STA610 Case Study 1

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14 October, 2021

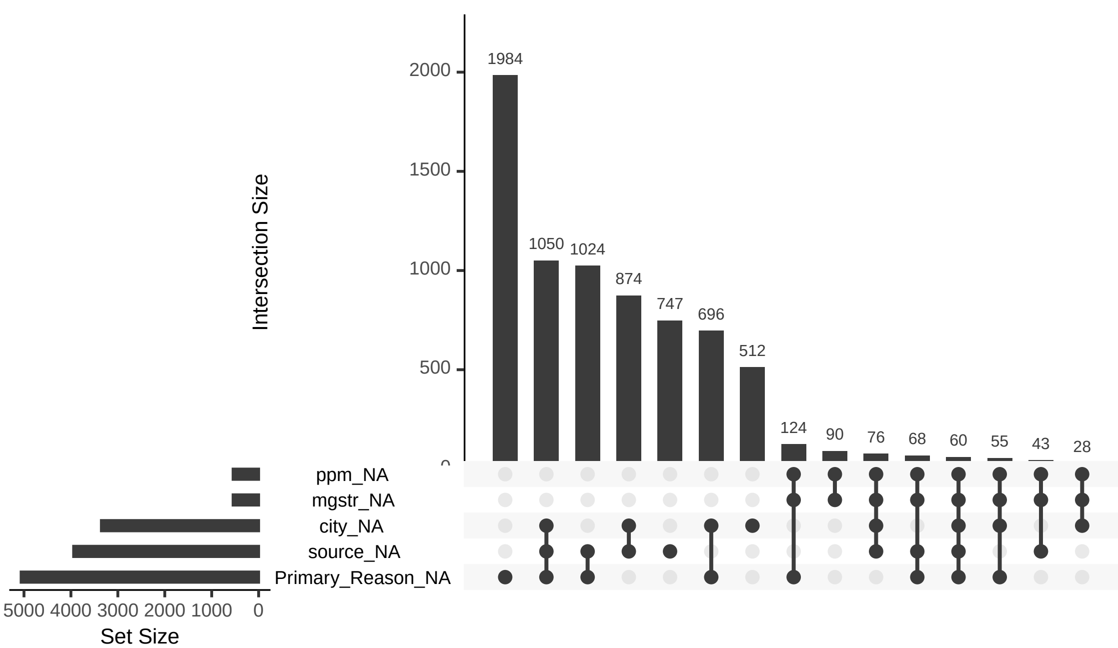
Introduction

Prescription opioid abuse plays an essential role in public health issues. The price of prescription opioids indicates the supply-demand relationship of drugs. This study case aims to explore the relationship between drugs' unit price and other factors. More specifically, our group's interest is to explore the factors related to the cost per milligram and the heterogeneity in the region. The dataset is provided by StreetRx, a reporting tool for people at large to anonymously report the price they paid or heard for diverted prescription drugs.

Our drug interest is Morphine. Morphine is used to "relieve moderate to severe pain and maybe habit-forming," especially with prolonged use (MedlinePlus).

EDA

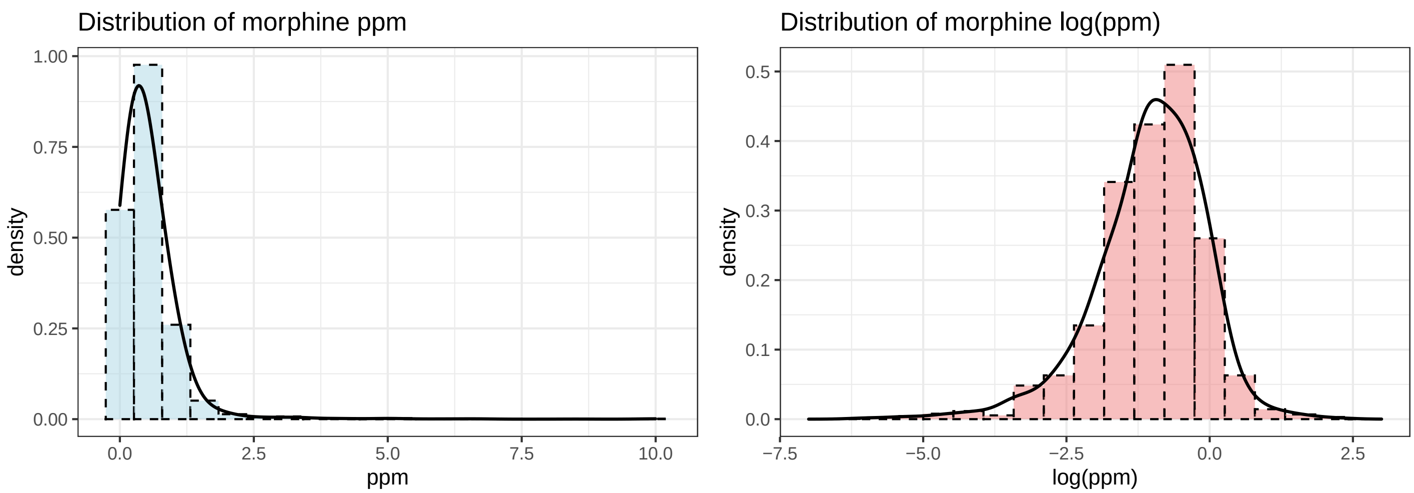
Missing Values



The dataset (Morphine) contains 9,268 observations with 13 variables. There are 13,443 empty cells (both the missing values and the blank). To maintain the statistical power and avoid bias, our group decided to recode the empty cells and "0 Reporter did not answer this question" in `Primary_Reason` (5061 in total) as "8 Prefer not to answer" and recode the empty cells in `source` (3942 in total) as "Blank" because of the high missing rates. Then, we removed other rows with missing values.

In addition, we think there is no reason that the price per milligram can be a non-positive value or values greater than 10 (may because some people input the total price by mistake). The number of the observations we have is 5,582 now.

Response Variable: Price per milligram



Whether we fit a hierarchical model or linear regression, the response variable should be normally distributed. From the histogram on the left, the distribution of `ppm` is clearly right-skewed. Since `ppm` is strictly non-negative, a log transformation may be appropriate. The distribution of `log(ppm)` is given above, and appears closer to the desired normal.

Grouping Variable: city, state, and USA_region

Since we want to analyze the heterogeneity in pricing by location, we have three choices of grouping variable, `city`, `state`, and `USA_region`.

City There are 1642 unique `city` values, and many cities have small sample size (i.e. less than 5 observations). We decide not o use `city` as the grouping variable (see appendix).

```
## [1] 1642
```

```
## [1] 52
```

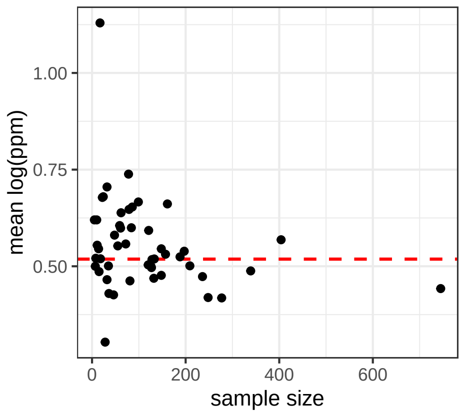
```
## [1] 5
```

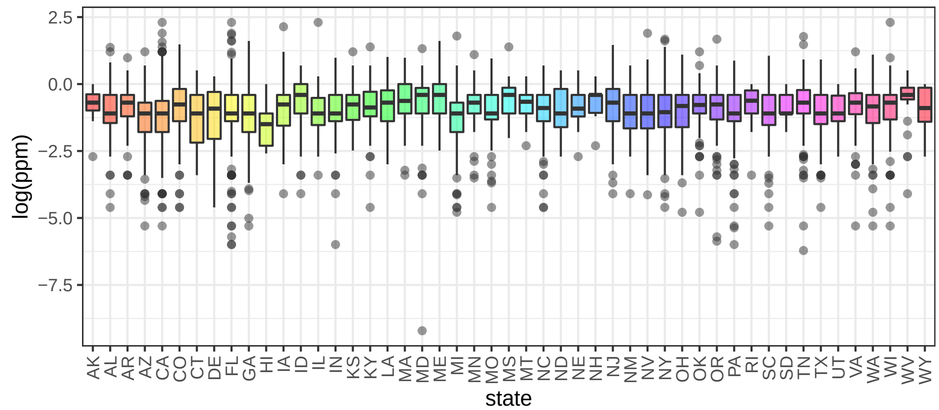
```
##  [1] Arizona        Alabama        Florida        New York       Texas
##  [6] Hawaii         Colorado       California     Pennsylvania   New Jersey
## [11] Washington, DC Oklahoma       Washington     Tennessee      Ohio
## [16] Oregon         Kentucky       North Carolina Nevada         Missouri
## [21] Illinois       Kansas         Michigan       Alaska         Georgia
## [26] Maryland       Minnesota      Arkansas       Wisconsin      Delaware
## [31] Montana        Iowa           Indiana        New Mexico     Massachusetts
## [36] Virginia       Louisiana      South Carolina Wyoming        Connecticut
## [41] Rhode Island   Maine          West Virginia  Utah           Nebraska
## [46] Vermont        Idaho          North Dakota   Mississippi    New Hampshire
## [51] South Dakota   Puerto Rico
## 52 Levels: Alabama Alaska Arizona Arkansas California Colorado ... Wyoming
```

State As for state, we examined the sample sizes in each group and decide to out filter Puerto Rico and Vermont, because they have less than 5 observations.

