

# A Take on the Effects of Residency Away From Work on Income Inequality

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ECON 483 Final Paper

March 16, 2020

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\*This paper serves as the initial research paper version for my continuing Honors Thesis (ECON 497). I greatly appreciate feedback as my research continues until the end of the year.

# Contents

<b>1</b>	<b>Introduction</b>	<b>3</b>
<b>2</b>	<b>Literature Review: Income Inequality</b>	<b>3</b>
<b>3</b>	<b>Methodology</b>	<b>5</b>
3.1	Data . . . . .	5
3.2	Models . . . . .	7
<b>4</b>	<b>Result</b>	<b>8</b>
4.1	Limitations . . . . .	12
4.1.1	Attempted OLS with Specific Locations . . . . .	12
4.1.2	Attempted LASSO . . . . .	12
<b>5</b>	<b>Conclusion</b>	<b>12</b>
	<b>References</b>	<b>14</b>
<b>A</b>	<b>Appendix</b>	<b>15</b>
A.1	Correlation Matrix . . . . .	15
A.2	Data Exploration Plots . . . . .	21
A.3	Regression With Core Interest Variables . . . . .	22
A.4	Regression With Core Interest Variables and Interaction . . . . .	23
A.5	Regression With Core Variables and Transportation Means . . . . .	24
A.6	Regression With Core Variables, Transportation Means, Migration . . . . .	25
A.7	Regression Result Without Socio-demographics . . . . .	26
A.8	Regression Result With Socio-demographics . . . . .	28
A.9	Attempted Regression With Spatial Location . . . . .	30
A.10	LASSO Regression . . . . .	34

# 1 Introduction

How does society structurally respond to rapid growth? Observe rising cities in the Pacific Northwest, notably Seattle, WA and Portland, OR. During the past decade, their boom in technological and digital engineering (HiTech) accompanied a rapid population growth and local economic success, placing these urban cities on list of international hubs for development and investment.<sup>1</sup>

As much as the robustness of these locations attract business and population, these MSAs are experiencing difficulties in resolving the negative spillovers caused by a dramatic increase in demand, and nearby suburban communities like Redmond and Spokane, WA are also affected by the repercussions of scarcity (Building Solutions 2017). Housing prices nearly doubled since 2012 (FHFA 2019). The homelessness crisis worsened (Greenstone 2019). Traffic congestion aggravated (Adam Millsap 2018). Then, rising MSAs like Seattle and Portland pool money to these areas in order to increase investments for large scale public transportation and infrastructure construction projects. Hence, many who could not afford living close to MSAs or those who prefer to live away from large metropolitan cities are naturally crowded out from the HiTech hubs. On the other hand, those who can afford and have incentive to take advantage of the high amenities available in concentrated urban areas crowd-in.

In light of this modern urbanization, I tackle the question “*What is the quantitative effect of residency away from workplace on income inequality?*” More commonly known as the spatial mismatch hypothesis, it is “serious limitations on black residential choice, combined with the steady dispersal of jobs from central cities, are responsible for the low rates of employment and low earnings of Afro-American workers” (Kain 1994). This term has now been more generalized in terms of a mismatch between location of people’s residencies and the location of job opportunities. As much as this topic is significant to assessing the current condition of financial inequality in our society, it is unfortunate to acknowledge that there is a lack of empirical research done on this issue. The most recent of the very few papers that discuss the affects of structural change in society on people’s lives is “Effects of Roads on Trade and Migration: Evidence from a Planned Capital City” Morten and Oliveira 2018. This paper is an attempt to bring light into a small portion of the larger problem of widespread inequality and reaction to change.

## 2 Literature Review: Income Inequality

It is logical to argue that with a more widely available and efficient transportation system, the significance of proximity between residence and employment location and difficulty in

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<sup>1</sup>The U.S. Office of Management and Budget defines these core locations as Metropolitan Statistical Area (MSA), “a core area containing a substantial population nucleus, together with adjacent communities having a high degree of economic and social integration with that core (Census 2010).”

accessing nearby public amenities should diminish because advanced transportation eliminates the high stakes and costs for living far from MSAs. However, metropolitan wage inequality and homelessness still exists and is increasing. This trend comes from economic, political, and social factors of MSAs. Notably, income distribution is affected by scale and rate of urban development, including economic activities and population migration (Sanchez 2002).

Additionally, it is observed that housing where public amenities are apparent, housing development often display specific price ranges, an economic opportunity for the upper class. Economic strata become clear between those who can afford some houses and those who cannot afford. The latter are pushed out of certain neighborhoods defined by spatial stratification as well. This development pattern intensify income inequalities within MSAs (Frumkin 2002). Not only housing prices are affected by access to transportation and other amenities, but also wage and work talent gap are widened. Unskilled and less specialized labor should move to MSAs for opportunities to grow only to be compensated with low wages, while the upper class that has skilled and specialized talent earn the income and choice to stay in either MSAs or emigrate outside (Sanchez 2002). This is the spatial mismatch hypothesis in action.

Also, both articles above describe a potential explanatory factor of income inequality that cannot be ignored: racial and ethnic discrimination. Sanchez states that, “discrimination has direct and indirect implications on labour conditions in terms of skill/education levels, job opportunities and potential for advancement.” Frumkin highlights that the groups that are exposed to such discrimination are more likely exposed to costly health and environment related issues, such as, air pollution, water quality, and mental illness. These groups are also more vulnerable to injuries from increased transportation vehicles.

Durlauf 1992 concisely summarizes a key takeaway,

“When redistribution from rich to poor in the urban center is large enough, wealthy agents (families) have an incentive to abandon the community and form their own neighborhoods... Stratification and the breaking up of the urban center are functions of realized income distribution.”

Here, the “Inequality and the Measurement of Residential Segregation by Income in American Neighborhoods” paper poses an interesting point to my question. It shows that income inequality and physical stratification is indeed not an ideal societal outcome, but it does not dispute that economic segregation across neighborhoods is important. A lack of exposure to middle-class “role models” leads to urban unemployment and social issues Watson 2009. This trend branches from an ambiguity for allocating public good and irregular commuting behavior for all income levels. Also, Watson shares,

“Residential decisions (made by the individuals in segregated economies) have implications for commuting behavior and the allocation of public goods. If residential choice is sensitive to income distribution, economic policies that moderate or amplify income inequality may shape the cities in which we live.”

She then quantifies this residential decision making by introducing a measure of income sorting, Centile Gap Index (CGI), based on income distributions of families in 216 U.S. cities, concluding that inequality can fully explain the rise in income segregation, a promising statement for my question.

### 3 Methodology

#### 3.1 Data

I will be utilizing micro-individual and household level data. Collected from American Community Survey (ACS), Public Use Microdata Sample (PUMS), Current Population Survey (CPS), and Survey of Income and Program Participation (SIPP) in 2018, all subsidiaries under the larger U.S. Census, these large datasets provide very specific information such as household demographics, income, wage, location of residence, travel time to work, place of work, nearest history of migration, insurance, occupation type, etc.

The advantage of using low level micro data over larger macro level data is the ability of questioning and answering how specific decision makings and characteristics of persons or households affect a larger entity as a whole. Hence, instead of the Gini index, a widely used indicator for income inequality that is considered macro level data, we use the Income-Poverty Ratio as the indicator for wealth and poverty, popularly practiced by the U.S. Census Bureau. (We denote the Income-Poverty Ratio is “Income/Poverty”.)

$$\text{Income/Poverty} = (\text{Income} + \text{Earnings}) / \text{Poverty Threshold}$$

The CPS provides specific guidelines on what money income or earnings composites or does not within income and earnings. Poverty threshold varies by size of household and age of the members. This threshold is used throughout the U.S. and are updated annually for inflation using the Consumer Price Index for All Urban Consumers (CPI-U). The Census Bureau notes that “although the thresholds in some sense reflect a family’s needs, they are intended for use as a statistical yardstick, not as a complete description of what people and families need to live” (Census 2019). Refer to Figure 1 for the full 2018 table.

The raw collective dataset’s dimension is approximately 3 million observations by 300 variables. We then calculate Income/Poverty for every individual. The  $\log(\text{Income/Poverty})$  will be used as the response variable throughout this paper because just Income/Poverty is extremely right skewed. The logarithmic makes the overall more normal. We also plot scatterplots and histograms to explore some of our variables of interest in Appendix A.2. **All variable names used in following models can be found in the *PUMS data dictionary* ([link](#)).**

Poverty Thresholds for 2018 by Size of Family and Number of Related Children Under 18 Years										
Size of family unit	Weighted average thresholds	Related children under 18 years								
		None	One	Two	Three	Four	Five	Six	Seven	Eight or more
One person (unrelated individual):	12,784									
Under age 65.....	13,064	13,064								
Aged 65 and older.....	12,043	12,043								
Two people:	16,247									
Householder under age 65.....	16,889	16,815	17,308							
Householder aged 65 and older.....	15,193	15,178	17,242							
Three people.....	19,985	19,642	20,212	20,231						
Four people.....	25,701	25,900	26,324	25,465	25,554					
Five people.....	30,459	31,234	31,689	30,718	29,967	29,509				
Six people.....	34,533	35,925	36,068	35,324	34,612	33,553	32,925			
Seven people.....	39,194	41,336	41,594	40,705	40,085	38,929	37,581	36,102		
Eight people.....	43,602	46,231	46,640	45,800	45,064	44,021	42,696	41,317	40,967	
Nine people or more.....	51,393	55,613	55,883	55,140	54,516	53,491	52,082	50,807	50,491	48,546
Source: U.S. Census Bureau.										

