THE IMPACT OF THE HYDE AMENDMENT ON EDUCATION OUTCOMES OF THE MARGINAL CHILD

by

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1 Introduction

For the past century, abortion access ranked among the most controversial social issues facing America. Even today, the country is strongly divided between the 'Right to Live' and the 'Right to Choose.' Whether it be Planned Parenthood scandals, Trump's promises to nominate a supreme court justice that will overturn Roe v. Wade or the Trump administration's attempt to cut federal funding to Planned Parenthood, it is clear that this issue of abortion access is far from resolved.

Abortion access can come in many shapes and sizes, creating a dynamic arena for policy and law. We have private providers that offer abortion services to those who can pay for it and public hospitals with entire divisions dedicated to these cases. Planned Parenthood plays a huge role in providing abortion services for women, ranging from funding to awareness and education and even clinics ready to perform abortions when needed.

Changes to abortion access also come in many different varieties. Beginning with *Roe v. Wade*, state and federal laws have since created a constantly changing and increasingly complicated environment for individuals who want an abortion. Now, when considering an abortion, it's not enough to simply consider financial feasibility and location of the closest clinic. Now you have to consider restrictions such as physician and hospital requirements, gestational limits, public funding, insurance coverage, state-mandated counseling, waiting periods, parental involvement, and the list goes on. On top of that, not all states have similar combinations of abortion access policies. While some states require that a woman must go through counseling on topics such as "the ability for a fetus to feel pain," ("An Overview of Abortion Laws" 2017) others require that the woman waits 24 hours between the initial appointment and the procedure.

While all of these policies and red tape seems complicated enough for individuals who seeks out an abortion, economists have taken up the task to observe changes in decision making and unintended consequences resulting from recent changes to abortion access. For example, prior to 1973 abortions were illegal in all but 5 states. Then on January 23^{rd}, 1973, abortions suddenly became legal for every U.S. citizen. Intuitively it makes sense that decision-making process would change as a result of this ruling, and in the years following we see this in the data. Following the increases in abortion access seen in the early 1970s, birth rates dropped by as much as 10% (Levine et al. 1996). Furthermore, economists began finding externalities unrelated to the purpose of these policy changes. Specifically, the economic literature shows that the liberalization of abortion access tended to elicit positive outcomes for future generations. The average standard of living for children born after *Roe v. Wade* begins to increase (Gruber, Levine, and Staiger 1997). As a result, children are less likely to become involved in crime (Donohue and Levitt 2000), consume more education and rely less on welfare (Ananat et al. 2006).

In this paper, I look to expand the literature on long-lasting impacts of abortion policy by studying the impact of the Hyde Amendment on future education outcomes. I use data collected from the 2010 American Community Survey (ACS) and Medicaid expenditure data collected from the Centers for Medicare & Medicaid Services (CMS). I use state Medicaid expenditures per person and state Medicaid expenditures per enrollee as proxies to measure the importance of Medicaid allocations on the decision to have an abortion. I create a dummy variable to indicate whether or not an individual's birth is impacted by the Hyde Amendment. I regress an interactive variable of the Hyde Amendment and the state Medicaid expenditures to analyze the impact of the Hyde Amendment on educational attainment for the future generation.

Results show that the coefficient for the proxy interaction variable is statistically significant and positive, suggesting that the Hyde Amendment resulted in positive selection. This result goes against the economic theory and literature surrounding abortion access and future outcomes. I conclude that this result is likely due to poor model specification and bias induced from omitted variables.

2 Policy Background

2.1 Abortion Access & The Hyde Amendment

The first major change in US abortion access came with the ruling of *Roe v. Wade*. Prior to this ruling, abortion was legal in only five states (Alaska, California, Hawaii, New York, Washington). Then from 1973 to 1976, all individuals living inside the U.S. had federally unrestricted access to abortions.

On September 30^{th}, 1976, the Ford administration passed the first federal law in an attempt to constrain the outcome of *Roe v. Wade*. The Hyde Amendment was originally passed as a law preventing federal funding to be used to directly fund an abortion by preventing the use of Medicaid funding to help finance an abortion except in cases where the pregnancy endangers the woman's life. Since 1976, the Hyde Amendment has been altered twice by federal policy but remains intact as an abortion-restricting policy today. In 1993, the Clinton administration passed the *Departments of Labor, Health, Human Services, and Education, and Related Agencies Appropriation Act, 1994* which added the cases of pregnancies due to rape or incest to the list of exceptions ("H.R.2518 - 103rd Congress (1993-1994): Departments of Labor, Health and Human Services, and Education, and Related Agencies Appropriations Act, 1994" 2017). In 2010, the Obama administration issued Executive Order 13535, extending the Hyde Amendment to remain intact under the Affordable Care Act (ACA) (*Executive Order 13535* 2010). Currently, the Trump administration is attempting to pass H.R. 7 (No Taxpayer Funding for Abortion and Abortion Insurance Full Disclosure Act of 2017) in order to permanently block taxpayer money from funding abortions ("House Votes to Make Hyde Amendment Permanent" 2017).

Forty-one years later, the Hyde Amendment still restricts abortion access for low-income individuals and, by extension, the decision to have a child. Medicaid continues to be an essential source of health coverage for over 74 million people (Sonfield 2017a). One in five women in reproductive age (15 to 44) are covered by Medicaid, totaling nearly 13 million women who are negatively impacted by the Hyde Amendment (Sonfield 2017a). This leaves the potential for many unwanted pregnancies with no option but to carry to term, regardless of the financial stability, family situation or readiness of the parents.

3 Literature Review

3.1 The Marginal Child & Selection

In abortion policy analysis, the concept of the 'marginal child' is a framework used to understand the changes in standards of living resulting from abortion policy changes. Several papers in the literature have discussed and analyzed the concept of the marginal child by addressing the question: how does abortion access change the decision to have a child? Economics can shine a light on this question by focusing on the selection problem.

Consider the world before *Roe v. Wade*. Any law-abiding woman who found herself pregnant must have the child. In this situation, there was no selection; there was no decision to be made because there was only one option once pregnant: have the child. After *Roe v. Wade*, selection came into play by allowing for two options. Given that you were pregnant, you were then able to choose to have the child or not have the child. In this new realm of decision-making with selection, the marginal child is defined as the child who is not born because of increases in abortion access.

Given the new realm of decision making with selection, what happens to the demographic of individuals born post-*Roe v. Wade*? Applying the marginal child as a framework, we can calculate the living standard of the average child and compare it to the predicted standard of living of the marginal child of the same cohort after increases in abortion access. To understand this framework, it is best to consider two different scenarios.

In scenario one, we have two individuals who find themselves pregnant and would like to have a child. Individual (1) is not financially ready to have a child while individual (2) is. In this scenario, we would expect individual (1) to have an abortion and individual (2) to carry to term, leaving the average child born in better circumstances than the marginal child. This type of selection is called *positive selection*.

In scenario two, we have individual (3) who is not financially ready to have a child and individual (4) who is. In addition, individual (4) did not expect this pregnancy and would not like to carry to term and individual (3) does not have the finances to fund an abortion. In this scenario, although both individuals would prefer an abortion, only individual (4) is able to have one, leaving the average child born in worse circumstances than the marginal child. This type of selection is called *negative selection*.

This framework of selection and the marginal child allows economists to observe how changes to abortion access impact outcomes for future generations. Gruber et al. (1998) take on this task by asking a general question: would the children who are not born because of abortion access have lived in better or worse circumstances than the average child in their cohort? Using differences-in-differences, Gruber takes advantage of the two natural experiments that happened in the 1970's. The first natural experiment being the 5 states who independently repealed anti-abortion laws and the second being the *Roe v. Wade* ruling. The results show a comprehensive increase in the standard of living for the average child, suggesting that increases in abortion access promote positive selection. The marginal child would have been 35% more likely to die as an infant, 40% more likely to live in poverty, 50% more likely to receive welfare, and 70% more likely to live in a single parent home. Furthermore, their estimates show that positive selection and decreasing individuals reliant on government welfare saved the government over $14 billion in welfare expenditures from 1970 to 1994 (Gruber, Levine, and Staiger 1997).

