The Effects of Homeless Shelter Occupancy on Non-Fatal Opioid Overdoses*

My subtitle if needed

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First sentence. Second sentence. Third sentence. Fourth sentence.

```
library(arrow)
```

```
Warning: package 'arrow' was built under R version 4.4.2


Attaching package: 'arrow'

The following object is masked from 'package:utils':

    timestamp
```

```
library(tidyverse)
```

```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v dplyr     1.1.4     v readr     2.1.5
v forcats   1.0.0     v stringr   1.5.1
v ggplot2   3.5.1     v tibble    3.2.1
v lubridate 1.9.3     v tidyr     1.3.1
v purrr     1.0.2
```

*Code and data are available at: [https://github.com/justinklip/toronto_shelter_overdose_study).

```
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x lubridate::duration() masks arrow::duration()
x dplyr::filter()       masks stats::filter()
x dplyr::lag()          masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
```

```r
library(here)
```

```
Warning: package 'here' was built under R version 4.4.2
```

```
here() starts at C:/Users/User/Desktop/toronto_shelter_overdose_project
```

1 Introduction

Overview Paragraph: Opioid overdoses have been a prominent issue in North America for some time. Opioid-related deaths have doubled in Canada from 2019 to the end of 2021 (https://www.cbc.ca/news/health/opioid-young-people-1.7174098). It has been well-documented that homeless people are a large subset of the population affected by this crisis, with more than 10% of opioid deaths in Toronto being attributed to individuals experiencing homelessness in 2023 (chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.toronto.ca/wp-content/uploads/2020/12/8d4b-TOIS-Coroner-Data_Final.pdf). Homeless opioid overdoses in shelters have climbed as well during the pandemic, with opioid deaths in Ontario shelters more than tripling during the pandemic (https://www.cbc.ca/news/canada/toronto/ont-shelters-overdose-deaths-1.7238916). There are a lot of factors that could play into this, but one question that is left to be asked is if the conditions in the shelters themselves may be contributing to this.

Results paragraph

Why it matters paragraph

Telegraphing paragraph: The remainder of this paper is structured as follows. **?@sec-data** describes how the data was acquired, how it was measured, and provides visualizations on the overdoses and occupancy in shelters. # Data {#sec-data}

1.1 Data Source

I make use of two data sources in order to run my analysis. Firstly I make use of Open Data Toronto's Daily Shelter Overnight Capacity Data (cite). Secondly I use Open Data Toronto's Fatal and Non-Fatal Suspected Opioid Overdoses in the Shelter System data set (cite). These data sets compile

Using the statistical programming language R (R Core Team 2023), the data was then cleaned, tested, and merged using (cite packages). The daily shelter attendance data was aggregated from the daily data in the shelter data base to a quarterly record in order to merge with the overdose data set. Details are in the appendix on how exactly observations were dropped and merged (cross-reference appendix). Some dummy variables were added into the data set in order to account for selection induced upon dropping missing values. Data such as

Overview text

1.2 Measurement

The Daily Shelter Overnight Capacity Data from Open Data Toronto is measured directly from administrative data (cite). According to Open Data Toronto, this administrative data comes from the Toronto Shelter and Support Services division's Shelter Management Information (SMIS) database. The data is generated as follows: a shelter records metrics in their shelter at exactly 4:00am every day (likely through a computer or check-in system) such as attendance numbers, capacity numbers, and respective capacity utilization rates, then uploads that data daily in compliance with the SMIS data requirements. Generally shelters measured occupancy and capacity in one of two ways: beds or rooms. Bed-based occupancy was used in shelters that had communal sleeping areas, whereas room-based occupancy was used for more family-oriented programs. An "individual" in this data set would counts as someone who was served in a service area or program (https://www.toronto.ca/city-government/data-research-maps/research-reports/housing-and-homelessness-research-and-reports/shelter-census/). Interestingly data is only recorded for the first quarter of 2023, this and other limitations of the data are discussed further in the ((**appendix?**))