Figure 1: 2018 Poverty Threshold Table

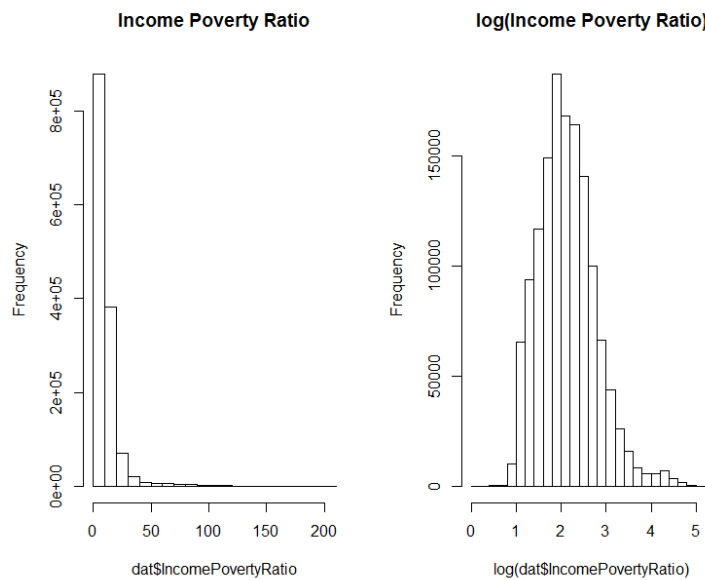


Figure 2: Histograms of Income/Poverty

### 3.2 Models

We introduce 8 models in total. The first 6 will be an accumulation from the very first for robustness check and capturing the behavior of Income/Poverty as much as possible by careful feature selection. 2 will be discussed in section 4.1 as part of other efforts I made to build a better model. We will assume that the travel time to work is a proxy for distance of residence away from work. Also, since we simply question how residency away from work affects income inequality (Income/Poverty), we assume that whether the two locations are in the same U.S. state or not encompasses the real difference between home and work place. Residency only occurs in the U.S. states, but the work place need not be in the same state. These two variables are our core variables of interest we start our model with. All 6 models of interest are listed as follows:

1.  $\log(\text{Income/Poverty}) = \beta_0 + \beta_1 \text{TravelTimeToWork} + \beta_2 \text{ResidencyWorkplaceSame}$
2.  $\log(\text{Income/Poverty}) = \beta_0 + \beta_1 \text{TravelTimeToWork} + \beta_2 \text{ResidencyWorkplaceSame} + \beta_3 (\text{TravelTimeToWork} * \text{ResidencyWorkplaceSame})$
3.  $\log(\text{Income/Poverty}) = \beta_0 + \beta_1 \text{TravelTimeToWork} + \beta_2 \text{ResidencyWorkplaceSame} + \beta_3 (\text{TravelTimeToWork} * \text{ResidencyWorkplaceSame}) + \beta_4 \text{TransitMeanToWork} + \beta_5 (\text{TravelTimeToWork} * \text{TransitMeanToWork})$
4.  $\log(\text{Income/Poverty}) = \beta_0 + \beta_1 \text{TravelTimeToWork} + \beta_2 \text{ResidencyWorkplaceSame} + \beta_3 (\text{TravelTimeToWork} * \text{ResidencyWorkplaceSame}) + \beta_4 \text{TransitMeanToWork} + \beta_5 (\text{TravelTimeToWork} * \text{TransitMeanToWork}) + \beta_6 \text{AnnualMigrationHistory}$
5.  $\log(\text{Income/Poverty}) = \beta_0 + \beta_1 \text{TravelTimeToWork} + \beta_2 \text{ResidencyWorkplaceSame} + \beta_3 (\text{TravelTimeToWork} * \text{ResidencyWorkplaceSame}) + \beta_4 \text{TransitMeanToWork} + \beta_5 (\text{TravelTimeToWork} * \text{TransitMeanToWork}) + \beta_6 \text{AnnualMigrationHistory} + \vec{\beta}_i \text{OtherRelatedChars}$
6.  $\log(\text{Income/Poverty}) = \beta_0 + \beta_1 \text{TravelTimeToWork} + \beta_2 \text{ResidencyWorkplaceSame} + \beta_3 (\text{TravelTimeToWork} * \text{ResidencyWorkplaceSame}) + \beta_4 \text{TransitMeanToWork} + \beta_5 (\text{TravelTimeToWork} * \text{TransitMeanToWork}) + \beta_6 \text{AnnualMigrationHistory} + \vec{\beta}_i \text{OtherRelatedChars} + \vec{\beta}_k \text{SocioDemographicVariables}$

The first OLS regression is done on two core variables of interest of this paper: travel time to work and whether or not residency is away from work place. This model returns the minimal answer to our question.

The second regression includes an interaction term for travel time to work and whether or not residency is away from work place. The effect on  $\log(\text{Income/Poverty})$  of a change in travel time to work will change depending on whether or not work place is in the same state as residency. If the state is not the same, many options of scenarios can be discussed

e.g. remote work or permanent address being different from local work address. Therefore, in light to accommodate the residency and work, individuals make choices where to live at what they can afford, potentially displaying a pattern in income stratification by location. The interaction term should capture the effect of this.

The third regression includes means of transportation to work and an interaction term with travel time to work. The differences across travel time to work can vary upon many factors, and the means of transit should be one of them. The travel time from location A to B by private car, subway, or bus will vary. This may include differences in income/poverty across individuals.

The fourth simply includes the history of migration of an individual over the past year. As introduced in the literature review, migration affects the type of labour and location of residency. Whether an individual lived at one location for some time, or came from a different state or country, or just moved into a residency will affect the basic decision makings individuals make to accommodate work. That is, I expect change in income inequality to be partially explained with this model.

The fifth includes the related non-sociodemographic factors that could directly alter an individual's decision making for labor, residency, migration, and income. These factors include age, household size, class of worker in industry, owning a child, current marriage status, work hours per week, work weeks per year, and having insurance from various sources (corporate, private, Medicare, other government assistance, Tricare, VAcare).

Finally, the sixth includes all other potentially significant sociodemographic factors that were not included in the fifth model. These factors that could affect income inequality are military serving history, education, sex, race, background in HiTech related subjects. It is logical to argue that these variables in some manner will affect  $\log(\text{Income/Poverty})$  and are popular topics for debate in academia and media.

With my large dataset, high dimensionality is not a problem. To check for potential multicollinearity, check the compute a coefficient of multiple determination for each independent variable included in our models (Appendix A.1). Observe that most variables have little to no correlation in magnitude to other variables with high significance, so multicollinearity will not likely affect our analysis to be hard to assess the relative importance of the independent variables. Therefore, we proceed to analyze our regression results.

## 4 Result

**All abbreviated variable names used in following models can be found in the *PUMS data dictionary* ([link](#)).**

Let us start with the first regression (Appendix A.3). If travel time to work increases by 1 minute, Income/Poverty will increase by 0.003411 percentage points on average, which is not



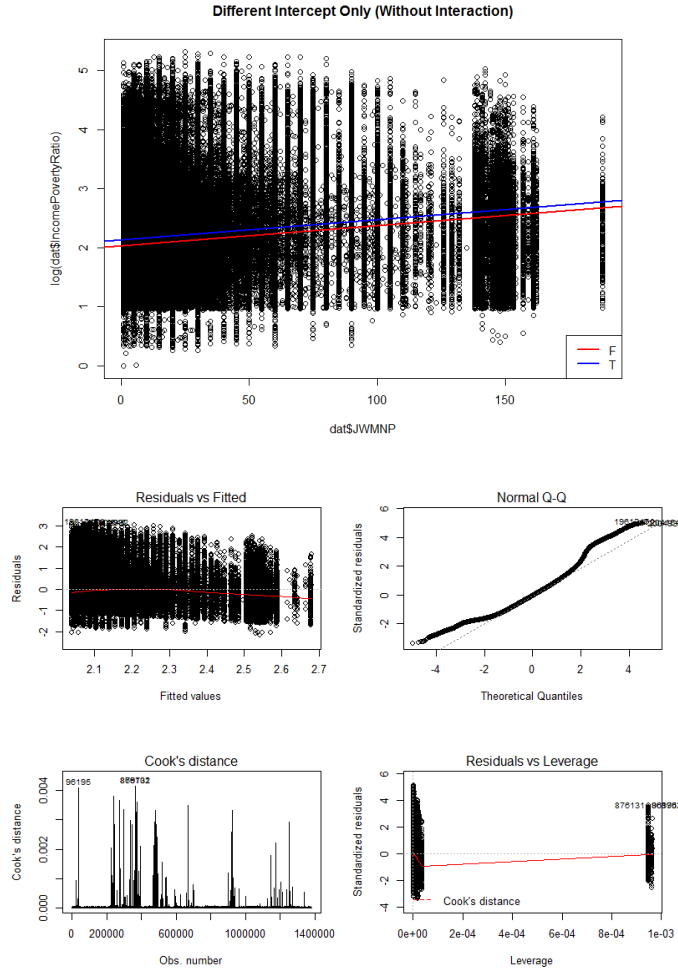


Figure 3: Model 1 Results

so little in magnitude. Since Income/Poverty is a ratio, even 0.003411 can be large in actual values. Continuing on, if residence and work place are different, the intercept is 2.036. If they are same, the intercept is  $2.036 + 0.09392 = 2.12992$ . All feature variables are individually significant at the near 100% confidence level and they are jointed significant as well. With such a high degrees of freedom, we can conclude that the results are strong. We see that the R-squared value is very small, 0.01573, so no strong correlation to be discovered yet. This result can be visualised graphically as two parallel linear lines with different intercepts. This initial regression has several issues: the residual plot suggests gradual deviation as fitted values increase, the normal QQ plot indicates there are many outliers, the results don't follow a normal distribution, and the Cook's distance and leverage plots indicate that there are many extremely influential individuals. Further examination of the results is warranted.

With our interaction term (Appendix A.4), we observe almost same results, but the coefficient for if residence and work place are equal decreased. R-squared did not change. Also,

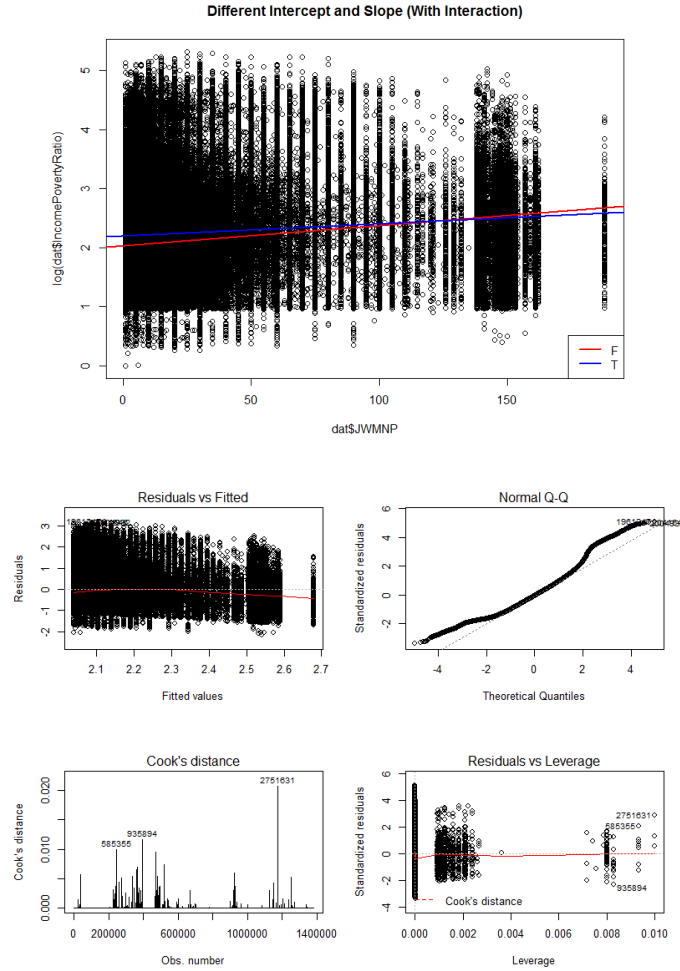


Figure 4: Model 2 Results

the interaction is only significant at the 99% confidence level. I believe that this is due to the lack of cases where the residence and work place's state are equal, only several thousand observations. With over a million observations indicating different locations of the two. If I had more data with cases where locations are equal, I believe that the strength of the results will greatly increase. In graphical terms, the slopes will be different too now with the interaction. We can see that the deviation in the residual plot slightly decreased and a large portion of overly influential individuals have been accounted for, but it still remains an issue. However, I think this is natural for this paper because income inequality can come in extreme cases, which this paper addresses.

