# **An Econometric Analysis of Housing Demand**

# Motivation

A common concept within the field of economics is elasticity (i.e., the idea that price for goods/services will generally change in context of the quantity of an item available within a market) (Hayes, 2021). Housing is one of many commonly mentioned market goods in both macro and microeconomics, and housing is often subject to price fluctuations within the market. However, housing units are also vastly variable in quality (from studio apartments to mansions), so analysis of housing markets generally requires ceteris paribus conditions to analyze. Thankfully, the U.S. Department of Housing and Urban Development (HUD) has an Office of Policy Development & Research that provides publicly available data on the 50<sup>th</sup> percentile/median market rate for housing (specifically for studio and one-four-bedroom housing units) in every area within the United States, including territories such as Puerto Rico and Guam. (US Housing and Urban Development - Office of Policy Development & Research, 2021) As medians are centers of mean generally less prone to skews and bias, my intent is to see whether the basic concept of elasticity holds well for housing across the United States, with a secondary goal of using linear regression to establish a general idea of exactly how elastic (or inelastic) the demand for housing is, assuming median housing quality is present for the median market rate present in the 2020 housing data from HUD.

# **Data Description**

As referenced in the above motivation statement, HUD has publicly available data for 50<sup>th</sup> percentile (median) rents for the entire United States as far back as 2001. The number of areas within the dataset is defined as n= 4766, accounting for several (if not all) counties, parishes, and municipalities within all states and territories in the United States. For the sake of using the most recent full calendar year, I am using the dataset for 2020 — as 2021 is not entirely over at the time of this project.

The dataset is an MS Excel spreadsheet with the following

- fips2010
- rent50 0
- rent50 1
- rent50 2
- rent50\_3
- rent50 4
- state
- cbsasub21
- areaname21
- county
- cousubcntyname

- name
- pop2017
- hu2017
- state alpha

For the purposes of SAS coding for this simple regression project, I have used "rent50\_0", "rent50\_1", "rent50\_2", "rent50\_3", "rent50\_4" as potential predictor variables, as well as pop2017, hu2017, and transformations of pop2017 and hu2017 as potential predictor variables. I will specifically refer to "rent50\_2" as my response variable in this written report from here on out, as two-bedroom housing units are often used as a benchmark for what constitutes affordable housing (Adamczyk, 2021), (Simone, 2021). Additionally, "rent50\_2" serves as the median number of bedrooms within the range of rent prices, giving another good reason to use it as a metric.

The other variables outside of the assorted rent variables, population variable, and housing unit variable are all categorical variables that entail things such as metropolitan statistical areas, counties, states/territories, and other assorted government codes that further detail each region.

# **Data Exploration**

I used the below SAS code snippet to import a slightly cleaned up version\* of the HUD data referenced earlier for this paper:

```
FILENAME CSV "/home/u49665201/sasuser.v94/STA3064/Copy 2 of
FY2021_50_County.csv" TERMSTR=CRLF;

/** Import the CSV file. **/

PROC IMPORT DATAFILE=CSV

OUT=HUDdata

DBMS=CSV

REPLACE;

RUN;

/** Print the results. **/

PROC PRINT DATA=HUDdata;

RUN;
```

From this point, I created a secondary dataset I called "Housing" with a few additional changes.

```
data Housing;

set HUDdata;

PtoH = pop2017/hu2017;

HtoP = hu2017/pop2017;

transPop = pop2017**-1;

transHu = hu2017**-1;

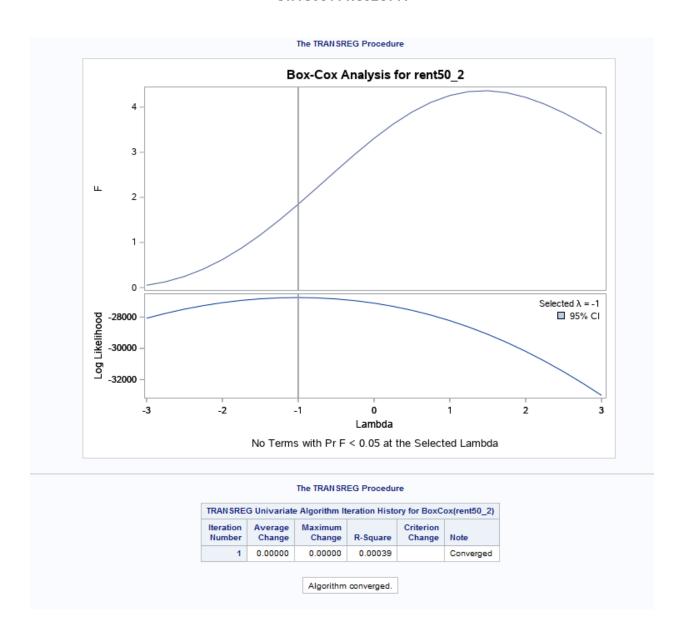
run;
```

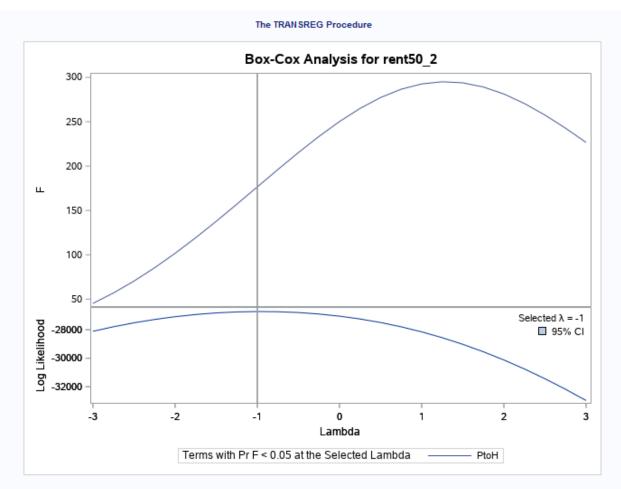
In this instance, the most classic example of elasticity would be present in the model "rent50\_2=hu2017" to mimic a classical "price=quantity" scenario. However, I made some additions for additional experimentation and exploration of this data.

The first addition I made was creating population: housing (defined as 'PtoH') and housing: population (defined as 'HtoP') ratios from pop2017 and hu2017. While these ratios would not necessarily create the scenario for classic elasticity, my initial assumption was that they could serve as proxy variables for housing scarcity in lieu of being able to use multiple regression for this project.

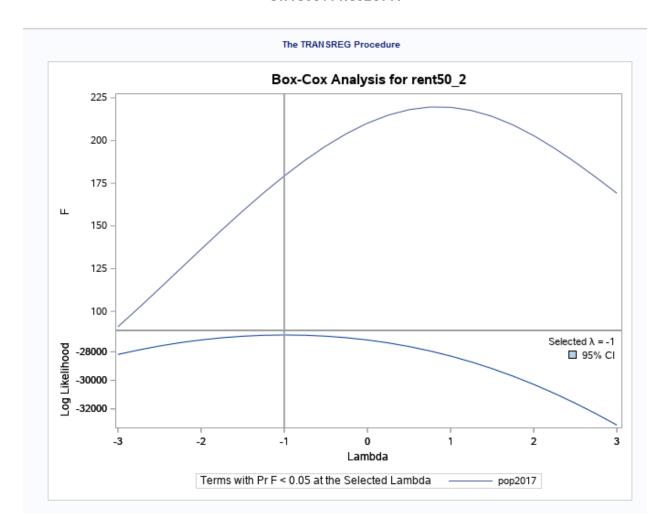
The second addition I made was adding transformations to the variables pop2017 and hu2017, based on the recommended Box-Cox transformation recommended by the output generated by the below code:

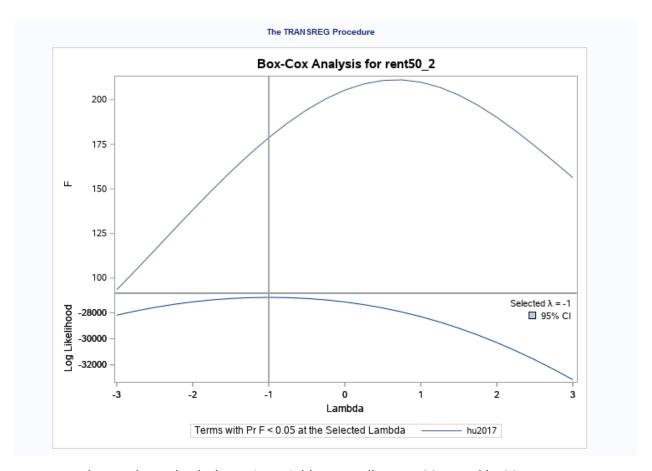
```
proc transreg data=Housing;
model boxcox(rent50_2)=identity(HtoP);
run;
proc transreg data=Housing;
model boxcox(rent50_2)=identity(PtoH);
run;
proc transreg data=HUDdata;
model boxcox(rent50_2)=identity(pop2017);
run;
proc transreg data=HUDdata;
model boxcox(rent50_2)=identity(hu2017);
run;
```





The TRANSREG Procedure							
TRANSREG Univariate Algorithm Iteration History for BoxCox(rent50_2)							
Iteration Number	Average Change	Maximum Change	R-Square	Criterion Change	Note		
1	0.00000	0.00000	0.03588		Converged		
		Algorithm	converged.				