Table 1: 5 States with Smallest Sample Size

Puerto Rico	Vermont	North Dakota	South Dakota	Wyoming
1	3	5	7	8

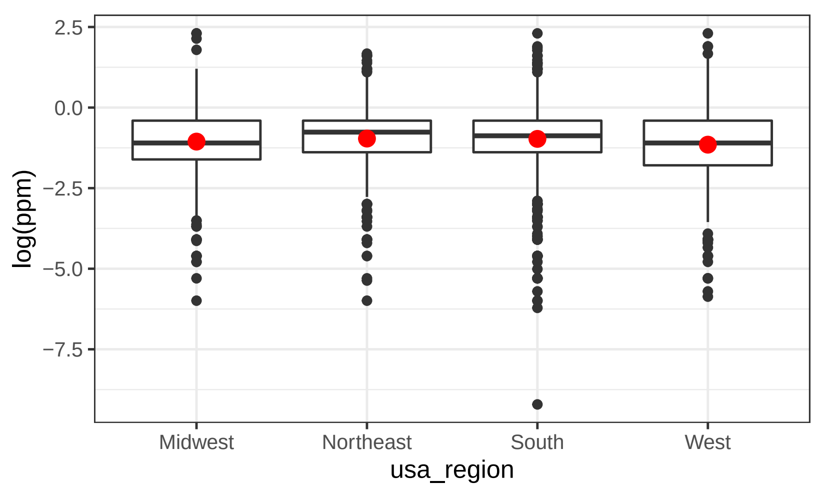




Then we inspect the state-level differences closer by plotting the group-level means agains the sample sizes. We observed that the within-state means for states with smaller sample sizes vary a lot, while the within-state means for states with higher sample sizes in general adhere more closely to the grand mean. This is conducive to the borrowing of information between states with a hierarchical model. From the above boxplot of `log(ppm)` against `state`, it is also evident that the `log(ppm)` distributions differ across states. This indicates the potential state-level differences in drug prices. Therefore, we decide to use state as our grouping variable at this stage.

Region From the boxplot we still see the `log(ppm)` distributions differ slightly across regions, though not that much as across states. We may also consider using region as the grouping variable.

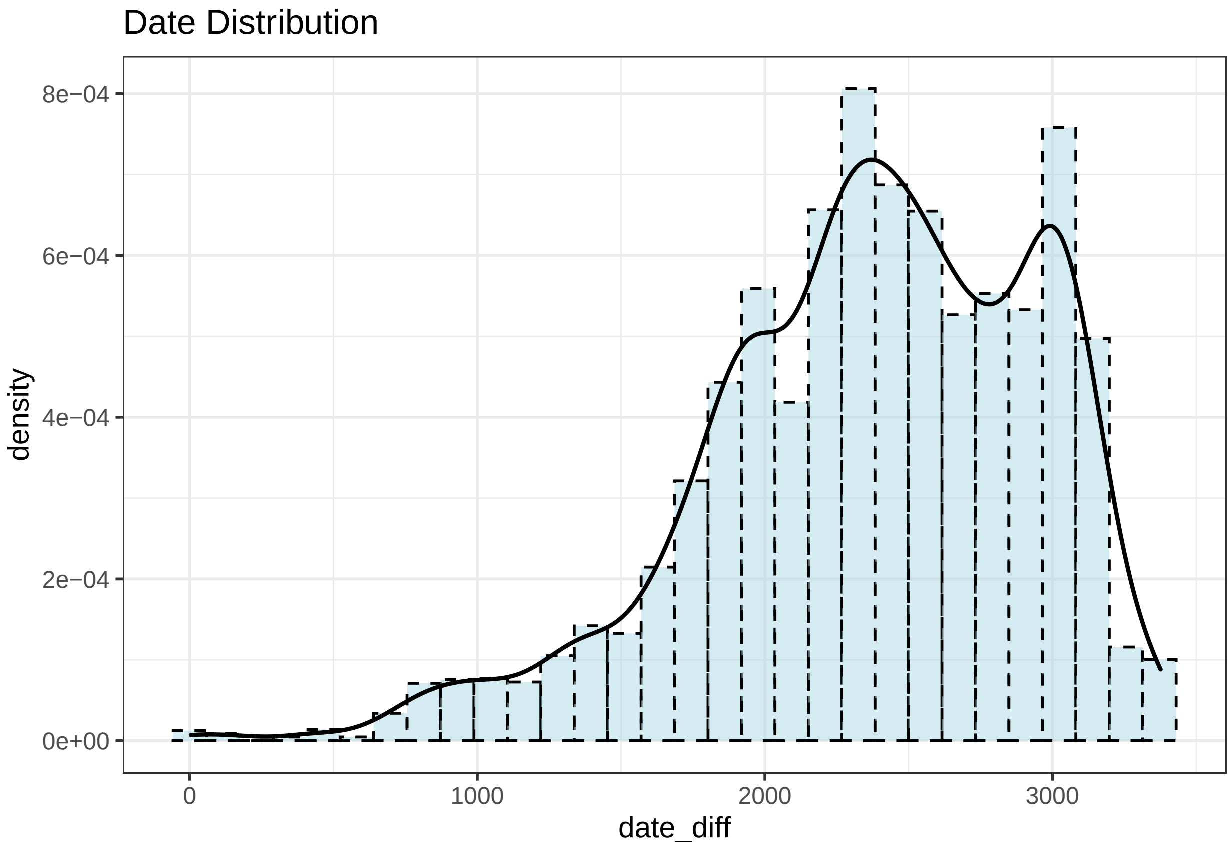
	usa_region	n	mean
1	Midwest	1168	−1.056
2	Northeast	674	−0.962
3	South	1953	−0.972
4	West	1773	−1.151