3.2 Selection & Future Outcomes

While Gruber and many other economists give insight to the impact of the marginal child in terms of living circumstances, another area to consider is the impact of abortion access on later-life outcomes. Extending the use of the natural experiments seen in the early 1970's, Donohue and Levitt (2001) famously tie together trends in abortion access and crime rates. With similar methodology used by Gruber, Donohue and Levitt show that the change in abortion access during the early 1970's led to substantial decreases in crime rates seen in the early 1990's with positive selection again being the mechanism for this result. From positive selection, the average child's standard of living increases in comparison to the marginal child. Due to the increased living standards, children born in the early to mid-1970's are raised in conditions that are less conducive to participating in crime later on in life, making the connection between abortion access and crime rates (Donohue and Levitt 2000).

Not all of the literature supports positive selection resulting from increased abortion access. Davido (2009) again uses the natural experiment seen in the early 1970's to base the claim that abortion access is not necessarily the main contributing factor to changes in later-life outcomes. Using a slightly modified model specification created by Ananat et al., a study that concludes that abortion access is positively correlated with enhances in later-life outcomes (Ananat et al. 2006), Davido proposes two alternative reasons for this trend. First, Davido claims that that the law changes are not exogenous and that liberal states tended towards early legalization. Although abortion became legally acceptable after *Roe v. Wade*, it likely only became socially acceptable in the liberal states. Second, because the early legalization states tended to be large and wealthy, that sample does not represent a random treatment of all states, possibly creating problems with the coefficients (Davido 2009).

4 Data

I use data from the American Community Survey, the Centers for Medicare & Medicaid Studies, the Census Population Survey and the Federal Reserve Bank of St. Louis. I collect individual education attainment for the dependent variable, containing individuals ranging from 10^{th} grade to 5 years of college. For the interaction term, I collect data for state Medicaid expenditures from 1980 and create a dummy variable indicating if an individual was conceived before or after the Hyde Amendment. Finally, I collect a set of control variables to mitigate any bias in the interaction term.[1]

[1] A full data description can be found in Appendix A.

4.1 Education

I use the American Community Survey (ACS) to examine educational attainment because of the dataset's extensive sampling of the U.S. population and the comprehensive supplementary variables available about each individual. Using the Integrated Public Use Microdata Series (IPUMS), I extract my samples from the 2010 ACS to include individual educational attainment levels. Educational attainment is measured by a categorical variable ranging from no schooling to 5 years of college. I remove any individuals not old enough to drop out of school in order to refine my sample to observations relevant to the question. I then recode educational attainment to a continuous variable, ranging from individuals from 10^{th} grade (10 years of schooling) to 5 years of college (18 years of schooling).[2]

Table 1: Educational Attainment (Continuous) Summary Table

Statistic	N	Mean	St. Dev.	Min	Max
Education (Continuous)	630,335	13.107	2.092	10	18

Table 2: Educational Attainment (Discrete) Summary Table

Variable	**Levels**	**n**	%	$\sum$%
Educational Attainment (Discrete)	Grade 10	48,475	7.7	7.7
	Grade 11	54,060	8.6	16.3
	Grade 12	218,524	34.7	50.9
	1 year of college	124,716	19.8	70.7
	2 years of college	43,600	6.9	77.7
	3 years of college	0	0.0	77.7
	4 years of college	104,547	16.6	94.2
	5+ years of college	36,413	5.8	100.0
	all	630,335	100.0	

One statistic to note is that there are no individuals in the category of '3 years of college,' even prior to any data manipulation. I attribute this as a manifestation of the sunk-cost fallacy such that individuals either stop after two years of college or complete

[2] I assume that the average amount of post-graduate schooling is two years (a master's degree), making 5 years of college equivalent to 18 years of schooling.

their bachelor's degree after four years.

4.2 Medicaid & Hyde Amendment

The policy variable in this analysis is an interaction term between the Hyde Amendment and state Medicaid expenditures. The Hyde Amendment variable is a dummy variable equaling 1 if an individual was born after the amendment passed and 0 otherwise. I remove any individuals conceived in the pre-*Roe v. Wade* era in order to focus on the time periods (1) between *Roe v. Wade* and the Hyde Amendment and (2) after the Hyde Amendment. State Medicaid expenditures have two forms: state expenditures per population and state expenditures per Medicaid enrollees. Expenditure data was provided by the Centers for Medicare & Medicaid Services (CMS), given in the form of yearly Medicaid expenditures from providers by state. Although the ideal year for this data to be collected from is 1976 (in order to align with the Hyde Amendment), the closest year the historical CMS data contained is 1980. The U.S. Census provided state population data in 1980. I indirectly calculated 1980 Medicaid Enrollment by using the 1981 March Census Population Survey (CPS) as a representative sample of the population's Medicaid enrollees, finding the proportion of individuals enrolled by state from the CPS and applying that proportion to the 1980 population to get Medicaid enrollment by state.

Table 3: Medicaid & Hyde Amendment Summary Table

Statistic	N	Mean	St. Dev.	Min	Max
Hyde Amendment	630,335	0.830	0.376	0	1
State Medicaid Expenditures (by state population)	630,335	67.269	39.069	0.000	217.220
State Medicaid Expenditures (by state enrollment)	630,335	730.346	270.533	0.000	1,393.380

Important values to note in this summary table are the minimum observations for state Medicaid expenditures. Although Medicaid was passed in 1965, it was not mandatory for states to join the program. Arizona was the last state to join Medicaid in 1982, whereas the all 49 other states had already joined by 1972. Because of this, Arizona had no Medicaid expenditures for the 1979-1980 fiscal year.

4.3 Control Variables

Control variables are obtained from the ACS and the Federal Reserve Bank of St. Louis. From the ACS, I collect variables for individual demographics, state fixed effects, and time fixed effects. I use sex and race as individual characteristics important to an individual's level of education. State fixed effects are included as the individual's birthplace (state of birth) and time fixed effects are included as the individual's birth year. I include state-time fixed effects by using unemployment rates (when the individual is 15 years old)[3] collected from the Federal Reserve Bank of St. Louis.

5 Empirical Strategy

5.1 Economic Theory

As seen in section 3.1, major changes in abortion access can bring rise to selection, in turn changing the demographics of future generations. Findings from Levitt, Gruber, and Ananat all suggest that positive selection resulting from the *Roe v. Wade* ruling created positive changes in the demographics, leaving the average child born better off than the marginal child.

The Hyde Amendment, on the other hand, works against the ruling of *Roe v. Wade*, opening up the realm for a different type of selection. To understand this, let us go back to scenario two from section 3.1. In the couple of years directly following *Roe v. Wade*, Medicaid could have been the deciding factor to give individual (3) the option to have an abortion. With Medicaid as an option for funding, both individuals can get an abortion and no children are born into undesirable circumstances. After the Hyde Amendment, the Medicaid funding is no longer available and we return to scenario two resulting in negative selection.

[3] I use unemployment rates when the individual is 15 years old because that is the most relevant unemployment rate when an individual is deciding to stay in or drop out of high school.

5.2 Regression Analysis

To test the impact of the Hyde Amendment on selection and the marginal child, first, consider a simple linear regression of future educational attainment (of the child) on abortion access (of the mother).

$$FutureEducation_i = \beta_0 + \beta_1 AbortionAccess_i \tag{1}$$

In this idealized model, β_1 refers to the impact that a mother's abortion access has on the education outcomes of the child. Previous research suggests that this β_1 is positive, generally meaning that increased abortion access results in positive selection. So, after the *Roe v. Wade* ruling, abortion access increases therefore so would future education outcomes. Alternatively, after the Hyde Amendment, abortion access decreases, therefore, future education outcomes also decrease.