As shown above, both the ratio variables as well as pop2017 and hu2017 are recommended to be transformed to the -1<sup>st</sup> power.

In addition to producing scatterplots for the classical "rent50\_2=hu2017" model, I also generated five additional scatterplots using the pop2017 variable, as well as the two transformed versions of those variables and the ratios of those variables using the following code:

```
proc sgplot data=Housing;
scatter X=rent50_2 Y=pop2017;
run;
proc sgplot data=Housing;
scatter X=rent50_2 Y=hu2017;
run;
proc sgplot data=Housing;
scatter X=rent50_2 Y=HtoP;
```

```
run;

proc sgplot data=Housing;

scatter X=rent50_2 Y=PtoH;

run;

proc sgplot data=Housing;

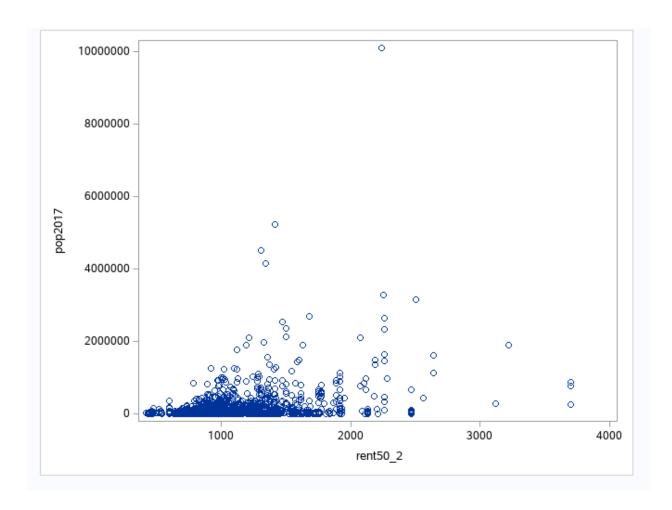
scatter X=rent50_2 Y=transHu;

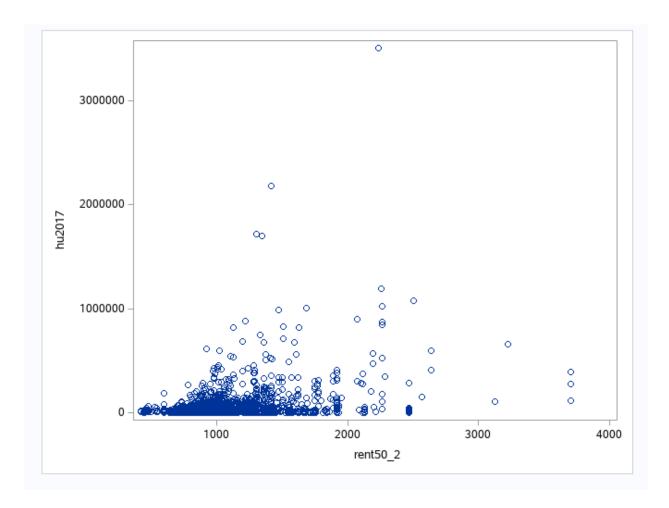
run;

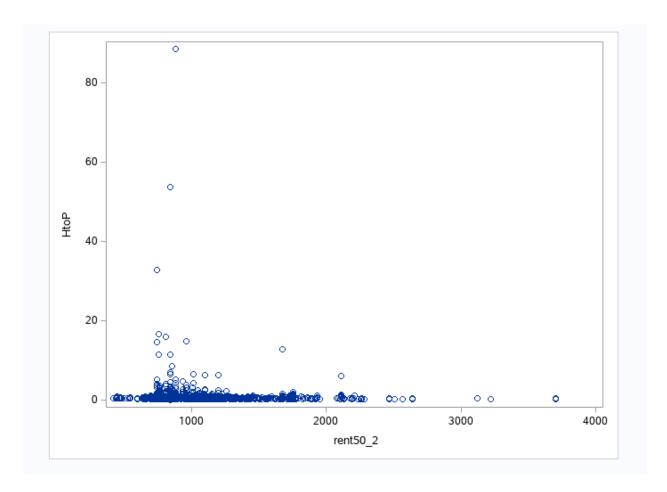
proc sgplot data=Housing;

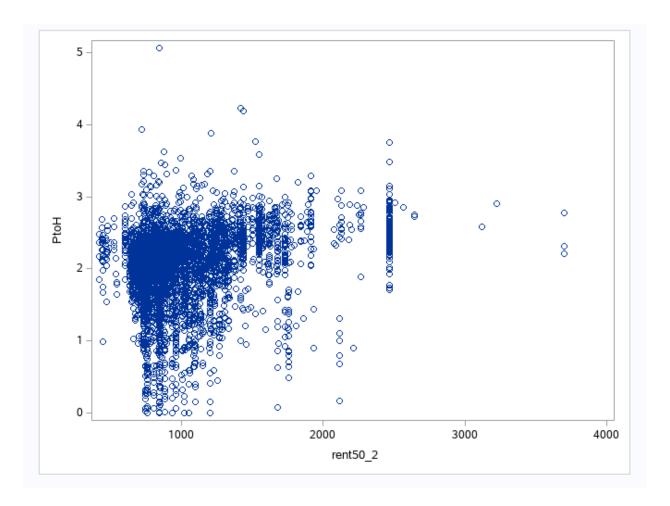
scatter X=rent50_2 Y=transPop;

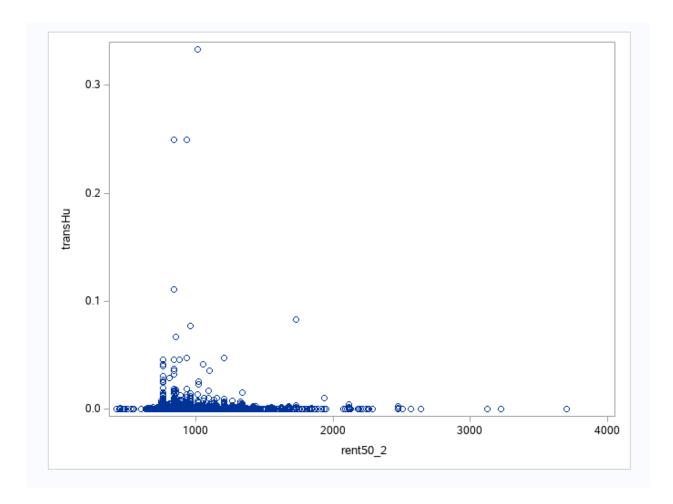
run;
```