The results from the first two models may be intuitive. The third and fourth are more interesting (Appendix A.5 and A.6). We now consider means of transportation and migration history in our model. Again, most variables are individually very significant except a few means of transit and travel time to work interactions, joint significance is satisfied, and

R-squared is still low. The residence-workplace-equal and travel time interaction's statistical significance increased. The coefficient (intercept) for going to work by bus, taxicab, bicycle, walking, and other methods were lower in comparison to riding personal vehicle. Using street-cars, subway, railroads, ferryboats, and motorcycles were higher in intercept. The coefficients (slope) from the interaction between transit mean and travel time in comparison to using personal vehicle were lower for all means except bicycle and other methods not specified. It seems like transit means to work may not be significant to our model. In terms of migration, those who have moved in the past year either within the U.S. or from outside are closer to poverty. This logically comprehends; those who have settled are likely to be more in a stable position in terms of livelihood, work, and moving. Hence, those who less worry about moving may imply better financial situations as well, but this is a different question.

We now interpret the results of fifth and sixth model (Appendix A.7 and A.8). Note that the sixth model includes much more information in the regression than the other. So, the robustness check can be contributed to very many factors, implying that the result is only meaningful as a whole. Effects of individual factors added are unclear and require much deeper analysis involving other econometric methods to deal with existing problems in this model like omitted variable bias. We determined that means of transportation is likely a significant variable for the overall model from above. This can be reconfirmed by the disappearing and reappearing of individual significance of by some of the transportation means and their interactions with travel time to work. Now, we observe that as age increases,  $\log(\text{Income}/\text{Poverty})$  increases significantly. Also, as household size increases  $\log(\text{Income}/\text{Poverty})$  decreases quite some percentage points. Select class of workers (federal employee, self-employed into owned business) observe a slightly positive positive while others (local government employee, self-employed, family business, no job) show significantly negative coefficients, all in comparison to those employed into for-profit private corporations. Owning children, not currently married, and not having insurance return results on  $\text{Income}/\text{Poverty}$  as we may expect. Other predictable results the models return are lower income/poverty for being lower education level, female, foreign born, or being certain races. We see that standard error decreased and R-squared increased. Although this can be good, it can also be misleading because as more variables are fitted in the regression, SE always decreases and R-squared always increases. I think some correlation is being well captured because R-squared increased considerably from model 4's R-square. Also, from model 6, the adjusted R-squared value is equal to multiple R-squared. The adjusted version penalizes overfitting models, so it is good to see that overfitting is not a concern for our models. Lastly, observe that the coefficients for travel time to work, residence-workplace-same variable, and their interaction decreased in magnitude without changing signs. This can be partially explained by the large increase in number of other feature variables.

## 4.1 Limitations

There are much to work on. Some related to additional research about my topic. Some related to data: analyzing information I already have and extracting the necessary fields then searching for the missing macro data that will provide additional more accurate insight into my question. In addition, with so much regressors and my method of choosing them, selection bias and omitted variable bias are large concern for this paper. We also cannot forget that dealing with real world data means that the data often do not meet the large and significant assumptions for econometric models (the OLS) to return meaningful outputs.

### 4.1.1 Attempted OLS with Specific Locations

Refer to Appendix A.9. This regression is identical to the sixth model above but with the states of residency and the location of place of work. The motivation behind this attempt is to hopefully see patterns from certain groups of states clustered to conclude a result specific to regions within the U.S. in terms of income inequality. However, the result returned is not very useful as too many dummy variables (one for each state or foreign country) were fit and most turned out to be not statistically significant. Those that did end up individually significant ended up showing no apparent patterns, i.e., no clustering on the U.S. map.

### 4.1.2 Attempted LASSO

Refer to Appendix A.10. The LASSO (Least Absolute Shrinkage and Selection Operator) is a shrinkage model that penalizes coefficients of the regression towards zero and determines which independent variables are most important to the model “with high probability” under low dimensionality. Keep these variables and their coefficients to run another OLS regression. From our results, most variables are individually significant, model is jointly significant, and the R-squared value is an astonishing 0.9841. However these results are a disguise to contradictory and incorrect interpretation. An example is the result that no health insurance has a positive coefficient, but no private health insurance or no public health insurance both have negative coefficients. Practitioners of the LASSO often wholeheartedly accept the machine generated answers to questions; however, like in this model, careful interpretation and valuable numbers are both required to conclude a reasonable answer to our research question.

## 5 Conclusion

I conclude with a brief recap and what I much work more on. I discussed the motivation and topic for my question, searching for a correlation between residency away from place of work and income inequality (Income/Poverty) with respect to various factors of demographics and potentially related independent variables to our response variable. I then shared the data

that I have gathered and demonstrated a graduate conglomeration of growing regressions starting with the barebones (travel time to work and whether residency equals to the state of place of work) for robustness check. Unfortunately, our models were able to potentially capture only a small portion of what income inequality may look like depending on where people live and work. Some of our variables of interest like means of transportation of class or worker turned out to be unreliable to reach a definitive conclusion to answer our question. However, our models were able to point out that income inequality does exist depending on the decisions people make on residency and working. Our model was also able to reconfirm potential other issues widely studied, e.g., women are underpaid compared to men or migratory decisions enhance inequality stratification. In enlightenment, it is significant to reassess the relationships and significance of the independent variables. Being able to pinpoint what information is missing from the regression and collect them or notice what must be fixed econometrically will gradually approach to an answer closer to the true answer to my question over many trials of improvement.

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## A Appendix

### A.1 Correlation Matrix

	row	column	correlation coefficient	correlation p-value
1	SPORDER	AGEP	-0.293173155199638	0
2	SPORDER	COW	-0.100015620626975	0
3	AGEP	COW	0.16751539791438	0
4	SPORDER	HINS1	0.0629227432563414	0
5	AGEP	HINS1	-0.00706875190494468	0
6	COW	HINS1	0.123053738937327	0
7	SPORDER	HINS2	0.0196025514395949	0
8	AGEP	HINS2	-0.0860194118491072	0
9	COW	HINS2	-0.129677537259218	0
10	HINS1	HINS2	-0.377635483833195	0
11	SPORDER	HINS3	0.0835325948202211	0
12	AGEP	HINS3	-0.452455700003008	0
13	COW	HINS3	-0.0921710266142001	0
14	HINS1	HINS3	-0.186574455239266	0
15	HINS2	HINS3	0.138573877389809	0
16	SPORDER	HINS4	-0.0708434589544589	0
17	AGEP	HINS4	0.097784603150415	0
18	COW	HINS4	0.0168304097517563	0
19	HINS1	HINS4	-0.38024901878316	0
20	HINS2	HINS4	-0.0524025003665242	0
21	HINS3	HINS4	0.0301563506187352	0
22	SPORDER	HINS5	0.0354556822604818	0
23	AGEP	HINS5	0.00949427666562267	0
24	COW	HINS5	-0.113705852679138	0
25	HINS1	HINS5	-0.131436804929724	0
26	HINS2	HINS5	-0.0118786130806702	0
27	HINS3	HINS5	0.0377884227888377	0
28	HINS4	HINS5	-0.0218641807003256	0
29	SPORDER	HINS6	0.0394891648070299	0
30	AGEP	HINS6	-0.0830295904598835	0
31	COW	HINS6	-0.0419934053339178	0
32	HINS1	HINS6	-0.0396158898500998	0
33	HINS2	HINS6	0.0183526141771989	0
34	HINS3	HINS6	0.100026018361904	0
35	HINS4	HINS6	-0.00573228398636791	1.27964305818296e-11
36	HINS5	HINS6	0.210637509506968	0
37	SPORDER	JWMNP	0.0034640245941818	4.28310643121321e-05
38	AGEP	JWMNP	0.0361016874013295	0
39	COW	JWMNP	-0.0329782692063925	0

40	HINS1	JWMNP	-0.0517759362454525	0
41	HINS2	JWMNP	0.0317536620645989	0
42	HINS3	JWMNP	0.0296400055028057	0
43	HINS4	JWMNP	0.0191329054431951	0
44	HINS5	JWMNP	0.0163499016419573	0
45	HINS6	JWMNP	-0.00953632956858533	0
46	SPORDER	JWTR	-0.00654690671847853	1.04360964314765e-14
47	AGEP	JWTR	-0.0818775723327928	0
48	COW	JWTR	0.0208778841548341	0
49	HINS1	JWTR	0.0673528718600721	0
50	HINS2	JWTR	-0.0157070471416587	0
51	HINS3	JWTR	0.00330886522291287	9.29173276609241e-05
52	HINS4	JWTR	-0.0519802732009477	0
53	HINS5	JWTR	-0.0213183617374509	0
54	HINS6	JWTR	0.00806156787829062	0
55	JWMNP	JWTR	-0.0141295294630106	0
56	SPORDER	MAR	0.232287827197648	0
57	AGEP	MAR	-0.472503961983488	0
58	COW	MAR	-0.12427200036973	0
59	HINS1	MAR	0.130139390324852	0
60	HINS2	MAR	0.00146904127806703	0.0827045812299496
61	HINS3	MAR	0.0971097664240233	0
62	HINS4	MAR	-0.118330470917622	0
63	HINS5	MAR	0.0320429629033391	0
64	HINS6	MAR	0.0344640583117667	0
65	JWMNP	MAR	-0.0462308889446848	0
66	JWTR	MAR	0.111651716628485	0
67	SPORDER	MIG	0.00581176512609798	6.65822952328199e-12
68	AGEP	MIG	-0.225297333031564	0
69	COW	MIG	-0.0382375840585221	0
70	HINS1	MIG	0.0444603429487545	0
71	HINS2	MIG	0.00920118878121723	0
72	HINS3	MIG	0.0652070792016852	0
73	HINS4	MIG	-0.0287106186673993	0
74	HINS5	MIG	-0.0420003581274567	0
75	HINS6	MIG	0.00245690827009161	0.00370720263112045
76	JWMNP	MIG	-0.0146708628380472	0
77	JWTR	MIG	0.0675329907406202	0
78	MAR	MIG	0.160118069213628	0
79	SPORDER	MIL	0.0190662277367147	0
80	AGEP	MIL	-0.0368785634440133	0
81	COW	MIL	-0.0983270806296266	0
82	HINS1	MIL	-0.0587140243654938	0

