Analysis of Affordability Factors among Low-Income Housing Residents

Indrajit Choudhury

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Executive Summary:

Using census data for low income households in New Jersey, Maryland and West Virginia, we have observed state to state differences with percentile-percentile plots, calculated basic statistics for each state and their PUMA regions and used logistic regression model data analysis methods to analyze key variables that are relevant to the affordability of property and rent for low income households. Additionally, we did a second set of analyses using an altered dataset to prove that our methodology holds.

Introduction:

We are given 2003 US Census Data for households for 3 states: New Jersey (NJ), Maryland (MD) and West Virginia (WV). This survey data primarily consists of different categorical identifiers of households as well as numerical variables regarding income, such as family income or household income. Using this data, we have 3 primary objectives:

1. Compare Distributions of Income, Rental Value and Property Value between NJ, MD and WV.

2. Compare the basic statistics between each state, producing tables of Median of Income, Proportion of Low Income Families, Proportion of Low Income, Affordable, Not-Crowded New Units and Proportion of Low Income, Affordable Not Crowded New units occupied by low-income families.

3. Produce logistic regression models for each state (Low Income Homeowners, Low Income Renters, Super Low Income Homeowners and Super Low Income Renters), to determine which variables that affected the Affordability.

Objective 1 Results:

The individual distribution of income, rental value and property value among NJ, MD and WV is the prior information we want to know. First, we merged the NJ, MD and WV data together into the state dataset. Next, we created a new variable called valuen, which was calculated as the midpoint of the household values indicated by the household value codes of the survey data. We also created two subsets of the state dataset: state1, which consists of those households within state that own their property and state2, which consists of those households within state that rent their property.

The first variable for state-by-state comparison was mean household income. Since the household income is highly susceptible to skewness, we accounted for this problem by studying the variable lhinc instead, which is the log of household income. Next, for the state dataset, we calculated various percentiles between 1 and 99 of lhinc for each of the three states and then graphed them using the SAS GPLOT procedure. This can be seen in Figure 1. Looking at this graph, we can see that the log of household income in WV is unilaterally smaller than the log of household income in either NJ or MD. Additionally, we noted that the log of household income appears to be roughly equivalent between NJ and MD up until roughly the 50^{th} percentile, where NJ slowly starts to have higher values after this point.

The second variable for comparison is household value. Since this only applies to homeowners, we only look at the state1 dataset. Using the same procedure as we did for household income, we accounted for skewness of valuen, the household value variable, by finding its log, lvalue, and once again calculated various percentiles of lvalues for all three states. We once again plotted this, as seen in Figure 2. Just like for household income, the graph seems to tell us that NJ and MD have significantly higher household values across all percentiles when compared to WV. When comparing NJ and MD, we note that while the difference does not appear significantly large, NJ appears to have higher household values across all percentiles than MD.

The third variable for comparison is monthly rental value. Since this only applies to renters, we only look at the state2 dataset. Using the same procedure as we did for the first two variables, we accounted for skewness of grent, the monthly rent variable by finding its log, lgrent, and once again calculated various percentiles of lgrent for all three states. We once again plot this, as seen in Figure 3. Just like for household income and household value, the graph seems to tell us that NJ and MD have significantly higher monthly rental values across all percentiles when compared to WV. When comparing NJ and MD, we once again note that while the difference does not appear significantly larger, NJ appears to have higher monthly rental values across all percentiles than MD.

Objective 2 Results:

Furthermore, we want to learn more about median of income, proportion of low income families, proportion of low income, affordable, not-crowded new units and proportion of low income, affordable not crowded new units occupied by low-income families.

First, we created a subset of state only pertaining to NJ, called stateNJ. Next, we sorted stateNJ by puma1, into which the state is subdivided. Then, we further subset stateNJ so that it only includes family household types. We then calculated the median value of household income for each PUMA region in NJ. Then, we define several important binary variables. Affordability (Aff) is equal to 1 when percentage of income going towards house (for homeowners) is less than 30% or percentage of income going towards rent (for renters) is less than 30% and is equal to 0 otherwise. Uncrowd is equal to 1 if the numbers of people in a household is less than or equal to the number of rooms and is equal to 0 otherwise. The variable new is equal to 1 if the household was built in 1990 or later (based on the year built code) and is equal to 0 otherwise.