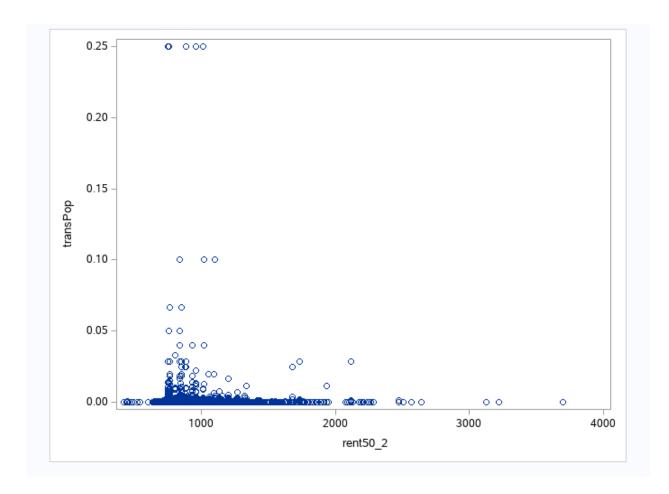






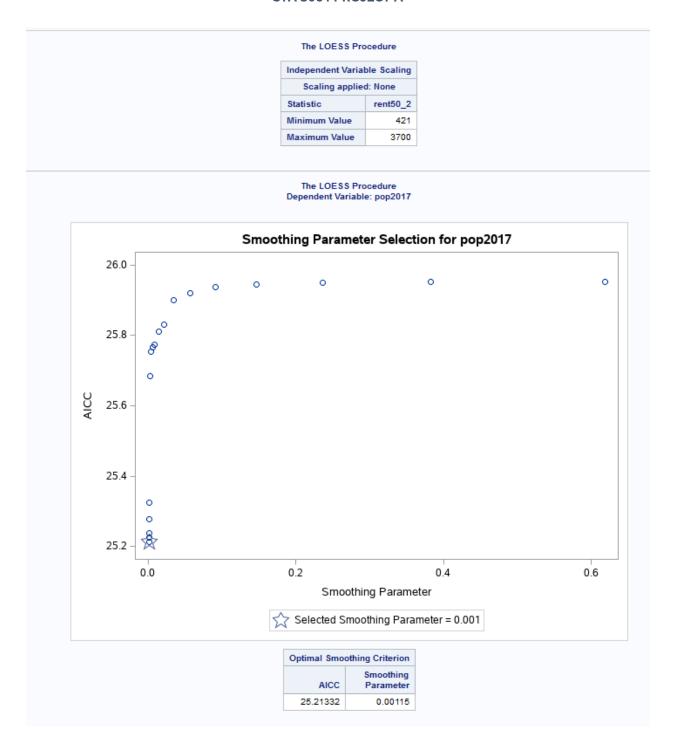






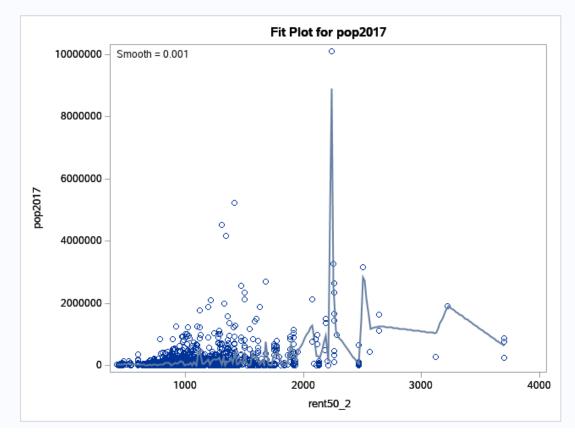
In addition to the previous code and output for proc sgplot, I also used the following code to generate LOESS curves:

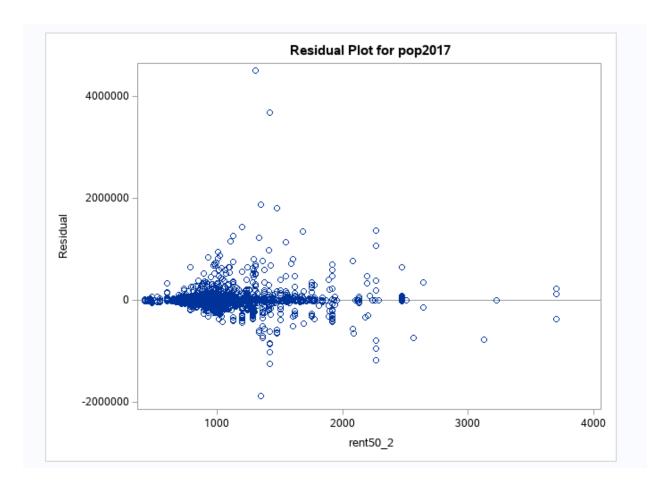
```
proc loess data=Housing;
       model pop2017=rent50_2;
run;
proc loess data=Housing;
       model pop2017=rent50_2;
run;
proc loess data=Housing;
       model pop2017=HtoP;
run;
proc loess data=Housing;
       model pop2017=PtoH;
run;
proc loess data=Housing;
       model transPop=rent50_2;
run;
proc loess data=Housing;
       model transHu=rent50_2;
run;
```

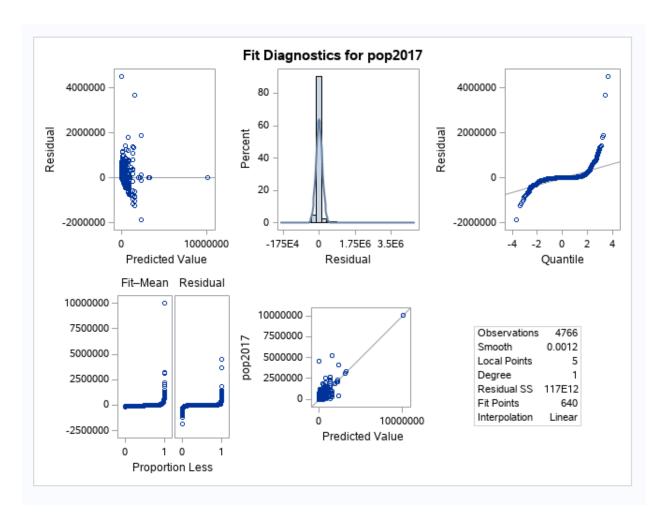


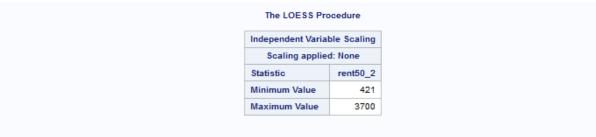
The LOESS Procedure Selected Smoothing Parameter: 0.001 Dependent Variable: pop2017

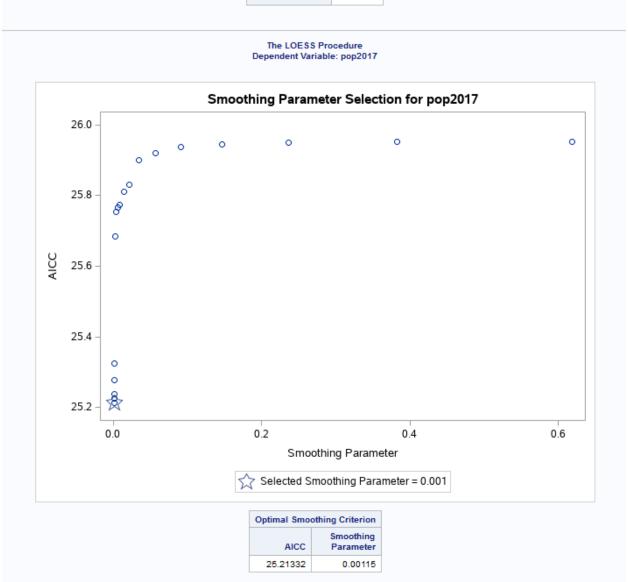
Fit Summary				
Fit Method	kd Tree			
Blending	Linear			
Number of Observations	4766			
Number of Fitting Points	640			
kd Tree Bucket Size	1			
Degree of Local Polynomials	1			
Smoothing Parameter	0.00115			
Points in Local Neighborhood	5			
Residual Sum of Squares	1.165671E14			
Trace[L]	608.05040			
GCV	6742449			
AICC	25.21332			