The variables in equation (1), however, are not available. I reconstruct the model to best fit the data I have collected. I create an alternative measure for abortion access that internalizes the impact of the Hyde Amendment on abortion access. As a proxy for dependence on Medicaid funding, I use an interaction term consisting of a dummy for children whose births were impacted by the Hyde Amendment and state Medicaid expenditures per person or per enrollee. For the Hyde Amendment dummy variable, individuals who were born in 1977 or before are assigned a dummy equal to 1, all others are set equal to 0. I choose 1977/1978 as the cutoff year for two reasons. First, I do not have the exact birthdays of individuals in my sample. Therefore, because the bill was passed on September 30^{th}, 1976, I must pick a specific year for when enforcement of the bill begins. September 30^{th}, 1976 is closer to January 1^{st}, 1977 than it is to January 1^{st}, 1976, so I choose to model the bill's enforcement beginning in 1977. Second, I must model the time between when a child is conceived and when a child is born. Again, because I do not have the exact birthdays of my sample, assuming full terms for childbearing average around nine months, I must round up the time between conception and birth to a full year. Due to this, the 1978 cohort is the first to be impacted by the Hyde Amendment.

I use the following linear regression model as my baseline for analysis on the impact of the Hyde Amendment on Education Attainment:

$$EDU_{ist} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} * H_t * M.pop_s + \boldsymbol{\beta_2} * X_{ist} + \boldsymbol{\beta_3} * Z_{st} + \boldsymbol{\beta_4} * u_s + \boldsymbol{\beta_5} * v_t + \varepsilon_{ist} \quad (2)$$

where

EDU is the categorical variable for educational attainment;
H is a dummy variable representing whether or not an individual was impacted by the Hyde Amendment;
M.pop is state Medicaid expenditures per state population;
X refers to individual and household characteristics;
Z refers to state-time varying variables;
u refers to state fixed effects;
v refers to year fixed effects;
$\boldsymbol{\varepsilon}$ is a random-error term.

I run a second linear regression after changing the interactive term for the Hyde Amendment.

$$EDU_{ist} = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1} * H_t * M.enroll_s + \boldsymbol{\alpha_2} * X_{ist} + \boldsymbol{\alpha_3} * Z_{st} + \boldsymbol{\alpha_4} * u_s + \boldsymbol{\alpha_5} * v_t + \varepsilon_{ist} \quad (3)$$

In equation (3), I change *M.pop* to *M.enroll* and use data on state Medicaid expenditures by state enrollment.

The hypothesis tests focus on $\widehat{\beta_1}$ and $\widehat{\alpha_1}$. The Null Hypothesis states that $\widehat{\beta_1}$ and $\widehat{\alpha_1}$ = 0. The Alternative Hypothesis states that $\widehat{\beta_1}$ and $\widehat{\alpha_1} \neq 0$.

6 Results

A table (4) displays the coefficients from equations (2) and (3). A tables of the full regression outputs, including regressions excluding FEs, can be found in Appendix B.

6.1 Regressions Output

Table 4: Full Regression Results

	Dependent variable: Educational Attainment	
	Educational Attainment (Continuous)	
	(1) Population	(2) Enrollment
Hyde*Medicaid (by state population)	0.008105***	
	(0.000096)	
Hyde*Medicaid (by state enrollment)		0.001002***
		(0.00001)
...	...	...
Constant	376.478***	391.711***
	(0.897)	(0.939)
Observations	630,335	630,335
R^2	0.285	0.288
Adjusted R^2	0.285	0.288
Residual Std. Error (df = 630272)	1.769	1.765
F Statistic (df = 62; 630272)	4,054.023***	4,117.638***
Note:		*p<0.1; **p<0.05; ***p<0.01

Both *Hyde*Medicaid (by state population)* and *Hyde*Medicaid (by state enrollment)* have positive coefficients with high levels of significance. Using these results, I reject the null hypothesis that the coefficient of the proxy variables is equal to zero, suggesting that the Hyde Amendment did have a statistically significant impact on education outcomes for the marginal child.

6.2 Interpretation

I use the follow equations to interpret the β coefficients in the context of the marginal child's future educational attainment.

$$\Delta Y = \beta * \Delta Medicaid \quad \text{for Hyde==1} \tag{4}$$

Equation (4) interprets the impact of state Medicaid expenditures on educational attainment for the marginal child born after enactment of the Hyde Amendment.

$$\Delta Y = \beta * \Delta Hyde * Medicaid_i \quad \text{for Birthplace}_i \tag{5}$$

Equation (5) interprets the impact of the Hyde Amendment on educational attainment for the marginal child in a given state.

The following tables break down state Medicaid expenditures by population and by enrollment.

Table 5: Breakdown of State Medicaid Expenditures (S.M.E.) by Population

S.M.E. Ranking	Medicaid by Population (by Enrollment)	State
Min	0.00 (0.00)	Arizona
Min (not Arizona)	13.25 (327.30)	Wyoming
25^{th} Percentile	40.20 (445.17)	Alabama
75^{th} Percentile	86.89 (705.99)	Michigan
Max	217.22 (1393.38)	D.C.

Table 6: Breakdown of State Medicaid Expenditures (S.M.E.) by Enrollment

S.M.E Ranking	Medicaid by Enrollment (by Population)	State
Min	0.00 (0.00)	Arizona
Min (not Arizona)	314.44 (24.00)	Florida
25^{th} Percentile	532.61 (45.86)	Tennessee
75^{th} Percentile	854.82 (64.38)	New Jersey
Max	1393.38 (217.22)	D.C.

I use equation (4) by comparing the state Medicaid expenditures between the 75^{th} and 25^{th} percentiles and between the max and min by population and by enrollment.

For example, I calculate the expected change in educational attainment for the marginal child due to differences in state Medicaid expenditures by population for the 75^{th} and 25^{th} percentiles as such:

$$\Delta Y = (0.008105) * (\$86.69 - \$13.25) = 0.60 \tag{6}$$

This result means that an increase in state Medicaid expenditures (around the time the Hyde Amendment passed) by \$73.44 per person predicts that children born after during the Hyde Amendment era will stay in school for 0.6 more years. The following table shows the interpretations for equation (4).

Table 7: Changes in Educational Attainment due to State Medicaid Expenditures (S.M.E.)

Differences in S.M.E. Rankings	By Population or Enrollment?	States	ΔEdu
Max - Min (not Arizona)	Population	D.C. - WY	1.65
75^{th} - 25^{th} Percentile	Population	MI - AL	0.60
Max - Min (not Arizona)	Enrollment	D.C. - FL	1.08
75^{th} - 25^{th} Percentile	Enrollment	NJ - TN	0.32

I use equation (5) by comparing individuals born before and after the Hyde Amendment passed for a given state.

For example, I calculate the expected change in educational attainment for the marginal child due to the Hyde Amendment for the state in the 75^{th} percentile in state Medicaid expenditures by population as such:

$$\Delta Y = (0.008105) * (1) * (\$86.89) = 0.70 \tag{7}$$

This result means that individuals born after the Hyde Amendment passed in the state of Michigan are expected to stay in school for 0.7 more years. The following table shows the interpretations for equation (5).

Table 8: Changes in Educational Attainment due to the Hyde Amendment

S.M.E. Ranking	By Population or Enrollment?	State	ΔEdu
Min (not Arizona)	Population	WY	0.11
25^{th} Percentile	Population	AL	0.33
75^{th} Percentile	Population	MI	0.70
Max	Population	D.C.	1.76
Min (not Arizona)	Enrollment	FL	0.32
25^{th} Percentile	Enrollment	TN	0.53
75^{th} Percentile	Enrollment	NK	0.86
Max	Enrollment	D.C.	1.40

7 Conclusion

By using a proxy to measure dependence on Medicaid, the results of my analysis show that the Hyde Amendment had a significant impact on the education outcomes for the marginal child. The significant, positive coefficient on the proxy variable suggests that the Hyde Amendment promoted positive selection, contrary to what economic theory predicts would happen.

