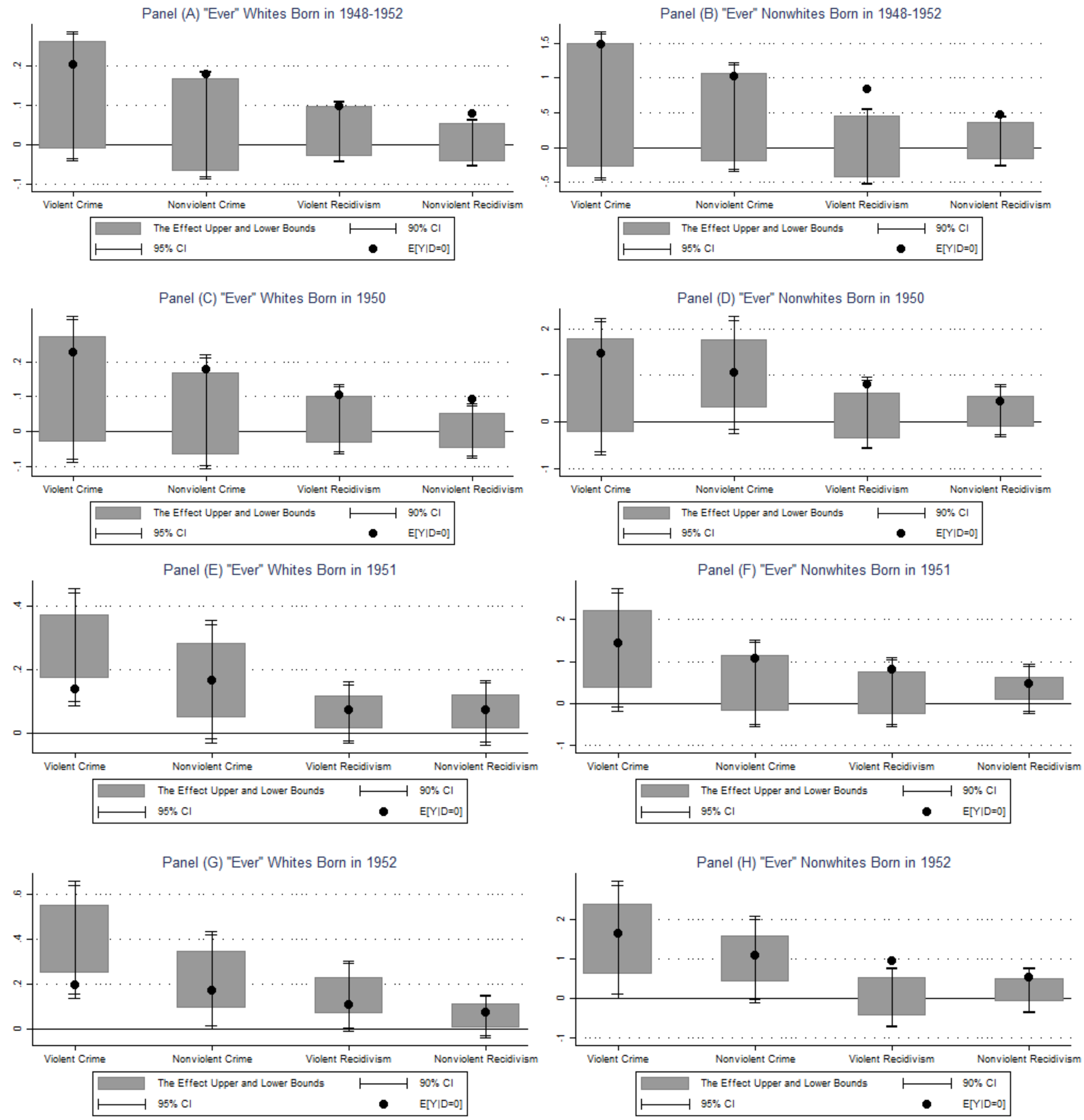

Note: The vertical axes in the figures are in the unit of percentage points.

Figure G.2.3. Estimated Bounds for the Local Average Treatment Effect of Military Service on the Incarceration Rates of Volunteers Born in 1951 and 1952




Note: The vertical axes in the figures are in the unit of percentage points.

Figure G.2.4. Estimated Bounds for the Average Treatment Effect of Military Service on the Incarceration Rates of Veterans




Note: The vertical axes in the figures are in the unit of percentage points.