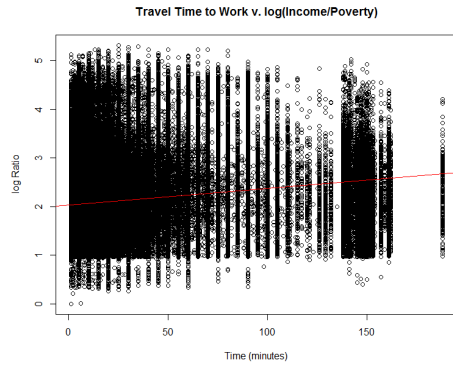
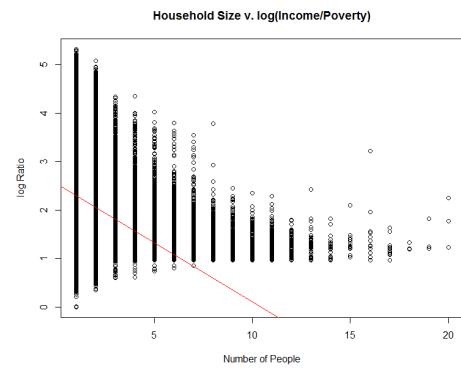
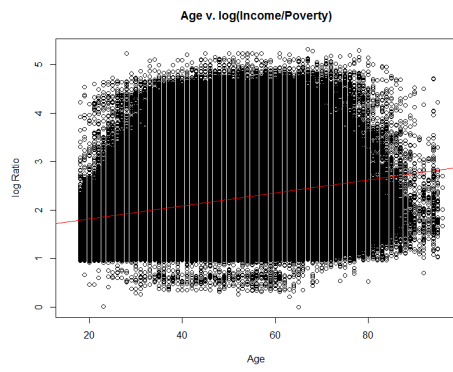
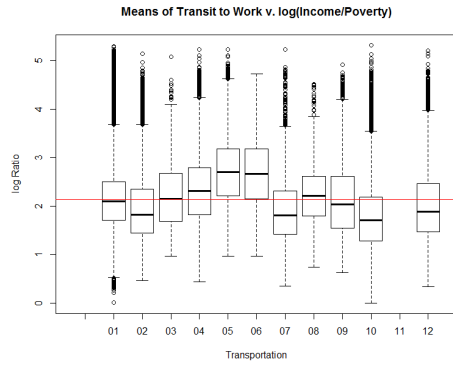


83	HINS2	MIL	-0.00962385046164662	0
84	HINS3	MIL	0.0913730419574771	0
85	HINS4	MIL	-0.0194944615604374	0
86	HINS5	MIL	0.405000918102109	0
87	HINS6	MIL	0.396846632112531	0
88	JWMNP	MIL	0.00347867347964395	3.97452869336234e-05
89	JWTR	MIL	-0.0137818167378073	0
90	MAR	MIL	0.0225406654791499	0
91	MIG	MIL	-0.011849493454902	0
92	SPORDER	SCH	0.139719222060433	0
93	AGEP	SCH	-0.343950178373034	0
94	COW	SCH	-0.0538316141280913	0
95	HINS1	SCH	0.0192981408573483	0
96	HINS2	SCH	-0.0257226515825785	0
97	HINS3	SCH	0.0724547050233404	0
98	HINS4	SCH	-0.0431421565674761	0
99	HINS5	SCH	-0.0214621222549396	0
100	HINS6	SCH	0.00851825166622836	0
101	JWMNP	SCH	-0.0564726375968306	0
102	JWTR	SCH	0.104103805380631	0
103	MAR	SCH	0.259135717794181	0
104	MIG	SCH	0.0811459874486243	0
105	MIL	SCH	-0.0472740535953233	0
106	SPORDER	SEX	0.000756446256039046	0.371589442453219
107	AGEP	SEX	-0.0108022869247707	0
108	COW	SEX	-0.0322816286310277	0
109	HINS1	SEX	-0.0156307726074924	0
110	HINS2	SEX	-0.000692840228274716	0.413146063112989
111	HINS3	SEX	0.00953686585518462	0
112	HINS4	SEX	-0.0413998797795618	0
113	HINS5	SEX	0.0346527076466448	0
114	HINS6	SEX	0.0889752915186557	0
115	JWMNP	SEX	-0.0709428149610695	0
116	JWTR	SEX	-0.0156627781499332	0
117	MAR	SEX	0.0328313442090759	0
118	MIG	SEX	0.00317074743277303	0.000180224304100918
119	MIL	SEX	0.17041591164351	0
120	SCH	SEX	0.0571618998622239	0
121	SPORDER	WKHP	-0.13650825102773	0
122	AGEP	WKHP	0.0779660577716462	0
123	COW	WKHP	0.0352646769936005	0
124	HINS1	WKHP	-0.165073658005588	0
125	HINS2	WKHP	0.0581331445871327	0

126	HINS3	WKHP	0.165421313551616	0
127	HINS4	WKHP	0.15053834619088	0
128	HINS5	WKHP	-0.0239457342174772	0
129	HINS6	WKHP	-0.00267502116912833	0.00157937209252434
130	JWMNP	WKHP	0.0999686160183059	0
131	JWTR	WKHP	-0.053107769286735	0
132	MAR	WKHP	-0.159919039979841	0
133	MIG	WKHP	-0.00326541263310285	0.000114762020282821
134	MIL	WKHP	-0.00692128071582313	4.44089209850063e-16
135	SCH	WKHP	-0.244424508521875	0
136	SEX	WKHP	-0.205647891526239	0
137	SPORDER	WKW	0.14314927394593	0
138	AGEP	WKW	-0.154965531243898	0
139	COW	WKW	-0.0035610237183971	2.59669638280613e-05
140	HINS1	WKW	0.149674781136149	0
141	HINS2	WKW	-0.0461246632105287	0
142	HINS3	WKW	-0.063621941748096	0
143	HINS4	WKW	-0.131545828964185	0
144	HINS5	WKW	-0.00293989450508001	0.000515529432554507
145	HINS6	WKW	-0.00158348881404485	0.0614299520698953
146	JWMNP	WKW	-0.0486507173764824	0
147	JWTR	WKW	0.0811187532018429	0
148	MAR	WKW	0.165884378210165	0
149	MIG	WKW	0.0631119291916097	0
150	MIL	WKW	-0.0443193513224042	0
151	SCH	WKW	0.231369121501509	0
152	SEX	WKW	0.0589842561697116	0
153	WKHP	WKW	-0.365705101444583	0
154	SPORDER	NATIVITY	0.0381234581351802	0
155	AGEP	NATIVITY	0.0359416196965243	0
156	COW	NATIVITY	-0.00896063864469188	0
157	HINS1	NATIVITY	0.103092393131163	0
158	HINS2	NATIVITY	-0.011527994832439	0
159	HINS3	NATIVITY	0.0302647238235555	0
160	HINS4	NATIVITY	-0.0416141783479958	0
161	HINS5	NATIVITY	0.0348125686784829	0
162	HINS6	NATIVITY	0.0384737790374089	0
163	JWMNP	NATIVITY	0.0607847967229784	0
164	JWTR	NATIVITY	0.0393347582930189	0
165	MAR	NATIVITY	-0.0835726938737324	0
166	MIG	NATIVITY	-0.0141224802123281	0
167	MIL	NATIVITY	0.0804220852543953	0
168	SCH	NATIVITY	-0.0280135270021205	0

169	SEX	NATIVITY	-0.0218820624075044	0
170	WKHP	NATIVITY	0.00996929872661089	0
171	WKW	NATIVITY	-0.00542732729555977	1.44850131889029e-10
172	SPORDER	OC	0.160964870329041	0
173	AGEP	OC	0.00200710296717957	0.0177518307582494
174	COW	OC	-0.0404831591447707	0
175	HINS1	OC	-0.048206920385259	0
176	HINS2	OC	0.0191217211625045	0
177	HINS3	OC	0.00907791944418645	0
178	HINS4	OC	0.00376682405283263	8.61439142285647e-06
179	HINS5	OC	0.0913549497592475	0
180	HINS6	OC	0.00175277509178638	0.0384199374615968
181	JWMNP	OC	0.0219312142990725	0
182	JWTR	OC	-0.183791139322721	0
183	MAR	OC	-0.0332617514820722	0
184	MIG	OC	-0.101305960893554	0
185	MIL	OC	-0.0889887503277775	0
186	SCH	OC	-0.0488920239956697	0
187	SEX	OC	0.00904728031685647	0
188	WKHP	OC	-0.0269691744206037	0
189	WKW	OC	0.0364883755061439	0
190	NATIVITY	OC	-0.0042851492366132	4.15839835010701e-07
191	SPORDER	RAC1P	0.0822746854843064	0
192	AGEP	RAC1P	-0.0906733540210365	0
193	COW	RAC1P	-0.0279274750052805	0
194	HINS1	RAC1P	0.0640239852937151	0
195	HINS2	RAC1P	0.00281269557802977	0.000892757425698942
196	HINS3	RAC1P	0.0504592073349663	0
197	HINS4	RAC1P	-0.0684459510064174	0
198	HINS5	RAC1P	0.00456853812519264	6.80297391753015e-08
199	HINS6	RAC1P	0.016749949103522	0
200	JWMNP	RAC1P	0.0410832045628344	0
201	JWTR	RAC1P	0.0476733268091735	0
202	MAR	RAC1P	0.0579127979227088	0
203	MIG	RAC1P	0.0214844294556104	0
204	MIL	RAC1P	0.0333344539280266	0
205	SCH	RAC1P	0.0329817344294272	0
206	SEX	RAC1P	0.00307026876063403	0.000287231442257951
207	WKHP	RAC1P	-0.0228495971650891	0
208	WKW	RAC1P	0.0256042280748037	0
209	NATIVITY	RAC1P	0.381387580288144	0
210	OC	RAC1P	-0.00920057104160938	0
211	SPORDER	SCIENGRLP	-0.132927985538798	0

212	AGEP	SCIENGRLP	0.0472694740993203	0
213	COW	SCIENGRLP	0.104688290410236	0
214	HINS1	SCIENGRLP	-0.175166392492845	0
215	HINS2	SCIENGRLP	0.000130961702345588	0.877066130081284
216	HINS3	SCIENGRLP	0.00615417662760083	3.61488616817951e-13
217	HINS4	SCIENGRLP	0.134998171035369	0
218	HINS5	SCIENGRLP	-0.000681597124403041	0.420767947549738
219	HINS6	SCIENGRLP	0.0122100208499343	0
220	JWMNP	SCIENGRLP	0.0493645585485788	0
221	JWTR	SCIENGRLP	0.0117634426666858	0
222	MAR	SCIENGRLP	-0.113990966911266	0
223	MIG	SCIENGRLP	0.0161003314964712	0
224	MIL	SCIENGRLP	0.043728844560992	0
225	SCH	SCIENGRLP	-0.05318892643324	0
226	SEX	SCIENGRLP	0.0325034469280112	0
227	WKHP	SCIENGRLP	0.127319015724119	0
228	WKW	SCIENGRLP	-0.0707739283256073	0
229	NATIVITY	SCIENGRLP	0.00874209749488883	0
230	OC	SCIENGRLP	0.00940052746836813	0
231	RAC1P	SCIENGRLP	-0.0124633410387037	0
232	SPORDER	SameResidenceWorkplace	-0.00257458951625886	0.00235745908598073
233	AGEP	SameResidenceWorkplace	0.00288555202554217	0.000653531130215601
234	COW	SameResidenceWorkplace	-0.00466815742801973	3.50830839934702e-08
235	HINS1	SameResidenceWorkplace	-0.00444716012097272	1.49700956075804e-07
236	HINS2	SameResidenceWorkplace	0.00229941367033954	0.00660704745993179
237	HINS3	SameResidenceWorkplace	0.00189347552679734	0.0253164674841888
238	HINS4	SameResidenceWorkplace	0.0035396139507802	2.90309328132565e-05
239	HINS5	SameResidenceWorkplace	-0.000407179149225659	0.630550411169744
240	HINS6	SameResidenceWorkplace	-0.00238975246195207	0.00476160334197595
241	JWMNP	SameResidenceWorkplace	0.0263815593981255	0
242	JWTR	SameResidenceWorkplace	0.00325875178646771	0.000118511073256
243	MAR	SameResidenceWorkplace	-0.00334574411397818	7.75200628044814e-05
244	MIG	SameResidenceWorkplace	0.00103195948242114	0.222870293635984
245	MIL	SameResidenceWorkplace	-0.00132804914210667	0.116725534384148
246	SCH	SameResidenceWorkplace	-0.00166846419237426	0.0487513870713254
247	SEX	SameResidenceWorkplace	-0.00621761681141667	2.06945571790129e-13
248	WKHP	SameResidenceWorkplace	0.00667153905907775	3.10862446895044e-15
249	WKW	SameResidenceWorkplace	-0.00227835942003688	0.00712043996889555
250	NATIVITY	SameResidenceWorkplace	-0.00458655977137502	6.04092154077307e-08
251	OC	SameResidenceWorkplace	-0.000169776209534962	0.841061069218457
252	RAC1P	SameResidenceWorkplace	-0.00164050296644245	0.0526559032907576
253	SCIENGRLP	SameResidenceWorkplace	-0.000307754607380446	0.716221034091058