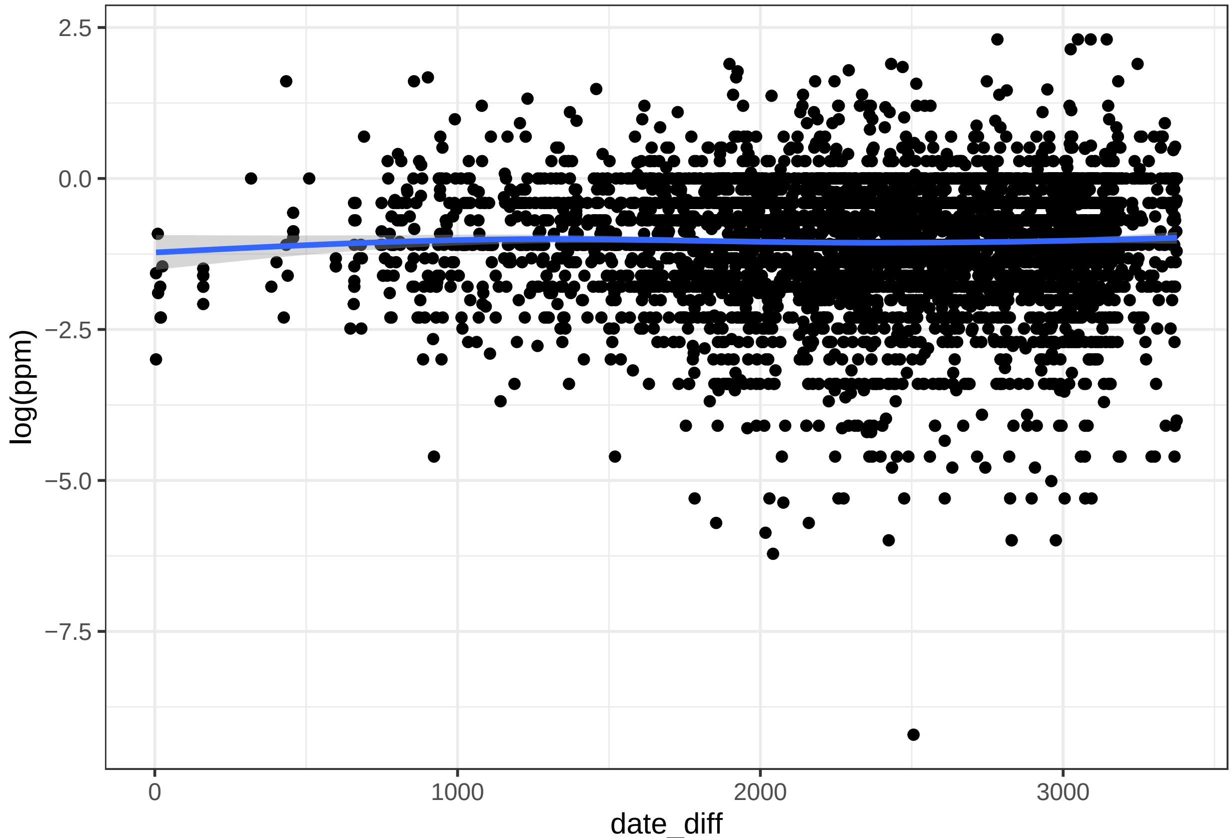


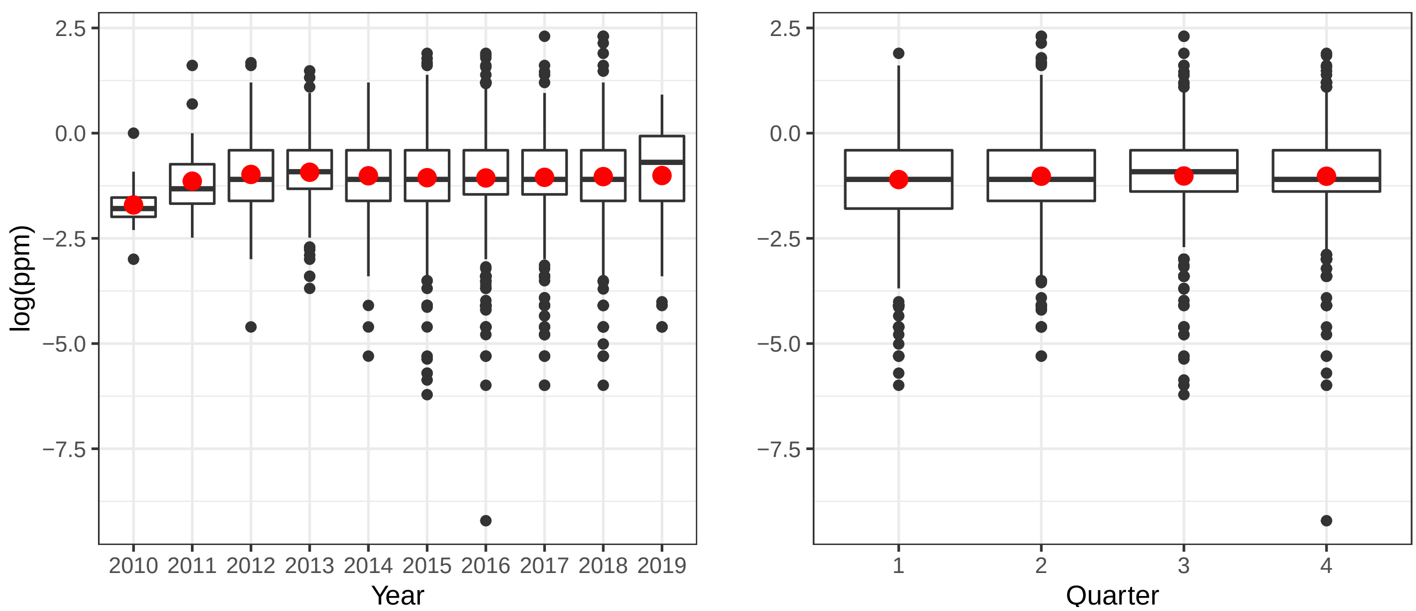
Date (price_date)

As for the `price_date`, we noticed some observations are prior to the establishment of StreetRx, which might be wrong inputs. We dropped the observations prior to 2010. For the rest observations, we came up with two ways of data cleaning on the date variable. The first choice is to choose a starting date and convert the feature as the date differences (`date_diff`) from that starting date. The second choice is to split this date variable into two components, `year` and `quarter`, so that we can explore the trend of unit drug price over time and the seasonality.

Our visualizations suggested there is no clear trend that the log value of per milligram price of morphine varies along with `date_diff`. However, for different `year` and `quarter`, the `log(ppm)` value varies a little bit (see appendix).

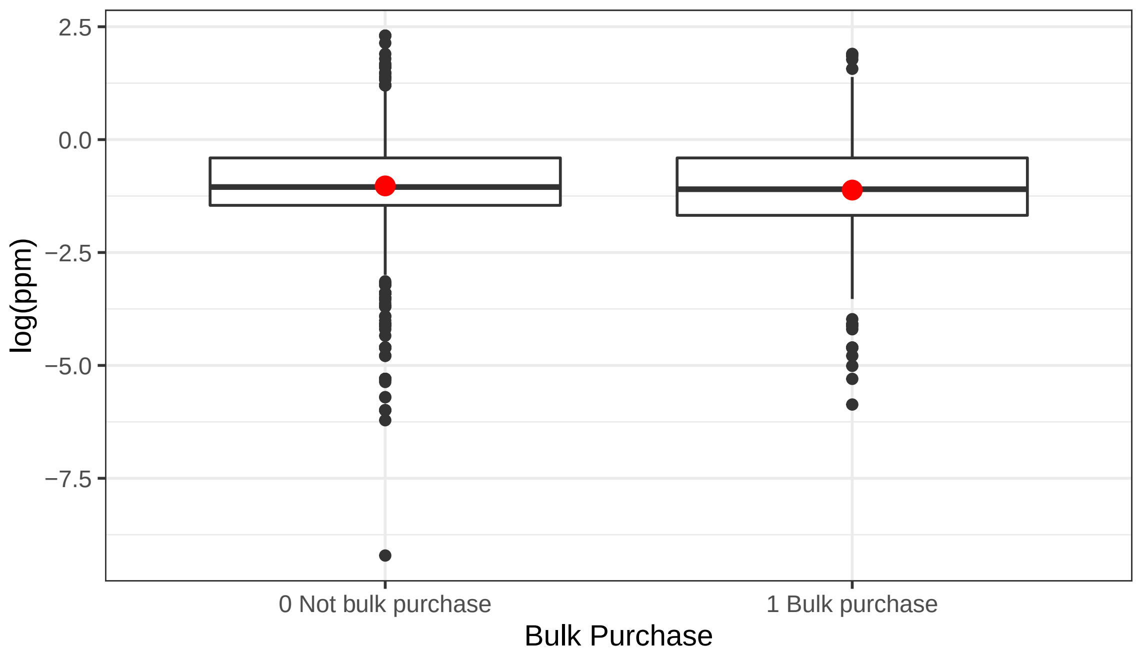






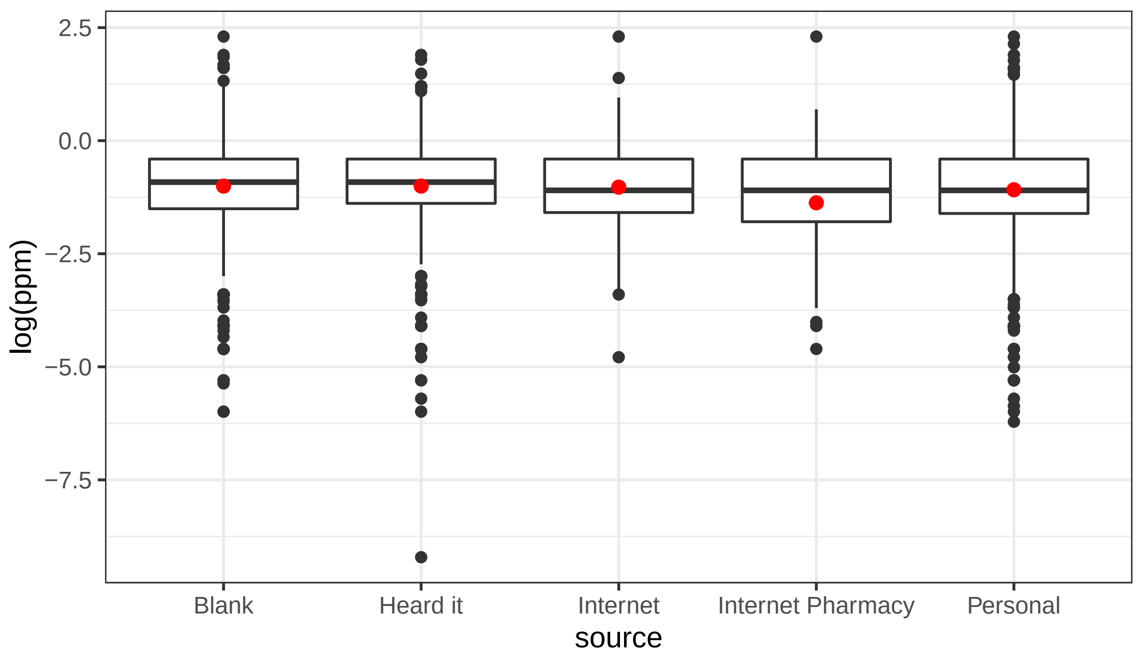
Bulk_purchase

There is no need to conduct any data cleaning on `bulk_purchase`. And from the boxplot (see appendix), there is a slight trend that the drug price may be lower if purchased in bulk. Therefore, `bulk_purchase` might be a potential predictor.



