

**A Panel Regression on Poverty in the  
United States from 2010-2017**

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## Abstract

This projects purpose was to explain a states total population that lives in poverty using independent variables of race, total population of unemployment, and educational attainment of people over the age of 25 as well as the total population of people over the age of 25. The final models used were a two-way LSDV with state and year as factors as well as a two-way de-mean. Corrections were run for multicollinearity and heteroskedasticity. The results of this project were that unemployment, the state you reside in, and year are all significant at any alpha when considering the population of a state that lives in poverty. Race and educational achievement were found to be statistically insignificant when controlling for location and year. The relationship between the total population that is unemployed, and the fitted values of poverty from our model is non-linear and takes on a similar hook shape across states as can be seen in the Appendix. The results of this study also show evidence that there is something unique about certain years such as 2011, and in some states 2013, that caused an increase in poverty even though unemployment decreased.

## Introduction

Poverty rates are something that economists frequently try to explain in order to make policy recommendations that will have some type of meaningful effect on the economy. This project will seek to provide some useful insights into possible correlations between the chosen dependent variable of the number of people that live in poverty by state for the years 2010-2017 while controlling for race, population of unemployed, and educational achievement of the total population that is 25 years and older by state for the years 2010 and 2017. It is the initial hypothesis of this project that the educational attainment of people that are 25 years and older is going to have the largest impact on the number of people that live in poverty in a given state. The model that will be used will be a log-log two-way LSDV to show the elasticity of the chosen dependent variable by the independent variables.

## Literature Review

As is often the case, I am not the first to decide to study the implications of various factors on the poverty rates of a given area. Gittell & Tebaldi 2010 ran a regression analysis of the effect of population with varying levels of education, unemployment rate, GDP growth, and various other independent variables such as tax and education burden on poverty rate change. Their results that are pertinent to my project are that they supported the evidence that a lack of formal education contributes to the poverty rates, that there is a non-linear relationship between unemployment and changes in poverty rates. Reading through a scholarly article by Campolieti, Michele; Gunderson, Morley; and Lee, Bryon entitled *The (Non) Impact of Minimum Wages on Poverty: Regression and Simulation Evidence for Canada*, I saw something in their research model that I wanted to avoid in my own. The researchers took the natural log of the poverty rate.

Logs allow us to see a percentage change in the data given a 1 percent increase of the independent variables in a log-log model, which is what they ran. The redundancy I wanted to avoid in my own model is that their results would have been translated as a percentage change of a percentage which if their results were significant, could have drastically overestimated the effect of X on Y.

## Models

The models that were used for this regression analysis were:

**$\ln(\text{Poverty}) = \beta_0 + \ln(\text{White}) + \ln(\text{Black}) + \ln(\text{Asian}) + \ln(\text{American Indian \& Native Alaskan}) + \ln(\text{Native Hawaiian \& Pacific Islander}) + \ln(\text{Total Population 25 and over}) + \ln(\text{Total Population of Unemployed}) + \text{Population 25 and over with less than 9}^{\text{th}} \text{ grade} + \text{Population 25 and over with 9-12 \& No Diploma} + \text{Population 25 and over with High School or Equiv.} + \text{Population 25 and over with Some College No Degree} + \text{Population 25 and over with Associates Degree} + \text{Population 25 and over with Bachelor Degree} + \text{Population 25 and over with Graduate Degree} + \text{Dummy State} + \text{Dummy Year}$**

Where poverty is the total number of people that live in poverty logged to show percentage change. Race is indicative of the total population that identified as that singular race, but also included those who also identify as Hispanic within those races and these values were logged to represent a percentage change in relation to the dependent variable. The academic achievement is already expressed as a percentage so it was decided that it would be unnecessary to log these variables as their interpretations would be a one percent increase of a percentage and would possibly confuse the results. Dummy variables for state and year were included in order to run a LSDV panel on this data. A de-mean panel was also run to get an adjusted R squared for

the purposes of F testing. This model shows the elasticity of the dependent variable in relation to the independent variable with year and location taken into account. Correction for multicollinearity and heteroskedasticity was run on the model to correct for any multicollinearity.

A simpler model was ultimately used.

**$\ln(\text{Poverty}) = \beta_0 + \ln(\text{Total Population of Unemployed}) + \text{Dummy State} + \text{Dummy Year}$**

An F test was conducted between the two models and the betas of all other variables were found to be statistically no different than zero. So, the model with the independent variables as logged total population of unemployed when controlling for location and year was used for the final LSDV and de-mean models.