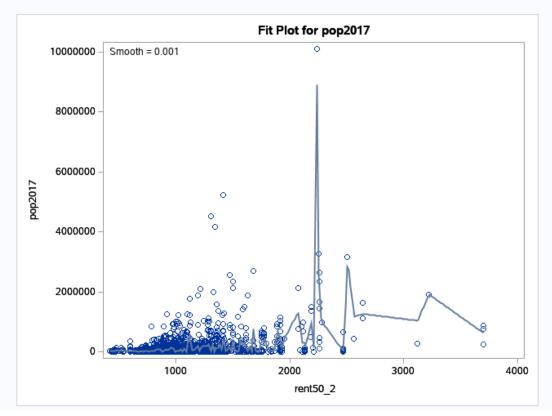


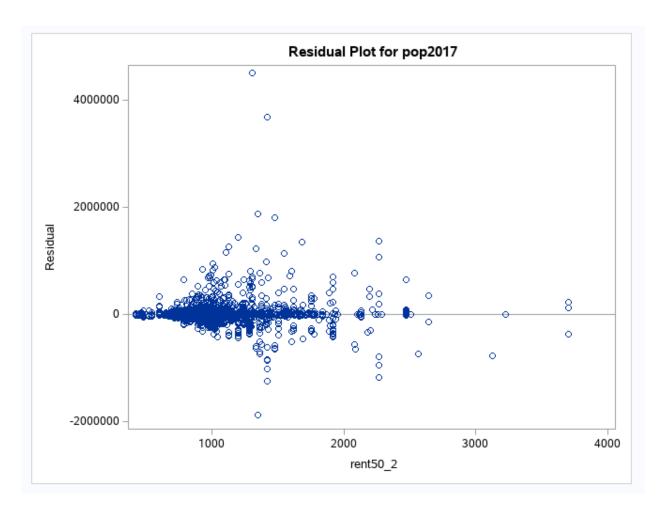


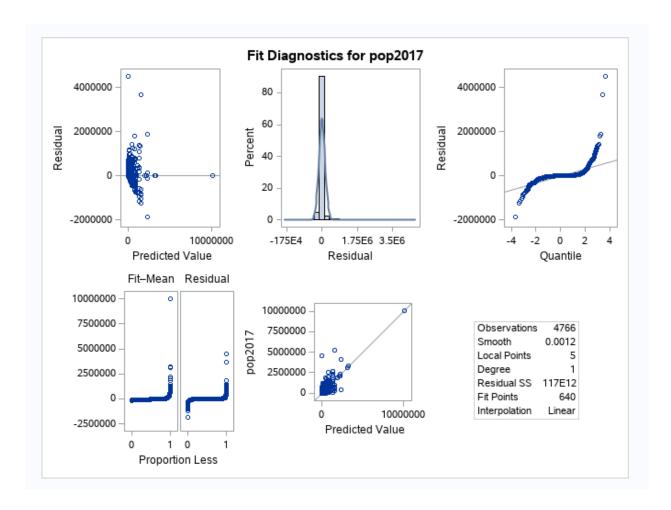


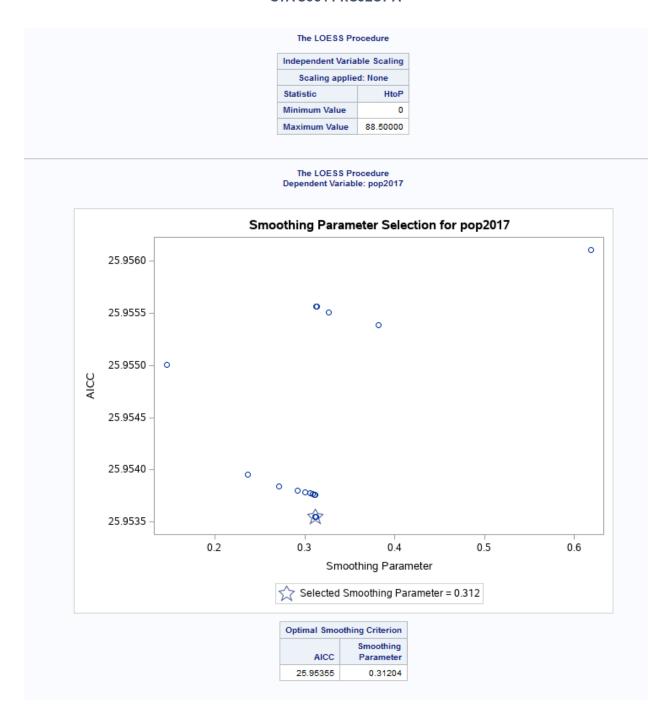
The LOESS Procedure Selected Smoothing Parameter: 0.001 Dependent Variable: pop2017

Fit Summary				
Fit Method	kd Tree			
Blending	Linear			
Number of Observations	4766			
Number of Fitting Points	640			
kd Tree Bucket Size	1			
Degree of Local Polynomials	1			
Smoothing Parameter	0.00115			
Points in Local Neighborhood	5			
Residual Sum of Squares	1.165671E14			
Trace[L]	608.05040			
GCV	6742449			
AICC	25.21332			



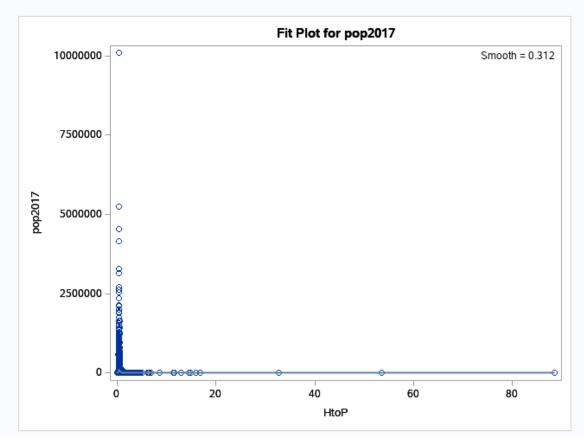


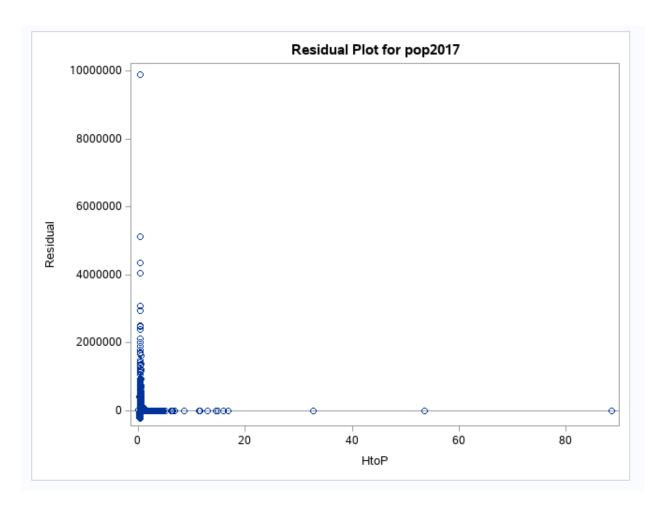


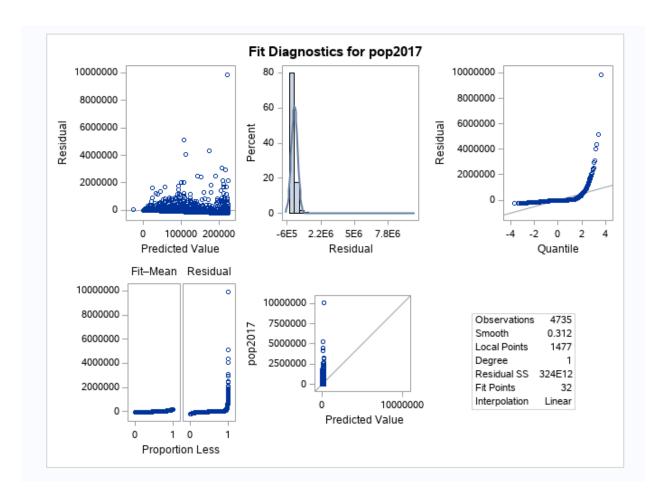


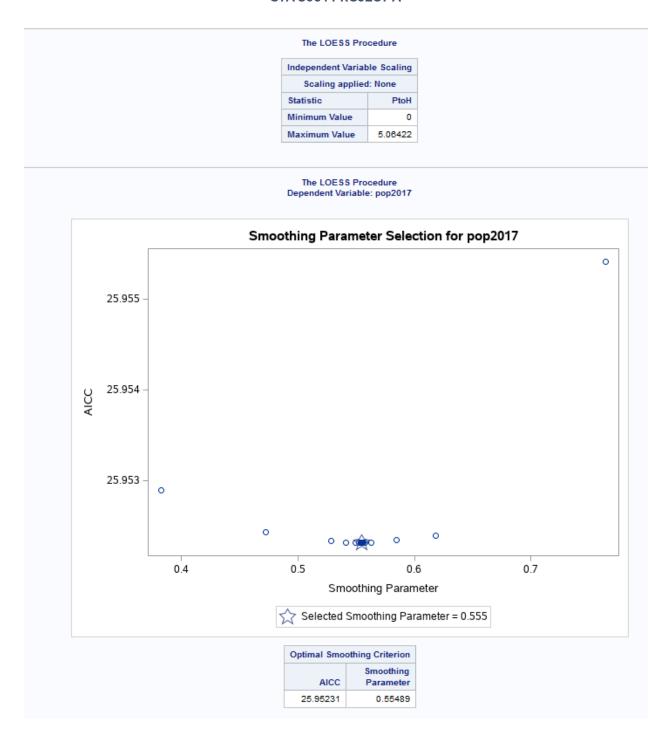
The LOESS Procedure Selected Smoothing Parameter: 0.312 Dependent Variable: pop2017

Fit Summary				
Fit Method	kd Tree			
Blending	Linear			
Number of Observations	4735			
Number of Fitting Points	32			
kd Tree Bucket Size	295			
Degree of Local Polynomials	1			
Smoothing Parameter	0.31204			
Points in Local Neighborhood	1477			
Residual Sum of Squares	3.241161E14			
Trace[L]	8.83183			
GCV	14510497			
AICC	25.95355			