There are two aspects of the coefficient that possibly give light to why the analysis is in discordance with economic theory. First, even though the coefficients are significantly positive, they are also very close to zero. While the coefficients are statistically significant, the size of the coefficients suggests no practical significance. Second, because of the unavailability of more specific and descriptive data in the realm of professional health services, it is likely that bias induced by unobservable factors is skewing the results. For example, consider California and Mississippi. California has a much higher level of Medicaid expenditures per enrollee than Mississippi. One characteristic unobserved in this model specification is the level of state education spending, which is likely positively correlated with the level of Medicaid expenditures. Given that this is the case, the proxy variable would be measuring the dependence of a state's population on Medicaid with positive bias from the positive correlation between state Medicaid expenditures and state education expenditures. Going forward, this analysis could be improved by including more individual-oriented health data as well as an enhanced model specification.

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Appendix A - Data

A.1 Numeric Variables

Table 9: Full Numeric Variables Summary Table

Statistic	N	Mean	St. Dev.	Min	Max
Educational Attainment (Continuous)	630,335	13.107	2.092	10	18
Hyde Amendment (Binary)	630,335	0.830	0.376	0	1
State Medicaid Expenditures (by state population)	630,335	67.269	39.069	0.000	217.220
State Medicaid Expenditures (by state enrollment)	630,335	730.346	270.533	0.000	1,393.380
Birth Year	630,335	1985	6.109	1974	1997
Year When 15 Years Old	630,335	2000	6.109	1989	2012
Age	630,335	25.470	6.109	13	36
State Unemployment Rate (when 15 y/o)	630,335	5.651	1.610	2.300	13.780

A.2 Categorical Variables

Table 10: Full Categorical Variables Summary Table

Variable	**Levels**	**n**	**%**	**$\sum$%**
Educational Attainment (Discrete)	Grade 10	48,475	7.7	7.7
	Grade 11	54,060	8.6	16.3
	Grade 12	218,524	34.7	50.9
	1 year of college	124,716	19.8	70.7
	2 years of college	43,600	6.9	77.7
	3 years of college	0	0.0	77.7
	4 years of college	104,547	16.6	94.2
	5+ years of college	36,413	5.8	100.0
	all	630,335	100.0	
Sex	Female	316,909	50.3	50.3
	Male	313,426	49.7	100.0
	all	630,335	100.0	
Race	White	492,673	78.2	78.2
	Black	77,286	12.3	90.4
	American Indian or Alaska Native	7,184	1.1	91.6
	Chinese	3,459	0.6	92.1
	Japanese	863	0.1	92.2
	Other Asian or Pacific Islander	11,271	1.8	94.0
	Other race	19,345	3.1	97.1
	Two major races	16,551	2.6	99.7
	Three or more major races	1,703	0.3	100.0
	all	630,335	100.0	
Birthplace	Alabama	9,781	1.6	1.6
	Alaska	2,260	0.4	1.9
	Arizona	9,407	1.5	3.4
	Arkansas	5,731	0.9	4.3
	California	77,683	12.3	16.6
	Colorado	8,729	1.4	18.0
	Connecticut	7,462	1.2	19.2
	Delaware	1,581	0.2	19.4
	District of Columbia	2,952	0.5	19.9
	Florida	25,143	4.0	23.9
	Georgia	16,466	2.6	26.5
	Hawaii	3,429	0.5	27.1
	Idaho	3,146	0.5	27.6
	Illinois	31,192	5.0	32.5
	Indiana	14,771	2.3	34.8
	Iowa	7,480	1.2	36.0

Kansas	6,398	1.0	37.0
Kentucky	9,340	1.5	38.5
Louisiana	11,835	1.9	40.4
Maine	2,893	0.5	40.9
Maryland	10,364	1.6	42.5
Massachusetts	14,120	2.2	44.8
Michigan	23,942	3.8	48.5
Minnesota	11,644	1.9	50.4
Mississippi	6,832	1.1	51.5
Missouri	13,299	2.1	53.6
Montana	2,165	0.3	53.9
Nebraska	4,377	0.7	54.6
Nevada	2,693	0.4	55.0
New Hampshire	2,503	0.4	55.5
New Jersey	17,826	2.8	58.3
New Mexico	4,091	0.7	58.9
New York	45,333	7.2	66.1
North Carolina	15,342	2.4	68.5
North Dakota	2,022	0.3	68.9
Ohio	28,553	4.5	73.4
Oklahoma	7,818	1.2	74.6
Oregon	6,958	1.1	75.7
Pennsylvania	28,407	4.5	80.2
Rhode Island	2,391	0.4	80.6
South Carolina	8,306	1.3	82.0
South Dakota	2,045	0.3	82.3
Tennessee	12,161	1.9	84.2
Texas	46,975	7.5	91.7
Utah	7,325	1.2	92.8
Vermont	1,342	0.2	93.0
Virginia	13,798	2.2	95.2
Washington	11,691	1.9	97.1
West Virginia	4,390	0.7	97.8
Wisconsin	12,550	2.0	99.8
Wyoming	1,393	0.2	100.0
all	630,335	100.0	

Appendix B - Regressions

B.1 FE Regressions

Table 11: Absent & State-Time FE Regression Results

	Dependent variable: Educational Attainment	
	Educational Attainment (Continuous)	
	(1) Absent FE	(2) State-Time FE
Hyde*Medicaid (by state population)	-0.003558^{***}	-0.003382^{***}
	(0.0001)	(0.0001)
Unemployment		-0.181^{***}
		(0.002)
sex=Male	-0.410^{***}	-0.412^{***}
	(0.005)	(0.005)
race=Black	-0.707^{***}	-0.684^{***}
	(0.008)	(0.008)
race=American Indian or Alaska Native	-0.962^{***}	-0.957^{***}
	(0.024)	(0.024)
race=Chinese	0.901^{***}	0.988^{***}
	(0.035)	(0.035)
race=Japanese	0.845^{***}	0.853^{***}
	(0.070)	(0.069)
race=Other Asian or Pacific Islander	0.237^{***}	0.301^{***}
	(0.020)	(0.019)
race=Other race	-0.794^{***}	-0.696^{***}
	(0.015)	(0.015)
race=Two major races	-0.454^{***}	-0.415^{***}
	(0.016)	(0.016)
race=Three or more major races	-0.538^{***}	-0.536^{***}
	(0.050)	(0.049)
Constant	13.634^{***}	14.641^{***}
	(0.005)	(0.010)
Observations	630,335	630,335
R^2	0.035	0.055
Adjusted R^2	0.035	0.055
Residual Std. Error	2.055 (df = 630324)	2.034 (df = 630323)
F Statistic	$2{,}317.093^{***}$ (df = 10; 630324)	$3{,}322.252^{***}$ (df = 11; 630323)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 12: State & Time FE Regression Results