## Data section

The source for the data on poverty was obtained from the United States Census Bureau's Small Area Income and Poverty Estimates. The educational attainment data comes from the American Fact Finder resource that is provided by the Census Bureau to enable exploration of the many publicly available datasets that they provide. Unemployment data was gathered from the United States Department of Agriculture Economic Research Service, without stating the obvious this is the economic research arm of the Department of Agriculture and was an excellent source of data. Population demographics were sourced from the United States Census Bureau's annual report by county that covers the population by age, sex, race, and Hispanic origin.

The dataset that I put together has 408 observations of state level data between 2010-2017. The relevant variables that were included are: year, state, total population, total population who identify as only White, Black, American Indian & Alaskan Native, Asian, Native Hawaiian

& Pacific Islander, number of people of all ages in poverty, number of people unemployed, total population 25 and over, educational attainment of population 25 and over.

The age range of 25 and over was decided upon since most people will have completed their educational career by this point and it included the largest portion of the population as far as age. This selection of age group also helped to eliminate any bias in number of people with less than a high school diploma. Educational attainment is measured in percentage of population 25 and over in the categories of: less than 9th grade, 9-12 grade with no diploma, high school diploma including equivalency, some college but no degree, associate degree, bachelor's degree, and graduate or professional degree.

Race and unemployment variables were logged to get a more meaningful explanation of the results by means of elasticity. The educational attainment variables are already in percentages, so they were not logged. Demographic and unemployment data were compiled from data sets that were based on county level data. The unemployment dataset gave a total for each state on each year and that was extracted using a pivot table in Excel and then transferring that table into another worksheet and pasting only the values. The demographic dataset was extraordinarily large, and a pivot table was also used to extract this data in the same fashion as the unemployment data. The other datasets were very straightforward in finding the appropriate column and copy and pasting into my dataset, but the data came from over 20 individual Excel spreadsheets.

## Results

The results of this project were different from what was expected. As stated in the introduction, it was the original hypothesis of this project that educational attainment would have

the largest effect on the amount of poverty in a given state. This was not the case! The total number of people that are unemployed, location, and year turned out to be the only variables that actually mattered in determining the total population living in poverty in a given state. The coefficient for the variable that was significant, which was population of unemployed was .1484 with a standard error of .019 . Since this was a double log panel this coefficient can be expressed as a 1 percent increase in the total population of unemployed in a given state will result in about a .148 percent increase in the total population of a state that lives in poverty. The results also show that the uniqueness of individual states and the uniqueness of the years in which this data was taken were also very significant, in fact many of the p-values are so close to zero that they can simply be considered zero. Because these dummy variables are used to bring something that could be residing in the error term into the model itself, specifically something that we cannot measure, they do not explicitly tell us what it is about these states and years that had such a significant effect on poverty.

Multicollinearity was an issue in the model including all independent variables. Some of the independent variables such as population were highly correlated with the other independent variables such as the number of people who identified as a given race. This was expected since these racial groups ultimately make up a good portion of the total population. When an auxiliary was run to check and see how much my independent variables explained total population, the R squared was 1 indicating perfect multicollinearity, so this variable was removed from the model. Suspecting more multicollinearity, I decided to run a correction for this and heteroskedasticity. What I found was that the standard error for my estimate actually increased after the correction was made. This is a result that I cannot explain since correcting for multicollinearity should

necessarily reduce the standard error of the estimate as multicollinearity specifically causes and inflation of the variance.

The results showed no correlation between any of the race or education attainment variables and poverty. The explanatory power of unemployment in our model combined with year and state resulted in an adjusted R-squared value of .077906, which is really low but not material to determining the relationship between unemployment and poverty. An f test was run on the unrestricted model with all variables included with year and state accounted for and the restricted model with just unemployment and year and state accounted for. The f statistic of 1.071457 was not greater than the critical f of 1.74936, meaning that the betas that were tested were statistically no different from zero. This is where the model was shortened to include only unemployment with state and year accounted for.

A test for endogeneity was run on residuals of the final uncorrected LSDV model, since residuals could not be sourced after a correction for multicollinearity and heteroskedasticity, and the fitted values of the same model. The LSDV was used because fitted values were not available from the de-mean models. The p-value of this regression was 1 and when plotting the relationship, no pattern could be seen. Another test was run between the residuals of the uncorrected LSDV model and the logged poverty variable. The p-value for this test was .6339 and the plot showed no patterns in the data. By validating the variables that were used with an f test and testing for correlation between the error term and my dependent variable I have eliminated as much endogeneity as possible with the current measures.