The Fatal and Non-Fatal Suspected Opioid Overdoses in the Shelter System Data Set (cite) comes from paramedic rather than shelter level data. This data only counts for specific kinds of shelters: shelter-hotels, emergency shelters, and shelter-hotels, meaning that when the data is merged, only shelters coming from this data set will be used. An entry in the data set is formed as follows: a shelter member or employee calls 911 for an emergency, when Paramedics arrive and if they determine on the scene that this is a suspected overdose, then that location gets an observation added to the data set. It's important to note also that if a particular address has less than 5 non-fatal overdoses in a particular quarter, then the true amount is not published for anonymity purposes. This data set also includes fatal overdoses, and a fatal overdose is only added as an entry if the Coroner's office determines the cause of death to be an overdose. This data is also not matched at the shelter level and is only aggregate statistics, so it will be ignored for the purpose of analysis since I am more interested in the relationship between capacity and overdoses.

1.3 Summary Statistics

Table 1: Summary Statistics for Non-Fatal Overdoses, Average Occupancy Rate, and Daily Average Users

Variable	Observations	Mean	Median	Standard Deviation	Minimum	Maximum
Non-Fatal Overdoses	271	7.206642	5.00000	10.058059	0.0000000	51.0000
Average Occupancy Rate	492	96.436265	99.39367	7.338487	21.8904348	100.0000
Daily Average Users	492	71.313895	44.08242	72.927412	0.0777778	383.0989

1.4 Outcome variables

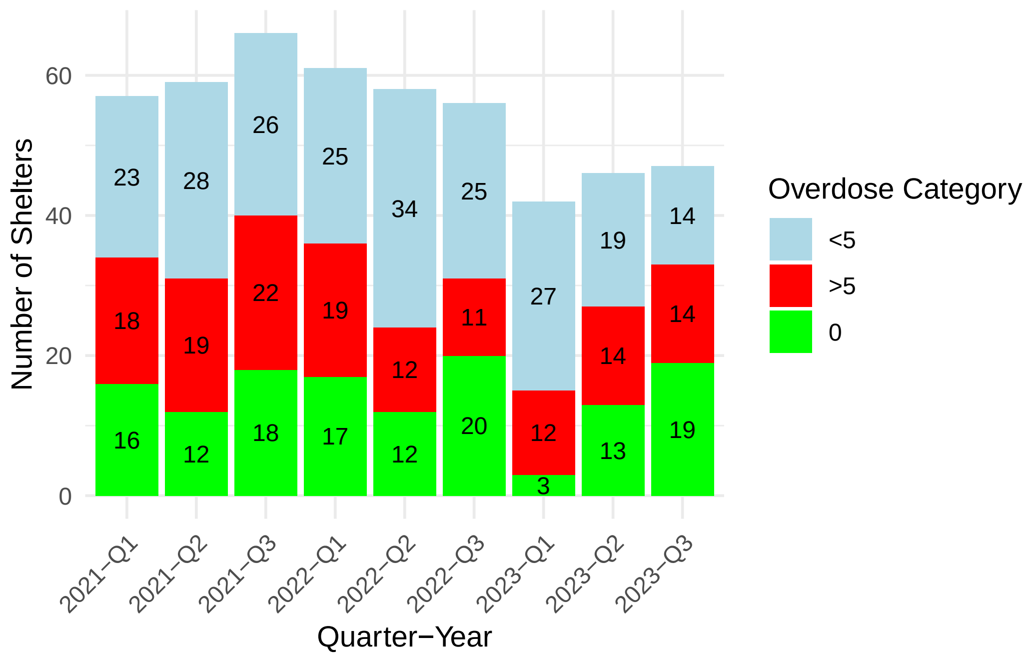

Figure 1: Shelters Overdoses by Quarter-Year By Data Category

?@fig-1 Provides information on the number of overdoses for each shelter in the data set from quarter to quarter. It is important to note that the data set does not include Q4 data. The first thing to note is that the number of shelters seems to decrease in 2023, this is likely consistent with COVID-19 specific shelters beginning to close. Another important thing to note is that the number of overdoses greater than 5 and the amount less than 5 are generally split evenly between the shelters. This suggests we have some "high overdose" level shelters, likely because they are bigger, and others which are smaller and less drug prone.