## A.2 Data Exploration Plots

### A.3 Regression With Core Interest Variables

First OLS regression output ONLY on the core interest vars:

Call:

```
lm(formula = log(IncomePovertyRatio) ~ SameResidenceWorkplace +  
    JWMNP, data = dat)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.1453	-0.4460	-0.0440	0.3738	3.1943

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	2.036e+00	8.283e-04	2458.314	< 2e-16 ***
SameResidenceWorkplaceTRUE	9.392e-02	1.942e-02	4.837	1.32e-06 ***
JWMNP	3.411e-03	2.302e-05	148.190	< 2e-16 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6306 on 1379245 degrees of freedom  
(15943 observations deleted due to missingness)

Multiple R-squared: 0.01573, Adjusted R-squared: 0.01572

F-statistic: 1.102e+04 on 2 and 1379245 DF, p-value: < 2.2e-16

## A.4 Regression With Core Interest Variables and Interaction

First OLS regression output BUT with interaction term:

Call:

```
lm(formula = log(IncomePovertyRatio) ~ SameResidenceWorkplace *  
    JWMNP, data = dat)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.1456	-0.4459	-0.0439	0.3738	3.1944

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	2.036e+00	8.288e-04	2456.934	< 2e-16 ***
SameResidenceWorkplaceTRUE	1.598e-01	3.304e-02	4.836	1.32e-06 ***
JWMNP	3.413e-03	2.304e-05	148.160	< 2e-16 ***
SameResidenceWorkplaceTRUE:JWMNP	-1.327e-03	5.387e-04	-2.464	0.0137 *

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6306 on 1379244 degrees of freedom

(15943 observations deleted due to missingness)

Multiple R-squared: 0.01573, Adjusted R-squared: 0.01573

F-statistic: 7348 on 3 and 1379244 DF, p-value: < 2.2e-16

## A.5 Regression With Core Variables and Transportation Means

OLS regression output with another interaction term:

Residuals:

Min	1Q	Median	3Q	Max
-2.1325	-0.4415	-0.0444	0.3688	3.4564

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	2.051e+00	8.798e-04	2330.780	< 2e-16 ***
SameResidenceWorkplaceTRUE	1.618e-01	3.282e-02	4.929	8.28e-07 ***
JWMNP	3.228e-03	2.552e-05	126.503	< 2e-16 ***
JWTR02	-1.943e-01	6.720e-03	-28.910	< 2e-16 ***
JWTR03	2.082e-01	4.197e-02	4.960	7.04e-07 ***
JWTR04	4.209e-01	9.114e-03	46.183	< 2e-16 ***
JWTR05	5.749e-01	1.652e-02	34.796	< 2e-16 ***
JWTR06	6.250e-01	4.830e-02	12.940	< 2e-16 ***
JWTR07	-1.360e-01	1.881e-02	-7.229	4.86e-13 ***
JWTR08	1.047e-01	2.035e-02	5.144	2.69e-07 ***
JWTR09	-5.418e-02	1.145e-02	-4.733	2.21e-06 ***
JWTR10	-2.581e-01	4.133e-03	-62.445	< 2e-16 ***
JWTR12	-1.881e-01	7.414e-03	-25.371	< 2e-16 ***
SameResidenceWorkplaceTRUE:JWMNP	-1.692e-03	5.356e-04	-3.159	0.00158 **
JWMNP:JWTR02	-1.258e-03	1.179e-04	-10.676	< 2e-16 ***
JWMNP:JWTR03	-4.579e-03	8.427e-04	-5.434	5.52e-08 ***
JWMNP:JWTR04	-6.156e-03	1.661e-04	-37.056	< 2e-16 ***
JWMNP:JWTR05	-2.012e-03	2.085e-04	-9.648	< 2e-16 ***
JWMNP:JWTR06	-3.158e-03	6.504e-04	-4.856	1.20e-06 ***
JWMNP:JWTR07	-9.597e-04	6.444e-04	-1.489	0.13638
JWMNP:JWTR08	-6.011e-04	6.639e-04	-0.905	0.36524
JWMNP:JWTR09	2.540e-03	4.255e-04	5.969	2.39e-09 ***
JWMNP:JWTR10	-5.464e-04	2.225e-04	-2.456	0.01405 *
JWMNP:JWTR12	1.304e-03	1.323e-04	9.858	< 2e-16 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6261 on 1379224 degrees of freedom

(15943 observations deleted due to missingness)

Multiple R-squared: 0.02959, Adjusted R-squared: 0.02957

F-statistic: 1828 on 23 and 1379224 DF, p-value: < 2.2e-16



## A.6 Regression With Core Variables, Transportation Means, Migration

OLS regression output on core and secondary interest vars:

Residuals:

Min	1Q	Median	3Q	Max
-2.1477	-0.4388	-0.0446	0.3660	3.5568

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	2.070e+00	9.015e-04	2296.029	< 2e-16 ***
SameResidenceWorkplaceTRUE	1.619e-01	3.272e-02	4.949	7.48e-07 ***
JWMNP	3.201e-03	2.544e-05	125.813	< 2e-16 ***
JWTR02	-1.801e-01	6.702e-03	-26.867	< 2e-16 ***
JWTR03	2.215e-01	4.184e-02	5.293	1.20e-07 ***
JWTR04	4.390e-01	9.088e-03	48.307	< 2e-16 ***
JWTR05	5.813e-01	1.647e-02	35.288	< 2e-16 ***
JWTR06	6.405e-01	4.815e-02	13.301	< 2e-16 ***
JWTR07	-1.205e-01	1.875e-02	-6.426	1.31e-10 ***
JWTR08	1.105e-01	2.029e-02	5.446	5.17e-08 ***
JWTR09	-3.042e-02	1.141e-02	-2.666	0.00768 **
JWTR10	-2.388e-01	4.126e-03	-57.866	< 2e-16 ***
JWTR12	-1.823e-01	7.392e-03	-24.662	< 2e-16 ***
MIG2	-2.017e-01	8.438e-03	-23.906	< 2e-16 ***
MIG3	-1.410e-01	1.568e-03	-89.917	< 2e-16 ***
SameResidenceWorkplaceTRUE:JWMNP	-1.633e-03	5.340e-04	-3.059	0.00222 **
JWMNP:JWTR02	-1.319e-03	1.175e-04	-11.221	< 2e-16 ***
JWMNP:JWTR03	-4.571e-03	8.401e-04	-5.441	5.30e-08 ***
JWMNP:JWTR04	-6.347e-03	1.656e-04	-38.317	< 2e-16 ***
JWMNP:JWTR05	-2.062e-03	2.079e-04	-9.918	< 2e-16 ***
JWMNP:JWTR06	-3.261e-03	6.484e-04	-5.029	4.92e-07 ***
JWMNP:JWTR07	-9.742e-04	6.424e-04	-1.517	0.12937
JWMNP:JWTR08	-5.647e-04	6.618e-04	-0.853	0.39349
JWMNP:JWTR09	2.291e-03	4.242e-04	5.400	6.65e-08 ***
JWMNP:JWTR10	-4.332e-04	2.218e-04	-1.954	0.05076 .
JWMNP:JWTR12	1.293e-03	1.319e-04	9.807	< 2e-16 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6242 on 1379222 degrees of freedom

(15943 observations deleted due to missingness)

Multiple R-squared: 0.03556, Adjusted R-squared: 0.03554

F-statistic: 2034 on 25 and 1379222 DF, p-value: < 2.2e-16

## A.7 Regression Result Without Socio-demographics

OLS without sociodemographic variables and (excluding location variables):