Using these variables, we computed the following three ratios: Ratio 1 (rat1) – Proportion of units that are low income, affordable and not crowded among new units, Ratio 2 (rat2) – Proportion of units that are low income, affordable and not crowded among new units occupied by low income families and Ratio 3 (rat3) – Proportion of low income families. These ratios, along with median household income are tabulated for each PUMA region in NJ and listed in the table in Figure 4. This same exact process is done for both MD and WV, with associated datasets stateMD and stateWV and their tabulated values of median household income, ratio 1, ratio 2 and ratio 3 can be seen in Figures 5 and 6. We can clearly see that for both NJ and MD, there is a high degree of variance in median income, ratio 1, ratio 2 and ratio 3 between PUMA regions, while for WV, the three PUMA regions are somewhat equivalent for all four variables.

Objective 3 Results:

In order to determine the factors related to affordability, we conducted logistic regression model analysis for each state. We will have 12 models, 4 for each state (NJ, MD, WV). For each state, we will have a model for low income homeowners, for low income renters, for super low income homeowners and for super low income renters. For any given PUMA region within a state, a household is considered "low income" if it follows the following criterion: if the household has less than or equal to 4 people and household income is less than 80% of the PUMA region's median household income times (1 – (4 – number of people)*0.1) and if the household has greater than 4 people and household income is less than 80% of the PUMA region's median household income times (1 + (number of people – 4)*0.08). Additionally, a household is considered "super low income" if it follows the exact same criterion as above, except that the 80% is replaced with 50%. The response variable for our models is Aff, which is a binary variable for affordability, as defined earlier. The explanatory variables included the categorical variables defined in objective 1, as well as several other categorical variables that we created. A basic description of these 19 can be seen in Figure 7.

Each of the 3 states are split into 4 subsets: 1. the set of observations that are low income homeowners, 2. the set of observations that are low income renters, 3. the set of observations that are super low income homeowners and 4. the set of observations that are super low income renters.

Each of these subsets (12 in total) will have its own logistic regression analysis, with Affordability treated as the response variable and the 19 explanatory variables described above. Looking at a single subset, say NJ Low Income Homeowners, we take this subset and save it as a csv file. Then, we load it onto R and perform preliminary analysis using the cv.glmnet and glmnet functions within the glmnet package. These functions indicated for us which of the 19 explanatory variables should be included in a logistic regression model. The R output for NJ Low Income Homeowners subset can be seen in Figure 8. This indicated to us that for NJ Low Income Homeowners, 16 of the 19 variables should be run in a logistic regression model, while the other 3 variables should be excluded from the model. Next, we go back to SAS and run a logistic regression procedure with these 16 variables as the explanatory variables. Consequently, we observed from the output that 2 of these 16 variables have high p-values (greater than 0.05, the significance level we chose to use) and thus are not significant within the logistic regression model. To account for this, we removed these two variables and ran the logistic regression model again with the 14 significant variables, the output of which can be seen in Figure 9. This same process is done to perform all 12 necessary logistic regression models. The results of the logistic regression models for NJ, MD and WV can be seen in Figures 10, 11 and 12 respectively.

Each of these tables specifies the State as well as the subsample and includes a listing of all 19 variables. Each of these variables were screened using R and then ran in a logistic regression model in SAS. We see a number next to each variable under the given subsample. This number is the associated coefficient for that variable in the logistic regression model ran for that subsample. We only include the coefficients that are significant (which means that the associated p-value next to that variable in the logistic regression model is less than our level of significance, which in our case we chose to be the standard $\alpha = 0.05$). In logistic regression model analysis, given a significant p value, a positive parameter estimate means that a one-unit increase in the categorical variable will have an associated increase in Affordability while a negative parameter estimate means that a one-unit increase in the categorical variable will have an associated decrease in Affordability. Let's take the variable TRVTIME as an example. TRVTIME is a numeric variable that represents the average commute time for employed persons in a household. When looking at NJ Low Income Renters, TRVTIME had a negative significant value of -0.00312 and when ran through the logistic regression model for NJ Super Low Income Renters, it had a positive significant value of 0.00517. This means that for Low Income Renters in NJ, an increased commute time on average decreases Affordability while for Super Low Income Renters in NJ, an increased commute time on average increases Affordability.

