Progress Report

Truck Stop Project

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2024-10-31

Agenda

1. WLIURA
2. Number of Truck Stops VS Restrictiveness ~ uncertain
3. Entry/Exit of Truck Stops VS Restrictiveness ~ negative relationship. High restrictiveness decreases entry and exit.
4. Few Truck stops vs Many Truck Stops , Restrictiveness ~ no relationship
5. Few vs Many entry , Restrictiveness ~ no relationship

Number of Truck Stops VS Restrictiveness

- uncertain

Number of Truck Stops VS Restrictiveness

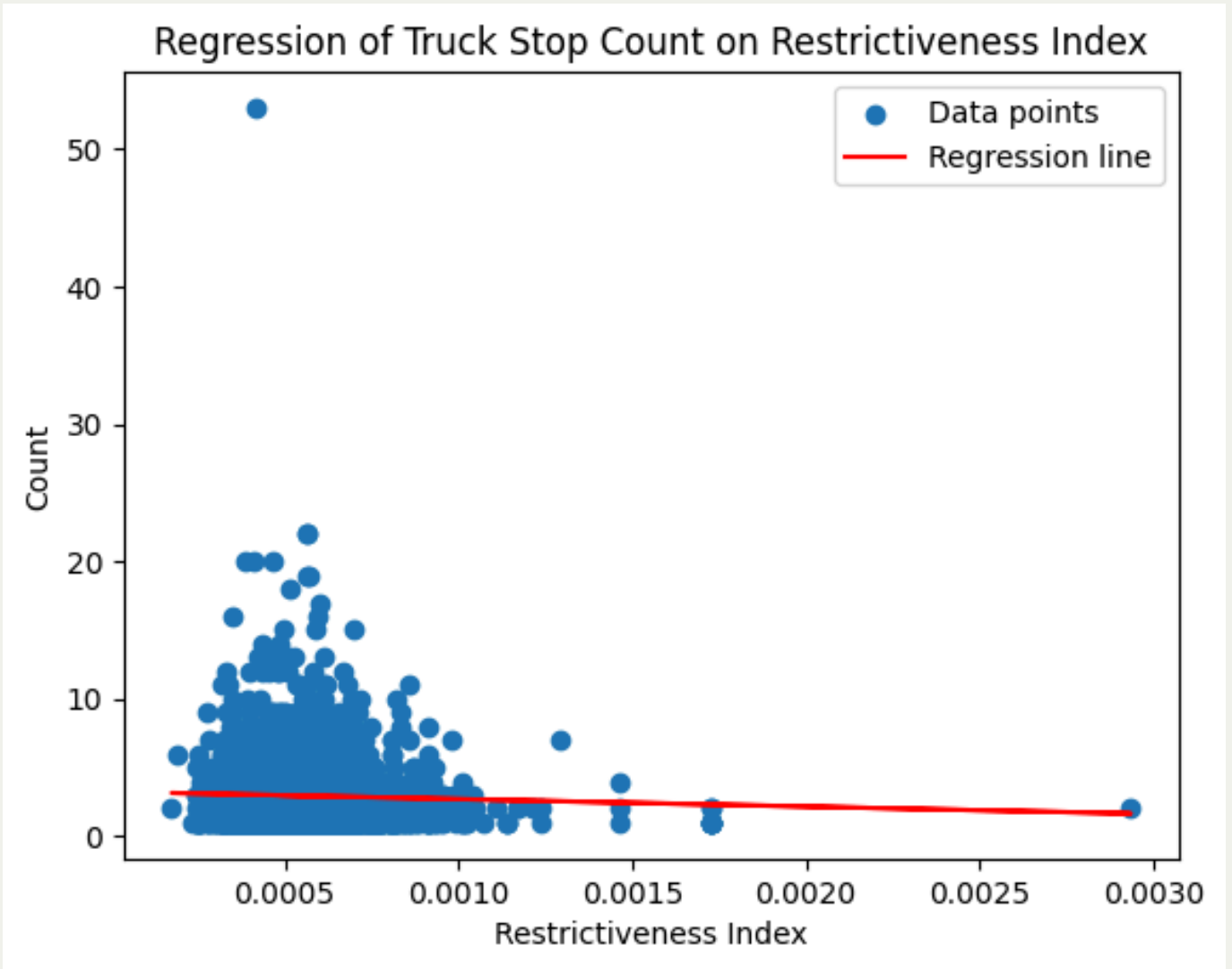
$$\text{NumTruckStop} = \beta_1 \cdot \text{RestricIndex} + \sum_{i=2}^{n} \beta_i Z_i + \epsilon$$

- Possible Controls
  - Near population center
  - 1 standard deviation cheaper land price
  - city/rural dummy , year/state fixed effect
  - trucking capacity

Number of Truck Stops VS Restrictiveness

1. Truck Strop Data contains year, county, number of truck stops
2. Restriction Index Data contains county, restrict index , does NOT contain year
3. Use only 2016 Truck Stop Data
4. Can time Variation on restriction index be found? yes but it takes work to compile and clean
5. I will only be using county data

$\text{NumTruckStop} = \beta_1 \cdot \text{RestricIndex}$



$\text{NumTruckStop} = \beta_1 \cdot \text{RestricIndex}$

OLS Regression Results

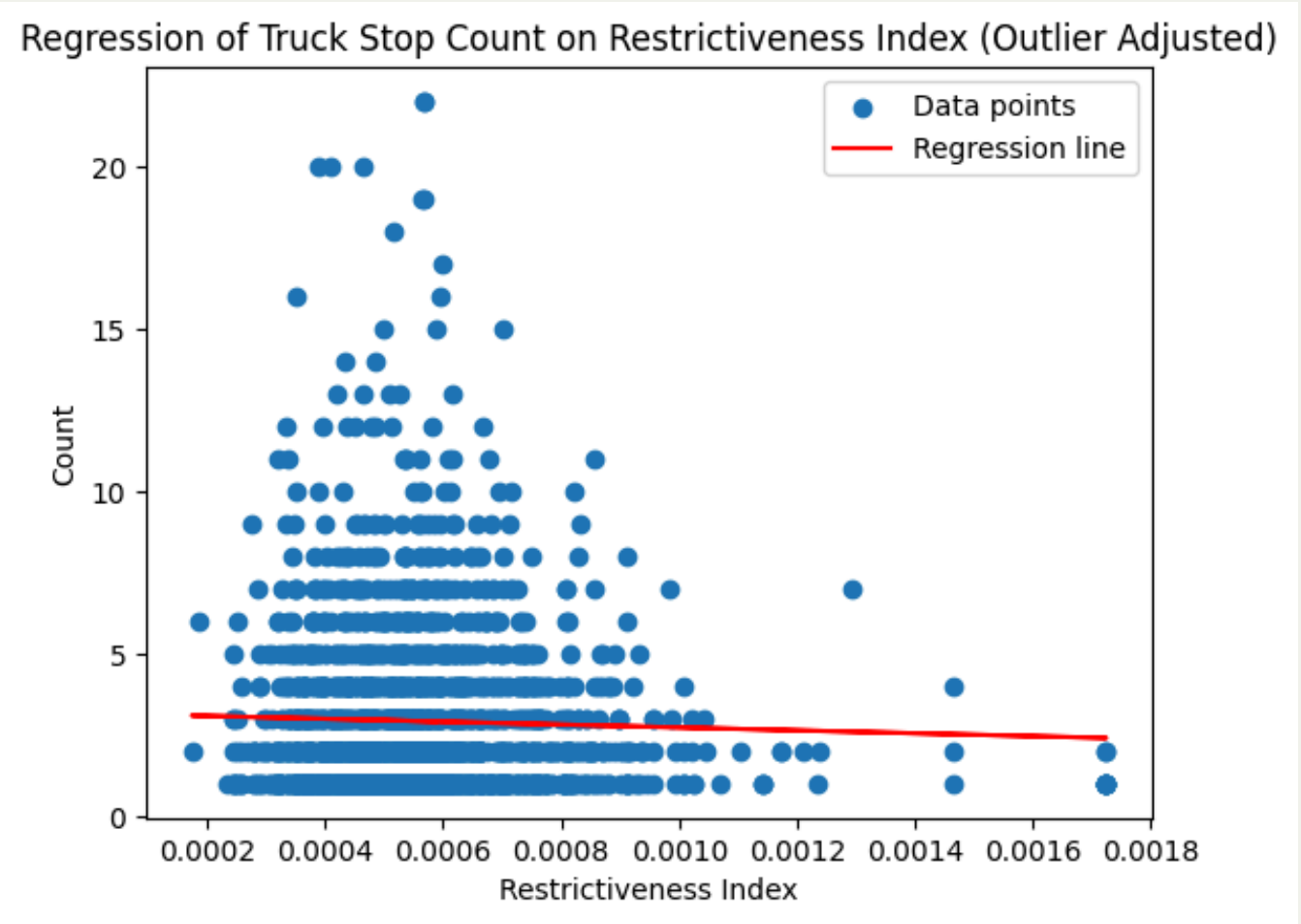
Dep. Variable:	cnt	R-squared:	0.001
Model:	OLS	Adj. R-squared:	0.001
Method:	Least Squares	F-statistic:	2.666
Date:	Wed, 30 Oct 2024	Prob (F-statistic):	0.103
Time:	21:51:45	Log-Likelihood:	-5150.3
No. Observations:	2117	AIC:	1.030e+04
Df Residuals:	2115	BIC:	1.032e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	3.2513	0.193	16.804	0.000	2.872	3.631
idx	-542.4838	332.226	-1.633	0.103	-1194.008	109.040

Omnibus:	2207.541	Durbin-Watson:	1.889
Prob(Omnibus):	0.000	Jarque-Bera (JB):	300055.589
Skew:	4.796	Prob(JB):	0.00
Kurtosis:	60.530	Cond. No.	5.54e+03

$\text{NumTruckStop} = \beta_1 \cdot \text{RestricIndex}$

adjust for outlier



$\text{NumTruckStop} = \beta_1 \cdot \text{RestricIndex}$

OLS Regression Results

Dep. Variable:	cnt	R-squared:	0.001
Model:	OLS	Adj. R-squared:	0.000
Method:	Least Squares	F-statistic:	1.953
Date:	Wed, 30 Oct 2024	Prob (F-statistic):	0.162
Time:	21:51:45	Log-Likelihood:	-4967.8
No. Observations:	2115	AIC:	9940.
Df Residuals:	2113	BIC:	9951.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	3.1740	0.185	17.186	0.000	2.812	3.536
idx	-445.6815	318.927	-1.397	0.162	-1071.125	179.762

Omnibus:	1218.167	Durbin-Watson:	1.861
Prob(Omnibus):	0.000	Jarque-Bera (JB):	11860.408
Skew:	2.581	Prob(JB):	0.00
Kurtosis:	13.389	Cond. No.	5.78e+03

Number of Truck Stops VS Restrictiveness

Conclusion

- No strong evidence
- investigate capacity of truck stops , instead of number of truck stops
- state fixed effects?

State Fixed Effects?