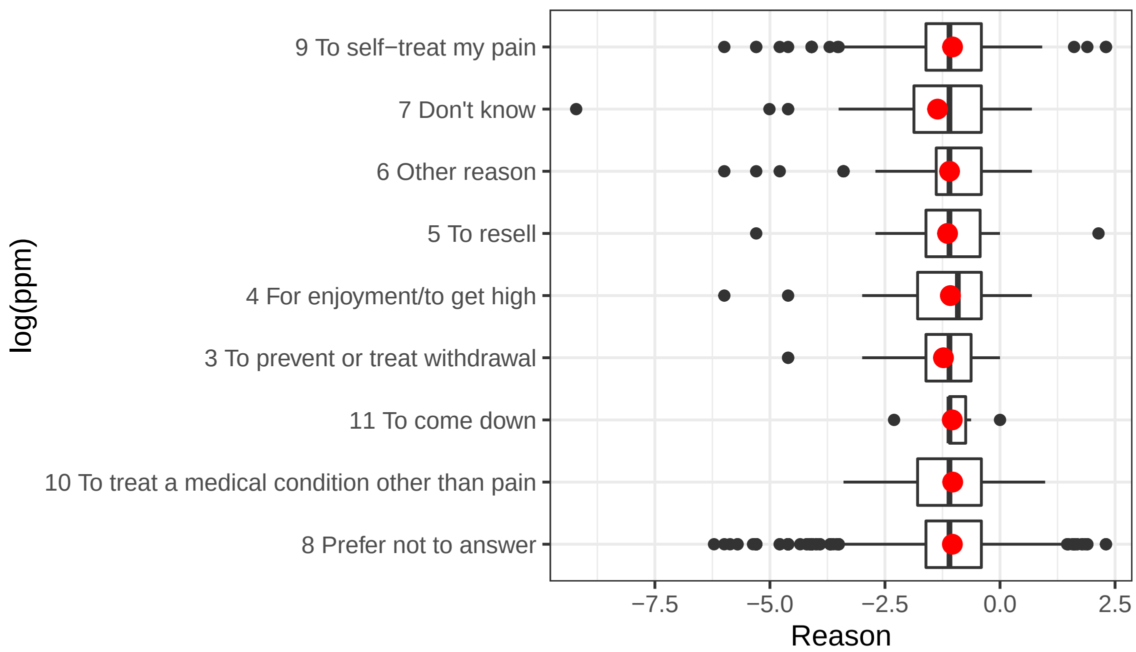
Source

We have recoded the missing value as "Blank" and the name of websites as "Internet". And we dropped the only observation whose `source` is "Drug Forum". From the boxplot, we see the `log(ppm)` value varies among different sources (see appendix).



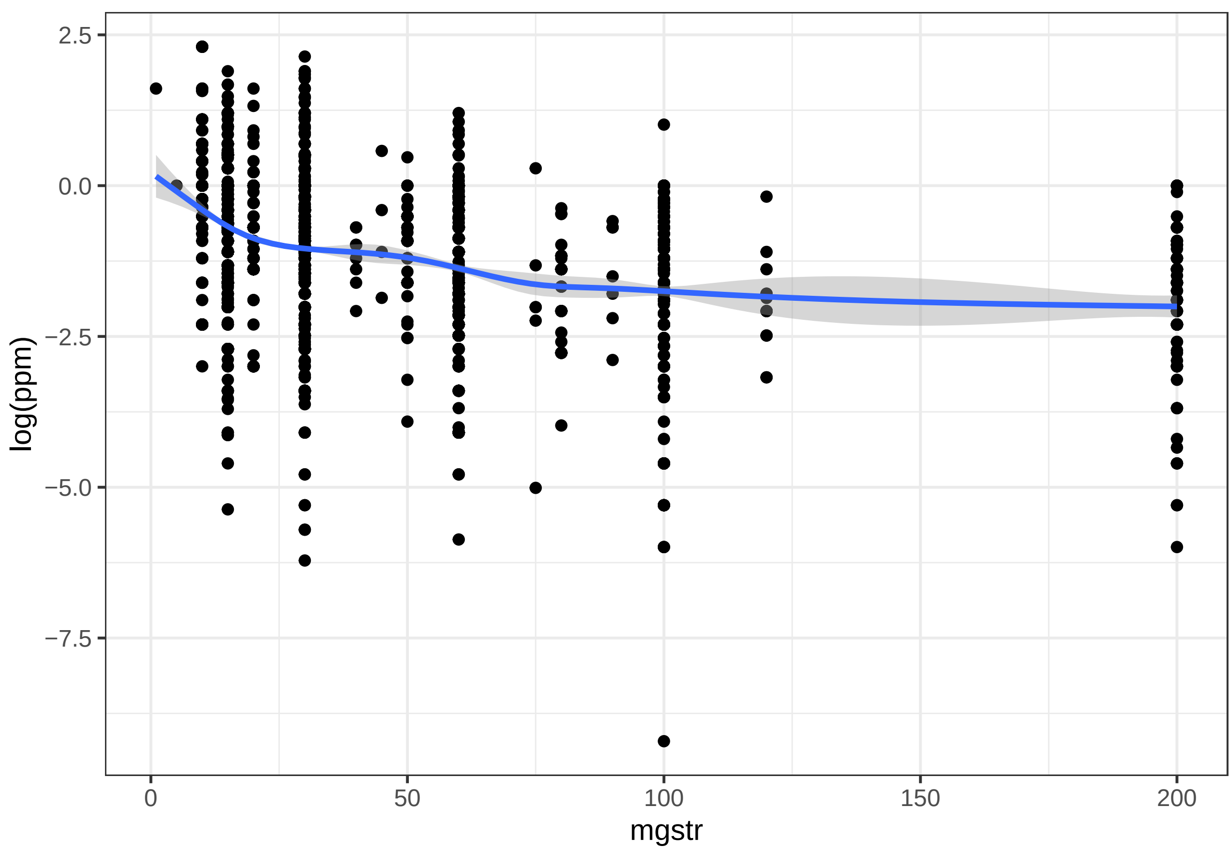
Primary Reason

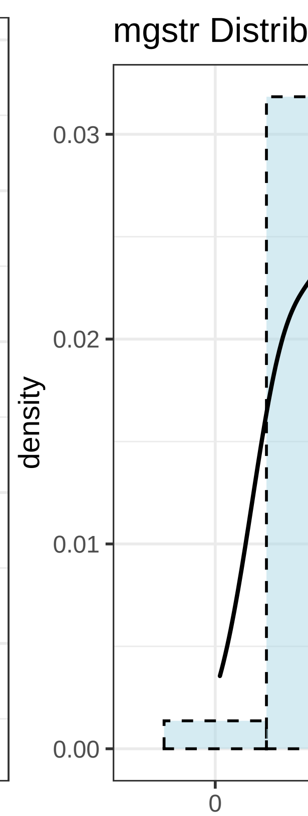
For `primary_reason`, we have converted the empty cells and "0 Reporter did not answer this question" to "8 Prefer not to answer". The `log(ppm)` value varies a lot among different reasons for purchasing the morphine (see appendix).



Dosage Strength (mgstr)

From the scatter plot of `log(ppm)` against `mgstr`, there is a slight trend that the larger the dosage strength, the smaller the per milligram price. We have also noticed that `mgstr` only takes 16 discrete values. Therefore, we consider to label it into 4 levels (“low”, “medium”, “medium high”, and “high”) based on the 0.25, 0.5, and 0.75 quantiles of `mgstr`.





