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In [232...

using CSV, DataFrames, GLM, RegressionTables, Gadfly, Plots

In [233...

# Enable printing of 1000 columns  
ENV["COLUMNS"] = 1000

Out[233...] 1000

Reading the Data

In [234...

fb\_data = CSV.read("dataset\_Facebook.csv", DataFrame)

Out[234...] 500 rows × 19 columns

	Page total likes	Type	Category	Post Month	Post Weekday	Post Hour	Paid	Lifetime Post Total Reach	Lifetime Post Total Impressions	Lifetime Engaged Users	Lifetime Post Consumers	Lifetime Post Consumptions	Impressions by people who have liked your Page	Lifetime Post reaches people in the feed
	Int64	String7	Int64	Int64	Int64	Int64	Int64?	Int64	Int64	Int64	Int64	Int64	Int64	Int64
1	139441	Photo	2	12	4	3	0	2752	5091	178	109	159	3078	
2	139441	Status	2	12	3	10	0	10460	19057	1457	1361	1674	11710	
3	139441	Photo	3	12	3	3	0	2413	4373	177	113	154	2812	

<b>4</b>	139441	Photo	2	12	2	10	1	50128	87991	2211	790	1119	61027	3
<b>5</b>	139441	Photo	2	12	2	3	0	7244	13594	671	410	580	6228	1
<b>6</b>	139441	Status	2	12	1	9	0	10472	20849	1191	1073	1389	16034	1
<b>7</b>	139441	Photo	3	12	1	3	1	11692	19479	481	265	364	15432	1
<b>8</b>	139441	Photo	3	12	7	9	1	13720	24137	537	232	305	19728	1
<b>9</b>	139441	Status	2	12	7	3	0	11844	22538	1530	1407	1692	15220	1
<b>10</b>	139441	Photo	3	12	6	10	0	4694	8668	280	183	250	4309	1
<b>11</b>	139441	Status	2	12	5	10	0	21744	42334	4258	4100	4540	37849	1
<b>12</b>	139441	Photo	2	12	5	10	0	3112	5590	208	127	145	3887	1
<b>13</b>	139441	Photo	2	12	5	10	0	2847	5133	193	115	133	3779	1
<b>14</b>	139441	Photo	2	12	5	3	0	2549	4896	249	134	168	3631	1
<b>15</b>	138414	Photo	2	12	4	5	1	22784	39941	887	337	417	34415	1
<b>16</b>	138414	Status	2	12	3	10	0	10060	19680	1264	1209	1425	17272	1
<b>17</b>	138414	Photo	3	12	3	3	0	1722	2981	163	123	148	1868	1
<b>18</b>	138414	Photo	1	12	2	12	1	53264	111785	1706	1103	1655	92512	3
<b>19</b>	138414	Status	3	12	2	3	0	3930	7509	130	86	112	5009	1
<b>20</b>	138414	Photo	3	12	1	11	0	1591	2825	121	88	111	2116	1
<b>21</b>	138414	Photo	2	12	1	3	0	2848	5066	200	142	184	3561	1
<b>22</b>	138414	Photo	1	12	7	10	0	1384	2467	15	15	20	2196	1
<b>23</b>	138414	Link	1	12	7	10	0	3454	6853	118	104	130	6282	1
<b>24</b>	138414	Photo	3	12	7	3	0	2723	4888	176	118	143	2964	1
<b>25</b>	138414	Status	2	12	6	10	0	8488	15294	1341	1270	1489	9684	1
<b>26</b>	138458	Status	2	12	6	3	0	8284	15104	1521	1462	1711	10266	1
<b>27</b>	138458	Status	2	12	5	11	0	19552	34143	2806	2531	3420	17748	1
<b>28</b>	138458	Photo	3	12	5	3	0	2478	4306	212	124	149	2612	1
<b>29</b>	138895	Photo	2	12	5	3	0	9560	18264	973	559	885	9217	1

30	138895	Video	1	12	4	11	1	36208	61262	1141	1068	1728	30131	1
:	:	:	:	:	:	:	:	:	:	:	:	:	:	:



In [235... `println(size(fb_data))`

(500, 19)

In [236... `names(fb_data)`

Out[236... 19-element Vector{String}:

```
"Page total likes"
"Type"
"Category"
"Post Month"
"Post Weekday"
"Post Hour"
"Paid"
"Lifetime Post Total Reach"
"Lifetime Post Total Impressions"
"Lifetime Engaged Users"
"Lifetime Post Consumers"
"Lifetime Post Consumptions"
"Lifetime Post Impressions by people who have liked your Page"
"Lifetime Post reach by people who like your Page"
"Lifetime People who have liked your Page and engaged with your post"
"comment"
"like"
"share"
"Total Interactions"
```

In [237... `describe(fb_data)`

Out[237... 19 rows × 7 columns

	variable	mean	min	median	max	nmissing	eltype
	Symbol	Union...	Any	Union...	Any	Int64	Type
1	Page total likes	1.23194e5	81370	129600.0	139441	0	Int64

	variable	mean	min	median	max	nmissing	eltype
	Symbol	Union...	Any	Union...	Any	Int64	Type
2	Type		Link		Video	0	String7
3	Category	1.88	1	2.0	3	0	Int64
4	Post Month	7.038	1	7.0	12	0	Int64
5	Post Weekday	4.15	1	4.0	7	0	Int64
6	Post Hour	7.84	1	9.0	23	0	Int64
7	Paid	0.278557	0	0.0	1	1	Union{Missing, Int64}
8	Lifetime Post Total Reach	13903.4	238	5281.0	180480	0	Int64
9	Lifetime Post Total Impressions	29585.9	570	9051.0	1110282	0	Int64
10	Lifetime Engaged Users	920.344	9	625.5	11452	0	Int64
11	Lifetime Post Consumers	798.772	9	551.5	11328	0	Int64
12	Lifetime Post Consumptions	1415.13	9	851.0	19779	0	Int64
13	Lifetime Post Impressions by people who have liked your Page	16766.4	567	6255.5	1107833	0	Int64
14	Lifetime Post reach by people who like your Page	6585.49	236	3417.0	51456	0	Int64
15	Lifetime People who have liked your Page and engaged with your post	609.986	9	412.0	4376	0	Int64
16	comment	7.482	0	3.0	372	0	Int64
17	like	177.946	0	101.0	5172	1	Union{Missing, Int64}
18	share	27.2661	0	19.0	790	4	Union{Missing, Int64}
19	Total Interactions	212.12	0	123.5	6334	0	Int64

## Handling the Columns with Space

In [238...

```
rename!(fb_data, Dict{:"Page total likes" => : "Page_total_likes",
                    : "Post Month" => : "Post_Month",
                    : "Post Hour" => : "Post_Hour",
                    : "Post Weekday" => : "Post_Weekday"}));
```

In [239... names(fb\_data)

Out[239... 19-element Vector{String}:  
 "Page\_total\_likes"  
 "Type"  
 "Category"  
 "Post\_Month"  
 "Post\_Weekday"  
 "Post\_Hour"  
 "Paid"  
 "Lifetime Post Total Reach"  
 "Lifetime Post Total Impressions"  
 "Lifetime Engaged Users"  
 "Lifetime Post Consumers"  
 "Lifetime Post Consumptions"  
 "Lifetime Post Impressions by people who have liked your Page"  
 "Lifetime Post reach by people who like your Page"  
 "Lifetime People who have liked your Page and engaged with your post"  
 "comment"  
 "like"  
 "share"  
 "Total Interactions"

In [240... dropmissing!(fb\_data, :**"like"**);  
 dropmissing!(fb\_data, :**"Paid"**);  
 dropmissing!(fb\_data, :**"share"**);  
 describe(fb\_data)

Out[240... 19 rows × 7 columns

	variable	mean	min	median	max	nmissing	eltype
	Symbol	Union...	Any	Union...	Any	Int64	DataType
1	Page_total_likes	1.23173e5	81370	129600.0	139441	0	Int64
2	Type		Link		Video	0	String7
3	Category	1.88687	1	2.0	3	0	Int64
4	Post_Month	7.02828	1	7.0	12	0	Int64
5	Post_Weekday	4.13333	1	4.0	7	0	Int64
6	Post_Hour	7.84444	1	9.0	23	0	Int64

	variable	mean	min	median	max	nmissing	eltype
	Symbol	Union...	Any	Union...	Any	Int64	DataType
7	Paid	0.280808	0	0.0	1	0	Int64
8	Lifetime Post Total Reach	14028.1	238	5290.0	180480	0	Int64
9	Lifetime Post Total Impressions	29857.0	570	9084.0	1110282	0	Int64
10	Lifetime Engaged Users	926.83	9	630.0	11452	0	Int64
11	Lifetime Post Consumers	804.156	9	555.0	11328	0	Int64
12	Lifetime Post Consumptions	1425.92	9	861.0	19779	0	Int64
13	Lifetime Post Impressions by people who have liked your Page	16916.3	567	6282.0	1107833	0	Int64
14	Lifetime Post reach by people who like your Page	6641.36	236	3478.0	51456	0	Int64
15	Lifetime People who have liked your Page and engaged with your post	614.135	9	416.0	4376	0	Int64
16	comment	7.55758	0	3.0	372	0	Int64
17	like	179.145	0	101.0	5172	0	Int64
18	share	27.2646	0	19.0	790	0	Int64
19	Total Interactions	213.968	0	125.0	6334	0	Int64

# 1. Multiple Regression Model

## (a) Fit the Model

In [241...

```
m1 = @formula(like~Category+Page_total_likes+Type+Post_Month+Post_Hour+Post_Weekday+Paid+comment)
```

Out[241...