- uncertain

Number of Truck Stops VS Restrictiveness

$$\text{NumTruckStop} = \beta_1 \cdot \text{RestricIndex} + \sum_{j=1}^{m} \gamma_j D_j + \epsilon$$

- Dj are the state dummy variables
- γ_j represents the coefficients for each state dummy variable.
- m is the number of states

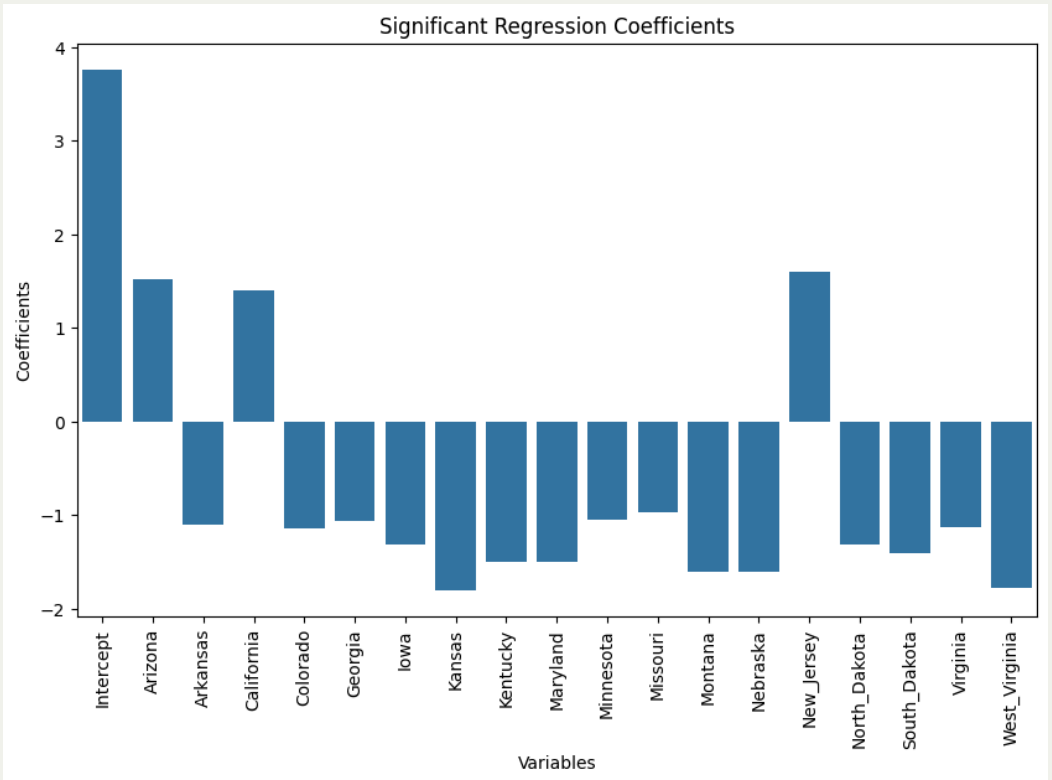
State Fixed Effect Regression

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	3.75994	0.38660	9.726	< 2e-16	***
idx	-467.56130	331.08081	-1.412	0.158034	
state_AlaskaTRUE	-1.68729	0.92481	-1.824	0.068225	.
state_ArizonaTRUE	1.52158	0.72991	2.085	0.037229	*
state_ArkansasTRUE	-1.10145	0.45895	-2.400	0.016485	*
state_CaliforniaTRUE	1.39602	0.51083	2.733	0.006333	**
state_ColoradoTRUE	-1.13918	0.53481	-2.130	0.033285	*
state_ConnecticutTRUE	-0.80028	1.04833	-0.763	0.445322	
state_DelawareTRUE	1.10768	1.44692	0.766	0.444035	
state_FloridaTRUE	-0.17516	0.48847	-0.359	0.719947	
state_GeorgiaTRUE	-1.05856	0.40852	-2.591	0.009632	**
state_IdahoTRUE	-1.04027	0.60547	-1.718	0.085924	.
state_IllinoisTRUE	0.21020	0.45817	0.459	0.646439	
state_IndianaTRUE	-0.56208	0.44736	-1.256	0.209100	
state_IowaTRUE	-1.30943	0.43549	-3.007	0.002672	**
state_KansasTRUE	-1.80284	0.43823	-4.114	4.04e-05	***
state_KentuckyTRUE	-1.50510	0.45179	-3.331	0.000879	***
state_LouisianaTRUE	0.84442	0.46613	1.812	0.070199	.
state_MaineTRUE	-1.20158	0.72998	-1.646	0.099906	.
state_MarylandTRUE	-1.50677	0.60594	-2.487	0.012974	*
state_MassachusettsTRUE	0.69914	0.83846	0.834	0.404471	
state_MichiganTRUE	0.03985	0.44234	0.090	0.928233	
state_MinnesotaTRUE	-1.05605	0.45533	-2.319	0.020474	*
state_MississippiTRUE	-0.85990	0.45635	-1.884	0.059662	.
state_MissouriTRUE	-0.97324	0.43671	-2.229	0.025950	*
state_MontanaTRUE	-1.60619	0.53774	-2.987	0.002851	**
state_NebraskaTRUE	-1.60981	0.48059	-3.350	0.000824	***
state_NevadaTRUE	-0.23140	0.73058	-0.317	0.751474	
state_New_HampshireTRUE	1.11379	1.05011	1.061	0.288976	
state_New_JerseyTRUE	1.59975	0.63904	2.503	0.012379	*
state_New_MexicoTRUE	-0.43387	0.59733	-0.726	0.467714	
state_New_YorkTRUE	-0.10029	0.49385	-0.203	0.839094	
state_North_CarolinaTRUE	-0.52132	0.43937	-1.187	0.235556	
state_North_DakotaTRUE	-1.31695	0.59115	-2.228	0.026004	*
state_OhioTRUE	-0.57681	0.43435	-1.328	0.184325	
state_OklahomaTRUE	-0.68230	0.45790	-1.490	0.136355	
state_OregonTRUE	-0.71817	0.63669	-1.128	0.259461	
state_PennsylvaniaTRUE	0.24550	0.45921	0.535	0.592966	
state_Rhode_IslandTRUE	-1.04442	1.75594	-0.595	0.552047	
state_South_CarolinaTRUE	0.97722	0.51050	1.914	0.055726	.
state_South_DakotaTRUE	-1.40199	0.51438	-2.726	0.006473	**
state_TennesseeTRUE	-0.40472	0.47648	-0.849	0.395765	
state_TexasTRUE	-0.49326	0.37750	-1.307	0.191475	
state_UtahTRUE	-0.16884	0.60546	-0.279	0.780379	
state_VermontTRUE	-1.22950	0.80651	-1.524	0.127547	
state_VirginiaTRUE	-1.13308	0.45558	-2.487	0.012956	*
state_WashingtonTRUE	-0.97479	0.61601	-1.582	0.113704	
state_West_VirginiaTRUE	-1.77249	0.62699	-2.827	0.004744	**
state_WisconsinTRUE	0.65698	0.44931	1.462	0.143839	
state_WyomingTRUE	-0.54761	0.61544	-0.890	0.373682	

Significant γ_j plots

$$\text{NumTruckStop} = \beta_1 \cdot \text{RestricIndex} + \sum_{j=1}^{m} \gamma_j D_j + \epsilon$$

Isolate 2 standard deviation coefficients



Number of Truck Stops VS Restrictiveness

- Conclusion
  - uncertain
  - $\text{Num\_Truck\_Stop} = \text{Entry} + \text{Exit} + \text{Initial\_Truck\_Stops}$
    - Investigate Entry, Exit and Initial Truck Stops (2006 data)
      - Same Analysis done on initial truck stop with the same conclusion

Restrictiveness and Entry?

- negative relationship

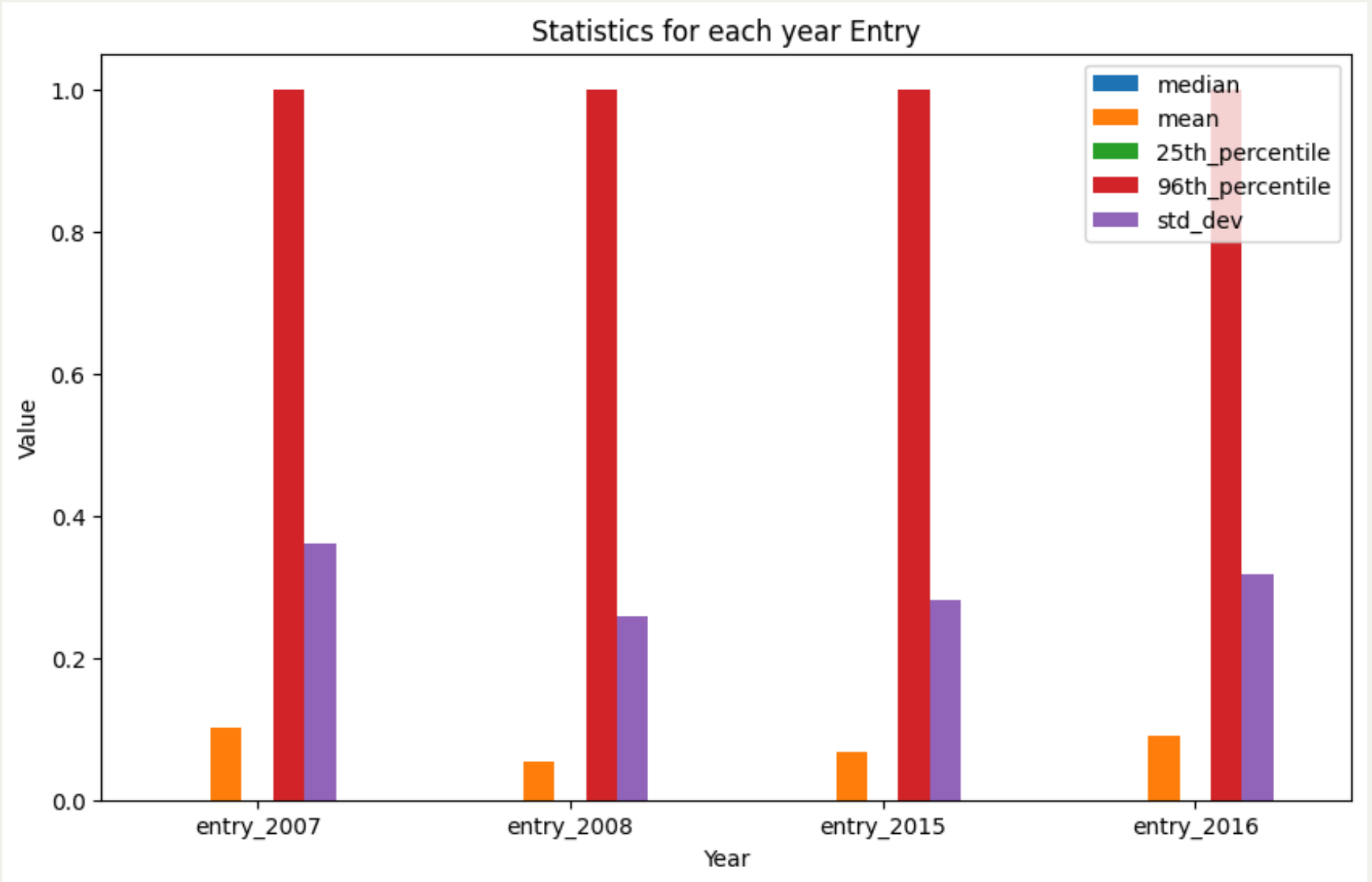
Restrictiveness and Entry?

1. Assume Constant Restrictiveness (in line with stylized facts from previous literature)
   - our data doesn't allow for variation in resitrctiveness

Restrictiveness and Entry?

- Data on entries
  - we see year
  - we see county
- we want to aggregate the years such that we have entries from 2006-2016
  - but we have to check for single year anomalys

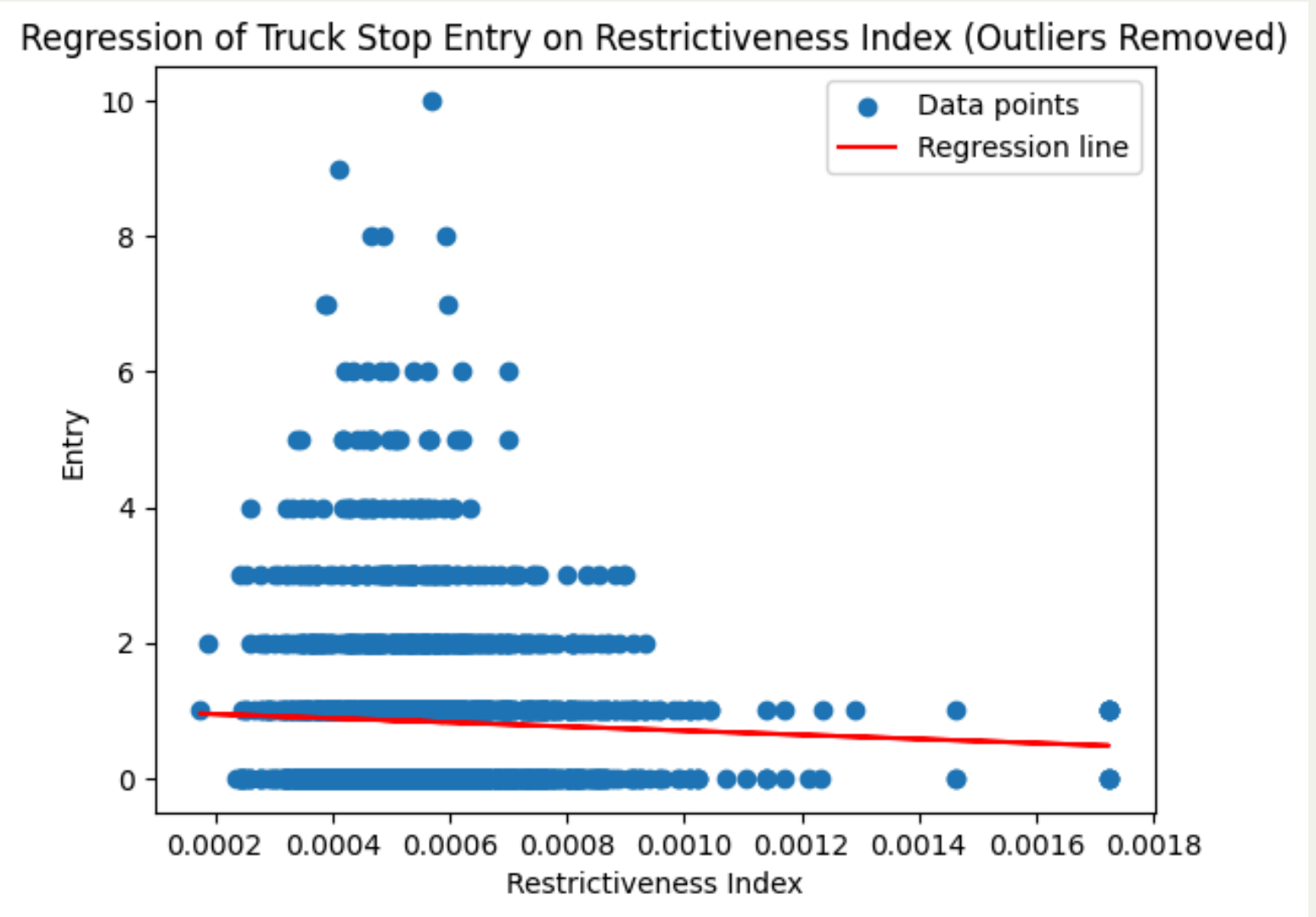
No Single Year Anomaly



We can now safely use 2006-2016 data

every 10 years on average 1~2 truck stop gets built

$$\text{NumEntries} = \beta_1 \cdot \text{RestricIndex} + \epsilon$$



Significant

- we have >2 standard deviations coefficient

OLS Regression Results

Dep. Variable:	entry_2006_2016	R-squared:	0.002
Model:	OLS	Adj. R-squared:	0.002
Method:	Least Squares	F-statistic:	4.661
Date:	Thu, 31 Oct 2024	Prob (F-statistic):	0.0310
Time:	00:34:20	Log-Likelihood:	-3525.1
No. Observations:	2260	AIC:	7054.
Df Residuals:	2258	BIC:	7066.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.0064	0.082	12.294	0.000	0.846	1.167
idx	-305.3128	141.419	-2.159	0.031	-582.637	-27.989