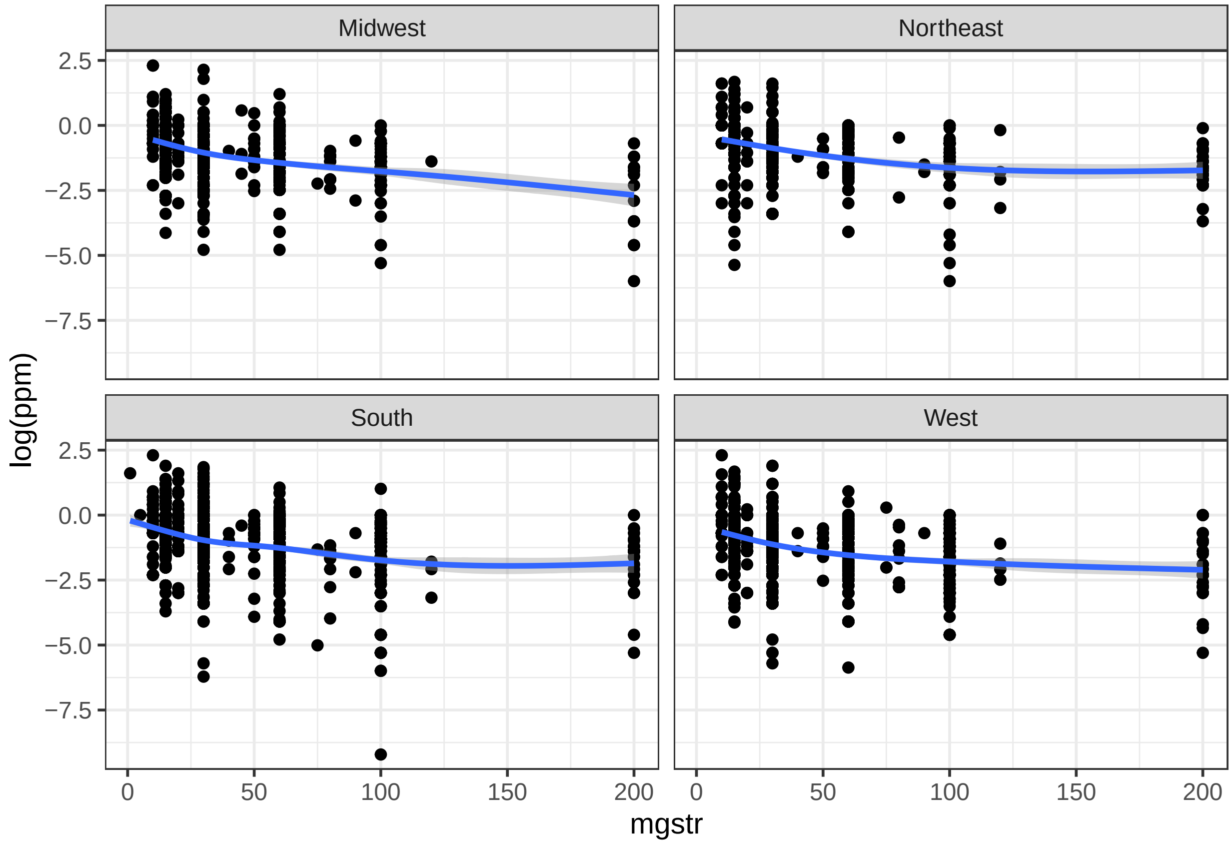
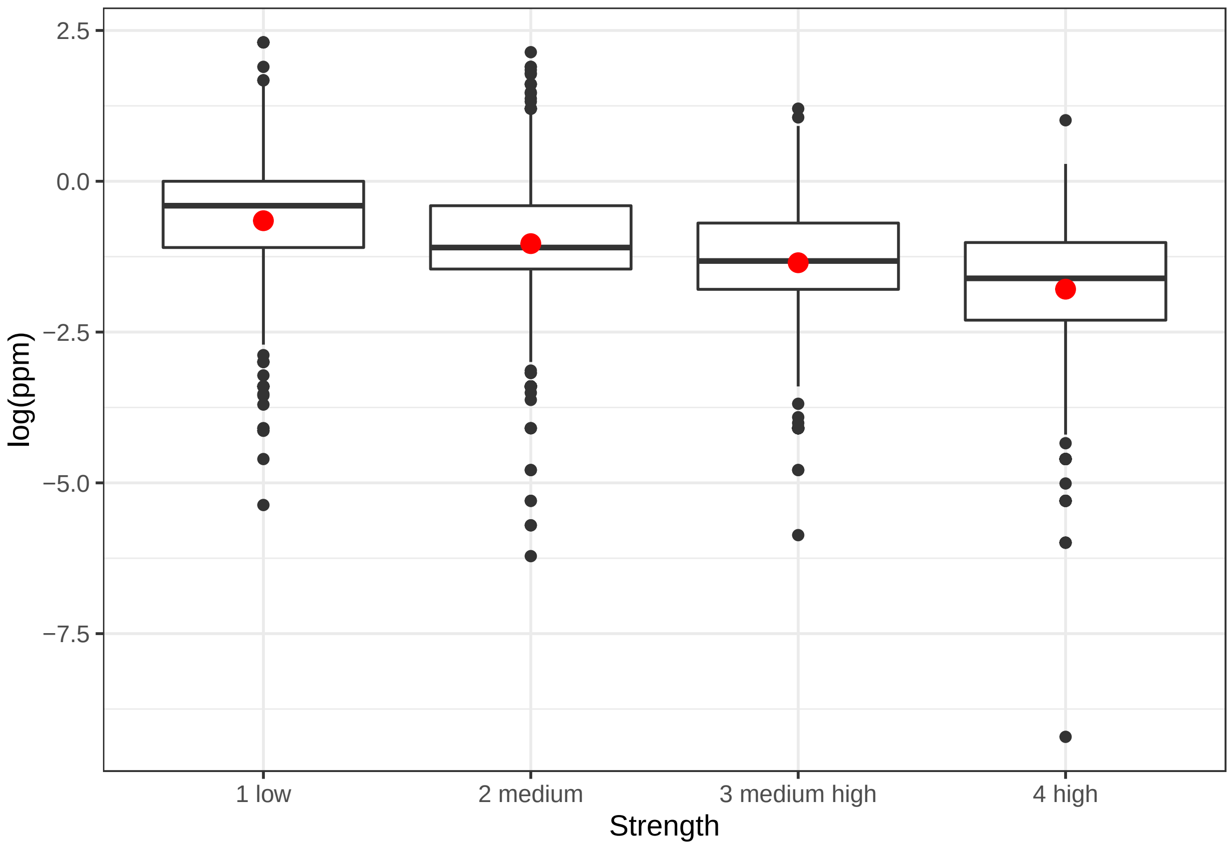


Table 2: Sample Size for mgstr Levels

1	5	10	15	20	30	40	45	50	60	75	80	90	100	120	200
1	1	166	1607	120	2192	8	4	51	819	6	34	7	446	14	92

	mgstr
25%	15
50%	30
75%	60



From the boxplot, we see a more clear trend that the `log(ppm)` values decrease as the dosage strength increase.

Model

Model Selection

Our research question is to investigate factors related to the per milligram price of morphine and explore heterogeneity in pricing by location. As discussed in the EDA part, we do not have enough data to estimate the effects in city-level. Meanwhile, the drug prices do not seem to change significantly across regions. Thus, state is a more preferable choice of accounting for location. Since many states have relatively small sample sizes, a hierarchical model allows us to borrow information across states.

Comparing three full models with different grouping variables, the AIC and BIC score also suggest choosing `state` as the group-level variable.

Grouping	AIC	BIC
City	15408.58	15428.46
State	15354.88	15374.76
Region	15400.48	15420.36

Grouping	AIC	BIC
City	14608.22	14820.21
State	14556.78	14768.77
Region	14590.59	14802.58

Our baseline model incorporates only the state-level random intercepts. For other individual level predictors, we add one variable to the model each time, and use both the Likelihood Ratio test and the BIC score to determine whether it should be added. The **LRT** is designed for nested models. While the BIC score considers both the likelihood and the model complexity, and gives a more general sense of model performance. The table below displays the results of model selection.

Our final model incorporates the grouping variable `state` and the individual level predictors `mgstr` (recoded as 4 levels), `bulk_purchase`, `quarter`, `source`. We also tried to using the full model as a starting point, and did stepwise backward elimination. The results agrees with our final model (See appendix).

bic <- up xiao +

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: log(ppm) ~ (1 | state)
##    Data: morph_data
##
##      AIC      BIC   logLik deviance df.resid
##  15354.9  15374.8  -7674.4  15348.9     5565
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -8.6783 -0.5560  0.1072  0.6427  3.7101
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  state    (Intercept) 0.01772  0.1331
##  Residual             0.91415  0.9561
## Number of obs: 5568, groups:  state, 50
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)  -0.9870     0.0255 42.0677  -38.71   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## Data: morph_data
## Models:
## modelb: log(ppm) ~ mgstr2 + (1 | state)
## modelc: log(ppm) ~ mgstr2 + bulk_purchase + (1 | state)
##        npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## modelb    6 14576 14616 -7281.9    14564
## modelc    7 14564 14610 -7274.8    14550 14.247  1  0.0001603 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## Data: morph_data
## Models:
## modelc: log(ppm) ~ mgstr2 + bulk_purchase + (1 | state)
## modeld: log(ppm) ~ year + mgstr2 + bulk_purchase + (1 | state)
##        npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## modelc    7 14564 14610 -7274.8    14550
## modeld   16 14567 14673 -7267.6    14535 14.428  9     0.1079
```

```
## Data: morph_data
```

```
## Models:
## modelc: log(ppm) ~ mgstr2 + bulk_purchase + (1 | state)
## modele: log(ppm) ~ quarter + mgstr2 + bulk_purchase + (1 | state)
##        npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## modelc    7 14564 14610 -7274.8    14550
## modele   10 14560 14626 -7270.0    14540   9.7  3     0.0213 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

## Data: morph_data
## Models:
## modelc: log(ppm) ~ mgstr2 + bulk_purchase + (1 | state)
## modelf: log(ppm) ~ date_diff + mgstr2 + bulk_purchase + (1 | state)
##        npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## modelc    7 14564 14610 -7274.8    14550
## modelf    8 14564 14617 -7273.9    14548 1.7621  1     0.1844

## Data: morph_data
## Models:
## modele: log(ppm) ~ quarter + mgstr2 + bulk_purchase + (1 | state)
## modelg: log(ppm) ~ quarter + source + mgstr2 + bulk_purchase + (1 | state)
##        npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## modele   10 14560 14626 -7270.0    14540
## modelg   14 14549 14641 -7260.4    14521 19.237  4  0.0007061 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

## Data: morph_data
## Models:
## modelg: log(ppm) ~ quarter + source + mgstr2 + bulk_purchase + (1 | state)
## modelh: log(ppm) ~ quarter + primary_reason + mgstr2 + bulk_purchase + (1 | state)
##        npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## modelg   14 14549 14641 -7260.4    14521
## modelh   18 14562 14681 -7263.1    14526     0  4          1

## Backward reduced random-effect table:
##
##             Eliminated npar  logLik   AIC    LRT Df Pr(>Chisq)
## <none>                   32 -7246.4 14557
## (1 | state)          0   31 -7279.8 14622 66.805  1  2.997e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Backward reduced fixed-effect table:
## Degrees of freedom method: Satterthwaite
##
##                Eliminated Sum Sq Mean Sq NumDF  DenDF  F value    Pr(>F)
## date_diff               1   0.01   0.005     1 5559.0   0.0067 0.9345712
## year                    2  10.55   1.172     9 5556.2   1.4951 0.1433668
## primary_reason          3  11.40   1.424     8 5550.9   1.8132 0.0697607 .
## quarter                 0   7.60   2.533     3 5553.1   3.2157 0.0218925 *
```

```
## mgstr2                   0 676.70 225.567     3 5553.1 286.3423 < 2.2e-16 ***
## bulk_purchase            0  11.03  11.032     1 5559.5  14.0040 0.0001843 ***
## source                   0  15.18   3.796     4 5555.1   4.8189 0.0007032 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Model found:
## log(ppm) ~ quarter + mgstr2 + bulk_purchase + source + (1 | state)
```