As one can imagine, 12 models with 19 potential explanatory variables yields a huge amount of information and insight that can be drawn, which can be seen all in Figures 10-12. We will now describe some of the overarching themes that can be observed as well as potential explanations. First, we look for any variables that are significant for all subsamples within a given state. We notice that for NJ, the variable UNCROWD is unilaterally significant, with a positive coefficient each time. This means that using our logistic regression models, we have determined that in NJ through all 4 subsamples, an uncrowded household has a greater chance of being affordable than a crowded household. One possible explanation for this would be that since we are only looking at low income and super low income households, tenants and realtors may impose some sort of financial penalty on people who share their household with too many additional other people and reward those who do not overcrowd their residences. The only other variable that is significant for all 4 subsamples of a state is the variable AGE in WV. AGE is significant, with a negative coefficient for all subsamples. This means that in WV, on average, an older head of household would have a less affordable household when compared to a younger head of household. Since we are only dealing with low income and super low income individuals, this might mean that older low-income homeowners and renters may typically be retirees who may have a harder time paying for their household or rent. Another type of pattern we want to observe is whether a variable is significant for numerous subsamples in a state, but has different signs for its coefficients. In NJ, we see that TRVTIME has a negative significant coefficient for Low Income Renters and a positive coefficient for Super Low Income Renters, No Vehicle has a positive significant coefficient for Low Income Homeowners and Low Income Renters but a negative significant coefficient for Super Low Income Renters and HS Degree has a negative significant coefficient for Low Income Homeowners but a positive significant coefficient for Super Low Income Renters. In MD, we notice that TRVTIME has a negative significant coefficient for Low Income Renters but a positive significant coefficient for Super Low Income Renters, and No Vehicle has a positive significant coefficient for Low Income Homeowners but a negative significant coefficient for Super Low Income Renters. In WV, we do not observe any coefficients that are significant with different signs through different subsamples. Note that for every single significant coefficient with different signs between subsamples, they always occurred when comparing a Low Income subset to a Super Low Income subset. A possible explanation for such differences could be that even among low income households in NJ and MD, there is a large disparity in socio-economic status between the income of those that have a marginally low income and those that are super low income. As a result, factors like average travel time, owning a vehicle and owning a high school degree may have a significantly different impact on Affordability of a household between the two subpopulations.

Analysis on Additional Dataset:

We also wanted to demonstrate a similar type of analysis for a different dataset, but the 2013 AHS dataset given to us did not appear to contain equivalent data as the 2003 Census Data we used. So, instead we decided to run the same analysis with a fictional scenario dataset as explained below.

From our previous analysis in Objective 1 and 2 we noticed that median income in WV appeared significantly smaller than MD’s or NJ’s and so we decided to simulate a dataset where only WV was changed. To “narrow the gap” between WV and the other two states, we consider a scenario in which households in WV receive a 50% increase in household income and family income with no changes to MD or NJ.

The fictional scenario requires the following 5 changes to WV observations only: 1. Multiply Household Income by 1.5, 2. Divide percentage of household income going towards household by 1.5, 3. Divide percentage of household income going towards monthly rent by 1.5, 4. Multiply Family Income by 1.5, and 5. Adjust log of household incomes accordingly.

