

SNARKY: Sharing Needles As a Result of Kowtowing to Yuppies

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Abstract:

Aim: People who inject drugs (PWID) in public have a higher risk of homelessness, incarceration, rushed injection, and overdose than people who do not inject drugs in public. There is limited research on the relationship between public injection and syringe sharing, a risk factor for infectious diseases. The aim of this study was to investigate longitudinal associations between frequency of public injection and syringe sharing among PWID in San Francisco and Los Angeles, California.

Methods: PWID (N=984) were recruited using targeted sampling and completed surveys during three study visits (baseline, 6-month, and 12-month) in 2016 and 2017. The explanatory variable was frequency of having injected in public (never, occasionally/sometimes, or usually/always), and the outcome variable was number of times having used syringes that had already been used by someone else in the past six months. Explanatory and outcome variables were measured across all three timepoints. We used a longitudinal negative binomial mixed-effects model to assess the relationship of interest.

Results: At baseline, 78% of participants had injected publicly in the past six months, with 38% of the sample reporting that they usually/always injected publicly. Over a quarter (26%) had injected with a previously used syringe in the six months preceding baseline, with an average of 20.9 instances of receptive syringe sharing during this period. The majority (83%) reported current homelessness at baseline. In multivariable analysis across all timepoints, participants who usually/always injected publicly had 1.71 (95% CI: 1.30, 2.24) times higher counts of receptive syringe sharing over the past six months, compared to those who never publicly injected, controlling for age, gender, homelessness, stimulant injecting, opioid injecting, and binge drinking.

#####LIZZY TO UPDATE#####

Conclusion: Usually/always injecting publicly is associated with a higher frequency of receptive syringe sharing among PWID, suggesting the need for safer environment interventions, such as supervised consumption sites.

Research Question

Among people who inject drugs (PWID), is frequency of public injection (e.g. on a sidewalk) associated with increased frequency of injecting with a syringe previously used by someone else?

Description of Study

This study was a randomized controlled trial to determine efficacy of an intervention to prevent people from helping others to inject drugs for the first time. 984 participants were recruited in San Francisco and Los Angeles using targeted sampling, and completed surveys at three study visits from 2016-2017.

For this analysis we ignored study arm and treated data over the three study visits (baseline, 6-month, and 12-month follow-up) as repeated measures. Surveys included data on demographic variables (age, gender, race), as well as time-varying variables including months homeless, types of substances used and routes of administration, frequency of substance use, frequency of injecting in public, and number of times in the past 6 months using syringes that were already used by someone else.

Description of Sample

One of the biggest challenges of this analysis was appropriately dealing with informative censoring with large loss-to-follow-up.

| | | Baseline | 6-month F/U | 12-month F/U |
|------------------|------------------------|-------------|--------------|--------------|
| Total | | 978 (100%) | 595 (60.8%) | 532 (54.4%) |
| Age | Min | 18 | 18 | 18 |
| | Median | 43 | 45 | 45 |
| | Max | 76 | 76 | 71 |
| Gender | Male | 739 (75.6%) | 437 (73.4%) | 387 (72.7%) |
| | Female | 225 (23%) | 149 (25%) | 139 (72.7%) |
| | Transgender | 14 (1.4%) | 9 (1.5%) | 6 (1.1%) |
| Race | Black | 196 (20%) | 141 (23.7%) | 126 (23.7%) |
| | Latinx | 228 (23.3%) | 131 (22%) | 114 (21.4%) |
| | White | 413 (42.2%) | 238 (40%) | 219 (41.2%) |
| | Other | 141 (14.4%) | 85 (14.3%) | 73 (13.7%) |
| Public Injection | Always/Usually | 376 (38.4%) | 171 (28.7%) | 125 (23.5%) |
| | Sometimes/Occasionally | 390 (39.9%) | 171 (35.8%) | 193 (36.3%) |
| | Never | 212 (21.7%) | 183 (30.8%) | 170 (32%) |
| Times Sharing | 0 | 723 (73.9%) | 507 (121.5%) | 462 (135.9%) |
| | 1 - 15 | 207 (21.2%) | 68 (34.8%) | 50 (38.9%) |
| | 16 - 30 | 21 (2.1%) | 3 (3.5%) | 3 (3.9%) |
| | 31+ | 27 (2.8%) | 8 (4.5%) | 8 (5.1%) |
| Months Homeless | 0 | 168 (17.2%) | 152 (25.5%) | 176 (33.1%) |
| | 1 - 6 | 138 (14.1%) | 33 (5.5%) | 346 (65%) |
| | 7 - 12 | 112 (11.5%) | 67 (11.3%) | 1 (0.2%) |
| | 13+ | 560 (57.3%) | 343 (57.6%) | 9 (1.7%) |
| Substance Use | Used stimulants | 674 (68.9%) | 330 (55.5%) | 253 (47.6%) |
| | Used opiates | 834 (85.3%) | 424 (71.3%) | 341 (64.1%) |
| | Binge drinking | 292 (29.9%) | 149 (25%) | 85 (16%) |