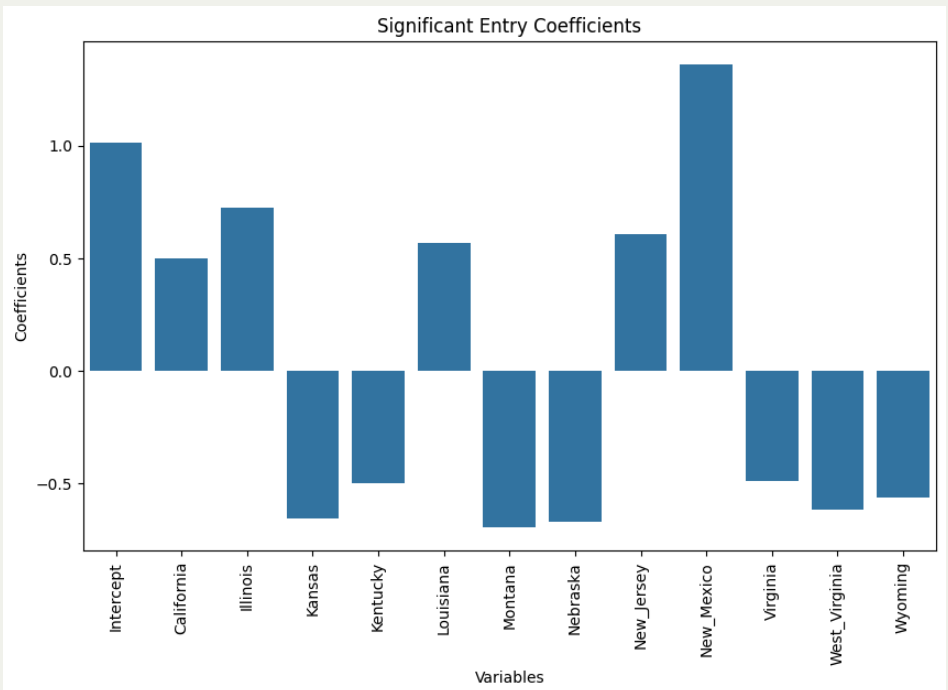
Omnibus:	1097.096	Durbin-Watson:	1.798
Prob(Omnibus):	0.000	Jarque-Bera (JB):	7396.042
Skew:	2.208	Prob(JB):	0.00
Kurtosis:	10.684	Cond. No.	5.84e+03

Add State Dummies

$$\text{NumEntries} = \beta_1 \cdot \text{RestricIndex} + \epsilon + \sum_{j=1}^{m} \gamma_j D_j + \epsilon$$

Isolate >2 standard deviation coefficients

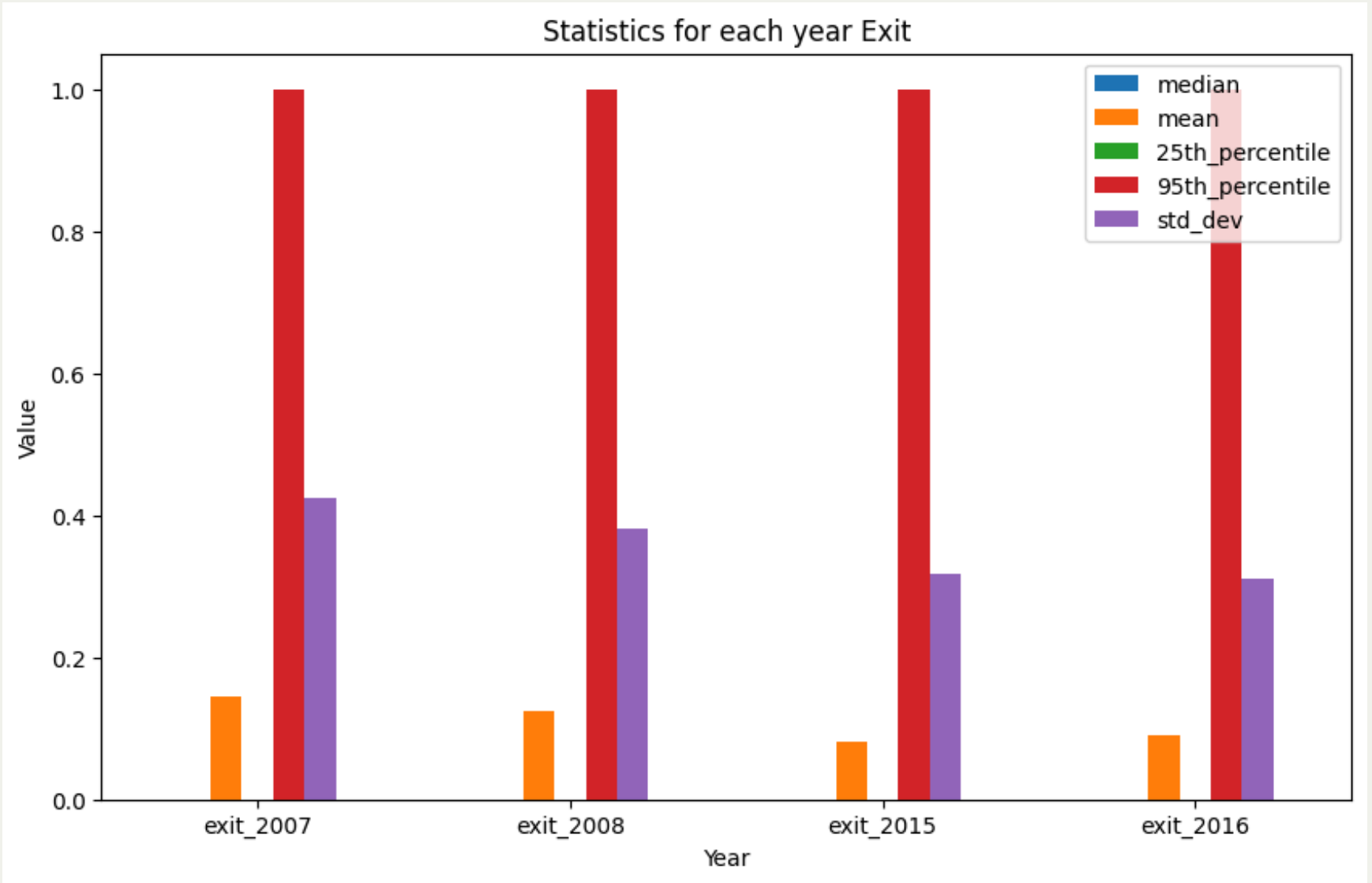
insignificant t stat for restrictive index



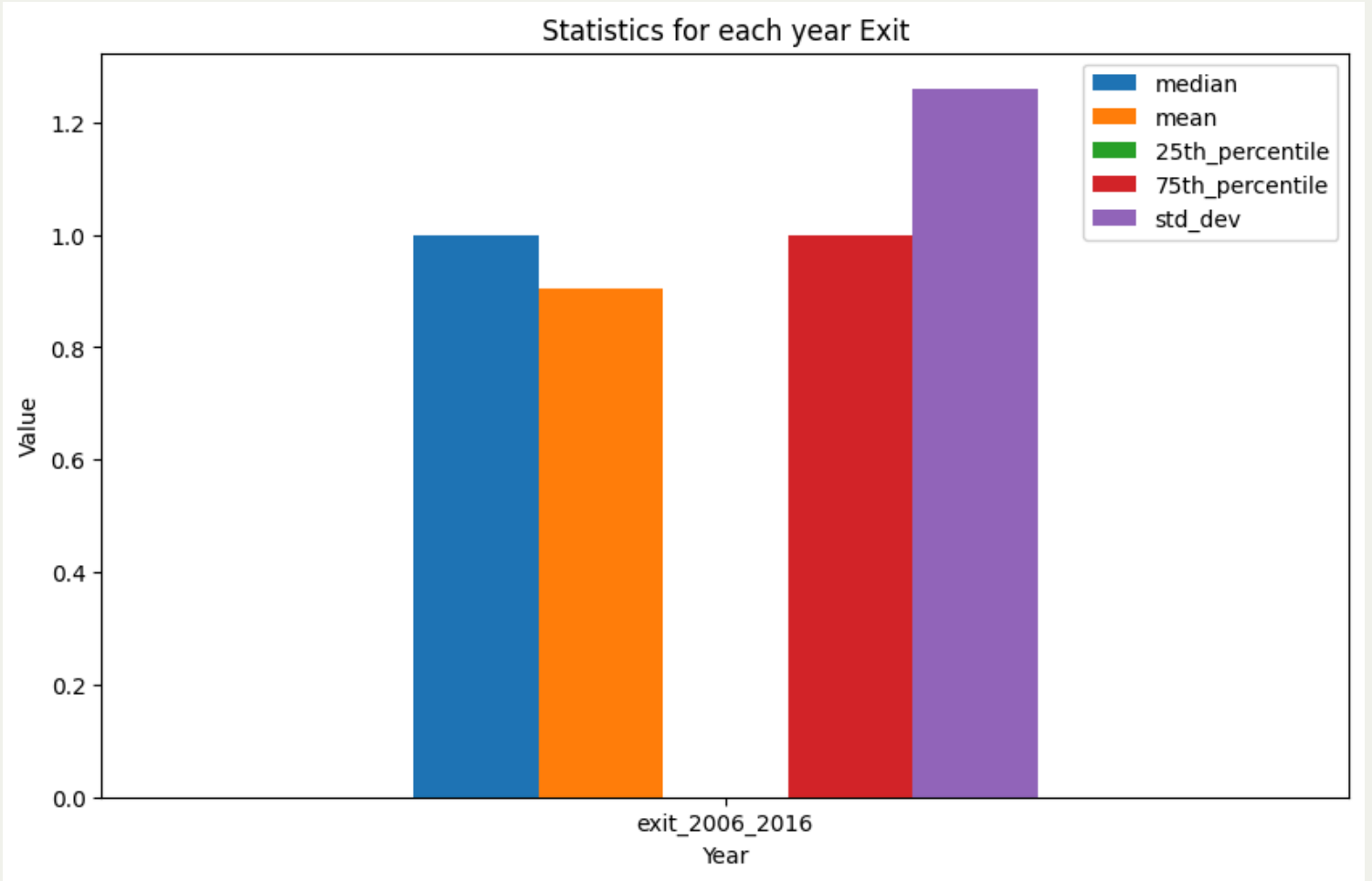
Restrictiveness and Exit?