Call:

```
lm(formula = formula3, data = dat)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.6705	-0.2947	-0.0516	0.2328	3.6580

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	1.366e+00	6.291e-03	217.170	< 2e-16 ***
SameResidenceWorkplaceTRUE	6.747e-02	2.453e-02	2.751	0.005943 **
JWMNP	1.837e-03	1.921e-05	95.625	< 2e-16 ***
JWTR02	4.415e-02	5.040e-03	8.760	< 2e-16 ***
JWTR03	2.059e-01	3.136e-02	6.564	5.24e-11 ***
JWTR04	3.963e-01	6.821e-03	58.098	< 2e-16 ***
JWTR05	4.719e-01	1.235e-02	38.214	< 2e-16 ***
JWTR06	4.697e-01	3.610e-02	13.013	< 2e-16 ***
JWTR07	9.503e-02	1.406e-02	6.760	1.38e-11 ***
JWTR08	5.075e-02	1.521e-02	3.338	0.000845 ***
JWTR09	9.688e-02	8.561e-03	11.315	< 2e-16 ***
JWTR10	4.371e-04	3.242e-03	0.135	0.892739
JWTR12	-5.589e-03	5.548e-03	-1.007	0.313730
MIG2	-1.200e-02	6.345e-03	-1.890	0.058692 .
MIG3	-8.407e-03	1.218e-03	-6.904	5.06e-12 ***
AGEP	6.069e-03	3.851e-05	157.619	< 2e-16 ***
SPORDER	-1.684e-01	4.251e-04	-396.124	< 2e-16 ***
COW2	2.387e-02	1.438e-03	16.599	< 2e-16 ***
COW3	-1.954e-02	1.559e-03	-12.540	< 2e-16 ***
COW4	-6.170e-04	1.871e-03	-0.330	0.741533
COW5	1.515e-01	2.418e-03	62.639	< 2e-16 ***
COW6	-6.253e-02	1.887e-03	-33.135	< 2e-16 ***
COW7	2.186e-01	2.229e-03	98.078	< 2e-16 ***
COW8	-1.226e-01	9.423e-03	-13.012	< 2e-16 ***
OCO	2.898e-01	3.527e-03	82.169	< 2e-16 ***
MAR2	-1.462e-01	2.959e-03	-49.406	< 2e-16 ***
MAR3	-9.515e-02	1.333e-03	-71.380	< 2e-16 ***
MAR4	-1.557e-01	3.104e-03	-50.169	< 2e-16 ***
MAR5	-1.195e-01	1.093e-03	-109.306	< 2e-16 ***
WKHP	1.595e-02	3.679e-05	433.683	< 2e-16 ***
WKW2	-5.140e-02	2.799e-03	-18.363	< 2e-16 ***

WKW3	-1.432e-01	1.819e-03	-78.713	< 2e-16	***
WKW4	-2.611e-01	2.056e-03	-127.001	< 2e-16	***
WKW5	-3.610e-01	2.604e-03	-138.622	< 2e-16	***
WKW6	-4.642e-01	2.624e-03	-176.919	< 2e-16	***
HINS12	-2.256e-01	1.133e-03	-199.042	< 2e-16	***
HINS22	-4.554e-02	1.384e-03	-32.904	< 2e-16	***
HINS32	-8.343e-02	1.862e-03	-44.810	< 2e-16	***
HINS42	1.137e-01	1.654e-03	68.711	< 2e-16	***
HINS52	-3.063e-02	2.739e-03	-11.184	< 2e-16	***
HINS62	-2.001e-03	3.030e-03	-0.660	0.508981	
SameResidenceWorkplaceTRUE:JWMNP	-1.066e-03	4.002e-04	-2.662	0.007760	**
JWMNP:JWTR02	-1.093e-03	8.812e-05	-12.405	< 2e-16	***
JWMNP:JWTR03	-2.424e-03	6.297e-04	-3.849	0.000119	***
JWMNP:JWTR04	-4.127e-03	1.242e-04	-33.220	< 2e-16	***
JWMNP:JWTR05	-1.329e-03	1.558e-04	-8.526	< 2e-16	***
JWMNP:JWTR06	-1.861e-03	4.860e-04	-3.828	0.000129	***
JWMNP:JWTR07	-1.410e-03	4.815e-04	-2.927	0.003418	**
JWMNP:JWTR08	-1.369e-04	4.961e-04	-0.276	0.782532	
JWMNP:JWTR09	9.177e-04	3.180e-04	2.886	0.003904	**
JWMNP:JWTR10	2.020e-04	1.670e-04	1.210	0.226376	
JWMNP:JWTR12	4.122e-04	9.884e-05	4.170	3.05e-05	***

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Signif. codes: 0 \*\*\* 0.001 \*\* 0.01 \* 0.05 . 0.1 1

Residual standard error: 0.4679 on 1379196 degrees of freedom

(15943 observations deleted due to missingness)

Multiple R-squared: 0.4581, Adjusted R-squared: 0.4581

F-statistic: 2.286e+04 on 51 and 1379196 DF, p-value: < 2.2e-16

## A.8 Regression Result With Socio-demographics

OLS with core, secondary, sociodemographic variables (excluding location variables)

Residuals:

Min	1Q	Median	3Q	Max
-2.6867	-0.2591	-0.0307	0.2170	3.7607

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	1.272e+00	7.424e-03	171.315	< 2e-16 ***
SameResidenceWorkplaceTRUE	6.955e-02	2.250e-02	3.091	0.001992 **
JWMNP	1.446e-03	1.768e-05	81.814	< 2e-16 ***
JWTR02	2.418e-02	4.630e-03	5.221	1.78e-07 ***
JWTR03	1.030e-01	2.877e-02	3.579	0.000344 ***
JWTR04	2.459e-01	6.268e-03	39.236	< 2e-16 ***
JWTR05	3.344e-01	1.133e-02	29.504	< 2e-16 ***
JWTR06	3.582e-01	3.311e-02	10.817	< 2e-16 ***
JWTR07	1.026e-01	1.290e-02	7.959	1.74e-15 ***
JWTR08	1.487e-02	1.395e-02	1.066	0.286536
JWTR09	5.440e-03	7.857e-03	0.692	0.488676
JWTR10	-1.624e-02	2.979e-03	-5.451	5.02e-08 ***
JWTR12	1.105e-02	5.096e-03	2.168	0.030193 *
MIG2	-7.284e-02	5.838e-03	-12.478	< 2e-16 ***
MIG3	-2.535e-02	1.118e-03	-22.671	< 2e-16 ***
AGEP	6.416e-03	3.645e-05	176.040	< 2e-16 ***
SPORDER	-1.511e-01	3.932e-04	-384.384	< 2e-16 ***
COW2	-4.088e-02	1.344e-03	-30.412	< 2e-16 ***
COW3	-6.203e-02	1.442e-03	-43.002	< 2e-16 ***
COW4	-7.189e-02	1.735e-03	-41.433	< 2e-16 ***
COW5	1.256e-01	2.378e-03	52.815	< 2e-16 ***
COW6	-9.278e-02	1.734e-03	-53.519	< 2e-16 ***
COW7	1.459e-01	2.050e-03	71.171	< 2e-16 ***
COW8	-1.569e-01	8.643e-03	-18.154	< 2e-16 ***
OCO	1.598e-01	3.350e-03	47.715	< 2e-16 ***
MAR2	-4.369e-02	2.727e-03	-16.021	< 2e-16 ***
MAR3	-3.605e-02	1.233e-03	-29.242	< 2e-16 ***
MAR4	-6.801e-02	2.857e-03	-23.806	< 2e-16 ***
MAR5	-9.702e-02	1.018e-03	-95.329	< 2e-16 ***
WKHP	1.354e-02	3.492e-05	387.783	< 2e-16 ***
WKW2	-6.885e-02	2.569e-03	-26.804	< 2e-16 ***
WKW3	-1.540e-01	1.670e-03	-92.238	< 2e-16 ***
WKW4	-2.676e-01	1.888e-03	-141.745	< 2e-16 ***
WKW5	-3.643e-01	2.392e-03	-152.272	< 2e-16 ***

WKW6	-4.637e-01	2.412e-03	-192.216	< 2e-16	***
HINS12	-1.670e-01	1.060e-03	-157.507	< 2e-16	***
HINS22	-1.702e-02	1.277e-03	-13.334	< 2e-16	***
HINS32	-3.675e-02	1.718e-03	-21.388	< 2e-16	***
HINS42	6.789e-02	1.523e-03	44.581	< 2e-16	***
HINS52	-3.567e-02	2.810e-03	-12.694	< 2e-16	***
HINS62	6.426e-02	3.152e-03	20.385	< 2e-16	***
MIL2	1.813e-01	5.705e-03	31.777	< 2e-16	***
MIL3	1.600e-01	6.501e-03	24.617	< 2e-16	***
MIL4	1.421e-01	5.655e-03	25.121	< 2e-16	***
SCH2	-2.897e-02	1.579e-03	-18.350	< 2e-16	***
SCH3	-3.179e-02	2.578e-03	-12.333	< 2e-16	***
SEX2	-1.609e-01	7.859e-04	-204.788	< 2e-16	***
NATIVITY2	-4.411e-02	"message"	-36.595	< 2e-16	***
RAC1P2	-7.036e-02	1.329e-03	-52.959	< 2e-16	***
RAC1P3	-5.855e-02	4.415e-03	-13.262	< 2e-16	***
RAC1P4	1.023e-01	1.757e-02	5.822	5.83e-09	***
RAC1P5	-6.698e-02	1.047e-02	-6.395	1.60e-10	***
RAC1P6	6.592e-02	1.756e-03	37.543	< 2e-16	***
RAC1P7	-2.177e-02	8.779e-03	-2.480	0.013155	*
RAC1P8	-4.580e-02	1.998e-03	-22.919	< 2e-16	***
RAC1P9	6.368e-04	2.402e-03	0.265	0.790916	
SCIENGRLP1	4.104e-01	1.907e-03	215.249	< 2e-16	***
SCIENGRLP2	3.656e-01	8.467e-04	431.820	< 2e-16	***
SameResidenceWorkplaceTRUE:JWMNP	-9.941e-04	3.671e-04	-2.708	0.006771	**
JWMNP:JWTR02	-6.293e-04	8.084e-05	-7.785	6.99e-15	***
JWMNP:JWTR03	-1.385e-03	5.776e-04	-2.397	0.016517	*
JWMNP:JWTR04	-2.612e-03	1.140e-04	-22.906	< 2e-16	***
JWMNP:JWTR05	-1.020e-03	1.429e-04	-7.137	9.52e-13	***
JWMNP:JWTR06	-1.458e-03	4.458e-04	-3.272	0.001069	**
JWMNP:JWTR07	-1.353e-03	4.417e-04	-3.063	0.002190	**
JWMNP:JWTR08	-6.767e-05	4.550e-04	-0.149	0.881773	
JWMNP:JWTR09	5.685e-04	2.917e-04	1.949	0.051308	.
JWMNP:JWTR10	-8.489e-05	1.532e-04	-0.554	0.579492	
JWMNP:JWTR12	2.255e-04	9.071e-05	2.486	0.012936	*

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Signif. codes: 0 \*\*\* 0.001 \*\* 0.01 \* 0.05 . 0.1 1

Residual standard error: 0.4291 on 1379179 degrees of freedom

(15943 observations deleted due to missingness)

Multiple R-squared: 0.5441, Adjusted R-squared: 0.5441

F-statistic: 2.421e+04 on 68 and 1379179 DF, p-value: < 2.2e-16

## A.9 Attempted Regression With Spatial Location

OLS without sociodemographic variables:

Call:

```
lm(formula = formula2, data = dat)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.6473	-0.2885	-0.0467	0.2302	3.5790

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	1.302e+00	7.047e-03	184.779	< 2e-16	***
SameResidenceWorkplaceTRUE	9.038e-02	1.685e-02	5.363	8.20e-08	***
ST02	7.058e-02	4.690e-02	1.505	0.132403	
ST04	7.272e-02	2.237e-02	3.251	0.001148	**
ST05	1.038e-02	2.078e-02	0.500	0.617383	
ST06	9.597e-02	1.881e-02	5.102	3.37e-07	***
ST08	1.653e-01	2.408e-02	6.863	6.72e-12	***
ST09	1.563e-01	1.933e-02	8.087	6.14e-16	***
ST10	-4.384e-02	2.077e-02	-2.111	0.034807	*
ST11	1.288e-01	1.886e-02	6.828	8.60e-12	***
ST12	1.790e-01	1.638e-02	10.926	< 2e-16	***
ST13	1.934e-02	1.466e-02	1.319	0.187254	
ST15	2.089e-02	5.038e-02	0.415	0.678389	
ST16	2.341e-02	2.742e-02	0.854	0.393340	
ST17	2.355e-02	1.753e-02	1.343	0.179296	
ST18	-4.346e-02	1.805e-02	-2.408	0.016061	*
ST19	2.345e-02	2.076e-02	1.130	0.258557	
ST20	-7.288e-03	2.038e-02	-0.358	0.720626	
ST21	-2.467e-02	1.772e-02	-1.392	0.163848	
ST22	2.488e-02	2.082e-02	1.195	0.232147	
ST23	6.195e-02	3.208e-02	1.931	0.053505	.
ST24	5.114e-02	1.722e-02	2.970	0.002977	**
ST25	1.464e-01	2.049e-02	7.146	8.92e-13	***
ST26	-7.167e-03	1.949e-02	-0.368	0.713107	
ST27	3.245e-02	2.109e-02	1.539	0.123912	
ST28	-1.591e-02	1.770e-02	-0.899	0.368563	
ST29	-1.428e-02	1.869e-02	-0.764	0.444967	
ST30	3.779e-02	4.148e-02	0.911	0.362383	
ST31	-3.685e-03	2.461e-02	-0.150	0.880963	
ST32	9.144e-02	2.587e-02	3.535	0.000408	***
ST33	1.245e-01	2.285e-02	5.450	5.05e-08	***

