Mental Health Outcomes of Internally Displaced Sexual Minority Men in Ukraine

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ABSTRACT

Russia's invasion of Ukraine has profoundly impacted its citizens, leading to widespread internal displacement. However, the mental health consequences of this displacement on vulnerable populations, such as men who have sex with men (MSM), remain underexplored. This study leverages recent survey data collected through respondent-driven sampling to examine the effects of internal displacement on depression among MSM. Linear and logistic regression models were employed to analyze the relationship between displacement and both depression scores and clinical depression status, adjusting for socio-demographic and behavioral factors. Mixed-effects modeling was further applied to account for correlations inherent in respondent-driven sampling.

Our findings reveal that displacement is associated with an overall increase in depression severity but is not linked to the development of clinical depression. These results highlight the urgent need for targeted mental health services and support systems for MSM individuals impacted by displacement.

INTRODUCTION

Motivation

On February 24, 2022, Russia launched a full-scale invasion of Ukraine, leading to substantial damages. Millions of Ukrainian citizens were affected, including being killed, tortured, displaced, or subjected to severe hardships due to Russian occupation[1]. The impacts of this war extend beyond physical harm, deeply affecting the mental health of the population. This study aims to explore the effect of internal displacement on the mental health of men who have sex with men (MSM), a highly marginalized and stigmatized group in Ukraine.

MSM represent a vulnerable population in Ukraine, where gay marriage remains illegal, compounding the challenges faced by LGBTQ+ individuals. These men experience significant stigma, which negatively affects their mental and physical health outcomes[2]. The societal norms in Ukraine contribute to various types of stigma, leading to exclusion from mainstream studies and restricted access to healthcare, particularly mental health services. Studies consistently show that MSM who experience higher levels of stigma are more likely to suffer from adverse mental health outcomes, such as depression and suicidal ideation, and often engage in riskier behaviors due to barriers in accessing appropriate care. During the war, men in Ukraine are also either at frontlines or at risk of conscription, which can worsen their mental health outcomes. A multitude of experiences, including life during war, experience of displacement, and various sources of stigma make it critical to understand how MSM's mental health has been impacted, so that they can receive adequate support and access to mental health services.

Although there is prior research on the mental health outcomes of MSM, the effect of internal displacement on this population, specifically in Ukraine, remains underexplored. In Lebanon, a 2021 study examined the mental health of externally displaced Syrian MSM and transgender women[4]. This study found a significant effect of displacement on depression. However, that study focused on external displacement, where individuals were displaced from Syria to Lebanon, which adds additional layers of stigma due to cross-border movement. The context of internal displacement within Ukraine may present different challenges and impacts, underscoring the need for further research in this area, which we aimed to undertake here.

Research Questions

In this study, we aim to examine the relationship between internal displacement and depression among men who have sex with men (MSM) in Ukraine, a population particularly vulnerable to the mental health impacts of both stigma and ongoing conflict. Our research focuses on the following questions:

1. What is the effect of internal displacement on depression scores among MSM?
2. Does internal displacement increase the likelihood of clinical depression (MHAI score ≥ 7) among MSM?
3. What other socio-demographic and psychosocial factors are associated with depression among MSM in Ukraine?
4. How does internal displacement interact with other psychosocial factors to influence depression severity?

These research questions are designed to address a significant gap in the literature regarding the mental health of internally displaced MSM populations during conflict. By using both continuous and binary measures of depression and applying mixed-effects modeling to account for respondent-driven sampling (RDS), this study seeks to provide a comprehensive understanding of how internal displacement interacts with socio-demographic and psychosocial factors to influence depression in this vulnerable group.

METHODS

Description of Data

The data for this study was collected as part of a bio-behavioral survey conducted by the Alliance for Public Health, a non-governmental organization working on HIV prevention in Ukraine. The data was collected through a respondent-driven sampling (RDS) method by 7 different NGOs in Ukraine. The survey was conducted in eight oblasts (regional administrative divisions) in Ukraine: Chernivtsi, Kharkiv, Kremenchuk, Kyiv, Lviv, Odesa, Poltava, and Rivne in 2023-2024. Seven local non-governmental organizations were responsible for gathering the survey data, with one organization covering both Kremenchuk and Poltava.

Data was collected across 12 categories: screening, socio-demographics, migration, narcotic substance use, sexual behavior, mental health, pre-exposure prophylaxis , HIV testing, HIV treatment, seeking medical care, stigma and discrimination, and testing results. For this study, we concentrated on screening information, socio-demographics, migration, narcotic substance use, and stigma and discrimination. HIV status was initially considered for inclusion in our analysis, but with only 18 HIV-positive cases in the dataset, the sample size was deemed too small for proper analysis.

In this study, we focus on depression as the primary mental health outcome. Depression was measured using a standardized depression scale, the Mental Health Assessment Inventory (MHAI)[10], through a survey administered to participants. Seven equally weighted questions were asked, adapted from the standard mental health screening questionnaire. Participants rated how often they had experienced specific feelings in the past two weeks, with response options of "Never," "Sometimes," "Often," and "Almost always," corresponding to scores of 0, 1, 2, and 3, respectively. Each participant's scores were summed, producing a total score ranging from 0 to 21, with a score of 7 or higher indicating clinical depression. In this analysis, both the continuous depression score and a binary clinical depression status were considered.

After subsetting the data to exclude variables not relevant to our research, we were left with 231 variables. Below, we provide an overview of the key variables used in this analysis:

Variable	Description	Range
Depression Score	Sum of responses to seven mental health screening questions, with each response scored from 0 to 3. Possible score range: 0 to 21.	0 to 21

Russian Effect	Perceived impact of the Russian invasion. Averaged across sub-questions to create a standardized scale.	-2 (strong negative) to +2 (strong positive)
Casual Stigma	Measured experiences like family exclusion.	0 = No, 1 = Yes
Extreme Stigma	Measured experiences like physical violence.	0 = No, 1 = Yes
Internalized Stigma	Measured feelings of shame due to sexual identity.	0 = No, 1 = Yes
Internal Displacement (Main Predictor)	Binary variable indicating if the participant was displaced before or after Russia's full-scale invasion of Ukraine.	0 = Not displaced, 1 = Displaced

This dataset, which reflects a diverse range of experiences and socio-demographic backgrounds, provides the basis for our analysis of the mental health outcomes of sexual minority men in Ukraine.

Missingness

The only variable of interest with missing data was income, where 550 entries (approximately 15% of the dataset) were missing. The missing entries appeared to be missing at random as there did not seem to be an obvious correlation between missingness and our outcome variable, depression score. We used the Multiple Imputation by Chained Equations via the mice package in R to impute the missing values[9]. Figure 1 (below) demonstrates that the means and variances of the imputed dataset closely resemble those of the pre-imputation dataset, indicating that the imputation process was robust and did not introduce significant bias.