Using this new data, we re-ran the analysis and the results are given in Figures 13-15. For the Objective 1 Analysis, we re-plotted the percentile-percentile plots for logs of Household Income, Household Value and Rental Value. The latter two plots stayed the same (Figures 2 and 3) since the household values and rental values for WV did not change, but the plot for log of Household Income (Figure 13) clearly shows WV’s log income to be a lot closer to MD and NJ’s, though still smaller than them for majority of percentile values. For the Objective 2 Analysis, since we did not change the NJ or MD data, both tables displaying values of median income and the three ratios stay the same (Figures 4 and 5). For WV, we notice that its table (Figure 14) has greater values both for median income as well as each of the three ratios. This logically makes sense as a 50% uniform increase in household income should be expected to increase both the median income as well as several ratios relating to higher Affordability.

For Objective 3, the logistic regression models for Affordability in NJ and MD stays the same (Figures 10 and 11). We run the same type of logistic regression model for WV using the modified data (Figure 15). The conclusions that we made regarding Affordability for NJ and MD stay the same and once again, the new models for WV give us a large amount of new data to analyze. We will only focus on variables significant for all subpopulations within WV. We noted earlier that for the part 1 data, age was the only variable that was significant for all 4 logistic regression models in WV (low income homeowner, low income renter, super low income homeowner, super low income renter) and they all had a negative coefficient value which indicated that according to those models, age is associated with a decrease in Affordability of households. For the new simulated datasets, we notice that are two variables significant in all 4 logistic regression models: Age and Old_Head. Both variables have negative coefficients in all four regression models. Age is a variable that represents age in general while Old_Head is a binary variable specifying whether the head of the household is classified as a senior citizen (65 or older) or not. We note that this analysis aligns with what we discussed in the first part of the project and the significance of Old_Head might be an indication that among lower income households in WV, senior citizens may have more trouble finding affordable housing when compared to their younger counterparts.

The main point of the extra credit analysis is to show that we have developed a robust analytic methodology and can easily be applied to different datasets compared to what we originally worked on.

Conclusion:

For household income, NJ and MD both have higher household incomes than WV for all percentiles, NJ and MD have somewhat equivalent household incomes for households at or below the median and NJ has slightly higher household incomes than MD for households above the median. Similar distribution patterns were also observed in household value and monthly rental value.

The distribution of median income, proportion of units that are low income, affordable and not crowded among new units, proportion of units that are low income, affordable and not crowded among new units occupied by low income families and proportion of low income families in each state by PUMA region suggested that both NJ and MD appear somewhat stratified in a socio-economic sense while WV appears a lot more uniform.

For factors related to affordability, in NJ, among low income homeowners, low income renters, super low income homeowners and super low income renters, an uncrowded household has a greater chance of being affordable than a crowded household; while in WV, an older head of household would have a less affordable household when compared to a younger head of household. However, the universal effects of variables on affordability were not observed thoroughly. In NJ, TRVTIME has a negative effect for affordability in Low Income Renters and a positive effect for affordability in Super Low Income Renters; No Vehicle has a positive effect for affordability in Low Income Homeowners and Low Income Renters but a negative effect for affordability in Super Low Income Renters; HS Degree has a negative effect for affordability in Low Income Homeowners but a positive effect for affordability in Super Low Income Renters. In MD, similar effects of TRVTIME and No Vehicle were also observed, but not in WV due to a possible large disparity in socio-economic status among these groups of subsamples.

After modifying the 2003 dataset with a 50% increase in family and household income in WV, the same outcomes were also obtained. Using the results of this study, we can suggest recommendations to policymakers in NJ, MD and WV. Two such recommendations could be that WV officials should look into new ways to provide housing assistance to low income senior citizens and that upon further investigation on the effects of overcrowding, NJ officials can similarly devise different household affordability strategies to either decrease overcrowding among low income households or to minimize financial penalties that are incurred as a result of it.