ST34	1.285e-01	1.714e-02	7.497	6.54e-14	***
ST35	2.785e-02	2.540e-02	1.096	0.273026	
ST36	-2.349e-02	1.711e-02	-1.373	0.169879	
ST37	3.668e-02	1.781e-02	2.060	0.039431	*
ST38	6.158e-02	2.703e-02	2.278	0.022709	*
ST39	-4.067e-02	1.740e-02	-2.338	0.019385	*
ST40	-2.785e-02	2.174e-02	-1.281	0.200024	
ST41	1.223e-01	2.561e-02	4.777	1.78e-06	***
ST42	-1.182e-02	1.693e-02	-0.698	0.485011	
ST44	6.467e-02	2.320e-02	2.787	0.005312	**
ST45	4.508e-02	1.839e-02	2.451	0.014248	*
ST46	-1.096e-02	3.189e-02	-0.344	0.731098	
ST47	-1.887e-02	1.556e-02	-1.213	0.225244	
ST48	4.452e-02	1.732e-02	2.570	0.010173	*
ST49	1.579e-01	2.859e-02	5.524	3.31e-08	***
ST50	7.488e-02	2.856e-02	2.622	0.008731	**
ST51	8.150e-02	1.702e-02	4.789	1.68e-06	***
ST53	1.405e-01	2.430e-02	5.784	7.29e-09	***
ST54	-4.571e-02	1.926e-02	-2.373	0.017630	*
ST55	1.923e-02	1.970e-02	0.976	0.329027	
ST56	-4.974e-04	3.515e-02	-0.014	0.988708	
AGEP	5.771e-03	3.806e-05	151.631	< 2e-16	***
SPORDER	-1.729e-01	4.206e-04	-411.175	< 2e-16	***
COW2	1.864e-02	1.421e-03	13.111	< 2e-16	***
COW3	-2.997e-02	1.540e-03	-19.464	< 2e-16	***
COW4	2.794e-03	1.849e-03	1.511	0.130786	
COW5	1.306e-01	2.409e-03	54.242	< 2e-16	***
COW6	-6.904e-02	1.863e-03	-37.060	< 2e-16	***
COW7	2.115e-01	2.201e-03	96.092	< 2e-16	***
COW8	-1.218e-01	9.295e-03	-13.098	< 2e-16	***
OCO	2.829e-01	3.467e-03	81.602	< 2e-16	***
MAR2	-1.393e-01	2.919e-03	-47.717	< 2e-16	***
MAR3	-8.947e-02	1.316e-03	-67.984	< 2e-16	***
MAR4	-1.573e-01	3.064e-03	-51.338	< 2e-16	***
MAR5	-1.270e-01	1.080e-03	-117.616	< 2e-16	***
JWMNP	1.384e-03	1.782e-05	77.669	< 2e-16	***
JWTR02	-5.177e-02	2.839e-03	-18.233	< 2e-16	***
JWTR03	5.934e-02	1.621e-02	3.661	0.000252	***
JWTR04	1.130e-01	3.127e-03	36.127	< 2e-16	***
JWTR05	3.058e-01	5.007e-03	61.076	< 2e-16	***
JWTR06	2.733e-01	1.745e-02	15.664	< 2e-16	***
JWTR07	2.003e-02	8.920e-03	2.246	0.024712	*
JWTR08	2.923e-02	9.472e-03	3.086	0.002029	**

JWTR09	7.525e-02	5.364e-03	14.028	< 2e-16	***
JWTR10	-2.611e-02	2.492e-03	-10.476	< 2e-16	***
JWTR12	7.495e-04	4.184e-03	0.179	0.857824	
WKHP	1.608e-02	3.633e-05	442.701	< 2e-16	***
WKW2	-5.952e-02	2.762e-03	-21.553	< 2e-16	***
WKW3	-1.470e-01	1.795e-03	-81.870	< 2e-16	***
WKW4	-2.608e-01	2.029e-03	-128.556	< 2e-16	***
WKW5	-3.580e-01	2.569e-03	-139.370	< 2e-16	***
WKW6	-4.613e-01	2.589e-03	-178.200	< 2e-16	***
MIG2	-2.567e-02	6.268e-03	-4.096	4.21e-05	***
MIG3	-4.840e-03	1.203e-03	-4.024	5.73e-05	***
POWSP002	9.511e-02	4.624e-02	2.057	0.039685	*
POWSP004	1.240e-02	2.249e-02	0.551	0.581531	
POWSP005	-3.067e-02	2.084e-02	-1.472	0.141094	
POWSP006	1.216e-01	1.887e-02	6.440	1.19e-10	***
POWSP008	-2.136e-02	2.415e-02	-0.884	0.376452	
POWSP009	7.233e-02	1.948e-02	3.714	0.000204	***
POWSP010	1.544e-01	2.089e-02	7.392	1.44e-13	***
POWSP011	3.041e-01	1.770e-02	17.179	< 2e-16	***
POWSP012	-1.263e-01	1.647e-02	-7.667	1.76e-14	***
POWSP013	4.072e-02	1.474e-02	2.762	0.005738	**
POWSP015	1.048e-01	5.041e-02	2.080	0.037548	*
POWSP016	-2.701e-02	2.764e-02	-0.977	0.328436	
POWSP017	8.347e-02	1.762e-02	4.737	2.17e-06	***
POWSP018	5.140e-02	1.811e-02	2.838	0.004545	**
POWSP019	-1.646e-02	2.073e-02	-0.794	0.427398	
POWSP020	6.028e-03	2.039e-02	0.296	0.767521	
POWSP021	4.488e-02	1.776e-02	2.527	0.011496	*
POWSP022	1.414e-02	2.087e-02	0.678	0.498059	
POWSP023	-4.497e-02	3.229e-02	-1.393	0.163760	
POWSP024	1.502e-01	1.731e-02	8.678	< 2e-16	***
POWSP025	9.510e-02	2.053e-02	4.633	3.61e-06	***
POWSP026	6.661e-02	1.958e-02	3.401	0.000671	***
POWSP027	5.920e-02	2.110e-02	2.805	0.005029	**
POWSP028	-3.410e-02	1.789e-02	-1.906	0.056640	.
POWSP029	3.250e-02	1.872e-02	1.736	0.082496	.
POWSP030	-2.773e-02	4.163e-02	-0.666	0.505396	
POWSP031	-1.308e-03	2.453e-02	-0.053	0.957458	
POWSP032	-8.003e-03	2.591e-02	-0.309	0.757381	
POWSP033	-2.018e-02	2.306e-02	-0.875	0.381458	
POWSP034	9.008e-02	1.726e-02	5.219	1.80e-07	***
POWSP035	1.037e-02	2.543e-02	0.408	0.683603	
POWSP036	1.876e-01	1.716e-02	10.935	< 2e-16	***



POWSP037	3.576e-03	1.789e-02	0.200	0.841538	
POWSP038	2.063e-03	2.636e-02	0.078	0.937623	
POWSP039	1.008e-01	1.746e-02	5.776	7.64e-09	***
POWSP040	1.034e-02	2.182e-02	0.474	0.635469	
POWSP041	-1.535e-03	2.561e-02	-0.060	0.952200	
POWSP042	7.216e-02	1.700e-02	4.246	2.18e-05	***
POWSP044	9.695e-02	2.341e-02	4.141	3.46e-05	***
POWSP045	-2.737e-02	1.849e-02	-1.480	0.138887	
POWSP046	-2.788e-02	3.166e-02	-0.880	0.378590	
POWSP047	4.435e-02	1.560e-02	2.844	0.004457	**
POWSP048	3.607e-02	1.739e-02	2.074	0.038081	*
POWSP049	-7.716e-02	2.863e-02	-2.695	0.007042	**
POWSP050	-1.141e-02	2.849e-02	-0.401	0.688782	
POWSP051	6.068e-02	1.708e-02	3.552	0.000382	***
POWSP053	4.840e-02	2.436e-02	1.987	0.046911	*
POWSP054	1.722e-02	1.930e-02	0.892	0.372213	
POWSP055	1.187e-02	1.978e-02	0.600	0.548214	
POWSP056	2.669e-02	3.473e-02	0.769	0.442105	
POWSP072	1.116e-01	8.413e-02	1.327	0.184649	
POWSP166	3.182e-01	4.060e-02	7.837	4.62e-15	***
POWSP251	2.295e-01	3.863e-02	5.940	2.85e-09	***
POWSP254	4.330e-01	4.101e-02	10.560	< 2e-16	***
POWSP301	3.786e-01	4.568e-02	8.287	< 2e-16	***
POWSP303	-1.593e-02	4.450e-02	-0.358	0.720306	
POWSP399	3.636e-01	4.999e-02	7.272	3.53e-13	***
POWSP555	1.716e-01	4.203e-02	4.083	4.44e-05	***
HINS12	-2.174e-01	1.124e-03	-193.399	< 2e-16	***
HINS22	-4.295e-02	1.367e-03	-31.423	< 2e-16	***
HINS32	-8.949e-02	1.837e-03	-48.709	< 2e-16	***
HINS42	1.340e-01	1.645e-03	81.427	< 2e-16	***
HINS52	-3.255e-02	2.711e-03	-12.010	< 2e-16	***
HINS62	-1.449e-02	2.990e-03	-4.847	1.25e-06	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4615 on 1379099 degrees of freedom

(15943 observations deleted due to missingness)

Multiple R-squared: 0.4728, Adjusted R-squared: 0.4728

F-statistic: 8357 on 148 and 1379099 DF, p-value: < 2.2e-16

## A.10 LASSO Regression

Summary of LASSO:

Call:

```
rlasso.formula(formula = formula, data = data, post = post, intercept = intercept,  
  model = model, control = control)
```

Post-Lasso Estimation: FALSE

Total number of variables: 250

Number of selected variables: 103

Residuals:

	Min	1Q	Median	3Q	Max
	-92.67302	-0.48111	-0.01726	0.55912	27.01928

	Estimate
(Intercept)	4.324
DIVISION6	0.016
DIVISION7	0.002
SPORDER	-0.557
REGION2	0.001
REGION3	0.010
ST04	0.007
ST08	-0.001
ST12	0.009
ST25	-0.017
ST48	0.000
ST50	-0.006
PWGTP	0.000
AGEP	0.003
CIT3	-0.005
CIT5	0.060
COW2	-0.003
COW3	-0.016
COW4	-0.008
COW6	-0.135
FER1	0.012
FER2	0.023
GCL1	-0.156
GCL2	-0.135
GCM5	-0.006
HINS12	-0.052