	Dependent variable: Educational Attainment	
	Educational Attainment (Continuous)	
	(1) State FE	(2) Time FE
Hyde*Medicaid (by state population)	-0.012061^{***}	0.006265^{***}
	(0.0001)	(0.0001)
Birth Year		-0.177^{***}
		(0.0004)
sex=Male	-0.408^{***}	-0.388^{***}
	(0.005)	(0.005)
race=Black	-0.704^{***}	-0.653^{***}
	(0.008)	(0.007)
race=American Indian or Alaska Native	-0.793^{***}	-0.761^{***}
	(0.025)	(0.021)
race=Chinese	0.872^{***}	0.964^{***}
	(0.035)	(0.031)
race=Japanese	0.906^{***}	0.732^{***}
	(0.070)	(0.061)
race=Other Asian or Pacific Islander	0.288^{***}	0.415^{***}
	(0.020)	(0.017)
race=Other race	-0.735^{***}	-0.667^{***}
	(0.015)	(0.013)
race=Two major races	-0.393^{***}	-0.259^{***}
	(0.016)	(0.014)
race=Three or more major races	-0.472^{***}	-0.365^{***}
	(0.050)	(0.044)
birthplace=Alaska	0.130^{***}	
	(0.048)	
birthplace=Arizona	-0.668^{***}	
	(0.030)	
birthplace=Arkansas	0.033	
	(0.034)	
birthplace=California	0.456^{***}	
	(0.022)	
birthplace=Colorado	0.091^{***}	
	(0.030)	
birthplace=Connecticut	0.550^{***}	
	(0.031)	
birthplace=Delaware	0.353^{***}	
	(0.055)	
birthplace=District of Columbia	2.521^{***}	
	(0.044)	
birthplace=Florida	-0.301^{***}	
	(0.024)	
birthplace=Georgia	0.023	
	(0.026)	
birthplace=Hawaii	0.212^{***}	
	(0.042)	
birthplace=Idaho	-0.136^{***}	
	(0.042)	
birthplace=Illinois	0.665^{***}	
	(0.024)	
birthplace=Indiana	-0.061^{**}	
	(0.026)	
birthplace=Iowa	0.337^{***}	
	(0.031)	
birthplace=Kansas	0.230^{***}	
	(0.033)	
birthplace=Kentucky	0.062^{**}	
	(0.029)	
birthplace=Louisiana	0.190^{***}	
	(0.028)	
birthplace=Maine	0.265^{***}	
	(0.043)	
birthplace=Maryland	0.504^{***}	

	(0.029)	
birthplace=Massachusetts	1.337***	
	(0.027)	
birthplace=Michigan	0.537***	
	(0.025)	
birthplace=Minnesota	0.626***	
	(0.028)	
birthplace=Mississippi	0.213***	
	(0.032)	
birthplace=Missouri	0.037	
	(0.027)	
birthplace=Montana	0.249***	
	(0.048)	
birthplace=Nebraska	0.259***	
	(0.037)	
birthplace=Nevada	−0.477***	
	(0.044)	
birthplace=New Hampshire	0.045	
	(0.045)	
birthplace=New Jersey	0.648***	
	(0.026)	
birthplace=New Mexico	−0.075**	
	(0.038)	
birthplace=New York	1.697***	
	(0.024)	
birthplace=North Carolina	0.030	
	(0.026)	
birthplace=North Dakota	0.412***	
	(0.049)	
birthplace=Ohio	0.242***	
	(0.024)	
birthplace=Oklahoma	0.067**	
	(0.031)	
birthplace=Oregon	−0.010	
	(0.032)	
birthplace=Pennsylvania	0.593***	
	(0.024)	
birthplace=Rhode Island	0.821***	
	(0.046)	
birthplace=South Carolina	0.132***	
	(0.030)	
birthplace=South Dakota	0.449***	
	(0.049)	
birthplace=Tennessee	−0.032	
	(0.027)	
birthplace=Texas	−0.108***	
	(0.023)	
birthplace=Utah	−0.060*	
	(0.031)	
birthplace=Vermont	0.378***	
	(0.059)	
birthplace=Virginia	0.122***	
	(0.027)	
birthplace=Washington	0.074***	
	(0.028)	
birthplace=West Virginia	−0.026	
	(0.037)	
birthplace=Wisconsin	0.475***	
	(0.027)	
birthplace=Wyoming	−0.118**	
	(0.058)	
Constant	13.735***	363.632***
	(0.021)	(0.804)
Observations	630,335	630,335
R^2	0.067	0.258
Adjusted R^2	0.066	0.258

Residual Std. Error	2.021 (df = 630274)	1.802 (df = 630323)
F Statistic	749.196*** (df = 60; 630274)	19,966.220*** (df = 11; 630323)
Note:		*p<0.1; **p<0.05; ***p<0.01

B.2 Full Regressions

Table 13: Full Regression Results

	Dependent variable: Educational Attainment	
	Educational Attainment (Continuous)	
	(1) Population	(2) Enrollment
Hyde*Medicaid (by state population)	0.008105***	
	(0.000096)	
Hyde*Medicaid (by state enrollment)		0.001002***
		(0.00001)
Birth Year	−0.183***	−0.190***
	(0.0005)	(0.0005)
Unemployment	−0.211***	−0.201***
	(0.002)	(0.002)
sex=Male	−0.390***	−0.390***
	(0.004)	(0.004)
race=Black	−0.650***	−0.649***
	(0.007)	(0.007)
race=American Indian or Alaska Native	−0.735***	−0.735***
	(0.022)	(0.022)
race=Chinese	1.069***	1.075***
	(0.030)	(0.030)
race=Japanese	0.884***	0.879***
	(0.061)	(0.061)
race=Other Asian or Pacific Islander	0.504***	0.508***
	(0.017)	(0.017)
race=Other race	−0.584***	−0.579***
	(0.013)	(0.013)
race=Two major races	−0.200***	−0.198***
	(0.014)	(0.014)
race=Three or more major races	−0.260***	−0.259***
	(0.044)	(0.044)
birthplace=Alaska	0.058	−0.195***
	(0.042)	(0.042)
birthplace=Arizona	0.070***	0.180***
	(0.026)	(0.026)
birthplace=Arkansas	−0.332***	−0.306***
	(0.029)	(0.029)
birthplace=California	−0.092***	0.002
	(0.020)	(0.019)
birthplace=Colorado	−0.021	−0.221***
	(0.026)	(0.026)
birthplace=Connecticut	0.259***	−0.024
	(0.027)	(0.027)
birthplace=Delaware	−0.140***	−0.186***
	(0.048)	(0.048)
birthplace=District of Columbia	−0.142***	0.237***
	(0.040)	(0.038)
birthplace=Florida	0.035*	0.042**
	(0.021)	(0.021)
birthplace=Georgia	−0.181***	−0.280***
	(0.023)	(0.023)
birthplace=Hawaii	−0.551***	−0.649***
	(0.037)	(0.037)
birthplace=Idaho	−0.122***	−0.222***
	(0.036)	(0.036)
birthplace=Illinois	0.007	−0.126***
	(0.021)	(0.021)
birthplace=Indiana	−0.167***	−0.383***
	(0.023)	(0.023)
birthplace=Iowa	−0.224***	−0.209***
	(0.027)	(0.027)
birthplace=Kansas	−0.182***	−0.295***
	(0.029)	(0.029)
birthplace=Kentucky	−0.210***	−0.209***