## Discussion



The results of this model are quite robust. No matter which variation of the model I used total number of people that are unemployed was always significant and the values for the beta and standard deviation fluctuated very little between models. The coefficient however is a discussion of substantive significance. The national unemployment rate is relatively low right now hovering at around 4% if it were to increase to 5%, we may expect a .148% increase in poverty on average. This is less than a quarter of a percent and the real question is how large of an increase is this really? Well if we consider California in 2013 with the highest overall number of people in the United States living in poverty between 2010-2017 at 6,328,064 people, a .148% increase is about 9,392 people. In my opinion this sounds like a lot when you consider almost 10,000 people going from living above the poverty line to now living a life of poverty with a 1% increase of the unemployment rate. What if unemployment went up by 5 percent? Well now we are discussing the possibility of about 50,000 people going from a life above the poverty line to living below it. This is of course on the extreme end of the spectrum but outlines the effects of unemployment in highly populated areas. The total population of people 25 and over initially showed statistical significance but was no longer significant when the model was corrected for multicollinearity and heteroskedasticity.

When plotting the relationship between unemployment and the fitted values that were obtained for poverty in our model a non-linear pattern can be seen across several sample states that were chosen. These plots can be found in the Appendix under the heading Graphs. What is really interesting about these plots is that they show that there was some event that occurred between 2010 and 2011 that increased poverty in almost all states regardless of whether or not unemployment increased. Some states saw another peak in poverty in 2013 and some did not. While the graphs vary in slightly different ways depending on what state you are looking at, they

all show a similar pattern of the data. Overall the story told with these plots is that after the increase in poverty in 2011 and sometimes in 2013, poverty in general, goes down when unemployment goes down. The fact that some states experienced additional peaks while others did not, lends more evidence to the unique qualities of each state and their individual resilience to change in the economic atmosphere.

I want to touch briefly on the results of this model that do not indicate statistical significance for the variables of educational attainment for the total population that is 25 years and over. This could be because a lot of people tend to use college as a means of escaping poverty and leaving the area in which they are experiencing poor economic conditions. Meaning that the insignificance of this variable could be attributed to most people moving after they get their education and moving to places where there is a demand for their job, which could or could not have a high rate of poverty.

## Conclusion

The conclusions of this project are as follows. Race is not statistically significant in explaining the poverty rate in a given state from 2010-2017. Educational achievement is not statistically significant when trying to explain poverty, but this study only went as far as measuring the educational attainment of those who are 25 years and older. It is possible that adding the data for those between the ages of 18 and 24 may affect the output of the model. However, it is my hypothesis that it will not. The total population of people 25 and over was not statistically significant, which was interesting since the total number of working age people who have already attained their educations would intuitively seem to have an effect but did not. The applicable implications of this project are that policies that affect unemployment have a direct

effect on the poverty rate throughout the United States. While each state has its own properties that make it more or less likely to experience high poverty rates, it is impossible to tell what those unique properties are without further studies that look at states individually to test hypotheses. Additionally, some occurrence from 2010 to 2011 and in some states 2013, seemed to cause an increase in poverty regardless of whether unemployment changed. Events that happen within a given year are primary influencers of the poverty rate of a given state and only further studies that look at the events during these years will reveal possible candidates for the causes of this unique happening. On a final thought, I enjoyed putting this project together and exploring the data. The application of econometrics has been clarified on a personal level.

## References

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- Gittel, R., & Tebaldi, E. (2010). POVERTY IN U.S. METROPOLITAN AREAS: WHAT ARE THE KEY DETERMINANTS AND WHAT IS THE ROLE OF LOCAL FISCAL STRUCTURE?1. *Public Finance and Management*, 10(3), 411-441. Retrieved from <https://search-proquest-com.htmlproxy.lib.csufresno.edu/docview/745780960?accountid=10349>
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- USDA ERS - Download Data. (n.d.). Retrieved from <https://www.ers.usda.gov/data-products/county-level-data-sets/download-data/>

## Appendix

### Codebook:

LOG\_ prefix indicates logged measurements.

Year	Year of estimate
State	State
TOT_POP	Total population of all ages
WHT	Total population of all ages that identify as White
BLK	Total population of all ages that identify as Black
AI_ALSK	Total population of all ages that identify as American Indian & Alaskan Native
ASN	Total population of all ages that identify as Asian
NH_PI	Total population of all ages that identify as Native Hawaiian & Pacific Islander
POV_AA	Total population of all ages in poverty
UN_EMP	Total population unemployed
TOT_POP_25	Total population 25 years old and over
LESS_9	Percent of population 25 years old and over with less than 9 <sup>th</sup> grade education
9_12_NO_D	Percent of population 25 years old and over with 9-12 <sup>th</sup> grade education but no diploma
HSC_EQU	Percent of population 25 years old and over with high school education including equivalency
SC_NO_D	Percent of population 25 years old and over with some college but no degree
ASSO	Percent of population 25 years old and over with an associate degree
BACH	Percent of population 25 years old and over with a bachelor's degree
GRAD	Percent of population 25 years old and over with a graduate or professional degree