<u>Appendix:</u>

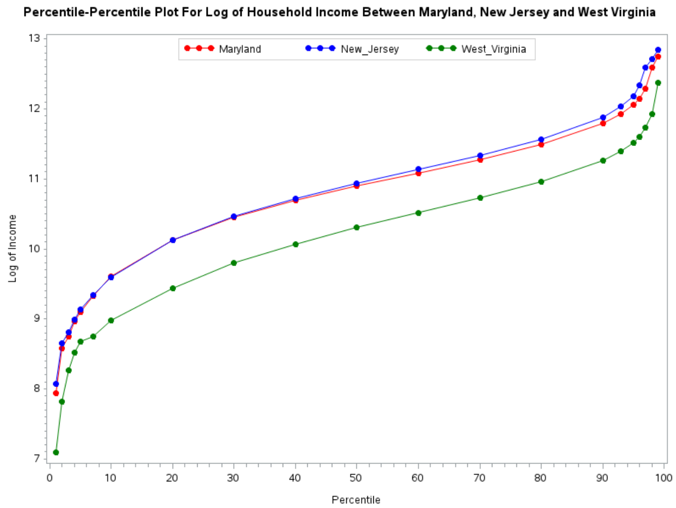

Figure 1

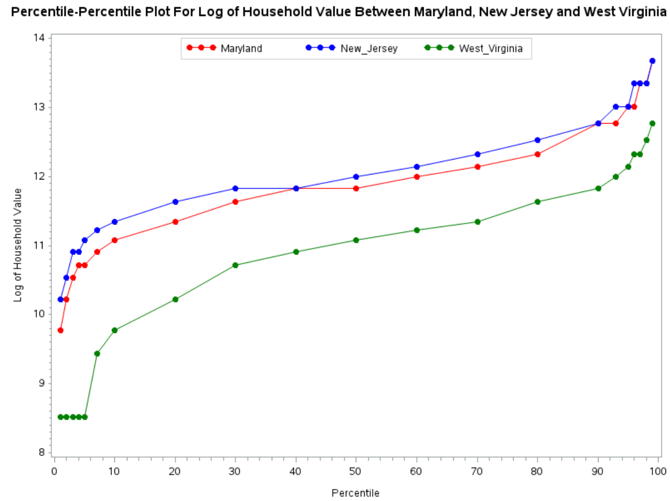

Figure 2

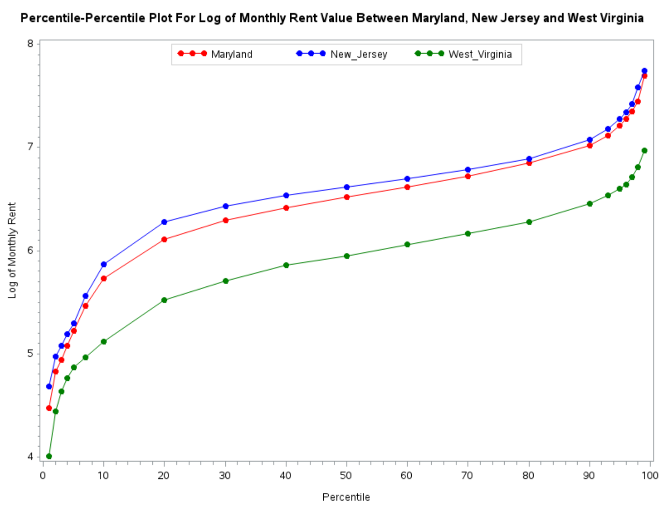

Figure 3

Basic Statistics for NJ

Obs	state	puma1	med	rat	rat2	rat3
1	NJ	34011	52500	0.06040	0.23600	0.39857
2	NJ	34012	58900	0.05006	0.19885	0.39782
3	NJ	34020	57300	0.09814	0.35811	0.40089
4	NJ	34030	78000	0.07855	0.28252	0.40760
5	NJ	34041	67500	0.06967	0.25960	0.38170
6	NJ	34042	72100	0.07619	0.31560	0.38991
7	NJ	34050	91500	0.07617	0.32084	0.38456
8	NJ	34060	55000	0.11478	0.26103	0.42095
9	NJ	34070	44000	0.03753	0.14732	0.37017
10	NJ	34080	65500	0.11842	0.26333	0.40512
11	NJ	34090	82500	0.10002	0.36626	0.38100
12	NJ	34101	69400	0.06360	0.19030	0.38519
13	NJ	34102	89700	0.07058	0.23852	0.40320
14	NJ	34110	57000	0.05683	0.18038	0.40362
15	NJ	34120	67600	0.08003	0.33574	0.37024