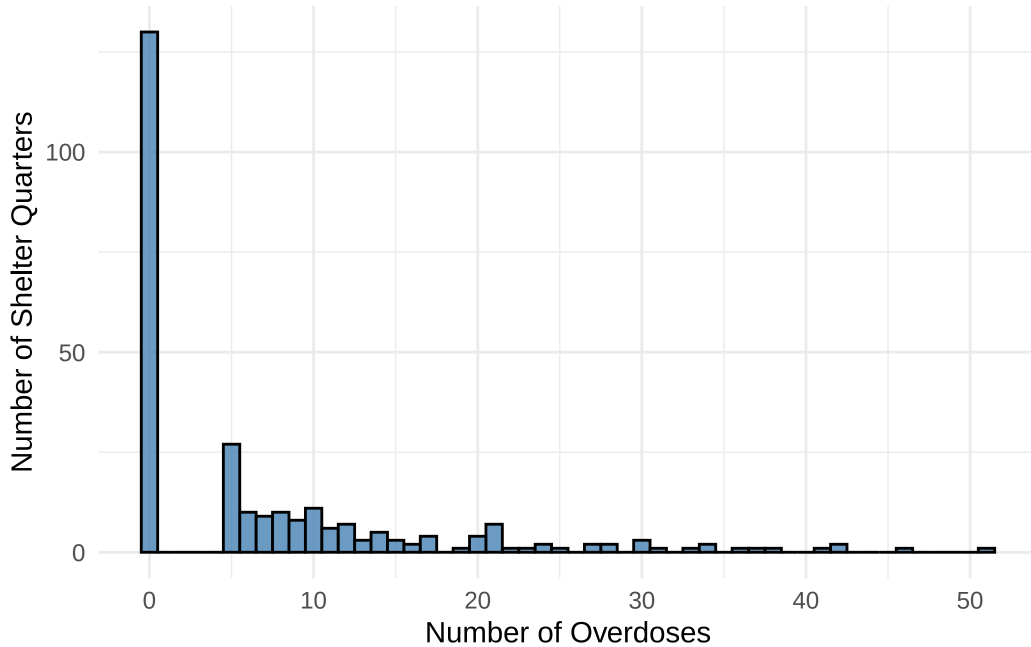

Figure 2: Distribution of Overdoses Counts, Shelter-By-Quarter, excluding nonzero less than 5 counts.

?@fig-2 Plots the distribution of the number of overdoses for each quarter in each shelter, except those that are marked "<5". The data seems to indicate a clear mass around 0, with about 150 out of approximately 500 total observations being located at this point. Considering the shape of the data, it would be reasonable to assume that there are less and less observations as the number of overdoses per quarter increases at a certain address. This motivates our decision making in section **?@sec-model**. ## Predictor variables