### Models:

#### **PLM two-way (State, Year) Unrestricted Model Uncorrected**

Twoways effects within Model

call:

```
plm(formula = LOG_POV_AA ~ LOG_WHT + LOG_BLK + LOG_AI_ALSK +
      LOG_NH_PI + LOG_ASN + LOG_TOT_25 + LOG_UN_EMP + LESS_9 +
      NINE_TO_12_NO_D + HSC_EQU + SC_NO_D + ASSO + BACH + GRAD,
      data = d, effect = "twoways", model = "within",
```

```
index = c("State", "Year"))
```

Balanced Panel: n = 51, T = 8, N = 408

Residuals:

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.086044	-0.016318	0.001184	0.015782	0.099825

Coefficients:

	Estimate	Std. Error	t-value	Pr(> t )
LOG_WHT	-0.3685396	0.2475099	-1.4890	0.1374
LOG_BLK	-0.0298485	0.0308295	-0.9682	0.3337
LOG_AI_ALSK	0.0313246	0.1055164	0.2969	0.7667
LOG_NH_PI	0.0059357	0.0536122	0.1107	0.9119
LOG_ASN	-0.0781036	0.0632676	-1.2345	0.2179
LOG_TOT_25	0.5222502	0.2418154	2.1597	0.0315 *
LOG_UN_EMP	0.1588767	0.0164278	9.6712	<2e-16 ***
LESS_9	0.0220980	0.0206518	1.0700	0.2854
NINE_TO_12_NO_D	0.0152953	0.0208113	0.7350	0.4629
HSC_EQU	0.0239478	0.0202210	1.1843	0.2371
SC_NO_D	0.0287194	0.0205964	1.3944	0.1641
ASSO	0.0189155	0.0205833	0.9190	0.3588
BACH	0.0143863	0.0207575	0.6931	0.4887
GRAD	0.0227011	0.0203778	1.1140	0.2661

---

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

Total Sum of Squares: 0.3538

Residual Sum of Squares: 0.25861

R-Squared: 0.26907

Adj. R-Squared: 0.11461

F-statistic: 8.83471 on 14 and 336 DF, p-value: < 2.22e-16

## PLM two-way (State, Year) Unrestricted Model Corrected

t test of coefficients:

	Estimate	Std. Error	t value	Pr(> t )
LOG_WHT	-0.3685396	0.5015864	-0.7347	0.4630
LOG_BLK	-0.0298485	0.0303700	-0.9828	0.3264
LOG_AI_ALSK	0.0313246	0.1335451	0.2346	0.8147
LOG_NH_PI	0.0059357	0.0584961	0.1015	0.9192
LOG_ASN	-0.0781036	0.0650890	-1.1999	0.2310
LOG_TOT_25	0.5222502	0.5110306	1.0220	0.3075
LOG_UN_EMP	0.1588767	0.0202507	7.8455	5.803e-14 ***
LESS_9	0.0220980	0.0202405	1.0918	0.2757
NINE_TO_12_NO_D	0.0152953	0.0194528	0.7863	0.4323
HSC_EQU	0.0239478	0.0206940	1.1572	0.2480
SC_NO_D	0.0287194	0.0201491	1.4253	0.1550

```

ASSO          0.0189155  0.0186698  1.0132    0.3117
BACH          0.0143863  0.0214750  0.6699    0.5034
GRAD          0.0227011  0.0214573  1.0580    0.2908
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

## PLM/De-Mean two-way (State, Year) Final Uncorrected

Twoways effects within Model

```

Call:
plm(formula = LOG_POV_AA ~ LOG_UN_EMP, data = d, effect = "twoways",
     model = "within", index = c("State", "Year"))

```

Balanced Panel: n = 51, T = 8, N = 408

```

Residuals:
      Min.      1st Qu.      Median      3rd Qu.      Max.
-0.09995599 -0.01522611  0.00092666  0.01475029  0.12810435

```

```

Coefficients:
              Estimate Std. Error t-value Pr(>|t|)
LOG_UN_EMP  0.148420   0.015441  9.6118 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

Total Sum of Squares:    0.3538
Residual Sum of Squares: 0.27975
R-Squared:               0.20931
Adj. R-Squared:          0.077906
F-statistic: 92.3868 on 1 and 349 DF, p-value: < 2.22e-16

```

## PLM/De-Mean two-way (State, Year) Final Corrected

t test of coefficients:

```

              Estimate Std. Error t value Pr(>|t|)
LOG_UN_EMP  0.148420   0.019264  7.7047 1.373e-13 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

## Unrestricted LSDV (State, Year) uncorrected

```

Residuals:
      Min       1Q   Median       3Q      Max
-0.086044 -0.016318  0.001184  0.015782  0.099825