```
## [1] 0.0213
```

Model	LRT.p.value	BIC
(1|state)		15374.76
(1|state) + mgstr2	0	14615.63
(1|state) + mgstr2 + bulk_purchase	2e-04	14610.01
(1|state) + mgstr2 + bulk_purchase + year	0.1079	14673.21
(1|state) + mgstr2 + bulk_purchase + quarter	0.0213	14626.19
(1|state) + mgstr2 + bulk_purchase + date_diff	0.1844	14616.87
(1|state) + mgstr2 + bulk_purchase + quarter + source	7e-04	14641.45
(1|state) + mgstr2 + bulk_purchase + quarter + source + primary_reason	1	14681.42

```
## Data: morph_data
## Models:
## modelg: log(ppm) ~ quarter + source + mgstr2 + bulk_purchase + (1 | state)
## modelgg: log(ppm) ~ quarter + source + mgstr2 + bulk_purchase + (1 | state) + quarter * bulk_purc
##         npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## modelg    14 14549 14641 -7260.4    14521
## modelgg   17 14549 14662 -7257.6    14515 5.4786  3     0.1399
```

```
## Data: morph_data
## Models:
## modelg: log(ppm) ~ quarter + source + mgstr2 + bulk_purchase + (1 | state)
## modelggg: log(ppm) ~ quarter + source + mgstr2 + bulk_purchase + (1 | state) + quarter * mgstr2
##          npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## modelg     14 14549 14641 -7260.4    14521
## modelggg   23 14558 14711 -7256.2    14512 8.3905  9     0.4953
```

```
## Data: morph_data
## Models:
## modelg: log(ppm) ~ quarter + source + mgstr2 + bulk_purchase + (1 | state)
## modelgggg: log(ppm) ~ quarter + source + mgstr2 + bulk_purchase + (1 | state) + bulk_purchase * m
##           npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## modelg      14 14549 14641 -7260.4    14521
## modelgggg   17 14549 14662 -7257.6    14515 5.402  3     0.1446
```

```
## Data: morph_data
## Models:
## modelg: log(ppm) ~ quarter + source + mgstr2 + bulk_purchase + (1 | state)
## modelggggg: log(ppm) ~ quarter + source + mgstr2 + bulk_purchase + (1 | state) + quarter * source
##            npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
```

```
## modelg       14 14549 14641 -7260.4    14521
## modelgggggg  26 14542 14714 -7244.8    14490 31.137 12   0.001877 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

## Data: morph_data
## Models:
## modelg: log(ppm) ~ quarter + source + mgstr2 + bulk_purchase + (1 | state)
## modelggggggg: log(ppm) ~ quarter + source + mgstr2 + bulk_purchase + (1 | state) + bulk_purchase *
##              npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## modelg         14 14549 14641 -7260.4    14521
## modelggggggg   18 14552 14672 -7258.2    14516 4.3824  4     0.3567