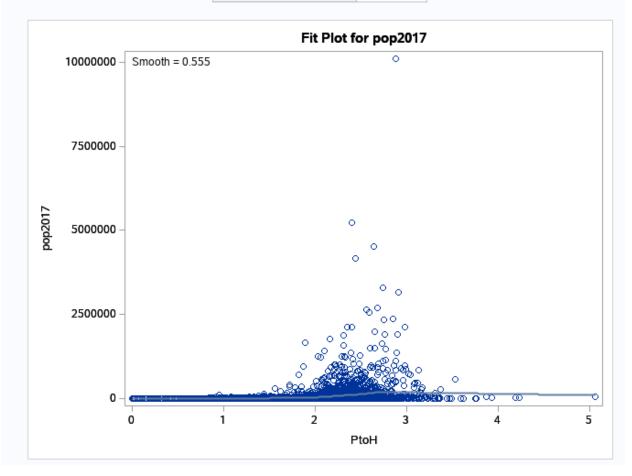


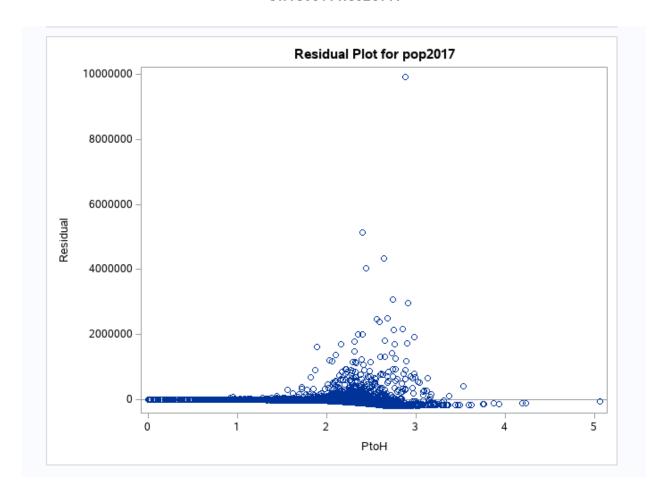


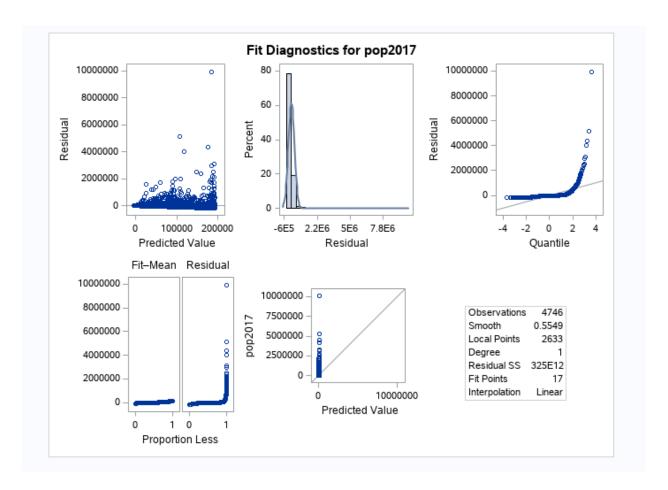


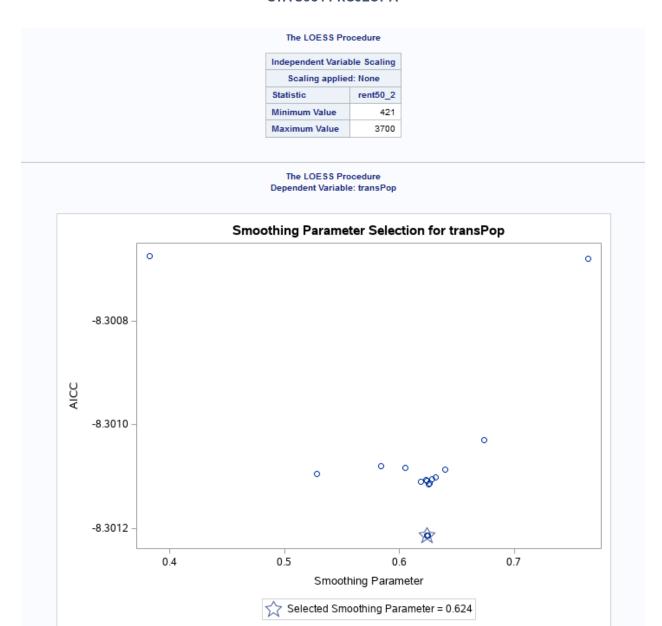
The LOESS Procedure Selected Smoothing Parameter: 0.555 Dependent Variable: pop2017

Fit Summary			
Fit Method	kd Tree		
Blending	Linear		
Number of Observations	4746		
Number of Fitting Points	17		
kd Tree Bucket Size	526		
Degree of Local Polynomials	1		
Smoothing Parameter	0.55489		
Points in Local Neighborhood	2633		
Residual Sum of Squares	3.249007E14		
Trace[L]	5.69377		
GCV	14458988		
AICC	25.95231		









Optimal Smoothing Criterion

AICC

-8.30121

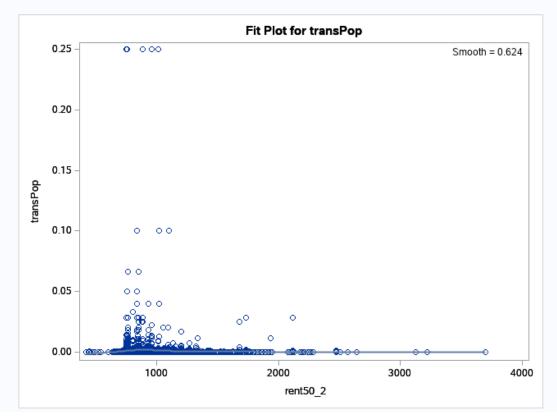
Smoothing

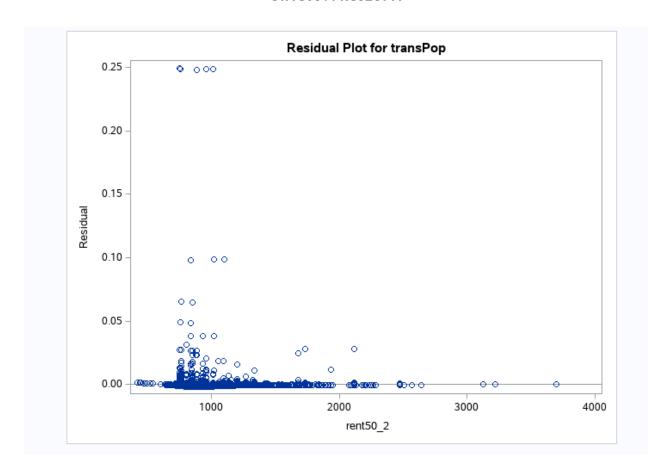
Parameter

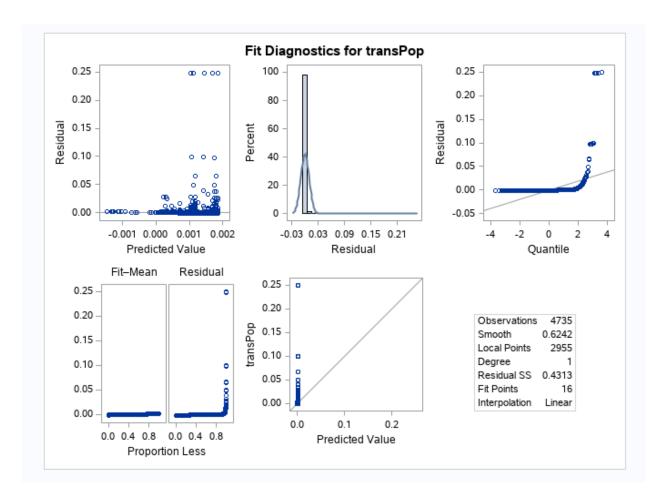
0.62418

The LOESS Procedure Selected Smoothing Parameter: 0.624 Dependent Variable: transPop

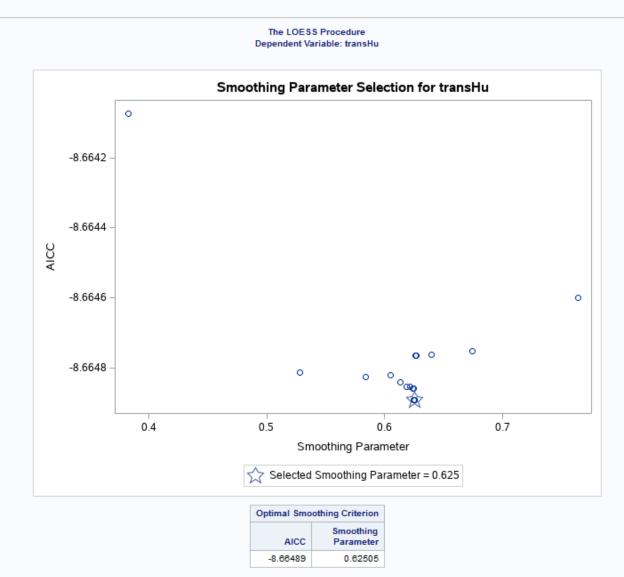
Fit Summary				
Fit Method	kd Tree			
Blending	Linear			
Number of Observations	4735			
Number of Fitting Points	16			
kd Tree Bucket Size	591			
Degree of Local Polynomials	1			
Smoothing Parameter	0.62418			
Points in Local Neighborhood	2955			
Residual Sum of Squares	0.43132			
Trace[L]	4.75369			
GCV	1.927657E-8			
AICC	-8.30121			