	(0.026)	(0.026)
birthplace=Louisiana	−0.006	0.015
	(0.024)	(0.024)
birthplace=Maine	−0.372***	−0.362***
	(0.038)	(0.037)
birthplace=Maryland	−0.148***	−0.284***
	(0.025)	(0.025)
birthplace=Massachusetts	−0.256***	−0.261***
	(0.024)	(0.024)
birthplace=Michigan	−0.058***	0.028
	(0.022)	(0.021)
birthplace=Minnesota	−0.416***	−0.871***
	(0.025)	(0.025)
birthplace=Mississippi	0.178***	0.179***
	(0.028)	(0.028)
birthplace=Missouri	0.015	−0.015
	(0.024)	(0.024)
birthplace=Montana	0.007	−0.255***
	(0.042)	(0.042)
birthplace=Nebraska	−0.320***	−0.501***
	(0.033)	(0.032)
birthplace=Nevada	−0.193***	−0.617***
	(0.039)	(0.039)
birthplace=New Hampshire	−0.026	−0.188***
	(0.040)	(0.040)
birthplace=New Jersey	0.248***	0.074***
	(0.022)	(0.022)
birthplace=New Mexico	−0.042	−0.008
	(0.033)	(0.033)
birthplace=New York	−0.387***	−0.236***
	(0.022)	(0.021)
birthplace=North Carolina	−0.161***	−0.481***
	(0.023)	(0.023)
birthplace=North Dakota	−0.221***	−0.460***
	(0.043)	(0.043)
birthplace=Ohio	−0.032	−0.222***
	(0.021)	(0.021)
birthplace=Oklahoma	−0.348***	−0.623***
	(0.027)	(0.027)
birthplace=Oregon	0.019	−0.100***
	(0.028)	(0.028)
birthplace=Pennsylvania	−0.057***	−0.086***
	(0.021)	(0.021)
birthplace=Rhode Island	−0.048	−0.002
	(0.041)	(0.040)
birthplace=South Carolina	0.066**	−0.029
	(0.026)	(0.026)
birthplace=South Dakota	−0.416***	−0.624***
	(0.043)	(0.043)
birthplace=Tennessee	−0.190***	−0.220***
	(0.024)	(0.024)
birthplace=Texas	−0.009	−0.110***
	(0.020)	(0.020)
birthplace=Utah	−0.308***	−0.402***
	(0.028)	(0.027)
birthplace=Vermont	−0.370***	−0.377***
	(0.052)	(0.052)
birthplace=Virginia	−0.184***	−0.290***
	(0.024)	(0.024)
birthplace=Washington	−0.035	−0.079***
	(0.024)	(0.024)
birthplace=West Virginia	0.203***	0.233***
	(0.032)	(0.032)
birthplace=Wisconsin	−0.388***	−0.423***
	(0.024)	(0.024)
birthplace=Wyoming	−0.044	−0.118**

	(0.051)	(0.051)
Constant	376.478***	391.711***
	(0.897)	(0.939)
Observations	630,335	630,335
R^2	0.285	0.288
Adjusted R^2	0.285	0.288
Residual Std. Error (df = 630272)	1.769	1.765
F Statistic (df = 62; 630272)	4,054.023***	4,117.638***
Note:		*p<0.1; **p<0.05; ***p<0.01

Appendix C - Code

Listings

Listing 1: Master File

```
#MASTER R FILE#
#install.packages(c('data.table','dtplyr','dplyr',
                  # 'ggplot2','lattice','xtable',
                  # 'reporttools','stargazer'))
#packages used: data.table, dtplyr, dplyr,
      #ggplot2, lattice,
      # xtable, reporttools, stargazer
#packages unused: tidyr, stringr, devtools, MASS, effects

# library(data.table)
# library(dtplyr)
#       library(dplyr)
# library(ggplot2)
# library(lattice)
#       library(xtable)
# library(reporttools)
# library(stargazer)
# library(tidyr)
# library(stringr)
# library(devtools)
# library(MASS)
# library(effects)

############################
#######DATA CONVERSION#######
############################
setwd('~/Desktop/ECON_DMP/R/script')
source('data_conversion.R')
      #packages: data.table
      #converts the following files to .RDS
      #(1) cps_1981
      #(2) state_data
      #(3) state_unemployment
      #(4) states
      #(5) acs_2010


############################
##########MEDICAID##########
```

```
##############################
setwd('~/Desktop/ECON_DMP/R/script')
source('medicaid.R')
      #data: cps_1981.csv, state_data.csv -> final_state.rds
      #packages: data.table, dtplyr, dplyr
      #(1) CPS -> find medicaid enrollment proportion
      #(2) State -> use medicaid expenditure data
      #(3) Merge state_data + cps
      #(4) find state medicaid expenditures per pop & per enrollee


##############################
#########UNEMPLOYMENT#########
##############################
setwd('~/Desktop/ECON_DMP/R/script')
source('unemployment.R')
      #data: state_unemployment.xls, states.csv -> final_unemployment.rds
      #packages: data.table, dtplyr
      #(1) Clean unemployment data
      #(2) Make compatible for merging by mapping abbreviations to statefips


##############################
##########EDUCATION##########
##############################
setwd('~/Desktop/ECON_DMP/R/script')
source('education.R')
      #data: acs_2010.csv -> final_acs.rds
      #packages: data.table, dtplyr, dplyr
      #(1) Clean ACS data
      #(2) Filter data
      #(3) Make compatible for merging
      #(4) create hyde, hs_dropout, col_enroll variables


##############################
############MERGE############
##############################
setwd('~/Desktop/ECON_DMP/R/script')
source('merge.R')
      #data: final_acs.rds, final_unemployment.rds, final_state.rds -> final_dmp.rds
      #packages: data.table, dtplyr, dplyr
      #(1) Merge Education, Unemployment, and Medicaid data
      #(2) Remove irrelevant variables


##############################
######DATA DESCRIPTION#######
##############################
setwd('~/Desktop/ECON_DMP/R/script')
source('data_description.R')
      #data: final_dmp.rds
      #packages: data.table, dtplyr, dplyr, ggplot2, lattice,
            #xtable, reporttools, stargazer
      #(1) Create a numeric variable data.frame & categorical variable data.frame
      #(2) Stargazer -> create table for numberic vars
      #(3) Reporttools::tableNominal -> create table for categorical vars
      #(4) Create graphs and figures


##############################
###########ANALYSIS##########
##############################
setwd('~/Desktop/ECON_DMP/R/script')
source('analysis.R')
      #data: final_dmp.rds
```

```
    #packages: data.table, dtplyr, dplyr,
        #ggplot2, lattice, stargazer, xtable
    #(1) Run OLS Regressions
    #(2) Stargazer -> create tables for regression output
    #(3)


##############################
########ORDINAL LOGIT########
##############################
#setwd('~/Desktop/ECON_DMP/R/script/unused')
#source('ordinal_logit_model.R')
    #data: final_dmp.rds
    #packages: MASS, effects
    #(1) Run Ordinal Logistic Regressions
    #(2) Effect -> interpretation of results
```

Listing 2: Data Conversion

```
#CONVERTING DATA: Raw -> RDS#
setwd('~/Desktop/ECON_DMP/R/data_raw')
library(data.table)

    cps_1981 = read.csv('cps_1981.csv') #medicaid enrollment
        cps_1981 = data.table(cps_1981)
        saveRDS(cps_1981, '../data_rds/cps_1981.rds')

    state_data = read.csv('state_data.csv') #medicaid expenditures
        state_data = data.table(state_data)
        saveRDS(state_data, '../data_rds/state_data.rds')

    state_unemployment = read.csv('state_unemployment.csv') #unemployment
        state_unemployment = data.table(state_unemployment)
        saveRDS(state_unemployment, '../data_rds/state_unemployment.rds')

    states = read.csv('states.csv') #state naming
        states = data.table(states)
        saveRDS(states, '../data_rds/states.rds')

    acs_2010 = read.csv('acs_2010.csv') #education
        acs_2010 = data.table(acs_2010)
        saveRDS(acs_2010, '../data_rds/acs_2010.rds')

#################################
rm(list=ls())
#################################
```