FormulaTerm

Response:

like(unknown)

Predictors:

Category(unknown)

Page\_total\_likes(unknown)

Type(unknown)

Post\_Month(unknown)

```
Post_Hour(unknown)
Post_Weekday(unknown)
Paid(unknown)
comment(unknown)
```

In [242... `model1 = lm(m1, fb_data)`

Out[242... `StatsModels.TableRegressionModel{LinearModel{GLM.LmResp{Vector{Float64}}, GLM.DensePredChol{Float64, CholeskyPivoted{Float64, Matrix{Float64}}}}, Matrix{Float64}}`

`like ~ 1 + Category + Page_total_likes + Type + Post_Month + Post_Hour + Post_Weekday + Paid + comment`

Coefficients:

	Coef.	Std. Error	t	Pr(> t )	Lower 95%	Upper 95%
(Intercept)	-76.0596	134.32	-0.57	0.5715	-339.982	187.863
Category	40.9061	9.67147	4.23	<1e-04	21.9028	59.9093
Page_total_likes	0.000477266	0.00146798	0.33	0.7452	-0.00240714	0.00336168
Type: Photo	15.2491	39.8225	0.38	0.7019	-62.9973	93.4955
Type: Status	-19.0594	47.4556	-0.40	0.6881	-112.304	74.185
Type: Video	19.5248	76.8518	0.25	0.7996	-131.48	170.529
Post_Month	1.70077	7.25882	0.23	0.8148	-12.5619	15.9635
Post_Hour	-0.406625	1.86435	-0.22	0.8274	-4.06984	3.25659
Post_Weekday	-1.58256	3.89916	-0.41	0.6850	-9.24394	6.07881
Paid	35.1066	17.6526	1.99	0.0473	0.421469	69.7917
comment	12.6549	0.371847	34.03	<1e-99	11.9243	13.3856

## R-Squared Values

In [243... `# R Square value of the model`  
`r2(model1)`

Out[243... 0.717372980012585

## Coefficient Significance

In [244... `coef(model1)`

```
Out[244...] 11-element Vector{Float64}:
 -76.05956033276802
 40.90605304627139
  0.00047726636210155047
 15.249068574473092
-19.05938067480692
 19.52481991626934
  1.7007699271319174
 -0.4066248513377943
 -1.5825611175721401
 35.10660018204332
 12.654937461963543
```

## Refit with Logarithm Transformation

```
In [245...] m1_log = @formula(log1p(like)~Category+log1p(Page_total_likes)+Type+Post_Month+Post_Hour+Post_Weekday+Paid)
model1_log = lm(mm, fb_data)
```

```
Out[245...] StatsModels.TableRegressionModel{LinearModel{GLM.LmResp{Vector{Float64}}, GLM.DensePredChol{Float64, CholeskyPivoted{Float64, Matrix{Float64}}}}, Matrix{Float64}}
```

:(log1p(like)) ~ 1 + Category + :(log1p(Page\_total\_likes)) + Type + Post\_Month + Post\_Hour + Post\_Weekday + Paid

Coefficients:

	Coef.	Std. Error	t	Pr(> t )	Lower 95%	Upper 95%
(Intercept)	-9.69856	10.5257	-0.92	0.3573	-30.3801	10.983
Category	0.40557	0.0610486	6.64	<1e-10	0.285618	0.525523
log1p(Page_total_likes)	1.15958	0.924691	1.25	0.2104	-0.657319	2.97647
Type: Photo	0.444327	0.251196	1.77	0.0775	-0.0492398	0.937893
Type: Status	0.709225	0.299309	2.37	0.0182	0.121122	1.29733
Type: Video	1.3856	0.48481	2.86	0.0044	0.433013	2.33819
Post_Month	-0.0377243	0.0403821	-0.93	0.3507	-0.11707	0.0416211
Post_Hour	-0.0155737	0.0117812	-1.32	0.1868	-0.0387222	0.00757471
Post_Weekday	-0.0559603	0.0245616	-2.28	0.0231	-0.104221	-0.00770015
Paid	0.285997	0.111235	2.57	0.0104	0.0674344	0.504559

```
In [246...] # R Square value of the model
r2(model1_log)
```

0.1479247827797423



Out[246...

In [247...

```
coef(model1_log)
```

Out[247...

```
10-element Vector{Float64}:
-9.698556404446071
 0.40557034980235973
 1.1595758609956286
 0.44432673727588945
 0.7092246134950749
 1.3856007166483466
-0.03772427706108226
-0.015573736135879092
-0.055960342598400256
 0.2859968739277099
```

## Models Dignostics

In [248...

```
regtable(model1, model1_log)
```

```
-----
              like      log1p(like)
              -----
              (1)      (2)
-----
(Intercept)      -76.060      -9.699
                  (134.320)    (10.526)
Category          40.906***    0.406***
                  (9.671)     (0.061)
Page_total_likes      0.000
                  (0.001)
Type: Photo        15.249      0.444
                  (39.823)    (0.251)
Type: Status      -19.059      0.709*
                  (47.456)    (0.299)
Type: Video        19.525      1.386**
                  (76.852)    (0.485)
Post_Month         1.701      -0.038
                  (7.259)    (0.040)
Post_Hour          -0.407      -0.016
                  (1.864)    (0.012)
Post_Weekday      -1.583      -0.056*
```

	(3.899)	(0.025)
Paid	35.107*	0.286*
	(17.653)	(0.111)
comment	12.655***	
	(0.372)	
log1p(Page_total_likes)		1.160
		(0.925)
-----		
Estimator	OLS	OLS
-----		
N	495	495
R2	0.717	0.148
-----		

## (C) Assumptions

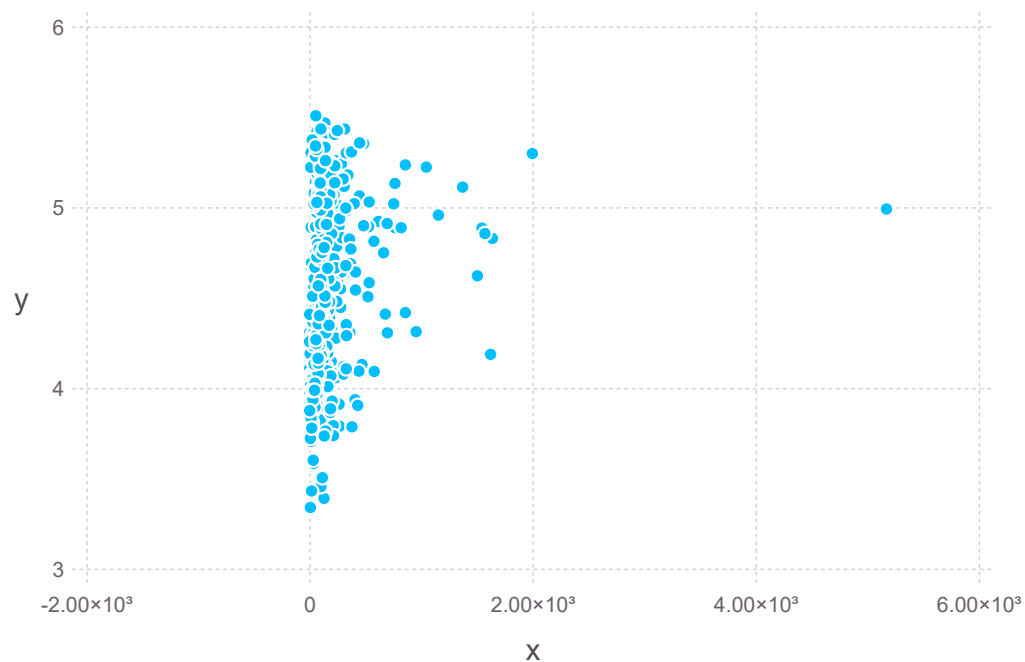
In [249...

```
# predicted values
pred1 = predict(model1_log)
# residuals
red1 = fb_data[:, :like] - pred1;
```

In [250...

```
# homoscedasticity Assumption
plot(x=red1,y=pred1, Geom.point)
```

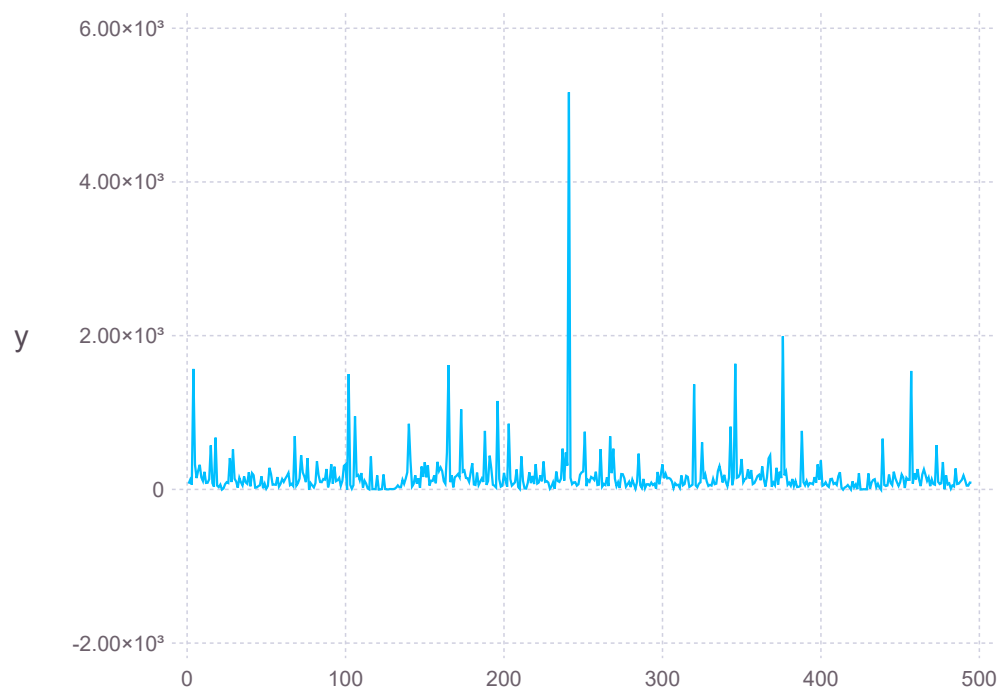
Out[250...



Here the variance is not same in different X value, so homoscedasticity assumption is not OK

```
In [251...  
# Independence Assumption  
plot(y=red1, Geom.line)
```

Out[251...