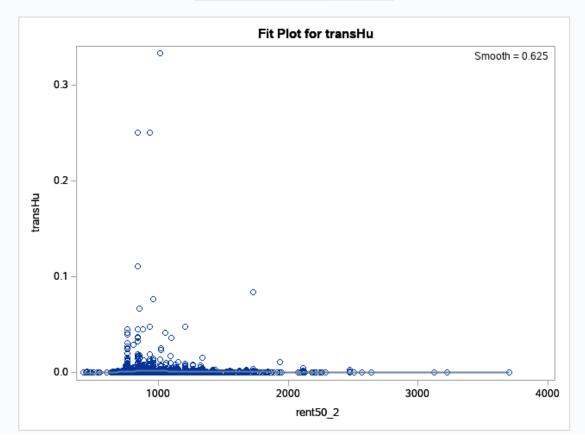


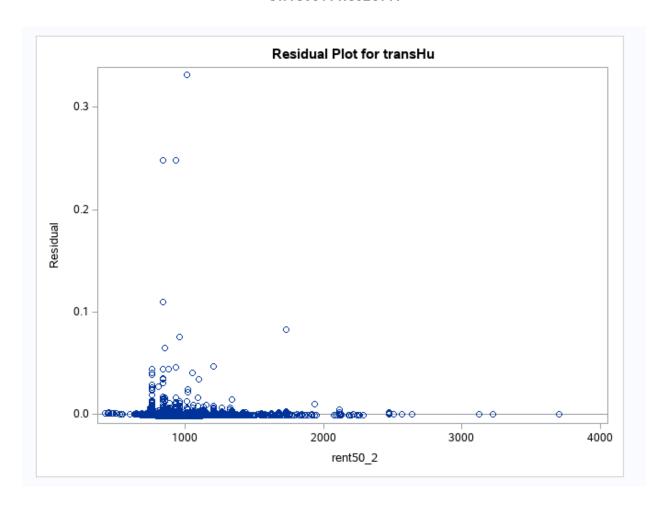


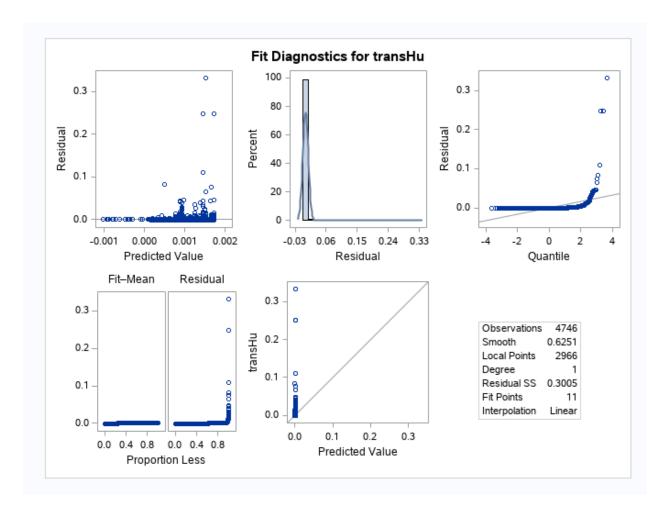


The LOESS Procedure Selected Smoothing Parameter: 0.625 Dependent Variable: transHu

Fit Summary						
Fit Method	kd Tree					
Blending	Linear					
Number of Observations	4748					
Number of Fitting Points	11					
kd Tree Bucket Size	593					
Degree of Local Polynomials	1					
Smoothing Parameter	0.62505					
Points in Local Neighborhood	2966					
Residual Sum of Squares	0.30052					
Trace[L]	4.69079					
GCV	1.336839E-8					
AICC	-8.66489					





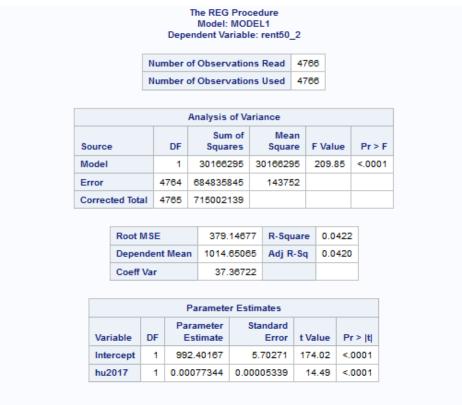


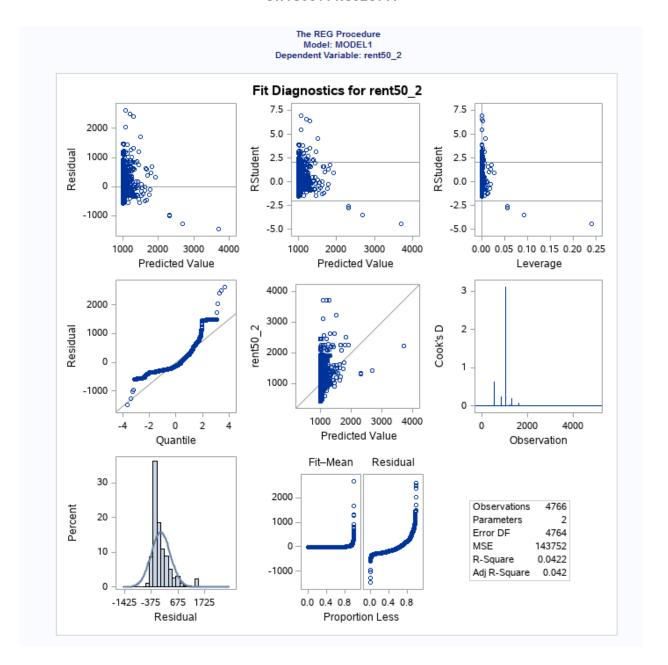
## **Model Fitting and Analysis**

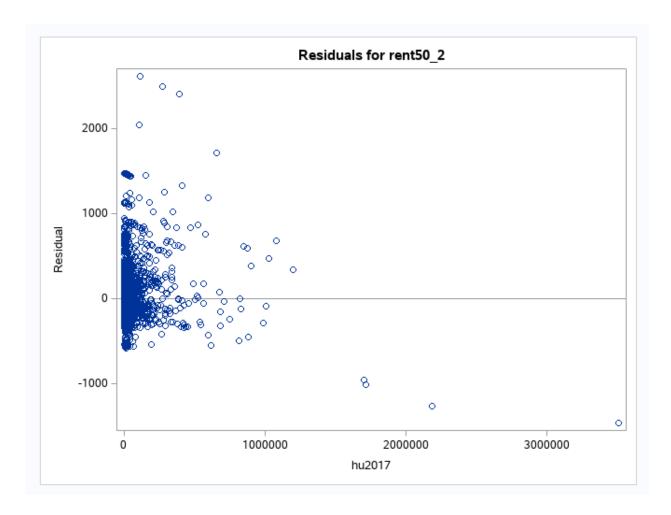
While I generated <u>several</u> potential models, I would like to start with the analysis of the initially assumed relationship of "rent50\_2" being the response variable, and "hu2017" being the predictor variable. Using the below code with the original HUD dataset;

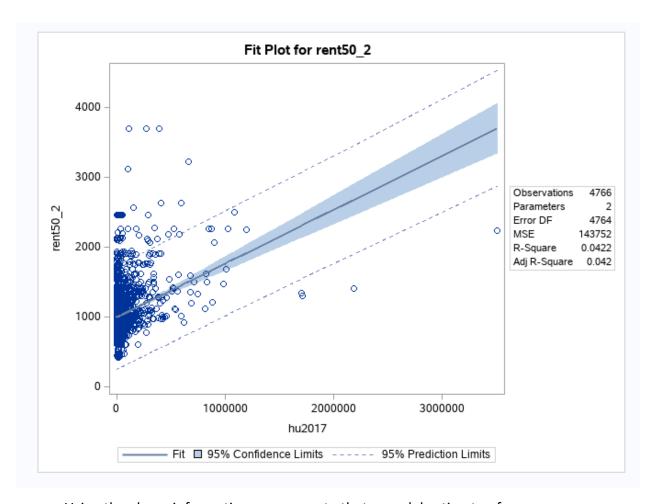
proc reg data=HUDdata; model rent50\_2=hu2017; run;

I generated the following output:









Using the above information, we can note that a model estimate of

rent50 2 = 992.40167 + 0.00077344X +
$$\epsilon$$

is not a very practical regression model. With an R-Square value of 0.0422, we can also note that the relationship between these two single variables is close to non-existent, despite what would make economic sense. It is, however, interesting to note that the 95% confidence intervals get wider with a larger number of housing units available.