- there is a significant negative relationship

No Single Year Anomaly

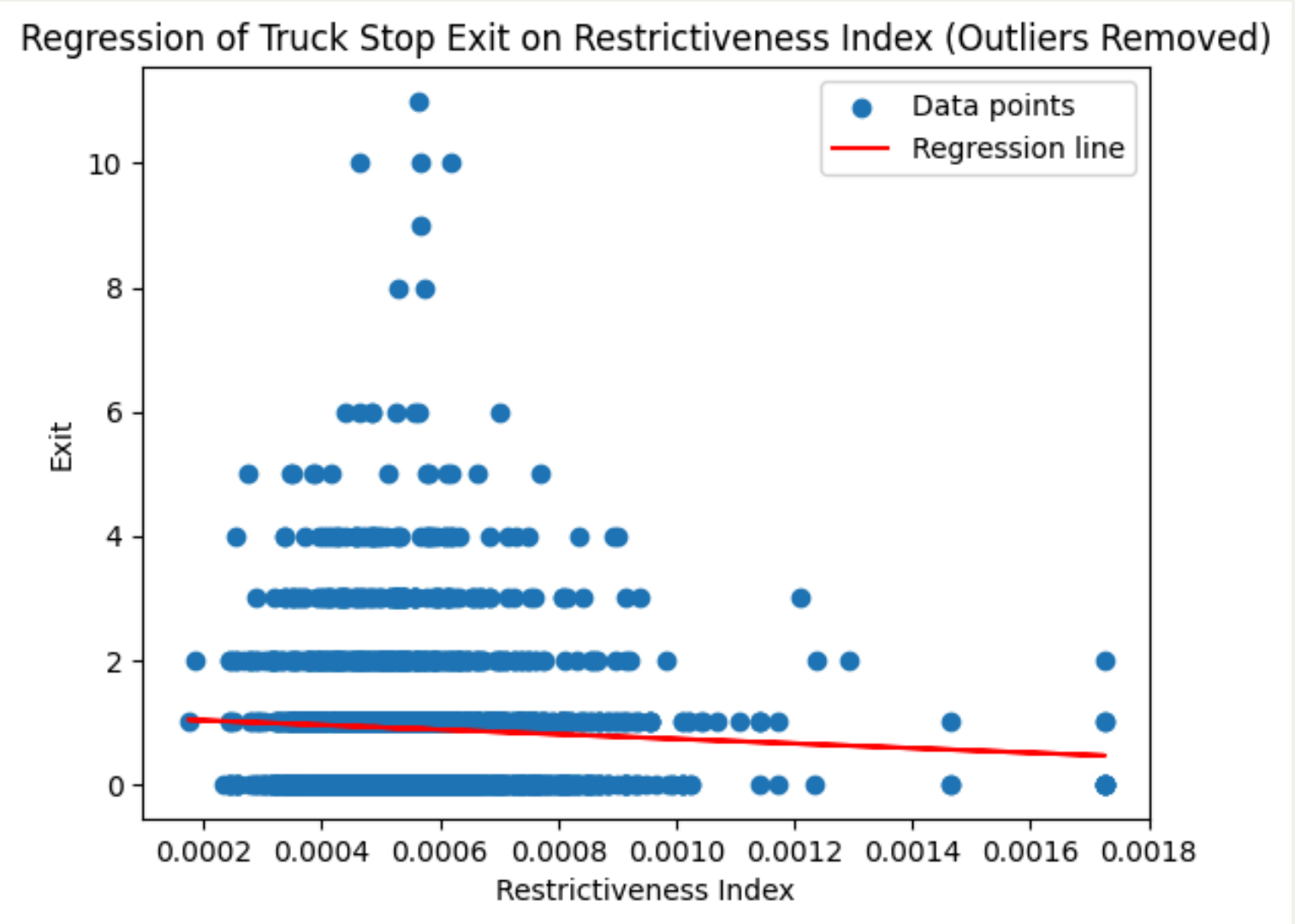


2006-2016 exit data is similar to entry data



Entry Data (for comparison to exit data)

$$\text{Num\_Exits} = \beta_1 \cdot \text{RestricIndex} + \epsilon$$



$\text{Num\_Exits} = \beta_1 \cdot \text{RestricIndex} + \epsilon$

OLS Regression Results

Dep. Variable:	exit_2006_2016	R-squared:	0.003
Model:	OLS	Adj. R-squared:	0.003
Method:	Least Squares	F-statistic:	6.709
Date:	Thu, 31 Oct 2024	Prob (F-statistic):	0.00965
Time:	13:15:02	Log-Likelihood:	-3562.5
No. Observations:	2260	AIC:	7129.
Df Residuals:	2258	BIC:	7140.
Df Model:	1		
Covariance Type:	nonrobust		

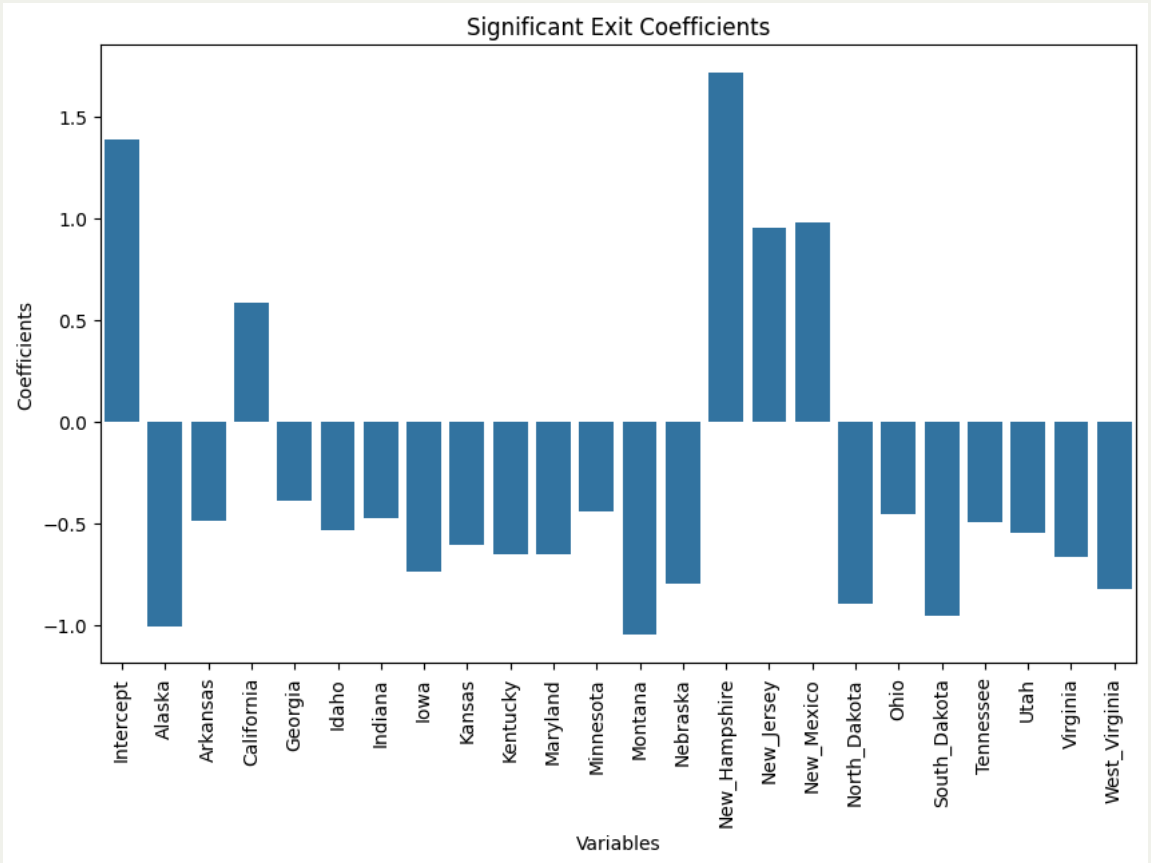
	coef	std err	t	P>|t|	[0.025	0.975]
const	1.1015	0.083	13.234	0.000	0.938	1.265
idx	-372.4324	143.782	-2.590	0.010	-654.391	-90.474

Omnibus:	1231.554	Durbin-Watson:	1.820
Prob(Omnibus):	0.000	Jarque-Bera (JB):	12556.826
Skew:	2.381	Prob(JB):	0.00
Kurtosis:	13.520	Cond. No.	5.84e+03

Significant Coefficients

Alaska has less exits, New Hampshire has a lot of exits

restriction index has significant t stat



Restrictiveness and Exit?

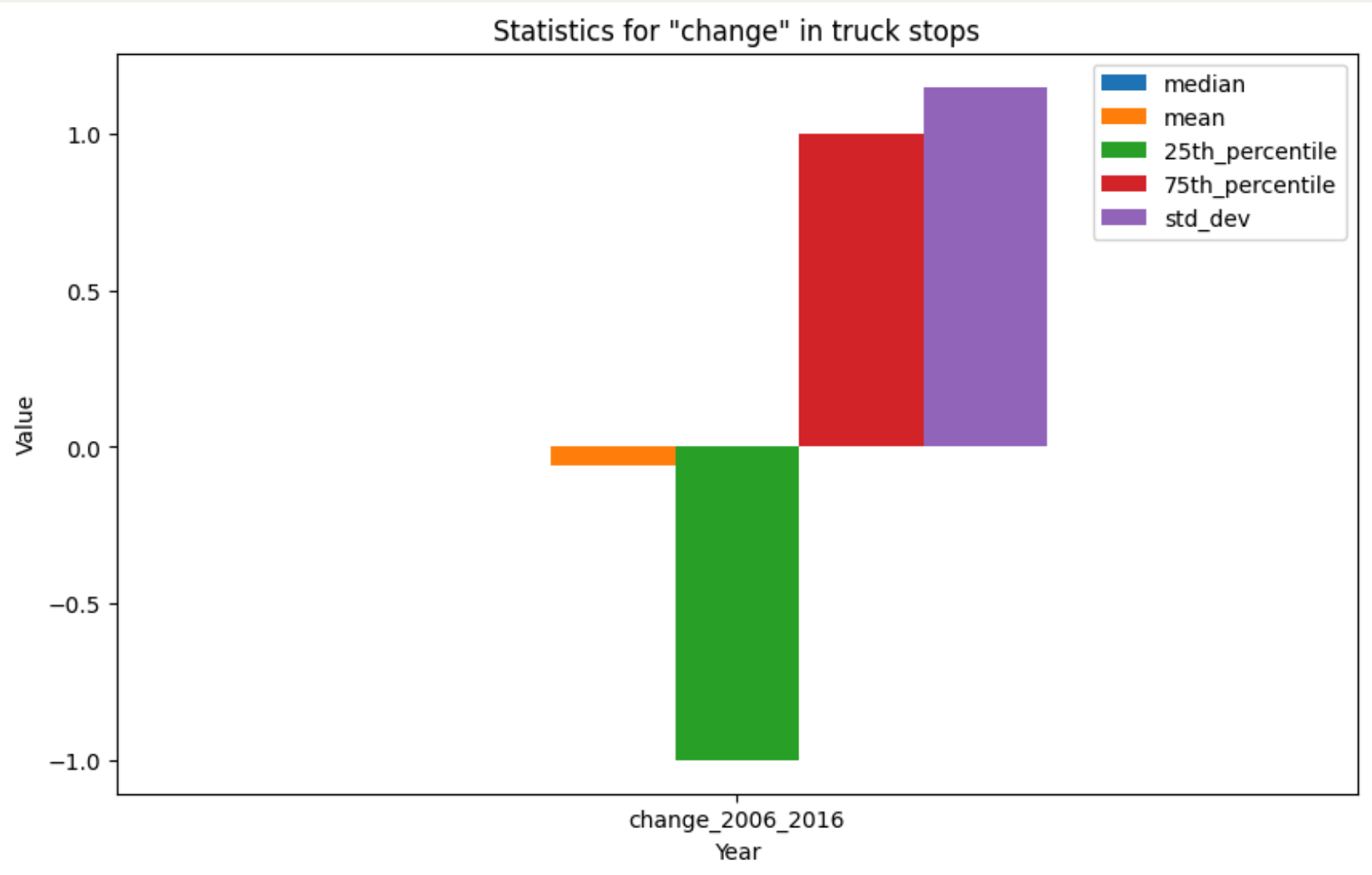
Conclusion

- Theory: high restrictiveness makes entry difficult which increases market power for existing truck stops
  - high restrictiveness biases towards status quo