Listing 3: State Medicaid Expenditures

```
#MEDICAID R FILE#
setwd('~/Desktop/ECON_DMP/R/data_rds')
library(data.table)
library(dtplyr)
    library(dplyr)
#############################################################
#############################################################
#############################################################

### Medicaid Enrollment ###
cps_1981 = readRDS('cps_1981.rds')
    cps_1981 = cps_1981 %>%
            select(statefip, himcaid) %>%
            count(statefip, himcaid) %>%
            rename(count=n) %>%
```

```
                        group_by(statefip) %>%
                        mutate(total = sum(count)) %>%
                        ungroup() %>%
                        filter(himcaid=='Yes') %>%
                        mutate(proportion = count/total)

### State Data ###
state_data = readRDS('state_data.rds')
        state_data =  state_data %>%
                select(-STATE_FIPS, -STATE_ABBREV) %>%
                rename(statefip=STATE_NAME) %>%
                rename(pop_1980=X1980_pop) %>%
                rename(med_exp_1980=X1980_med_exp) %>%
                mutate(pop_1980 = as.numeric(gsub(',', '', as.character(pop_1980)))) %>%
                mutate(med_exp_1980 = as.numeric(gsub(',', '', as.character(med_exp_1980)))) %>%
                inner_join(cps_1981) %>%
                mutate(enroll_1980 = proportion*pop_1980) %>%
                mutate(enroll_1980 = round(enroll_1980, digits=0)) %>%
                mutate(exp_per_pop = med_exp_1980/pop_1980) %>%
                mutate(exp_per_enroll = med_exp_1980/enroll_1980) %>%
                mutate(exp_per_pop = round(exp_per_pop, digits=2)) %>%
                mutate(exp_per_enroll = round(exp_per_enroll, digits=2)) %>%
                select(statefip, exp_per_pop, exp_per_enroll)

saveRDS(state_data, '../data_final/final_medicaid.rds')

##################################
rm(list=ls())
##################################
```

Listing 4: Unemployment

```
#UNEMPLOYMENT R FILE#
setwd('~/Desktop/ECON_DMP/R/data_rds')
library(data.table)
library(dtplyr)
        library(dplyr)
############################################################
############################################################
############################################################

states = readRDS('states.rds')
        states = states %>%
                select(name, abbreviation) %>%
                rename(statefip=name) %>%
                rename(abb=abbreviation) %>%
                mutate(statefip = as.character(statefip)) %>%
                mutate(abb = as.character(abb)) %>%
                mutate(statefip = replace(statefip, abb=='DC', 'District of Columbia')) %>%
                mutate(statefip=factor(statefip))

state_unemployment = readRDS('state_unemployment.rds')
        state_unemployment = state_unemployment %>%
                                mutate(DATE = as.character(DATE)) %>%
                                mutate(year = substr(DATE,1,4)) %>%
                                select(-DATE, -X) %>%
                                melt(id.vars=c('year'),
                                        #measure.vars=(''), -> includes all but ID
                                        variable.name=('abb'),
                                        variable.factor=FALSE,
                                        value.name=('unemployment')
                                        ) %>%
                                group_by(abb, year) %>%
                                summarize(unemployment=mean(unemployment)) %>%
                                ungroup() %>%
```

```
                        mutate(unemployment = round(unemployment, digits=2)) %>%
                        mutate(abb = substr(abb,1,2)) %>%
                        mutate(year = as.numeric(year)) %>%
                        inner_join(states) %>%
                        select(statefip, year, unemployment)

saveRDS(state_unemployment, '../data_final/final_unemployment.rds')

################################
rm(list=ls())
################################
```

Listing 5: Educational Attainment

```
#EDUCATION R FILE#
setwd('~/Desktop/ECON_DMP/R/data_rds')
library(data.table)
library(dtplyr)
      library(dplyr)
############################################################
############################################################
############################################################

#note: used Stata to separate factor variables b/f loading data
acs_2010 = readRDS('acs_2010.rds') # note: survey=2010; information=2009
      acs_2010 = acs_2010 %>%
            select(statefip, sex, birthyr, race, bpl, educ, age,
                      statefip_label, sex_label, age_label, race_label,
                      bpl_label, educ_label) %>%
            mutate(statefip_label = as.character(statefip_label)) %>%
            mutate(sex_label = as.character(sex_label)) %>%
            mutate(age_label = as.character(age_label)) %>%
            mutate(race_label = as.character(race_label)) %>%
            mutate(bpl_label = as.character(bpl_label)) %>%
            mutate(educ_label = as.character(educ_label)) %>%
            filter(statefip <=56, bpl<=56,
                   age>=1, educ>=4, birthyr >=1974) %>%
            #drop people living outside US, born outside US,
            #under 16 y-o, before 10th grade,
            #born before 1974 (after roe v. wade)
            mutate(statefip_label = factor(statefip_label)) %>%
            mutate(sex_label = factor(sex_label)) %>%
            mutate(bpl_label = factor(bpl_label)) %>%
            mutate(educ_label = factor(educ_label, ordered=TRUE,
                            levels = c('Grade 10', 'Grade 11', 'Grade 12',
                                       '1 year of college', '2 years of college', '3 years of college
     ',
                                       '4 years of college', '5+ years of college'))) %>%
            mutate(race_label = factor(race_label,
                            levels = c('White', 'Black/Negro', 'American Indian or Alaska Native',
                                       'Chinese', 'Japanese', 'Other Asian or Pacific Islander',
                                       'Other race, nec', 'Two major races',
                                       'Three or more major races'))) %>%
            select(-statefip, -sex, -race, -bpl, -educ, -age_label) %>%
            rename(statefip=statefip_label) %>%
            rename(sex=sex_label) %>%
            rename(race=race_label) %>%
            rename(bpl=bpl_label) %>%
            rename(educ=educ_label) %>%
            mutate(hyde = ifelse(birthyr <=1977, 0, 1)) %>% #hyde, 1=unaffected
            mutate(c.educ=ifelse(as.numeric(educ)==1, 10, #creating cont. edu variable
                  ifelse(as.numeric(educ)==2, 11,
                  ifelse(as.numeric(educ)==3, 12,
                  ifelse(as.numeric(educ)==4, 13,
                  ifelse(as.numeric(educ)==5, 14,
```

```
                    ifelse(as.numeric(educ)==6, 15,
                    ifelse(as.numeric(educ)==7, 16,
                    ifelse(as.numeric(educ)==8, 18, 0) #average post-grad schooling is 2 years
                    ))))))
                    ))

saveRDS(acs_2010, '../data_final/final_education.rds')

####################################
rm(list=ls())
####################################
#HS_Dropout & Col_Enroll Variables
      #variables needed: educ & age
      # gen grade_change = grade - grade_ly
      # gen enrollment_change = enroll - enroll_ly
# *hs_dropout*
      #   gen hs_dropout=17 // to make sure that there is no incorrect coding
      #     replace hs_dropout=0 if grade_change==1 & enrollment_change==0
      #     replace hs_dropout=1 if enrollment_change==-1
      #     replace hs_dropout=. if grade_ly<9 | grade_ly>11
      #     replace hs_dropout=. if enrollment_change==0 & grade_change!=1
# *col_enroll*
      #   gen col_enroll=17 // to make sure that there is no incorrect coding
      #     replace col_enroll=0 if enrollment_change==-1
      #     replace col_enroll=1 if grade_change==1 & enrollment_change==0
      #     replace col_enroll=. if grade_ly!=12
      #     replace col_enroll=. if enrollment_change==0 & grade_change!=1
```

Listing 6: Merging Data Sets

```
#MERGE R FILE#
setwd('~/Desktop/ECON_DMP/R/data_final')
library(data.table)
library(dtplyr)
      library(dplyr)
####################################################################
####################################################################
####################################################################

final_education = readRDS('final_education.rds')
      final_education = final_education %>%
                    mutate(year_when_15=birthyr+15)

final_unemployment = readRDS('final_unemployment.rds')
      edu.unemp = final_unemployment %>%
                    rename(year_when_15=year) %>%
                    rename(bpl=statefip) %>%
                    inner_join(final_education,
                               by=c('year_when_15', 'bpl'))
                    #maps unemp rate by bpl/state when individual=15 y-o

final_medicaid = readRDS('final_medicaid.rds')
      final_medicaid = final_medicaid %>%
                rename(bpl=statefip)
      edu.unemp.med = edu.unemp %>%
                inner_join(final_medicaid)

saveRDS(edu.unemp.med, '../final_dmp.rds')

####################################
rm(list=ls())
####################################
```