While no other variables had missing data, some categorical variables had respondents who refused to answer specific questions. In these cases, we opted to retain a separate "refused to answer" category. We believed that this non-response could carry meaningful information, and treating it as its own category would allow us to capture potential underlying patterns behind the refusal to answer.

	Mean	Standard Deviation
Non-Imputed Income	659.3	462.56
Imputed Income	662.1	469.42

Figure 1. Differences Between Imputed and Non-Imputed Income

Sampling Design

As mentioned previously, RDS was used to recruit people to take the survey. RDS begins by recruiting an initial batch of participants, referred to as "seeds." For this study, a total of 70 seeds were used to recruit the other participants in the study. The distribution of the number of seeds per city can be seen in Figure 2 on the right. Each seed received coupons after participating in the survey, which they used to recruit others within their social networks. This process continued with each new participant receiving coupons to recruit additional participants, forming recruitment chains known as recruitment trees. Each tree has a seed at its root, with subsequent waves of recruits forming branches below. Since both the respondent's ID and their recruiter's ID were recorded, we were able to construct visualizations of the recruitment trees, as shown in Figure 3 below. The tree shown in Figure 3 is a relatively long tree, with 166 nodes, 20 waves, and a maximum width of 16. For comparison, on average the recruitment trees had 45 nodes, 5 waves and a maximum width of 11. In theory, we expected 70 recruitment trees - one for each seed. However, due to data cleaning where participants who did not meet the inclusion criteria were removed, some participants' recruiter IDs did not correspond to any included participant. For visualization purposes, we treated these participants as new seeds, resulting in 91 total recruitment trees.

Number of seeds per city

City	Number of Seeds
Rivne	8
Chernivtsi	3
Kharkiv	9
Kremenchuk	3
Kyiv	11
Lviv	13
Odesa	12
Poltava	11

Figure 2.

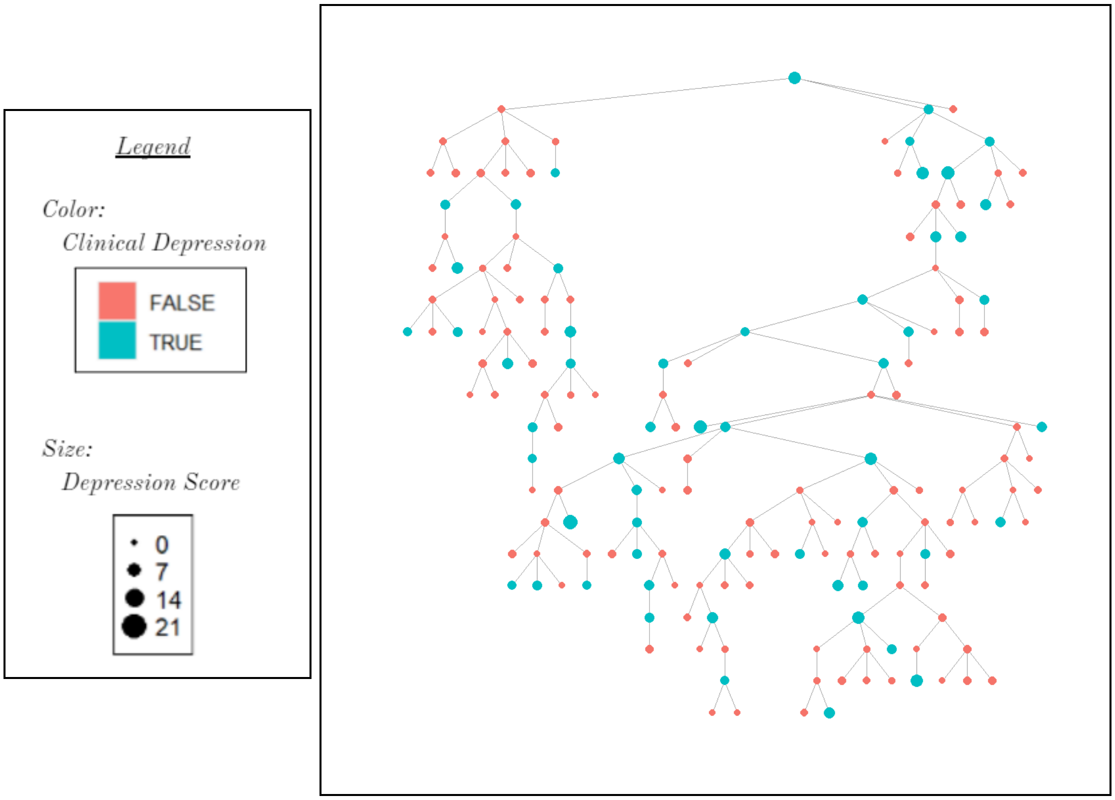

Figure 3. Example Recruitment Tree

In RDS, individuals within the same social network are likely to share certain characteristics, leading to correlations among respondents within the same recruitment tree[11]. This assumption is supported by Figure 4, which illustrates that participants recruited by someone with depression are significantly more likely to be depressed themselves. Given this non-independence of data, particularly within recruitment trees, we could not treat our data as fully independent.