```

Coefficients:

	Estimate	Std. Error	t value
(Intercept)	8.126243	2.633603	3.086
d\$LOG_WHT	-0.368540	0.247510	-1.489
d\$LOG_BLK	-0.029849	0.030830	-0.968
d\$LOG_AI_ALSK	0.031325	0.105516	0.297
d\$LOG_NH_PI	0.005936	0.053612	0.111
d\$LOG_ASN	-0.078104	0.063268	-1.234
d\$LOG_TOT_25	0.522250	0.241815	2.160
d\$LOG_UN_EMP	0.158877	0.016428	9.671
d\$LESS_9	0.022098	0.020652	1.070
d\$NINE_TO_12_NO_D	0.015295	0.020811	0.735
d\$HSC_EQU	0.023948	0.020221	1.184
d\$SC_NO_D	0.028719	0.020596	1.394
d\$ASSO	0.018916	0.020583	0.919
d\$BACH	0.014386	0.020757	0.693
d\$GRAD	0.022701	0.020378	1.114
d\$DummyStateAlaska	-2.079145	0.306862	-6.776
d\$DummyStateArizona	0.207210	0.246970	0.839
d\$DummyStateArkansas	-0.344802	0.078439	-4.396
d\$DummyStateCalifornia	1.559293	0.376166	4.145
d\$DummyStateColorado	-0.197788	0.130508	-1.516
d\$DummyStateConnecticut	-0.655967	0.123795	-5.299
d\$DummyStateDelaware	-1.536499	0.230946	-6.653
d\$DummyStateDistrict of Columbia	-1.718516	0.354753	-4.844
d\$DummyStateFlorida	1.019857	0.185688	5.492
d\$DummyStateGeorgia	0.591194	0.109148	5.416
d\$DummyStateHawaii	-1.584590	0.408261	-3.881
d\$DummyStateIdaho	-1.027469	0.161060	-6.379
d\$DummyStateIllinois	0.594603	0.164538	3.614
d\$DummyStateIndiana	0.118754	0.106893	1.111
d\$DummyStateIowa	-0.617098	0.138158	-4.467
d\$DummyStateKansas	-0.594232	0.103224	-5.757
d\$DummyStateKentucky	-0.007995	0.132707	-0.060
d\$DummyStateLouisiana	0.040555	0.052694	0.770
d\$DummyStateMaine	-1.298724	0.194754	-6.669
d\$DummyStateMaryland	-0.343000	0.123831	-2.770
d\$DummyStateMassachusetts	-0.017135	0.141528	-0.121
d\$DummyStateMichigan	0.470430	0.132717	3.545
d\$DummyStateMinnesota	-0.264270	0.141860	-1.863
d\$DummyStateMississippi	-0.242883	0.088840	-2.734
d\$DummyStateMissouri	0.035204	0.076052	0.463
d\$DummyStateMontana	-1.531992	0.229150	-6.686
d\$DummyStateNebraska	-0.978893	0.128743	-7.603
d\$DummyStateNevada	-0.576652	0.140348	-4.109
d\$DummyStateNew Hampshire	-1.570499	0.265041	-5.925
d\$DummyStateNew Jersey	0.106059	0.161138	0.658
d\$DummyStateNew Mexico	-0.626247	0.248628	-2.519
d\$DummyStateNew York	1.057972	0.237902	4.447
d\$DummyStateNorth Carolina	0.500209	0.160371	3.119
d\$DummyStateNorth Dakota	-1.867587	0.239499	-7.798
d\$DummyStateOhio	0.574424	0.138621	4.144
d\$DummyStateOklahoma	-0.300714	0.258757	-1.162
d\$DummyStateOregon	-0.293852	0.149374	-1.967
d\$DummyStatePennsylvania	0.540358	0.151373	3.570
d\$DummyStateRhode Island	-1.354962	0.191752	-7.066
d\$DummyStateSouth Carolina	-0.045063	0.034913	-1.291
d\$DummyStateSouth Dakota	-1.625148	0.253881	-6.401



d\$DummyStateTennessee	0.220308	0.070636	3.119
d\$DummyStateTexas	1.392224	0.264632	5.261
d\$DummyStateUtah	-0.666066	0.184361	-3.613
d\$DummyStateVermont	-1.893594	0.326478	-5.800
d\$DummyStateVirginia	0.109037	0.125196	0.871
d\$DummyStateWashington	0.021530	0.202034	0.107
d\$DummyStateWest Virginia	-0.735975	0.231655	-3.177
d\$DummyStateWisconsin	-0.150719	0.116707	-1.291
d\$DummyStateWyoming	-2.167575	0.237733	-9.118
d\$DummyYear2011	0.049141	0.006649	7.391
d\$DummyYear2012	0.071054	0.009789	7.259
d\$DummyYear2013	0.087682	0.012824	6.837
d\$DummyYear2014	0.101503	0.016556	6.131
d\$DummyYear2015	0.084078	0.020611	4.079
d\$DummyYear2016	0.057050	0.024401	2.338
d\$DummyYear2017	0.044825	0.028444	1.576