Figure 4

Basic Statistics for MD

Obs	state	puma1	med	rat	rat2	rat3
1	MD	24100	55000	0.07303	0.35150	0.38550
2	MD	24201	68165	0.11085	0.43995	0.35204
3	MD	24202	57000	0.06726	0.27422	0.36236
4	MD	24300	36010	0.19721	0.37165	0.39862
5	MD	24401	56200	0.12538	0.41961	0.38665
6	MD	24402	75000	0.06575	0.30314	0.35450
7	MD	24403	72000	0.09090	0.34808	0.34356
8	MD	24404	60000	0.04250	0.20277	0.34941
9	MD	24501	77000	0.07247	0.25611	0.37614
10	MD	24502	93000	0.11751	0.36181	0.37740

Figure 5

Basic Statistics for WV

Obs	state	puma1	med	rat	rat2	rat3
1	WV	54100	39000	0.13401	0.38258	0.41421
2	WV	54200	36600	0.13784	0.46974	0.38975
3	WV	54300	36800	0.14604	0.41228	0.41256

Figure 6

Variable Number	Variable Name	Description	Type of Variable	Values Taken
1	PERSONS	Number of People Living in Household	Categorical	Defined in Project Description/Census Documentation
2	VEHICL	Number of Vehicle Owned by Household	Categorical	Defined in Project Description/Census Documentation
3	SEX	Gender of Head of Household	Binary	Defined in Project Description/Census Documentation
4	AGE	Age of Head of Household	Categorical	Defined in Project Description/Census Documentation
5	EDUC	Educational Attainment of Head of Household	Categorical	Defined in Project Description/Census Documentation
6	TRVTIME	Average Travel Time (Commute) of Employed People in Household	Categorical	Defined in Project Description/Census Documentation
7	UNCROWD	Uncrowded Household	Binary	Defined in Project Description/Census Documentation
8	NEW	New Household	Binary	Defined in Project Description/Census Documentation
9	No_Vehicle	Household with No Vehicles	Binary	= 1 if VEHICL = 0, else = 0
10	Young_Head	Head of Household is a Young Individual	Binary	= 1 if AGE < 30, else = 0
11	Young_Female_Head	Head of Household is a Young Female	Binary	= 1 if Young_Head = 1 AND SEX = 2, else = 0
12	Short_Commute	Household with Short Commute Time on Average	Binary	= 1 ifTRVTIME < 45, else = 0
13	Partner_Household	Household with exactly 2 members	Binary	= 1 if PERSONS = 2, else = 0
14	Family_Household	Household with 3 or more members	Binary	= 1 if PERSONS > 2, else = 0
15	Female_Led_Family	Family with Female Head of Household	Binary	= 1 if Family_Household = 1 AND SEX = 2, else = 0
16	Old_Head	Head of Household is an Old Individual	Binary	= 1 if AGE > 64, else = 0
17	HS_Degree	Head of Household has at least a High School Degree	Binary	= 1 if EDUC > 8, else = 0
18	College_Degree	Head of Household has at least a College Degree	Binary	= 1 if EDUC >11, else = 0
19	Female_No_College	Head of Household is a Female with No College Degree	Binary	= 1 if College_Degree = 0 AND SEX = 2, else = 0

Figure 7

```
> b$beta
19 x 1 sparse Matrix of class "dgCMatrix"
                            s0
PERSONS             0.009468806
VEHICL              0.002250219
SEX                -0.020803044
AGE                 0.004143285
EDUC                .
TRVTIME             .
uncrowd            -0.055647185
new                -0.020201321
No_Vehicle         -0.079176361
Young_Head          0.012927431
Young_Female_Head   0.039643459
Short_Commute       .
Partner_Household   0.089069760
Family_Household    0.002166674
Female_Led_Family   0.019416899
Old_Head            0.052756235
HS_Degree           0.021111241
College_Degree     -0.015675924
Female_No_College  -0.032889024
```