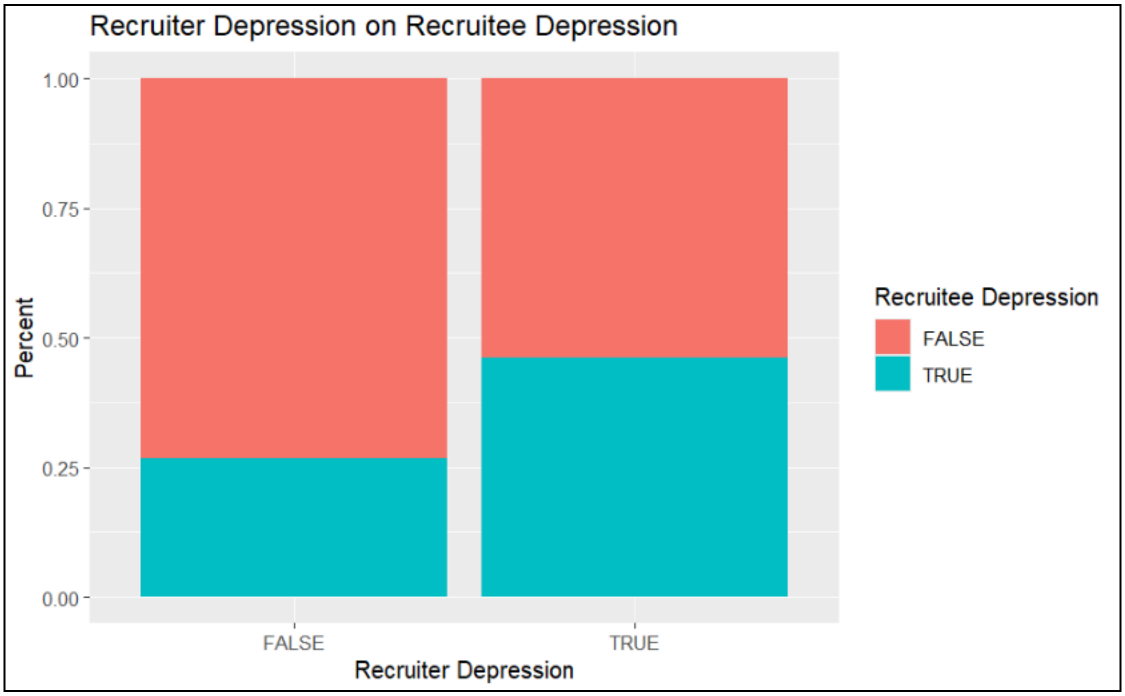

Figure 4. Distribution of Recruiter and Corresponding Recruitee Clinical Depression

To account for this, we developed three different approaches to address the correlation within the recruitment trees which will be discussed in the next section.

Covariate Selection

The initial step in our modeling process was the selection of primary covariates. This selection was guided by a conceptual analysis of the problem and aimed to include variables that were believed to influence the depression score, as well as those of particular interest for interpretation. The variables were grouped into categories reflecting those in the survey: socio-demographics, substance use, stigma, effects of Russian occupation, and experiences of violence.

Socio-demographics:

- **Age**: Measured as a continuous variable, ranging from 15 to 59.
- **City**: One of the 8 cities where the survey centers were located, representing the city in which the participant took the survey.
- **Income**: Scaled by the cost of living in each city[12], using the price of bread to adjust for city-specific factors.

- **Occupation**: Categorized into 3 levels—permanent job, student, or 'other' - which included housekeeping and domestic activities, pensioner, commercial sex, freelance, business owners, temporary workers, odd jobs, unemployed and people with disability.
- **Education level**: Categorized into 3 levels—"Up to secondary education complete", "Incomplete/basic higher education", and "Complete Higher Education".
- **Marital status**: Categorized into 4 levels—single, married to women, and partnered (Either to men or women), or no answer.

Substance use: This category included both the frequency and type of drug and alcohol usage.
Stigma: Contained binary variables for whether participants experienced any casual, extreme, or internalized stigma due to their sexual preference.
Effect of Russian occupation: Included 3 variables—binary variables for military experience and displacement status after the invasion began, as well as a variable called "Russian effect," which was described in the introduction.
Experiences of violence: Contained binary variables measuring whether participants had experienced threats, physical abuse, or verbal humiliation.

To account for the correlation within our data, we evaluated three approaches:

1. **Random Effect for Recruiter[5]:** This approach assumes that observations associated with the same recruiter are correlated, while those from different recruiters are not. We found this approach to be the most suitable as it aligns with the assumption that individuals recruited by the same person may share similarities affecting their depression scores.
2. **Random Effect for Recruitment Tree[6]:** This method assumes that individuals within the same recruitment tree are equally correlated. However, we deemed this assumption too stringent and potentially unrealistic in practice.
3. **Recruiter's Depression Score as Covariate:** Including the recruiter's depression score as a covariate was considered, but it led to diminished significance of other covariates due to being highly correlated with most of the other variables included in the model. The recruiter's depression score accounted for substantial variance, obscuring the effects of other variables.

Given these considerations, we chose to adjust our models according to the first approach. The models using the other two methods are detailed in the appendix.

Methods Applied

Two methods were considered for modeling the data: linear regression and logistic regression.

In linear regression, the response variable, depression score, was treated as a numeric variable. We addressed potential outliers by binning depression scores of 17 and above to a maximum value of 17. This approach was employed to handle extreme values more robustly and to prevent them from disproportionately influencing the results. Linear regression allowed us to examine the relationship between depression scores and predictor variables while accommodating continuous outcomes. Linear regression is beneficial for understanding how predictors influence the magnitude of depression scores.

In logistic regression, the depression score was categorized into binary outcomes: clinical depression (values of 7 or higher) and non-clinical depression (values of 6 or lower). This threshold for clinical depression is suggested in the MHAI[10]. This transformation enabled us to model the probability of a binary outcome based on predictor variables, which is useful for classification purposes and interpreting the likelihood of clinical depression based on the predictors.

The distribution of the continuous depression score can be seen in figure 4, and the distribution of the binary clinical depression status can be seen in figure 5 below. Both methods were applied to comprehensively assess the relationships in the data and validate the robustness of our findings across different modeling approaches.