Pr(>|t|)

(Intercept)	0.002200 **
d\$LOG_WHT	0.137428
d\$LOG_BLK	0.333650
d\$LOG_AI_ALSK	0.766750
d\$LOG_NH_PI	0.911908
d\$LOG_ASN	0.217881
d\$LOG_TOT_25	0.031502 *
d\$LOG_UN_EMP	< 2e-16 ***
d\$LESS_9	0.285376
d\$NINE_TO_12_NO_D	0.462882
d\$HSC_EQU	0.237129
d\$SC_NO_D	0.164121
d\$ASSO	0.358768
d\$BACH	0.488746
d\$GRAD	0.266071
d\$DummyStateAlaska	5.57e-11 ***
d\$DummyStateArizona	0.402061
d\$DummyStateArkansas	1.48e-05 ***
d\$DummyStateCalifornia	4.30e-05 ***
d\$DummyStateColorado	0.130581
d\$DummyStateConnecticut	2.11e-07 ***
d\$DummyStateDelaware	1.17e-10 ***
d\$DummyStateDistrict of Columbia	1.94e-06 ***
d\$DummyStateFlorida	7.84e-08 ***
d\$DummyStateGeorgia	1.16e-07 ***
d\$DummyStateHawaii	0.000125 ***
d\$DummyStateIdaho	5.89e-10 ***
d\$DummyStateIllinois	0.000348 ***
d\$DummyStateIndiana	0.267380
d\$DummyStateIowa	1.09e-05 ***
d\$DummyStateKansas	1.93e-08 ***
d\$DummyStateKentucky	0.951997
d\$DummyStateLouisiana	0.442057
d\$DummyStateMaine	1.06e-10 ***
d\$DummyStateMaryland	0.005919 **
d\$DummyStateMassachusetts	0.903707
d\$DummyStateMichigan	0.000449 ***
d\$DummyStateMinnesota	0.063349 .
d\$DummyStateMississippi	0.006590 **
d\$DummyStateMissouri	0.643734

d\$DummyStateMontana	9.60e-11	***
d\$DummyStateNebraska	2.91e-13	***
d\$DummyStateNevada	5.00e-05	***
d\$DummyStateNew Hampshire	7.71e-09	***
d\$DummyStateNew Jersey	0.510870	
d\$DummyStateNew Mexico	0.012239	*
d\$DummyStateNew York	1.18e-05	***
d\$DummyStateNorth Carolina	0.001971	**
d\$DummyStateNorth Dakota	7.99e-14	***
d\$DummyStateOhio	4.33e-05	***
d\$DummyStateOklahoma	0.246001	
d\$DummyStateOregon	0.049980	*
d\$DummyStatePennsylvania	0.000409	***
d\$DummyStateRhode Island	9.24e-12	***
d\$DummyStateSouth Carolina	0.197683	
d\$DummyStateSouth Dakota	5.18e-10	***
d\$DummyStateTennessee	0.001972	**
d\$DummyStateTexas	2.56e-07	***
d\$DummyStateUtah	0.000349	***
d\$DummyStateVermont	1.53e-08	***
d\$DummyStateVirginia	0.384413	
d\$DummyStateWashington	0.915196	
d\$DummyStateWest Virginia	0.001626	**
d\$DummyStateWisconsin	0.197443	
d\$DummyStateWyoming	< 2e-16	***
d\$DummyYear2011	1.17e-12	***
d\$DummyYear2012	2.73e-12	***
d\$DummyYear2013	3.82e-11	***
d\$DummyYear2014	2.45e-09	***
d\$DummyYear2015	5.65e-05	***
d\$DummyYear2016	0.019974	*
d\$DummyYear2017	0.115983	

---

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

Residual standard error: 0.02774 on 336 degrees of freedom

Multiple R-squared: 0.9995, Adjusted R-squared: 0.9994

F-statistic: 9153 on 71 and 336 DF, p-value: < 2.2e-16

## LSDV two-way (State, Year) Final Corrected

t test of coefficients:

