THE POPULATION EFFECT OF ELIMINATING HOMELESSNESS ON HIV VIRAL SUPPRESSION AMONG PEOPLE WHO USE DRUGS

SUPPLEMENTAL APPENDIX

This supplemental material includes the results of the sensitivity analyses, as well as additional information regarding the statistical analyses employed, including the imputation-based marginal modeling approach and the bootstrapping procedure.
We describe here the principles and mechanics of the imputation-based marginal modeling approach. We begin with a formal description of the observed data. Let \( i = 1, 2, \ldots, n \) denote the subjects, where \( n = 706 \). For participant \( i \), let \( X_i \) denote homelessness status at first behavioral study assessment (\( X_i = 1 \) if homelessness, 0 otherwise), and let \( Z_i = \{Z_{i1}, Z_{i2}, \ldots, Z_{ik}\} \) denote the vector of \( k \) measured covariates for participant \( i \). Let \( Y_i \) represent HIV RNA plasma viral suppression observed during the first routine clinical care assessment during the study period, where \( Y_i = 1 \) if virally suppressed (i.e., <50 copies/mL) and \( Y_i = 0 \) if unsuppressed. The observed proportion of participants virally suppressed is denoted by \( p_{obs} \). In this sample, \( p_{obs} = \frac{\sum_{i=1}^{N} Y_i}{N} = \frac{267}{706} \times 100 = 37.8\% \).

First, homelessness and all other covariates were examined in association with viral suppression (defined as <50 copies/mL) in bivariate analyses. Since the outcome of interest was non-rare, we used modified Poisson regression to estimate the unadjusted prevalence ratio. As described by Zou et al. [1], the REPEATED statement in SAS PROC GENMOD is used to implement sandwich error estimation to correct for standard error misspecification that occurs when Poisson regression is used to model a binomially distributed outcome. To identify the independent relationship between homelessness and viral suppression, we adjusted for all covariates described in the Methods section of the primary manuscript in multivariable analyses.

We then applied an imputation-based marginal modeling approach to estimate the population intervention effect of homelessness on viral suppression in the study.
sample. This approach has a number of benefits over more traditional regression-based analyses. First, results are presented on an additive (rather than a multiplicative scale), which is often more relevant for public health intervention [2]. Second, in contrast to traditional regression analyses in which effect estimates are conditional on other covariates, our approach presents marginal relationships (i.e., relevant to the entire population) [3]. Marginal effect estimates (also called population health intervention effects) are frequently more informative in understanding how a particular public health intervention on an exposure might change an outcome of interest across the entire population [3-5].

To obtain the population health intervention effect of homelessness on viral suppression, we used information from the models described above. First, we obtain the predicted value of $Y_i$ for each participant given the modified Poisson regression model described above, as follows:

$$\Pr(Y_i = 1)_{pred} = \exp(\beta_0 + \beta_x X_i + \beta Z_i)$$

where $\beta_x$ represents the effect estimate for homeless and $\beta$ represents the vector of effect estimates for the $k$ other covariates (see Table 2). Based on these values, the expectation of the viral suppression prevalence for the entire study population (based on the model) is given by:

$$p_{pred} = \frac{\sum_{i=1}^{N} \Pr(Y_i = 1)_{pred}}{N}$$
If model specification is correct, $p_{obs} \approx p_{pred}$ (that is, the proportion of study participants actually suppressed should be similar to that estimated by the model). In our analysis, 

$$p_{pred} = \frac{\sum_{i=1}^{N} \Pr(Y_i = 1)}{N} = \frac{267.00}{706} \times 100 = 37.8\%.$$ 

Next, we predict the outcome for each individual had the homeless persons been housed. To do so, we create an imputed dataset with identical outcome and covariates values, but in which $X_i$ for all participants is equal to zero (i.e., homelessness is eliminated). We then apply equation (1) to this dataset, and calculate $\Pr(Y_i = 1)_{housed}$, the probability of viral suppression for each study participant under the counterfactual scenario in which all persons were housed. Specifically:

$$\Pr(Y_i = 1)_{housed} = \exp(\beta_0 + \beta X_i 0 + \beta Z_i)$$

(3)

The expectation of the viral suppression prevalence for the entire study population under this scenario is given by:

$$p_{housed} = \frac{\sum_{i=1}^{N} \Pr(Y_i = 1)_{housed}}{N}$$

(4)

The population health intervention effect on the additive scale ($PHIE_{abs}$) is given by:

$$PHIE_{abs} = p_{housed} - p_{pred}$$

(5)

And the population health intervention effect on the relative scale ($PHIE_{rel}$) is given by:

$$PHIE_{rel} = \frac{p_{housed} - p_{pred}}{p_{pred}}$$

(6)

As there is no straightforward analytic estimate of standard errors for these population-level effects, confidence intervals for both intervention effect estimates are obtained
with a bootstrapping technique [6]. From our sample, we drew 1000 bootstrapped samples. In each of these bootstrapped samples we followed the steps above to determine $p_{\text{housed}}$ and $PHIE_{\text{rel}}$. From the 1000 estimates, we selected the value representing the 2.5th percentile for the lower confidence limit and the 97.5th percentile value for the upper confidence limit to form the confidence intervals for the population health intervention effect estimates.
**Figure S1.** Estimated population effect of housing 50% of the homeless population on viral suppression prevalence among HIV-infected people who use drugs in Vancouver

**Panel A : Full Sample (N = 706)**

- **Empirical Data:** 38%
- **Crude Model:** 42%
- **Adjusted Model:** 41%

**Panel B : Homeless At Baseline (N = 223)**

- **Empirical Data:** 22%
- **Crude Model:** 34%
- **Adjusted Model:** 31%

Note: bootstrapping was used to calculate 95% confident limits.

* Models adjusted for year of interview, age, gender, ethnicity, educational attainment, ever hospitalized for a mental illness, history of injection drug use, history of incarceration, history of sex trade involvement, methadone program participation (past 6 months), any addiction treatment (past 6 months), and recent employment.
**Figure S2.** Estimated population effect of housing persons not engaged in addiction treatment on viral suppression prevalence among HIV-infected people who use drugs in Vancouver

**Panel A : Full Sample (N = 706)**

![Bar chart showing viral suppression prevalence for full sample](chart1)

<table>
<thead>
<tr>
<th></th>
<th>Empirical Data</th>
<th>Crude Model</th>
<th>Adjusted Model*</th>
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<tbody>
<tr>
<td>Proportion Virally Suppressed</td>
<td>38%</td>
<td>42%</td>
<td>41%</td>
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</table>

**Panel B : Homeless At Baseline (N = 223)**

![Bar chart showing viral suppression prevalence for homeless sample](chart2)

<table>
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* Models adjusted for year of interview, age, gender, ethnicity, educational attainment, ever hospitalized for a mental illness, history of injection drug use, history of incarceration, history of sex trade involvement, methadone program participation (past 6 months), any addiction treatment (past 6 months), and recent employment.
ELECTRONIC APPENDIX REFERENCES