All the observations look random, So the independent assumption hold

In [252...

```
# Exogeneity assumption  
plot(x = fb_data[:, :like], y=red1)
```

Out[252...

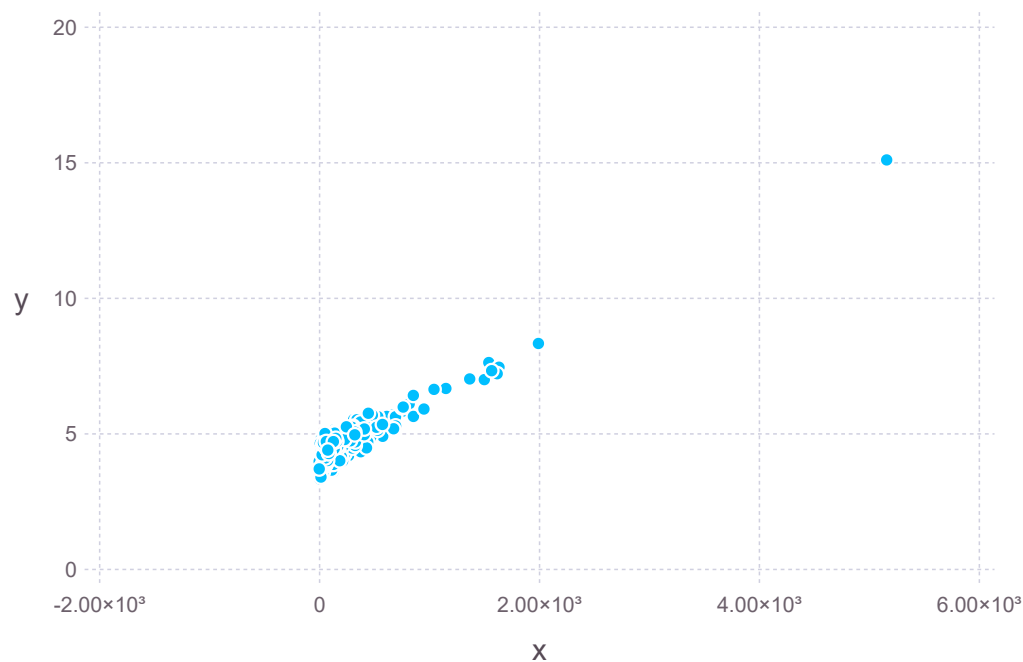


	Coef.	Std. Error	t	Pr(> t )	Lower 95%	Upper 95%
(Intercept)	-3.25106	8.61178	-0.38	0.7060	-20.1722	13.67
Category	0.315722	0.0502231	6.29	<1e-09	0.217039	0.414404
log1p(Page_total_likes)	0.587934	0.75657	0.78	0.4375	-0.898632	2.0745
Type: Photo	0.329696	0.205415	1.61	0.1091	-0.0739186	0.733311
Type: Status	0.601503	0.2447	2.46	0.0143	0.120698	1.08231
Type: Video	1.12752	0.396544	2.84	0.0047	0.348364	1.90669
Post_Month	-0.0215118	0.0330175	-0.65	0.5150	-0.0863873	0.0433636
Post_Hour	-0.0146333	0.00962802	-1.52	0.1292	-0.0335512	0.0042846
Post_Weekday	-0.0346999	0.0201187	-1.72	0.0852	-0.0742306	0.00483083
Paid	0.138856	0.0913942	1.52	0.1293	-0.040722	0.318435
Total_Interactions	0.00168251	0.000108109	15.56	<1e-43	0.00147009	0.00189493

```
In [255...
# predicted values
pred1_test = predict(model1_test)
# residuals
red1_test = fb_data[:, :like] - pred1_test;
```

```
In [256...
# homoscedasticity Assumption
plot(x=red1_test, y=pred1_test, Geom.point)
```

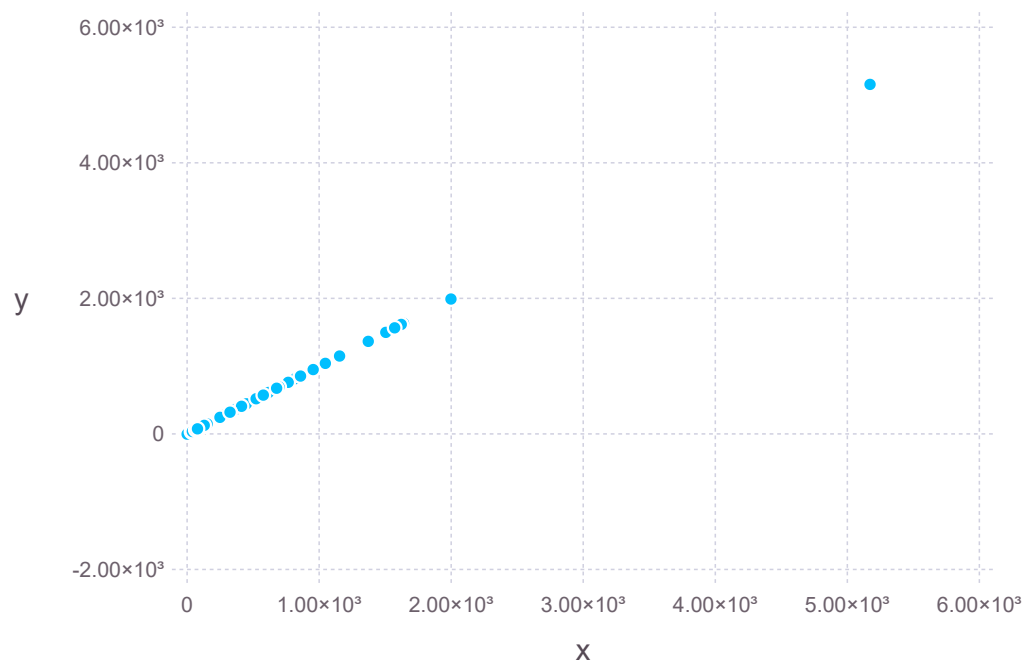
Out[256...



We can observed that after adding more variables (not all) the homoscedasticity assumption behavior is varying from the previous

```
In [257...  
# Exogeneity assumption  
plot(x = fb_data[:, :like], y=red1_test)
```

Out[257...



The Exogeneity assumption is not changed from the previous

In [258...

```
regtable(model1, model1_log, model1_test)
```

	like	log1p(like)	
	(1)	(2)	(3)
(Intercept)	-76.060 (134.320)	-9.699 (10.526)	-3.251 (8.612)
Category	40.906*** (9.671)	0.406*** (0.061)	0.316*** (0.050)
Page_total_likes	0.000 (0.001)		
Type: Photo	15.249 (39.823)	0.444 (0.251)	0.330 (0.205)
Type: Status	-19.059 (47.456)	0.709* (0.299)	0.602* (0.245)



Type: Video	19.525 (76.852)	1.386** (0.485)	1.128** (0.397)
Post_Month	1.701 (7.259)	-0.038 (0.040)	-0.022 (0.033)
Post_Hour	-0.407 (1.864)	-0.016 (0.012)	-0.015 (0.010)
Post_Weekday	-1.583 (3.899)	-0.056* (0.025)	-0.035 (0.020)
Paid	35.107* (17.653)	0.286* (0.111)	0.139 (0.091)
comment	12.655*** (0.372)		
log1p(Page_total_likes)		1.160 (0.925)	0.588 (0.757)
Total_Interactions			0.002*** (0.000)
-----			
Estimator	OLS	OLS	OLS
-----			
N	495	495	495
R2	0.717	0.148	0.432
-----			

After doing Logarithm transformation and adding some Extra variable from the dataset the performanace of the Multiple Linear Regression is increasing and some assumptions are really closed to be hold. So, we can assume that doing some appropriate transformation and evaluating assumption after adding variables will be the possible remedy to handle this.

## (b) Dropping Some Variables and Observe the Result

```
In [259... m1_drop = @formula(log1p(like)~Category+Type+Paid+Total_Interactions)
model1_drop = lm(m1_drop, fb_data)
```

```
Out[259... StatsModels.TableRegressionModel{LinearModel{GLM.LmResp{Vector{Float64}}, GLM.DensePredChol{Float64, CholeskyPivoted{Float64, Matrix{Float64}}}}, Matrix{Float64}}

:(log1p(like)) ~ 1 + Category + Type + Paid + Total_Interactions
```

Coefficients:

	Coef.	Std. Error	t	Pr(> t )	Lower 95%	Upper 95%
(Intercept)	3.20202	0.201682	15.88	<1e-45	2.80574	3.59829
Category	0.329537	0.0492241	6.69	<1e-10	0.23282	0.426254
Type: Photo	0.318409	0.201101	1.58	0.1140	-0.0767211	0.713539
Type: Status	0.587141	0.238663	2.46	0.0142	0.118207	1.05607
Type: Video	1.13495	0.392664	2.89	0.0040	0.363431	1.90647
Paid	0.151624	0.0910276	1.67	0.0964	-0.0272303	0.330479
Total_Interactions	0.00170306	0.000107904	15.78	<1e-44	0.00149105	0.00191508

In [260...

```
regtable(model1, model1_log, model1_test, model1_drop)
```

	like		log1p(like)	
	(1)	(2)	(3)	(4)
(Intercept)	-76.060 (134.320)	-9.699 (10.526)	-3.251 (8.612)	3.202*** (0.202)
Category	40.906*** (9.671)	0.406*** (0.061)	0.316*** (0.050)	0.330*** (0.049)
Page_total_likes	0.000 (0.001)			
Type: Photo	15.249 (39.823)	0.444 (0.251)	0.330 (0.205)	0.318 (0.201)
Type: Status	-19.059 (47.456)	0.709* (0.299)	0.602* (0.245)	0.587* (0.239)
Type: Video	19.525 (76.852)	1.386** (0.485)	1.128** (0.397)	1.135** (0.393)
Post_Month	1.701 (7.259)	-0.038 (0.040)	-0.022 (0.033)	
Post_Hour	-0.407 (1.864)	-0.016 (0.012)	-0.015 (0.010)	
Post_Weekday	-1.583 (3.899)	-0.056* (0.025)	-0.035 (0.020)	
Paid	35.107* (17.653)	0.286* (0.111)	0.139 (0.091)	0.152 (0.091)
comment	12.655*** (0.372)			
log1p(Page_total_likes)		1.160	0.588	