Statistical Model

We converted our research question into a parameter of interest using a series of longitudinal regression models where:

$$\begin{aligned} \log(E[Y|\mathbf{X}]) = & \beta_0 + \beta_{0i} + (\beta_1 + \beta_{1i} + \beta_{1j})X_{1ij} + (\beta_2 + \beta_{2i} + \beta_{2j})X_{2ij} + \\ & \beta_3X_3 + \beta_4X_4 + (\beta_5 + \beta_{5i} + \beta_{5j})X_{5ij} + \\ & (\beta_6 + \beta_{6i} + \beta_{6j})X_{6ij} + (\beta_7 + \beta_{7i} + \beta_{7j})X_{7ij} \end{aligned}$$

where:

- ▶ Y = number of times shared syringes (outcome)
- ▶ X_1 = frequency of public injection (exposure)
- ▶ X_2 = homelessness status
- ▶ X_3 = gender
- ▶ X_4 = age
- ▶ X_5 = any stimulant injection
- ▶ X_6 = any opiate injection
- ▶ X_7 = any binge drinking

All variables have a recall period of 6 months, where applicable.

Methods used to fit model and derive inference

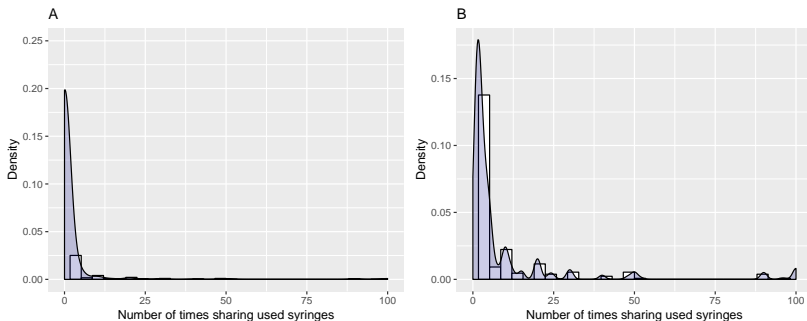
We fit 3 models to answer this question: GEE, and mixed effects models using both poisson and negative binomial distributions.

The **GEE model** estimated the marginal effects of public injection frequency on receptive syringe sharing across the three timepoints, controlling for homelessness, gender, age, stimulant or opiate injection, and binge drinking. GEEs treat the correlation between subjects as a “nuisance” parameter. We did this using the gee package in R, assuming an exchangeable correlation structure and a poisson distribution.

The **mixed effects models** estimate the marginal longitudinal effect of public injection frequency on receptive syringe sharing, controlling for the same confounders, but allow for both a random intercept term and a random effect term for frequency of public injection (our exposure), homelessness, and the substance use variables. These models use maximum likelihood to estimate the coefficients in the model, but rely on correct specification of both the mean model and the correlation structure of the residual errors. We did this using the glmer function in the MASS package in R, specifying family = "poisson", and using the glmer.nb function in the lme4 package in R for the negative binomial model. For the mixed models we calculated 95% confidence intervals using the sandwich estimator.