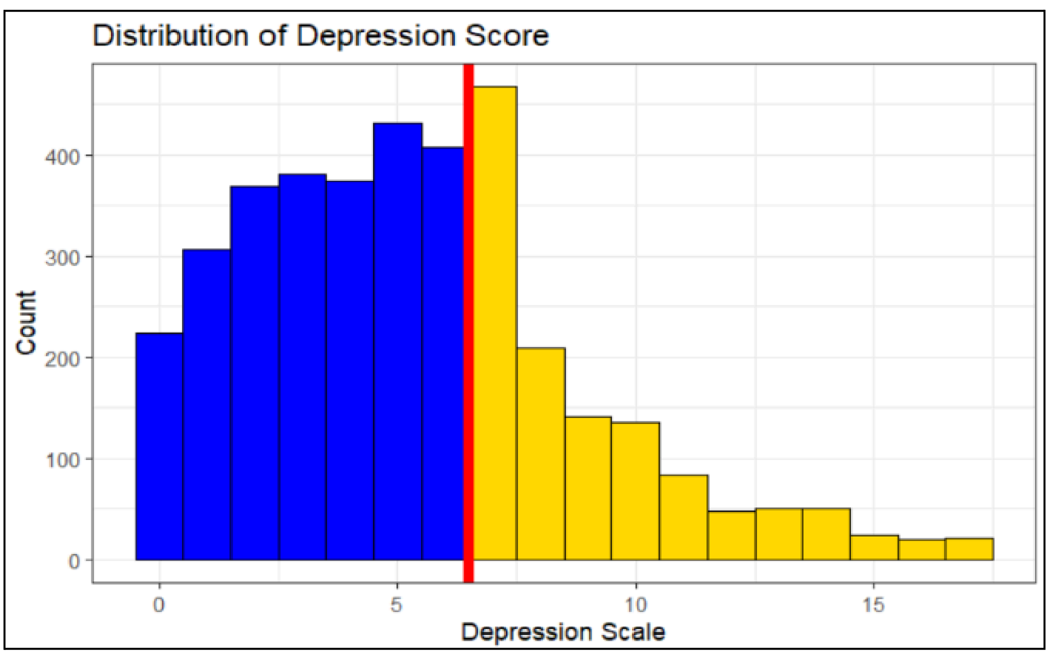

Figure 5. Distribution of Numeric Depression Score

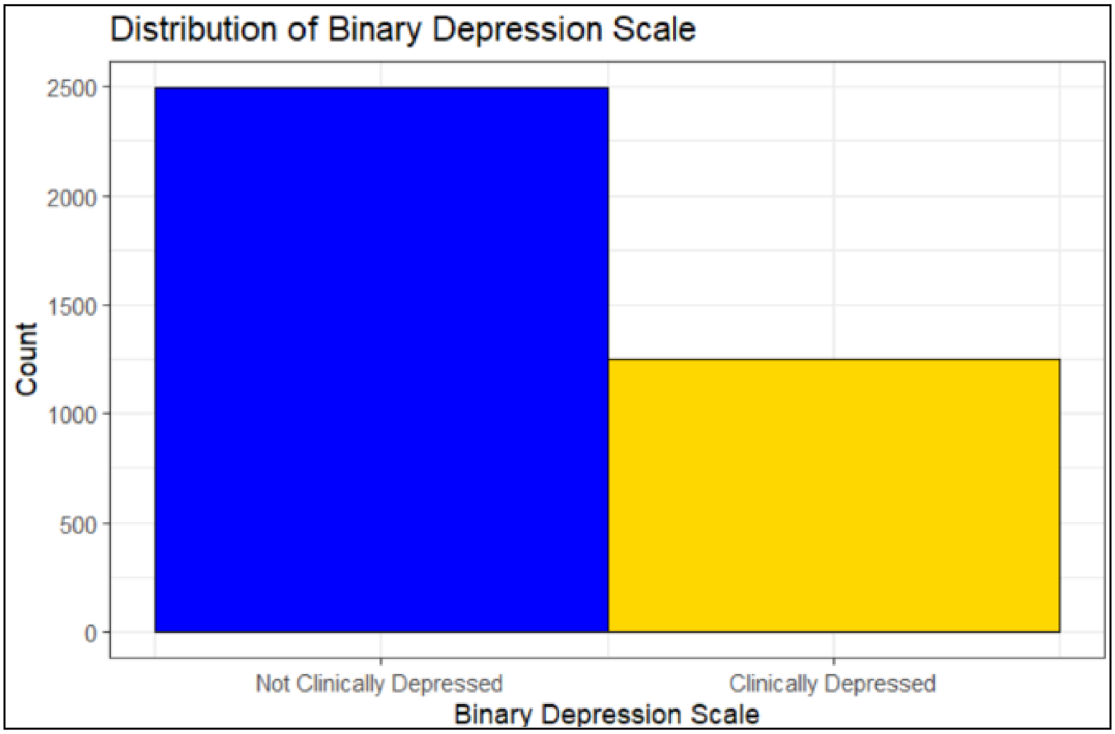

Figure 6. Distribution of Binary Depression Score

Modeling

In this analysis, the following baseline categories were used as reference levels for categorical variables:

- City: Rivne

- Stigma: No stigma reported for casual, extreme, or internalized stigma (used as the baseline for all three stigma measures)

- Experienced Violence: "No answer" serves as the reference category for the experienced violence variable

- Internally Displaced Status: Not internally displaced

- Marital Status: Single

- Total Drug Use: No drug use reported

- Alcohol Use Frequency: No alcohol use (none reported)

- Education Level: Up to secondary education complete (no higher education)

- Military Experience: No military experience

- Occupation: Permanent job

These baseline categories serve as reference groups in the regression and mixed effects models, allowing for comparison of all other categories relative to these baseline levels. The formula for the resulting general model can be seen below.

$$
\begin{aligned}
f(depression\_scale_{ij}) = &\beta_0 + \beta_1 I(Chernivtsi_{ij}) + \beta_2 I(Kharkiv_{ij}) + \beta_3 I(Kremenchuk_{ij}) \\
&+ \beta_4 I(Kyiv_{ij}) + \beta_5 I(Lviv_{ij}) + \beta_6 I(Odesa_{ij}) \\
&+ \beta_7 I(Poltava_{ij}) + \beta_8 (Income_{ij}) + \beta_9 I(CasualStigma_{ij}) \\
&+ \beta_{10} I(ExtremeStigma_{ij}) + \beta_{11} I(InternalizedStigma_{ij}) \\
&+ \beta_{12} I(PhysicalHarms_{ij}) + \beta_{13} I(Threats/Other_{ij}) + \beta_{14} I(VerbalHumiliation_{ij}) \\
&+ \beta_{15} I(InternallyDisplaced_{ij}) + \beta_{16} I(MarriedWomen_{ij}) \\
&+ \beta_{17} I(PartnershipNoAnswer_{ij}) + \beta_{18} I(Partnered_{ij}) + \beta_{19} I(DrugNoAnswer_{ij}) \\
&+ \beta_{20} I(DrugUse > 12M_{ij}) + \beta_{21} I(DrugUse12M_{ij}) + \beta_{22} I(AlcoholEveryDay_{ij}) \\
&+ \beta_{23} I(AlcoholNotEveryDay)_{ij} + \beta_{24} (Age_{ij}) + \beta_{25} I(HigherEducation_{ij}) \\
&+ \beta_{26} I(IncompleteHigherEdu_{ij}) + \beta_{27} (RussianEffect_{ij}) \\
&+ \beta_{28} I(MilitaryExperience_{ij}) + \beta_{29} I(OtherOccupation_{ij}) + \beta_{30} I(Student_{ij}) + a_{ij}
\end{aligned}
$$

Where $depression\_scale_{ij}$ represents the depression score of the *j*th recruitee of the *i*th recruiter. In the linear regression context the function f is simply the identity function, whereas in the logistic regression case,

$$f(depression\_scale_{ij}) = log(\frac{Pr(depression\_scale_{ij} \geq 7)}{1 - Pr(depression\_scale_{ij} \geq 7)})$$

In the model that was adjusted for the RDS design, $a_{ij} = \epsilon_{ij} + \delta_i$ and in the unadjusted model $a_{ij} = \epsilon_{ij}$, where ϵ_{ij} is the random error component and δ_i is the random effect of the *i*th recruiter.

We additionally considered using ordinal regression due to our outcome only taking integer values from 0 to 21. However, we thought that fitting an ordinal regression on an outcome with 22 categories would result in a loss of too much interpretability.

Furthermore, we could find no validated way to bin the depression score variable other than the binary method described above.