		(0.925)	(0.757)	
Total_Interactions			0.002***	0.002***
			(0.000)	(0.000)
-----				
Estimator	OLS	OLS	OLS	OLS
-----				
N	495	495	495	495
R2	0.717	0.148	0.432	0.425
-----				

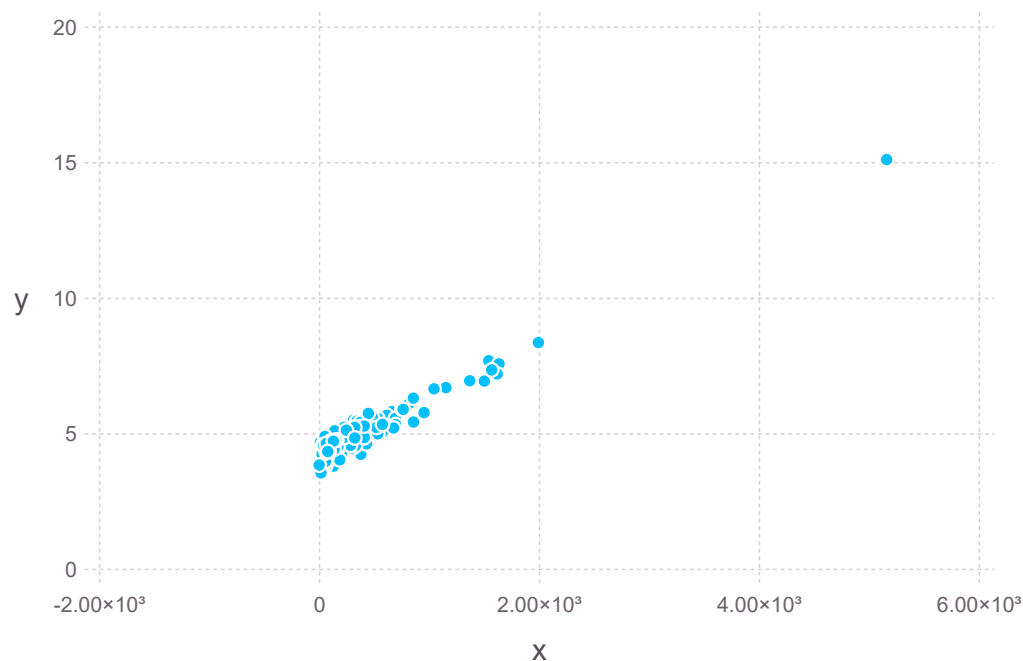
In [261...

```
# predicted values
pred1_drop = predict(model1_drop)
# residuals
red1_drop = fb_data[:, :like] - pred1_drop;
```

In [262...

```
# homoscedasticity Assumption
plot(x=red1_drop, y=pred1_drop, Geom.point)
```

Out[262...



After dropping some variables from the model, we don't find any significant improvement on the basis of **R2** value and Assumptions. So, directly dropping variables might not be a convenient remedy for the regression problem. Otherwise, fixing is more effective way to handle this

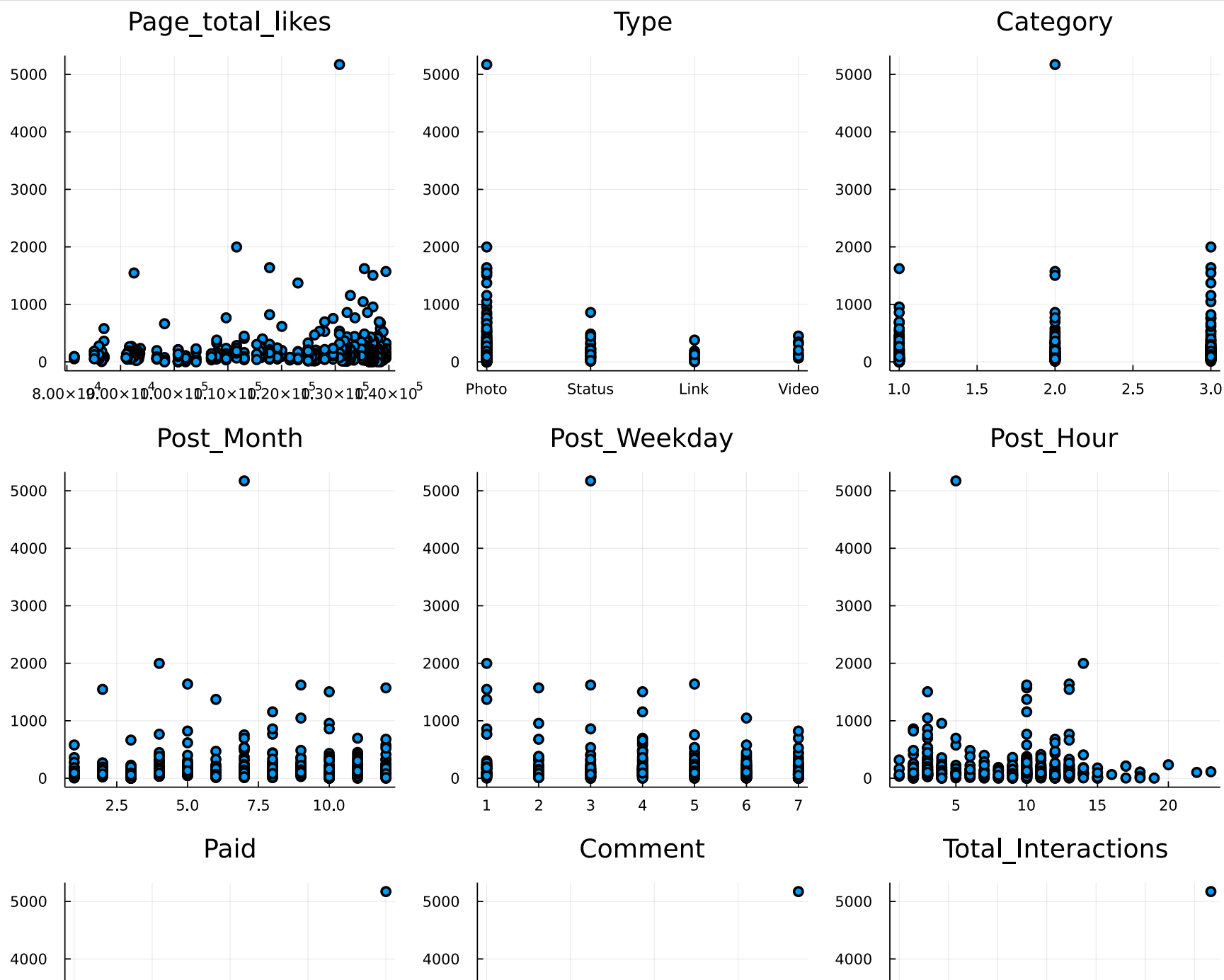
## (d) Non-Linear Association

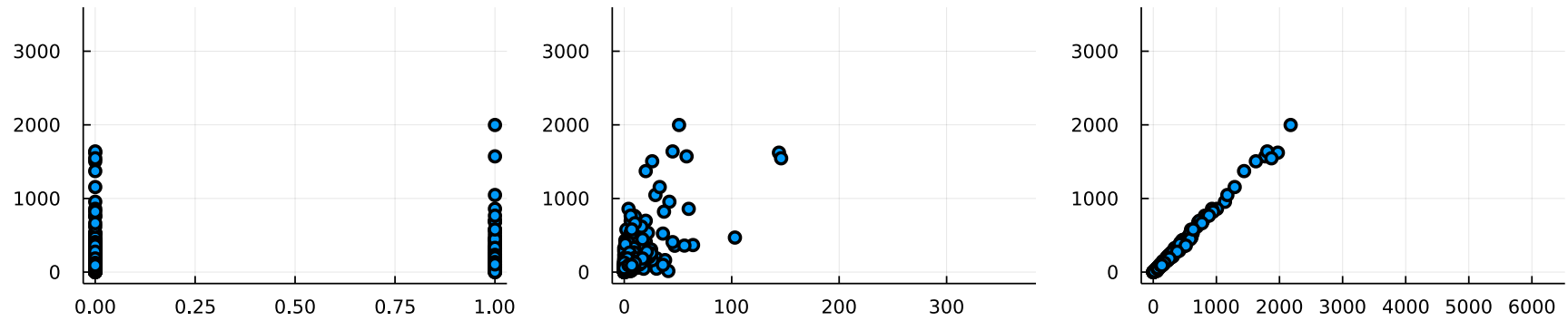
In [263...

```
p1 = scatter(fb_data[:, :Page_total_likes], fb_data[:, :like], title = "Page_total_likes");
p2 = scatter(fb_data[:, :Type], fb_data[:, :like], title = "Type");
p3 = scatter(fb_data[:, :Category], fb_data[:, :like], title = "Category");
p4 = scatter(fb_data[:, :Post_Month], fb_data[:, :like], title = "Post_Month");
p5 = scatter(fb_data[:, :Post_Weekday], fb_data[:, :like], title = "Post_Weekday");
p6 = scatter(fb_data[:, :Post_Hour], fb_data[:, :like], title = "Post_Hour");
p7 = scatter(fb_data[:, :Paid], fb_data[:, :like], title = "Paid");
p8 = scatter(fb_data[:, :comment], fb_data[:, :like], title = "Comment");
p9 = scatter(fb_data[:, :Total_Interactions], fb_data[:, :like], title = "Total_Interactions");
```

```
Plots.plot(p1, p2, p3, p4, p5, p6, p7, p8, p9, layout = (3, 3), legend = false)
plot!(size=(1000, 1000))
```

Out[263...