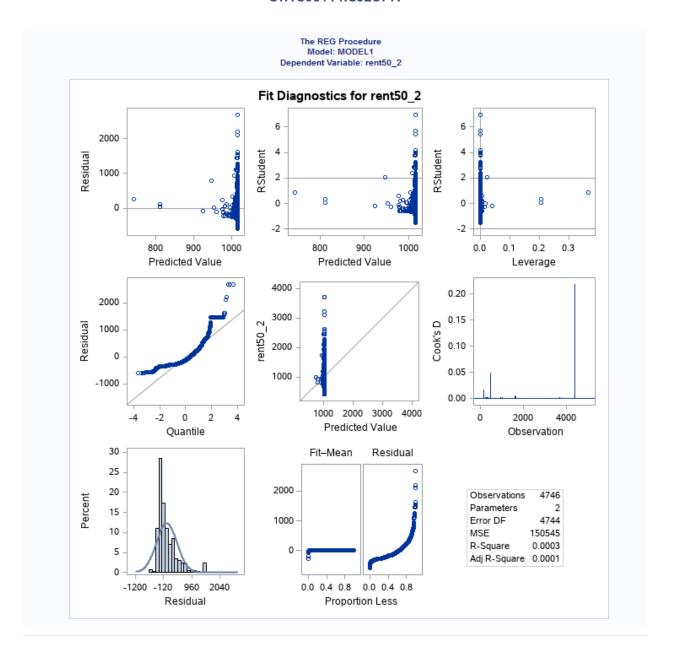
Looking at the residual graphs, this model violates *several* assumptions; predominantly on constant variance and normality, as the observations curve away from a normal distribution, and seem to clump together on top of each other in a line. I would hesitate to say that the relationship is not linear...although it specifically lines up in a vertical pattern that is almost close to having an undefined slope. In economics, this data would still be useful, as it shows housing has extremely inelastic demand that veers close to perfectly inelastic demand (Minnesota State University, 2017), although this model is effectively useless for statistical prediction, and does not meet the statistical definition for linearity, either.

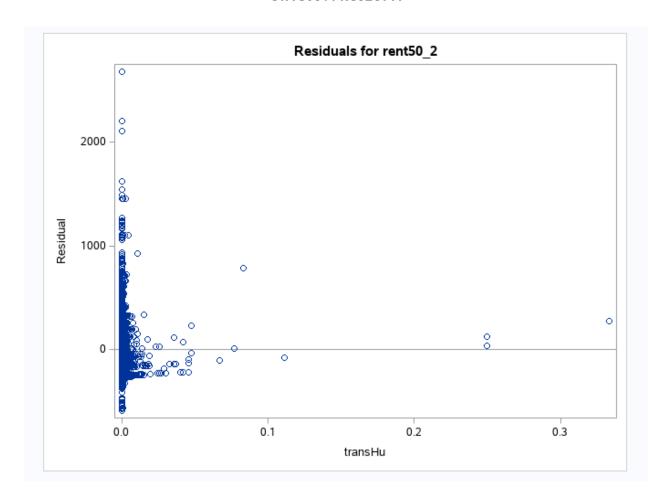
As noted from the previous section with Box-Cox transformations, I used the modified housing data with a transformation of -1 and coded this proc reg statement

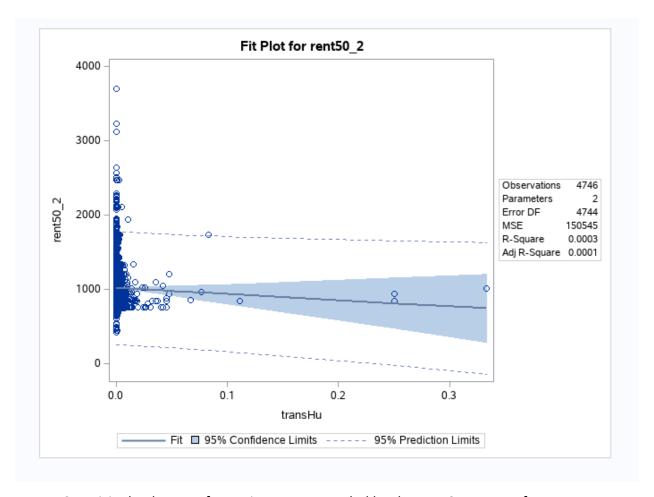
proc reg data=Housing; model rent50\_2=transHu; run;

to generate the following output:

	The REG Procedure Model: MODEL1 Dependent Variable: rent50_2										
	Number of Observations Read 4788										
		Numbe	r of	Observ	ations l	Ised				4746	3
		Numbe	r of	Observ	ations v	vith M	lissing	Value	5	20	)
				Aı	nalysis	of Var	iance				
Sc	Source			DF	Sur Squa	n of ires			F Value		Pr >
Me	Model			1	203	901	203901 1		1.3	5	0.244
Er	гог			4744	714187	171	150545				
С	orre	cted Tot	al	4745	714391	072					
	,										_
		Root N	ISE		388.00175 R-Square		0.0	0003	3		
		Depen	dent	Mean	1015.28845 Adj R-Sq 0		0.0	0001			
		Coeff \	/ar		38.21591						
				Pa	ramete	Estir	nates				
	Vai			ameter stimate			t Va	t Value   1		>  t	
	Int	itercept		1016	8.11525 5		.67672 179.0		.00	<.0	0001
	tra	ansHu 1 -821		-821	.67499	706.03177		-1	-1.16 0		2446







Surprisingly, the transformation recommended by the Box-Cox output from proc transreg made this model even less useful. The above output leads to the following equation of

that provides practically no use, as it has an R-Square value of 0.0003. I would almost say that there is almost *no relationship* between these two variables when it is transformed like this.

There is *one* model that produced slightly better results than the original "rent50\_2=hu2017" model. Namely, using the ratio of population to housing units as a proxy for housing scarcity produced marginally better results, although not by much. By using this code;

proc reg data=Housing; model rent50\_2=PtoH; run;

# I was able to produce the below output:

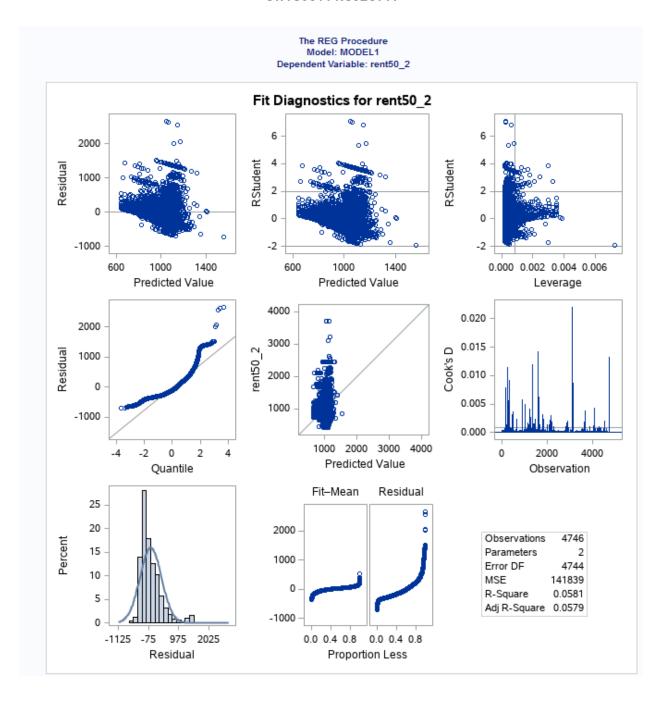
### The REG Procedure Model: MODEL1 Dependent Variable: rent50\_2

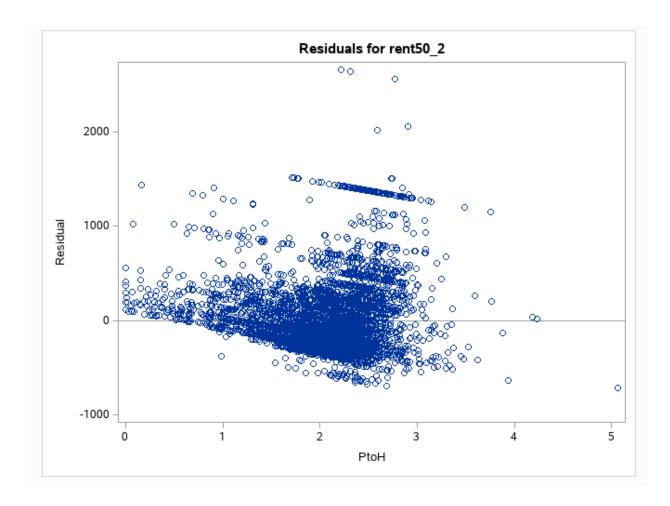
Number of Observations Read	4766
Number of Observations Used	4748
Number of Observations with Missing Values	20