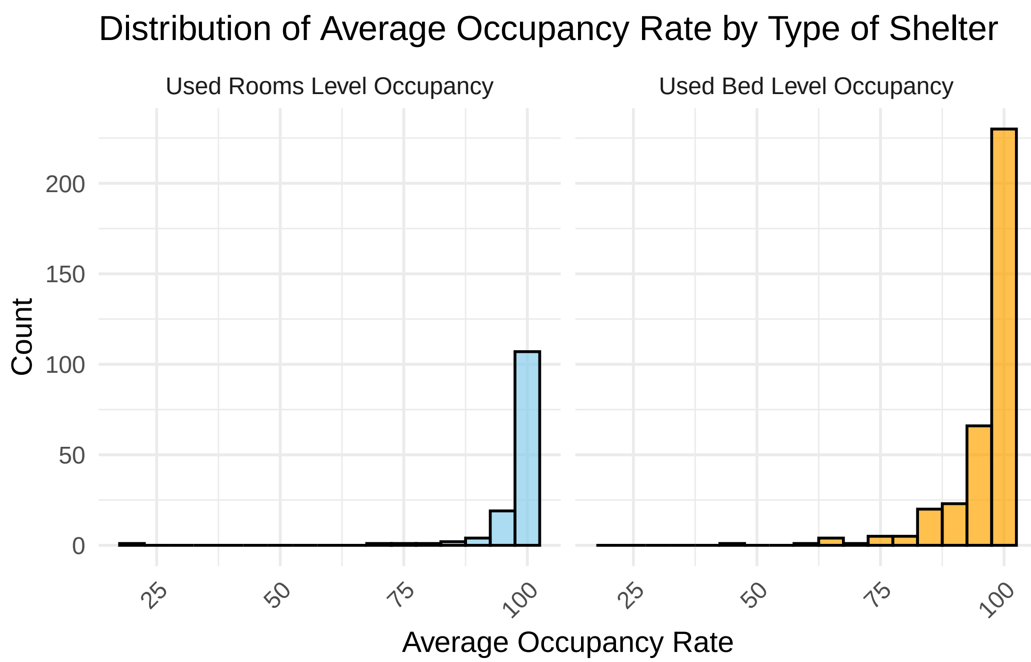

Figure 3: Distribution of Average Quarterly Occupancy Rates in Toronto Shelters by Type of Shelter

?@fig-3 Plots the distribution of the average occupancy rate by quarter-year, as seen in some quarters, some shelters do have less than 100 percent occupancy, although a lot spend their time at the 95-100 percent occupancy rate. For the bed data there are a lot more observations with less than 95 to 100 percent occupancy. This makes sense as it is a lot easier for a shelter to fill up all their rooms than it is to fill all their beds.

2 Model {sec-model}

The model section is split into two parts: firstly I try to impute the values of the number of overdoses for the missing data using a predictive mean matching approach. With these new observations, I construct a model that attempts to relate overdose rates to occupancy and daily shelter attendance.

Here we briefly describe the Bayesian analysis model used to investigate… Background details and diagnostics are included in Appendix C.

2.1 Model set-up

Define y_i as the number of seconds that the plane remained aloft. Then β_i is the wing width and γ_i is the wing length, both measured in millimeters.

$$
\begin{aligned}
y_i|\mu_i, \sigma &\sim \text{Normal}(\mu_i, \sigma) && (1)\\
\mu_i &= \alpha + \beta_i + \gamma_i && (2)\\
\alpha &\sim \text{Normal}(0, 2.5) && (3)\\
\beta &\sim \text{Normal}(0, 2.5) && (4)\\
\gamma &\sim \text{Normal}(0, 2.5) && (5)\\
\sigma &\sim \text{Exponential}(1) && (6)
\end{aligned}
$$

We run the model in R (R Core Team 2023) using the `rstanarm` package of Goodrich et al. (2022). We use the default priors from `rstanarm`.

2.1.1 Model justification

We expect a positive relationship between the size of the wings and time spent aloft. In particular…

We can use maths by including latex between dollar signs, for instance θ.

3 Results

Our results are summarized in **?@tbl-modelresults**.

4 Discussion

4.1 First discussion point

If my paper were 10 pages, then should be be at least 2.5 pages. The discussion is a chance to show off what you know and what you learnt from all this.

4.2 Second discussion point

Please don't use these as sub-heading labels - change them to be what your point actually is.

4.3 Third discussion point

4.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

Appendix

A Additional data details

B Surveys, Sampling, Observational Data, and Idealized Methodology.

Ultimately while I was able to determine the relation between homeless shelter occupancy and overdose rates, a lot of data related factors made detailed analysis difficult. In this segment I detail potential ways research designs could be done within Toronto to determine the channels in which Toronto's shelters could target overdose rates within their shelters.

B.1 Observational Data and Causality

The first issue was the method of data collection done that led to truncation issues. Since any shelter that had less than 5 overdoses in a quarter was just given the marking "<5" for anonymity, it meant that estimation was incredibly difficult and required the simplification of assuming all shelters of these types just had 4. In an idealized set of observational data, this would be available.

Secondly was the issue of measurement of the dependent variables: while the distinction between bed-based and room-based occupation metrics was made in the paper, the measurement of occupancy rate is more so a proxy for the desired metric of interest – living conditions. The assumption being that more crowded

C Model details

C.1 Posterior predictive check

C.2 Diagnostics

References

Goodrich, Ben, Jonah Gabry, Imad Ali, and Sam Brilleman. 2022. "rstanarm: Bayesian applied regression modeling via Stan." https://mc-stan.org/rstanarm/.

R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.