Figure 8

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	1.6991	0.0319	2833.3313	<.0001
PERSONS	1	-0.0242	0.00441	30.1318	<.0001
AGE	1	-0.0236	0.000375	3953.5329	<.0001
uncrowd	1	0.4151	0.0202	421.0991	<.0001
new	1	0.1638	0.0111	217.4491	<.0001
No_Vehicle	1	0.3941	0.00993	1574.5068	<.0001
Young_Head	1	-0.2714	0.0226	143.6440	<.0001
Young_Female_Head	1	-0.3082	0.0326	89.5161	<.0001
Partner_Household	1	-0.4507	0.00885	2590.6565	<.0001
Family_Household	1	-0.2064	0.0166	153.6447	<.0001
Female_Led_Family	1	-0.1428	0.0130	120.9354	<.0001
Old_Head	1	-0.2094	0.0116	324.1176	<.0001
HS_Degree	1	-0.2173	0.00711	932.9496	<.0001
College_Degree	1	0.1854	0.00842	485.2358	<.0001
Female_No_College	1	0.2973	0.00809	1350.9112	<.0001

Figure 9

State	Variable Number	Variable	Low Income Homeowner	Low Income Renter	Super Low Income Homeowner	Super Low Income Renter
NJ	1	PERSONS	-0.0242	-0.0532	0	0
NJ	2	VEHICL	-0.0236	-0.0368	0	0
NJ	3	SEX	0	0.1116	0.2811	0
NJ	4	AGE	0	0	-0.0145	-0.00122
NJ	5	EDUC	0	0	0	0.0285
NJ	6	TRVTIME	0	-0.00312	0	0.00517
NJ	7	UNCROWD	0.4151	0.2212	0.4971	0.2969
NJ	8	NEW	0	0.2796	0	0
NJ	9	No_Vehicle	0.3941	0.0429	0	-0.5516
NJ	10	Young_Head	-0.2714	0	0	0
NJ	11	Young_Female_Head	-0.3082	0	0	0
NJ	12	Short_Commute	0	0	0	0
NJ	13	Partner_Household	-0.4507	0	-0.397	0
NJ	14	Family_Household	-0.2064	0	0	0
NJ	15	Female_Led_Family	-0.1428	0	0	0
NJ	16	Old_Head	-0.2094	0	-0.2478	-0.3762
NJ	17	HS_Degree	-0.2173	0	0	0.0434
NJ	18	College_Degree	0.1854	0	0	0
NJ	19	Female_No_College	0.2973	0	0	0

Figure 10

State	Variable Number	Variable	Low Income Homeowner	Low Income Renter	Super Low Income Homeowner	Super Low Income Renter
MD	1	PERSONS	-0.0538	-0.0683	0	-0.133
MD	2	VEHICL	-0.0666	-0.1397	0	0
MD	3	SEX	0.1926	0.1839	0	0
MD	4	AGE	-0.0205	0	-0.0138	-0.00523
MD	5	EDUC	0	0.0289	0	0.0804
MD	6	TRVTIME	0	-0.00139	0	0.00227
MD	7	UNCROWD	0.1604	0.2923	0	0
MD	8	NEW	0.3567	0.2488	0	0
MD	9	No_Vehicle	0.1938	0	0	-0.3862
MD	10	Young_Head	-0.3743	0	0	0
MD	11	Young_Female_Head	0	0	0	0
MD	12	Short_Commute	0	0.1595	0	0
MD	13	Partner_Household	-0.2067	0	-0.2623	0
MD	14	Family_Household	0	0	0	0
MD	15	Female_Led_Family	0	0	0	0
MD	16	Old_Head	-0.4655	0	-0.5009	-0.1516
MD	17	HS_Degree	0	0	0	0
MD	18	College_Degree	0.1868	0	0.2094	0
MD	19	Female_No_College	0	0	0	0