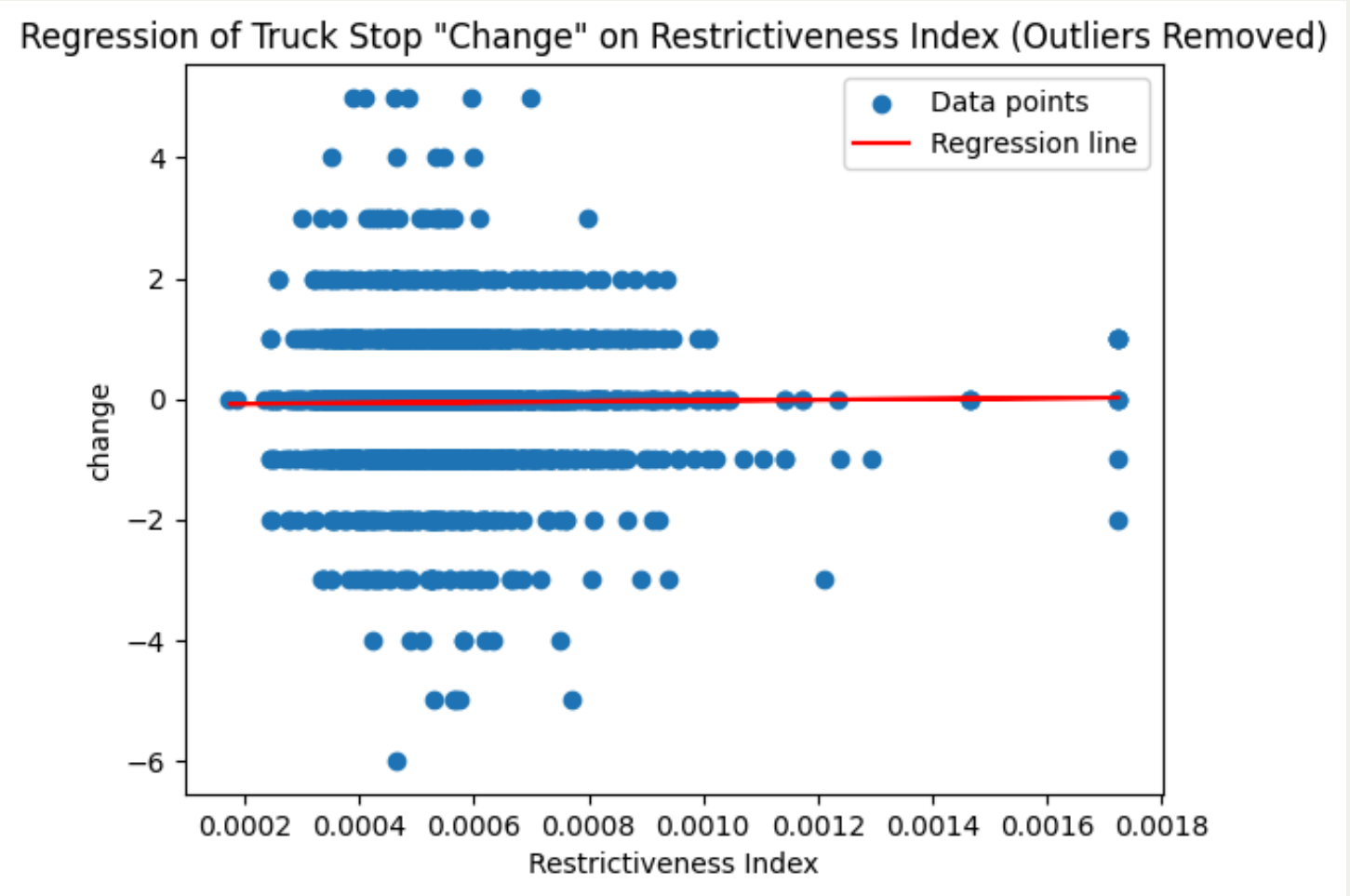
Restrictiveness and Change?

- $\text{Num\_Truck\_Stop} = \text{Entry} + \text{Exit} + \text{Initial\_Truck\_Stops}$
- $\text{Change} = \text{Entry} + \text{Exit}$

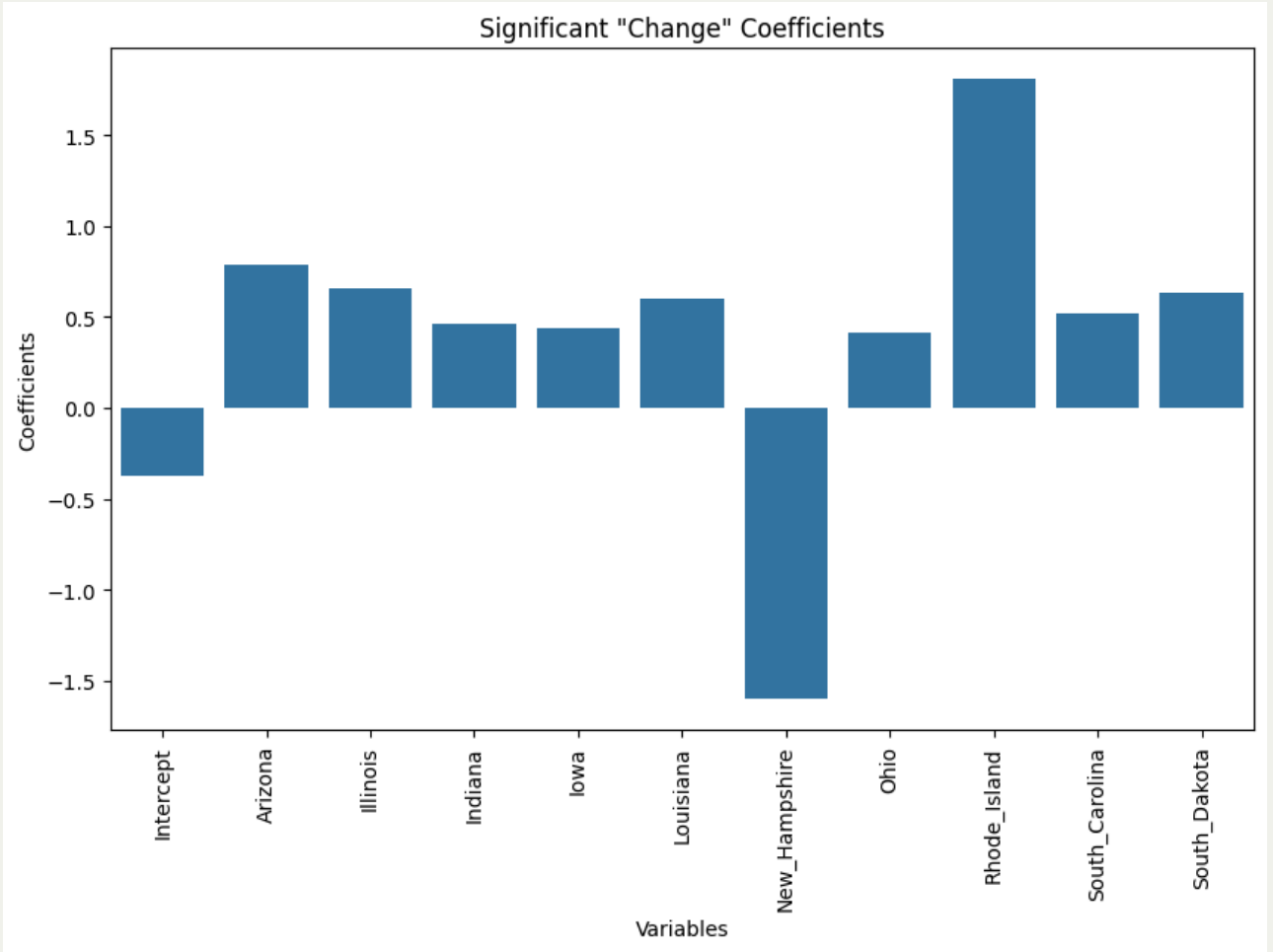
Inline with our theory



Inline with our theory (insignificant t stat)



New Hampshire stands out but nothing else



Taking Stock

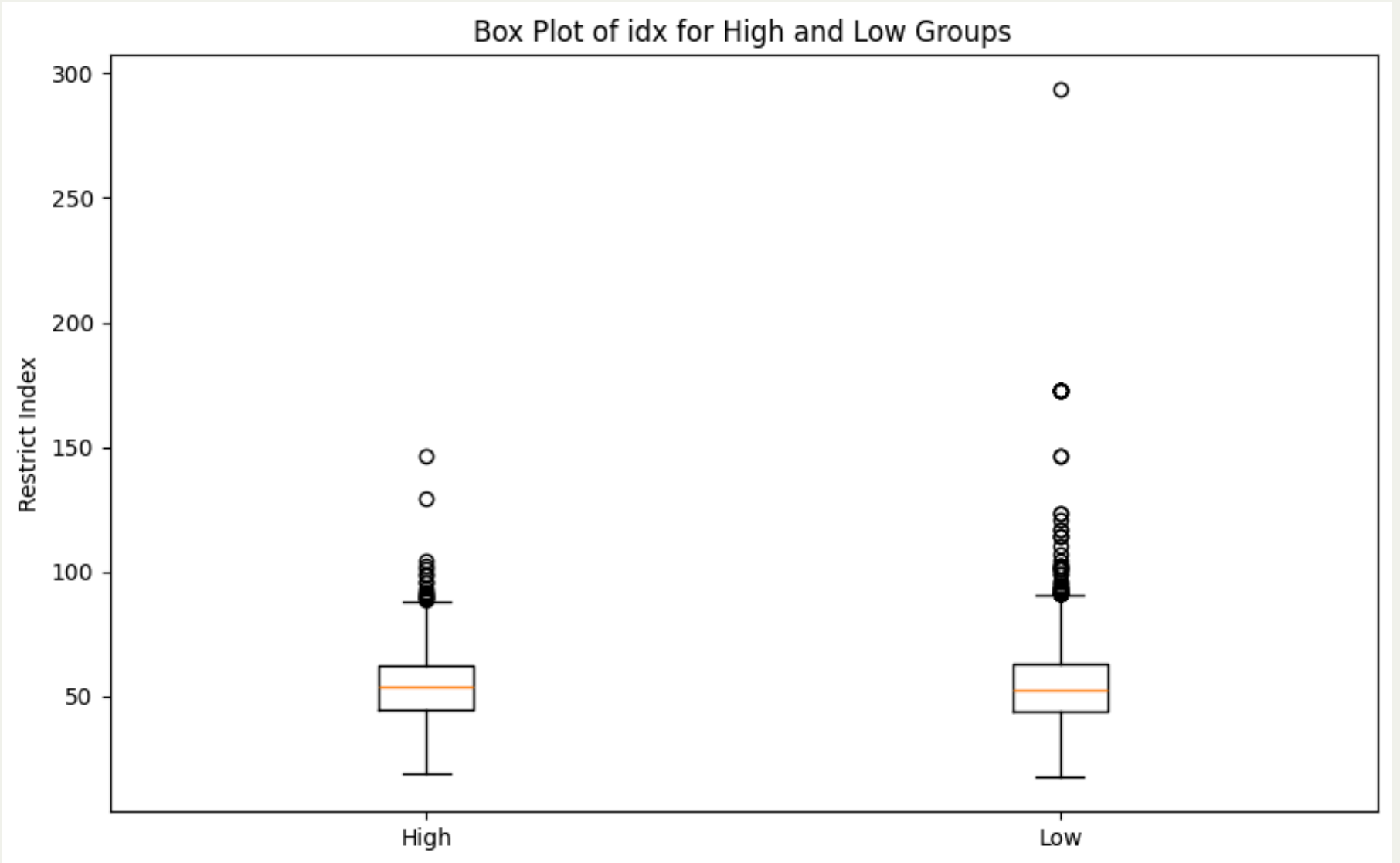
1. Number of Truck Stops VS Restrictiveness
    - uncertain
2. Entry/Exit of Truck Stops VS Restrictiveness
    - negative relationship. High restrictiveness decreases entry and exit.
3. Few Truck stops vs Many Truck Stops , Restrictiveness
    - no

2nd Attempt
High/Low analysis

Median Split high and low group

1. split by median (there are outliers in data) (median =2, number of truck stops)
2. create high and low bins
3. Plot Restrict Index