## Data: morph_data
## Models:
## modelg: log(ppm) ~ quarter + source + mgstr2 + bulk_purchase + (1 | state)
## modelgggggggg: log(ppm) ~ quarter + source + mgstr2 + bulk_purchase + (1 | state) + source * mgstr
##               npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## modelg          14 14549 14641 -7260.4    14521
## modelgggggggg   26 14566 14738 -7257.1    14514 6.4869 12     0.8896
```

final model

Our final model is

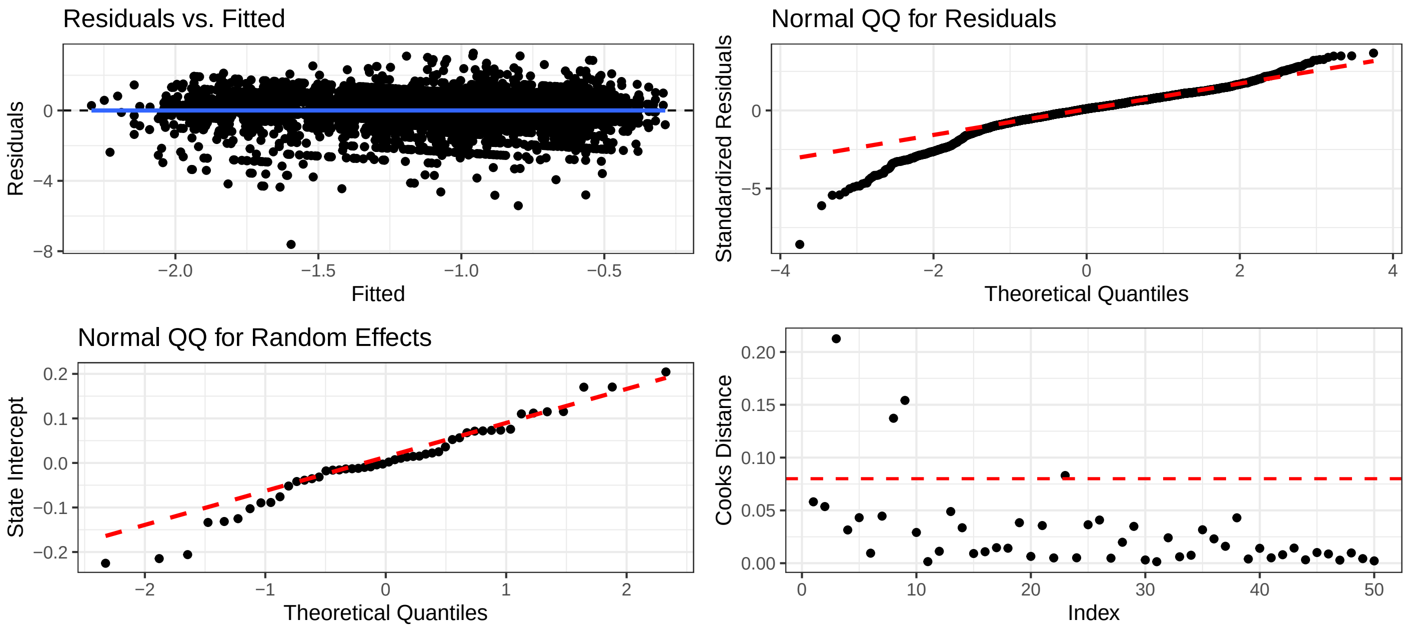
$$log(y_{ij}) = \beta_0 + b_{0j} + \beta_1 M_{ij} + \beta_2 B_{ij} + \beta_3 Q_{ij} + \beta_4 S_{ij} + \epsilon_{ij}$$

$$b_{0j} \sim \mathcal{N}(0, \tau^2) \perp \epsilon_{ij} \overset{iid}{\sim} \mathcal{N}(0, \sigma^2)$$

The response variable and predictors are defined as:

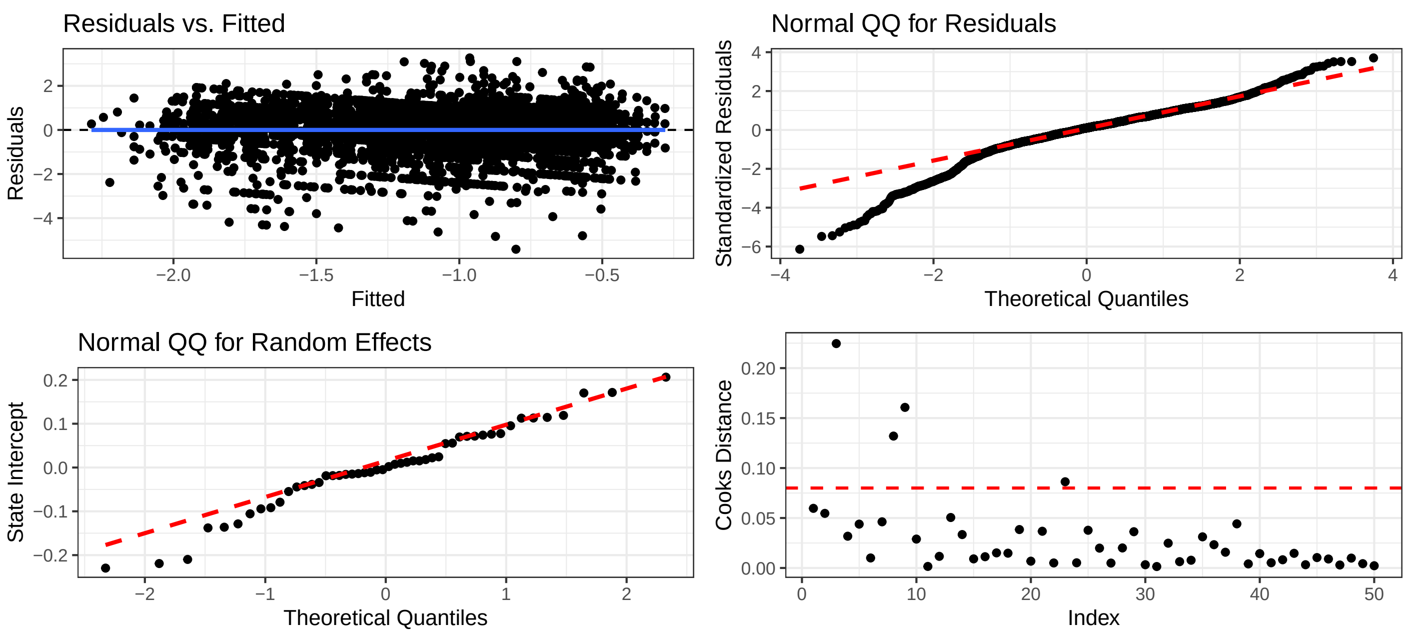
- $y_i j$: Per miligram price of morphine for individual i in state j
- M_{ij}: Dosage strength in mg of the units purchased, labeled into 4 levels
- B_{ij}: Bulk purchase, an indicator for whether 10+ units were purchased at once
- Q_{ij}: Quarter of the reported purchase
- S_{ij}: Source of information (report purchases they did not personally make)

Model Diagnostics

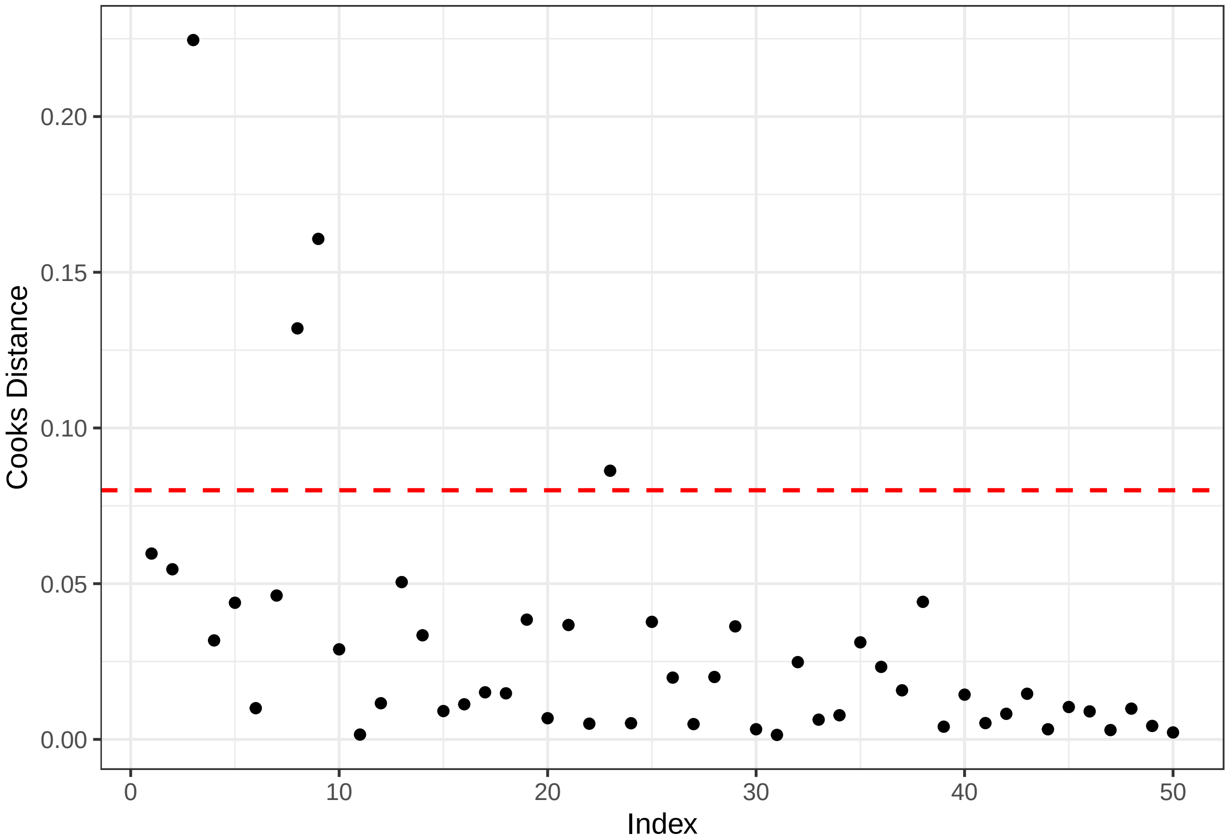


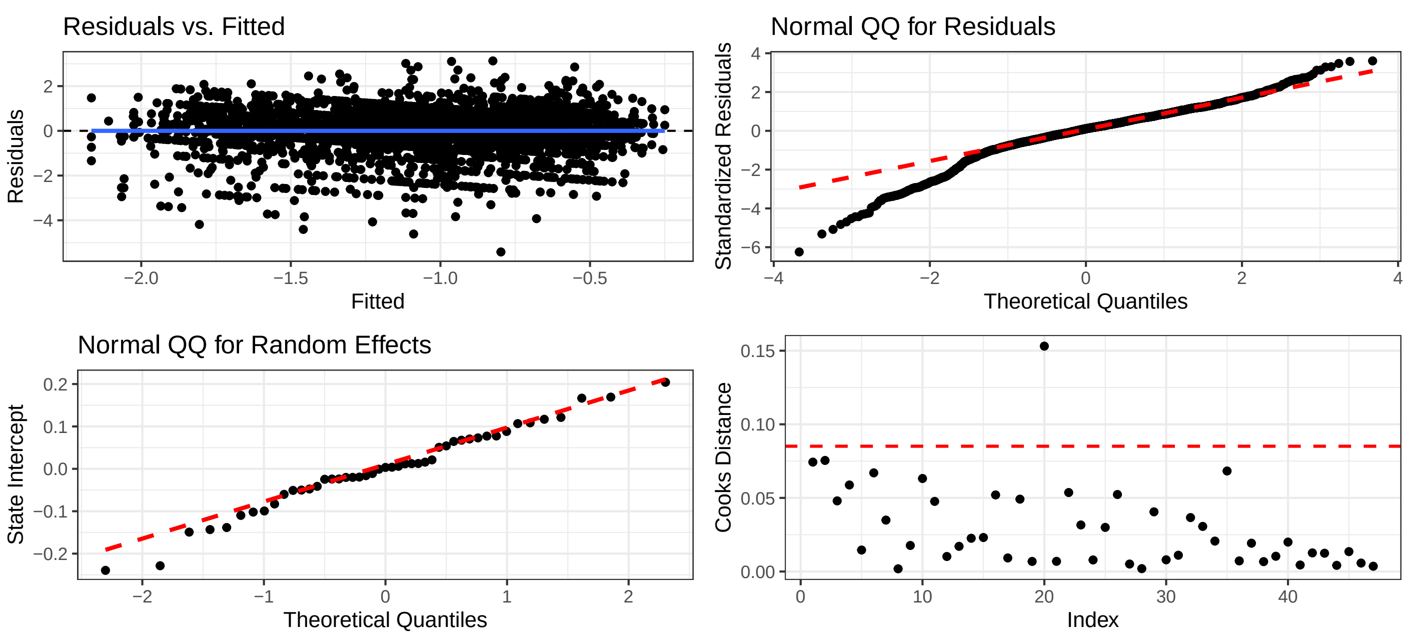
- `Residual vs. Fitted plot`: The residuals spread equally around the horizontal line, indicating there is no non-linear relationships.
- `Normal QQ plot for residuals`: The normality assumption is slightly met since our residuals adhere around the diagonal line but have heavy tails on both sides. We also have one data point deviate severely from the diagonal line.
- `Normal QQ plot for Random Effects`: We can accept the random effects are normally distributed. But we still have three outliers.
- `Cook's Distance`: We have 3 highly influential states (Florida, Pennsylvania, and California) whose Cook's distance exceeds the $\frac{4}{n}$ cutoff, where n denotes the number of states.

To address the violated assumptions, we tried to remove the data point with the lowest residual and the influential groups. However, this did not improve the normality of residuals very much (see appendix). Moreover, the influential states have considerable sample size (1382 observations). Therefore, we decide only drop the individual level outlier but keep all the groups.



State	Cook's Distance
Florida	0.2246
California	0.1320
Pennsylvania	0.1607
Michigan	0.0863





	Estimate	exp(Estimate)	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-0.6346	0.5301	0.0393	296.1819	-16.1290	0.0000
quarter2	0.0854	1.0891	0.0321	5550.5948	2.6578	0.0079
quarter3	0.0841	1.0877	0.0332	5555.0726	2.5349	0.0113
quarter4	0.0844	1.0881	0.0341	5551.1650	2.4759	0.0133
sourceHeard it	0.0633	1.0653	0.0335	5556.1197	1.8904	0.0588
sourceInternet	-0.0041	0.9959	0.0625	5555.5822	-0.0656	0.9477
sourceInternet Pharmacy	-0.3227	0.7242	0.1016	5548.9347	-3.1743	0.0015
sourcePersonal	-0.0398	0.9609	0.0281	5557.7473	-1.4157	0.1569
mgstr22 medium	-0.3816	0.6827	0.0279	5549.1951	-13.6631	0.0000
mgstr23 medium high	-0.7000	0.4966	0.0365	5554.7006	-19.1836	0.0000
mgstr24 high	-1.1197	0.3264	0.0420	5559.7107	-26.6889	0.0000
bulk_purchase1 Bulk purchase	-0.1141	0.8922	0.0296	5557.9880	-3.8488	0.0001

	Estimate
τ^2	0.0161
σ^2	0.7772

Conclusion

Fixed Effects

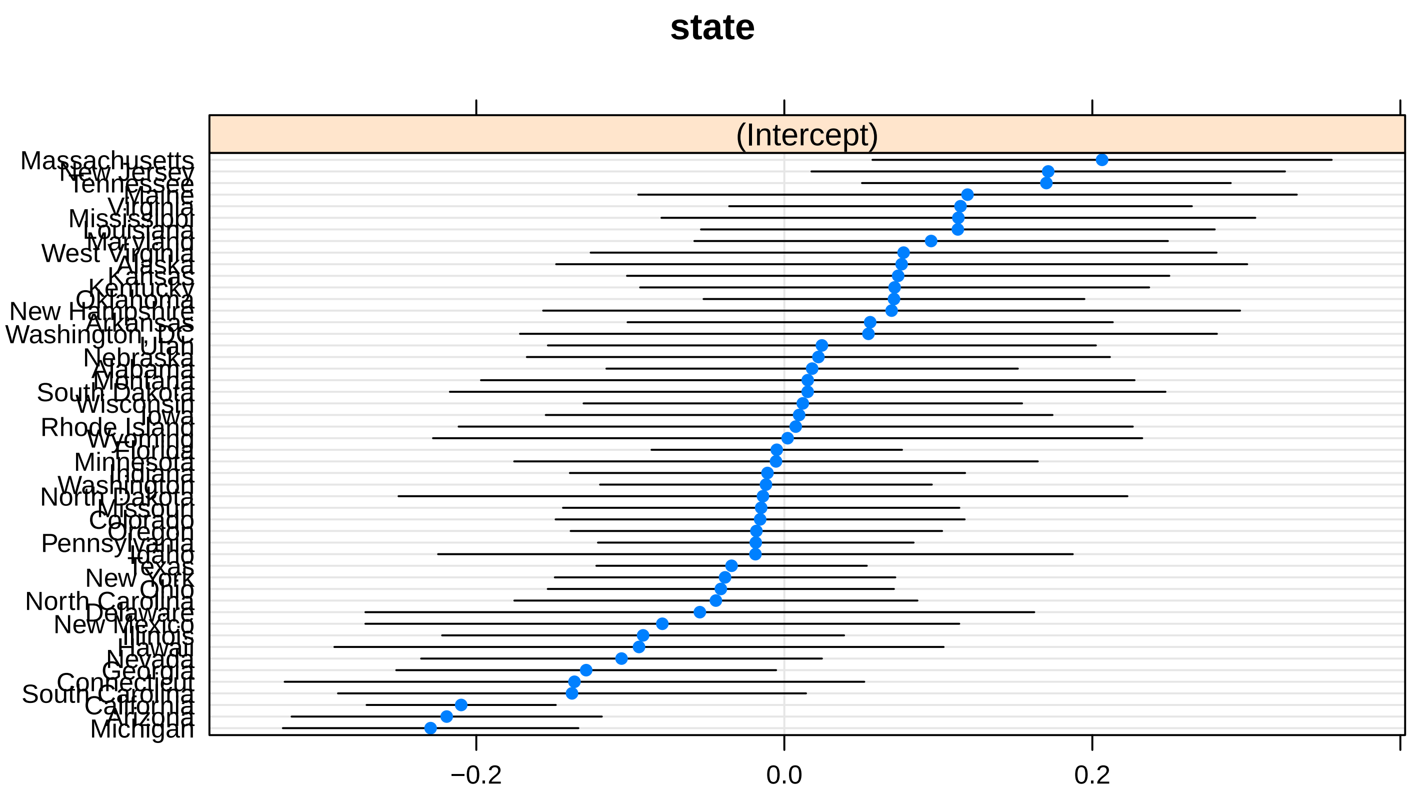
```
## [1] 0.0391
```

- Quarter (baseline: Quarter1): Compared with quarter 1, holding all other predictors unchanged, purchasing the morphine in quarter 2, the per milligram price of the drug will increase by a multiplicative effect of $e^{0.0853} = 1.0891$ (about 8.91%). Similarly, if the drug is purchased in quarter 3 or quarter 4, the drug price will increase by 8.77% and 8.81% respectively.
- Source (baseline: Blank): Compared with unkown source, holding all other predictors unchanged, the per milligram drug price heard from other person will increase by a multiplicative effect of $e^{0.0633} = 1.0653$ (about 6.53%). Similarly, the price information obtained from the internet, internet pharmacy, or personal purchase will decrease by 0.41%, 27.58%, and 3.91% respectively.
- Dosage Strength (baseline: Low): Compared with low dosage strength, holding all other predictors unchanged, the per milligram price of morphine will decrease by a multiplicative effect of $e^{-0.3816} = 0.6827$ (about 31.73%) if it has medium dosage strength. Similarly, if the dosage strength is medium high or high, the drug price will decrease by 50.34% and 67.36% respectively.
- Bulk Purchase (baseline: Not bulk purchase): Compared with non-bulk purchase, holding all other predictors unchanged, the unit price of morphine will decrease by a multiplicative effect of $e^{0.1141} = 0.8922$ (about 10.78%).

Random Effects

The estimated across-state variance is $\widehat{\tau^2} = 0.0161$, which also describes the variation attributed to the random intercept. The estimated within-state variance is $\widehat{\sigma^2} = 0.7772$, which describes the unexplained variation. The estimated interclass correlation is $\frac{\widehat{\tau^2}}{\widehat{\tau^2}+\widehat{\sigma^2}} \approx 0.02$. Therefore, we have little correlation within the same state.