	Estimate	Std. Error
(Intercept)	11.8484194	0.2199471
d\$LOG_UN_EMP	0.1484197	0.0178506
d\$DummyStateAlaska	-2.1690319	0.0382296
d\$DummyStateArizona	0.2223755	0.0118593
d\$DummyStateArkansas	-0.3971003	0.0137288
d\$DummyStateCalifornia	1.5794477	0.0419778
d\$DummyStateColorado	-0.3125077	0.0080908
d\$DummyStateConnecticut	-0.8540076	0.0084232
d\$DummyStateDelaware	-1.7795004	0.0414557
d\$DummyStateDistrict of Columbia	-1.8980963	0.0249080
d\$DummyStateFlorida	1.0639219	0.0270337

d\$DummyStateGeorgia	0.5656803	0.0175676
d\$DummyStateHawaii	-1.5198270	0.0309933
d\$DummyStateIdaho	-1.1032985	0.0238981
d\$DummyStateIllinois	0.5243654	0.0225123
d\$DummyStateIndiana	0.0448977	0.0081801
d\$DummyStateIowa	-0.7615745	0.0152570
d\$DummyStateKansas	-0.7449220	0.0155844
d\$DummyStateKentucky	-0.0788102	0.0103496
d\$DummyStateLouisiana	0.0383590	0.0150114
d\$DummyStateMaine	-1.4167237	0.0256396
d\$DummyStateMaryland	-0.4299876	0.0106397
d\$DummyStateMassachusetts	-0.2065460	0.0093822
d\$DummyStateMichigan	0.4627626	0.0183520
d\$DummyStateMinnesota	-0.4030681	0.0122506
d\$DummyStateMississippi	-0.2380873	0.0133974
d\$DummyStateMissouri	-0.0118611	0.0085635
d\$DummyStateMontana	-1.5237596	0.0340805
d\$DummyStateNebraska	-1.1511158	0.0289577
d\$DummyStateNevada	-0.6956382	0.0156303
d\$DummyStateNew Hampshire	-1.8239038	0.0310690
d\$DummyStateNew Jersey	-0.0445504	0.0216681
d\$DummyStateNew Mexico	-0.6200349	0.0185800
d\$DummyStateNew York	1.0121099	0.0267389
d\$DummyStateNorth Carolina	0.5044954	0.0153612
d\$DummyStateNorth Dakota	-2.0331991	0.0438877
d\$DummyStateOhio	0.5559688	0.0177812
d\$DummyStateOklahoma	-0.2626248	0.0121023
d\$DummyStateOregon	-0.3465920	0.0124421
d\$DummyStatePennsylvania	0.4883768	0.0191198
d\$DummyStateRhode Island	-1.6244635	0.0250558
d\$DummyStateSouth Carolina	-0.0760629	0.0082905
d\$DummyStateSouth Dakota	-1.7235589	0.0402421
d\$DummyStateTennessee	0.1877915	0.0085846
d\$DummyStateTexas	1.3886380	0.0289226
d\$DummyStateUtah	-0.8087754	0.0250737
d\$DummyStateVermont	-2.1746336	0.0459232
d\$DummyStateVirginia	-0.0071281	0.0126856
d\$DummyStateWashington	-0.0501973	0.0146380
d\$DummyStateWest Virginia	-0.8246121	0.0233229
d\$DummyStateWisconsin	-0.2249671	0.0078706
d\$DummyStateWyoming	-2.2829017	0.0425393
d\$DummyYear2011	0.0487250	0.0058160
d\$DummyYear2012	0.0686545	0.0065871
d\$DummyYear2013	0.0820923	0.0071374
d\$DummyYear2014	0.0948593	0.0092280
d\$DummyYear2015	0.0734031	0.0114100
d\$DummyYear2016	0.0419270	0.0128758
d\$DummyYear2017	0.0279115	0.0163018
	t value	Pr(> t )
(Intercept)	53.8694	< 2.2e-16 ***
d\$LOG_UN_EMP	8.3146	2.084e-15 ***
d\$DummyStateAlaska	-56.7370	< 2.2e-16 ***
d\$DummyStateArizona	18.7511	< 2.2e-16 ***
d\$DummyStateArkansas	-28.9246	< 2.2e-16 ***
d\$DummyStateCalifornia	37.6258	< 2.2e-16 ***
d\$DummyStateColorado	-38.6251	< 2.2e-16 ***
d\$DummyStateConnecticut	-101.3879	< 2.2e-16 ***