In [264... `names(fb_data)`

Out[264... 19-element Vector{String}:  
 "Page\_total\_likes"  
 "Type"  
 "Category"  
 "Post\_Month"  
 "Post\_Weekday"  
 "Post\_Hour"  
 "Paid"  
 "Lifetime Post Total Reach"  
 "Lifetime Post Total Impressions"  
 "Lifetime Engaged Users"  
 "Lifetime Post Consumers"  
 "Lifetime Post Consumptions"  
 "Lifetime Post Impressions by people who have liked your Page"  
 "Lifetime Post reach by people who like your Page"  
 "Lifetime People who have liked your Page and engaged with your post"  
 "comment"  
 "like"  
 "share"  
 "Total\_Interactions"

## 2. Repeat Procedure with Another Outcome Variables

In [265... `m2 = @formula(comment~Category+Page_total_likes+Type+Post_Month+Post_Hour+Post_Weekday+Paid)`

Out[265... FormulaTerm  
 Response:  
 comment(unknown)

Predictors:  
 Category(unknown)  
 Page\_total\_likes(unknown)  
 Type(unknown)  
 Post\_Month(unknown)  
 Post\_Hour(unknown)  
 Post\_Weekday(unknown)  
 Paid(unknown)

In [266... `model2 = lm(m2, fb_data)`

Out[266... `StatsModels.TableRegressionModel{LinearModel{GLM.LmResp{Vector{Float64}}, GLM.DensePredChol{Float64, CholeskyPivoted{Float64, Matrix{Float64}}}}, Matrix{Float64}}`

`comment ~ 1 + Category + Page_total_likes + Type + Post_Month + Post_Hour + Post_Weekday + Paid`

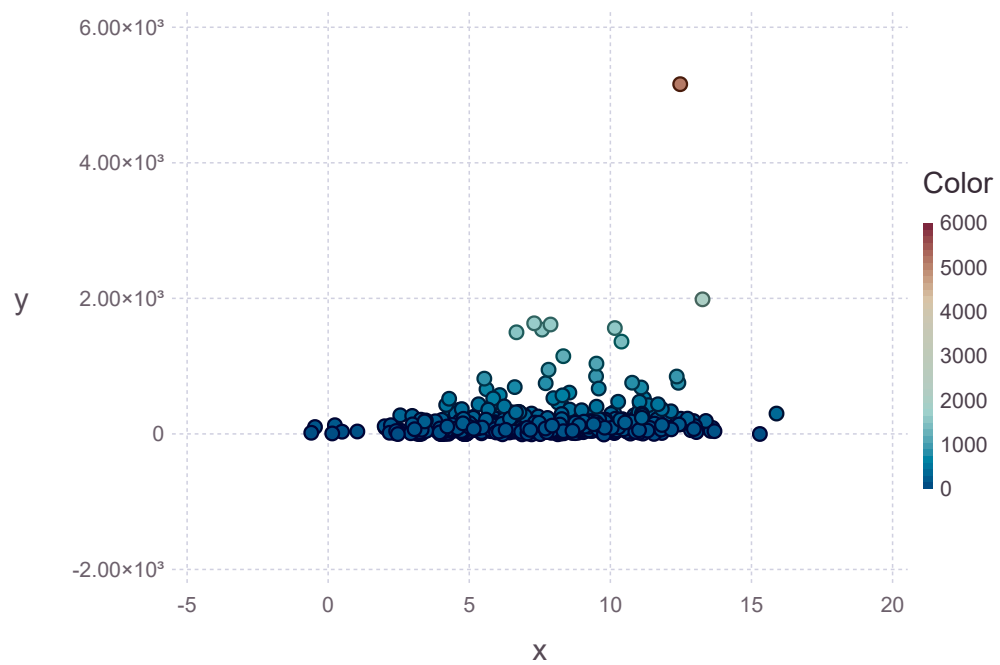
Coefficients:

	Coef.	Std. Error	t	Pr(> t )	Lower 95%	Upper 95%
(Intercept)	-15.4458	16.3873	-0.94	0.3464	-47.6447	16.7532
Category	0.38268	1.18089	0.32	0.7460	-1.93761	2.70297
Page_total_likes	0.000230311	0.000178956	1.29	0.1987	-0.000121314	0.000581935
Type: Photo	3.06945	4.86088	0.63	0.5280	-6.48154	12.6204
Type: Status	4.92695	5.79066	0.85	0.3953	-6.45093	16.3048
Type: Video	6.7184	9.3797	0.72	0.4742	-11.7115	25.1483
Post_Month	-1.03585	0.885153	-1.17	0.2425	-2.77506	0.703354
Post_Hour	0.0246612	0.22766	0.11	0.9138	-0.42266	0.471982
Post_Weekday	-0.747369	0.47493	-1.57	0.1162	-1.68054	0.185806
Paid	3.33185	2.15031	1.55	0.1219	-0.893211	7.55692

In [267... `# predicted values`  
`pred2 = predict(model2)`  
`# residuals`  
`red2 = fb_data[:, :like] - pred2;`

In [268... `# Homoscedasticity assumption`  
`plot(x=pred2, y=red2, color=fb_data[:, :like])`

Out[268...

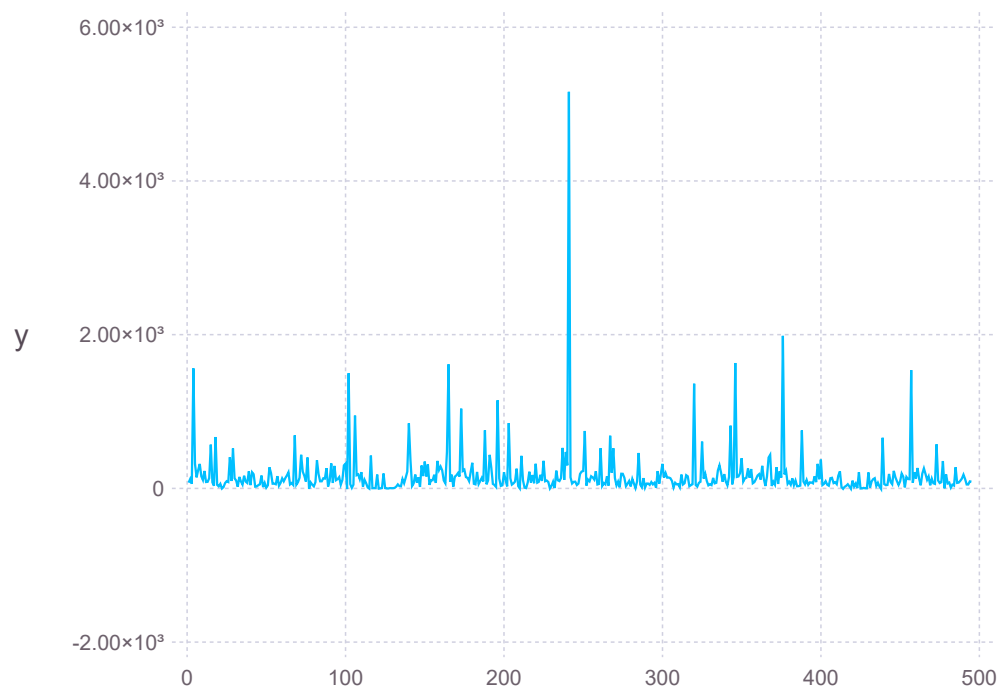


In [269...

```
# independence  
plot(y=red2, Geom.line)
```

Out[269...

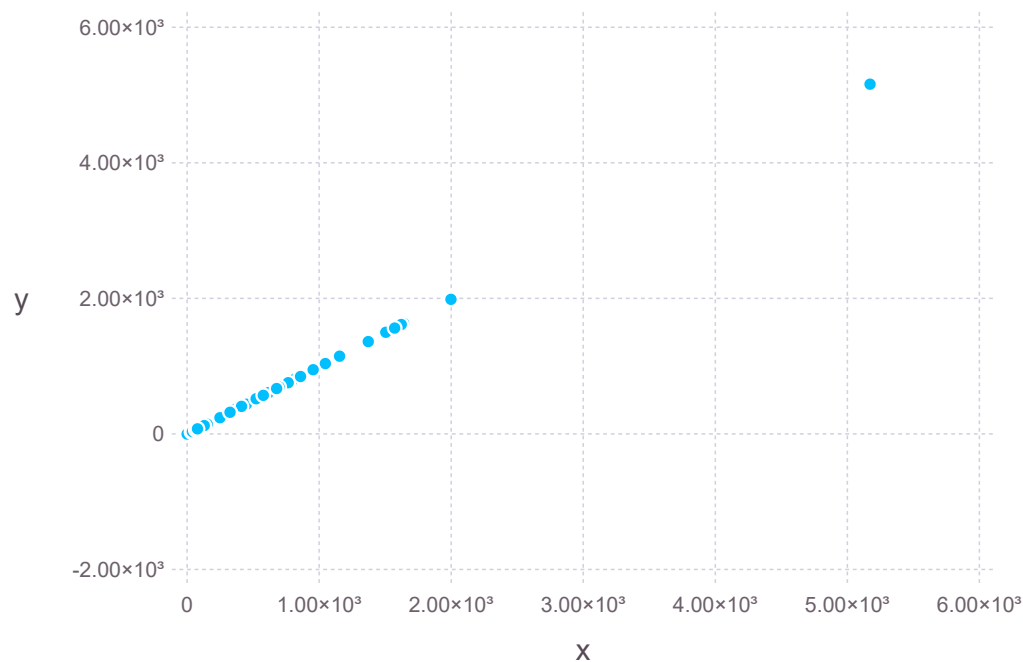




In [270...

```
# Exogeneity assumption  
plot(x = fb_data[:, :like], y=red2)
```

Out[270...



```
In [271...] m3 = @formula(share~Category+Page_total_likes+Type+Post_Month+Post_Hour+Post_Weekday+Paid)
```

```
Out[271...] FormulaTerm
Response:
share(unknown)
Predictors:
Category(unknown)
Page_total_likes(unknown)
Type(unknown)
Post_Month(unknown)
Post_Hour(unknown)
Post_Weekday(unknown)
Paid(unknown)
```

```
In [272...] model3 = lm(m3, fb_data)
```

```
Out[272...] StatsModels.TableRegressionModel{LinearModel{GLM.LmResp{Vector{Float64}}, GLM.DensePredChol{Float64, CholeskyPivoted{Float64, Matrix{Float64}}}}, Matrix{Float64}}
```

share ~ 1 + Category + Page\_total\_likes + Type + Post\_Month + Post\_Hour + Post\_Weekday + Paid