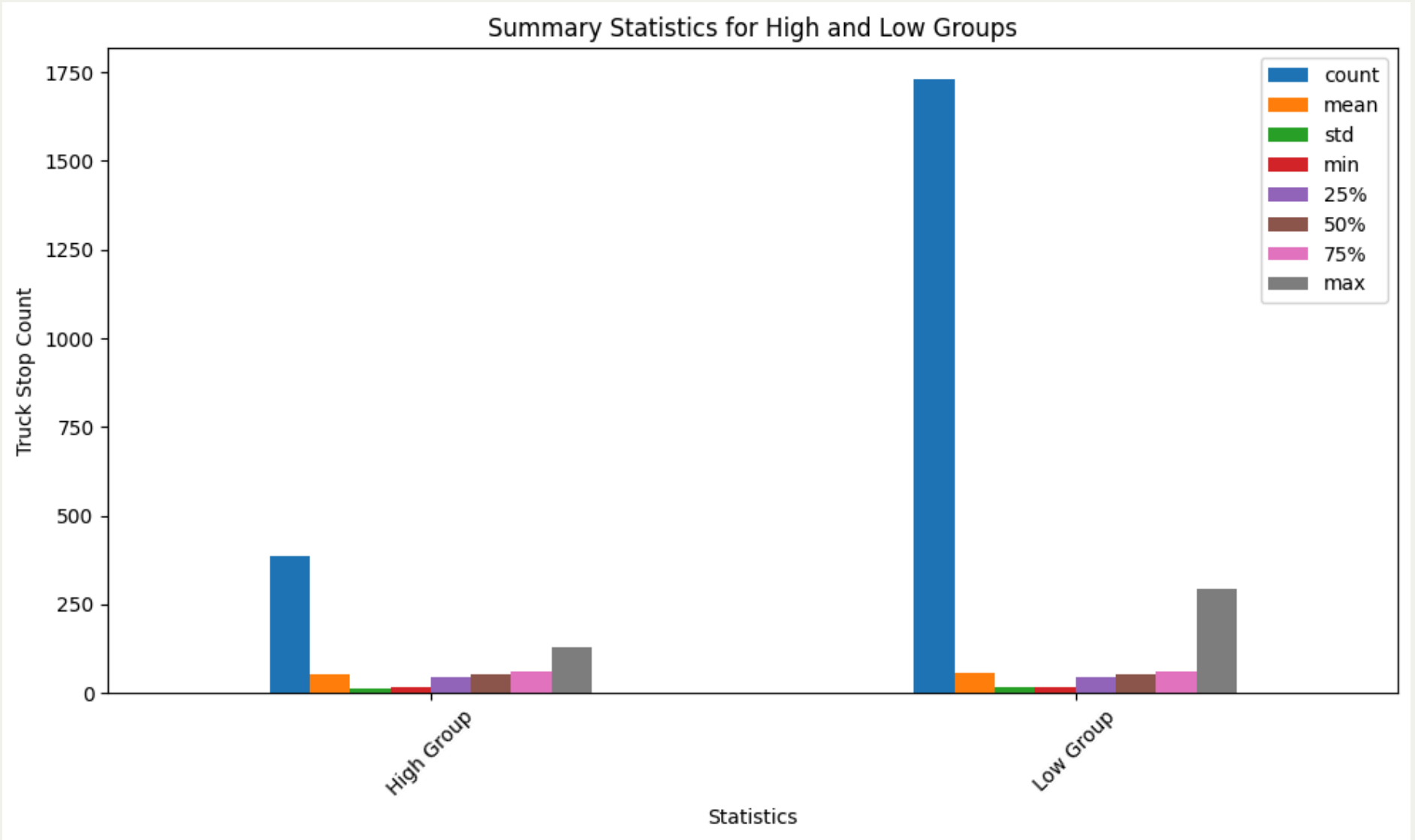
Plot


Box Plot of idx for High and Low Groups
Restrict Index
300
250
200
150
100
50
High
Low

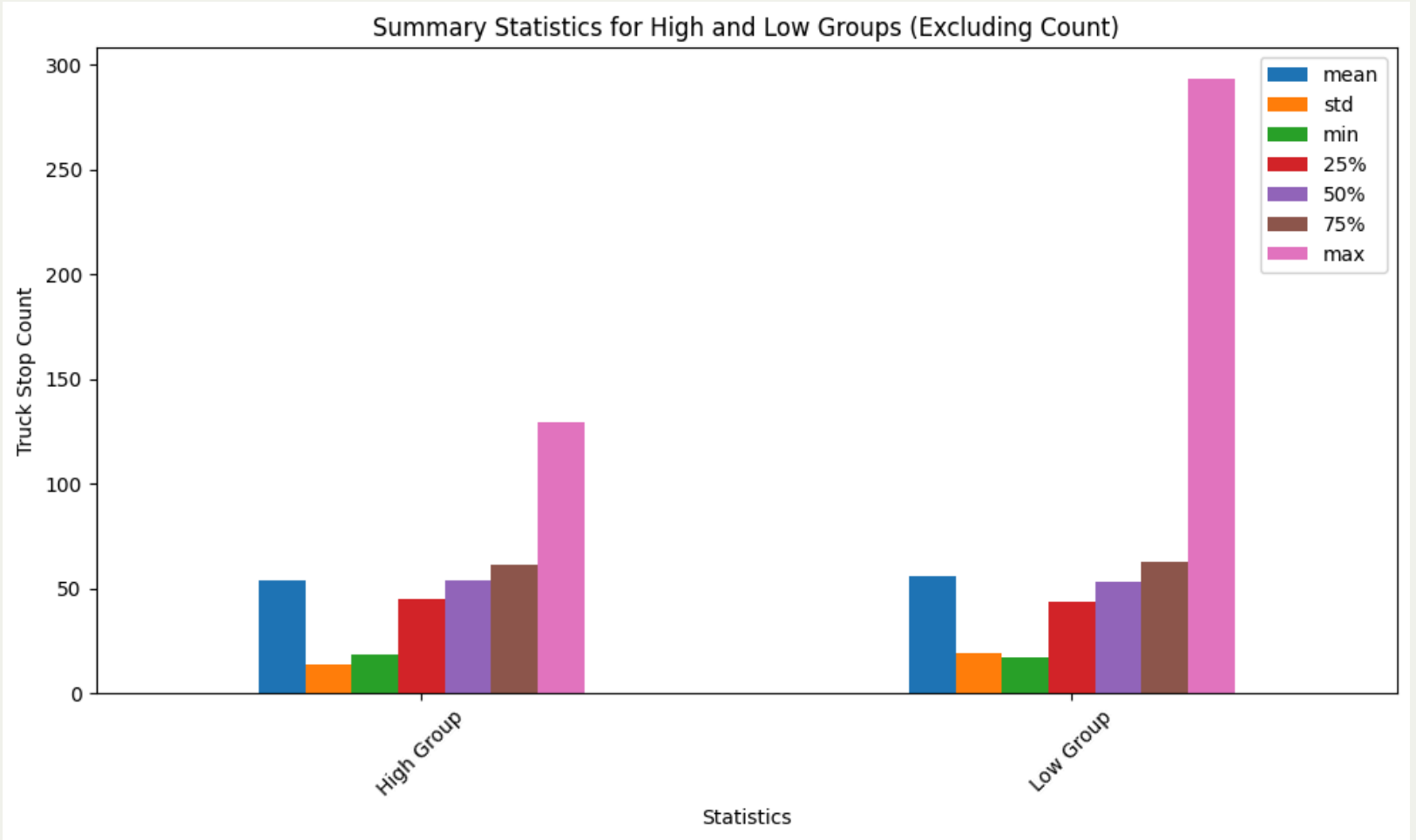
1 standard deviation Outlier Split high and low group

1. split by outlier (outlier_threshold=median+std =2+2.7, number of truck stops)
2. 4.7 truck stop split high vs low bin
3. Plot Restrict Index