RESULTS

Initially, 3,886 survey responses were collected. However, after excluding participants who did not meet the selection criteria of being cisgender gay men over the age of 14, as well as those with missing data, the dataset was reduced to 3,744 observations.

Table 1

Sample characteristics among MSM individuals recruited through respondent driven sampling in Ukraine, N=3744

	Internally Displaced (N=315)	Not Displaced (N=3429)	Overall (N=3744)
Age			
Mean (SD)	29.9 (8.03)	29.8 (8.22)	29.8 (8.21)
Median [Min, Max]	28.0 [18.0, 57.0]	28.0 [15.0, 69.0]	28.0 [15.0, 69.0]
Monthly Income (Hryvnia)			
Mean (SD)	14400 (12300)	15400 (11400)	15300 (11500)
Median [Min, Max]	11000 [0, 74000]	14000 [0, 150000]	13500 [0, 150000]
Missing	62 (19.7%)	488 (14.2%)	550 (14.7%)
Marital Status			
Married to a woman	28 (8.9%)	204 (5.9%)	232 (6.2%)
No answer	5 (1.6%)	63 (1.8%)	68 (1.8%)
Partnered	109 (34.6%)	1163 (33.9%)	1272 (34.0%)
Single	173 (54.9%)	1999 (58.3%)	2172 (58.0%)
Drug Use			
No, never happened	184 (58.4%)	2384 (69.5%)	2568 (68.6%)
No Answer	9 (2.9%)	77 (2.2%)	86 (2.3%)
Yes, I have, but more than 12 months ago	62 (19.7%)	665 (19.4%)	727 (19.4%)
Yes, in the last 12 months	60 (19.0%)	303 (8.8%)	363 (9.7%)
Alcohol Use			
Never	30 (9.5%)	409 (11.9%)	439 (11.7%)
Every day	50 (15.9%)	429 (12.5%)	479 (12.8%)
Not every day	235 (74.6%)	2591 (75.6%)	2826 (75.5%)

Figure 7. Table 1 for Key Variables in Dataset, separated by Internal Displacement

Linear Regression

Figure 7 below presents the forest plot for the RDS-adjusted linear regression model. The plot includes the 95% confidence intervals for each variable, with non-significant intervals colored black and significant intervals highlighted in red. The predictor of interest, internal displacement, is highlighted in blue for visibility.

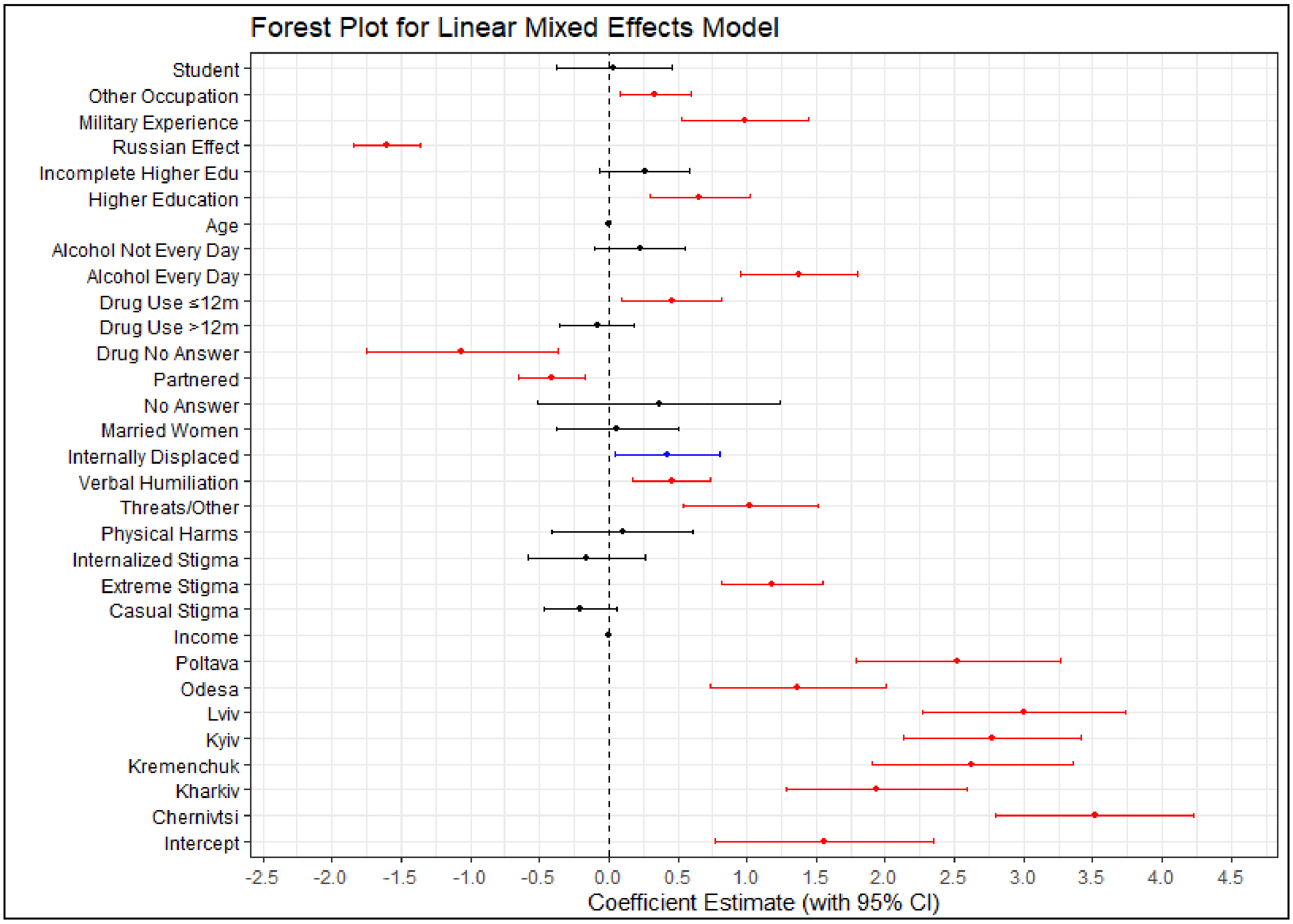

Figure 8. Forest Plot for Linear Mixed Effects Model

As indicated by the forest plot, the 95% confidence interval for internal displacement does not contain 0, suggesting a statistically significant impact on depression score. Specifically, as shown in Figure 14 in the appendix, individuals who are internally displaced have, on average, a depression score 0.42 units higher than those who are not internally displaced, holding all other variables constant.