Coefficients:

	Coef.	Std. Error	t	Pr(> t )	Lower 95%	Upper 95%
(Intercept)	-2.87188	32.4438	-0.09	0.9295	-66.6196	60.8758
Category	6.98957	2.33794	2.99	0.0029	2.39584	11.5833
Page_total_likes	0.000168141	0.000354298	0.47	0.6353	-0.000528007	0.00086429
Type: Photo	8.81314	9.62361	0.92	0.3602	-10.096	27.7223
Type: Status	13.6812	11.4644	1.19	0.2333	-8.84483	36.2072
Type: Video	39.2938	18.57	2.12	0.0349	2.8062	75.7814
Post_Month	-1.13299	1.75243	-0.65	0.5182	-4.57629	2.31031
Post_Hour	-0.471665	0.450722	-1.05	0.2959	-1.35727	0.413945
Post_Weekday	-0.789744	0.94027	-0.84	0.4014	-2.63725	1.05776
Paid	6.65855	4.25719	1.56	0.1185	-1.70626	15.0234

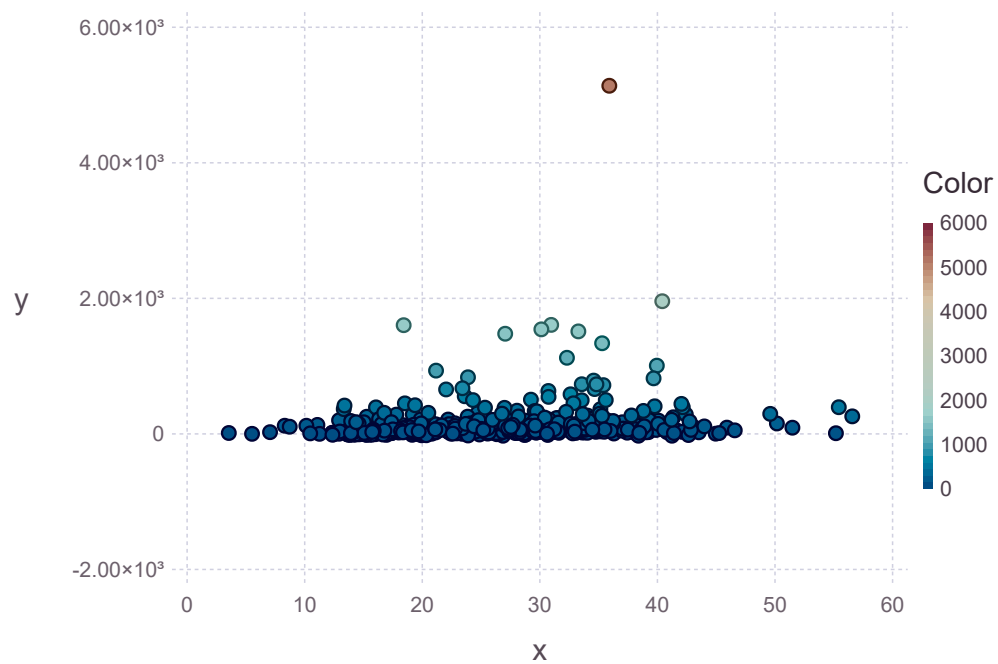
In [273...

```
# predicted values
pred3 = predict(model3)
# residuals
red3 = fb_data[, :like] - pred3;
```

In [274...

```
# Homoscedasticity assumption
plot(x=pred3, y=red3,color=fb_data[, :like])
```

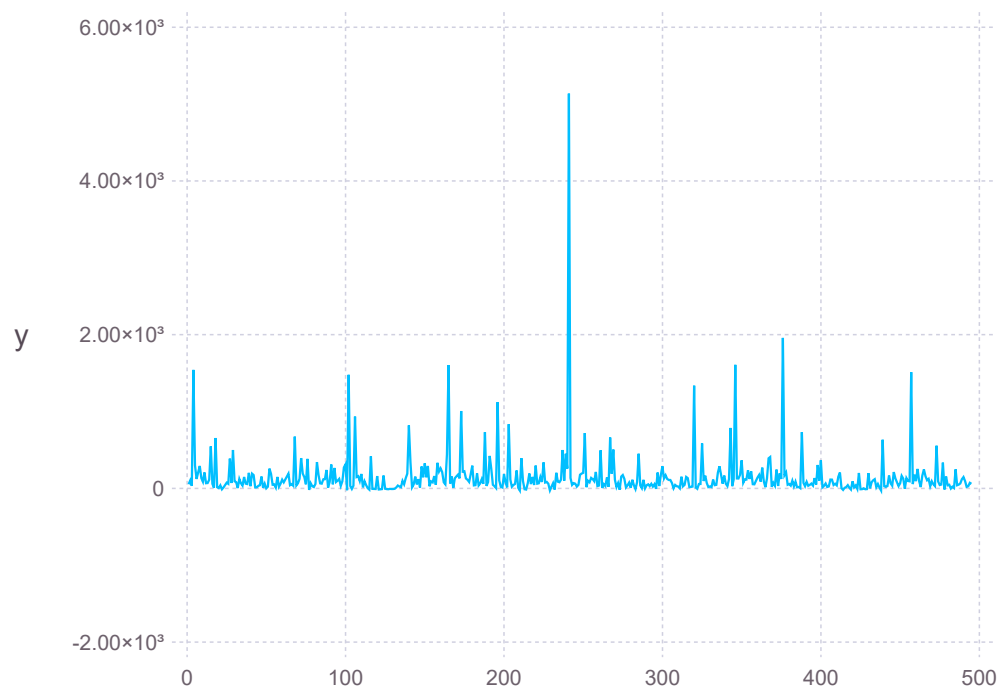
Out[274...



In [275...

```
# independence  
plot(y=red3, Geom.line)
```

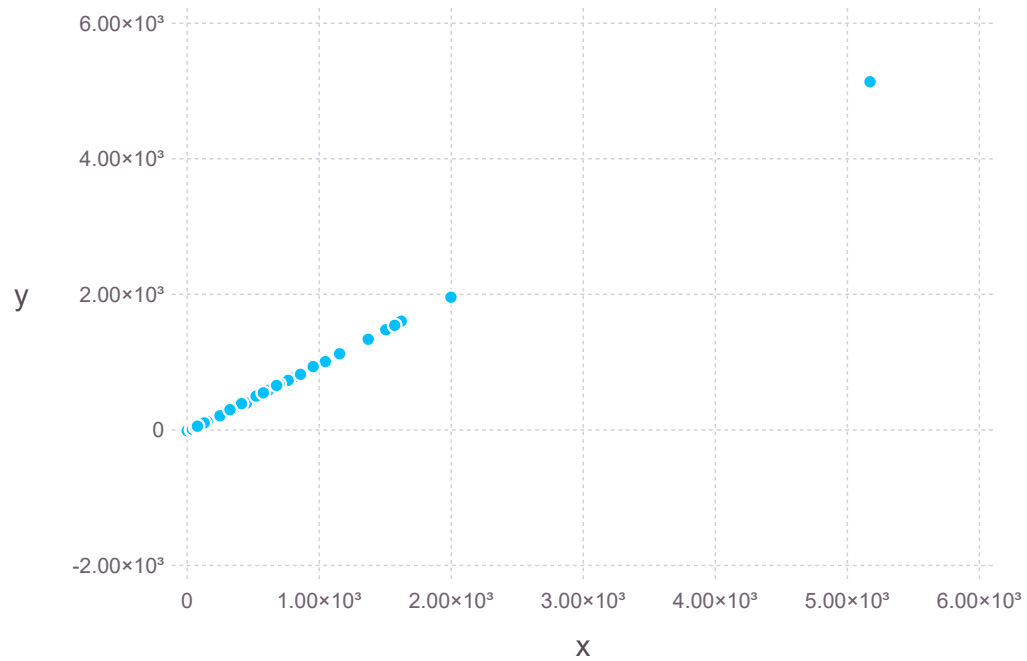
Out[275...



In [276...

```
# Exogeneity assumption  
plot(x = fb_data[!, :like], y=red3)
```

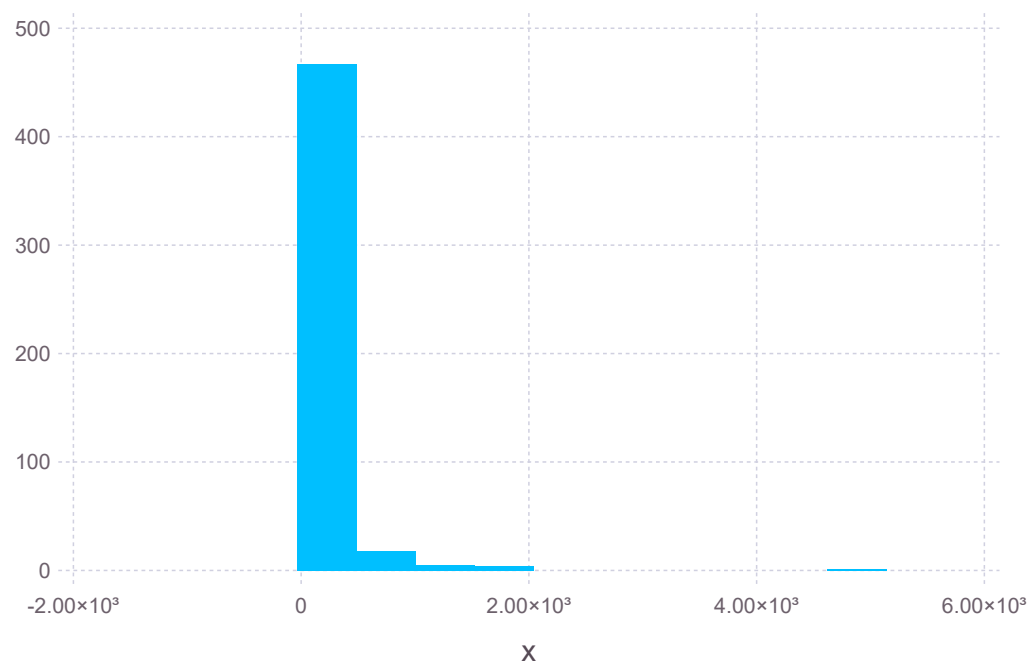
Out[276...