Listing 7: Data Description

```
#DATA DESCRIPTION R FILE#
setwd('~/Desktop/ECON_DMP/R/')
      final = readRDS('final_dmp.rds')
      #statefip does note include DC
      #female==1, male==2
      #educ states at grade10==1
library(data.table)
library(dtplyr)
      library(dplyr)
library(ggplot2)
library(lattice)
      library(xtable)
library(reporttools)
library(stargazer)
###############################################################
###############################################################
###############################################################
#plot.reg1 = ggplot(final, aes(exp_per_pop, c.educ))
#       plot.reg2 + geom_point()
#plot.reg2 = ggplot(final, aes(exp_per_enroll, c.educ))
###############################################################
###############################################################
###############################################################
final_numeric = final %>%
      select(c.educ, hyde, exp_per_pop, exp_per_enroll,
            birthyr, year_when_15, age, unemployment)
stargazer(final_numeric,
            title='Numeric Variables Summary Table',
            no.space=TRUE,
            font.size='normalsize',
            single.row=TRUE,
            column.sep.width='0pt',
            digit.separator="")

final_categorical = final %>%
            select(educ, sex, race, bpl)
tableNominal(final_categorical, font.size='tiny')


################################
rm(list=ls())
################################
```

Listing 8: Analysis

```
#ANALYSIS R FILE#
setwd('~/Desktop/ECON_DMP/R/')
      final = readRDS('final_dmp.rds')
      #statefip does note include DC
      #female==1, male==2
      #educ states at grade10==1
library(data.table)
library(dtplyr)
      library(dplyr)
library(ggplot2)
library(lattice)
library(stargazer)
library(xtable)
###############################################################
###############################################################
###############################################################
noFE = lm(c.educ ~ hyde:exp_per_pop + race + sex,
      data=final)
state = lm(c.educ ~ hyde:exp_per_pop + race + sex + bpl,
      data=final)
```

```
time = lm(c.educ ~ hyde:exp_per_pop + race + sex + birthyr,
      data=final)
unemp = lm(c.educ ~ hyde:exp_per_pop + race + sex + unemployment,
      data=final)
reg1 = lm(c.educ ~ hyde:exp_per_pop + race + sex + unemployment + bpl + birthyr,
      data=final)
reg2 = lm(c.educ ~ hyde:exp_per_enroll + race + sex + unemployment + bpl + birthyr,
      data=final)
############################################################
############################################################
############################################################
stargazer(noFE,
            unemp, title='Absent & State-Time FE Regression Results',
            no.space=TRUE,
            font.size='tiny',
            column.sep.width='0pt',
            digits = 6,
            digit.separator="")
stargazer(state, time,
            title='State & Time FE Regression Results',
            no.space=TRUE,
            font.size='tiny',
            column.sep.width='0pt',
            digits = 6,
            digit.separator="")
stargazer(reg1, reg2,
            title='Full Regression Results',
            no.space=TRUE,
            font.size='tiny',
            column.sep.width='0pt',
            digits = 6,
            digit.separator="")
############################################################
############################################################
############################################################
summary(final)
# B(pop) = 0.008105 - mean = $67.27
      final %>% filter(exp_per_pop==0)
      #min = $0 (by population) = Arizona = $0 (by enrollment)
      final %>% filter(exp_per_pop==13.25)
      #min (!Arizona) = $13.25 (by population) = Wyoming = $327.30 (by enrollment)
      final %>% filter(exp_per_pop==40.20)
      #25 percentile = $40.20 (by population) = Alabama = $445.17 (by enrollment)
      final %>% filter(exp_per_pop==86.89)
      #75 percentile = $86.89 (by population) = Michigan = $705.99 (by enrollment)
      final %>% filter(exp_per_pop==217.22)
      #max = $217.22 (by population) = D.C. = $1,393.38 (by enrollment)
# B(enroll) = 0.001002 - mean = $730.30
      final %>% filter(exp_per_enroll==0)
      #min = $0 (by population) = Arizona = $0 (by population)
      final %>% filter(exp_per_enroll==314.44)
      #min (!Arizona) = $314.44 (by enrollment) = Florida = $24.00 (by population)
      a=final %>% filter(exp_per_enroll==532.61)
      #25 percentile = $532.61 (by enrollment) = Tennessee = $45.86 (by population)
      final %>% filter(exp_per_enroll==854.82)
      #75 percentile = $854.82 (by enrollment) = New Jersey = $64.38 (by population)
      final %>% filter(exp_per_enroll==1393.38)
      #max = $1,393.38 (by enrollment) = D.C. = $217.22 (by population)
b_pop=0.008105
b_enroll=0.001002
      ####(delta)Y(1) = (beta)*(delta)Medicaid for Hyde==1
      b_pop*(86.69-13.25) #75%-25%
            #(delta)Y = 0.60
      b_enroll*(854.82-532.61) #75%-25%
            #(delta)Y = 0.32
      b_pop*(217.22-13.25) # max-min
```

```
            #(delta)Y = 1.65
      b_enroll*(1393.38-314.44) # max-min
            #(delta)Y = 1.08
      ####(delta)Y(2) = (beta)*(delta)Hyde*(Medicaid) for a given bpl
      b_pop*(13.25) #min
            #(delta)Y = 0.11
      b_pop*(40.20) #25%
            #(delta)Y = 0.33
      b_pop*(86.89) #75%
            #(delta)Y = 0.70
      b_pop*(217.22) #max
            #(delta)Y = 1.76
      b_enroll*(314.44) #min
            #(delta)Y = 0.32
      b_enroll*(532.61) #25%
            #(delta)Y = 0.53
      b_enroll*(854.80) #75%
            #(delta)Y = 0.86
      b_enroll*(1393.38) #max
            #(delta)Y = 1.40

type1=c('Min','Min(!Arizona)','25th Percentile','75th Percentile','Max')
medicaid_by_pop1=c(0,13.25,40.20,86.89,217.22)
state1=c('Arizona','Wyoming','Alabama','Michigan','D.C.')
medicaid_by_enroll1=c(0,327.30,445.17,705.99,1393.38)

type2=c('Min','Min(!Arizona)','25th Percentile','75th Percentile','Max')
medicaid_by_enroll2=c(0,314.44,532.61,854.82,1393.38)
state2=c('Arizona','Florida','Tennessee','New Jersey','D.C.')
medicaid_by_pop2=c(0,24.00,45.86,64.38,217.22)

medicaid_data_pop = data.frame(type1, medicaid_by_pop1, state1, medicaid_by_enroll1, stringsAsFactors=
    FALSE)
medicaid_data_enroll = data.frame(type2, medicaid_by_enroll2, state2, medicaid_by_pop2,
    stringsAsFactors=FALSE)
      xtable(medicaid_data_pop)
      xtable(medicaid_data_enroll)



#################################################################
#################################################################
#################################################################
# summary(reg1)
# coefficients(reg1)
# confint(reg1, level=0.95)
# fitted(reg1)
# residuals(reg1)
# anova(reg1)
# vcov(reg1)
# influence(reg1)

#REGULAR - stargazer(linear.1, linear.2, probit.model, title="Regression Results",
#align=TRUE, dep.var.labels=c("Overall Rating","High Rating"),
#covariate.labels=c("Handling of Complaints","No Special Privileges",
#                    "Opportunity to Learn","Performance-Based Raises","Too Critical","Advancement"),
#omit.stat=c("LL","ser","f"), no.space=TRUE)
#CONFIDENCE INTERVALS - stargazer(linear.1, linear.2, title="Regression Results",
#dep.var.labels=c("Overall Rating","High Rating"),
#covariate.labels=c("Handling of Complaints","No Special Privileges",
#                    "Opportunity to Learn","Performance-Based Raises","Too Critical","Advancement"),
#omit.stat=c("LL","ser","f"), ci=TRUE, ci.level=0.90, single.row=TRUE)


##################################
rm(list=ls())
```

```
################################
```