Other significant variables associated with depression score include the Russian effect, the “no answer” category for drug use, city variables (compared to the baseline of Rivne), and daily alcohol use. Notably:

- **Russian Effect:** A one-unit increase in the Russian effect is associated with a 1.60 unit decrease in depression score. This result may seem counterintuitive initially but aligns with the coding of the Russian effect variable, where negative values indicate a higher negative impact from the Russian invasion, thus leading to higher depression scores.

- **Alcohol Use:** Daily alcohol users have, on average, a depression score 1.38 units higher than non-drinkers, when holding all else constant.
- **Extreme Stigma:** Individuals experiencing extreme stigma have an average depression score 1.18 units higher than those who have not experienced extreme stigma.

Interestingly, the age and income variables have very narrow confidence intervals centered around zero. The narrowness of the confidence intervals is likely due to a discrepancy in the unit values of the age, income, and depression score variables. Since age and income have not been transformed, a one unit increase in age is a one year increase, and a one unit increase in income is one hryvnia, neither of which are likely to make a large impact on someone's depression score. However, the reason that income is not statistically significant in this study is currently unclear. Additionally, the effect sizes for the city variables are notably large. This is partly due to Rivne being used as the baseline, given its lower average depression score. However, the substantial effect sizes observed for other cities, especially considering Rivne's more rural and potentially less progressive context, remain unexpected.

Logistic Regression

Figure 8 displays the forest plot for the RDS-adjusted logistic regression model. The color palette used is consistent with the linear regression plot, with significant variables highlighted in red and insignificant variables in black.

In the logistic regression model, internal displacement status is now considered insignificant because the confidence interval includes the value of 1. This change is likely due to the logistic regression coefficient representing the effect on the probability of exceeding the clinical depression threshold, rather than a unit increase in the depression score, which affects the magnitude of the coefficients.

Noteworthy variables in the logistic regression model include:

- **Extreme Stigma:** The odds of developing clinical depression nearly double for individuals experiencing extreme stigma.
- **Military Experience:** Similarly, individuals with military experience have nearly double the odds of developing clinical depression.

- **Experience of Threats and Other Violence:** The odds of developing clinical depression more than double for individuals who have experienced threats and other forms of violence.

Additionally, a comparison with the fixed effects model shown in Figure 13 in the appendix reveals that drug use within the last 12 months has become insignificant. The confidence intervals for predictors have also widened. This is attributed to the incorporation of random effects to account for dependent observations, which reduces the effective independent sample size and subsequently decreases statistical power.

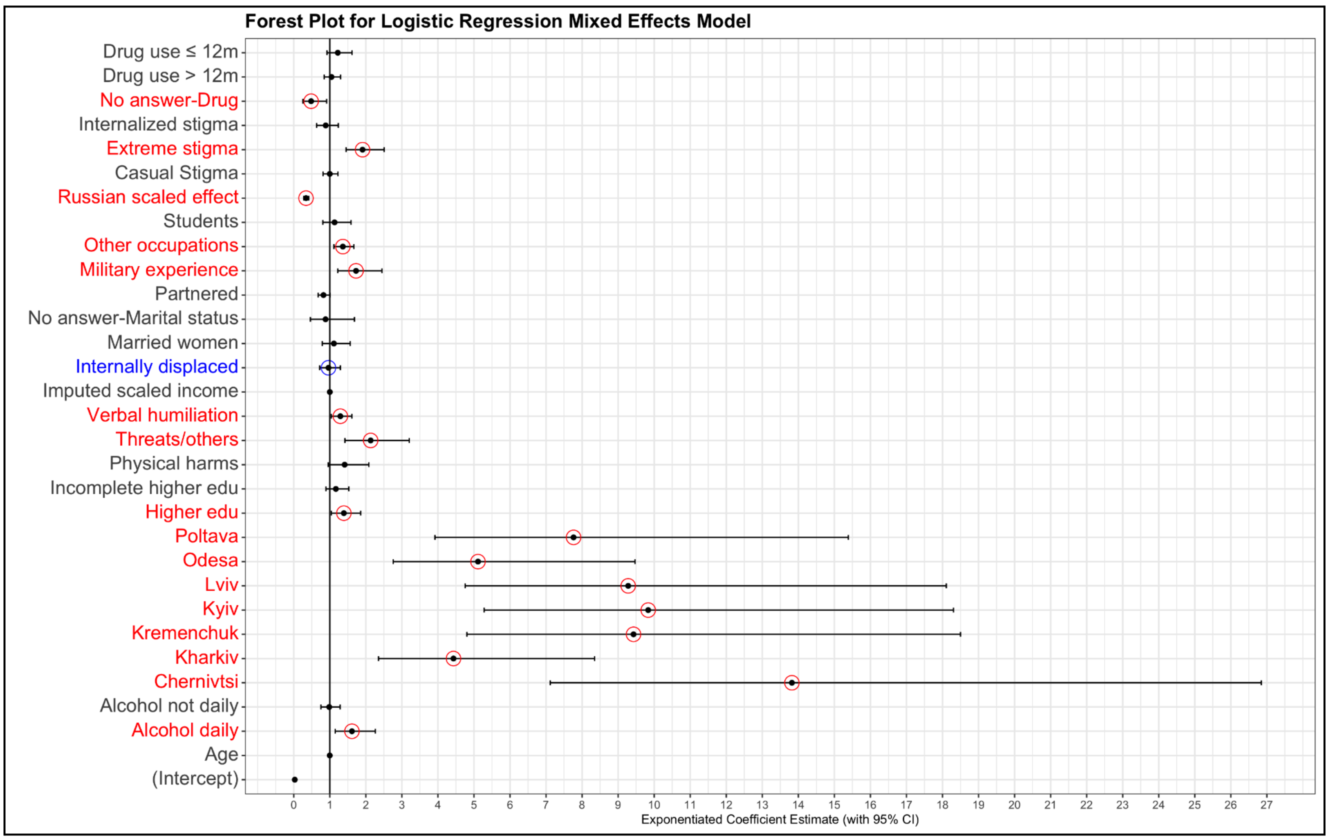

Figure 9. Forest Plot for Logistic Mixed Effects Model

DISCUSSION

The primary objective of this study was to analyze the impact of internal displacement on the mental health outcomes of sexual minority men in Ukraine following the Russian invasion. Our focus was on cisgender men who have sex with men (MSM) over the age of 14 in Ukraine—a population with limited resources and often overlooked mental health needs. The ongoing legal challenges surrounding same-sex marriage in Ukraine further highlight the importance of addressing this population's mental health.