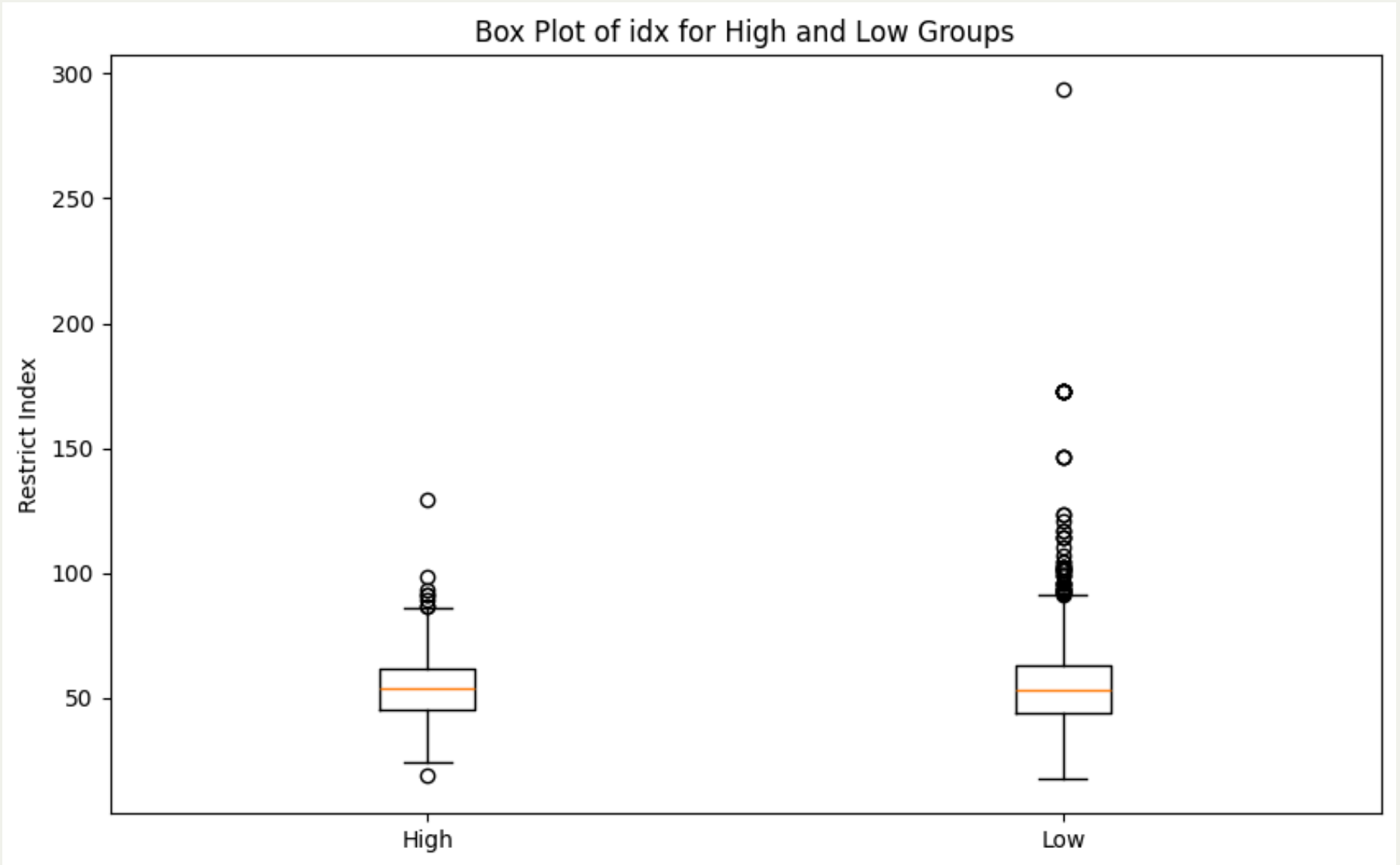
Skewed Observation on 1 sd



Skewed Observations but still roughly similar



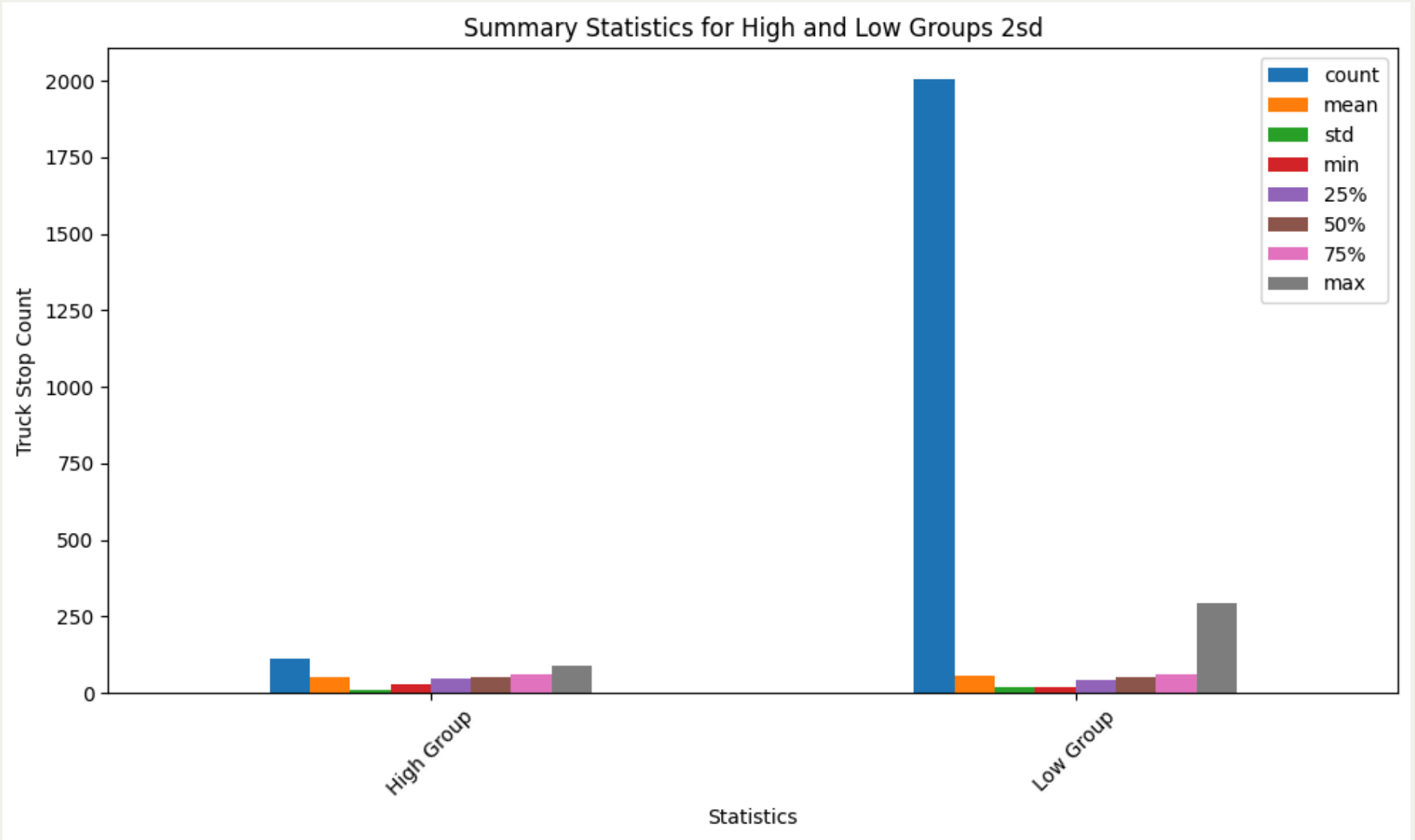
1sd high low split outlier results



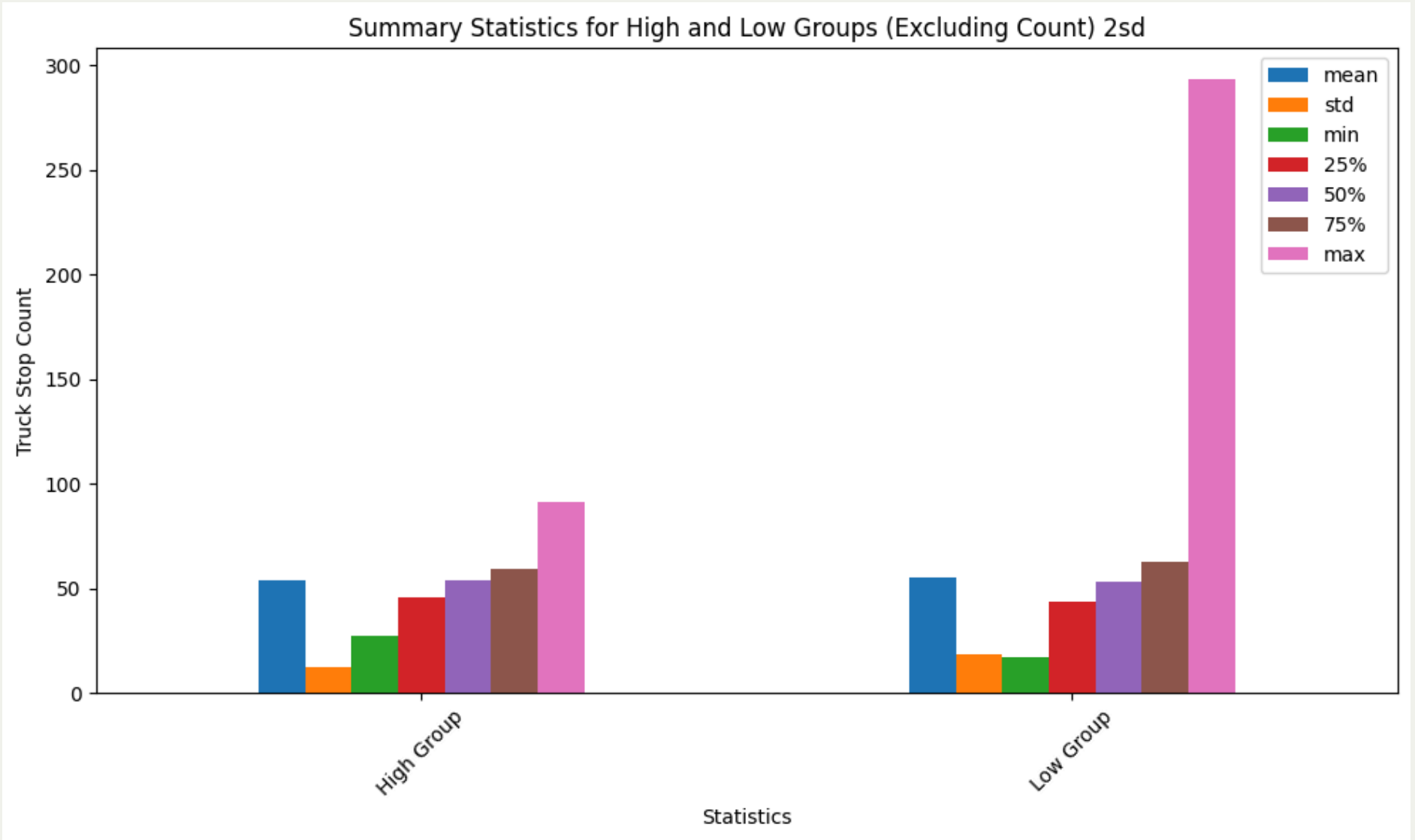
Try for 2 standard deviation split

1. split by outlier (outlier_threshold=median+2*std =2+2.7, number of truck stops)
2. truck stop split high vs low bin
3. Plot Restrict Index

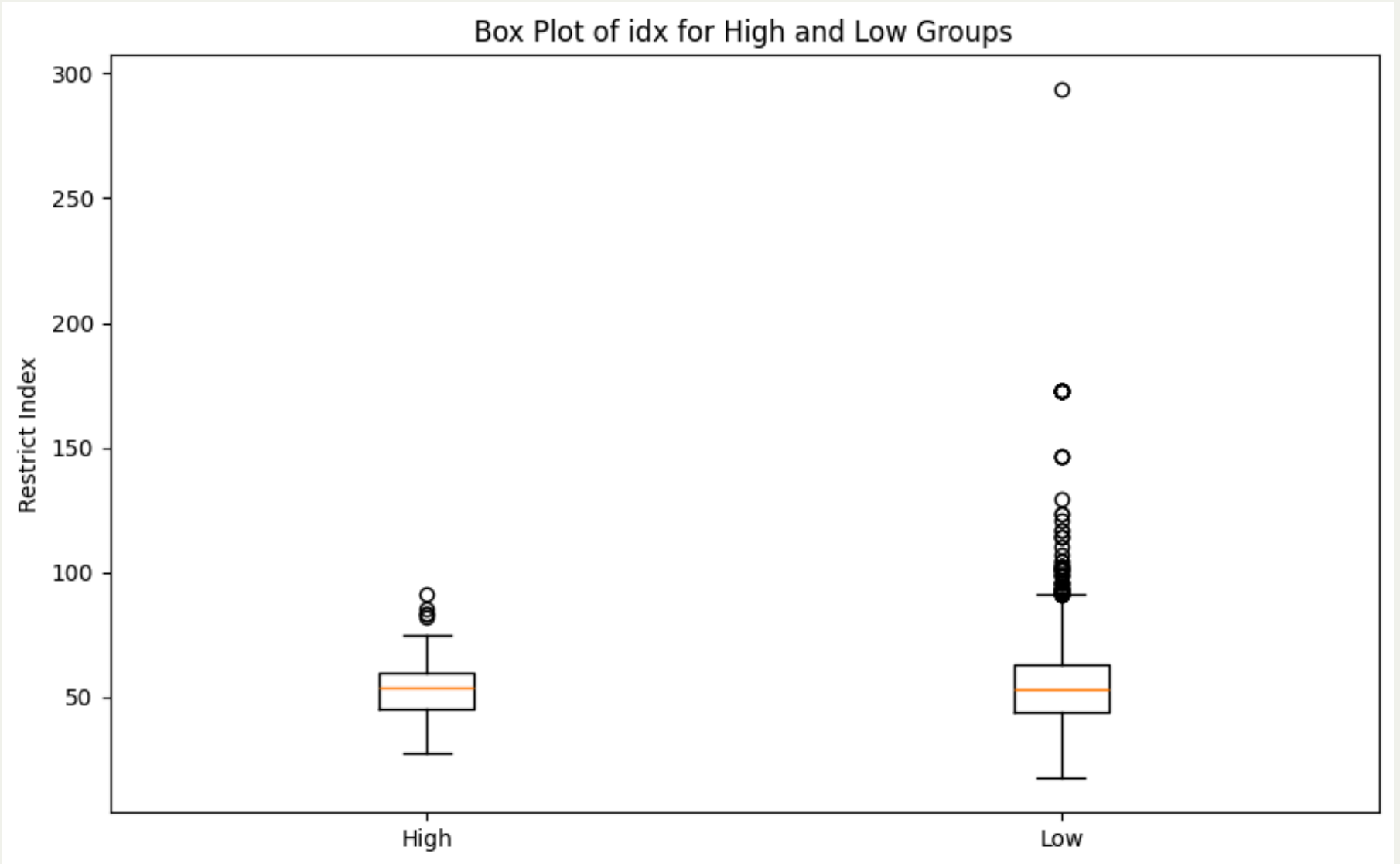
We get similar results



2sd high low outlier split results



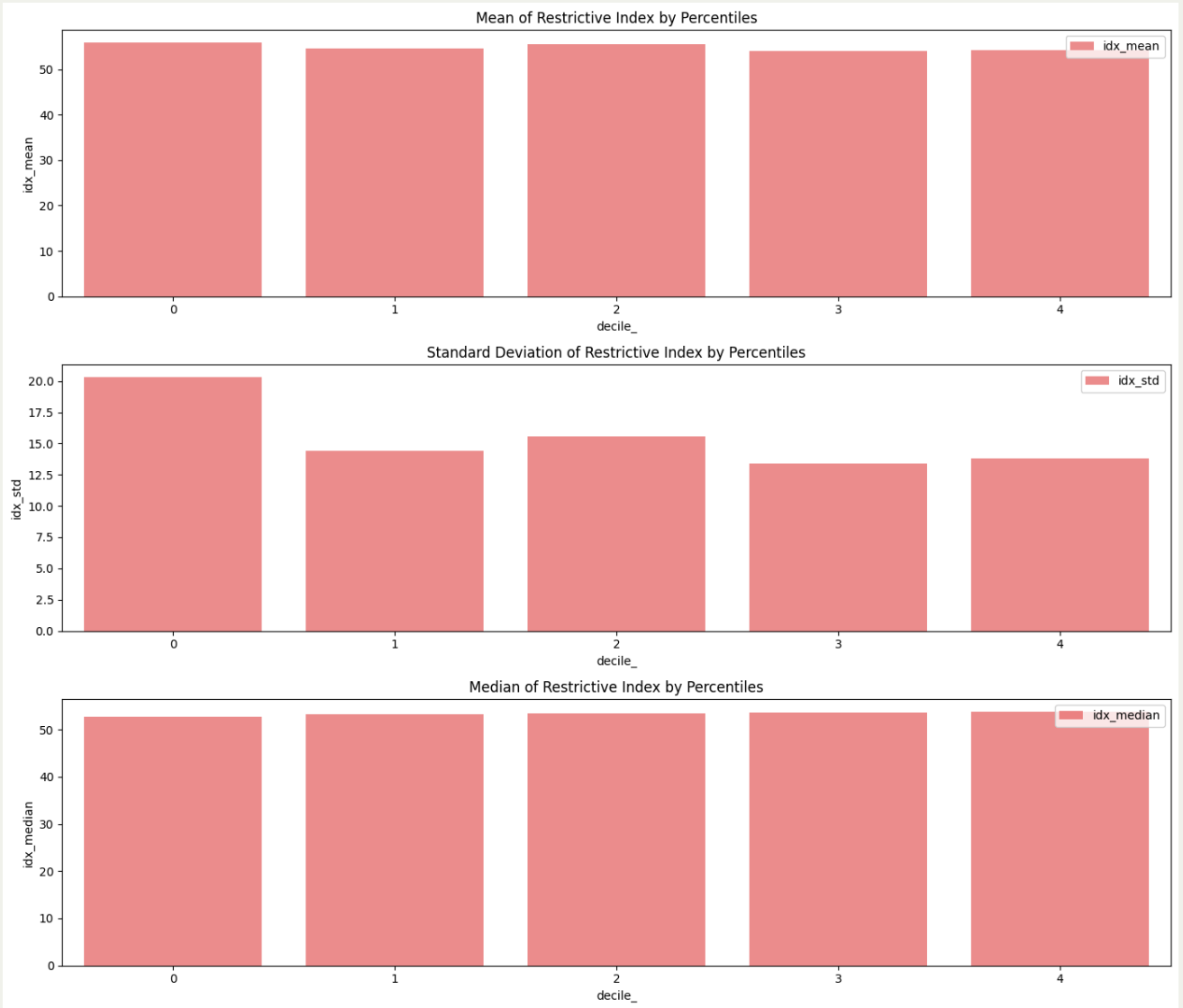
2sd high low outlier split results



Percentiles Split

1. divide truck stop count into percentiles
2. look into characteristics of each percentile bin
3. No discernible difference in restrictiveness