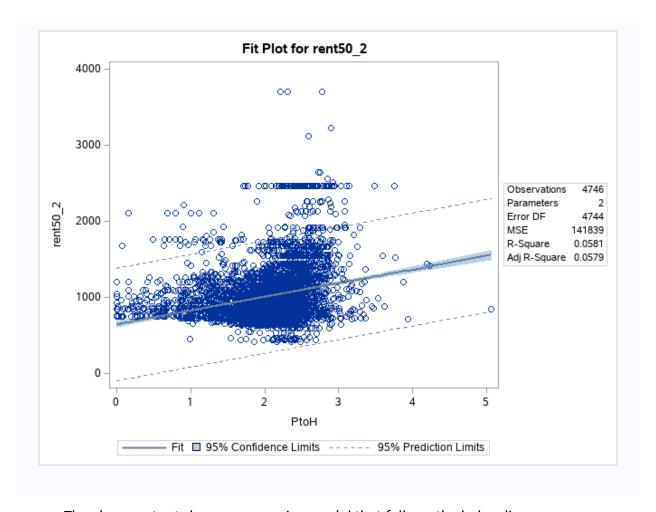
Analysis of Variance								
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F			
Model	1	41505258	41505258	292.62	<.0001			
Error	4744	672885814	141839					
Corrected Total	4745	714391072						

Root MSE	376.61564	R-Square	0.0581
Dependent Mean	1015.28845	Adj R-Sq	0.0579
Coeff Var	37.09445		

Parameter Estimates									
Variable	DF	Parameter Estimate	t Value	Pr >  t					
Intercept	1	645.80518	22.28048	28.99	<.0001				
PtoH	1	179.79938	10.51078	17.11	<.0001				







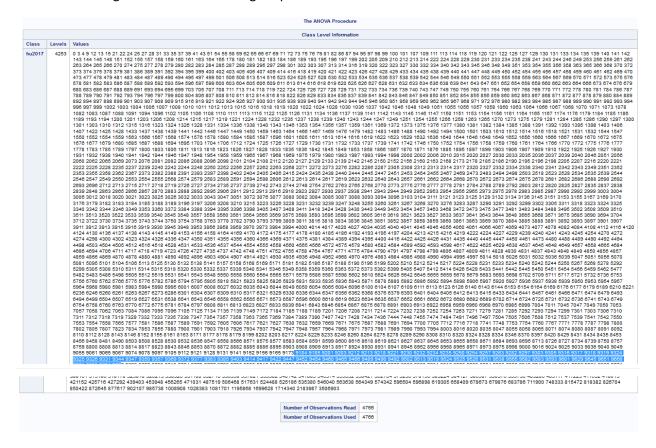
The above output shows a regression model that follows the below line:

The above output also presents with an ever so slightly more promising R-square value of 0.0581. Additionally, it can be noted that the residuals still show a linear, clumped pattern, but they *are* somewhat more spread out than the other models I was able to generate and fit somewhat closer to a normal distribution than evaluating the quantity of housing units without the context of population sizes...which would model situations where multiple people might be applying for one unit simultaneously, but only one person can get that housing unit.

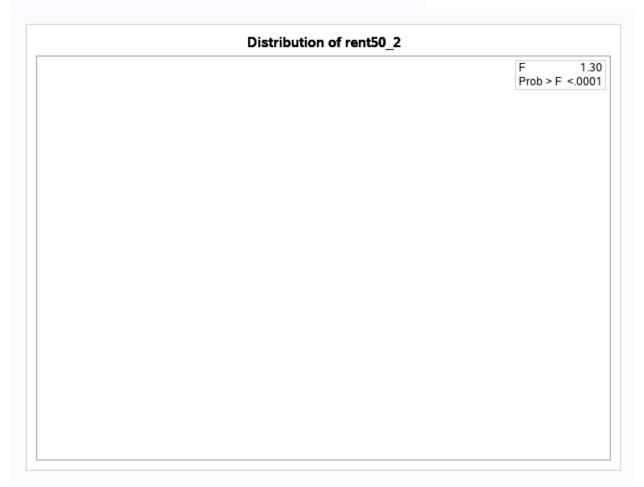
Lastly, I ran a proc ANOVA data step for both the classic "Price=Quantity" demand curve that would be reflected with "rent50\_2=hu2017", as well as my modified "rent50\_2=PtoH" model with the following code:

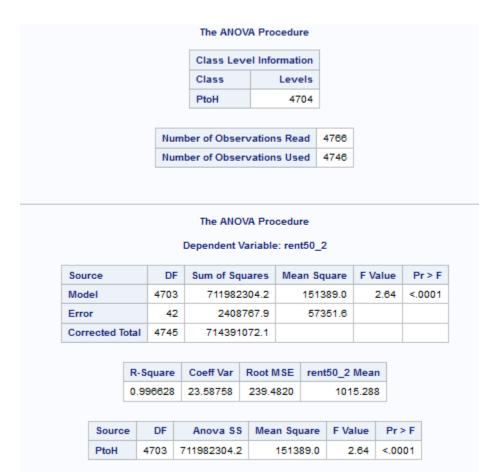
```
proc ANOVA data=Housing;
class hu2017;
model rent50_2=hu2017;
run;
proc ANOVA data=Housing;
class PtoH;
model rent50_2=PtoH;
run;
```

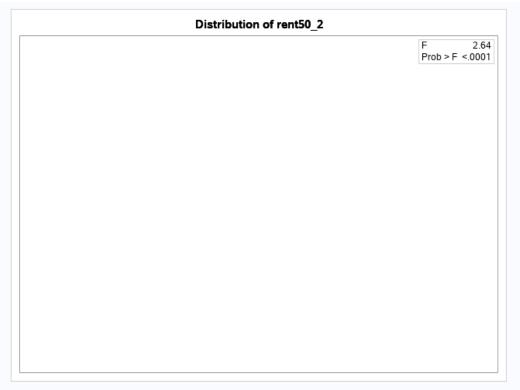
The above code generated the following output:



#### The ANOVA Procedure Dependent Variable: rent50\_2 Pr > F Source DF Sum of Squares | Mean Square | F Value Model 4252 654451619.9 153916.2 1.30 <.0001 Error 513 118032.2 60550519.5 4765 715002139.3 Corrected Total R-Square Coeff Var Root MSE rent50\_2 Mean 0.915314 33.85975 343.5581 1014.651 Source DF Anova SS Mean Square F Value Pr > F hu2017 4252 654451619.9 153916.2 1.30 <.0001



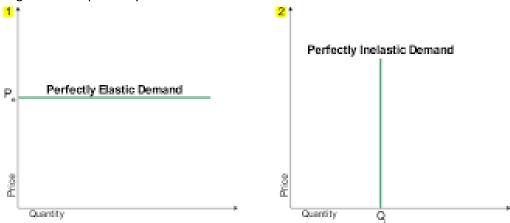




Due to the *contradictory* ANOVA output, I am honestly unsure as to whether I should reject the null hypothesis or not. The F-Test statistics are 1.30 and 2.64 for the first and second model, which would imply to keep the null hypothesis that there is no relationship for now (which would make sense, given the other metrics). However, the p-values for the ANOVA tests are both <.0001, which would imply to reject the null hypothesis in favor of the alternative hypothesis that there is a statistically meaningful relationship of rent to housing quantity.

## **Conclusion**

While the data applied to a simple regression model does *not* support the traditionally understood economic idea that prices are caused by quantity alone, it does yield other interesting insights. Namely, the distribution of the observations and residuals seems to imply that the demand for housing is close to perfectly inelastic.



In layman's terms, without other factors to consider such as house quality (which is wildly variable, considering that everything from studio apartments to mansions exist), region, proximity to work, etc; people will pay nearly anything for shelter. This would still make economic sense, considering that necessities such as food and healthcare are typically inelastic, while goods such as video games, luxury goods, and other non-essentials typically have more elastic demand. As shelter is one of the core things necessary for human survival and a basic standard of living, it would make sense that it also has an extremely inelastic demand akin to food and healthcare. While this observation is neutral, it can be interpreted in a vast number of ways on the political spectrum, which can and does impact economic policy regarding affordable housing.

## **Additional Notes**

\*The original dataset from HUD was slightly modified to account for SAS being unable to read 'ñ', 'ó', 'í ', 'á', or 'ü' in context of several observations of Puerto Rican regions without additional coding— the following characters were changed to 'n', 'o', 'l', 'a', and 'u' in the dataset for the sake of SAS being able to read the observations. (Although I would like to fix this for the sake of language integrity, the documentation that detailed fixing this would probably take more time to learn than one week — especially given how complex the dataset is for analysis purposes as is. Thus, I deemed it more time efficient to change the special characters in MS Excel.)

## **References**

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