d\$DummyStateDelaware	-42.9253	< 2.2e-16	***
d\$DummyStateDistrict of Columbia	-76.2042	< 2.2e-16	***
d\$DummyStateFlorida	39.3553	< 2.2e-16	***
d\$DummyStateGeorgia	32.2002	< 2.2e-16	***
d\$DummyStateHawaii	-49.0373	< 2.2e-16	***
d\$DummyStateIdaho	-46.1667	< 2.2e-16	***
d\$DummyStateIllinois	23.2924	< 2.2e-16	***
d\$DummyStateIndiana	5.4886	7.804e-08	***
d\$DummyStateIowa	-49.9162	< 2.2e-16	***
d\$DummyStateKansas	-47.7991	< 2.2e-16	***
d\$DummyStateKentucky	-7.6148	2.499e-13	***
d\$DummyStateLouisiana	2.5553	0.0110323	*
d\$DummyStateMaine	-55.2554	< 2.2e-16	***
d\$DummyStateMaryland	-40.4134	< 2.2e-16	***
d\$DummyStateMassachusetts	-22.0147	< 2.2e-16	***
d\$DummyStateMichigan	25.2159	< 2.2e-16	***
d\$DummyStateMinnesota	-32.9019	< 2.2e-16	***
d\$DummyStateMississippi	-17.7711	< 2.2e-16	***
d\$DummyStateMissouri	-1.3851	0.1669121	
d\$DummyStateMontana	-44.7106	< 2.2e-16	***
d\$DummyStateNebraska	-39.7517	< 2.2e-16	***
d\$DummyStateNevada	-44.5056	< 2.2e-16	***
d\$DummyStateNew Hampshire	-58.7049	< 2.2e-16	***
d\$DummyStateNew Jersey	-2.0560	0.0405221	*
d\$DummyStateNew Mexico	-33.3711	< 2.2e-16	***
d\$DummyStateNew York	37.8516	< 2.2e-16	***
d\$DummyStateNorth Carolina	32.8422	< 2.2e-16	***
d\$DummyStateNorth Dakota	-46.3273	< 2.2e-16	***
d\$DummyStateOhio	31.2672	< 2.2e-16	***
d\$DummyStateOklahoma	-21.7004	< 2.2e-16	***
d\$DummyStateOregon	-27.8563	< 2.2e-16	***
d\$DummyStatePennsylvania	25.5430	< 2.2e-16	***
d\$DummyStateRhode Island	-64.8337	< 2.2e-16	***
d\$DummyStateSouth Carolina	-9.1747	< 2.2e-16	***
d\$DummyStateSouth Dakota	-42.8297	< 2.2e-16	***
d\$DummyStateTennessee	21.8754	< 2.2e-16	***
d\$DummyStateTexas	48.0123	< 2.2e-16	***
d\$DummyStateUtah	-32.2560	< 2.2e-16	***
d\$DummyStateVermont	-47.3537	< 2.2e-16	***
d\$DummyStateVirginia	-0.5619	0.5745411	
d\$DummyStateWashington	-3.4292	0.0006777	***
d\$DummyStateWest Virginia	-35.3563	< 2.2e-16	***
d\$DummyStateWisconsin	-28.5833	< 2.2e-16	***
d\$DummyStateWyoming	-53.6657	< 2.2e-16	***
d\$DummyYear2011	8.3777	1.335e-15	***
d\$DummyYear2012	10.4226	< 2.2e-16	***
d\$DummyYear2013	11.5016	< 2.2e-16	***
d\$DummyYear2014	10.2795	< 2.2e-16	***
d\$DummyYear2015	6.4332	4.120e-10	***
d\$DummyYear2016	3.2563	0.0012395	**
d\$DummyYear2017	1.7122	0.0877535	.

---

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

Tests:

## **F-Test using Adjusted R squared from PLM Restricted and PLM**

### **Unrestricted**

$$((\text{unrestricted Rsqr} - \text{restricted Rsqr})/q)/((1 - \text{unrestricted Rsqr})/DF)$$

**H0:  $\ln(\text{White}) = \ln(\text{Black}) = \ln(\text{Asian}) = \ln(\text{American Indian \& Native Alaskan}) = \ln(\text{Native Hawaiian \& Pacific Islander}) = \ln(\text{Total Population 25 and over}) = \ln(\text{Population 25 and over with less than 9}^{\text{th}} \text{ grade}) = \ln(\text{Population 25 and over with 9-12 No Diploma}) = \ln(\text{Population 25 and over with High School or Equiv.}) = \ln(\text{Population 25 and over with Some College No Degree}) = \ln(\text{Population 25 and over with Associates Degree}) = \ln(\text{Population 25 and over with Bachelor Degree}) = \ln(\text{Population 25 and over with Graduate Degree}) = 0$**

Where each variable indicates the beta value for that variable.

$$((.11461 - .077906)/13)/((1 - .11461)/336)$$

F Statistic: 1.071457

$$qf(.95, df1=13, df2=336)$$

Critical F: 1.74936

**F = 1.071457 < Crit. F = 1.74936 Fail to reject null.**

**Betas are statistically no different from zero.**

Graphs:



