In [277...

```
# error distribution  
using Gadfly  
plot(x=red3, Geom.histogram(bincount=10))
```

Out[277...



In [278...

```
regtable(model2, model3)
```

	comment	share
	(1)	(2)
(Intercept)	-15.446 (16.387)	-2.872 (32.444)
Category	0.383 (1.181)	6.990** (2.338)
Page_total_likes	0.000 (0.000)	0.000 (0.000)
Type: Photo	3.069 (4.861)	8.813 (9.624)
Type: Status	4.927 (5.791)	13.681 (11.464)
Type: Video	6.718 (9.380)	39.294* (18.570)
Post_Month	-1.036	-1.133

	(0.885)	(1.752)
Post_Hour	0.025	-0.472
	(0.228)	(0.451)
Post_Weekday	-0.747	-0.790
	(0.475)	(0.940)
Paid	3.332	6.659
	(2.150)	(4.257)
-----		
Estimator	OLS	OLS
-----		
N	495	495
R2	0.018	0.043
-----		

In [279...

```
m2_log = @formula(log1p(comment)~Category+log1p(Page_total_likes)+Type+Post_Month+Post_Hour+Post_Weekday+Paid)
m3_log = @formula(log1p(share)~Category+log1p(Page_total_likes)+Type+Post_Month+Post_Hour+Post_Weekday+Paid)
model2_log = lm(m2_log, fb_data)
```

Out[279...

```
StatsModels.TableRegressionModel{LinearModel{GLM.LmResp{Vector{Float64}}, GLM.DensePredChol{Float64, CholeskyPivoted{Float64, Matrix{Float64}}}}, Matrix{Float64}}
```

```
:(log1p(comment)) ~ 1 + Category + :(log1p(Page_total_likes)) + Type + Post_Month + Post_Hour + Post_Weekday + Paid
```

Coefficients:

	Coef.	Std. Error	t	Pr(> t )	Lower 95%	Upper 95%
(Intercept)	-10.2293	10.0858	-1.01	0.3110	-30.0466	9.58791
Category	0.109983	0.0584973	1.88	0.0607	-0.00495623	0.224923
log1p(Page_total_likes)	0.981862	0.886047	1.11	0.2684	-0.759102	2.72283
Type: Photo	0.288885	0.240698	1.20	0.2306	-0.184054	0.761825
Type: Status	0.651607	0.2868	2.27	0.0235	0.0880819	1.21513
Type: Video	1.18567	0.464549	2.55	0.0110	0.272891	2.09845
Post_Month	-0.035807	0.0386944	-0.93	0.3552	-0.111836	0.0402225
Post_Hour	-0.00584081	0.0112888	-0.52	0.6051	-0.0280219	0.0163402
Post_Weekday	-0.0385887	0.0235351	-1.64	0.1017	-0.084832	0.00765467
Paid	0.291965	0.106587	2.74	0.0064	0.0825363	0.501393

In [280...

```
model3_log = lm(m3_log, fb_data)
```

```
StatsModels.TableRegressionModel{LinearModel{GLM.LmResp{Vector{Float64}}, GLM.DensePredChol{Float64, CholeskyPivoted{Float64, Matrix{Float64}}}}, Matrix{Float64}}
```



```
Out[280... t64, Matrix{Float64}}}, Matrix{Float64}}
```

```
:(log1p(share)) ~ 1 + Category + :(log1p(Page_total_likes)) + Type + Post_Month + Post_Hour + Post_Weekday + Paid
```

Coefficients:

	Coef.	Std. Error	t	Pr(> t )	Lower 95%	Upper 95%
(Intercept)	7.25892	8.57994	0.85	0.3980	-9.59952	24.1174
Category	0.431007	0.0497634	8.66	<1e-16	0.333229	0.528786
log1p(Page_total_likes)	-0.448924	0.753756	-0.60	0.5517	-1.92995	1.03211
Type: Photo	0.366645	0.204761	1.79	0.0740	-0.0356827	0.768973
Type: Status	0.64526	0.24398	2.64	0.0084	0.165872	1.12465
Type: Video	1.51791	0.39519	3.84	0.0001	0.741417	2.29441
Post_Month	0.00506501	0.0329172	0.15	0.8778	-0.0596129	0.0697429
Post_Hour	-0.029601	0.00960335	-3.08	0.0022	-0.0484703	-0.0107316
Post_Weekday	-0.0342254	0.0200212	-1.71	0.0880	-0.0735644	0.00511364
Paid	0.0927782	0.0906727	1.02	0.3067	-0.0853816	0.270938

```
In [281...
```

```
regtable(model2_log, model3_log)
```

	log1p(comment)	log1p(share)
	(1)	(2)
(Intercept)	-10.229 (10.086)	7.259 (8.580)
Category	0.110 (0.058)	0.431*** (0.050)
log1p(Page_total_likes)	0.982 (0.886)	-0.449 (0.754)
Type: Photo	0.289 (0.241)	0.367 (0.205)
Type: Status	0.652* (0.287)	0.645** (0.244)
Type: Video	1.186* (0.465)	1.518*** (0.395)
Post_Month	-0.036 (0.039)	0.005 (0.033)
Post_Hour	-0.006 (0.011)	-0.030** (0.010)
Post_Weekday	-0.039	-0.034

	(0.024)	(0.020)
Paid	0.292**	0.093
	(0.107)	(0.091)
-----		
Estimator	OLS	OLS
-----		
N	495	495
R2	0.059	0.204
-----		

In [282...

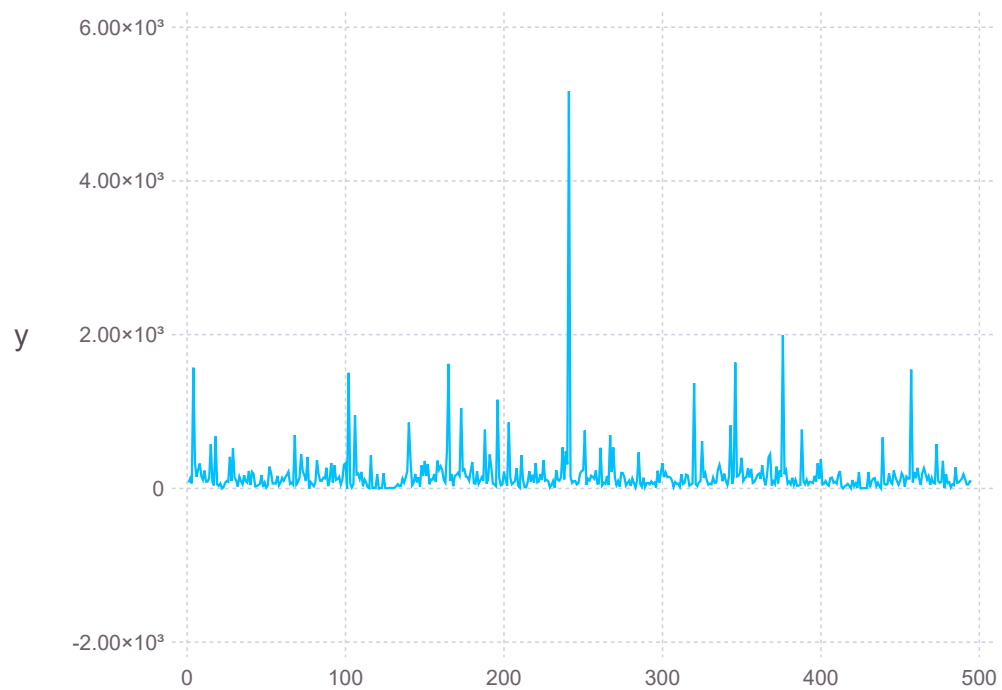
```
# predicted values
pred2_log = predict(model2_log)
# residuals
red2_log = fb_data[:, :like] - pred2_log;

# predicted values
pred3_log = predict(model3_log)
# residuals
red3_log = fb_data[:, :like] - pred3_log;
```

In [283...

```
# independence
plot(y=red2_log, Geom.line)
```

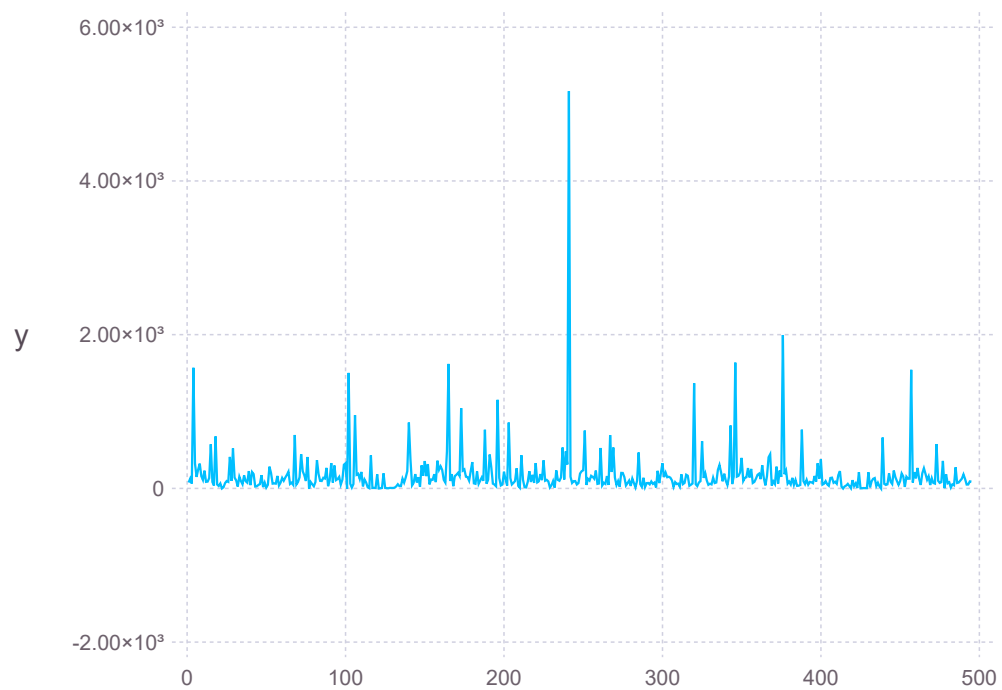
Out[283...