Figure 11

State	Variable Number	Variable	Low Income Homeowner	Low Income Renter	Super Low Income Homeowner	Super Low Income Renter
WV	1	PERSONS	0	-0.048	0	0
WV	2	VEHICL	-0.0414	0	0	0
WV	3	SEX	0.2632	0.1825	0.2045	0
WV	4	AGE	-0.011	-0.00894	-0.00904	-0.0154
WV	5	EDUC	0	0.00563	0.0632	0.0564
WV	6	TRVTIME	0	-0.00401	0	0
WV	7	UNCROWD	0.6088	0.1262	0	0
WV	8	NEW	0.5835	0	0.5384	0
WV	9	No_Vehicle	0.2743	0	0	0
WV	10	Young_Head	0	0	0	0
WV	11	Young_Female_Head	0	0.1309	0	0
WV	12	Short_Commute	0	0	0.3289	0
WV	13	Partner_Household	0	0	0	0
WV	14	Family_Household	0	-0.1382	0	0
WV	15	Female_Led_Family	0	0	0	0
WV	16	Old_Head	-0.4472	-0.1042	-0.3503	0
WV	17	HS_Degree	0	0	0	0
WV	18	College_Degree	0	0	0	0
WV	19	Female_No_College	0	0	0	0

Figure 12

Additional Figures

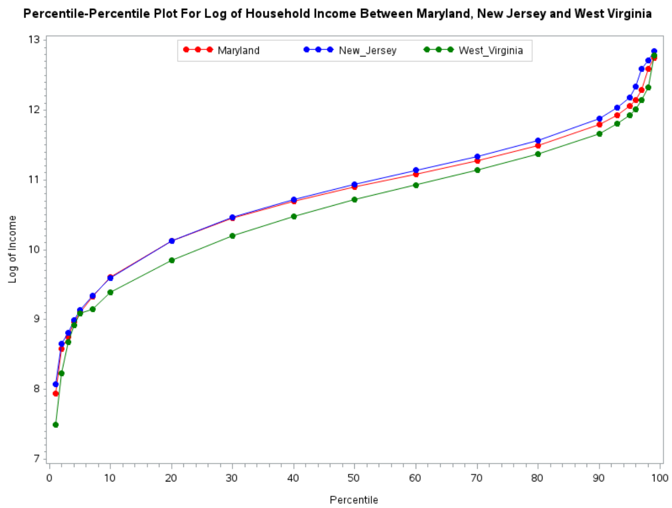

Figure 13

Basic Statistics for WV

Obs	state	puma1	med	rat	rat2	rat3
1	WV	54100	58500	0.21408	0.61119	0.41421
2	WV	54200	54900	0.19421	0.66182	0.38975
3	WV	54300	55200	0.21546	0.60825	0.41256

Figure 14

State	Variable Number	Variable	Low Income Homeowner	Low Income Renter	Super Low Income Homeowner	Super Low Income Renter
WV	1	PERSONS	-0.1649	0	0	0
WV	2	VEHICL	0	0	0	0
WV	3	SEX	0.2578	0.3426	0	0.2252
WV	4	AGE	-0.013	-0.0205	-0.00499	-0.02
WV	5	EDUC	0	0	0.0742	0.0147
WV	6	TRVTIME	-0.00823	-0.0167	0	-0.0104
WV	7	UNCROWD	0	0	0	0
WV	8	NEW	0.4207	0	0.5034	0.3173
WV	9	No_Vehicle	0	0.2693	0	0
WV	10	Young_Head	0	0	0	0
WV	11	Young_Female_Head	0	0	0	0
WV	12	Short_Commute	0	0	0	0
WV	13	Partner_Household	0	0	0	0.1277
WV	14	Family_Household	0	-0.2536	0	0
WV	15	Female_Led_Family	0	0	0	0
WV	16	Old_Head	-0.6909	-0.3143	-0.6305	-0.302
WV	17	HS_Degree	0	0	0	0
WV	18	College_Degree	0	0	0.2718	0.4267
WV	19	Female_No_College	0	0	0	0

Figure 15