HINS32	-0.301
HINS42	0.133
HINS52	-0.015
HINS62	0.209
HINS72	0.012
JWMNP	0.000
MAR2	-0.392
MAR3	-0.256
MAR4	-0.298
MARHM2	-0.023
MARHT2	0.009
MIG3	-0.014
NWAV3	-0.011
NWLA3	-0.007
OIP	0.000
PAP	0.000
RELP01	-1.843
RELP02	-0.965
RELP03	-0.762
RELP04	-0.729
RELP05	-1.091
RELP06	-1.059
RELP07	-0.664
RELP08	-0.982
RELP09	-0.895
RELP10	-0.963
RELP11	-1.162
RELP12	-1.191
RELP13	-1.370
RELP15	-1.160
RELP17	-0.335
SCH2	0.008
SCHG14	0.082
SCHG15	0.005
SCHG16	-0.004
SCHL09	0.023
SCHL11	0.015
SCHL13	0.018
SCHL14	0.032
SCHL15	0.066
SCHL16	0.022
SCHL18	-0.010
SCHL20	-0.003

SEMP	-0.149
SEX2	-0.013
SSIP	0.000
SSP	0.000
WAGP	-0.149
WKHP	-0.004
WKW3	0.046
WKW4	0.102
WKW5	0.125
WKW6	0.112
WRK1	0.050
ANC2	-0.022
ANC4	-0.008
DECADE2	0.048
DECADE7	0.031
DECADE8	0.112
DIS2	0.034
ESR4	-0.012
HICOV2	0.138
MSP2	-0.171
NATIVITY2	0.007
PAOC2	0.009
PAOC4	0.041
PERNP	0.149
PINCP	0.000
PRIVCOV2	-0.054
PUBCOV2	-0.236
QTRBIR2	-0.001
RAC1P2	-0.027
RCO	0.088
SCIENGP2	-0.022
SCIENGRLP1	-0.026
SFN1	-0.387
SFR2	-0.047
SFR3	0.425

Residual standard error: 1.424

Multiple R-squared: 0.9841

Adjusted R-squared: 0.9841

How many variables to keep:

[1] 103

Post-LASSO OLS Regression output:

Call:

```
lm(formula = formula, data = dattemp)
```

Residuals:

Min	1Q	Median	3Q	Max
-92.323	-0.482	-0.015	0.568	26.917

Coefficients: (11 not defined because of singularities)

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	4.205e+00	3.639e-02	115.554	< 2e-16	***
DIVISION6TRUE	3.341e-02	7.148e-03	4.674	2.96e-06	***
DIVISION7TRUE	1.471e-02	8.850e-03	1.662	0.096555	.
SPORDER	-5.102e-01	3.890e-03	-131.174	< 2e-16	***
REGION2TRUE	1.302e-02	4.020e-03	3.238	0.001204	**
REGION3TRUE	1.039e-02	4.725e-03	2.200	0.027823	*
ST04TRUE	3.158e-02	1.078e-02	2.930	0.003391	**
ST08TRUE	-1.729e-02	1.092e-02	-1.583	0.113412	
ST12TRUE	2.783e-02	7.117e-03	3.911	9.21e-05	***
ST25TRUE	-3.826e-02	9.951e-03	-3.845	0.000121	***
ST48TRUE	2.823e-03	9.366e-03	0.301	0.763129	
ST50TRUE	-4.237e-02	3.080e-02	-1.376	0.168923	
PWGTP	-8.990e-05	1.917e-05	-4.691	2.72e-06	***
AGEP	3.982e-03	2.000e-04	19.906	< 2e-16	***
CIT3TRUE	-4.542e-02	1.476e-02	-3.076	0.002096	**
CIT5TRUE	7.255e-02	8.051e-03	9.011	< 2e-16	***
COW2TRUE	-1.438e-02	5.205e-03	-2.763	0.005731	**
COW3TRUE	-2.364e-02	5.412e-03	-4.367	1.26e-05	***
COW4TRUE	-1.960e-02	6.584e-03	-2.977	0.002910	**
COW6TRUE	-1.321e-01	7.140e-03	-18.499	< 2e-16	***
FER1TRUE	9.337e-02	1.446e-02	6.456	1.08e-10	***
FER2TRUE	7.017e-02	5.880e-03	11.935	< 2e-16	***
GCL1TRUE	-2.140e-01	1.218e-02	-17.578	< 2e-16	***
GCL2TRUE	-1.814e-01	6.963e-03	-26.051	< 2e-16	***
GCM5TRUE	-2.302e-02	2.292e-02	-1.004	0.315365	
HINS12TRUE	-5.952e-02	5.203e-03	-11.439	< 2e-16	***
HINS32TRUE	-2.257e-01	1.433e-02	-15.742	< 2e-16	***
HINS42TRUE	1.929e-01	1.382e-02	13.956	< 2e-16	***
HINS52TRUE	-4.397e-02	1.024e-02	-4.294	1.76e-05	***
HINS62TRUE	3.034e-01	1.418e-02	21.398	< 2e-16	***
HINS72TRUE	3.545e-02	2.122e-02	1.670	0.094844	.
JWMNP	-2.891e-04	6.185e-05	-4.675	2.94e-06	***

MAR2TRUE	-4.096e-01	9.378e-03	-43.684	< 2e-16	***
MAR3TRUE	-2.586e-01	4.837e-03	-53.454	< 2e-16	***
MAR4TRUE	-3.086e-01	9.891e-03	-31.206	< 2e-16	***
MARHM2TRUE	NA	NA	NA	NA	
MARHT2TRUE	1.668e-02	3.815e-03	4.372	1.23e-05	***
MIG3TRUE	-2.049e-02	4.978e-03	-4.116	3.85e-05	***
NWAV3TRUE	-6.834e-02	2.135e-02	-3.201	0.001369	**
NWLA3TRUE	-2.435e-02	5.443e-03	-4.474	7.68e-06	***
OIP	-5.635e-06	5.153e-07	-10.933	< 2e-16	***
PAP	-2.867e-05	4.475e-06	-6.407	1.48e-10	***
RELPO1TRUE	-1.903e+00	5.148e-03	-369.648	< 2e-16	***
RELPO2TRUE	-1.070e+00	1.373e-02	-77.971	< 2e-16	***
RELPO3TRUE	-1.071e+00	6.373e-02	-16.801	< 2e-16	***
RELPO4TRUE	-9.403e-01	4.462e-02	-21.074	< 2e-16	***
RELPO5TRUE	-1.240e+00	2.277e-02	-54.465	< 2e-16	***
RELPO6TRUE	-1.238e+00	2.196e-02	-56.352	< 2e-16	***
RELPO7TRUE	-9.612e-01	4.560e-02	-21.080	< 2e-16	***
RELPO8TRUE	-1.318e+00	4.307e-02	-30.604	< 2e-16	***
RELPO9TRUE	-1.148e+00	2.547e-02	-45.064	< 2e-16	***
RELPO10TRUE	-1.184e+00	2.420e-02	-48.912	< 2e-16	***
RELPO11TRUE	-1.363e+00	3.103e-02	-43.921	< 2e-16	***
RELPO12TRUE	-1.338e+00	2.088e-02	-64.108	< 2e-16	***
RELPO13TRUE	-1.492e+00	1.372e-02	-108.700	< 2e-16	***
RELPO15TRUE	-1.350e+00	2.333e-02	-57.857	< 2e-16	***
RELPO17TRUE	-4.254e-01	3.198e-02	-13.303	< 2e-16	***
SCH2TRUE	3.941e-02	1.601e-02	2.461	0.013858	*
SCHG14TRUE	1.553e-01	5.019e-02	3.094	0.001973	**
SCHG15TRUE	-7.934e-03	1.587e-02	-0.500	0.617087	
SCHG16TRUE	-4.042e-02	1.513e-02	-2.672	0.007550	**
SCHLO9TRUE	NA	NA	NA	NA	
SCHL11TRUE	NA	NA	NA	NA	
SCHL13TRUE	NA	NA	NA	NA	
SCHL14TRUE	NA	NA	NA	NA	
SCHL15TRUE	NA	NA	NA	NA	
SCHL16TRUE	NA	NA	NA	NA	
SCHL18TRUE	NA	NA	NA	NA	
SCHL20TRUE	NA	NA	NA	NA	
SEMP	6.773e-05	1.053e-07	643.445	< 2e-16	***
SEX2TRUE	-7.105e-02	8.507e-03	-8.352	< 2e-16	***
SSIP	-1.455e-05	2.055e-06	-7.081	1.43e-12	***
SSP	5.676e-06	4.594e-07	12.356	< 2e-16	***
WAGP	6.454e-05	8.293e-08	778.294	< 2e-16	***
WKHP	-3.437e-03	1.423e-04	-24.153	< 2e-16	***

WKW3TRUE	5.603e-02	6.843e-03	8.187	2.68e-16	***
WKW4TRUE	1.098e-01	8.232e-03	13.342	< 2e-16	***
WKW5TRUE	1.360e-01	1.131e-02	12.026	< 2e-16	***
WKW6TRUE	1.247e-01	1.153e-02	10.820	< 2e-16	***
WRK1TRUE	5.300e-02	6.821e-03	7.770	7.84e-15	***
ANC2TRUE	-2.895e-02	3.562e-03	-8.129	4.34e-16	***
ANC4TRUE	-1.583e-02	4.652e-03	-3.403	0.000667	***
DECADE2TRUE	1.281e-01	2.932e-02	4.369	1.25e-05	***
DECADE7TRUE	4.404e-02	8.442e-03	5.217	1.82e-07	***
DECADE8TRUE	1.229e-01	1.088e-02	11.297	< 2e-16	***
DIS2TRUE	5.066e-02	6.118e-03	8.281	< 2e-16	***
ESR4TRUE	-6.295e-02	2.132e-02	-2.953	0.003152	**
HICOV2TRUE	1.679e-01	1.007e-02	16.678	< 2e-16	***
MSP2TRUE	-1.845e-01	9.556e-03	-19.306	< 2e-16	***
NATIVITY2TRUE	6.933e-03	5.483e-03	1.265	0.206048	
PAOC2TRUE	3.558e-02	7.697e-03	4.623	3.79e-06	***
PAOC4TRUE	8.357e-02	7.733e-03	10.807	< 2e-16	***
PERNP	NA	NA	NA	NA	
PINCP	7.651e-05	7.705e-08	992.925	< 2e-16	***
PRIVCOV2TRUE	-7.261e-02	8.985e-03	-8.081	6.42e-16	***
PUBCOV2TRUE	-3.374e-01	1.460e-02	-23.108	< 2e-16	***
QTRBIR2TRUE	-8.179e-03	3.359e-03	-2.435	0.014898	*
RAC1P2TRUE	-3.158e-02	5.886e-03	-5.365	8.11e-08	***
RCOTRUE	NA	NA	NA	NA	
SCIENGP2TRUE	-3.824e-02	3.740e-03	-10.224	< 2e-16	***
SCIENGRLP1TRUE	-3.718e-02	7.436e-03	-5.000	5.73e-07	***
SFN1TRUE	-3.761e-01	2.015e-02	-18.663	< 2e-16	***
SFR2TRUE	-9.101e-02	2.510e-02	-3.626	0.000288	***
SFR3TRUE	5.012e-01	2.716e-02	18.457	< 2e-16	***

---

Signif. codes: 0 \*\*\* 0.001 \*\* 0.01 \* 0.05 . 0.1 1

Residual standard error: 1.424 on 976619 degrees of freedom

Multiple R-squared: 0.9841, Adjusted R-squared: 0.9841

F-statistic: 6.576e+05 on 92 and 976619 DF, p-value: < 2.2e-16