Our findings reveal a nuanced relationship between internal displacement and mental health outcomes among MSM in Ukraine. Linear regression analysis demonstrated that internal displacement has a statistically significant association with increased depression severity, with displaced individuals showing an average depression score 0.42 units higher than non-displaced individuals, controlling for other variables. Other factors significantly associated with higher depression scores included extreme stigma, daily alcohol use, and certain city effects, with Rivne serving as the baseline for comparison. Interestingly, a variable capturing the "Russian effect" was associated with lower depression scores, a result explained by its coding, where negative values reflect greater adverse impact from the invasion.

In contrast, logistic regression analysis found that internal displacement was not significantly associated with exceeding the clinical depression threshold, likely due to the difference in how logistic regression models probability rather than score increments. However, other variables, such as extreme stigma, military experience, and experiencing threats or violence, were significantly associated with increased odds of clinical depression. These findings underline the importance of addressing intersecting stressors beyond displacement, such as stigma and exposure to violence, to mitigate mental health challenges in this population.

Interestingly, income was not found to be a statistically significant predictor of depression in this study, a finding that remains unexplained. Prior research has often shown income to be inversely associated with depression, with higher income linked to lower depression risk. This discrepancy may be due to the limited variation in income among participants or the social and economic instability caused by the invasion, which could weaken the protective effect of income. Further research is needed to explore whether the disrupted socio-economic context of Ukraine neutralizes the usual relationship between income and mental health.

Finally, the logistic regression model revealed wider confidence intervals for predictors, attributed to the use of random effects, which reduced the effective sample size. This highlights the complexity of accounting for the respondent-driven sampling design while interpreting results.

One notable limitation of this study is the potential for response bias inherent in survey-based research. Participants may not always respond truthfully, either intentionally or unintentionally, and some questions may be misinterpreted or ignored. The prevalence of non-responses to certain questions also impacts the study's results. Furthermore, the use of respondent-driven sampling (RDS) introduces challenges in accounting for dependence between observations. Since all participants beyond the initial seeds were recruited through their social networks, this design assumes that everyone has a social network. This could potentially limit the perceived effect size of internal displacement, as one might expect that displacement could lead to increased social isolation.

Future research could explore several avenues based on our findings. The "city" variable, which was highly significant in all models, suggests a substantial impact of location on depression scores. Investigating the effects of city-specific factors in greater detail could provide valuable insights. Additionally, expanding the study to include measures of anxiety and PTSD could offer a more comprehensive understanding of mental health outcomes. HIV prevalence, initially of interest but omitted due to data limitations, could be a compelling variable to include in future research, either as an additional predictor or as an outcome variable.

APPENDIX

Table 1 Cont'd

	Internally Displaced (N=315)	Not Displaced (N=3429)	Overall (N=3744)
Education			
Up to Secondary Education Complete	45 (14.3%)	440 (12.8%)	485 (13.0%)
Complete Higher Education	129 (41.0%)	1472 (42.9%)	1601 (42.8%)
Incomplete/Basic Higher Education	141 (44.8%)	1517 (44.2%)	1658 (44.3%)
Prior Military Experience			
No	290 (92.1%)	3242 (94.5%)	3532 (94.3%)
Yes	25 (7.9%)	187 (5.5%)	212 (5.7%)
Occupation			
Permanent job	117 (37.1%)	2076 (60.5%)	2193 (58.6%)
Other	174 (55.2%)	1059 (30.9%)	1233 (32.9%)
Student	24 (7.6%)	294 (8.6%)	318 (8.5%)
City			
Rivne	7 (2.2%)	291 (8.5%)	298 (8.0%)
Chernivtsi	18 (5.7%)	247 (7.2%)	265 (7.1%)
Kharkiv	65 (20.6%)	719 (21.0%)	784 (20.9%)
Kremenchuk	36 (11.4%)	232 (6.8%)	268 (7.2%)
Kyiv	68 (21.6%)	681 (19.9%)	749 (20.0%)
Lviv	21 (6.7%)	273 (8.0%)	294 (7.9%)
Odesa	85 (27.0%)	734 (21.4%)	819 (21.9%)
Poltava	15 (4.8%)	252 (7.3%)	267 (7.1%)

Figure 10. Table 1 continued, Other Variables from Dataset

Table 2

Mental health and stigma characteristics of sampled MSM, N=3744

	Internally Displaced (N=315)	Not Displaced (N=3429)	Overall (N=3744)
Depression Cutoff			
Does not meet cutoff	184 (58.4%)	2309 (67.3%)	2493 (66.6%)
Meets cutoff	131 (41.6%)	1120 (32.7%)	1251 (33.4%)
Casual Stigma			
Has experienced	97 (30.8%)	900 (26.2%)	997 (26.6%)
Has not experienced	218 (69.2%)	2529 (73.8%)	2747 (73.4%)
Extreme Stigma			
Has experienced	35 (11.1%)	373 (10.9%)	408 (10.9%)
Has not experienced	280 (88.9%)	3056 (89.1%)	3336 (89.1%)
Internalized Stigma			
Has experienced	29 (9.2%)	218 (6.4%)	247 (6.6%)
Has not experienced	286 (90.8%)	3211 (93.6%)	3497 (93.4%)

Figure 11. Table 2 of Depression and Stigma

```
Linear mixed model fit by REML ['lmerMod']
Formula: depression_scale ~ city + imputed_income_scaled + stigma_k1_to_k3_casual +
    stigma_k4_to_k6_extreme + stigma_k7_internalized + experienced_violence_category +      internally_displaced + marital_status_a3 + total_drug_use +
    alcohol_use_frequency_e3 + age_s1 + education_level + russian_effect_scaled +      military_experience + occupation + (1 | issued_to_with_seeds)
   Data: model3_data

REML criterion at convergence: 19283.4

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.2425 -0.6493 -0.0684  0.5112  4.1496

Random effects:
 Groups               Name        Variance Std.Dev.
 issued_to_with_seeds (Intercept) 1.722    1.312
 Residual                         8.517    2.918
Number of obs: 3744, groups:  issued_to_with_seeds, 1638

Fixed effects:
                                                     Estimate Std. Error t value
(Intercept)                                         1.5573761  0.4043468   3.852
cityChernivtsi                                      3.5143649  0.3667181   9.583
cityKharkiv                                         1.9314587  0.3339895   5.783
cityKremenchuk                                      2.6258899  0.3730937   7.038
cityKyiv                                            2.7713160  0.3268610   8.479
cityLviv                                            3.0000638  0.3761063   7.977
cityOdesa                                           1.3701503  0.3244399   4.223
cityPoltava                                         2.5224566  0.3785076   6.664
imputed_income_scaled                              -0.0001484  0.0001283  -1.157
stigma_k1_to_k3_casualYes                          -0.2054942  0.1344278  -1.529
stigma_k4_to_k6_extremeYes                          1.1771159  0.1847691   6.371
stigma_k7_internalizedYes                          -0.1592121  0.2170645  -0.733
experienced_violence_categoryPhysical harms         0.1011518  0.2612913   0.387
experienced_violence_categoryThreats/Other          1.0230370  0.2505060   4.084
experienced_violence_categoryVerbal humiliation     0.4561448  0.1446584   3.153
internally_displacedYes                             0.4219573  0.1925413   2.192
marital_status_a3Married_women                      0.0633184  0.2273800   0.278
marital_status_a3No_answer                          0.3672802  0.4484523   0.819
marital_status_a3Partnered                         -0.4163624  0.1228590  -3.389
total_drug_useNo Answer                            -1.0573221  0.3537231  -2.989
total_drug_useYes, I have, but more than 12 months ago -0.0822349  0.1392333  -0.591
total_drug_useYes, in the last 12 months            0.4534813  0.1853212   2.447
alcohol_use_frequency_e3Every day                   1.3806675  0.2171611   6.358
alcohol_use_frequency_e3Not every day               0.2245235  0.1668181   1.346
age_s1                                             -0.0005593  0.0075611  -0.074
education_levelComplete Higher Education            0.6537183  0.1841427   3.550
education_levelIncomplete/Basic Higher Education    0.2581170  0.1691329   1.526
russian_effect_scaled                              -1.6028918  0.1243586 -12.889
military_experienceYes                              0.9876159  0.2338478   4.223
occupationOther                                     0.3386408  0.1313168   2.579
occupationStudent                                   0.0389415  0.2160762   0.180
```