Compare models (1)

Since we have count data, we first created a histogram of the outcome (number of times sharing needles after someone else had already used them, over the prior six months). The left panel (A) includes all participants, and the right panel (B) includes only participants who reported sharing needles at least once during the recall period.



This shows us that the vast majority of participants (more than half) reported zero for the outcome, which may cause problems for a poisson model. It is also extremely right-skewed, also implying that a negative binomial model may be a better fit.

Compare models (2)

We also want to compare models with a few different tests, to see which appears to have the best fit.

1. Since the mixed models are nested, we can use a likelihood ratio test:

| Model | Log Likelihood | P-value |
|------------|----------------|---------|
| Poisson | -2232.145 | |
| Neg Binom. | -1223.066 | 0 |

This tells us that the negative binomial model is significantly preferred over the poisson model.

2. We can also compare the AIC of the mixed models, though this involves comparing likelihoods that ignore the repeated measures in our study:

| Model | AIC |
|------------|----------|
| Poisson | 4488.289 |
| Neg Binom. | 2472.132 |

This also suggests that the negative binomial model is a better fit.

Compare models (3)

We are concerned about strong violations of the assumption of no informative censoring, for our GEE model. Yet we are also concerned about overdispersion, as well as the large number of zeros in our outcome, both of which may cause our poisson mixed methods model to be a poor fit.

For these reasons, it is not surprising that the negative binomial model may be the best fit.

We are not able to run comparison tests of fit for GEE compared to our mixed models, so one of the best things to do is to look at our results, including standard error.

Results

| | GEE (Poisson) | | Mixed Model (Poisson) | | Mixed Model (Neg Binom.) | |
|---------------------------------|------------------|----------|--------------------------|---------|-----------------------------|---------|
| Predictor | Est. | p-value* | Est. | p-value | Est. | p-value |
| Never publicly inject | ref | | ref | | ref | |
| Sometimes/Often publicly inject | 1.41 | 0.09 | 2.4 | 1.1e-21 | 3.28 | 0.00066 |
| Usually/Always publicly inject | 2.28 | 0.01 | 3.69 | 2.4e-40 | 7.99 | 7.7e-08 |
| Housed at study visit | ref | | ref | | ref | |
| Homeless at study visit | -1.33 | 0.08 | 1.21 | 0.08 | 0.89 | 0.73 |
| Male | ref | | ref | | ref | |
| Female | -0.12 | 0.82 | 1.03 | 0.94 | 1.31 | 0.47 |
| Transgender | 0.13 | 0.9 | 1.11 | 0.95 | 1.07 | 0.96 |
| Age (year) | -2.87 | 2.7e-05 | 0.6 | 0.77 | 1.14 | 0.94 |
| No stimulant use | ref | | ref | | ref | |
| Stimulant use | -0.02 | 0.31 | 0.96 | 0.001 | 0.98 | 0.08 |
| No opiate use | ref | | ref | | ref | |
| Opiate use | 0.29 | 0.57 | 0.65 | 2.6e-05 | 1.87 | 0.03 |
| No binge drinking | ref | | ref | | ref | |
| Binge drinking | -0.21 | 0.72 | 0.71 | 0.00068 | 1.74 | 0.09 |

*p-values based on robust SEs

We can see from these results that the inference is similar across models, though the magnitude of the effect is much stronger in the negative binomial model, and the standard error is much larger for the GEE model.

Attempt a compelling graph related to your research question

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MAKE THE GRAPH - Lizzy

% % % % % % % % % % % % % % % %

Discussion

Interpret your results both with regard to the substantive question of interest as well as any statistical issues.

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DO THIS SLIDE - Lizzy

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