Percentiles Split Result



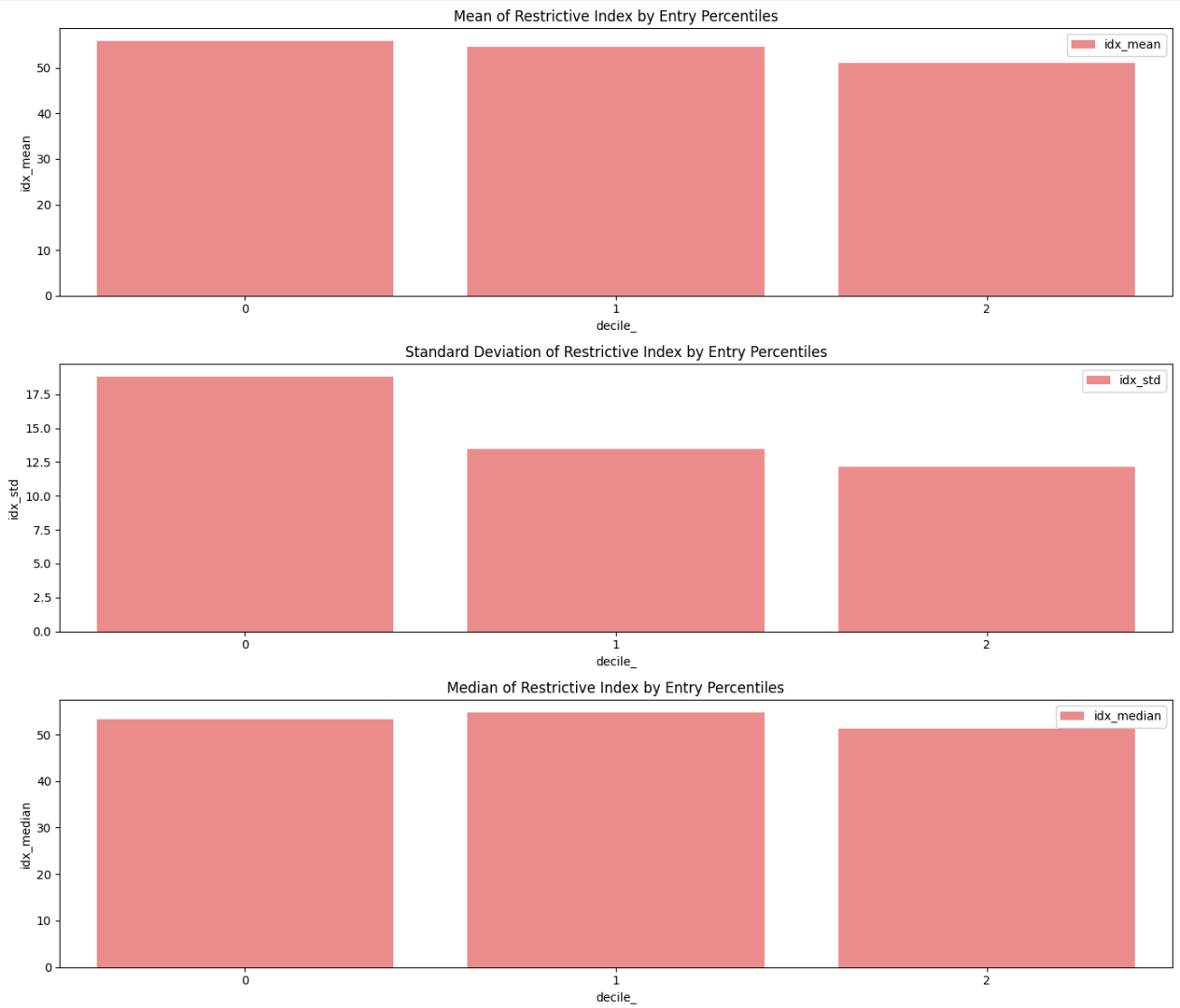
Taking Stock

1. Number of Truck Stops VS Restrictiveness
    - uncertain
2. Entry/Exit of Truck Stops VS Restrictiveness
    - negative relationship. High restrictiveness decreases entry and exit.
3. Few Truck stops vs Many Truck Stops , Restrictiveness
    - no
4. Few vs Many entry , Restrictiveness

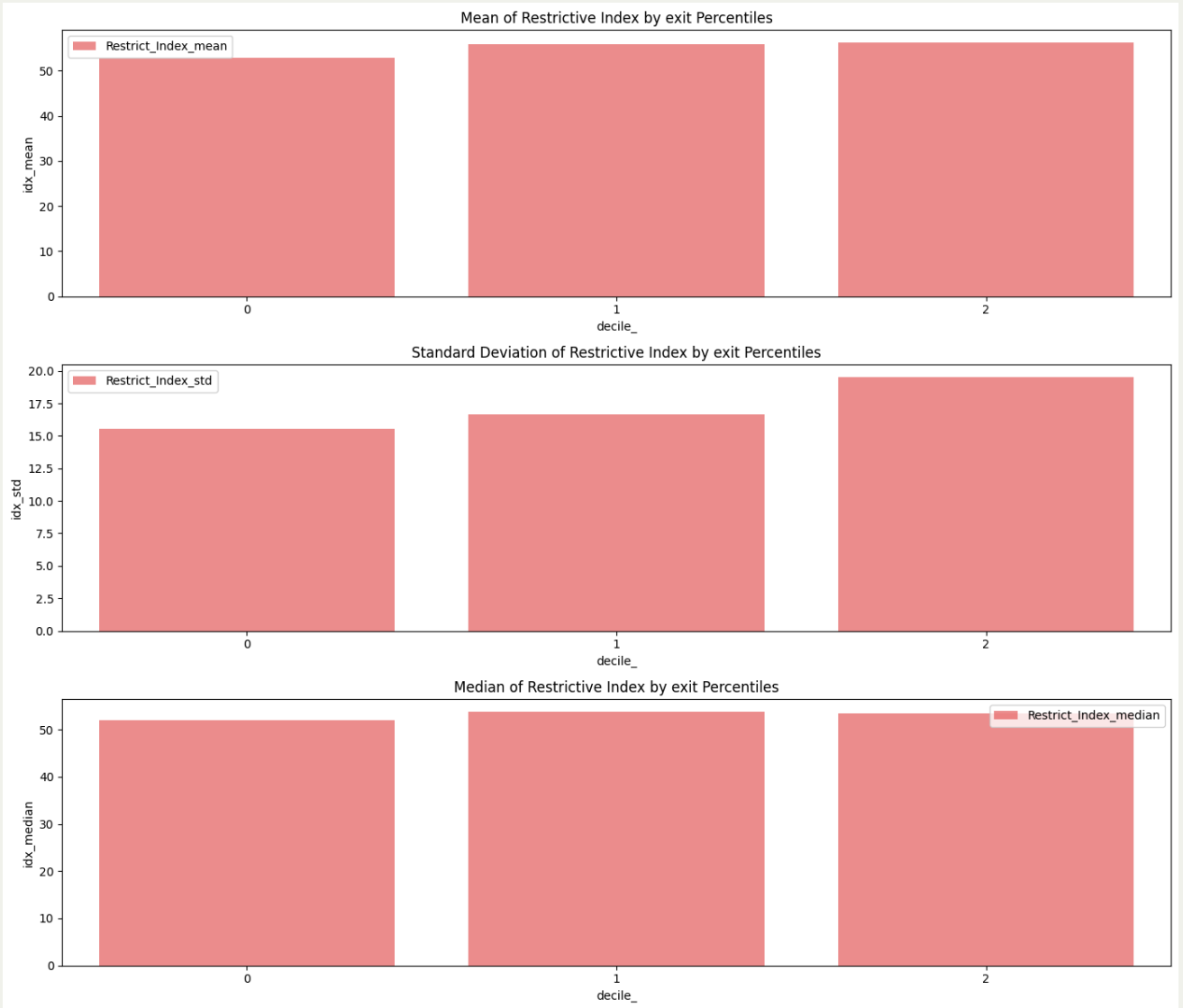
Entry Percentile Split

1. divide truck stop entry count into percentiles
    1. look into characteristics of each percentile bin
    2. Result: No discernible difference in restrictiveness

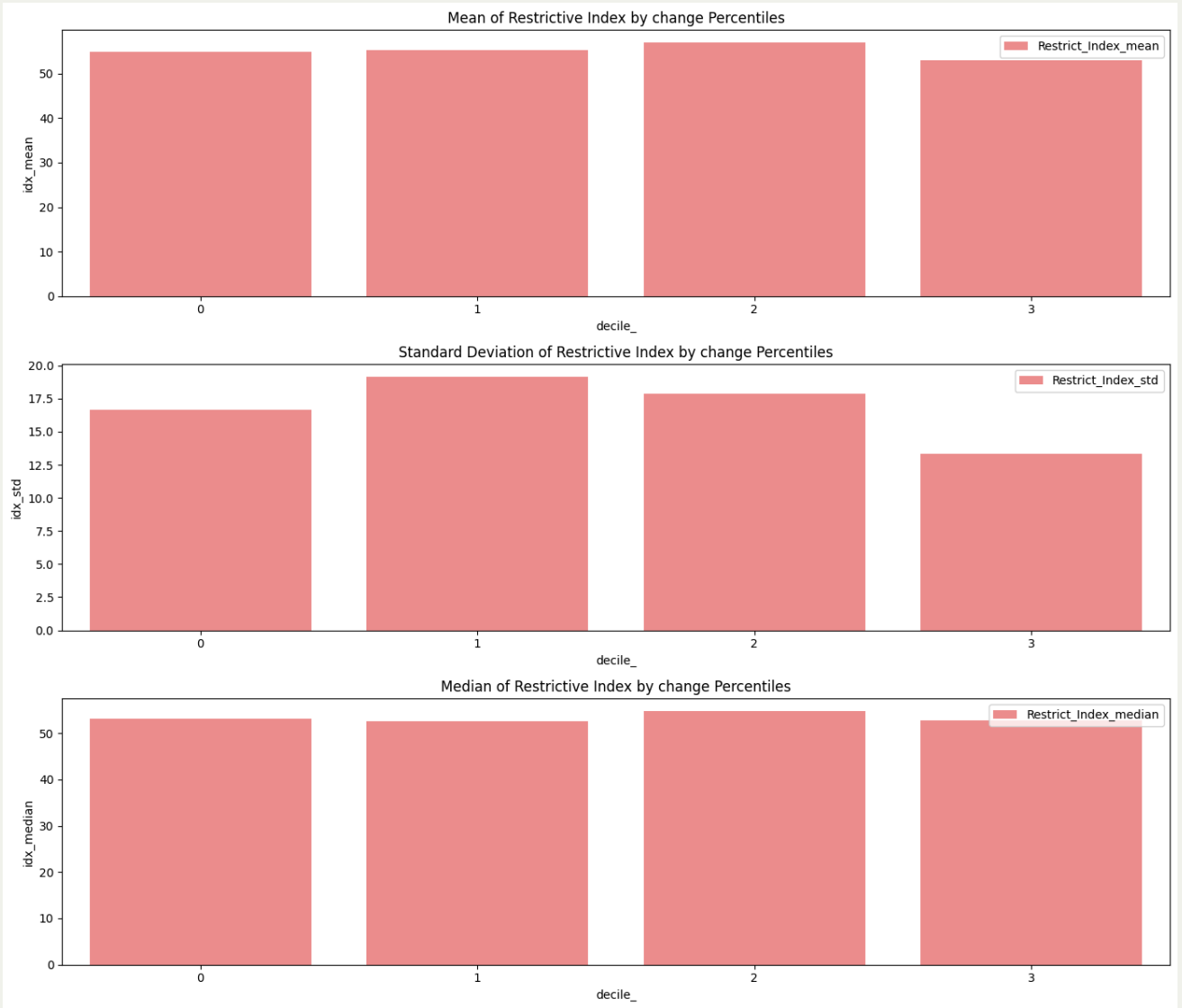
Entry Percentile Split



Exit Percentile Split



Change Percentile Split



Taking Stock

$$\text{Num\_Truck\_Stop} = \text{Entry} + \text{Exit} + \text{Initial\_Truck\_Stops}$$

1. Number of Truck Stops VS Restrictiveness
    - uncertain
    - Initial Truck Stops is uncertain as well
2. Entry/Exit of Truck Stops VS Restrictiveness
    - negative relationship. High restrictiveness decreases entry and exit.
3. Few Truck stops vs Many Truck Stops , Restrictiveness
    - no relationship (2006,2016 data)
4. Few vs Many entry , Restrictiveness
    - no relationship

End