Figure 12. Linear Regression Output Table

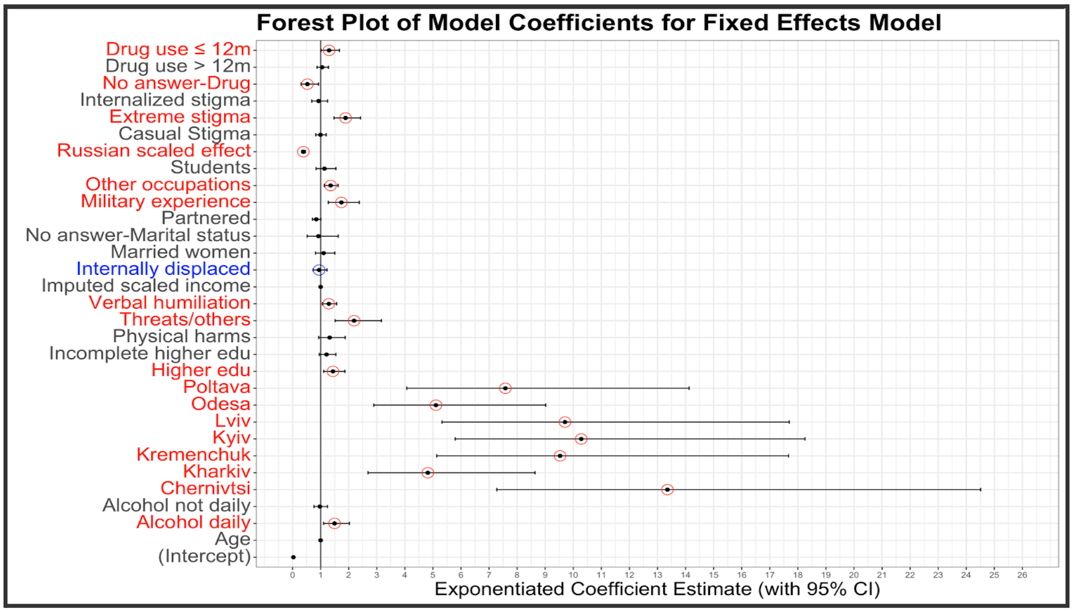

Figure 13. Forest Plot for Logistic Fixed Effects Model

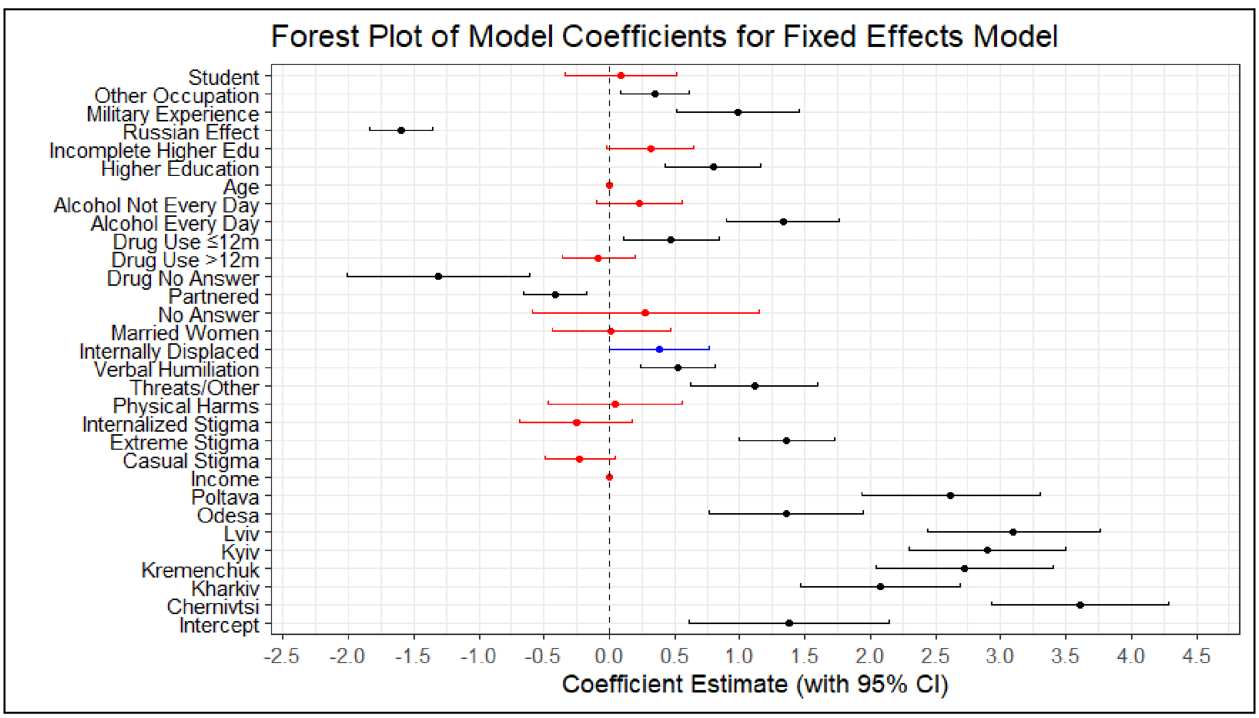

Figure 14. Forest Plot for Linear Fixed Effects Model

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