```
## $state
```



From the random intercepts plot, we can also see that different states have different base per milligram morphine prices. The prices ranges from $e^{-0.2297} = 0.7948$ (Michigan) to $e^{0.2063} = 1.2292$ (Massachusetts). These estimates are based on the baseline condition of all other predictors, which are purchasing in quarter 1, from an unknown source, with low dosage strength, and not purchased in bulk.

grpvar	term	grp	condval	condsd	exp(condval)
state	(Intercept)	Massachusetts	0.2063322	0.0760657	1.2291615
state	(Intercept)	New Jersey	0.1713437	0.0784374	1.1868986
state	(Intercept)	Tennessee	0.1701571	0.0610791	1.1854911
state	(Intercept)	Maine	0.1189453	0.1090783	1.1263083
state	(Intercept)	Virginia	0.1144124	0.0766384	1.1212144
state	(Intercept)	Mississippi	0.1130184	0.0983669	1.1196526
state	(Intercept)	Louisiana	0.1126790	0.0850980	1.1192726
state	(Intercept)	Maryland	0.0953321	0.0784374	1.1000241
state	(Intercept)	West Virginia	0.0774447	0.1036649	1.0805225
state	(Intercept)	Alaska	0.0761966	0.1144620	1.0791747
state	(Intercept)	Kansas	0.0739183	0.0898259	1.0767188
state	(Intercept)	Kentucky	0.0716252	0.0843160	1.0742527
state	(Intercept)	Oklahoma	0.0712079	0.0630790	1.0738045
state	(Intercept)	New Hampshire	0.0696657	0.1154392	1.0721497
state	(Intercept)	Arkansas	0.0557536	0.0803693	1.0573371
state	(Intercept)	Washington, DC	0.0546268	0.1154392	1.0561464
state	(Intercept)	Utah	0.0244102	0.0907733	1.0247106
state	(Intercept)	Nebraska	0.0221270	0.0965797	1.0223736
state	(Intercept)	Alabama	0.0180621	0.0681530	1.0182262
state	(Intercept)	Montana	0.0152198	0.1082528	1.0153362
state	(Intercept)	South Dakota	0.0151629	0.1185281	1.0152784
state	(Intercept)	Wisconsin	0.0120061	0.0726320	1.0120785
state	(Intercept)	Iowa	0.0096280	0.0839329	1.0096745
state	(Intercept)	Rhode Island	0.0074025	0.1116730	1.0074300
state	(Intercept)	Wyoming	0.0021434	0.1174711	1.0021456
state	(Intercept)	Florida	-0.0049114	0.0414968	0.9951007
state	(Intercept)	Minnesota	-0.0054051	0.0867296	0.9946095
state	(Intercept)	Indiana	-0.0109387	0.0654690	0.9891209
state	(Intercept)	Washington	-0.0119301	0.0549568	0.9881408
state	(Intercept)	North Dakota	-0.0138529	0.1207307	0.9862426
state	(Intercept)	Missouri	-0.0150272	0.0656503	0.9850851
state	(Intercept)	Colorado	-0.0157019	0.0677492	0.9844208
state	(Intercept)	Oregon	-0.0181378	0.0615237	0.9820257
state	(Intercept)	Pennsylvania	-0.0185311	0.0522822	0.9816395
state	(Intercept)	Idaho	-0.0187574	0.1051288	0.9814174
state	(Intercept)	Texas	-0.0342430	0.0447943	0.9663367
state	(Intercept)	New York	-0.0384718	0.0563999	0.9622588
state	(Intercept)	Ohio	-0.0412173	0.0573466	0.9596206
state	(Intercept)	North Carolina	-0.0444309	0.0667705	0.9565417
state	(Intercept)	Delaware	-0.0548465	0.1107876	0.9466304
state	(Intercept)	New Mexico	-0.0792024	0.0983669	0.9238529
state	(Intercept)	Illinois	-0.0917013	0.0665798	0.9123777
state	(Intercept)	Hawaii	-0.0943523	0.1009117	0.9099622
state	(Intercept)	Nevada	-0.1057041	0.0663908	0.8996908
state	(Intercept)	Georgia	-0.1286539	0.0629182	0.8792782
state	(Intercept)	Connecticut	-0.1362571	0.0960053	0.8726183
state	(Intercept)	South Carolina	-0.1378602	0.0775222	0.8712204
state	(Intercept)	California	-0.2098077	0.0313387	0.8107401
state	(Intercept)	Arizona	-0.2192177	0.0513864	0.8031469
state	(Intercept)	Michigan	-0.2296611	0.0489520	0.7948029

Limitation