In [284...

```
# independence  
plot(y=red3_log, Geom.line)
```

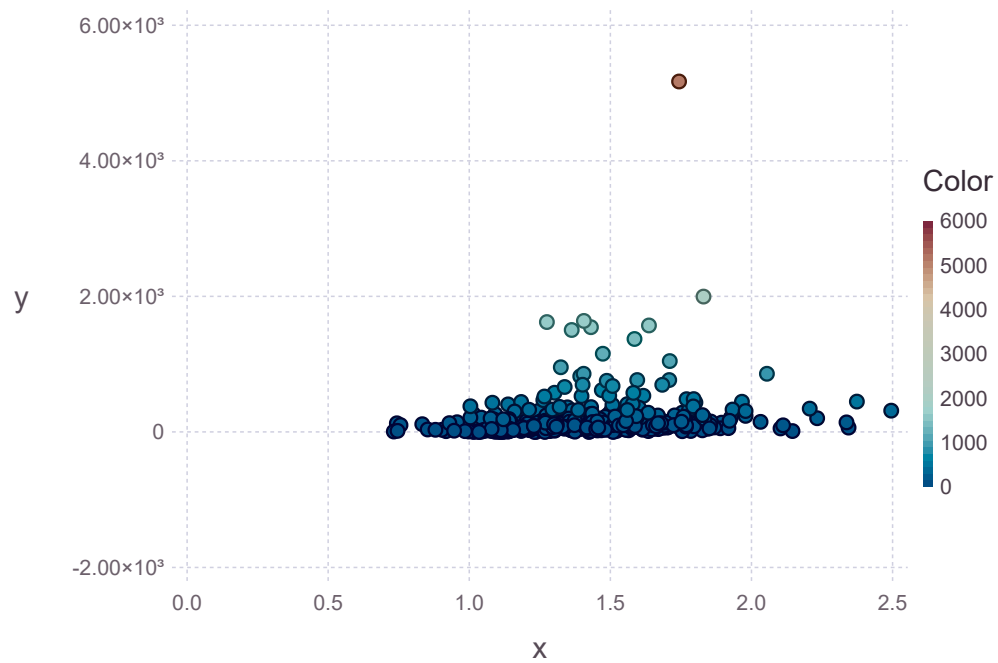
Out[284...



In [285...

```
# Homoscedasticity assumption  
plot(x=pred2_log, y=red2_log,color=fb_data[:, :like])
```

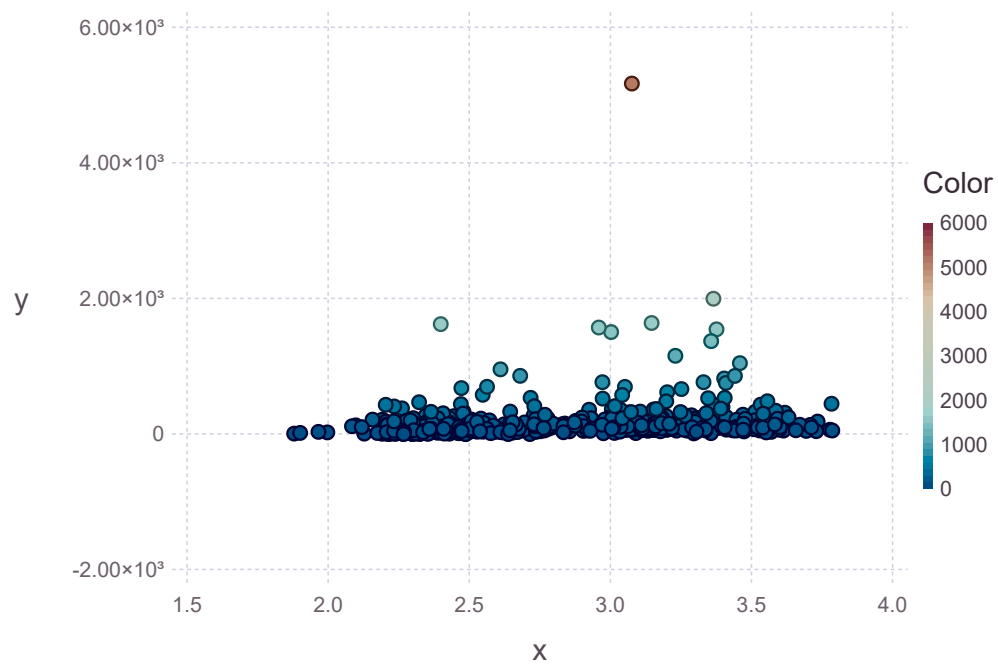
Out[285...



In [286...

```
# Homoscedasticity assumption  
plot(x=pred3_log, y=red3_log,color=fb_data[:, :like])
```

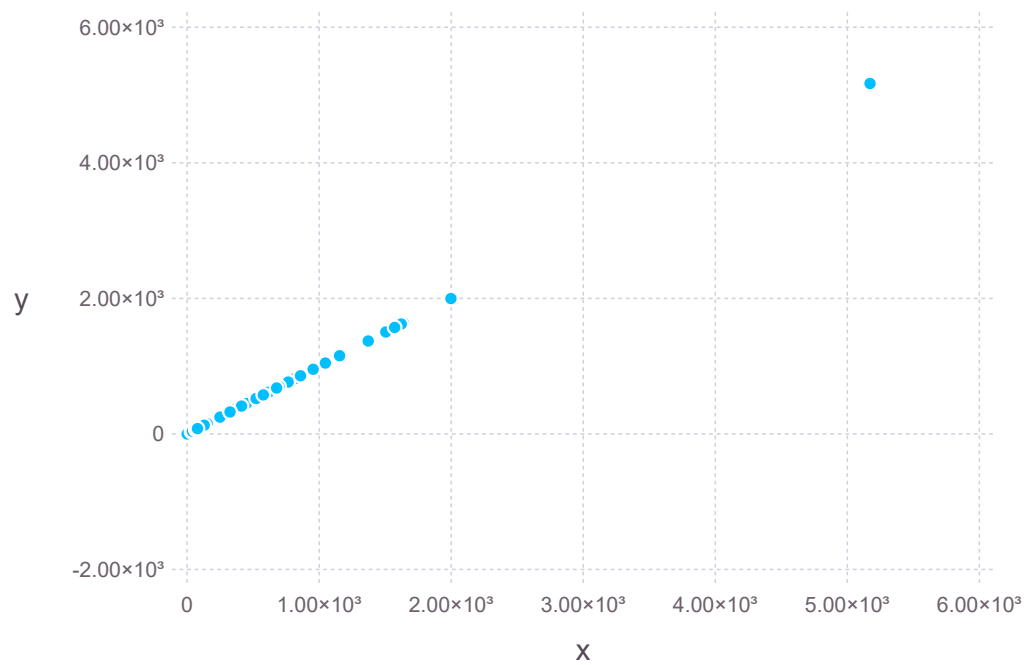
Out[286...



In [287...

```
# Exogeneity assumption  
plot(x = fb_data[:, :like], y=red2_log)
```

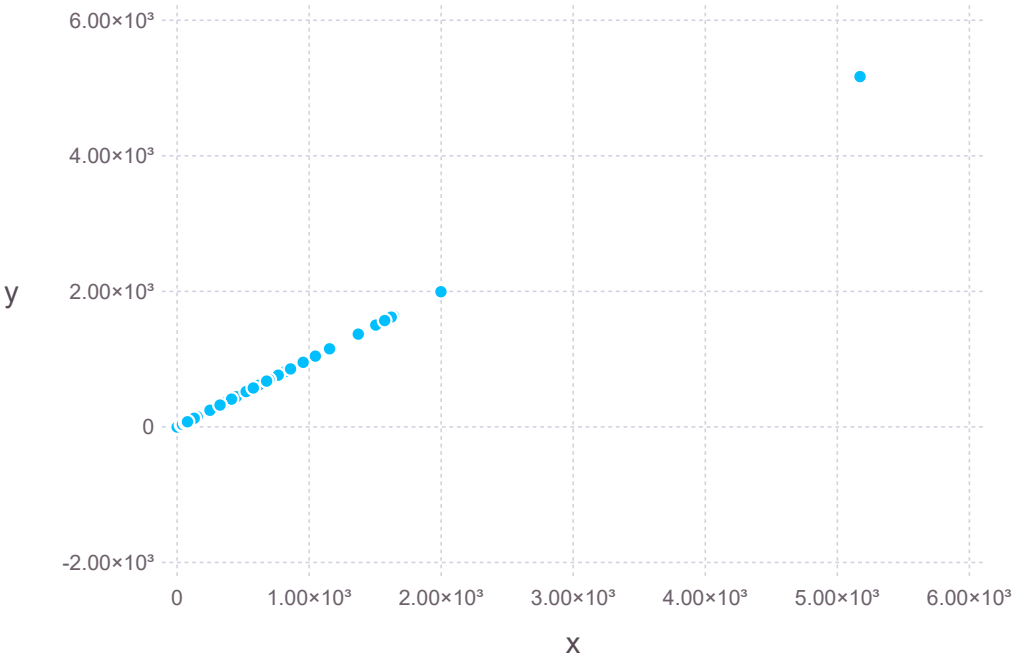
Out[287...



In [288...

```
# Exogeneity assumption  
plot(x = fb_data[, :like], y=red3_log)
```

Out[288...



In [ ]:

In [ ]: